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The impact of industrial competitiveness on carbon emission intensity: evidence From improved EKC model

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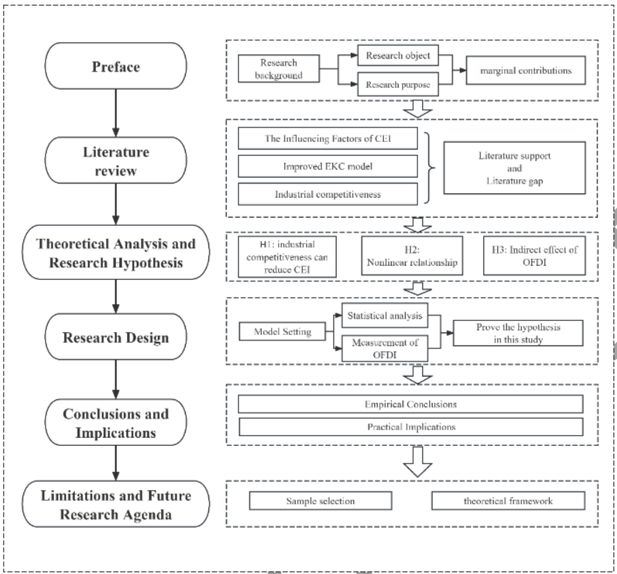
Graphical abstract



Abstract

Industrial sector is regarded as the main source of carbon dioxide emission, and prior studies have mostly examined the effects of carbon reduction policies on the competitiveness of industries. However, whether and how industrial competitiveness affects carbon emission intensity (CEI) remains unclear. We improve the traditional Environmental Kuznets Curve (EKC) and introduce industrial life cycle characteristics into the model. Additionally, we empirically investigate the impact mechanism of industrial competitiveness on CEI based on the panel data of 30 provinces in China from 2008 to 2019. The results show that: (1) Improving industrial competitiveness can significantly reduce CEI, in which outward foreign direct investment (OFDI) has a partial mediating role. (2) regional heterogeneities exist in the carbon mitigating effect of the industrial competitiveness, as it is larger and significant in the Northeast and West, but it is not significant in the East and Central. (3) The demarcation point between the investment-driven stage and the innovation-driven stage is -0.6993, and the demarcation point between the innovation-driven stage and the wealth-driven stage is -0.2776. (4) The carbon reduction effect of the industrial competitiveness is larger and significant in the investment-driven stage and the innovation-driven stage, but it is not significant in the wealth-driven stage. Accordingly, for countries in the world, improving industrial competitiveness and then realizing industrial upgrading is an effective way to reduce carbon emission intensity.

Keywords: industrial competitiveness; carbon emission intensity; outward foreign direct investment (OFDI);

Reducing carbon emission intensity (CEI) has emerged as a crucial approach to foster the sustainable and high-quality growth of China's economy, and accomplish the objective of "double carbon", which means the carbon emission will peak by 2030 and become carbon emission neutral by 2060. Since the Reform and Opening Up, China's long-term and rapid economic development has been brought, which is widely recognized as the "Chinese miracle". However, the economic mode has been overly dependent on factor investment and energy consumption during this past period, inevitably, it has resulted in some problems such as environmental degradation and carbon emission exacerbating. Nowadays, China is faced with a dual challenge that industrial mode is urgently needed transformed, and energy saving and carbon reduction is heavily loaded, and all sectors from societies attach great importance to such problems and consider methods to mitigate carbon emissions intensity and transform the industrial modes. Moreover, some official actions and relevant measures have been started first, China' government sector has incorporated carbon intensity into the management framework of macroeconomic policy objectives. In the "14th Five-Year Plan", China has set the

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goal of an 18% reduction in carbon intensity. And at the Climate Ambition Summit, president Xi has proposed that China's CEI would decline by almost 65% by 2030, in comparison to the levels recorded in 2005.

Industry is the key sector for energy saving and emission reduction (Feng *et al.* 2018). In 2020, China's energy consumption from industrial sector accounted for more than 65% of the country's total energy consumption. Industrial carbon reduction is the key path to achieve the target of carbon dioxide peaking in 2030, so the reduction of industrial CEI need be given top priority. According to the "2020 Annual Report on the Progress of the Global Carbon Market", the time required for industries to achieve carbon neutrality is ranked as follows: electricity < transportation < construction < industry, which shows that achieving industrial carbon neutrality is a process of long-term strategic deployment.

Industrial competitiveness is the combined capacity of industry to compete for factor inputs and achieve economic efficiency. Industrial competitiveness can help improve the efficiency of carbon reduction, so it is necessary to clarify the impact of industrial competitiveness on the carbon intensity. However, existing literature does not provide an in-depth discussion and answer. According to the model of "Diamond Theory" of Michael E. Porter, industrial competitiveness is formed by four main factors: factors of production, circumstances of necessity, and industries that are associated and provide assistance, corporate strategy and corporate structure and peer competition, as well as two auxiliary factors: government behaviors and opportunities. The interaction between these factors has a certain comprehensive effect on the magnitude of carbon emissions.

The impact of industrial competitiveness on carbon intensity can be described by the extended Environmental Kuznets Curve (EKC), and the curve can correspond to the four stages of an industry's life cycle. Considering the nonlinear relationship between industrial competitiveness and the carbon intensity, we further develop the model of double-threshold regression to explore the demarcation point between the stages. We construct an evaluation indicator system of comprehensive industrial competitiveness, including scale competitiveness, performance competitiveness, innovation competitiveness and ecological competitiveness, and adopts the factor analysis method to measure the industrial competitiveness index. China has committed to the world to reach the point of maximum carbon emissions by 2030 and completely eliminate carbon emissions by 2060. This study aims to enhance the effectiveness of China's carbon reduction efforts and effectively accomplish the "double carbon" objective. To do this, the research focuses on analyzing panel data from 30 provinces in China between 2008 and 2019. The research methodology used in this article is shown in **Figure 1**.

The main research question of this paper is the impact of industrial competitiveness on CEI, and the main marginal contributions are as follows:(1) This paper extends the application of the Environmental Kuznets Curve (EKC) and confirms the significant contribution of industrial competitiveness to the reduction of CEI. (2) We find that industrial competitiveness reduces CEI through foreign direct investment. (3) We calculated the demarcation points of different stages of the Environmental Kuznets Curve (EKC). Based on these cut-off points, we can accurately grasp the stage of industrial development corresponding to each region in China, so that we can adopt targeted policies to improve the efficiency of carbon emission reduction and help China realize the "double carbon" goal. Other countries can also follow the research paradigm provided in this paper to dynamically grasp the corresponding stage of industrial development in their regions, adopt correct low-carbon development strategies, and improve the efficiency of global emission reduction.

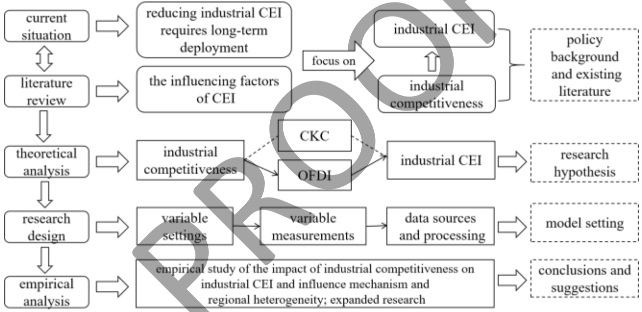

Figure 1 Flowchart of the research process

1. Literature review

1.1. Research status of literature

Regarding the influencing factors of CEI, national scholar and foreign scholar have conducted a lot of research, as shown in Table 1. Studies have shown that economic growth is the main factor influencing the reduction of CEI (Zhang *et al.* 2014; Pan *et al.* 2019). Economic agglomeration can promote CEI (Yan *et al.* 2022), but digital economy can significantly reduce CEI (Chen, 2022). From the perspective of production factors, Zhang *et al.* (2020) using the panel data from prefecture-level cities in China, and Cheng *et al.* (2018) using panel data from 30 provinces in China over the years 1999 to 2015, they all found that technological progress plays an important role in reducing CEI. Chishti *et al.* (2023) found that positive shocks to human capital have a favorable impact on the efficiency of sustainable development. Li et al (2024) found that female executives would contribute to the reduction of energy consumption per unit of output of the firm through green innovation. Wang *et al.* (2020) found that improving management level and reducing industrial intermediate input can significantly reduce CEI. In addition, Liang *et al.* (2019) found that innovation indicators such as the number of patent authorizations and foreign direct investment have a significant negative impact on CEI. Liu *et al.* (2022) used the data of 30 provinces in China from 2000 to 2019, they found that green innovation inhibits CEI. Zaman *et al.* (2023) demonstrated that green technology is a key determinant of green economic growth by studying the G7. And Li *et al.* (2022) found that the application of industrial robots promotes carbon intensity reduction. From the perspective of related and supporting industries, promoting financial development and the increase of financial geographic density will be accompanied by the marginal decreasing trend of CEI (Wang & Zheng, 2021; Yan *et al.* 2022). From the perspective of corporate strategy, Ali *et al.* (2022) found that the consumption of renewable energy and non-renewable energy have a positive influence of 0.27% and 0.75% on CEI. In addition, adopting carbon reduction technologies, reducing energy intensity (Zhang *et al.* 2016; Yan *et al.* 2018; Jiang, 2016), adopting alternative energy (Vujović *et al.* 2018), improving the energy structure (Dong *et al.* 2016), establishing an inter-regional cooperation mechanism on carbon reduction, expanding foreign trade (Wang & Zheng, 2021), improving energy efficiency (Cheng *et al.* 2013; Ren *et al.* 2022) and participating in global value chains (Liu & Zhao, 2021) are all effective ways to inhibit CEI. From a corporate structure standpoint, distortions in the industrial structure would not only result in a rise in local CEI (Corporate Environmental Impact), but also generate reverse spillover effects to neighboring regions (You *et al.* 2022). The modernization of the industrial infrastructure has a substantial impact on the lowering of carbon emissions intensity (CEI).(Wang & Zheng, 2021), and the spillover effect of the industry structure is significant (Song *et al.* 2020). From the perspective of government behavior, the increase in urbanization rate and population density has a positive effect on CEI (Dong *et al.* 2016; Xu *et al.* 2022). Apart from this, new urbanization construction (Han *et al.* 2019), digital city construction (Yang *et al.* 2022), smart city construction (Liu *et al.* 2022), carbon tax policy (Liu *et al.* 2021; Fu *et al.* 2021), carbon trading system (Tang *et al.* 2021; Xuan *et al.* 2020; Yu & Luo, 2022), environmental regulation (Zhang *et al.* 2022), and the regional cooperation strategy of energy conservation and emissions reduction (Cheng *et al.* 2013) are all conducive to reducing CEI.

Some scholars have studied regional heterogeneity, dynamic evolution and influencing factors of the CEI of agriculture (Pang *et al.* 2020; Cui *et al.* 2022; Zang *et al.* 2022), traffic department (Huang *et al.* 2022; Liu *et al.* 2021; Chen *et al.* 2022), business (Nag & Parikh, 2000). In addition, Azam *et al.* (2021) have compared the relative performance of the industrial, service, and agricultural sectors in reducing carbon, and they found that the economic efficiency and energy efficiency of the industrial sector are above the average. But there is a paucity of literature that limits carbon intensity to the industrial sector and examines the factors that influence it. Chen *et al.* (2018) found that the agglomeration of industrial enterprises is conducive to reducing industrial CEI. Yu *et al.* (2018) based panel data from 1995 to 2015 and found that there is β conditional convergence of CEI convergence of 24 industrial sectors in China will be influenced by factors such as capital intensity and per-capita value addition. Zeng *et al.* (2022) found that the number of R&D personnel and the dependence of foreign trade have a significant negative effect on industrial CEI, while urban population density has a positive effect on industrial CEI. Fang *et al.* (2022) found that digitalization significantly reduces the CEI of manufacturing industry.

1.2. Summary of literature

In summary, research on the influencing factors of CEI is relatively extensive. There are analyses from different perspectives, including economic considerations, production factors, linked and supporting industries, business strategy, and corporate structure are all important components to consider, and government behavior. Existing literature has neglected the two factors of demand conditions and opportunities, which are difficult to be measured by separate indicators. But the above factors have two-way effect on each other, forming a diamond system of industrial competitiveness. And the existing literature ignores the role of OFDI in the benchmark regression. In addition, in order to better explain the conclusions of this work, we extend the original EKC model.

Table 1 Literature Analysis on Factors Affecting CEI

The Influencing Factors of CEI	Economic Factors	economic growth, economic agglomeration, digital economy, circular economy
	Production Factors	technological progress, human capital, management level, industrial intermediate input, patent authorizations, foreign direct investment, green investment, green innovation, green technology, the application of industrial robots,
	Related and Supporting Industries	financial development and financial geographic density
	Enterprise Strategy, Corporate Structure, Peer Competition	renewable energy, carbon reduction technologies, energy intensity, alternative energy, energy structure, an inter-regional cooperation mechanism on carbon reduction, foreign trade, energy efficiency, global value chains; industrial structure
	Government Behavior	urbanization rate, population density, new urbanization construction, digital city construction, smart city construction, carbon tax policy, carbon trading system, environmental regulation, the regional cooperation strategy

Given this, study analyzes the correlation between industrial competitiveness and industrial CEI from a holistic standpoint. We take the panel data of 30 provinces in China as the research object to empirically study the impact of industrial competitiveness on industrial CEI, demonstrating the effect of industrial competitiveness on industrial CEI, extending the EKC model, and analyzing the profile effects of the OFDI. At last, We provide policy recommendations for the reduction of industrial CEI from the perspective of upgrading regional competitiveness.

2. Theoretical analysis and research hypothesis

2.1. Industrial Competitiveness and CEI

According to the Environmental Kuznets Curve (EKC), the environment deteriorates with economic growth during the early phase of economic development, there is a positive correlation between economic growth and environmental improvement, after a certain stage of development. By defining environmental upgrading as a reduction in carbon intensity (Tian *et al.* 2020), the carbon intensity also shows an inverted U-shaped EKC curve. Since technological progress is generally a gradual process that evolves over time, the inverted U-shaped curve is determined by four stages S1, S2, S3, and S4, as shown in **Figure 2** below. Since economic growth is also a function of time, the two inverted U-shaped curves are not only applicable to the time scale but also to the economic scale.

More than 84% of energy consumption and carbon emissions come from the industrial sector (Yang, 2015). During the first phase of industrialization, the expansion of scale requires the consumption of great amount of energy to enhance competitiveness, and there exists a direct relationship between economic competitiveness and carbon emissions. In the later stage of industrial development, improving industrial competitiveness depends mainly on technological progress, and energy-intensive industries represented by coal are at risk of asset stranding, resulting in a decline in carbon emissions. That is, there is a negative link exists between industrial competitiveness and carbon emissions. Industrial competitiveness and total industrial carbon emissions show an inverted "U" curve.

Industrial CEI is determined by both industrial carbon emissions and industrial economic growth. In the early stage of industrial development, both economic growth and technological progress contribute to carbon emissions. But industrial competitiveness have been driven more by the progress of carbon-intensive technology, carbon intensity has risen. In the late stage of industrial development, with the upgrading of industrial competitiveness through technological progress, industrial carbon emission decreases and the industrial economy grows, carbon intensity decreases. In the middle stage of industrial development, the high demand for energy and the consumption structure of coal-dominated energy lead to high industrial growth at the cost of high energy consumption and emissions. Accompanied by rising industrial competitiveness, industrial carbon emissions and the industrial economy are rising. However, the impact of inhibitory factors on reducing carbon emissions is less significant compared to the impact of economic expansion on increasing emissions (Zhang & Da, 2015), that is the CEI decreases. The calculated results of industrial CEI from 1997 to 2019 also show that the CEI of each region has a decreasing trend, with different degrees of upward fluctuations in 2003 and 2008.This dynamic character is consistent with the energy conservation and and industrial restructuring policies of the Chinese government since the new century. Overall, industrial competitiveness and industrial CEI show an inverted "U" curve.

The traditional EKC model is only applicable to economic development and carbon emission levels. Therefore, based on the above analysis, this study extends the inverted "U" curve law of total industrial carbon emission and industrial CEI to the industrial competitiveness scale, forming an improved EKC model. Compared with the traditional EKC model, the improved EKC model is no longer limited to the changes in carbon emissions intensity over time and economic development, but portrays the changes in carbon emissions intensity with the development of industrial competitiveness. The improved EKC model is able to visualize the inherent complex relationship between CEI and time evolution, economic growth, technological progress, and energy consumption with curve diagrams. In the stage of S1, the growth of industrial CEI is mainly driven by the progress of carbon-intensive technology. In the stage of S2, technological progress can mitigate the growth rate of industrial CEI to a certain extent, but economic growth plays a leading role in reducing industrial CEI. In the stage S3 and S4, industrial CEI is mainly driven by technological progress in carbon emission reduction. Combined with Porter's "four-stage theory" of industrial competitiveness development based on industrial life cycle theory, S1, S2, S3, and S4 are correspond to the factor-driven stage, investment-driven stage, innovation-driven stage and wealth-driven stage in this study. Due to the limitation of data resources in China, the industrial competitiveness and industrial CEI discussed below are in the stage of S2, S3 and S4. Industrial CEI decreases with economic growth and technological progress. Therefore, this paper proposes:

Hypothesis H1: The upgrading of industrial competitiveness can reduce CEI.

Hypothesis H2: The influence of industrial competitiveness on CEI is nonlinear

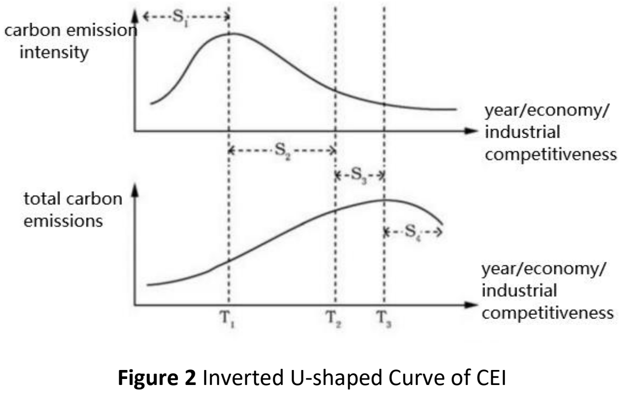

Figure 2 Inverted U-shaped Curve of CEI

2.2. Industrial competitiveness, OFDI and CEI

International industrial transfer is mainly the transfer of production, sales and even research and development of part of an industry from one economy to another by means of cross-economy direct investment, resulting in the migration of the spatial distribution of the industry. According to the theory of comparative advantage and marginal industry expansion, sunset industries and marginal industries that already at a comparative disadvantage in its own country should be selected for outward foreign direct investment (OFDI), so as to promote the industrial transfer of the investing country, develop overseas markets and maximize profits.

The gradient transfer theory points out that the degree of economic development of different countries and regions varies, and industries will be transferred from the high-gradient countries to low-gradient countries. China's industry is transforming into an innovative and technology-intensive industry, labor-intensive and resource-intensive industries that have lost their comparative advantage will be transferred overseas through OFDI. As the demand for raw materials for China's economic development increases sharply and the costs of domestic production rise rapidly, the development of China's resource-dependent industries is limited by the supply of factors of production. In order to break through the bottleneck of resource constraints, the chain of resource extraction and processing is transferred to the developing countries with mineral resources and energy. Relying on the rich mineral resources and relatively low factor prices in host countries, industrial enterprises with excessive energy use and significant emissions of pollutants and relatively weak capacity of technological innovation have gradually shifted to overseas, and it can guarantee the supply of China's natural resources and reduce the operating costs. For example, the mining industry has the dual non-green characteristics of limited internal energy conservation and external destruction of resource and environment, and it is a typical "marginal industry" in China's outward FDI.

Table 2. Evaluation Index of Industrial Competitiveness

Total index	**First-level Indicators**	**Second-level Indicators**	**Calculation formula**	**Symbols**
Competitiveness of Industrial Enterprises above Scale	Scale Competitiveness	number of industrial enterprises (units)	——	X_1
		employment of industrial enterprises (ten thousand people)	——	X_2
		industrial added value(billion yuan)	——	X_3
		industrial sales output value (billion yuan)	——	X_4
		total fixed assets(billion yuan)	——	X_5
		total utilization of foreign capital (billion yuan)	foreign capital	X_6
		current assets turnover (billion yuan)	——	X_7
	Performance Competitiveness	total profit (billion yuan)	——	X_8
		revenue from main business (billion yuan)	——	X_9
		total assets contribution rate (%)	(total profit + total tax + interest payments) / average total assets	X_{10}
		cost profit rate (%)	total profit / total cost	X_{11}
		total labor productivity (billion yuan / ten thousand people)	industrial added value/average of all employees	X_{12}
		asset-liability ratio (%)	liabilities/assets	X_{13}
	Innovation Competitiveness	R&D investment intensity (%)	R&D funding / main business income	X_{14}
		percentage of R&D personnel (%)	number of R&D personnel/number of industrial employees	X_{15}
		R&D cost (%)	new product development funds /main business income	X_{16}
		patent approval rate (%)	number of valid invention patents/patent applications	X_{17}
		number of new product projects (items)	——	X_{18}
		export proportion of new product (%)	new product export sales income / new product sales revenue	X_{19}
	Ecological Competitiveness	investment in waste water treatment (ten thousand yuan)	industrial waste water treatment projects completed investment	X_{20}
		investment in waste gas treatment (ten thousand yuan)	industrial waste gas treatment projects completed investment	X_{21}
		total investment in solid waste treatment (ten thousand yuan)	industrial solid waste treatment projects completed investment	X_{22}

Note: indicates that the second-level indicators are not required to calculate the formula, and can be obtained directly

The behavior of industrial transfer above will have a significant effect on China's environment. Through the external expansion of industries, the overall resource consumption of domestic industries can be improved, thereby improving the quality of the environment. OFDI has brought green spillovers to China and improved air pollution (Zhou *et al.* 2019; Zhou & Li, 2021). OFDI improves China's total factor energy efficiency and reduces carbon emissions (He *et al.* 2023). Besides, increasing OFDI has a catalytic effect on China's economy, improves total factor economic efficiency (Pan *et al.* 2022) and promotes the growth of total factor productivity (Pan *et al.* 2020). OFDI reduces China's carbon emissions while bringing about economic growth, thereby reducing carbon intensity. In addition, the greater the industrial competitiveness of a region, the greater its capacity for OFDI. Accordingly, this paper proposes:

Hypothesis H3: Industrial competitiveness affects CEI through OFDI.

3. Research design

3.1. Model setting

To test the relationship between industrial competitiveness and CEI, the model of linear regression equation (1) and the model of double panel threshold regression equation (2) are developed:

$$\text{carbon}_{it} = \alpha_0 + \alpha_1 \text{compet}_{it} + \gamma \text{controls}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

$$\begin{aligned} \text{carbon}_{it} = {} & \beta_1 \text{compet}_{it} I\left(q_{it} < \gamma_1\right) + \beta_2 \text{compet}_{it} I\left(\gamma_2 > q_{it} \geq \gamma_1\right) \\ & + \beta_3 \text{compet}_{it} I\left(q_{it} \geq \gamma_2\right) + \delta \text{controls}_{it} + \mu_i + \varepsilon_{it} \end{aligned} \tag{2}$$

Among them: carbon_{it} is the CEI, compet_{it} is the industrial competitiveness, controls are a set of control variables. $I(\cdot)$ is an indicator function, when the conditions in parentheses are satisfied, the value is 1, otherwise 0. q_{it} is the threshold variable of industrial competitiveness, γ_1 and γ_2 is the threshold value to be estimated. μ_i represents the individual fixed effect, λ_t represents the time-fixed effect, and ε_{it} represents the random disturbance.

To test the mechanism of industrial competitiveness affecting CEI, the mediation model of "chain reaction" is constructed on the basis of equation (1). Equation (3) takes OFDI as the explained variable used to assess the immediate impact of industrial competitiveness on outward foreign direct investment (OFDI).. Equation (4) is a model that introduces OFDI into the baseline model.

$$\text{OFDI}_{it} = \beta_0 + \beta_1 \text{compet}_{it} + \tau \text{controls}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

$$\text{carbon}_{it} = \rho_0 + \rho_1 \text{compet}_{it} + \rho_2 \text{OFDI}_{it} + \xi \text{controls}_{it} + \mu_i + \lambda_t \tag{4}$$

3.2. Variable settings and measurements

3.2.1. Measurement of industrial competitiveness

Drawing on the research of He and Zhang (2018), we constructs an evaluation indicator system of comprehensive industrial competitiveness, including scale competitiveness, performance competitiveness, innovation competitiveness and ecological competitiveness. Under the framework of the first-level indicators, the specific indicators should not only reflect the characteristics of the first-level indicators, but also the data availability of second-level indicators is considered. The precise indicators are shown in Table 2 below:

After establishing the evaluation index system of industrial competitiveness, it is necessary to assign weights to each indicator scientifically. Although the large number of indicators can help us measure regional industrial competitiveness more accurately, it increases the complexity of statistical processing. Especially the correlation covariance among indicators, which carries a lot of repetitive information and is not conducive to measurement. In order to compress the indicators and minimize the information loss, the factor analysis method of panel data in multivariate statistics is used to extract common factors from the variable group, thus reducing the number of variables to achieve the purpose of dimension reduction.

The original data is standardized to eliminate the differences in magnitudes and dimensions between variables, and then KMO and Bartlett Sphericity tests are performed to determine whether the indicators are appropriate for doing factor analysis. The findings are shown in Table 3. The KMO score of 0.883 suggests that factor analysis is appropriate to be performed. Bartlett is to test whether the data come from the population subjected to a multivariate normal distribution. The sig value is 0.000<0.05, which indicates that the data come from the population subjected to a multivariate normal distribution, and there are common factors among the indicators, which is suitable for further analysis.

Table 3. KMO and Bartlett Tests

KMO Sampling Suitability Quantity		0.883
Bartlett Sphericity Test	Approximate Chi-square	3752.562
	df	231
	sig.	0.000***

Table 4. Interpretation of the Total Variance

Component	Initial Eigenvalue			Extraction of the Square Sum of Loads		
	Total	Variance Proportion	Cumulative %	Total	Variance Proportion	Cumulative %
1	9.756	44.347	44.347	944.753	42.943	42.943
2	3.167	14.394	58.741	282.490	12.840	55.784
3	2.020	9.180	67.920	235.987	10.727	66.510
4	1.757	7.985	75.905	206.685	9.395	75.905

According to the correlation coefficient matrix of the variables is used to pick the principal component approach for extracting the key components. From the variance of the principal factors (table omitted), it can be seen that the common degree of all the variables are above 60% and the majority of them are above 80%, which indicates that the retrieved common factors provide a robust explanatory capability for each variable and can represent the information to be conveyed by the first-level indicators more accurately.

Based on the principle of total variance explained and cumulative percentage of variance over 75%, four common factors are extracted in this paper (Table 4). Among them, the first common element has a variance contribution rate of 44.347%, the second common factor has a variance contribution rate of 14.394%, the third common factor has a variance contribution rate of 9.180%, and the fourth common factor has a variance contribution rate of 7.985%. The initial eigenvalue is greater than 1, which can represent the most of the information. They are the most important factors among the extracted common factors and are more important for the evaluation of industrial competitiveness.

According to the principle of 0.5, the interpretation of each indicator in the component matrix on various factors is not significant. To better explain the practical meaning of each factor, it is necessary to revolve the component matrix. And the variance maximization orthogonal rotation of the initial factor is selected. It can be seen from the rotated component matrix (table omitted) that the common factor F1 has a high load on X1, X2, X3, X4, X5, X6, X7, which mainly reflect the overall strength of the enterprise scale, internal and external capital turnover, so F1 is named the scale factor. The common factor F2 has a high load on X14, X15, X16, X17, X18, X19, and these indicators mainly reflect the innovation ability of enterprises, so F2 is named the innovation factor. The common factor F3 has a high load on X8, X9, X10, X11, X12, X13, which mainly reflect the business performance of enterprises, so F3 is named the performance factor. The common factor F4 has a high load on X20, X21, X22, which mainly reflect the external environmental governance of enterprises, so F4 is named the ecological factor.

The regression method is used to calculate the scores of each common factor, and then the scores are weighted and averaged with the variance contribution ratio of the eigenvalues of the rotated common factors as the weights, so as to calculate the comprehensive level of regional industrial competitiveness from 2008 to 2019. And the scores are calculated by the formula:

$$F = \frac{r_1}{r_1 + r_2 + \dots r_7} F_1 + \frac{r_2}{r_1 + r_2 + \dots r_7} F_2 + \dots + \frac{r_7}{r_1 + r_2 + \dots r_7} F_7 \quad (5)$$

The results of industrial competitiveness index in China's regions are as follows in Table 5. It can be seen that China's regional industrial competitiveness is uneven, with differences in competitive advantages. The provinces with stronger industrial competitiveness include Jiangsu, Shandong, Guangdong, Zhejiang, Henan, Shanghai and Fujian, and they are mainly concentrated in the eastern region. The provinces with weaker industrial competitiveness include Hainan, Ningxia, Qinghai, Guizhou, Guangxi, Gansu, Yunnan, Jilin, Chongqing and Xinjiang, and they are mainly concentrated in the western region. China's regional industrial competitiveness shows a trend of high in the East and low in the West, and a tendency for inter-provincial differences to continue to expand.

The results of measuring the industrial competitiveness index of each region in China are shown in Table A1 in the appendix. As can be seen from the table, China's regional industrial competitiveness is uneven, and there are differences in competitive advantages. Provinces with strong industrial competitiveness include Jiangsu, Shandong, Guangdong, Zhejiang, Henan, Shanghai and Fujian, and are mainly concentrated in the eastern region. Provinces with weaker industrial competitiveness include Hainan, Ningxia, Qinghai, Guizhou, Guangxi, Gansu, Yunnan, Jilin, Chongqing and Xinjiang, and are mainly concentrated in the western region. China's regional industrial competitiveness shows a trend of higher in the east and lower in the west, with inter-provincial differences continuing to widen.

3.2.2. Measurement of CEI

CEI refers to the carbon dioxide emissions produced for each unit of industrial GDP. It quantifies the connection between the economy and carbon emissions. If a nation's economy is experiencing growth while the carbon dioxide emissions produced per unit of added value are decreasing, it suggests that the country is adopting a low-carbon development approach. The carbon emissions per unit of GDP is a suitable metric for assessing national energy policy and the efficacy of carbon reduction efforts (Sun, 2005). Existing scholars generally combine the factors of carbon emission with the data of energy consumption to estimate CO_2 emissions (Zhang *et al.* 2016; Li *et al.* 2020). The CEADs team conducted a study where they analyzed 602 coal samples from 100 major coal mining regions in China. They discovered that the emission factors suggested by the IPCC are often overestimated compared to the real emission factors. Given that using energy statistics to estimate CO2 emissions has a series of potential problems, such as the limited inclusion of energy sources and rough calculations. The carbon emissions data in this study are obtained directly from CEADs, which contains multi-scale carbon emissions data on energy consumption in China and other developing economies, covering 47 economic sectors, and emissions from 17 fossil fuel combustion-related processes. Finally, The carbon emissions per unit of industrial added value are used to characterize the industrial CEI.

The results of carbon intensity measurements are consistent with those of existing studies. Carbon emission reduction in China's green, low-carbon and recycling economy presents inter-regional differences, and the spatial distribution presents obvious non-equilibrium characteristics with a trend of progressive evolution (Di *et al.* 2023). Provincial CEI has obvious spatial agglomeration characteristics (Wang & Zheng, 2021; Liang *et al.* 2019; Cheng *et al.* 2013), and although it decreases year by year, the interregional differences remain stable (Wang *et al.* 2019; Zhang & Fan, 2022), showing a trend of western strength and eastern weakness (Wang & Zheng, 2021).

3.2.3. Measurement of OFDI

OFDI has an indirect mechanism. Considering the high volatility of the flows of OFDI, and it prone to missing and omission. Apart from this, the residual value of the flows of OFDI in the previous period may continue to influence its green spillover effects. Therefore, we choose the stock of OFDI (non-financial) to measure the level of OFDI, which is converted into billions of yuan using the exchange rate between the US dollar and the RNB (annual average), and adjusted for GDP deflators (2008 as the base period) and logarithm treatment.

3.2.4. Measurement of Control Variables

(1)Energy price (EP): The price effect is controlled by using the fuel and power price index in the purchasing price index of industrial producers with the base period of 2008. In theory, the higher the price of energy is bound to bring about an increase in the production costs of industrial enterprises. To reduce the cost of energy use caused by the price rise, enterprises need to continuously increase research and development and enhance the level of equipment. Thus forcing industrial enterprises to make technological innovations in green production. The optimization of production and management processes has improved the efficiency of energy, with the continuous improvement of the level of technology to reduce the carbon emissions, reducing CEI.

Table 5. Results of Descriptive Statistics

Variable Type	Variable Symbol	Sample Size	Mean Value	Standard Deviation	Minimum	Maximum
Explained Variable	Carbon	360	0.055	0.040	0.009	0.196
Explanatory Variable	Compet	360	0.000	0.616	-1.081	1.742
Mediator Variable	OFDI	360	14.318	1.770	8.137	18.536
Control Variables	EP	360	4.631	0.102	4.224	4.924
	EE	360	7.541	3.020	0	11.600
	LIR	360	0.428	0.375	0.048	2.590
	GOV	360	0.253	0.112	0.100	0.758
	KNS	360	0.001	0.001	0.001	0.003

Table 6. Results of the Root Per Unit Test

Variables	LLC-test	IPS-test	ADF-Fisher-Chi-square	Conclusion
Carbon	-16.490*** (0.000)	-3.272*** (0.001)	102.398*** (0.001)	stationary
Compet	-8.333*** (0.000)	-6.174*** (0.000)	154.527*** (0.000)	stationary
OFDI	-10.987*** (0.000)	-4.2481*** (0.000)	105.330*** (0.000)	stationary
EP	-10.861*** (0.000)	-7.638*** (0.000)	392.757*** (0.000)	stationary
EE	-7.364*** (0.000)	-7.768*** (0.000)	286.597*** (0.000)	stationary
LIR	-14.939*** (0.000)	-2.493*** (0.006)	127.112*** (0.000)	stationary
GOV	-6.259*** (0.000)	-2.657*** (0.004)	111.701*** (0.000)	stationary
KNS	-4.906*** (0.000)	-2.548*** (0.000)	86.662** (0.014)	stationary

***Note**: *, * * and * * * represent the statistical significance of 10 %, 5 % and 1 % respectively; p values for each statistic are in parentheses*

(2) Energy endowment (EE): Raw coal production is used to control the effect of resource endowment. Regional resource endowment is an important factor affecting CEI (Zhao *et al.* 2011). The more energy-rich the region, the lower the cost of energy. The local industrial enterprises will have a kind of inertia, there is insufficient demand and impetus for transformation and upgrading and technological progress. And they are more inclined to use their comparative advantages to develop some industrial primary products with strong energy dependence and low added value. They gradually form a mode of high carbon emission development, which have an adverse impact on the reduction of regional CEI.

(3)The ratio of light and heavy industries (LIR): The ratio of the aggregate production value of light and heavy industries above the scale is used to control the structural effect. High-carbon industries mainly come from heavy industries, and the CEI of heavy industry is much larger (more than 10 times) than that of the light industry. Reducing the CEI (Carbon Emissions Intensity) is challenging in regions with a heavy industrial structure, high energy consumption, significant pollution, and a lengthy transformation and upgrading process. If the industrial structure of an area is characterized by a low level of heavy industries, minimal reliance on energy, minimal pollution, and a low CEI (Carbon Emissions Index).

(4)The degree of government intervention (GOV): The extent of government involvement is quantified by calculating the ratio of local government budgetary expenditures to GDP, which helps to regulate the impact of policies. When the market fails to effectively regulate the allocation of resource factors and their prices, the government steps in as a "visible hand" to intervene and regulate accordingly. This intervention helps improve the efficiency of resource allocation and stabilize the market for factor prices. It creates a favorable environment for enterprise development and has a positive impact on reducing the CEI. On the other hand, when the market runs smoothly and develops in a coordinated way, excessive government intervention will reduce the innovation vitality of industrial enterprises, which is not conducive to reducing CEI.

(5) Knowledge spillover effect (KNS): The proportion of the number of teachers in higher education to the number of laborers is chosen as the proxy variable to control the knowledge spillover effect. A region with strong industrial competitiveness will have a positive external effect on the industrial enterprises in the surrounding areas, which is manifested as the knowledge spillover effect. Regions that undertake the spillover effects can reduce CEI through technological imitation, learning, and communication.

3.3. Data sources and processing

The data in this study mostly originate from the China Industrial Statistical Yearbook, the China Science and Technology Statistical Yearbook, the Statistical Yearbooks of provinces, and the yearly statistics of industrial firms over a certain threshold available on the website of the National Bureau of Statistics. As the carbon emission data for the year 2019 has not been released yet, and there is a significant lack of relevant data for Tibet, this empirical analysis utilizes balanced panel data from 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) from 2008 to 2019. And the missing data of the indicators in individual years are supplemented by interpolation or replaced by zero according to the actual situation. In order to reduce the sample fluctuation, the non-ratio data are logarithmically processed, and all the time-value variables are converted to 2008 as the price benchmark. Table 5 displays the findings of descriptive statistics for the relevant variables. The findings of descriptive statistics reveal the discrepancy in CEI, industrial competitiveness and foreign direct investment in different regions of China is relatively large, which indicates that this study has certain practical significance.

4. Empirical snalysis

4.1. Stationarity test of panel data

Before conducting empirical analysis on the panel data, it is necessary to ensure the stability of the data to avoid the possible "pseudo regression" in the subsequent regression analysis. The three tests of LLC, IPS and ADF-Fisher are used in this study. The original hypothesis is the existence of unit root. When the test results accept the original hypothesis, it means that the panel data is not stable. On the contrary, it means that the panel data is stable. The results of the tests are shown in Table 6 below, and all of them show smoothness.

Table 7. Results of Benchmark Regression

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Compet	-0.023*** (-5.04)	-0.023*** (-5.02)	-0.023*** (-5.00)	-0.022*** (-4.76)	-0.019*** (-4.23)	-0.017*** (-4.02)
EP	——	-0.015 (-1.51)	-0.015 (-1.50)	-0.015 (-1.53)	-0.018* (-1.92)	-0.016* (-1.75)
EE	——	—	0.0001 (0.04)	0.0001 (0.15)	0.0002 (0.34)	0.0004 (0.71)
LIR	——	—	—	-0.010 (-1.51)	-0.012** (-1.99)	-0.008 (-1.28)
GOV	——	—	—	—	0.117*** (5.65)	0.107*** (5.35)
KNS	——	—	—	—	—	-0.026*** (-5.37)
_cons	0.066*** (38.48)	0.138*** (2.89)	0.138*** (2.88)	0.142*** (2.97)	0.138*** (3.02)	0.114** (2.60)
time-fixed effect	yes	yes	yes	yes	yes	yes
province-fixed effect	yes	yes	yes	yes	yes	yes
N	360	360	360	360	360	360
R^2	0.359	0.363	0.363	0.368	0.426	0.475

*Note: *, **, and *** represent the statistical significance of 10%, 5%, and 1% respectively; Z-statistic for each statistic are in parentheses, as below.*

4.2. Benchmark regression

Before estimating the panel linear regression, first of all, we should determine whether to choose the mixed-effect model, the choice between the random-effect model and the fixed-effect model is determined by the use of the F-test and the Hausman test. When the F-test yields a significant result, it indicates that the fixed-effect model is superior than the mixed-effect model. When the Hausman test passes the original hypothesis, the random-effects model is chosen, otherwise, the fixed-effects model is chosen. The results showed that the P-value of the F-test is 0.0000, it means that the fixed-effect model is selected. the F value of the Hausman-test is 28.18, and the accompanying probability is P=0.0002, it means that the original hypothesis is rejected and the fixed-effect model is selected. At the same time, in order to control the impact of time differences on the regression results, the time-fixed effect is added, and the two-way fixed effect model is used for regression analysis. As shown in Table 7, column (1) is the regression result without adding control variables, column (2)-(6) is the regression result with adding control variables one by one.

From column (6) of Table 8, it can be judged that the elasticity coefficient of industrial competitiveness is -0.0173, and it is significant at the 1% level. It indicates that enhancing industrial competitiveness can reduce CEI, and it verifies the hypothesis H1. It also indicates that the influence of China's industrial competitiveness on CEI has crossed the factor-driven stage of S1.

The regression findings of control variables reveal that the extent of government interference has a substantial and favorable effect on CEI, suggesting that China's market operation is hindered by government intervention, leading to a decline in the innovation capacity of industrial businesses and lead to the waste of resources and inefficiency, and adversely affect the reduction of CEI. The knowledge spillover effect has a significant negative impact on CEI. That's because the knowledge spillover process has imitative, communicative and incentive effects, they can effectively reduce the carbon intensity of industry in surrounding areas.

The regression results of the control variables show that the increase in energy prices has a negative impact on CEI.

The higher the energy price, the higher the cost of industrial production, enterprises have to improve production equipment, which forces enterprises to carry out green technological innovation and improve energy utilization efficiency, which in turn reduces CEI. The higher the energy endowment, the higher the CEI. The more energy-rich the region, the lower the cost of energy will be, and the demand and motivation for transformation and upgrading and technological progress of regional industrial enterprises will be insufficient. Moreover, these regions are more inclined to develop industrial primary products that are more energy-dependent and have low added value, which will have a negative impact on the reduction of regional CEI. The higher the ratio of light and heavy industries, the lower the CEI. If the industrial structure of a region favors light industry, then the energy dependence is small and the CEI is low. The degree of government intervention has a significant positive impact on CEI, indicating that when the market is running smoothly and the internal coordinated development, excessive government intervention will reduce the innovation vitality of industrial enterprises, which is not conducive to the reduction of CEI. Knowledge spillover effect has a significant negative impact on CEI. This is because the knowledge spillover process has imitation effect, exchange effect and incentive effect, which can effectively reduce the carbon intensity of industries in neighboring regions.

4.3. Robustness test

4.3.1. Substitution of core industrial competitiveness

In order to test the robustness of the linear model, the industrial competitiveness is re-measured by using the Stochastic Frontier Approach (SFA). We use the value added of industry as the output variable, and the total fixed assets and the number of employed person in industrial enterprises as the input variable. The results of the regression are shown in Table 8 column (1) below. We can see that the industrial competitiveness still has a significant negative impact on CEI, which indicates that the result is robust.

4.3.2. Shrinkage processing

In this paper, for the missing data in individual years, we use the method of interpolation to make up or replace them with zero, which may result in extreme values and outliers in the sample. In order to exclude this problem, the variables are subjected to 1% shrinking tails of upper and lower, and the results of regression are shown in column (2). There is no discernible alteration compared with the benchmark regression, which proves that the result is robust.

4.3.3. Exclusion of data samples from some years

Since China entered the post-industrial era around 2010, it may lead to a certain gap between the data before 2010 and the data in the latter decades, which may result in biased results. Therefore, the data for 2008 and 2009 are excluded, and the impact of industrial competitiveness on CEI is examined again. The results are shown in column (3), which still shows that the relationship between industrial competitiveness and CEI is robust.

4.3.4. Endogenous processing

In the econometric model above, there may be some endogenous problems. First, there may be "measurement error" in the industrial competitiveness of this paper. Second, industrial CEI is affected by many factors, and the number of control variables in this paper is limited, which may lead to the problem of missing variables. If the estimation method of general panel data is used, the results may be biased and inconsistent. In order to avoid the endogeneity problems caused by missing variables and model misspecification, the degree of topographic relief (RDLS) is selected as instrumental variable of industrial competitiveness for the endogeneity test based on the OLS regression. Topographic relief is a comprehensive characterization of the regional altitude and the degree of surface cutting. Based on the definition and calculation formula of topographic relief studied by Feng et al (2007), the data of digital elevation model (SRTM 90 m) is resampled into 1 km. And the model is applied to calculate the kilometer grid data set of land terrain relief in China. Topographic relief is used to reflect the complexity of the terrain in each region, and the larger the value of the topographic relief is, the steeper the terrain is, and the more difficult to construct infrastructure, which makes it difficult for industrial development. While the lower the value of topographic relief is, the flatter the terrain is, which makes it more suitable for industrial development. So topographic relief is related to the explanatory variables. Moreover, the degree of topographic relief is a natural factor, which is not directly related to other variables, that is, it has an "exclusivity constraint". In addition, considering that the degree of topographic relief is a constant variable that does not change over time, 2SLS regression is conducted by using the multiplication of the degree of topographic relief and the virtual variables for each year as an instrumental variable group.

Column (4) in Table 8 reports the regression result of instrumental variable. The impact of industrial competitiveness on CEI is still significantly negative, indicating that the conclusion is robust. Meanwhile, the F value in the first stage is 37.53 , and the Kleibergen-Paaprk LM statistic is 80.002, corresponding to the P value of 0.0000, indicating that there is no under-identification problem. The value of Cragg-Donald Wald F is 19.925, which is greater than the critical value of 11.52 and the empirical value of 10, indicating that there is no problem of weak instrumental variable. In summary, the instrumental variable selected in this paper is reasonable. The result of the 2SLS regression with instrumental variable show that there is still a significant negative impact of industrial competitiveness on CEI after considering endogeneity, which indicates that the regression result is robust.

4.3.5. Dynamic panel regression

To enhance the reliability of the result, this article further employs the dynamic panel model to assess the reliability of the benchmark regression., and we select the systematic GMM method for the regression. From the regression result of column (5) in Table 8, we can see that the p-value of AR (1) is less than 0.05 and the p-value of AR (2) test is greater than 0.1, indicating that there is no second-order autocorrelation in the difference of the disturbance term of the regression equation. While the P-value of the Hansen test is greater than 0.1, which indicates that the instrumental variable is valid. The results show that industrial competitiveness still has a significantly negative effect on CEI, which proves the robustness of the regression result again.

Table 8. Test of Robustness

Variable	(1) Replace the core explanatory variable	(2) Shrinkage processing	(3) Excluding 2008 and 2009 samples	(4) 2SLS regression	(5) Sys-GMM regression
carbon(-1)	——	——	——	——	0.893*** (12.46)
compet	-0.084*** (-8.48)	-0.019*** (-4.39)	-0.011*** (-2.79)	-0.013*** (-2.98)	-0.009** (-2.17)
EP	-0.013 (-1.53)	-0.014 (-1.43)	-0.023** (-2.52)	0.015 (1.23)	-0.021 (-1.43)
EE	0.0001 (0.03)	0.0004 (0.73)	0.001 (1.48)	0.004*** (8.99)	0.0007 (1.34)
LIR	-0.007 (-1.32)	-0.005 (-0.91)	-0.010* (-1.91)	0.030*** (6.32)	-0.0002 (-0.02)
GOV	0.102*** (5.56)	0.110*** (5.38)	0.185*** (8.51)	0.107*** (4.66)	-0.015 (-0.83)
KNS	-0.033*** (-7.31)	-0.026*** (-5.31)	-0.033*** (-5.93)	-0.007*** (-7.41)	-0.009 (-1.37)
_cons	0.115*** (2.83)	0.101** (2.19)	0.116*** (2.62)	-0.089 (-1.48)	0.069 (1.07)
F	131.170***	111.330***	136.420***	——	——
Hausman	29.200***	28.010***	22.770***	——	——
Hansen test P-value	——	——	——	——	1.000
AR(1) test p-value	——	——	——	——	0.018
AR(2) test P-value	——	——	——	——	0.809
time-fixed effect	yes	yes	yes	——	——
province-fixed effect	yes	yes	yes	——	——
N	360	360	300	360	330
R^2	0.551	0.477	0.463	0.517	——

Table 9. Results of the Threshold Effect Test

Explanatory variable	Threshold variable	Number of thresholds	Threshold value	Confidence interval	Fstat	Prob	crit10	crit5	crit1	bs times
compet	compet	Single	-0.280	(-0.278，-0.302)	20.500	0.063	17.529	22.109	29.639	300
		Double	-0.699	(-0.676，-0.823)	24.780	0.023	16.209	21.247	25.633	
			-0.278	(-0.276，-0.290)						
		Triple	——	——	14.080	0.440	26.991	31.793	48.917	

Table 10. Results of Benchmark Regression and Threshold Regression

Variable	Threshold model
compet($q_{it}<\gamma_1$)	-0.021*** (-3.52)
compet($\gamma_2>q_{it}\geq\gamma_1$)	-0.037*** (-6.83)
compet($q_{it}\geq\gamma_2$)	-0.006 (-1.18)
_cons	0.133*** (5.37)
time-fixed effect	——
province-fixed effect	——
N	360
R^2	0.450

4.4. Nonlinear analysis

Considering the nonlinear relationship between industrial competitiveness and the carbon intensity (**Figure 2**), we further develop the model of threshold regression equation (2) to explore the demarcation point between the stages.

Before conducting the threshold regression analysis, the threshold effect of the model and the number of possible thresholds should be tested. In this study, single-threshold and double-threshold and triple-threshold tests are conducted with industrial competitiveness as the threshold variable, and the results of the tests are shown in Table 9 below. The test results indicate that the value of the single-threshold F-statistic is 20.50, which exceeds the threshold value of 17.5288 at the 10% significance level. Therefore, the single-threshold test is considered significant at the 10% level and is deemed successful. The double-threshold

F-statistic has a value of 24.78, which exceeds the threshold value of 21.2468 at the 5% significance level. Therefore, the double-threshold test is considered significant at the 5% level and is deemed successful. Nevertheless, the triple-threshold F-statistic has a value of 14.08, which falls below the threshold value of 26.9906 at the 10% significance level. Therefore, the triple-threshold test does not pass. The double-threshold model is determined to be more significant than the single-threshold model. Therefore, this article opts to design the double-threshold model.

Table 11. Results of Impact Mechanism Test

variable	OFDI (1)	carbon (2)	OFDI (3)	carbon (4)
compet	0.490*** (2.60)	-0.016*** (-3.67)	7.535*** (3.66)	-0.003** (-2.48)
OFDI	——	-0.003** (-2.30)	——	-0.003** (-2.42)
control variables	yes	yes	yes	yes
_cons	9.577*** (4.97)	0.142*** (3.14)	5.041 (0.48)	0.001 (0.01)
F	42.460***	110.490***	——	——
Hausman	154.250***	19.080***	——	——
time-fixed effect	yes	yes	——	——
province-fixed effect	yes	yes	——	——
N	360	360	360	360
R^2	0.904	0.484	0.305	0.525

Table 12. Regional regression results

variable	Northeast	East	Central	West
	(1)	(2)	(3)	(4)
compet	-0.052*** (-3.82)	-0.002 (-0.54)	-0.007 (-0.70)	-0.020* (-1.71)
control variables	yes	yes	yes	yes
_cons	0.177 (0.98)	0.108*** (5.81)	0.068 (1.07)	0.258*** (3.44)
F	8.410***	27.590***	7.230***	69.790***
Hausman	11.130***	51.900***	24.430***	79.270***
time-fixed effect	yes	yes	yes	yes
province-fixed effect	yes	yes	yes	yes
N	36	120	72	132
R^2	0.668	0.427	0.575	0.432

The regression result with the double-threshold model is shown in Table 11 below. From Table 9 and Table 10, it can be seen that the value of the first threshold is -0.6993 and the value of the second threshold is -0.2776. When the industrial competitiveness in the region is lower than −0.6993, the coefficient before the industrial competitiveness is −0.0212. And it is significant at the 1% level, indicating that for every 1% increase in industrial competitiveness, CEI decreases by 0.0212%. When the industrial competitiveness is above -0.6993 and below -0.2776, the coefficient before the industrial competitiveness is −0.0370. And it is significant at the 1% level, indicating that for every 1% increase in industrial competitiveness, CEI decreases by 0.0370%. When the industrial competitiveness is above -0.2776, the coefficient before the industrial competitiveness is −0.0063, and it is not significant. It indicates that the demarcation point between the correlation coefficient between the investment-driven stage of S2 and the innovation-driven stage of S3 is -0.6993, while the demarcation point between the innovation-driven stage of S3 and the wealth-driven stage of S4 is -0.2776.

Comparing the coefficients before the industrial competitiveness at different stages, we find that the carbon reduction effect of the industrial competitiveness is larger and significant in the stage of S2 and S3, but it is not significant in the stage of S4. The conclusion is consistent with the theoretical analysis above. The deep shadow labeled in Table 1 in the appendix indicates that the industrial competitiveness is lower than -0.6993. Provinces in this range include HaiNan, GanSu, QingHai, and NingXia. We can find that these provinces in the stage of S2 are mainly concentrated in the West. The paler shadow labeled in Table 1 in the appendix indicates that the industrial competitiveness is above -0.2776. We can find that these provinces in the stage of S4 are mainly concentrated in the East and Central. The remaining provinces in Table 1 in the appendix indicates that the industrial competitiveness is above -0.6993 and below -0.2776, and these provinces in the stage of S3 are mainly concentrated in the North-East and West. As the the most of the provinces in the Northeast and West are in the stage of S2 and S3, the carbon reduction effect of industrial competitiveness is significant. The most of the provinces in the East and Central are in the stage of S4, the carbon reduction effect of industrial competitiveness is not significant. After grasping the stage of each region, it is possible to implement appropriate policies according to regional characteristics, thus improving the efficiency of China's carbon reduction. Demonstrated that the hypothesis H3.

4.5. Influence mechanism test

Table 11 reports the regression result of the mechanism test, column (1) is the regression result of model (3) and column (2) is the regression result of model (4). The coefficient before industrial competitiveness in column (1) is 0.4901, that is, for every 1% increase in industrial competitiveness, OFDI rises by 0.4901%, which indicates that upgrading industrial competitiveness can promote regional OFDI. The coefficient before the core explanatory variable and the mechanism variable in column (2) are both significantly negative, indicating that OFDI has a partial mediating effect in industrial competitiveness affecting carbon intensity, which verifies the hypothesis H3.

OFDI is an important channel for industrial upgrading. Industrial transfer helps to utilize foreign markets and resources to realize domestic industrial restructuring and upgrading. By transferring marginal industries that are already at a comparative disadvantage through OFDI, the region can concentrate on the development of advantaged and emerging industries, and this may have a certain reverse effect on local industrial competitiveness. In order to avoid the endogeneity problems, this paper conducts endogeneity test with instrumental variables. Column (3) is the endogeneity test result of model 3, and column (4) is the endogeneity test result of model 4, and the results show that the mediating effect of OFDI in the process of industrial competitiveness affecting CEI is robust.

4.6. Heterogeneity test

The results of regional regression are shown in Table 12 below, and the coefficients before industrial competitiveness are all negative, indicating that upgrading regional industrial competitiveness can reduce CEI. Comparing the coefficients before the industrial competitiveness in columns (1)-(4), it can be found that the carbon reduction effect of the industrial competitiveness is larger and significant in the Northeast and West, but it is not significant in the East and Central. Accordingly, China should pay more attention to improving the industrial competitiveness of the provinces in the Northeast and West to improve the efficiency of carbon reduction.

5. Conclusions and implications

5.1. Empirical conclusions

The theoretical analysis concludes that the impact of industrial competitiveness on CEI is characterized by the Environmental Kuznets Curve (EKC), and we correspond the curve to the four stages of the industrial life cycle. Considering the nonlinear relationship between industrial competitiveness and the carbon intensity, we further develop the double-threshold regression model to explore the demarcation point between the stages. We construct an evaluation indicator system of comprehensive industrial competitiveness, including scale competitiveness, performance competitiveness, innovation competitiveness and ecological competitiveness, and adopts the method of factor analysis to measure the industrial competitiveness index. The panel data of 30 provinces in China from 2008 to 2019 are selected to empirically study the impact of industrial competitiveness on CEI. The main findings of the study are as follows:

(1)Improving industrial competitiveness can significantly reduce CEI, and this conclusion remains robust after a series of tests, which means that China had crossed the factor-driven stage of S1.

(2)Outward foreign direct investment (OFDI) has a partial mediating role in the process of industrial competitiveness affects carbon intensity.

(3)The carbon reduction effect of the industrial competitiveness is larger and significant in the Northeast and West, but it is not significant in the East and Central.

(4)The demarcation point between the investment-driven stage of S2 and the innovation-driven stage of S3 is -0.6993, and the demarcation point between the innovation-driven stage of S3 and the wealth-driven stage of S4 is -0.2776. Provinces in this stage of S2 are mainly concentrated in the West, including Hainan, Gansu, Qinghai, and Ningxia. Provinces in this stage of S3 are mainly concentrated in the North-East and West, including Jilin, Chongqing, Guangxi, Guizhou, Yunnan, and Xinjiang. The remaining provinces are in this stage of S4, and they are mainly concentrated in the East and Central.

(5)The marginal effect of industrial competitiveness on CEI is −0.0212 in the stage of S2, the marginal effect is −0.0370 in the stage of S3, and the marginal effect is −0.0063 in the stage of S4. The carbon reduction effect of the industrial competitiveness is larger and significant in the stage of S2 and S3, but it is not significant in the stage of S4.

5.2. Practical implications

Based on the above research conclusions, in order to achieve the carbon peak as soon as possible and achieve the carbon neutrality more easily, this paper proposes the following suggestions:

First, enhancing regional industrial competitiveness. The government should increase factor inputs to industry in the Northeast and West, especially those provinces still in the investment-driven stage of S2. It is necessary to accelerate the elimination of low value-added products and backward production capacity to achieve structural adjustment. The Government should increase investment and encourage enterprises to introduce advanced equipment to improve the scale competitiveness and promote the industrial upgrading. For provinces in the innovation-driven stage of S3, it is necessary to promote enterprises to become the main body of technological innovation, and cultivate a number of large enterprise groups with R&D capabilities and the core technology in the market competition. Those enterprise need to develop independent and innovative skills to gradually build regional brands and expand market demand. At the same time, enterprises should emphasize the research and development of low-carbon technologies. Thus, the efficiency of carbon emission reduction in China can be improved.

Second, accelerating the transfer of industries abroad. China's factors of production are no longer sufficient to carry the development of resource-dependent industries. To get rid of its heavy dependence on indigenous resources and its enormous pressure on the environment, China should make full use of "the Belt and Road" policy to accelerate the transfer of industries to countries along the

Belt and Road. The main destinations for the transfer of China's industrial should be countries in Asia, Africa and Latin America, because these countries are able to accept the resource advantages in the process of industrial transfer. After the entry into force of the China-ASEAN Free Trade Agreement, China should further complement resources and share our advantages. At the same time, the local government should encourage the behavior of outward foreign direct investment (OFDI), and focus on the development of advantageous and emerging industries.

Third, promoting the development of industrial clustering. The government should make full use of the effect of knowledge spillover and focus on the geographical concentration and spatial planning of industries. China should develop a number of industrial clusters to form economies of scale and enhance the international competitiveness of industries, which can form a spatial linkage mechanism for carbon emission reduction and technological innovation. It can also build an information sharing network of energy-saving among enterprises to minimize the cost of carbon reduction for enterprises. While encouraging industrial enterprises to form low-carbon alliances to help them effectively reduce CEI.

6. Limitations and future research agenda

Despite the comprehensive study completed in both theory and practice, this work still has limits and inadequacies. Therefore, it is crucial to further delve into the inquiry. Firstly, there are concerns about the selection of samples and the ability to handle them. This study used panel data from 30 provinces in China spanning from 2008 to 2019. Future research endeavors might explore the possibility of investigating industrial businesses as the subject of investigation. Future research might focus on analyzing the impact of competition in various industrial sectors, such as construction, energy and heat supply, and service industries, in order to investigate the variations in impacts based on the unique features of each industry. Conclusions drawn in this article may be corroborated by using data from other nations as well. Simultaneously, it is possible to increase the quantity of samples and the duration in years. Furthermore, this research utilizes the concepts of comparative advantage and marginal industrial growth as the theoretical framework. It also examines the relationship between outward foreign direct investment (OFDI) and the internal mechanism of industrial competitiveness in terms of CEI. However, at various phases of industrial growth, the pathway via which industrial competitiveness impacts CEI may vary. This aspect requires further comprehensive investigation in future research. Ultimately, this work employs threshold regression as a research method, so compensating for the limitations of linear regression. In the future, we may further embrace more sophisticated research methodologies and juxtapose the outcomes of various data analysis approaches. We can comprehensively elucidate the underlying principles governing the outcomes and enhance the reliability and discourse around the study findings.

Data availability statement

The research includes the original contributions, which may be found in the article/supplementary material. If you have any more questions, please contact the corresponding author.

Conflict of interest

The authors affirm that the study was carried out without any commercial or financial connections that may be seen as a possible conflict of interest.

Appendix

Table A1. Data of Regional Industrial Competitiveness

region	Province\year	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	2009	2008
North-East	Liaoning	-0.075	-0.082	-0.164	-0.152	-0.061	0.070	0.155	0.071	0.131	0.239	0.192	0.047
	JiLin	-0.412	-0.521	-0.433	-0.431	-0.453	-0.376	-0.486	-0.222	-0.486	-0.373	-0.391	-0.446
	HeiLongJiang	-0.470	-0.510	-0.370	-0.336	-0.289	-0.260	-0.232	-0.119	0.040	-0.074	-0.069	0.243
East	Beijing	-0.356	-0.053	-0.271	-0.264	-0.159	-0.236	-0.259	-0.163	-0.276	-0.345	-0.103	-0.102
	TianJin	-0.091	0.152	-0.093	0.063	0.202	0.152	0.121	0.101	0.204	0.048	0.045	0.049
	HeBei	0.127	0.270	0.220	0.153	0.142	0.323	0.265	-0.147	-0.009	0.004	-0.121	-0.041
	Shanghai	0.087	0.403	0.338	0.262	0.242	0.231	0.147	0.266	0.259	0.262	0.387	0.280
	JiangSu	1.528	1.742	1.607	1.738	1.641	1.553	1.643	1.618	1.578	1.586	1.642	1.612
	ZheJiang	0.881	0.890	0.735	0.832	0.850	0.806	0.761	0.570	0.572	0.660	0.761	0.649
	FuJian	0.408	0.127	0.151	0.219	0.285	0.253	0.316	0.195	0.204	0.191	0.193	0.125
	Shandong	1.032	1.083	1.454	1.381	1.268	1.354	1.373	1.549	1.722	1.425	1.423	1.445
	Guangdong	1.574	1.730	1.393	1.369	1.485	1.304	1.330	1.511	1.387	1.723	1.495	1.348
	HaiNan	-0.703	-0.616	-0.773	-0.716	-0.647	-0.674	-0.676	-0.498	-0.664	-0.578	-0.584	-0.725
Central	Shanxi	-0.060	-0.399	-0.252	-0.366	-0.342	-0.441	-0.247	-0.315	-0.204	-0.275	-0.180	-0.097
	AnHui	0.041	0.087	0.041	0.073	0.009	-0.020	-0.023	-0.061	-0.120	-0.161	-0.136	-0.244
	Jiangxi	0.063	-0.063	-0.070	-0.136	-0.207	-0.127	-0.212	-0.251	-0.332	-0.266	-0.280	-0.251
	Henan	0.538	0.412	0.550	0.652	0.536	0.692	0.689	0.409	0.572	0.472	0.432	0.461
	HuNan	0.092	0.273	0.088	0.030	0.015	-0.004	0.069	0.102	0.063	0.012	-0.073	-0.060
	HuBei	0.026	0.132	0.030	0.043	0.008	0.006	-0.002	0.018	-0.034	0.087	0.149	0.055
West	Chongqing	-0.182	-0.083	-0.179	-0.215	-0.170	-0.278	-0.402	-0.497	-0.422	-0.402	-0.301	-0.314

Guangxi	-0.394	-0.612	-0.403	-0.427	-0.416	-0.427	-0.435	-0.450	-0.481	-0.417	-0.526	-0.559
Sichuan	0.046	0.030	0.024	-0.066	-0.072	-0.035	-0.086	-0.085	-0.166	-0.174	-0.093	-0.118
GuiZhou	-0.407	-0.508	-0.491	-0.504	-0.526	-0.493	-0.542	-0.508	-0.488	-0.649	-0.670	-0.611
YunNan	-0.379	-0.506	-0.446	-0.487	-0.452	-0.579	-0.540	-0.456	-0.550	-0.459	-0.508	-0.457
Shaanxi	-0.120	-0.030	-0.088	-0.156	-0.123	-0.091	-0.043	0.158	0.137	0.009	-0.060	-0.008
GanSu	-0.551	-0.739	-0.628	-0.569	-0.637	-0.571	-0.633	-0.592	-0.773	-0.664	-0.546	-0.530
NeiMengGu	-0.122	-0.320	-0.128	-0.190	-0.200	-0.262	-0.053	-0.121	0.065	-0.101	-0.236	-0.294
Qinghai	-1.081	-0.985	-0.722	-0.719	-0.749	-0.765	-0.842	-0.779	-0.823	-0.830	-0.822	-0.637
NingXia	-0.548	-0.650	-0.615	-0.525	-0.607	-0.649	-0.659	-0.824	-0.834	-0.750	-0.704	-0.699
XinJiang	-0.492	-0.654	-0.507	-0.557	-0.572	-0.456	-0.495	-0.480	-0.274	-0.202	-0.315	-0.120

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