

Article

Coupled Coordination and Drivers of Green Technology Innovation and Carbon Emission Efficiency

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Abstract: The coupled and coordinated development of green technology innovation and carbon emission efficiency in the Yangtze River Economic Belt is crucial for its realization of green and low-carbon transformation. Based on the panel data of the Yangtze River Economic Belt from 2011 to 2021, the comprehensive evaluation levels of green technological innovation and carbon emission efficiency were measured, and the coupling degree of coordination model and panel Tobit model were constructed to empirically analyze the coupling degree of coordination and driving factors of the two. The results show that, overall, the comprehensive evaluation value of green technology innovation level in the Yangtze River Economic Zone shows an upward trend; the value of carbon emission efficiency first rises and then falls. From the perspective of spatial distribution, both of them present the characteristic of “high in the east and low in the west”. The coupling coordination degree shows a growing trend and initially realizes the basic coordination. The coupling degree of coordination shows a significant negative correlation between the energy structure and the coupling degree of both of them, while urbanization level, environmental regulation, industrial structure, level of economic development, degree of openness, and labor level all show a significant positive correlation.

Keywords: Yangtze River Economic Belt of China; green technology innovation; carbon emission efficiency; coupling coordination degree; driving factors



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1. Introduction

China’s rapid economic development has been accompanied by the highest carbon emissions in the world. In order to accelerate the process of carbon emission reduction and achieve sustainable development, the Chinese government has made a commitment to the world that “China’s carbon emissions will peak by 2030 and achieve carbon neutrality by 2060”. In recent years, China has been giving top priority to the “dual carbon” goal. The Yangtze River Economic Belt is the main battlefield for China’s ecological civilization, accounting for 46.9% of China’s GDP and occupying an important position in the national economy. However, the Yangtze River Economic Belt has long relied on traditional industrial enterprises with high energy consumption and pollution to develop its economy, which has caused tremendous ecological and environmental pressure, and is a key area for China’s carbon emissions. This crude economic development mode cannot be sustained, and therefore it is necessary to promote the Yangtze River Economic Belt to realize a green and low-carbon transformation. The Political Bureau of the Central Committee of the Communist Party of China (CPC) held a meeting on 27 November 2023 to consider the “Opinions on Certain Policy Measures to Further Promote the High-Quality Development of the Yangtze River Economic Belt”, which emphasizes “synergistically pushing forward carbon reduction, pollution reduction, greening, and growth”, and “adhering to scientific and technological innovation as the main driving force”. From the above, we can see that green technology innovation is of great theoretical and practical significance to the low-carbon transformation of the Yangtze River Economic Belt and the realization of the

goal of “double carbon”. Green technology innovation integrates the two development concepts of “green” and “innovation”, and improving the level of green technology innovation can effectively improve energy efficiency, promote green development, and achieve harmonious coexistence between human beings and nature. In fact, China’s green technology innovation level has been at the forefront in the world [1] and has made outstanding contributions to global sustainable development. In summary, strengthening the level of green technology innovation can promote the low-carbon transformation of the Yangtze River Economic Zone and achieve sustainable development.

2. Literature Review

Green technological innovation is an inevitable choice to realize low-carbon transition. Now, the relevant research results mainly focus on evaluation measurement and influencing factors. First, in terms of the evaluation of green technology innovation, most scholars choose a single indicator to measure the level of green technology innovation, such as Bode E using R&D expenditure to represent the level of green technological innovation [2]; Hamamoto, Yang et al. measuring the level of green technological innovation and using part of the increase in R&D investment caused by environmental regulation [3,4]; the authorized amount of green technology patents [5]; and urban patent applications [6]. A small number of scholars measure the level of green technology innovation by constructing an indicator system to measure the comprehensive value, such as Sun, etc., [7–10]. Han measures the level of green technological innovation by using input–output indicators [7]. Lin Yan constructs the indicator system to measure the comprehensive value of green technology innovation level from the three dimensions of innovation input, innovation output, and support level of green technology, respectively [11]. Secondly, in terms of influencing factors, the studies mainly include financial R&D and education expenditures [12], digital transformation [13], level of economic development and population size [14], science and technology finance [15], government environmental attention [16], and environmental regulation [17].

Since the “dual carbon” goal was proposed, more and more scholars have been researching carbon emission efficiency, and combing through the relevant literature at home and abroad, we can see that it mainly focuses on the three aspects of concept definition, measurement methodology, and influencing factors. For concept definition, early scholars used the ratio of GDP to carbon emissions during the study period [18], the ratio of unit energy consumption to GDP [19], and other single-factor indicators to measure carbon emission efficiency. Yang Hongliang et al. [20] believe that the measurement of carbon emission efficiency with single-factor indicators is simple and easy to understand, but there are a lot of shortcomings. Therefore, in recent years, more and more scholars have constructed the indicator system to measure carbon emission efficiency from a multi-factor perspective, i.e., to obtain the smallest carbon dioxide emission and the largest economic output without increasing the inputs of labor, capital, and energy [21]. The measurement methods of multifactor indicators are mainly divided into parametric methods represented by stochastic frontier analysis (SFA) [22,23] and nonparametric methods represented by data envelopment analysis (DEA). The DEA model is often used in the measurement of carbon emission efficiency, but because the traditional DEA model does not introduce slack variables and ignores the influence of the external environment and stochastic perturbation factors, the results of the measurement deviate from the actual situation. Therefore, relevant improvement models are mostly adopted at this stage; for example, Wang Yong et al. [24], Wang Xinping et al. [25], and Xu Yingqi et al. [26] measured the carbon emission efficiency of entire China, its regions and cities, by using the improvement models. In terms of influencing factors, it is found that the level of economic development, energy intensity, industrial structure, urbanization level, and technological innovation [25–27] are closely related to the improvement in carbon emission efficiency.

From the existing literature, the relevant research on the relationship between green technological innovation and carbon emission efficiency mainly focuses on the relationship

between traditional technological innovation and carbon emission efficiency, which is specifically categorized into the following three aspects. Firstly, technological innovation is considered to be able to reduce carbon emissions and improve carbon emission efficiency. Sun Zhenqing et al. divided the level of technological innovation into the input and output of technological innovation and found that the input of technological innovation is more helpful in carbon emission reduction than the output of technological innovation [28]. When Li Jianbao et al. and Xu et al. studied the factors affecting the efficiency of carbon emissions, they found that technological progress and technological innovation were important ways to improve the efficiency of carbon emissions [29,30]. Secondly, it is believed that carbon emission reduction can promote technological innovation. Fan Decheng et al. conducted a study based on the market perspective, and the results show that carbon emission reduction alliance can promote enterprise low-carbon technological innovation [31]. Thirdly, there was a study on the coupling relationship between technological innovation and carbon emission efficiency. Feng Junhua et al. used the coupling coordination and relative development degree model to analyze the coupling coordination relationship between the technological innovation and carbon emission efficiency of Chinese industrial enterprises, and the study showed that technological innovation and carbon emission efficiency present the characteristics of mutual promotion in the early stage and gradual inhibition in the late stage [32].

In summary, a large number of scholars have carried out a lot of research on green technological innovation, carbon emission efficiency, and the impact of technological innovation on carbon emission efficiency and have achieved rich results, but few scholars have studied the coupling relationship between green technological innovation and carbon emission efficiency. Based on this, this paper will take the Yangtze River Economic Belt as the research area to explore the coupling coordination degree and driving factors of green technology innovation and carbon emission efficiency. Compared with the existing research, the research results of this paper are mainly reflected in the following three aspects: ① Existing research on how to construct the indicator system of green technological innovation level is not yet a unified standard, and most scholars still use a single indicator to measure the level of green technological innovation. In this paper, through the construction of a green technology innovation evaluation index system for a comprehensive level of measurement, the indicator system is enriched to measure the level of green technology innovation. ② There is existing research on the relationship between traditional technological innovation and carbon emission efficiency. In recent years, some scholars have begun to explore the impact of green technological innovation on carbon emission efficiency, but the research results are fewer, and no scholars have made a relevant study on the coupling and coordination of green technological innovation and carbon emission efficiency yet. In this paper, research on the coupling and coordination of the two has enriched the theory of coupling and coordinated development of green technological innovation and carbon emission efficiency. ③ There are only studies on the driving factors of the coupling and coordinated development of traditional technological innovation and carbon emission efficiency in the existing research, and there is no analysis of the driving factors of the coordinated development of green technological innovation and carbon emission efficiency. This paper analyzes the driving role of selected factors on the coupled and coordinated development of green technological innovation and carbon emission efficiency by reading the literature, selecting some factors from outside, and introducing the panel Tobit model.

3. Study Area, Methods, and Data

3.1. Study Area

The Yangtze River Economic Belt (YREB) cuts across the east, central, and west regions of China, covering nine provinces and two cities in Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Yunnan and Guizhou, accounting for about 21.4% of China's total area and relying on the Yangtze River's golden waterway. It has a unique locational advantage and development potential. Therefore, this paper selects

the Yangtze River Economic Belt as the study area to explore the coupled and coordinated research on green technology innovation and carbon emission efficiency and the driving factors.

3.2. Research Methodology

3.2.1. Entropy Weight TOPSIS Gray Correlation Projection Method

TOPSIS is a distance-based multi-criteria decision-making method, whose basic principle is to derive positive and negative ideal solutions from the standardized decision matrix, and calculate the closeness between feasible solutions and positive and negative ideal solutions as the basis for judging the advantages and disadvantages of feasible solutions. The basic principle of the gray correlation projection method is based on the cosine value of the angle between the feasible solution and the ideal solution to reflect the degree of similarity between the two; the larger the cosine value, the closer the feasible solution is to the ideal solution. The TOPSIS gray correlation projection method combines the two organically to improve the accuracy of the calculation results. In this paper, we refer to the approach of Fan Decheng et al. [33] to construct the TOPSIS gray correlation projection model based on the entropy weight method.

(1) Constructing positive and negative ideal decision matrices

Suppose the object being evaluated is i ($i = 1, 2, \dots, m$), the evaluation index is j ($j = 1, 2, \dots, n$), time scale is t ($t = 1, 2, \dots, q$), and $Q(t)$ is then the original matrix. The original evaluation matrix can be constructed as Equation (1):

$$Q(t) = \{q_{ij}(t)_{m \times n}\} \quad (1)$$

Before using the data for research and measurement, it is necessary to eliminate the influence of the original data outline of each indicator, and this paper adopts the extreme value processing method for standardization. Equations (2) and (3) are as follows:

$$x_{ij}(t) = \frac{q_{ij}(t) - \min_i q_{ij}(t)}{\max_i q_{ij}(t) - \min_i q_{ij}(t)} \quad (\text{Benefit-based indicators}) \quad (2)$$

$$x_{ij}(t) = \frac{\max_i q_{ij}(t) - q_{ij}(t)}{\max_i q_{ij}(t) - \min_i q_{ij}(t)} \quad (\text{Cost-based indicators}) \quad (3)$$

The standardized matrix is obtained as $X(t) = \{x_{ij}(t)_{m \times n}\}$, and the maximum and minimum values of each evaluated object under the j th indicator at the moment t are positive and negative ideal scenarios, respectively (Equation (4)):

$$x_{0j}^+ = \max(x_{ij}(t)) \quad x_{0j}^- = \min(x_{ij}(t)) \quad (4)$$

(2) Constructing positive and negative ideal gray correlation coefficient matrices

Gray correlation theory analyzes the degree of correlation between each evaluation object and the reference object to judge the degree of superiority of each evaluation object. Assuming that the reference object is $X_{0j}^*(t) = \{x_{01}^*(t), \dots, x_{0n}^*(t)\}$, according to the gray correlation theory, at the moment t , the j th evaluation index of the i th object of the gray correlation coefficient is shown in Equation (5):

$$\delta_{ij}(t) = \frac{\min_i \min_j |\Delta| + \lambda \max_i \max_j |\Delta|}{|\Delta| + \lambda \max_i \max_j |\Delta|} \quad (5)$$

where $\Delta = x_{0j}^*(t) - x_{ij}(t)$, λ is the resolution coefficient, and $\lambda \in [0, 1]$, generally taken as 0.5. The positive and negative ideal gray correlation coefficient matrix can be obtained as Equation (6):

$$E^\pm(t) = \left\{ \delta_{ij}^\pm(t) \right\}_{(m+1) \times n} \quad (6)$$

$$\text{Style: } \delta_{01}^\pm(t) = \dots = \delta_{0n}^\pm(t) = 1$$

(3) Entropy method for weighted gray correlation coefficient matrix

In the comprehensive evaluation of multiple indicators, the relative importance of each indicator needs to be considered, and thus the weight of each indicator needs to be measured. This paper selects the entropy method to calculate the weight, which is an objective measurement of the weight, and is more desirable in multi-criteria problems. The steps of assigning weights using the entropy value method are as follows:

Step 1: Calculate the percentage of the i th evaluated object under the j th indicator at moment t (Equation (7)):

$$p_{ij}(t) = \frac{x_{ij}(t)}{\sum_{i=1}^m x_{ij}(t)} \quad (7)$$

Step 2: Calculate the entropy value of the j th indicator at moment t : $e_j(t) = -k \sum_{i=1}^m p_{ij}(t) \ln[p_{ij}(t)]$; where $k > 0$, $e_j(t) > 0$. If there is only one value of j and t in Equation, then $p_{ij}(t) = 1/m$. Then, we obtain $e_j(t) = k \ln m$, so we take $k = 1/\ln m$;

Step 3: Calculate the utility value of the indicator $g_j(t) = 1 - e_j(t)$, where the larger $e_j(t)$ is, the smaller $g_j(t)$ is, and vice versa;

Step 4: Calculate the weight of the j th indicator (Equation (8)):

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

Step 5: Derive the matrix of weighting coefficients for positive and negative ideal gray correlations: $F^\pm(t) = w_i(t) \times E^\pm(t)$.

(4) Gray correlation projection method

The positive and negative ideal gray correlation projection values are calculated as follows (Equation (9)):

$$D_I^\pm(t) = \|a_i(t)\| \cdot \cos \theta_i(t) = \sum_{j=1}^n \delta_{ij}(t) \frac{w_j^2(t)}{\sqrt{\sum_{j=1}^n w_j^2(t)}} = \sum_{j=1}^n \delta_{ij}^\pm(t) \bar{w}_j(t) \quad (9)$$

Among them, $a_i(t) = \{w_1(t)\delta_{i1}(t), \dots, w_n(t)\delta_{in}(t)\}$, $\bar{W}(t) = \{\bar{w}_1(t), \dots, \bar{w}_n(t)\}$, and $\cos \theta_i(t)$ are in the range of $[0, 1]$. The smaller $\theta_i(t)$ is, the larger the cosine value, and the closer the evaluated object is to the ideal object; the larger $\theta_i(t)$ is, the smaller the cosine value, and the farther the evaluated object is from the ideal object. Thus, the gray correlation projection closeness can be calculated as Equation (10):

$$y_i(t) = \frac{D_i^{+2}(t)}{D_i^{+2}(t) + D_i^{-2}(t)} \quad (10)$$

where $y_i(t)$ is the gray correlation projection coefficient. It is proved that when $y_i(t)$ is larger, the evaluated object is closer to the positive ideal object; when $y_i(t)$ is smaller, the evaluated object is closer to the negative ideal object.

3.2.2. Undesired Output Super-Efficiency SBM Models

In 2011, Tone proposed the SBM model based on the introduction of slack variables in the DEA model [34]. However, this model is unable to rank multiple effective decision units and does not consider the impact of non-expected outputs on the efficiency value of decision units. In order to compensate for such shortcomings, Tone continuously improved the SBM model and finally proposed the non-expected output super-efficiency SBM model [35], and the formulas are as follows (Equation (11)):

$$\rho^* = \min \frac{\frac{1}{m} \sum_{i=1}^m \frac{\bar{x}_i}{x_{i0}}}{\frac{1}{s_1 + s_2} (\sum_{q=1}^{s_1} \frac{\bar{y}_q^w}{y_{q0}^w} + \sum_{q=1}^{s_2} \frac{\bar{y}_q^b}{y_{q0}^b})}$$

$$s.t. \begin{cases} \bar{x} \geq \sum_{j=1, \neq k}^n \lambda_j x_j \\ \bar{y}^w \leq \sum_{j=1, \neq k}^n \lambda_j y_j^w \\ \bar{y}^b \geq \sum_{j=1, \neq k}^n \lambda_j y_j^b \\ \bar{x} \geq x_0, 0 \leq \bar{y}^w \leq y_0^w, \bar{y}^b \geq y_0^b, \lambda \geq 0 \end{cases} \quad (11)$$

where ρ^* is the target efficiency value; n, m, s_1, s_2 denote the number of decision units, input indicators, desired outputs, and non-desired outputs, respectively; $x_{i0}, y_{q0}^w, y_{q0}^b$ are the inputs, desired outputs, and non-desired outputs after the introduction of non-desired outputs, respectively; and $\bar{x}_i, \bar{y}_q^w, \bar{y}_q^b$ represent the slack variables of the three, respectively.

3.2.3. Coupled Coordination Degree Models

In order to quantitatively measure the coupling coordination degree between green technology innovation and carbon emission efficiency, this paper introduces the coupling degree model; combined with existing research, the specific formula is as follows: (Equations (12)–(14)):

$$W = 2\sqrt{X_1 X_2} / (X_1 + X_2) \quad (12)$$

$$T = \alpha X_1 + \beta X_2 \quad (13)$$

$$S = \sqrt{W \times T} \quad (14)$$

In the formula, X_1 represents the level of green technology innovation; X_2 represents carbon emission efficiency; W represents the degree of coupling; T represents the comprehensive evaluation index, S represents the degree of coupling coordination, $S \in [0, 1]$, and the closer the value of S is to 1, the higher the degree of coupling coordination between green technological innovation and carbon emission efficiency; α and β are the degree of contribution of the two systems, taking $\alpha = \beta = 0.5$.

3.2.4. Panel Tobit Models

Because the coupling degree of coordination measured by the coupling degree of coordination model is a limited value located between 0 and 1, it is easy to generate errors if the traditional least squares (OLS) method is used to regress the limited explanatory variables. The panel Tobit model effectively avoids this problem in the pre-model setting, so this paper selects the panel Tobit model. The specific form of the Tobit model is as follows (Equation (15)):

$$y_i = \begin{cases} c_1, & \text{if } y_i^* \leq c_1 \\ x_i \beta + \varepsilon_i, & \text{if } c_1 \leq y_i^* \leq c_2 \\ c_2, & \text{if } y_i^* \geq c_2 \end{cases} \quad (15)$$

where denotes the vector of regression parameters, is the explanatory variable, is the explained variable, and is the vector of values of the explained variable.

3.3. Selection of Variables

3.3.1. Green Technology Innovation Indicator System

For the construction of a green technology innovation index system, referring to the practice of Lin Yan [11] and Xu Xiaodong et al. [36], the three dimensions of green technology innovation inputs, green technology innovation outputs, and green technology support level are selected as the guideline layer and combined with the research. Then, eight indicators are selected as the indicator layer to construct the green technology innovation index system. New product development expenditure, R&D investment intensity, and the proportion of R&D personnel with a master's degree or above are selected to represent green technological innovation inputs. Industrial added value/secondary industry added value, technology market turnover, and the total number of green patent applications are selected to represent the green technological innovation outputs, of which the total number of green patent applications is the sum of the number of green patent applications and the number of utility patents authorized. GDP per capita and urban road area per capita are selected to represent the level of green technological support. The specific indicators are shown in Table 1.

Table 1. Green technology innovation evaluation index system.

Standardized Layer	Indicator Layer	Weights
Green technology innovation inputs (0.377)	New product development expenditures	0.112
	Intensity of investment in R&D	0.129
	Percentage of R&D personnel with master's degree or above	0.135
Green technology innovation outputs (0.364)	Value added of industry /value added of secondary industry	0.138
	Technology market turnover	0.110
	Total green patent applications	0.115
Level of green technology support (0.259)	GDP per capita	0.124
	Urban road space per capita	0.135

3.3.2. Carbon Emission Efficiency Indicator System

For the construction of a carbon emission efficiency indicator system, this paper draws on the research of Xu Yingqi [26] and Li Jianbao et al. [29] and selects capital, labor, and energy as the input indicators (Table 2). The capital input indicator adopts the capital stock, with 2011 as the base period, and the capital stock in the base period is calculated according to the formula of the modified base period proposed by Reinsdorf [37]. The depreciation rate is set at 9.6% with reference to the research of Zhang Jun [38]. The labor input indicator adopts the urban unit employed persons in provinces and cities. The energy input indicator selects the total energy consumption, and some missing values are calculated according to the growth rate of the total energy consumption. Energy consumption and some missing values are calculated according to the growth rate of total energy consumption.

Table 2. Carbon emission efficiency evaluation index system.

Indicator Category	Form	Specific Indicators
Input indicators	Capital investment	Capital stock
	Labor input	Employed persons in urban units
	Energy inputs	Total energy consumption

Table 2. Cont.

Indicator Category	Form	Specific Indicators
Output indicators	Expected outputs Non-expected outputs	GDP Carbon footprint

GDP is selected as the desired output and carbon emissions as the non-desired output. Carbon emissions were calculated with reference to the IPCC method published in 2006 with the following formula (Equation (16)):

$$C = \sum_{j=1}^n \alpha_j \times \beta_j \times A_j \quad (16)$$

where C is the total carbon emissions, A is the total energy consumption, α_j is the j th standard coal conversion coefficient, and β_j is the j th energy carbon emission coefficients. For each energy coefficient, refer to the China Energy Statistics Yearbook.

3.4. Data Sources

In order to ensure the scientificity of the results of the research on the coupling coordination and driving factors of green technological innovation and carbon emission efficiency in the Yangtze River Economic Belt, the data involved in this paper came from the China Statistical Yearbook, China Energy Statistical Yearbook, China Science and Technology Statistical Yearbook, and statistical yearbooks of provinces and cities. The total number of green patent applications came from the specialized database of the State Intellectual Property Office of China, and the missing data of individual years were made up using the interpolation method. In order to exclude the influence of price fluctuation, the constant price was treated with 2011 as the base period.

4. Results and Analysis

4.1. Measurement Analysis of Green Technology Innovation and Carbon Efficiency

4.1.1. Analysis of Green Technology Innovation Measurement

By constructing the green technology innovation index evaluation system, the entropy weight TOPSIS gray correlation projection method is used to comprehensively measure the green technology innovation level of the Yangtze River Economic Zone, and the results are shown in Table 3.

Table 3. Comprehensive evaluation value of green technology innovation level of provinces and cities in the Yangtze River Economic Belt.

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Mean
Shanghai	0.775	0.772	0.762	0.754	0.765	0.770	0.762	0.762	0.773	0.759	0.774	0.766
Jiangsu	0.670	0.707	0.729	0.728	0.710	0.717	0.734	0.725	0.729	0.715	0.690	0.714
Zhejiang	0.433	0.449	0.447	0.449	0.460	0.472	0.471	0.486	0.497	0.521	0.511	0.472
Anhui	0.274	0.283	0.307	0.328	0.351	0.373	0.381	0.389	0.382	0.403	0.404	0.352
Lower reaches	0.538	0.553	0.561	0.565	0.572	0.583	0.587	0.590	0.595	0.600	0.595	0.576
Jiangxi	0.232	0.243	0.236	0.243	0.260	0.267	0.293	0.279	0.273	0.265	0.312	0.264
Hubei	0.391	0.416	0.439	0.462	0.481	0.494	0.483	0.464	0.478	0.475	0.454	0.458
Hunan	0.322	0.306	0.316	0.296	0.313	0.320	0.332	0.318	0.347	0.358	0.353	0.326
The middle stretches of a river	0.315	0.321	0.330	0.334	0.351	0.361	0.369	0.354	0.366	0.366	0.373	0.349
Chongqing	0.291	0.282	0.276	0.287	0.301	0.301	0.270	0.261	0.254	0.275	0.266	0.279
Sichuan	0.314	0.322	0.332	0.339	0.375	0.379	0.403	0.435	0.393	0.406	0.402	0.373
Guizhou	0.178	0.166	0.179	0.203	0.219	0.211	0.198	0.199	0.204	0.252	0.259	0.206
Yunnan	0.220	0.225	0.240	0.260	0.24	0.238	0.212	0.198	0.185	0.201	0.222	0.223
Upper reaches	0.251	0.249	0.257	0.272	0.286	0.282	0.271	0.273	0.259	0.283	0.287	0.270
Mean	0.373	0.379	0.387	0.395	0.408	0.413	0.413	0.411	0.410	0.421	0.422	0.403

As can be seen from Table 1, from the criterion layer, the weight of green technology innovation input (0.377) is the largest, green technology innovation output (0.364) is the second largest, and the weight of green technology support level (0.259) is the smallest, which indicates that green technology innovation input has the greatest impact on the level of green technology innovation. From the perspective of the indicator layer, the weight of industrial added value/secondary industry added value (0.138) is the largest; this indicates that industrial structure has the strongest impact on the improvement in the green technology innovation level.

Table 3 shows that during the study period, the level of green technological innovation in the Yangtze River Economic Belt as a whole shows an upward trend, from 0.373 in 2011 to 0.422 in 2021. From the point of view of spatial distribution, there are obvious regional differences in the level of green technology innovation in the Yangtze River Economic Belt. For Shanghai, Jiangsu, Zhejiang, and Anhui, as representatives of the downstream green technology innovation, their comprehensive evaluation values are the largest, with an average value of 0.576. The middle reaches of the Yangtze River represented by Jiangxi, Hubei, and Hunan are the second largest, with a mean value of 0.349. The upper reaches of the Yangtze River represented by Chongqing, Sichuan, Guizhou, and Yunnan are the smallest, with a mean value of 0.270, which is generally characterized by “high in the east and low in the west”.

4.1.2. Analysis of Carbon Efficiency Measures

In this paper, Matlab 2020b software is utilized to construct the non-expected output super-efficiency SBM model in order to measure the carbon emission efficiency of the Yangtze River Economic Belt more objectively and reasonably, and the specific results are shown in Table 4.

Table 4. Carbon emission efficiency values of provinces and municipalities in the Yangtze River Economic Belt.

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Mean
Shanghai	1.120	1.115	1.115	1.125	1.117	1.128	1.126	1.126	1.121	1.147	1.133	1.125
Jiangsu	1.186	1.216	1.024	1.014	1.022	1.018	1.025	1.016	1.053	1.046	1.079	1.064
Zhejiang	1.014	1.101	1.087	1.077	1.072	1.111	1.116	1.130	1.174	1.129	1.122	1.111
Anhui	0.818	0.795	0.788	1.004	0.747	0.705	0.720	0.693	0.715	0.637	0.664	0.762
Lower reaches	1.057	1.057	1.003	1.055	0.989	0.990	0.997	0.991	0.991	1.016	1.000	1.013
Jiangxi	0.793	0.758	0.737	0.696	0.654	0.630	0.615	0.614	0.632	0.583	0.629	0.671
Hubei	0.588	0.591	0.680	0.663	0.662	0.637	0.657	0.718	0.707	0.741	0.702	0.664
Hunan	0.646	0.638	0.747	1.005	1.017	1.009	1.001	1.003	0.679	0.627	0.631	0.837
The middle stretches of the Yangtze River	0.675	0.662	0.722	0.788	0.778	0.758	0.758	0.778	0.673	0.651	0.654	0.718
Chongqing	0.575	0.569	0.640	0.610	0.591	0.557	0.556	0.571	0.624	0.587	0.614	0.588
Sichuan	0.597	0.611	0.593	0.599	0.586	0.583	0.603	0.611	0.639	0.568	0.583	0.599
Guizhou	0.419	0.428	0.447	0.471	0.438	0.413	0.411	0.411	0.424	0.385	0.383	0.425
Yunnan	0.482	0.483	0.507	0.504	0.501	0.470	0.466	0.447	0.509	0.472	0.492	0.484
Upper reaches	0.518	0.523	0.546	0.546	0.529	0.506	0.509	0.510	0.549	0.503	0.518	0.523
Mean	0.757	0.755	0.760	0.797	0.764	0.751	0.754	0.758	0.752	0.720	0.730	0.755

As can be seen from Table 4, in the time series, the overall trend of carbon emission efficiency values in the Yangtze River Economic Belt during the study period first increases and then decreases. Among them, the overall rising trend is obvious during the period of 2013–2014, which is related to the fact that the carbon emission efficiency of Anhui Province and Hunan Province rises significantly during this period. There are two obvious decreasing trends during the period of 2014–2020. Among them, during the 2014–2015 period, the carbon emission efficiency of all provinces and municipalities except Jiangsu Province and Hunan Province declined, with Anhui Province experiencing the largest decline, which may be due to the fact that China’s overall economy was in the doldrums

during this period due to the impact of the macroeconomic environment and overcapacity in the country. In addition, the Yangtze River Economic Belt, as a part of China, naturally experienced a decline in its overall economy during the 2019–2020 period. This may be due to the fact that China's overall economy was in the doldrums due to the macroeconomic environment and domestic overcapacity.

In terms of spatial distribution, there are obvious regional differences in the carbon emission efficiency value of the Yangtze River Economic Belt, with Shanghai, Jiangsu, Zhejiang, and Anhui representing the downstream region with the largest carbon emission efficiency value, with an average value of 1.013; except for Anhui, the carbon emission efficiency value of the region is greater than 1, which is in the production frontier; Jiangxi, Hubei, and Hunan represent the middle reaches of the region with the second largest carbon emission efficiency value, with an average value of 0.718; and Chongqing, Sichuan, Guizhou, and Yunnan represent the upstream region with the smallest carbon emission efficiency value, with an average value of 0.523. Overall, this shows the characteristics of “east high and west low”. The upstream region, represented by Chongqing, Sichuan, Guizhou, and Yunnan, has the smallest carbon emission efficiency value, with an average value of 0.523, and the whole region shows the characteristic of “high in the east and low in the west”. This may be due to the fact that the downstream region is located on the east coast of China, with a developed economy, basically completing the transformation of industrialization. The tertiary industry occupies a major position, resulting in low carbon emissions, while the upstream region is located inland, with an underdeveloped economy and backward technology, and it still relies on the development of the economy by high-consumption, high-pollution industrial enterprises, which results in a large amount of carbon emissions.

4.2. Analysis of the Coupled Harmonization of Green Technology Innovation and Carbon Efficiency

According to the comprehensive evaluation value of green technology innovation and carbon emission efficiency obtained from the calculation, the coupling coordination degree of the Yangtze River Economic Belt from 2011 to 2021 is measured by using the coupling coordination degree model, as shown in Table 5. In order to more clearly reflect the development level of the coupling coordination between green technological innovation and carbon emission efficiency in the Yangtze River Economic Belt, referring to the practice of Wang Xuefeng et al., the coupling coordination degree is divided into five grades: severe dysfunctional stage (0–0.2), primary dysfunctional stage (0.2–0.4), intermediate coordination stage (0.4–0.6), good coordination stage (0.6–0.8), and high-quality coordination stage (0.8–1.0) five levels [39].

Table 5. Coupling harmonization degree of green technology innovation and carbon emission efficiency in the Yangtze River Economic Belt.

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Shanghai	0.919	0.908	0.936	0.934	0.937	0.939	0.936	0.935	0.922	0.935	0.940
Jiangsu	0.907	0.919	0.893	0.884	0.886	0.885	0.893	0.886	0.886	0.889	0.896
Zhejiang	0.790	0.789	0.811	0.805	0.811	0.826	0.827	0.837	0.841	0.846	0.844
Anhui	0.617	0.605	0.631	0.721	0.635	0.628	0.640	0.628	0.624	0.608	0.627
Jiangxi	0.582	0.567	0.569	0.541	0.539	0.537	0.541	0.533	0.528	0.516	0.569
Hubei	0.546	0.547	0.630	0.611	0.635	0.631	0.642	0.671	0.655	0.689	0.666
Hunan	0.559	0.539	0.617	0.703	0.720	0.720	0.725	0.717	0.589	0.584	0.588
Chongqing	0.498	0.479	0.535	0.502	0.515	0.502	0.488	0.496	0.514	0.523	0.539
Sichuan	0.524	0.527	0.523	0.513	0.539	0.553	0.578	0.594	0.583	0.563	0.577
Guizhou	0.194	0.191	0.194	0.201	0.205	0.203	0.200	0.200	0.201	0.212	0.213
Yunnan	0.375	0.364	0.391	0.352	0.398	0.381	0.367	0.328	0.387	0.396	0.403
Mean	0.592	0.585	0.612	0.615	0.620	0.619	0.622	0.620	0.612	0.615	0.626

As can be seen from Table 5, the coupling coordination degree of the Yangtze River Economic Belt during the study period is low as a whole, but shows an upward trend, from 0.592 in 2011 to 0.626 in 2021, crossing from the moderate coordination stage to the good coordination stage. However, there are significant differences in the coupling coordination degree of each province and city, with the highest coupling coordination degree being Shanghai, which has been in the high-quality coordination stage. Conversely, the lowest is Guizhou Province, which crossed into the primary dysfunctional stage in 2014. This indicates that the Yangtze River Economic Belt still needs to further explore the balance point of coordinated development of green technology innovation and carbon emission efficiency.

The natural breakpoint method of ArcGIS 10.7 software was applied to classify the degree of coupling coordination into five stages, namely, severe dysfunction, primary dysfunction, moderate coordination, good coordination, and quality coordination, and the spatial distribution of the degree of coupling coordination was plotted for the years 2011, 2014, 2017 and 2021 (Figure 1). Overall, it seems that the coupling coordination degree of green technology innovation and carbon emission efficiency in the Yangtze River Economic Belt from 2011 to 2021 is mainly in the coordination stage, and there are spatial differences. The overall presentation of the characteristics is “high in the east and low in the west”. Specifically, Shanghai and Jiangsu have been in the high-quality coordination stage. Table 5 shows that Zhejiang Province entered the high-quality coordination stage from the good coordination stage in 2013, realizing the hierarchical leap and showing a year-on-year growth trend from 2014 onwards. Jiangxi Province showed a fluctuating downward trend in the medium coordination stage, which may be due to the province’s declining carbon emission efficiency. The coupling coordination degree of the remaining provinces is in a fluctuating upward trend, among which Hubei and Guizhou provinces achieved tier crossing in 2013 and 2014, respectively, and the trend of the coupling coordination degree of Hunan Province was an inverted “U” curve during 2013–2018. Hunan Province achieved tier crossing in a well-coordinated stage, while the rest of the years were in the medium coordination stage, which is closely related to the carbon emission efficiency of Hunan Province.

4.3. Drivers of Coupled Harmonization of Green Technology Innovation and Carbon Efficiency

In order to further explore the main driving factors affecting the coupling coordination degree of green technology innovation and carbon emission efficiency in the Yangtze River Economic Belt, this paper uses the panel Tobit model to analyze them.

4.3.1. Variable Selection and Model Construction

The coupling and coordination of green technology innovation and carbon emission efficiency are affected by many factors. In order to grasp the main driving factors that may promote the coupling and coordinated development of green technology innovation and carbon emission efficiency in the Yangtze River Economic Belt, we have sorted out the literature on the influencing factors of green technology innovation and carbon emission efficiency in recent years. This paper mainly refers to the existing studies [25,26,40,41] and selects the variables of urbanization level (x_1), environmental regulation (x_2), industrial structure (x_3), economic development level (x_4), degree of openness to the outside world (x_5), energy structure (x_6), and labor force level (x_7) to be identified as the factors that may be closely related to the coupling coordination degree. It also uses the proportion of urban resident population to the total population, the investment in industrial governance, and the investment in the total population as the main driving factors of green technological innovation and carbon emission efficiency. Of the total population, the amount of investment completed in industrial governance, the share of industrial value added in the secondary industry, GDP, the share of total import and export in GDP, the share of electricity consumption, and the logarithm of the number of employed persons were determined, respectively.

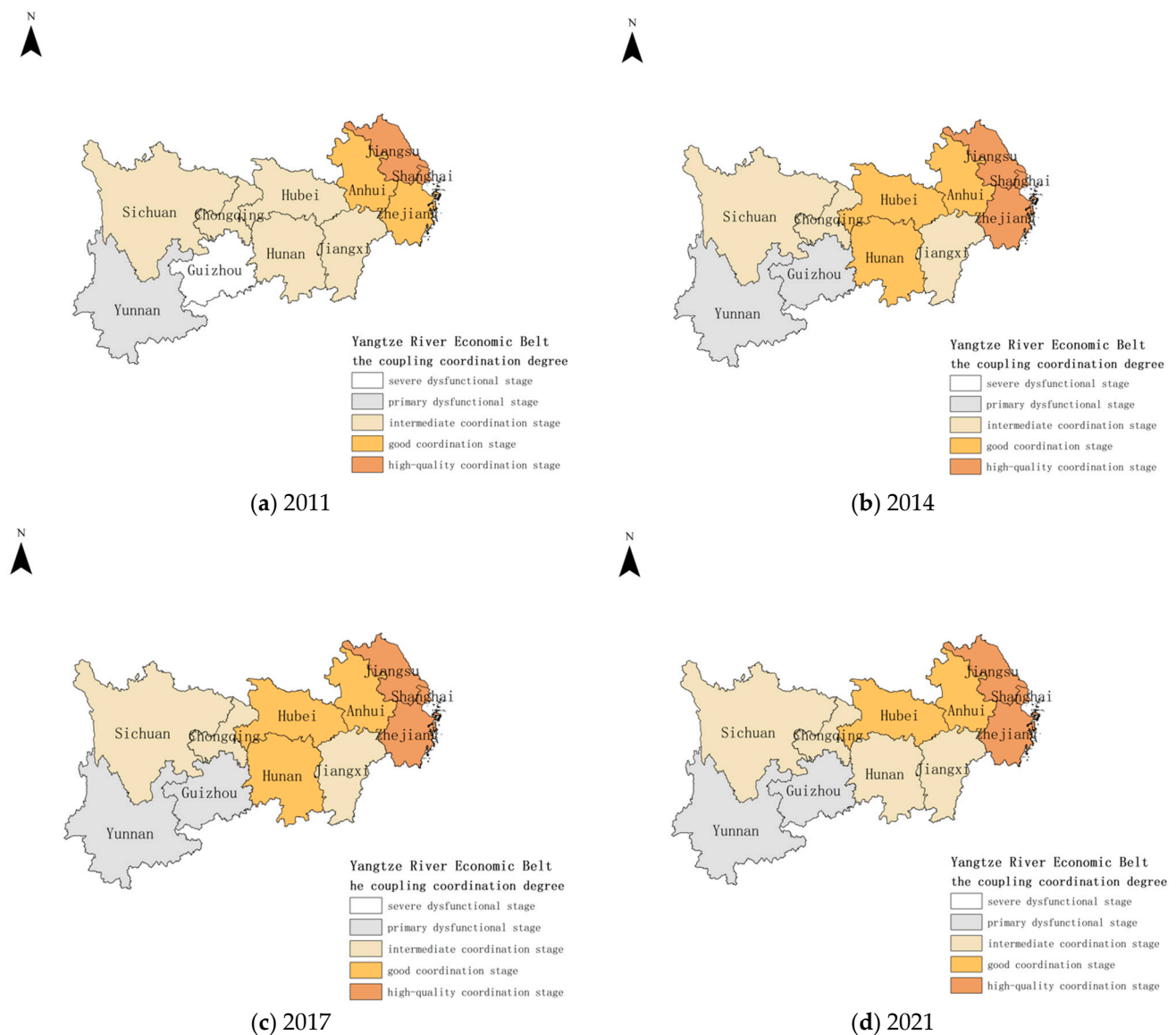


Figure 1. Spatial evolution of the coupled coordination degree of green technology innovation and carbon emission efficiency in the Yangtze River Economic Belt. Note: This map is produced based on standard maps downloaded from the Standard Map Service System of the Ministry of Natural Resources, with no modifications to the base map. (Review number: GS(2019)1822 Supervised by the Ministry of Natural Resources).

Based on the above variables, the panel Tobit model benchmark is refined into the following form (Equation (17)):

$$eff = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_0 \quad (17)$$

where α is the constant term; β_1 – β_7 are the regression coefficients of each explanatory variable; and β_0 is the random error term.

4.3.2. Analysis of Results

Using stata16.0 software, the drivers of coupling coordination degree are analyzed based on the above model. As can be seen from Table 6, the LR value in the regression model test of the Yangtze River Economic Belt rejects the original hypothesis, so the panel Tobit model can be selected for empirical analysis.

Table 6. Estimated results of the regression model for the drivers of coupled coordination degree.

Variant	p-Value
X ₁	0.003 ***
X ₂	0.010 ***
X ₃	0.033 **
X ₄	0.000 ***
X ₅	0.000 ***
X ₆	0.000 ***
X ₇	0.000 ***
_cons	0.001 ***
Log_L	230.554
LR(chi)	92.300
Prob>chi	0.000

Note: **, *** indicate significant at the 5%, and 1% levels, respectively.

From the regression results, overall, the *p*-values of the variables are significant at the 1% level, except for the contribution of industrial structure to the degree of coupling coordination, which is significant at the 5% level. Except for the significant negative correlation between energy structure and the coupling coordination degree of the two, the rest of the indicators show a significant positive correlation with it. Among them, the inhibitory effect of energy structure on the coupling degree of coordination is significant at the 1% level, indicating that the Yangtze River Economic Belt still mainly relies on primary energy with high carbon emissions to develop its economy, which has caused a great burden on the ecological environment. Therefore, in order to achieve the green and low-carbon transformation of the Yangtze River Economic Belt, it is necessary to optimize the energy structure. The promotional effect of industrial structure on the coupling coordination degree is significant at the 5% level, and the promotional effect of the urbanization level, the environmental regulation, the level of economic development, the degree of openness to the outside world, and the effect of labor force on the coupling coordination degree are significant at the 1% level, which suggests that with the aggregation of industries and labor force to the cities and towns, the level of urbanization increases and thereby promotes economic development. In the short term, environmental regulation brings more challenges to enterprises and inhibits economic development, but in the long term, it can force enterprises to continuously increase the intensity of industrial R&D investment, improve the contribution of independent green technological innovation, force enterprises to transform to a green and low-carbon technology industry to drive economic growth, effectively inhibit carbon emissions, reduce industrial pollution, and thus improve the efficiency of carbon emissions.

5. Conclusions and Recommendations

5.1. Main Conclusions

Based on the basic data of 11 provinces and cities in the Yangtze River Economic Belt from 2011 to 2021, this paper analyzes the coupling coordination degree and driving factors of green technology innovation and carbon emission efficiency, which are analyzed by constructing a model, and the following conclusions are drawn.

- (1) From the time series, on the whole, the comprehensive evaluation value of green technology innovation level in the Yangtze River Economic Zone shows a rising trend, and the industrial structure has the greatest influence on improving the level of green technology innovation. The value of carbon emission efficiency firstly rises and then declines; from the perspective of spatial distribution, there is a certain degree of similarity between the level of green technology innovation and carbon emission efficiency in the Yangtze River Economic Zone, which both show a decrease from the east coast to the west inland level. This occurs according to spatial evolution law.

- (2) Overall, the coupling coordination degree of green technology innovation and carbon emission efficiency in the Yangtze River Economic Belt from 2011 to 2021 shows an upward trend, crossing from the moderate coordination stage to the good coordination stage, and the coordination relationship between the two systems of green technology innovation and carbon emission efficiency is gradually strengthened. Specifically, Shanghai Municipality and Jiangsu Province have been in the high-quality coordination stage, with the exception of Jiangxi Province, which fluctuates and decreases in the medium coordination stage. The coupling coordination degree of the remaining provinces is in a fluctuating upward trend, among which Hubei Province and Guizhou Province have realized a hierarchical leap. From the point of view of spatial distribution, all provinces show the characteristic of “high in the east and low in the west”.
- (3) From the influencing factors of the coupling coordination degree, it can be seen that, from the significance point of view, the P value of each variable is significant at the 1% level, except for the promotion effect of industrial structure on the coupling coordination degree, which is significant at the 5% level. In terms of the direction of action, except for the energy structure and the degree of coordination of the coupling of the two, it showed a significant negative relationship. The level of urbanization, environmental regulation, industrial structure, economic development, labor force, and the degree of openness to the outside world are all significantly positively correlated with it.

5.2. Recommendations for Countermeasures

Based on the above conclusions, the following recommendations are made:

- (1) Implement differentiated emission reduction strategies. According to the law of economic development, downstream areas should continue to vigorously develop emerging industries and high-tech industries and guide the regular upgrading and optimization of industrial structures to realize green transformation. Middle and upper reaches should continue to develop traditional industries on the basis of protecting the ecological environment, and all regions should give full play to their respective advantages and actively participate in inter-regional industrial cooperation and technical exchanges to realize local development and promote the overall development level of the Yangtze River Positive Belt at the same time. The development level of the Yangtze River positive belt as a whole will be improved continuously.
- (2) Increase opening up to the outside world. Opening up to the outside world is an inevitable choice for China to promote green and low-carbon transformation, and it is a key driving force for China's economic development. Increasing opening up to the outside world can introduce advanced technologies and make up for technical deficiencies. To promote the opening up of the Yangtze River Economic Belt to the outside world at a higher level, on the one hand, the opening up of special features should be coordinated, and the middle and lower reaches of the Yangtze River should be supported in exploring differentiated opening-up paths based on the characteristics of their locations. On the other hand, it should be opened up in a linked manner, and the provinces in the Yangtze River Economic Belt should formulate a mechanism for synergistic development. The lower reaches of the Yangtze River, which are more open to the outside world, should provide support for the middle and upper reaches of the Yangtze River to make better use of the international market and resources, and the upper reaches of the Yangtze River should provide support for the middle and lower reaches of the Yangtze River to expand the inland trade network.
- (3) Set reasonable low-carbon standards and optimize industrial structure. On the one hand, the implementation of low carbon standards will increase the production cost of products and eliminate some enterprises in the Yangtze River Economic Belt whose carbon emissions do not meet the standards, or will prompt advanced enterprises to increase investments in green technological innovation, improve energy utilization,

reduce carbon emissions, and realize green and low-carbon transformation. On the other hand, the strict carbon emission standards will prompt the development of high-tech industries, productive service industries, and other low-carbon industries, which can be effectively reduced to a lower level. On the other hand, the strict carbon emission standards will prompt people to develop low-carbon industries such as high-tech industries and production service industries, and the vigorous development of these new industries can effectively reduce the proportion of traditional industrial enterprises, optimize the industrial structure, and play a positive role in promoting the green and low-carbon transformation.

- (4) Play a coordinating role in the government to strengthen the cooperation mechanism of industry–university–research institutes and accelerate green technological innovation. Government departments should introduce a legal system to safeguard the innovation mechanism of industry–university–research collaboration, clarify the responsibilities and obligations of all parties, and strengthen the innovation coordination mechanism among enterprises, universities, and research institutes by setting up a contact meeting system. Government departments should give full play to their own organizational and coordinating capabilities, encourage more subjects to participate in the industry–university–research cooperation system, effectively promote the cooperative relationship between universities, research institutes, and enterprises, increase the input of green technology innovation talents, and improve the level of green technology innovation.
- (5) Build a clean and low-carbon energy system. The Yangtze River Economic Zone is in the middle stage of development, and it still needs to vigorously develop its economy, which cannot be separated from energy production and consumption. If we want to promote the low-carbon development of the region under the “dual-carbon” goal, on the one hand, we should accelerate the cross-stage transformation of energy sources, abandon the development concept of moving from coal to oil and natural gas to new energy sources, and implement a leapfrog energy structure. This will aid us to vigorously promote the use of new energy sources such as natural gas, solar energy, and wind energy, and to correspondingly reduce dependence on fossil energy sources such as coal. On the other hand, it will cause the low-carbon exploitation of fossil energy sources. Coal and other fossil energy sources drive the economic development of the Yangtze River Economic Zone. The energy transition process is long, and the market share of new energy sources is still relatively low, so it is still unable to completely get rid of the dependence on fossil energy. Therefore, fossil energy extraction technology can be innovated to improve the recycling rate of fossil energy.

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