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Original Paper

Study on the Spatial-temporal Evolution Characteristics and Trajectory of the Coupling Coordination Degree between Carbon Emission Intensity and High-quality Development of Energy-intensive Industries

Caijiang Zhang[1], Yu Zhou[1], & Zhangwen Li[1*]

[1] School of Economics and Finance, South China University of Technology, Guangzhou, China

[*] Zhangwen Li, Zhuhai-Tech Industrial Development Zone Nanping Science and Technology Industrial Park Management Committee, Zhuhai, China

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Abstract

This paper constructs the index of high-quality development of energy-intensive industries and calculates the coupling coordination degree between high-quality development and carbon emission intensity. In this study, the dynamic evolution process, regional inequality and convergence characteristics of the coupling coordination degree are investigated using kernel density estimation, Dagum Gini coefficient, and convergence analysis. The results show that (1) the full-sample coupling coordination degree fluctuates in medium levels, showing a two-stage inverted U-shaped trend. In addition, the highest coupling coordination degree occurred in the eastern region, followed by western provinces, and the lowest in the central regions. (2) Results of kernel density estimation showed a shift in coupling coordination degree from bipolar to unipolar; (3) the Dagum Gini coefficient shows that the general, inter-regional, and intra-regional variations all show an upward trend, suggesting a significant elevated polarization effect. Additionally, the primary determinants influencing the Dagum Gini coefficient reveal a pattern of "inter-regional variation - antagonism - hypervariable density." (4) absolute convergence exists in the overall sample and in the eastern region, while it is not significant in the central and western regions. Based on the aforementioned findings, this study proposes policy implications for different regions in China.

Keywords

energy-intensive industries, coupling coordination degree, high-quality development, carbon emissions intensity

1. Introduction

Since the beginning of China's reform and opening-up policy in 1978, the economy has been growing at a high speed for over forty years, but with extensive economic development and severe environmental pollution. The concept of high-quality economic development was put forward in the 19th CPC National Congress, marking the shift of China's economy from high-speed growth to high-quality development. The introduction of the *dual-carbon target* indicates that the goal of China's economic development has changed to high-quality development in parallel with a high level of protection.

In the 19th National Congress of the Communist Party of China, China's economy has shifted from the stage of high-speed growth to the stage of high-quality development, China's economy has gradually stepped into the stage of prioritizing the quality of economic development. President Xi pointed out that we should focus on synchronizing high-quality development and high-level protection, take the *dual carbon target* as the lead, and promote the gradual shift from dual control of energy consumption to dual control of carbon emissions. In the new development stage, digging deeper into the relationship between high-quality development and carbon emissions is an important hand to realize the dual strategic objectives of high-quality development and dual carbon. The 14th Five-Year Plan states that it will resolutely curb the blind development of high-energy-consumption and high-emission projects and promote green transformation to realize positive development. After entering the deep end of China's economic reform, how to realize the high energy-intensive industries to industry high-quality development and carbon emission intensity of the balance is the focus of the current work.

Carbon emission reduction in energy-intensive industries is essential for realizing China's dual carbon target (carbon peaking by 2030 and carbon neutrality by 2060). Energy-intensive industries consume large amounts of energy, which will boost energy costs. Furthermore, energy-intensive industries emit a large number of pollutants, such as the production and treatment of a large number of chemical substances in the chemical industry, in addition to the presence of wastewater, waste liquids, and toxic waste, which may bring about air, water, and soil pollution, which will aggravate the environmental pressures. The energy-intensive industries are responsible for one-third of global carbon emissions and two-thirds of carbon emissions in the EU (Bataille et al., 2018; Gerres et al., 2019). Nearly 67.9% of China's energy consumption and 83.1% of its carbon dioxide emissions are contributed by the industrial sector, which accounts for 40.1% of the GDP, while emissions from energy-intensive industries account for 80% of the total emissions from the industrial sector. In addition, emissions risk the health of the surrounding population (Jacobson et al., 2019).

In summary, the dual-carbon target for energy-intensive industries is time-critical, task-heavy, and challenging. To study the carbon reduction path of energy-intensive industries in the current situation where the energy intensity of society has been reduced, it is necessary first to judge the decoupling effect between the development status of the industry and its carbon emissions, which is not addressed by existing studies. This paper explores the dynamic evolution trajectory and characteristics of the high-quality development of energy-intensive industries by constructing the coupling coordination degree between the high-quality development of the industry and the industry's carbon emissions, which helps to provide a reference for the subsequent policy formulation.

Based on the above analysis, this paper takes energy-intensive industries as the research object, constructs high-quality development indicators for energy-intensive industries, and studies the decoupling effect between them and carbon emissions. The content of this paper is organized as follows: In the next section, this manuscript reviews the research on the relationship between high-quality development and carbon emission intensity. In section 3, we introduced the methodology, the variable selection, and the data sources. Then, in section 4, we construct a model of the coupling coordination degree and use kernel density estimation and Dagum Gini coefficient to study the spatiotemporal and dynamic evolution characteristics of the coupling coordination degree. In section 5, we study the convergence characteristics of the coupling coordination degree. In Section 6, we discuss the main conclusions of the article. Finally, the main conclusions of the paper are summarized, and policy recommendations are made accordingly.

2. Literature Review

High-quality development is a composite concept that embodies a new version of development in the new era of China's economic development, which is divided into innovative capacity, level of coordination, green and sustainable development, openness, and sharing. Since the proposal of the new development concept, a large amount of relevant research on high-quality development has emerged (Zhang E. & Fang, 2022). The existing literature on high-quality development focuses on the construction of the high-quality development index, mainly from the five aspects of innovation, coordination, green, openness, and sharing, while there are differences in the subdivision of secondary indicators (Pan et al., 2021). A small number of studies have been subdivided into the high-quality development of specific industries, such as tourism, construction, sports (Han et al., 2023; Wei & Li, 2018).

From the perspective of methods in constructing indicators of high-quality development, the existing literature has been conducted more often by constructing composite indicators using the principal component analysis (PCA) to measure a complex concept, such as Tao (2020) and Zhou et al. (2020). However, the principal component analysis method's disadvantage of losing the original variables' economic meaning has led to some criticism. At present, the weighting method and entropy weighting method are generally used to solve this problem. The weighting method tends to use exogenously weights, which is prone to subjective influence. Therefore, the entropy weight method with endogenized weights is considered a better evaluation method and has been widely used in recent years (Li Z. et al., 2022; Shen et al., 2022; Zhao et al., 2020).

Involving the relationship between carbon emission intensity and high-quality development, the relationship between economic growth and carbon emissions was initially verified in the existing literature, such as the study based on the environmental Kuznets curve (Yao et al., 2019; C. Zhang et al., 2023), which indicates that the inverted-U shaped relationship between carbon emissions and economic growth. In addition, some studies examine decoupling effects from the perspective of effect decomposition, which include decoupling studies of carbon emissions and economic growth based on the log mean Divisia index (LMDI) method (Lin & Tan, 2017; Y.-J. Zhang & Da, 2015) and sensitivity analysis based on the Ghosh model (Yan et al., 2016). Among them, the Tapio decoupling model is the main application of the decoupling model, and its idea is to divide the decoupling state by calculating the decoupling elastic value to judge the decoupling level of a group of variables. For example, Song et al. (2020) have studied the decoupling and coupling relationship between carbon emissions and economic growth in central provinces, construction, and transportation sectors based on the Tapio decoupling model. On the other hand, the existing literature studies the spatial-temporal evolution of the economic-environment coupling relationship by constructing the coupling coordination degree (Shi et al., 2020; Xing et al., 2019). Not only that, but the coupling coordination degree can also study the relationship among three groups of variables. For example, Wang et al. (2022) used the coupling coordination degree to study the coupling relationship among the industrial economy, natural resources, and environment. Furthermore, the kernel density estimation method and Dagum Gini coefficient have gradually become the essential methods for spatial evolution and analysis of variance in the study of the spatial and temporal evolution of coupling coordination degree in the field of low carbon economy (Bai et al., 2023; Zhang X. et al., 2023).

Energy-intensive industries play an essential role in the *dual-carbon target*. Liu et al. (2021) found that energy-intensive industries are mainly distributed in Shandong, Jiangsu, Henan, and Guangdong provinces by using the location Gini coefficient and industrial concentration. Environmental regulation and government intervention are important drivers of the spatial diffusion of energy-intensive industries. As for the influencing factors of energy-intensive industries, the existing studies believe that they are mainly divided into the following aspects: technology improvement and substituting energy with capital, environmental investment (Tan & Lin, 2018; Xue et al., 2022), industrial scale and labor productivity (Lin & Tan, 2017), government intervention, environmental regulations (Åhman et al., 2017), and international trade (Zhang X. et al., 2022).

A comprehensive analysis of existing studies shows that the research on high-quality development is limited to the construction level of the indicator system at present. Generally, the new development concept is adopted as mainstream for constructing high-quality development indicators. The principal component analysis and entropy weight method are mostly used. However, there has not been the application of the entropy weight TOPSIS method in the construction of the high-quality development indicator system. In addition, there is less research on the coupling coordination degree in specific industries in the existing literature, and in particular, there is no research related to the high-quality development of energy-intensive industries for the time being. Furthermore, the interaction between high-quality economic development and carbon emissions in energy-intensive industries has not been widely discussed. Thus, this paper's research makes a marginal contribution.

3. Methodology and Data

3.1 Variable Selection and Data Source

3.1.1 Carbon Emission Intensity of Energy-intensive Industries

According to *China's National Economic Classification 2011* and *China's National Economic Classification 2017*, the six major energy-intensive industries include petroleum, coal, and other fuel processing industries (in 2017 and later, in prior years referred to the nuclear fuel processing industry), chemical raw materials and chemical products manufacturing industry, non-metallic mineral products industry, ferrous metal smelting and calendering industry, non-ferrous metal smelting and calendering industry, and electricity, heat, gas and water production and supply industry.

Due to the lack of an official China carbon emissions database, the current academic research mainly adopts the recommended algorithm of IPCC (Intergovernmental Panel on Climate Change), as shown in the Equation (1).

$$CE = \sum_{j}^{n} EC_j \times NCV_j \times CC_j \times O_j \times \frac{44}{12} \tag{1}$$

Where EC_j is the consumption of the j th fossil fuel, NCV_j is the net calorific value of the j th fossil fuel, and CC_j represents the carbon content per unit calorific value of the j th energy source. O_j is the carbon oxidation rate of j th fossil fuels, and 44/12 is the ratio of the molecular weight of carbon dioxide to carbon atoms.

There are also some scientific research institutions that have accounted for China's carbon emissions based on the above algorithm, and this study utilizes one of them, namely, the open-access CEADs carbon emission database by industry and province (https://www.ceads.net/data/province/). The carbon intensity of energy-intensive industries is measured as the ratio of the carbon emissions of these industries to their value added.

3.1.2 Construction of High-quality Development Indicators

The current research has not yet agreed on measuring high-quality development. The common practice is to construct a comprehensive indicator, such as the construction based on growth facets and social outcomes and the construction based on the new development concept (Shen et al., 2022). The latter approach was utilized in this study, which measured the level of high-quality development of energy-intensive industries from the five perspectives of innovation, coordination, greenness, openness, and sharing, proposed by China's central government in 2018. The construction of indicators are presented in Table 1. It can be noticed that the indicators contain both subsystems and specific indicators. In addition, the matrix values using the entropy weight TOPSIS method are also displayed in column 4 of

Table 1. Column 5 demonstrates the direction of the specific indicators. For metrics where a more immense value is considered more favorable, they are denoted as "+" and vice versa.

(1) Innovation. The way innovation is measured is generally calculated in two directions: inputs and outputs. In particular, followed by Zhang and Li (2022) and Liu et al. (2021), R&D inputs are calculated by the R&D personnel (full-time equivalent) for labor input; R&D outputs are calculated using the number of patents granted, which is widely used in the current literature (Czarnitzki & Delanote, 2015). Moreover, it is a better indicator of high-quality innovation outputs than the number of patent applications, as not all patent applications get granted (Cinnirella & Streb, 2017).

(2) Coordination. Referring to the study of Gao and An (2022) and Zheng and He (2022), the share of industrial revenues in regional GDP embodies the regional industrial structure and, therefore, reflects the coordinated level of development of energy-intensive industries.

(3) Green. This study uses three indicators to measure green development: air pollutants, wastewater, and solid waste, which are regarded as the three main indicators of industrial pollution (Zhang H. et al., 2020). These indicators are labeled as "-" in the fifth column of Table 1 as they are often used as a non-desired output in existing research (Fan et al., 2019; Li Y. et al., 2020).

(4) Openness. For energy-intensive industries, the ratio of the industry's total imports and exports to GDP is used as a measure of data relevance and data availability (Adebayo et al., 2022; Wang Q. & Zhang, 2021).

(5) Sharing. Sharing implies the principle of being people-oriented, and regions with higher levels of sharing have a better material life with a higher flow of people and logistics capacity (Haseeb et al., 2020). Therefore, this paper uses road network density, railroad network density, and freight volume as proxy variables for sharing.

Table 1. Construction of Indicators

Systems	Subsystems	Specific indicators	Weights	Direction
High-quality development	Innovation	R&D personnel (full-time equivalent)	0.0822	+
		Counts of patents granted	0.0871	+
	Coordination	Revenues/GDP	0.1143	+
	Green	Sulfur dioxide emissions	0.0915	-
		Wastewater chemical oxygen demand (COD) emissions	0.0915	-
		Solid waste emissions	0.0932	-
	Openness	Import and export amount/GDP	0.1023	+
	Sharing	Road network density	0.0874	+
		Railroad network density	0.0719	+
		Volume of freight	0.1105	+
Carbon emissions intensity		Carbon emissions per unit of output	1.0000	-

Notes. Solid waste emission data was missing in 2018 and 2019, so it was replaced using the moving average method.

3.1.3 Data Source

The sample dataset used for analysis in this paper covers 30 provinces in China from 2007 to 2019. The data on carbon emissions of energy-intensive industries come from the CEADs database; the data for constructing the high-quality development index of energy-intensive industries come from the China Statistical Yearbook, China Industrial Statistical Yearbook, China Science and Technology Statistical Yearbook, the EPS database, and the patent database of the State Intellectual Property Office, among others. Hong Kong, Macao, Taiwan, and Tibet are not included in this study due to missing data or non-comparable statistical caliber.

3.2 Construction of the Coupling Coordination Degree

Coupling is initially a concept in engineering, also widely used in social science research, which refers to the degree of interdependence of information between two or more systems. This paper utilizes the carbon emission and high-quality development level of energy-intensive industries to construct the degree of coupling coordination using the entropy weight TOPSIS method (Chen P., 2021). The measure of the coupling coordination degree D is given in the Equation (2).

$$D = \left(C \times T\right)^{0.5} \tag{2}$$

$$C = \frac{2\sqrt{Y_1 Y_2}}{Y_1 + Y_2} \tag{3}$$

$$T = \alpha_1 Y_1 + \alpha_2 Y_2 \tag{4}$$

Where Y_1 and Y_2 represent the level of high-quality development of energy-intensive industries and carbon emissions, respectively; D is the coupling coordination degree of carbon emissions and high-quality development level of energy-intensive industries; is the coupling degree of the two; is the comprehensive coordination index, α_1 and α_2 are the share of high-quality development of energy-intensive industries and carbon emissions, respectively, and the volume of the value depends on the relative importance of the high-quality development of energy-intensive industries and the intensity of carbon emissions. The present study believes the two are equally important, so it is set. In this study, we consider the importance of the above indicators to be equal; therefore, we set $\alpha_1 = \alpha_2 = 0.5$. The classification criteria for the level of coupling coordination according to the existing literature are shown in Table 2.

Table 2. Criteria for Coupling Coordination

Level of coupled coordination	E: Low	D: Medium-low	C: Medium	B: Medium-High	A: High
Coupling coordination degree	[0, 0.2]	(0.2, 0.4]	(0.4, 0.6]	(0.6, 0.8]	(0.8, 1]

First, the variables Y_1 and Y_2 were standardized using the range method:

$$Y_{ij}=\begin{cases}\dfrac{X_{ij}-\min\left(X_{ij}\right)}{\max\left(X_{ij}\right)-\min\left(X_{ij}\right)} & X_{ij}\text{ is postive indicator}\\ \dfrac{\max\left(X_{ij}\right)-X_{ij}}{\max\left(X_{ij}\right)-\min\left(X_{ij}\right)} & X_{ij}\text{ is negative indicator}\end{cases} \tag{5}$$

Where X_{ij} represented the original value of the j th indicator of province i; and $\max(X_{ij})$ and $\min(X_{ij})$ are the maximun and minimun values of X_{ij}. Subsequently, the information entropy E_j is calculated by:

$$E_j=-\sum_{i=1}^{n}\left[\frac{Y_{ij}}{\sum_{i=1}^{n}Y_{ij}}\ln\left(\frac{Y_{ij}}{\sum_{i=1}^{n}Y_{ij}}\right)\right] \tag{6}$$

Then, we calculate metric weights W_j based on information entropy：

$$W_j=\frac{E_j}{\sum_{j=1}^{m}E_j} \tag{7}$$

In the fourth step, the weighting matrix of the indicators is constructed by:

$$R=\left(r_{ij}\right)_{n\times m} \tag{8}$$

Where $r_{ij}=W_j\times Y_{ij}$. After that, we identify the optimal and least optimal solutions based on the weighting matrix:

$$Q_j^{+}=\left(\max r_{i1},\max r_{i2},\dots,\max r_{im}\right) \tag{9}$$

$$Q_j^{-}=\left(\min r_{i1},\min r_{i2},\dots,\min r_{im}\right) \tag{10}$$

Calculate the Euclidean distance between the solution r from the optimal and the worst solution:

$$d_i^{+}=\sqrt{\sum_{j=1}^{m}\left(Q_j^{+}-r_{ij}\right)^2} \tag{11}$$

$$d_i^{-}=\sqrt{\sum_{j=1}^{m}\left(Q_j^{-}-r_{ij}\right)^2} \tag{12}$$

Calculate relative proximity:

$$C_i=\frac{d_i^{-}}{d_i^{+}+d_i^{-}} \tag{13}$$

Among them, the relative proximity ranges from 0 to 1, where the larger it is, the higher the level of high-quality development or the lower the intensity of carbon emissions.

3.3 Kernel Density Estimation

Kernel density estimation (KDE) is a non-parametric estimation method for point data density visualization, which describes the actual data distribution based on the intrinsic properties of the data without any prior information. Kernel density estimation curves can be interpreted from single period sample data, from horizontal comparisons and from vertical comparisons. Studying the horizontal position of the kernel density curve of the sample data of a single period can indicate the overall degree of coupling coordination, and the height and width of the peaks of the kernel density curve can reflect the degree of aggregation of the degree of coupling coordination in a particular interval. In addition, the number of peaks can depict the degree of polarisation of the sample data. The degree of lag in the kernel density curve can be described as the distance between the province with the highest (or lowest) coupling coordination degree and the province, and the greater the trailing, the greater the degree of variation within the region. In addition, a vertical comparison of the kernel density curves of samples from several periods in the same region can identify the dynamic evolution of the distributional characteristics of the degree of coupling coordination in that region, while a horizontal comparison of the morphology of the kernel density curves of several regions can capture the differences in their trajectories of change in the coupling coordination degree.

In order to visualize the dynamic evolution process of the coupling coordination degree of high-quality development of energy-consuming industries and carbon emissions, this section uses the non-parametric kernel density estimation method with Gaussian normal distribution to deeply analyze the distribution location, shape, and other characteristics of the coupling coordination degree. The formula for kernel density estimation is shown as follows:

$$\hat{f} = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{r - R_i}{h}\right) \tag{14}$$

$$K(r) = \frac{1}{\sqrt{2\pi}} e^{-\frac{r^2}{2}} \tag{15}$$

where $\hat{f}$ denotes the kernel density value, h denotes the bandwidth of the Kernel density estimation, $K(r)$ denotes the Gaussian kernel function, r denotes the estimated locus, and R_i is the sample i.

3.4 Dagum Gini Coefficient

Previous studies have generally used traditional measures of inequality, such as the Thiel index and the classical Gini coefficient, which implicitly assume normal distribution and homoskedasticity and assume that there is no crossover between subgroups of samples, which makes it difficult to disaggregate the indexes into several sub-indices with reasonable economic meaning. Therefore, we use the Dagum Gini coefficient introduced by Dagum (1987) to reveal the differences in the spatial distribution of high-quality development and carbon emission intensity in energy-intensive industries and the sources of the differences. Compared with the traditional Gini coefficient or Theil index, the Dagum Gini coefficient solves the problem of overlapping regional sample data and has certain advantages in analyzing the characteristics of spatial differences (Shen et al., 2022).

The overall Dagum Gini coefficient is calculated as shown in Equation (16). where n denotes the number of individuals (regions) and μ is the mean value of the coupling coordination degree. $y_{ji}(y_{hr})$ denotes the coupling coordination degree in the region j (or h) within individual i (or r), respectively. The Dagum Gini coefficient consists of three components: the contribution of intra-regional variation G_w, the contribution of inter-regional variation G_{nb}, and the contribution of hypervariance density G_t, represented in Equation (17).

$$G=\frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji}-y_{hr}|}{2n^2\mu} \tag{16}$$

$$G=G_w+G_{nb}+G_t \tag{17}$$

The calculations of intra-regional variation contribution G_w, inter-regional variation contribution G_{nb}, and the hypervariance density contribution G_t are shown in Equation (18)-(20).

$$G_w=\sum_{j=1}^{k}G_{jj}p_js_j \tag{18}$$

$$G_{nb}=\sum_{j=2}^{k}\sum_{h=1}^{j-1}G_{jh}(p_js_h+p_hs_j)D_{jh} \tag{19}$$

$$G_t=\sum_{j=2}^{k}\sum_{h=1}^{j-1}G_{jh}(p_js_h+p_hs_j)(1-D_{jh}) \tag{20}$$

Where G_{jj} is the intra-regional variation of region j, as shown in Equation (21); G_{jh} is the inter-regional variation between region j and h, as shown in Equation (22); D_{jh} is the relative impact between region j and h, as shown in Equation (23).

$$G_{jj}=\frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}|y_{ji}-y_{jr}|}{2n_j^2\mu_j} \tag{21}$$

$$G_{jh}=\frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji}-y_{hr}|}{n_jn_h(\mu_j+\mu_h)} \tag{22}$$

$$D_{jh}=\frac{d_{jh}-p_{jh}}{d_{jh}+p_{jh}} \tag{23}$$

Where d_{jh} and p_{jh} denotes the weighted average of coupling coordinated imbalance between high-quality development and carbon emissions intensity, as shown in Equation (24) and (25).

$$d_{jh}=\int_0^{\infty}dF_j(y)\int_0^{y}(y-x)dF_h(x) \tag{24}$$

$$p_{jh}=\int_0^{\infty}dF_h(y)\int_0^{y}(y-x)dF_j(y) \tag{25}$$

Where $F_j(x)$ and $F_h(x)$ are the continuous density distribution functions of regions j and h, respectively.

3.5 Convergence Analysis

β convergence is divided into absolute β convergence and conditional β convergence. Absolute β convergence refers to the fact that different regions will tend to the same steady state, while conditional β convergence refers to the fact that different regions will tend to their respective steady states based on their different initial states. The estimations between absolute β convergence and conditional β convergence are similar. The formula for absolute convergence is shown below:

$$\frac{\ln D_{it}-\ln D_{i0}}{T}=\alpha+\beta\ln D_{i0}+\varepsilon_t \tag{26}$$

Where T is the sample period length, α and β are the parameters to be estimated, and ε is the residual of the estimation. The coupling coordination degree of each region is considered convergent when $\beta < 0$, and vice versa, it is considered divergent. The formula for conditional β convergence is shown below.

$$\ln D_{it} - \ln D_{it-1} = \alpha + \beta \ln D_{it-1} + \varepsilon_t \tag{27}$$

After the coefficients are calculated, the convergence velocity γ, steady-state value θ, and semi-convergence period τ can be further calculated by the following formulas:

$$\gamma = \frac{\alpha}{1-\beta} \tag{28}$$

$$\theta = -\ln \frac{1+\beta}{t} \tag{29}$$

$$\tau = \frac{\ln 2}{\theta} \tag{30}$$

4. Empirical Results

4.1 The Results of the Coupling Coordination Degree

The results of calculating the coupling coordination degree between carbon emissions and high-quality development in energy-intensive industries are shown in Table 3. The temporal trend of the coupling coordination degree of the whole sample and the sub-sample is shown in Figure 1. The results show significant differences in the coupling coordination degree at different stages of economic development and in different regions.

The mean value of the full sample's coupling coordination degree fluctuates between 0.56 and 0.59, all falling within the range of C grade, which shows that, from the perspective of the full sample, the coupling coordination degree of high-quality development and carbon intensity is at a medium level.

The distribution of the coupling coordination degree of the sub-sample, on the other hand, shows divergent differences. Further, in terms of the eastern, central, and western provinces in China, during the sample period, the mean value of the coupling coordination degree in the eastern region is basically above 0.6 except for 2009, which fell into the range of grade B, which is significantly higher than that of the central and western regions, indicating that the coupling coordination degree in the eastern region is basically at a medium-high level. The average value of the coupling degree of coordination between the two fluctuated within the range of 0.52 to 0.58, which are both below the full sample average value but also within the range of level C, suggesting that the coupling coordination degree in the central and western regions is at a low to moderate level. In addition, the coupling coordination degree of the central region is always lower than that of the western region, which indicates that the coupling coordination degree of high-quality development and carbon emission intensity in the central region is the worst in the sample, which may be related to the fact that the central region has more energy-intensive industries and insufficient green technology levels.

Moreover, the coupling coordination degree of the full sample and subsample showed the same trend over time, exhibiting a two-stage inverted U-shaped trend. In the first stage (2005-2009), the first inverted U-shaped trend was observed; in the second stage (2009-2019), an inverted U-shaped trend with a higher mean value and more extensive time period than that of the first stage was observed. We believe the reason for this may be that in 2008, China established the Ministry of Environmental Protection, which elevated the rank of environmental protection in national policy, prioritized environmental protection alongside economic development, and strengthened environmental regulation. In addition, the superimposed negative impact of the 2008 financial crisis led to a certain degree of slippage in the level of high-quality development.

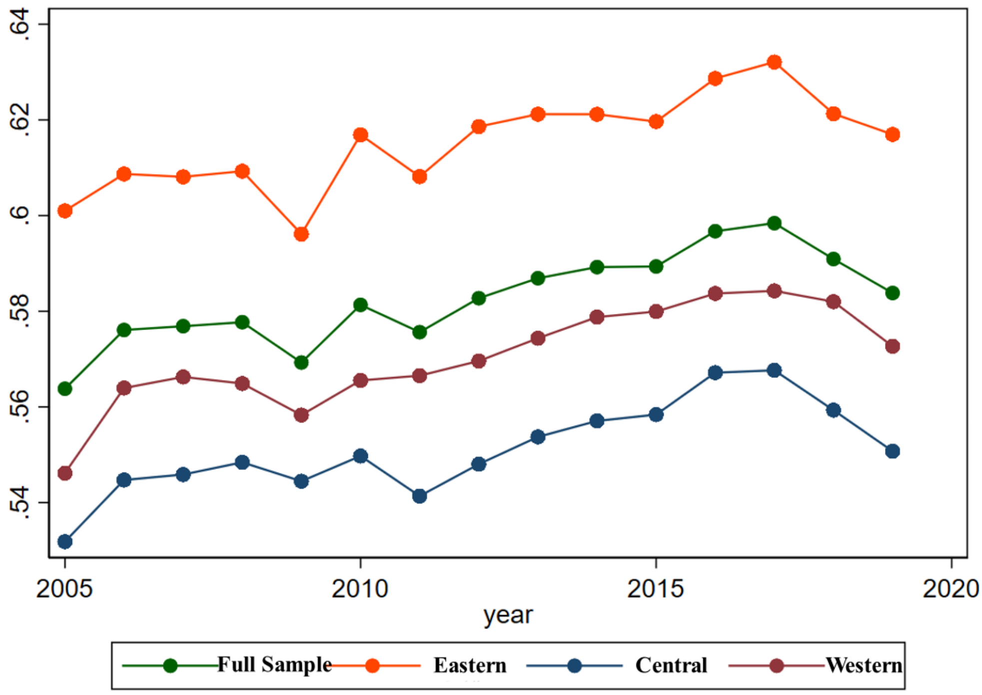

Figure 1. Time Trend of the Coupling Coordination Degree between Carbon Emission Intensity and High-quality Development in Energy-intensive Industries

Table 3. Results of the Coupling Coordination Degree of High-quality Development and Carbon Emission Intensity in Energy-intensive Industries

Province	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	0.8177	0.8268	0.8261	0.8365	0.8292	0.8366	0.8418	0.8437	0.8447	0.8437	0.8377	0.8400	0.8432	0.8453	0.8499
Tianjin	0.8063	0.8089	0.8078	0.8068	0.8012	0.8029	0.8037	0.8059	0.8105	0.8238	0.8151	0.8227	0.8242	0.8174	0.8149
Hebei	0.6038	0.6037	0.5889	0.5891	0.5826	0.5473	0.4717	0.4919	0.4650	0.4837	0.5096	0.5402	0.5563	0.2972	0.2484
Shanxi	0.6671	0.6713	0.6680	0.6598	0.6583	0.6490	0.6196	0.6136	0.6082	0.6190	0.6331	0.6583	0.6453	0.6216	0.6057
InnerMongolia	0.6621	0.6509	0.6472	0.6311	0.6253	0.6228	0.5578	0.5533	0.5670	0.5627	0.5526	0.5859	0.5628	0.5002	0.4228
Liaoning	0.6818	0.6784	0.6687	0.6725	0.6641	0.6586	0.6254	0.6369	0.6310	0.6311	0.6281	0.6811	0.6742	0.6659	0.6539
Jilin	0.7253	0.7274	0.7279	0.7245	0.7235	0.7226	0.7032	0.7093	0.7106	0.7120	0.7154	0.7411	0.7403	0.7408	0.7367
Heilongjiang	0.7144	0.7147	0.7151	0.7106	0.7075	0.7074	0.6698	0.6699	0.6755	0.6732	0.6722	0.7144	0.7160	0.7188	0.7108
Shanghai	0.7985	0.8095	0.8132	0.8154	0.8134	0.8240	0.8306	0.8332	0.8314	0.8352	0.8357	0.8398	0.8431	0.8425	0.8433
Jiangsu	0.6594	0.6598	0.6602	0.6567	0.6536	0.6367	0.6083	0.6061	0.5806	0.5773	0.5599	0.5804	0.5766	0.5585	0.5263

Zhejiang	0.7186	0.7258	0.7222	0.7240	0.7254	0.7292	0.7220	0.7288	0.7343	0.7386	0.7451	0.7652	0.7653	0.7704	0.7757
Anhui	0.7292	0.7407	0.7371	0.7445	0.7387	0.7457	0.7309	0.7336	0.7419	0.7472	0.7415	0.7571	0.7614	0.7497	0.7434
Fujian	0.7430	0.7467	0.7419	0.7421	0.7349	0.7366	0.7276	0.7297	0.7341	0.7379	0.7445	0.7631	0.7627	0.7575	0.7518
Jiangxi	0.7289	0.7431	0.7516	0.7623	0.7573	0.7674	0.7600	0.7680	0.7643	0.7702	0.7634	0.7699	0.7703	0.7682	0.7734
Shandong	0.6017	0.6096	0.5969	0.6030	0.5996	0.5868	0.5453	0.5373	0.5528	0.5446	0.5080	0.5302	0.5676	0.4368	0.3581
Henan	0.6540	0.6720	0.6643	0.6733	0.6760	0.6619	0.6353	0.6526	0.6555	0.6412	0.6516	0.6941	0.7075	0.7135	0.7237
Hubei	0.7072	0.7117	0.7114	0.7178	0.7179	0.7086	0.6853	0.6948	0.7141	0.7213	0.7288	0.7511	0.7522	0.7553	0.7514
Hunan	0.7037	0.7122	0.7127	0.7197	0.7226	0.7306	0.7176	0.7259	0.7307	0.7380	0.7435	0.7668	0.7835	0.7672	0.7640
Guangdong	0.7025	0.7086	0.7072	0.7077	0.7087	0.7086	0.6809	0.6996	0.7176	0.7179	0.7447	0.7534	0.7493	0.7521	0.7384
Guangxi	0.6887	0.6924	0.6936	0.7015	0.7020	0.7050	0.7184	0.7210	0.7199	0.7265	0.7114	0.7498	0.7491	0.7448	0.7401
Hainan	0.7687	0.7659	0.7687	0.7692	0.7704	0.7777	0.7765	0.7772	0.7750	0.7759	0.7791	0.7833	0.7836	0.7869	0.7886
Chongqing	0.7363	0.7574	0.7596	0.7592	0.7594	0.7604	0.7631	0.7666	0.7742	0.7766	0.7813	0.8005	0.8021	0.8047	0.8088
Sichuan	0.6777	0.6797	0.6837	0.6933	0.6904	0.6829	0.6777	0.6783	0.6750	0.6758	0.6880	0.7295	0.7357	0.7456	0.7381
Guizhou	0.6969	0.7003	0.7027	0.7079	0.7055	0.7071	0.7037	0.7053	0.7126	0.7212	0.7257	0.7423	0.7399	0.7424	0.7392
Yunnan	0.7379	0.7432	0.7428	0.7316	0.7214	0.7262	0.7021	0.7055	0.7136	0.7236	0.7282	0.7434	0.7493	0.7482	0.7518
Shaanxi	0.7136	0.7212	0.7216	0.7269	0.7294	0.7286	0.7262	0.7213	0.7234	0.7229	0.7236	0.7494	0.7526	0.7478	0.7403
Gansu	0.7483	0.7609	0.7635	0.7586	0.7605	0.7615	0.7506	0.7579	0.7615	0.7632	0.7745	0.7866	0.7868	0.7807	0.7574
Qinghai	0.7686	0.7739	0.7741	0.7687	0.7673	0.7777	0.7720	0.7698	0.7693	0.7716	0.7626	0.7628	0.7627	0.7574	0.7581
Ningxia	0.7548	0.7651	0.7616	0.7589	0.7550	0.7577	0.7396	0.7461	0.7457	0.7453	0.7430	0.7507	0.7384	0.7298	0.7229
Xinjiang	0.7222	0.7186	0.7166	0.7184	0.7151	0.7067	0.6809	0.6684	0.6591	0.6543	0.6553	0.6699	0.6632	0.6595	0.6445

4.2 Kernel Density Estimation

Based on the above measurement results of the coupling coordination degree, this paper drew the Gaussian kernel density distribution curve of the coupling coordination degree in 2005, 2009, 2015, and 2019, shown in Figure 2. The evolution trajectory of the coupling degree of coordination is as follows: First, the peak of the distribution of the coupling degree of coordination between carbon emissions intensity and high-quality development of energy-intensive industries gradually shifts to the right over time, which indicates that the overall coupling coordination level between high-quality development and carbon emissions intensity is in the process of upgrading. The high-quality development level of energy-intensive industries shows a trend of decoupling from carbon emission intensity from the full-sample perspective. Second, the wave peak shows a trend that the height gradually flattened and the width increased, which indicates that the inter-region gap is expanding in the sample period. Third, the number of wave peaks changes from "one main peak and small right peak" to "single main peak" in the early period, indicating a shift in coupling coordination degree from bipolar to unipolar.

The above results show that although there is a trend of continuous increase in the average level of coupling coordination degree over time. However, there is a significant polarization effect. On the one hand, the coupling coordination degree of some provinces decreases rather than increases over time, indicating an anti-coupling effect between high-quality development and carbon intensity in these provinces; on the other hand, in the early part of the sample period, there was a group of "leaders" with high coupling coordination degree. As time progresses, some of the provinces that were lagging behind have caught up with them, suggesting potential convergence.

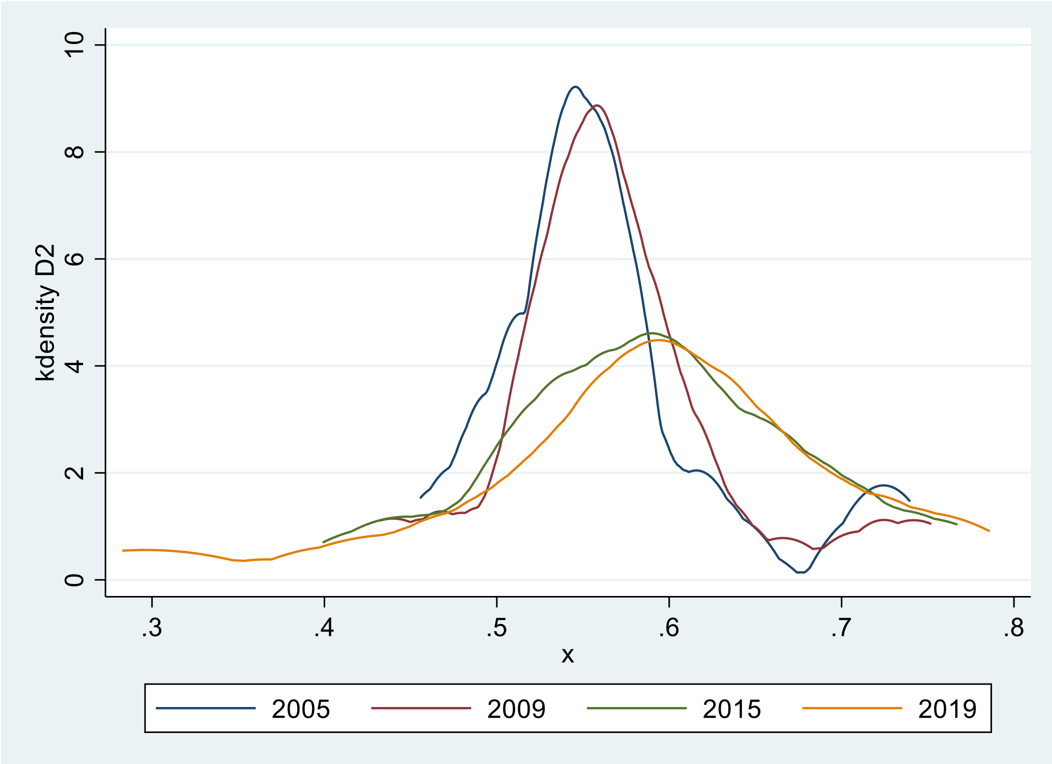

Figure 2. Gaussian Kernel Density Distribution of the Coupling Coordination Degree

4.3 Dagum Gini Coefficient and Its Decomposition

The trend of the overall difference in the Gini coefficient of the coupling coordination degree of high-quality development and carbon emission intensity in energy-intensive industries is shown in Figure 3. The results show that the inequality in the coupling coordination degree between carbon emissions intensity and high-quality development is increasing. For spatial characteristics, the overall difference in coupling coordination degree improved from 0.06 in 2005 to 0.11 in 2019, with an increase of 0.05, an average annual increase of 4.42%.

Therefore, we infer that for energy-intensive industries, some specific regions have achieved the dual target of high-quality development of the industry and carbon emission intensity reduction simultaneously. In contrast, few regions have failed to keep up with the coupling progress, leading to the continuous widening of the gap. For regions with a better economic foundation, the well-developed import and export trade revenues in energy-intensive industries have supported the high profits of the industries, and at the same time, in conjunction with the high innovation efficiency, the technological level of the industries has been further upgraded, which, on the one hand, enhances the total factor productivity of the sector, and on the other hand, green energy-saving and emission reduction technologies have made it possible to realize the benignly coupled development of high-quality development and carbon emission intensity. As for the regions with a poorer economic foundation in the previous period, the influence mechanism mentioned above has not been exerted, and the assessment pressure on the local governments leads them to choose only one of economic development and environmental protection, which leads to the decline of the coupling coordination degree in these regions.

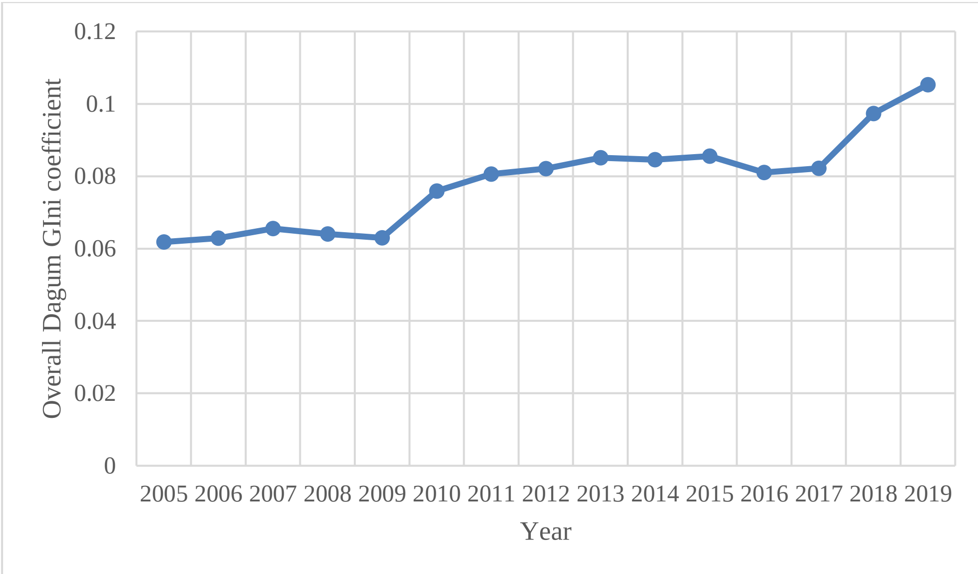

Figure 3. Trends of the Overall Dagum Gini Coefficient of the Coupling Coordination Degree

The **intra-regional variations** of coupling coordination degrees are illustrated in Figure 4. The average value of intra-regional variation was higher in the eastern region (0.098) than in the central region (0.061) and the western region (0.038). When combining the above empirical facts with the findings in section 4.1, it can be concluded that the eastern region has the highest average coupling coordination degree, but also the highest intra-regional variation, and the Eastern region has the highest inequality in coordination degree; the western region has a higher coupling coordination degree and the least intra-regional inequality; and the central region has the lowest overall coordination degree, but also higher inequality.

The time trend of intra-regional variations in the eastern, central, and western regions is similar to the overall Dagum Gini coefficients, all showing an upward trend. Within the eastern region, intra-regional variations exhibit a three-stage trend, as shown in Table 6. From 2005 to 2009, they fluctuated slightly between 0.083 and 0.088; from 2010 to 2015, they remained relatively stable at around 0.1; and in the period from 2016 to 2019, they demonstrated a V-shaped pattern, initially decreasing and then increasing; meanwhile, intra-regional variations in the central region show continuous growth throughout the sample period and maintain the highest growth rate (from 0.0277 in 2005 to 0.0999 in 2019); The Western region exhibits a double-inverted U-shaped growth pattern (the first set of inverted-U from 2005 to 2008, and the left half of the second set of inverted-U from 2009 to 2019).

Based on the above empirical evidence, we can infer that the eastern region of China contributes the most to intra-regional differences in coupling levels, although it is worth noting that the central region has also continued to increase its contribution. We can assume that the sharp growth trend of the overall Dagum Gini coefficient in the third stage results from the combined growth of the eastern and central regions.

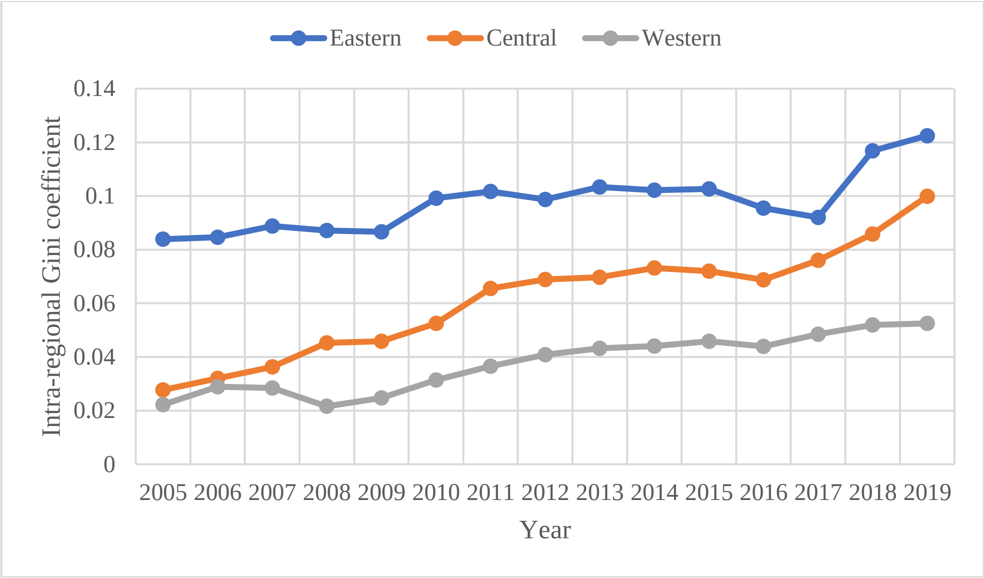

Figure 4. Trends of Intra-regional Variations of the Coupling Coordination Degree

Inter-regional variation measures the difference in means within groups of coupling coordination degree. The evolution of Inter-regional variations of the coupling coordination degree is presented in Figure 5. It can be concluded that the average values of inter-regional variations showed an "East-Central (0.098) > East-West (0.085) > Central-West(0.053)" pattern. The inter-regional variations for Eastern-Central, Eastern-Western, and Central-Western also show growth over time but with different growth rates, with Central-Western (8.08%) > Eastern-Western (3.15%) > Eastern-Central (2.63%). This suggests that the intergroup differences in coupling coordination degree, while continuing to increase, are in the process of convergence and that the differences in coupling coordination degree between regions will converge to some fixed amount, which is related to the internal characteristics of the region, such as natural resource endowment.

In summary, the growth of the overall Dagum Gini coefficient stems from both the effect of the growth of intra-regional differences and the growth of inter-regional inequality levels, and the coefficients of variation of the two are approximate.

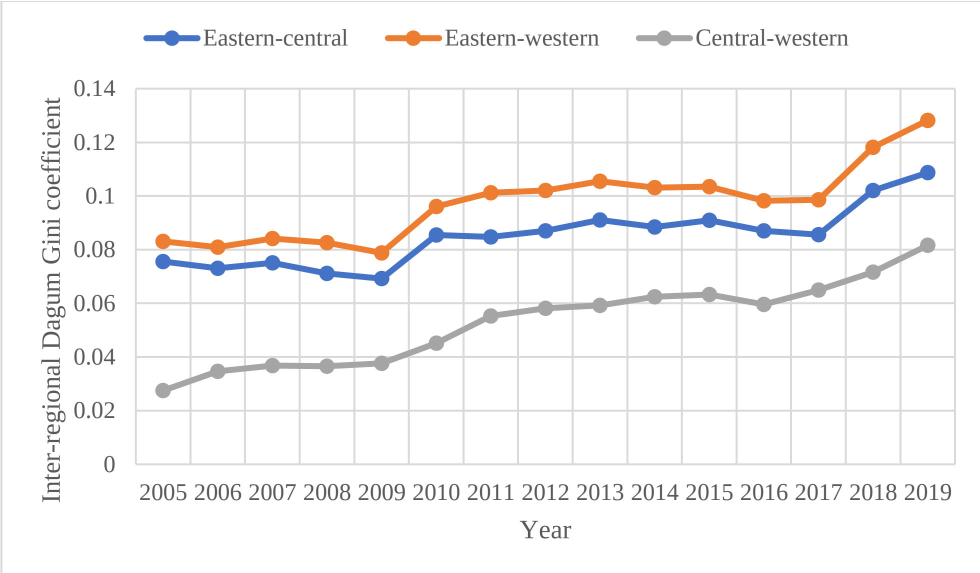

Figure 5. Trends of Inter-regional Variations of the Coupling Coordination Degree

Table 4. Dagum Gini Coefficients and Their Decomposition

	Intra-regional variations			Inter-regional variations			
Year	Eastern	Central	Western	East-central	East-west	Central-west	Gini
2005	0.0839	0.0277	0.0222	0.0756	0.0831	0.0275	0.0618
2006	0.0846	0.0320	0.0289	0.0730	0.0809	0.0346	0.0628
2007	0.0888	0.0363	0.0285	0.0751	0.0842	0.0368	0.0655
2008	0.0871	0.0453	0.0216	0.0712	0.0826	0.0366	0.0640
2009	0.0866	0.0458	0.0247	0.0692	0.0788	0.0376	0.0630
2010	0.0992	0.0525	0.0314	0.0855	0.0961	0.0451	0.0759
2011	0.1017	0.0655	0.0366	0.0847	0.1012	0.0553	0.0806
2012	0.0987	0.0689	0.0408	0.0870	0.1021	0.0581	0.0821
2013	0.1034	0.0697	0.0432	0.0911	0.1055	0.0592	0.0851
2014	0.1022	0.0732	0.0441	0.0885	0.1031	0.0624	0.0846
2015	0.1027	0.0720	0.0459	0.0910	0.1035	0.0633	0.0855
2016	0.0955	0.0688	0.0439	0.0870	0.0982	0.0596	0.0810
2017	0.0920	0.0760	0.0485	0.0856	0.0986	0.0650	0.0822
2018	0.1169	0.0858	0.0520	0.1020	0.1182	0.0716	0.0973
2019	0.1225	0.0999	0.0525	0.1087	0.1282	0.0816	0.1053

The contributions of three differences in the coupling coordination degree are presented in Table 5, and the trends of contribution are presented in Figure 6. Overall, the contribution rate of intra-regional differences and the contribution rate of hypervariable density coefficients both show a fluctuating upward trend with a growth rate of 4.36% and 8.49%, respectively. The inter-regional contribution shows a smooth fluctuating trend with an average growth rate of -0.68%.

The temporal evolution of the contribution rates is divided into three stages. The first stage occurred from 2005 to 2008, when the contribution rate of inter-regional differences was the highest, followed by intraregional differences and finally, the contribution rate of hypervariable density; the second stage took place from 2009 to 2013, when the contribution rates crossed over several times; and the third phase took place after 2013, when the contribution rate of hypervariable density rose all the way to the highest level, followed by the intraregional contribution rate, and finally the interregional contribution rate. The above empirical facts indicate that in the first stage, intra-regional variation has the most significant impact on the coupling coordination degree; in the second stage, the difference between the three contributions is not significant, while in the third stage, the hypervariable density contribution has the most significant impact on the coupling coordination degree.

Combined with the results of the overall Gini coefficient, it can be found that the proportion of intra-group differences to the overall Gini coefficient is basically the same, the proportion of inter-group contributions to the Gini coefficient has continued to decline, while the proportion of hypervariable density contributions has continued to rise. In summary, the largest source of inequality in the coupling coordination degree between high-quality development level and carbon emission intensity in energy-intensive industries during the sample period is hypervariable density, followed by intra-regional differences.

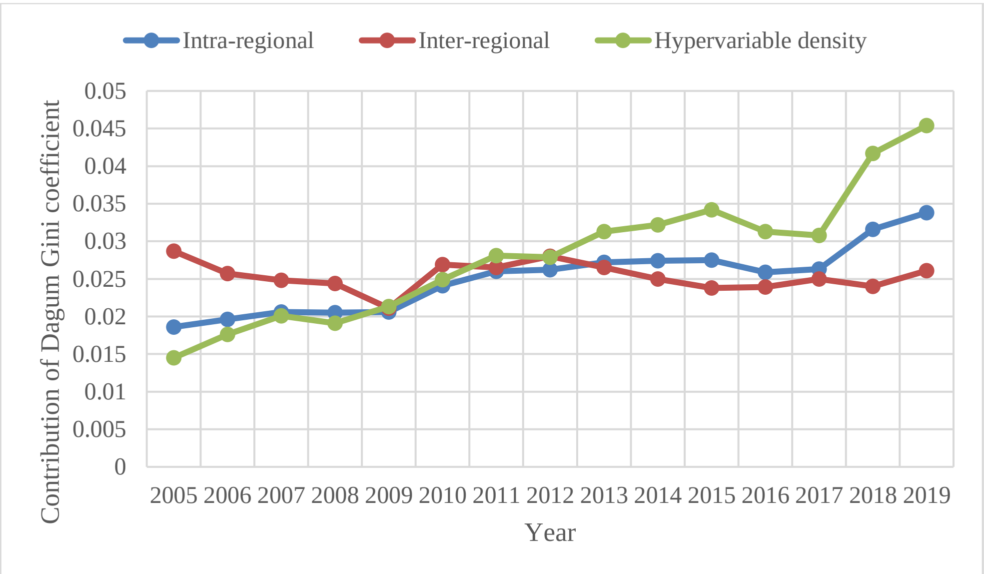

Figure 6. Trends of Contribution Rate of the Coupling Coordination Degree

Table 5. Contribution and Contribution Rate of the Dagum Gini Coefficient

Year	Contribution			Contribution Rate		
	Intra-regional variations	Inter-regional variations	Hypervariable density	Intra-regional variations	Inter-regional variations	Hypervariable density
2005	0.0186	0.0287	0.0145	30.08%	46.39%	23.53%
2006	0.0196	0.0257	0.0176	31.15%	40.82%	28.03%
2007	0.0206	0.0248	0.0201	31.41%	37.90%	30.69%
2008	0.0205	0.0244	0.0191	31.97%	38.14%	29.89%

2009	0.0206	0.0211	0.0213	32.75%	33.43%	33.82%
2010	0.0241	0.0269	0.0249	31.72%	35.47%	32.81%
2011	0.0260	0.0265	0.0281	32.24%	32.94%	34.82%
2012	0.0262	0.0280	0.0279	31.91%	34.07%	34.02%
2013	0.0272	0.0265	0.0313	32.02%	31.18%	36.80%
2014	0.0274	0.0250	0.0322	32.37%	29.57%	38.06%
2015	0.0275	0.0238	0.0342	32.12%	27.88%	40.00%
2016	0.0259	0.0239	0.0313	31.90%	29.50%	38.60%
2017	0.0263	0.0250	0.0308	32.01%	30.45%	37.54%
2018	0.0316	0.0240	0.0417	32.45%	24.68%	42.87%
2019	0.0338	0.0261	0.0454	32.12%	24.78%	43.10%

5. The Convergence Characteristics of Coupling Coordination Degree

5.1 Unit Root Test

It is necessary to test whether the variables are mean stationary to avoid spurious long-run relationships in our convergence analysis. Only if the error term of the estimation follows a stationary process, all variables will be cointegrated. Therefore, unit root tests were carried out for the coupling coordination degree of the full sample and subsamples using the HT test and the IPS test (Harris & Tzavalis, 1999; Im et al., 2003), with the results presented in Table 6. The coupling coordination degree of high-quality development level and carbon emission intensity of energy-intensive industries all reject the null hypothesis at the 1% significance level. Therefore, the coupling coordination degree satisfies stationarity over the sample period and is suitable for conducting convergence analysis.

Table 6. Results of Unit Root Tests

	Full-sample	Eastern	Central	Western
IPS	-2.3606***	-2.3606***	-2.3606***	-2.3606***
LLC	-5.1260***	-5.1260***	-5.1260***	-5.1260***

Notes. *, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively.

5.2 Convergence Analysis of Coupling Coordination Degree

In this research, the convergence of the coupling coordination degree is tested according to Equation (25), and the results are presented in Table 7. Columns (1)-(2) report the absolute convergence of the whole sample under the fixed effect of uncontrolled and controlled time, respectively, and columns (3)-(5) report the results of the eastern, central, and western sub-sample estimations with time and individual double fixed effect, respectively. The estimated parameters for absolute convergence and the steady-state values, convergence speeds, and semi-convergence periods calculated from the parameters are also reported in Table 7.

The results show that the β coefficient of energy-intensive industries is significantly negative at the 1% level, indicating that from the national perspective, the catch-up effect can be realized, and there is a significant absolute convergence trend between the high-quality development degree of energy-intensive industries and the carbon emission intensity.

However, the results of sub-sample estimation show that only the eastern region passes the absolute convergence results, and the convergence coefficient is greater than that of the whole country, indicating that the coupling coordination degree of energy-intensive industries in the eastern region is converging. Although the coefficients in the central and western parts were negative, they did not pass the coefficient test and could not prove a significant trend. The results of absolute convergence determine that the catch-up speed of coupling coordination degree in the eastern region is faster than in other regions. This result is corroborated by the results obtained in the kernel density estimation; that is, the coupling coordination degree in some regions is improved faster.

Table 7. Absolute Convergence Results for the Full-sample and Sub-samples

	(1) Full-sample	(2) Full-sample	(3) Eastern	(4) Central	(5) Western
β	-0.223***	-0.193***	-0.396***	-0.006	-0.051
	(-6.551)	(-5.458)	(-5.422)	(-0.139)	(-1.204)
α	0.131***	0.121***	0.246***	0.016	0.046*
	(6.618)	(6.013)	(5.544)	(0.734)	(1.952)
Ind-FE	Control	Control	Control	Control	Control
Time-FE	Not-control	Control	Control	Control	Control
N	420	420	168	126	126
Convergence results	Absolute convergence	Absolute convergence	Absolute convergence	-	-
γ	0.107114	0.101425	0.176218	-	-
θ	2.891372	2.853489	3.143238	-	-
τ	0.239729	0.242912	0.22052	-	-

Notes. *, **, *** imply the significance at the 10%, 5%, and 1% levels, respectively.

6. Discussion

This study utilizes the TOPSIS entropy weight method to construct the coupling coordination degree of high-quality development and carbon emission intensity of energy-intensive industries. It is found that the coupling coordination degree shows a pattern of east-west-central decreasing sequentially. In general, China’s level of economic development shows a downward pattern from the east towards the central and western regions. Why is the pattern of coupling coordination degree different from that of the economic development level? We try to make a more detailed explanation based on realistic evidence.

China’s energy resources endowment is characterized by a high level of coal and a low level of oil and gas. The coal industry plays a significant role in energy-intensive industries. The two most extensive regions for raw coal extraction in China, Shanxi and Inner Mongolia province, are situated in the central area and account for over 90% of the country’s output. The fundamental attention is on the primary processing of raw coal between them. Raw coal is characterized as a kind of bulk stock, with typically 50% of the sales price dedicated to logistics expenses for domestic sales, with low value added. Coal development in these two provinces is lacking in green technology enablement. Despite efforts to limit carbon emissions, energy-intensive industries in these regions have not accomplished high-quality development.

Another noteworthy point is that the coupling coordination degree of energy-intensive industries showed a gradual upward trend before 2017, i.e., natural decoupling between high-quality development and carbon emission intensity existed in high energy-intensive industries; however, the coupling coordination degree transferred to a downward trend after then. We speculate that at the end of 2016, China's State Council promulgated the *Comprehensive Work Program for Skill Emission Reduction* and began to tighten its grip on energy conservation and emission reduction and clean energy retrofit efforts (coal-to-gas and coal-to-electricity transformation). Consistent with Chen et al. (2022), the Coal-to-gas policy damaged GDP, especially in the short term. Despite the short-term reduction of emissions, the dual target perspective of high-quality development and carbon emission reduction has instead led to a decline in the coupling coordination degree.

7. Conclusion

This study takes energy-intensive industries in 30 provinces of China as a research sample from 2005 to 2019 to explore the dynamic evolution trajectory and its characteristics of the coupled coordination degree of high-quality development of energy-intensive industries and the carbon emission intensity of the industries. This paper is mainly divided into four parts to carry out the research on the spatial characteristics of coupling coordination degree. First, the indicators of high-quality development level and coupling coordination degree of energy-intensive industries are constructed; subsequently, the trend of coupling coordination degree is investigated by kernel density estimation, and the inequality of coupling coordination degree is investigated by using Dagum Gini coefficient; finally, the absolute convergence of coupling coordination degree is investigated.

The study obtains the following conclusions: first, the full-sample coupling coordination degree between high-quality development and carbon intensity is at a medium level (C-grade). The results of the sub-sample calculations show that the coupling coordination degree in the eastern region is basically at a medium-high level (B-grade) during the sample period, while the coupling coordination degree in the western region is below the average level, and the central region is the lowest. The coupling coordination degree shows a two-stage inverted U-shaped trend over time, with the second stage having a higher mean value and a more extensive time period; second, the results of kernel density estimation show that while the overall coupling coordination degree is increasing, the coupling coordination degree is decreasing in some specific regions, and there is a tendency to expand the differences between regions. And there is a shift in coupling coordination degree from bipolar to unipolar; third, the Dagum Gini coefficient shows that the inter-regional and intra-regional variations all show an upward trend, suggesting a significant elevated polarization effect. Additionally, intra-regional variations in the first period (2005-2009) mainly affected the Dagumu Gini coefficient when viewed from a contribution rate standpoint. In the following phase (2009-2013), the impact of the three variations is comparable. During the third phase (2013-2019), the primary source of the Dagum Gini coefficient's contribution is the hypervariable density; fourth, convergence analysis shows that there is an absolute convergence trend in the whole country at present, but it is only contributed by the eastern region, and the absolute convergence trend in the central and western regions is not significant.

The above findings reveal the coupling coordination degree of energy-intensive industries under the dual-objective perspective, which helps local governments to make discretionary decisions on energy-intensive industries according to the characteristics of local economic development. From the perspective of the whole of China, it is necessary to continue implementing the *new development concepts* of innovation, coordination, green, openness, and sharing. Under the ambitious *dual-carbon targets*, there is a need to land on high-quality economic development and use market-based environmental regulations to mitigate carbon emissions by promoting low-carbon innovation rather than using administrative regulations such as coal-to-gas policies to reach carbon emissions.

For central regions, it is needed to focus on the high-quality development of energy-intensive industries and the coordinated development of carbon emission intensity. The central regions with a low renewable energy endowment had taken over the relatively outdated production capacity from the eastern region in the 2000s, which led to its higher transition difficulty under the *dual-carbon target.* Local government should promote the high-quality development of energy-intensive industries, especially the coal industry. First, Local governments should encourage these enterprises to carry out innovations actively to establish a cleaner production process. Second, central regions should focus on researching and introducing intelligent manufacturing equipment, such as high-end coal machine equipment and intelligent equipment. Furthermore, local governments in central regions should encourage energy-intensive industries with the conditions to shift to the western region with higher renewable energy endowments so that energy-intensive industries can shift from *high energy consumption and high emissions* to *high energy consumption and low emissions*.

The Western regions need to attract energy-intensive industries, which can increase the share of energy consumed locally and reduce dependence on long-distance energy transmission. The main ways to do this are to build infrastructure to host energy-intensive industries and to subsidize the relocation of energy-intensive industries. However, local governments in the western region are currently facing severe financial problems, which are insufficient to carry out large-scale construction of infrastructure for energy-intensive industries. Therefore, the central government should set up a special fund to target energy-intensive industry infrastructure construction. In addition, financial institutions could be encouraged to provide financial support for enterprises with better energy efficiency and emission reduction to relocate to the western regions.

Although the coupling coordination degree of the eastern regions is in the convergence process, focusing on the synergistic development of the twin objectives is still needed. It should continue to give full play to the advantages of the eastern regions in terms of innovative resources, strengthen basic research, promote cooperation between industry, universities, and research institutes, and realize critical technological research and the transformation of innovative achievements so as to enhance the energy-intensive industries' energy efficiency.

Author contribution

Caijiang Zhang: supervision, project administration, funding acquisition. Yu Zhou: conceptualization, investigation, methodology, software, formal analysis, writing — original draft, visualization. Zhangwen Li: investigation, data curation, writing — review and editing.

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