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Research on Industrial Energy Efficiency in the Yangtze River Delta from the Perspective of Carbon Emission Reduction

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Abstract

Under the "double carbon" perspective, it is urgent for the Yangtze River Delta region to improve energy efficiency, promote energy conservation and carbon reduction, and accelerate the green transformation and development of the economy. Select the panel data of the central cities of the Yangtze River Delta from 2005 to 2019, take carbon emissions as the unintended output, use the Super-SBM method to measure industrial energy efficiency, and use Tobit regression to empirically test the main drivers of industrial energy efficiency. The results show that: (1) The overall industrial energy efficiency is low but fluctuates slowly. which was lower than 1 in Jiangsu, Zhejiang and Anhui provinces. The industrial input-output structure is unbalanced and the technical efficiency level is not high. (2) The positive driving factors of industrial energy efficiency are environmental regulation, enterprise scale and urbanization. Economic growth, energy consumption structure and energy technology level have a negative inhibitory effect, and the impact of environmental regulation and economic growth is sluggish. Therefore, the Yangtze River Delta region should continue to implement green production and environmental protection policies, introduce advanced technology and high-end talents, optimize the structure of production factors, and transform the development mode of energy-intensive industries.

Keywords

Industrial Energy Efficiency; Carbon Emission; Super-SBM; Panel Tobit Regression.

1. Introduction

In September 2021, the "Opinions on Implementing the New Development Concept in an All-round Way to Achieve Carbon Peak and Carbon Neutralization" pointed out that the integration of the Yangtze River Delta must strengthen the task orientation of green and low-carbon economic development, establish the regional ecological economic benchmark of economic leading and ecological demonstration, and lead the green transformation of national economic development. In October of the same year, the "Action Plan for Achieving Carbon Peak by 2030" required that all regions should take the elimination of industrial inefficient capacity as the core to promote energy conservation and carbon reduction measures, and strive to take the lead in achieving carbon peak in industry. However, the Yangtze River Delta region has a large scale of industrial production and a deep degree of concentration. The contradiction between the persistent energy consumption demand and the scarcity of fossil energy reserves is deep-rooted. The further stimulation of the energy premium under global inflation poses a threat to energy security. In addition, the pace of green economy development in three provinces and one city is inconsistent, and the construction of the system of sustainable energy utilization is in the initial stage. In the current environment where the energy efficiency of the world's major economies has an asymmetric impact on carbon emissions [1], the Yangtze River Delta should strengthen the monitoring of carbon emissions from industrial production, coordinate and optimize the structure of industrial energy input, reduce pollution emissions and improve

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energy efficiency, lay out the industrial production system with low energy consumption and low carbon emissions, scientifically implement the requirements of industrial carbon peak development, and promote win-win regional economic and ecological benefits.

2. Review of Relevant Research

The academic community first introduced the DEA-ML model framework to measure the energy efficiency of the Yangtze River Delta and explore its changing characteristics, combined with panel regression to verify the influencing factors of energy efficiency [2,3], and used the improved LMDI factorization method to decompose the changes in industrial energy consumption intensity in the central cities of Jiangsu, Zhejiang and Shanghai into changes in energy consumption technology, energy output and energy consumption structure, confirming the core role of technological innovation in improving energy efficiency [4]. When developing export-oriented economy in the Yangtze River Delta, which benefits from the opening-up policies, there is an interaction between the advanced reverse technology spillover and energy efficiency derived from investment attraction [5], and the reverse technology spillover generated by capital export promotes production technology innovation, which is beneficial to improving energy efficiency [6]. In addition, the differentiated economic model and political system barriers of various cities are potential incentives to affect energy efficiency. The government breaks down the political system barriers, strengthens social governance cooperation and promotes economic co-construction, which has a positive effect on urban functional integration and market integration, and ultimately leads to the improvement of energy efficiency [7]. The horizontal comparative study of energy efficiency in the Yangtze River Delta mainly includes the analysis of static characteristics, dynamic evolution differences and sources of heterogeneity of energy efficiency drivers in urban agglomeration [8-10]. Among the three major urban agglomerations, Beijing-Tianjin-Hebei has the highest energy efficiency [10], and the energy efficiency in Yangtze River Delta is higher than the Pearl River Delta [8,9]. The distribution of energy conservation and emission reduction potential of each urban agglomeration indicates that the Yangtze River Delta should improve energy efficiency by means of unilateral breakthrough emission reduction strategy [9].

The existing research results are based on a broader input-output perspective, ignoring the difference in the contribution of different types of energy inputs to total output. Most industrial pollution emissions come from the use of fossil energy. Therefore, when measuring energy efficiency, the dominant role of energy input on unintended output should be taken into account so that energy efficiency reflects the characteristics of energy input and output. As a new member of the Yangtze River Delta integration, Anhui's green production level is related to the development of its own height and quality, and also has an important impact on the overall green economic transformation of the region. Therefore, this paper brings Anhui into the study of energy efficiency in the Yangtze River Delta, focuses on the carbon emission reduction benefits of industrial production, measures and evaluates the industrial energy efficiency in the Yangtze River Delta (hereinafter referred to as industrial energy efficiency) as an involuntary output, tracks its dynamic changes and structural characteristics, empirically studies the main drivers of industrial energy efficiency, and provides suggestions and suggestions for optimizing industrial production and developing low-carbon economy in the Yangtze River Delta.

3. Measurement and Analysis of Industrial Energy Efficiency

3.1. Calculation Method

Industrial production input and output are affected by uncontrollable subjective and objective factors such as economy, society and environment, and its heterogeneity is difficult to observe. The characteristics of energy utilization based on specific production laws often ignore this difference, which makes the accurate measurement of energy efficiency into a dilemma. By combing and comparing the existing research results, it is found that the DEA model framework is a relatively good energy efficiency evaluation tool in the field of energy economy research in the future [10]. The reason is that the DEA model does not need to preset a specific form of production function when evaluating the relative rationality of the input and output of the factors in the production decision-making unit. The cutting-edge production function is constructed by analyzing the input and output observation data, and the input-output optimal planning model is set up with the help of the production possibility set to realize the quantification of production performance, effectively avoiding the measurement error caused by the production heterogeneity. Therefore, this paper selects the Super-SBM model to measure industrial energy efficiency. The advantage of this method is that while incorporating involuntary output into the efficiency evaluation system, it retains the relaxation characteristics of input-output variables, and achieves a theoretical breakthrough in the comparable efficiency of effective decision-making units [11]

Super-SBM model is an efficiency measure function obtained by redefining the production possibility set based on the improved SBM model In all decision-making units DMU, the investment of any DMU $x \in R^q$,voluntary output $y^d \in R^{\mu_1}$,involuntary output $y^i \in R^{\mu_2}$,expressed as a matrix:

$$X=[x_1,\cdots,x_n] \in R^{q\times n}>0,\quad Y^d=[y_1^d,\cdots,y_n^d] \in R^{\mu_1\times n}>0,\quad Y^i=[y_1^i,\cdots,y_n^i] \in R^{\mu_2\times n}>0.$$

The set of production possibilities is as follows:

$$p=\left\{\left(x,y^d,y^i\right)\middle| x\geqslant X\lambda, y^d\leqslant Y^d\lambda, y^i\leqslant Y^i\lambda, \lambda\geqslant 0\right\} \tag{1}$$

Based on the objective of sorting and measuring the effective DMU, the production possibility set is redefined as:

$$p(x_0,y_0)=\left\{\left(\bar{x},\bar{y}^d,\bar{y}^i\right)\middle| \bar{x}\geqslant\sum_{i=1}^{n}\lambda_i x_i, \bar{y}^d\leqslant\sum_{i=1}^{n}\lambda_i y_i^d, \bar{y}^i\leqslant\sum_{i=1}^{n}\lambda_i y_i^i, \bar{y}^d\geqslant 0, \lambda\geqslant 0\right\} \tag{2}$$

Under the new production regulation conditions, the efficiency measurement function is:

$$TE=\min \frac{1}{q}\sum_{i=1}^{q}\frac{\bar{x}_i}{x_{i0}} \Bigg/ \frac{1}{\mu_1+\mu_2}\left(\sum_{r=1}^{\mu_1}\frac{\bar{y}_r^d}{y_{r0}^d}+\sum_{i=1}^{\mu_2}\frac{\bar{y}_1^i}{y_{10}^i}\right) \tag{3}$$

From (1) to (3), x_0 and y_0 are the evaluated inputs and outputs, λ is the envelope multiplier representing the contribution of input and output to efficiency, $\bar{x}$, $\bar{y}^d$, $\bar{y}^i$ are the relaxation-terms of input, voluntary output, and involuntary output respectively. And TE is the efficiency value. TE greater than 1 means that the input-output structure of industrial production is reasonable, achieving the organic unity of industrial growth and carbon emission reduction, with both economic and ecological benefits; When TE is less than 1, it means that there is benefit loss caused by waste of input or unreasonable output in industrial production. The higher TE is, the better the industrial production benefit is. On the contrary, the more serious the benefit loss is.

3.2. Indicator System

Most cities in the Yangtze River Delta only count the total consumption of specific types of energy by industrial enterprises above designated size, so measuring the industrial energy efficiency of enterprises above designated size as an alternative indicator of overall industrial energy efficiency.

3.2.1. Input

Capital. The permanent inventory method is used to calculate the fixed capital of industrial enterprises above the city's designated size. The base period capital is obtained by the growth rate method:

$$K_t = I_t + (1 - \varphi_t) K_{t-1} \tag{4}$$

$$K_0 = \frac{I_0}{g + \varphi_t} \tag{5}$$

During steady growth, the capital output ratio remains unchanged, the change in capital stock equals the change in investment, the investment growth rate g equals the GDP growth rate [13], the amount of fixed assets investment takes the difference between the original value of fixed assets [14], and the depreciation rate of industrial capital φ_t take 8.56% [15].

Labor. The labor factor input is expressed by the average number of industrial employees.

Energy. Select nine kinds of energy that consume the most in industrial production: coal, coke, gasoline, kerosene, diesel oil, fuel oil, gaseous natural gas, liquid natural gas, and liquefied petroleum gas, convert them into standard coal according to the current national standards, and sum up to get the total energy consumption. The main utilization of crude oil is refining and reprocessing. The purpose of developing the oil processing industry in cities is to seek self-sufficiency or trade in industrial energy, rather than directly consume crude oil. The inclusion of crude oil in the energy efficiency measurement is not only contrary to the fact of industrial production, but also leads to repeated calculation of carbon emissions, so it is eliminated.

3.2.2. Output

Voluntary output. Measured by industrial output above designated size, this indicator includes the value of intermediate products. The reason is that the value of the final product cannot be separated from the production and consumption process of intermediate products, and the input and consumption of energy are throughout. This recalculated indicator selection method [16] can reflect the energy consumption and carbon emissions in the actual industrial production process.

Unvoluntary output. Most of the carbon emissions from industrial production come from the energy release of energy consumption. Based on IPCC, carbon emissions are obtained from carbon emission factors of specific types of energy:

$$CO_2 = \sum_{i=1}^{9} CO_{2,i} = \sum_{i=1}^{9} \gamma_i \kappa_i \xi_i \delta_i \times \frac{44}{12} \gamma_i \tag{6}$$

γ_i is the energy consumption, κ_i is the lower calorific value, ξ_i is the carbon content, δ_i is the oxidation rate, and 44/12 is the molecular weight of carbon dioxide. The conversion standards involved in the above processes are derived from the "General Principles for the Calculation of Comprehensive Energy Consumption 2020" and the "Guidelines for National Greenhouse Gas Inventories 2006". The input-output data is derived from the Statistical Yearbook of the central city of the Yangtze River Delta, supplemented by the Statistical Yearbook of China's Cities, the Statistical Yearbook of China's Energy, and the Statistical Yearbook of each province, and very few loss data are supplemented by the growth rate method and interpolation method. In this paper, all value variables are converted into comparable series with the base period of 2005, and Taizhou City, where the input-output data is seriously missing, is eliminated.

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3.3. Industrial Energy Efficiency Analysis

Table 1. Average annual industrial energy efficiency of cities in the Yangtze River Delta

Provinces and cities (regions)	TE	PE	SE
Shanghai	1.310	1.425	0.919
Nanjing	0.909	0.971	0.938
Wuxi	0.775	0.797	0.967
Changzhou	0.716	0.735	0.976
Suzhou	0.722	0.782	0.926
Nantong	0.765	0.801	0.958
Yancheng	0.880	0.9173	0.958
Yangzhou	0.942	0.957	0.983
Zhenjiang	1.084	1.104	0.982
Hangzhou	0.911	0.937	0.974
Ningbo	0.668	0.688	0.973
Jiaxing	0.648	0.670	0.966
Huzhou	0.788	0.850	0.928
Shaoxing	0.875	0.894	0.978
Jinhua	0.770	0.816	0.945
Zhoushan	0.649	0.931	0.735
Taizhou	0.298	0.306	0.976
Hefei	0.924	0.995	0.925
Wuhu	0.756	0.833	0.904
Ma'anshan	0.643	0.687	0.936
Tongling	0.913	1.178	0.772
Anqing	0.746	0.871	0.858
Chuzhou	0.609	1.229	0.501
Chizhou	0.407	1.338	0.303
Xuanchen	0.699	1.184	0.594
Jiangsu	0.848	0.883	0.961
Zhejiang	0.701	0.762	0.934
Anhui	0.712	1.040	0.724
the Yangtze River Delta	0.776	0.916	0.875

Note: TE, PE and SE represent comprehensive efficiency, pure technical efficiency and scale efficiency respectively

The calculated average industrial energy efficiency of the Yangtze River Delta from 2005 to 2019 is shown in Table 1. In general, the industrial energy efficiency value of most cities is lower than 1, the carbon emission reduction effect of industrial production is not good, the application level of advanced production technology is insufficient, and the obvious loss of scale benefits leads to more significant energy utilization inefficiency. The industrial energy efficiency value and technical efficiency value of Shanghai and Zhenjiang are higher than 1. The carbon emission control effect of the two cities on industrial production is better, and the low-carbon production technology is more developed. From the provincial perspective, the industrial energy efficiency values of Shanghai and Jiangsu are higher than the average value of 0.776, while Anhui and Zhejiang are lower than the average level. The industrial energy efficiency of the three provinces of Jiangsu, Zhejiang and Anhui is lower than 1, which indicates that the problems of low energy efficiency and high carbon emission rate generally exist in the industrial production of the three provinces. Jiangsu has the best carbon emission control effect, while Zhejiang and Anhui have the same carbon emission reduction effect. From the perspective of decomposition of industrial energy efficiency in the three provinces, Jiangsu and Zhejiang have good industrial production scale effect, while Anhui has the lowest scale effect. In terms of the application of carbon emission reduction technology, Anhui has the highest technical efficiency value and has reached the effective level, while the contribution rate of industrial energy efficiency technology in Jiangsu and Zhejiang is low, and the technology is not effective. The industrial production situation in the Yangtze River Delta has a significant gap between provinces and regions. Shanghai has a large industrial scale and the best use of green production technology; Anhui has a small industrial scale but attaches importance to the use of green production technology. Jiangsu and Zhejiang maintain a higher energy input-output efficiency through a more scientific production scale. According to Figure 1, the industrial energy efficiency in the Yangtze River Delta is slowly fluctuating, but generally at an inefficient level. Although the industrial energy efficiency has gradually improved, it has not met the requirements of green and low-carbon industrial production targets.

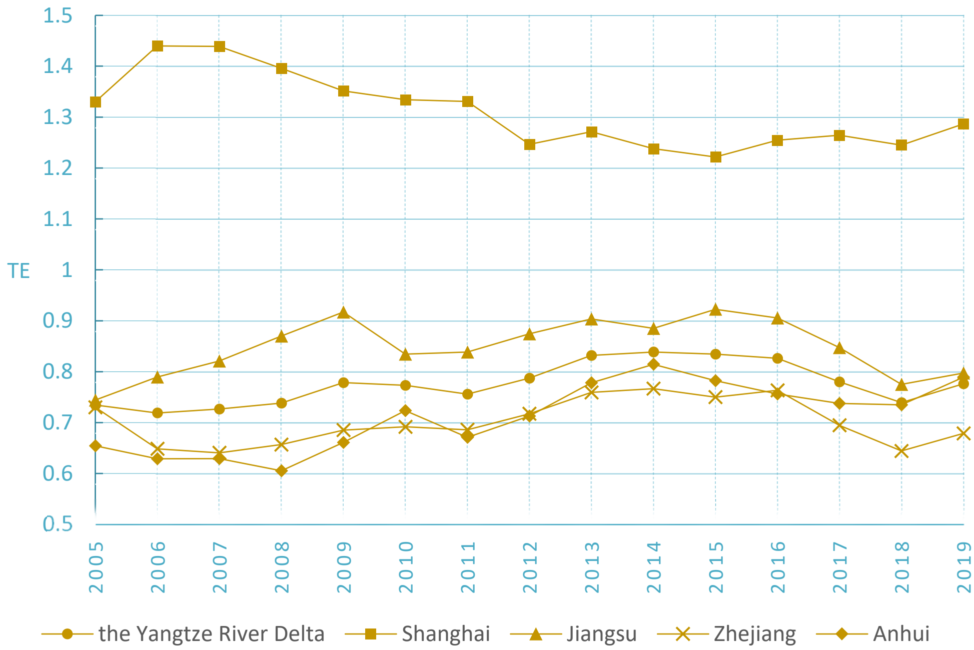

Figure 1. Average annual industrial energy efficiency value of the Yangtze River Delta

4. Analysis of Driving Factors of Industrial Energy Efficiency

4.1. Model Settings

Since the lower limit of industrial energy efficiency value is 0 and discrete truncation, it belongs to the restricted data meeting the constraints of industrial production, and the dependent variable restricted Tobit regression model has a good effect on its analysis, so the random effect panel Tobit model is selected to empirically test the driving factors of industrial energy efficiency:

$$iee_{m,n}=\begin{cases}0 & iee^{*}_{m,n}\leqslant 0\\ iee^{*}_{m,n}=\alpha X_{m,n}+\varepsilon_{m,n}+\eta & iee^{*}_{m,n}>0\end{cases} \tag{7}$$

For the sake of empirical comprehensiveness, establishing the fixed effect panel model:

$$iee_{m,n}=\alpha X_{m,n}+\varepsilon_{m,n}+\sigma_{m}+\tau_{n}+\eta \tag{8}$$

m and n respectively represent the city and year, $iee_{m,n}$ is industrial energy efficiency value, $iee^{*}_{m,n}$ is the potential variable, $X_{m,n}$ is the industrial energy efficiency factor variable, α is the undetermined parameter vector, η and ε are constant term and random term respectively, σ_m and τ_n represent individual effect and time effect respectively. The specific sub-items of $X_{m,n}$ are as follows:

$$X_{m,n}=\alpha_1 ed_{m,n}+\alpha_2 er_{m,n}+\alpha_3 sts_{m,n}+\alpha_4 op_{m,n}+\alpha_5 etl_{m,n}+\alpha_6 es_{m,n}+\alpha_7 ers_{m,n}+\alpha_8 ur_{m,n} \tag{9}$$

In formula (9), ed, er, sts, op, etl, es, ers and ur respectively represent economic growth, environmental regulation, scientific and technological investment, opening-up, energy technology level, enterprise scale, energy consumption structure and urbanization.

The industrial energy efficiency in this paper is based on the measurement of industrial production and operation activities. The regular input and output will cause the change of industrial energy efficiency to have a lag, that is, the current energy efficiency is affected by the input and output of the previous period [12,17]. To measure this effect, a dynamic panel regression model is established:

$$iee_{m,n}=p_1 iee_{m,n-1}+p_2 iee_{m,n-2}+\alpha X_{m,n}+\varepsilon_{m,n}+\eta \tag{10}$$

The economic and environmental factors that affect industrial energy efficiency have an objective lag. The policy role of government finance on industrial production is not obvious in the short term [8,17]. The accumulation of industrial capital benefiting from economic growth will take a long time to complete [4]. Therefore, the model (10) is expanded accordingly:

$$iee_{m,n}=p_1 iee_{m,n-1}+p_2 iee_{m,n-2}+q_1 ed_{m,n-1}+q_2 er_{m,n-1}+q_3 sts_{m,n-1}+\alpha X_{m,n}+\varepsilon_{m,n}+\eta \tag{11}$$

Formula(10),(11) include the lagging items of industrial energy efficiency, economic growth, environmental regulation and scientific and technological investment, and the subscripts n-1 and n-2 represent the variables lagging behind the first and second phases.

4.2. Variable Setting and Description

4.2.1. Exogenous Variables

Enterprise size. There are significant differences in energy efficiency among enterprises, which has an important impact on the overall energy efficiency level of the region [18]. The larger the enterprise scale, the higher the energy efficiency [19], measured by the proportion of the output value of large industrial enterprises in the output value of industrial enterprises on the scale [18].

Energy consumption structure. Coal plays a dominant role in China's energy consumption structure, and the development of industrial use of coal in cities in the Yangtze River Delta will have an undeniable impact on the overall energy efficiency between cities and regions. Therefore, the ratio of industrial coal consumption to total energy consumption is used to measure the energy consumption structure [4,17].

Opening up. The level of export-oriented economy in the Yangtze River Delta is relatively high. The use of foreign capital by domestic industrial enterprises has an impact on energy consumption. The energy utilization status of foreign industrial enterprises will make industrial energy efficiency show an external feature. The opening up feature is measured by the actual amount of foreign investment used per unit of GDP growth [20].

Urbanization. Urbanization reflects changes in the endowment of labor factors, resulting in changes in the input structure of factors and thus affecting energy efficiency. It is expressed by reference to the ratio of urban permanent population to the total population by the National Bureau of Statistics.

Energy technology level. The energy consumption per unit output value of the whole society within a certain period of time [21] has a certain measuring effect on energy technology and

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energy utilization. The larger the index, the lower the effective energy utilization rate, and the improvement of energy technology is beneficial to improving energy efficiency [22].

4.2.2. Predetermined Variable

Industrial energy efficiency is closely related to economic development, and economic growth is expressed in per capita GDP [2,17]. Policies and systems have a significant impact on energy efficiency of enterprises [18]. The environmental regulation policy controls the emission of pollutants, which is beneficial to promoting the efficient use of energy [23]. The proportion of environmental protection fiscal expenditure in total fiscal expenditure is used to express the environmental regulation strength. Scientific and technological innovation is an important source of economic development. The Yangtze River Delta has become an economic growth pole without strong government support for science and technology. The proportion of scientific and technological financial expenditure in GDP [21] is used to measure the government's support for science and technology. It takes a period of time for economic development to promote the accumulation of industrial capital and policies to make up for the shortage of industrial production factors, which has a lag effect on industrial input-output activities. Therefore, economic growth, environmental regulation, scientific and technological financial support and their respective lag period are included as the pre-determined variables in the dynamic panel regression of industrial energy efficiency.

4.2.3. Description

The source and processing method of dependent variable data are the same as that of input-output data. In order to weaken the possible heteroscedasticity and multicollinearity of the model, all variables are logarithmic, and the descriptive statistics of variables are shown in Table 2

Table 2. Descriptive statistics of variables

variable	mean value	standard deviation	minimum	maximum
iee	-0.294	0.304	-1.100	0.301
er	-5.564	0.736	-6.843	-3.510
sts	-3.670	0.929	-6.089	-2.153
op	-1.109	0.641	-2.470	0.261
etl	-0.811	0.599	-1.851	0.595
ed	10.784	0.588	9.535	11.904
es	-1.250	0.492	-2.246	-0.435
ers	-0.336	0.265	-1.022	-0.016
ur	-0.502	0.208	-0.949	-0.113

4.2.4. Stability Test

Table 3. Unit root test

explanatory variable	Im–Pesaran–Shin test		Harris–Tzavalis test	
	P-value	Z-statistic	P-value	rho-statistic
ed	0.000	-4.082	0.007	0.427
es	0.001	-3.149	0.004	0.466
etl	0.009	-2.193	0.012	0.526
er	0.000	-4.511	0.000	0.330
sts	0.000	-3.469	0.005	0.422
ur	0.000	-4.031	0.004	0.416
ers	0.000	-3.584	0.015	0.544
op	0.009	-2.365	0.020	0.518

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In order to avoid the "false regression" caused by the unit root of the panel data, the unit root test was carried out on the explanatory variables. The results listed in Table 5 show that the variables are stable. The p value of Kao cointegration test is 0.000, and the ADF value is -4.177. The variables have a long-term equilibrium relationship. The model has research significance.

4.3. Regression Result

Table 4. Regression of industrial energy efficiency drivers

variable	(1)	(2)	(3)	(4)	(5)
	FE	ran-tobit	one-step difference GMM		
L.iee			0.503*** (8.840)	0.506*** (8.970)	0.499*** (8.670)
L2.iee			-0.185*** (-3.430)	-0.186*** (-3.470)	-0.184*** (-3.440)
ed	-0.119** (0.044)	-0.100** (0.035)	-0.127*** (-2.730)		
L.ed				-0.191** (-2.310)	-0.184** (-2.210)
er	0.049** (0.022)	0.045** (0.021)	0.041** (1.990)	0.052** (2.460)	0.043** (1.680)
L.er					0.023** (1.030)
sts					
L.sts					
es	0.108*** (0.031)	0.054** (0.032)	0.060** (1.960)	0.065** (2.120)	0.062** (2.001)
etl	-0.176*** (0.035)	-0.063** (0.034)	-0.130*** (-3.380)	-0.128*** (-3.370)	-0.128*** (-3.390)
ur	0.191** (0.098)	0.218** (0.088)	0.238** (2.402)	0.241** (2.451)	0.240** (2.451)
ers	-0.287*** (0.085)	-0.185** (0.093)	-0.218*** (2.591)	-0.195** (2.310)	-0.185** (2.202)
op					
η	1.517** (0.536)	1.392** (0.436)			
Hausman test	35.569*** (0.001)				
LR test		121.08*** (0.000)			
AR(1)			-11.140** (0.012)	-11.074*** (0.009)	-11.142** (0.011)
AR(2)			0.910 (0.363)	0.701 (0.482)	0.850 (0.393)
Sargan test			32.142 (0.480)	29.756 (0.472)	34.637 (0.429)
N	375	375	300	300	300

Note: ***, ** and * are significant at the level of 1%, 5% and 10% respectively; values of t and p in brackets

Column (1) and (2) in Table 4 are the estimated results of the static panel model. The estimated coefficients of economic growth, energy technology level and energy consumption structure on industrial energy efficiency are negative, while the estimated coefficients of environmental regulation, enterprise size and urbanization are positive, and are all valid at the 5% significant level. Both Hausman and likelihood ratio test reject the original hypothesis at a significant level of 1%, confirming the reliability of the regression results of the model. Columns (3), (4) and (5) are the results of dynamic panel model regression. The estimated coefficient of economic growth lag on industrial energy efficiency is negative, while environmental regulation and its lag have a positive effect on industrial energy efficiency. The impact of industrial input-output efficiency in the past period on industrial energy efficiency in the current period has been verified. The estimated coefficients of enterprise scale and urbanization are positive, and the estimated coefficients of energy technology level and energy consumption structure are negative. The dynamic regression results are significant at the level of 5%. The autocorrelation test of the disturbance item shows that the second-order sequence is not significant at the 10% level, the differential autocorrelation coefficient of the disturbance item is not 0, and the over-recognition test p value is higher than 0.1, indicating that the instrumental variable is effective.

The results show that the rapid economic growth in the Yangtze River Delta has led to excessive energy consumption per unit output value, resulting in low industrial energy efficiency and increased carbon emissions, and that the rapid economic growth has a sustained inhibitory effect on improving industrial energy efficiency. The government-led environmental protection policy has a lasting effect on improving industrial energy efficiency and alleviating industrial carbon emissions. The continuous improvement of urbanization level has provided sufficient labor factors for industrial scale production, enhanced the importance of the use efficiency of unit labor factors, and promoted industrial energy efficiency. The larger the scale of the enterprise, the higher the energy efficiency, which means that reducing the flow cost of factors, strengthening the technical cooperation between enterprises and promoting the specialization of production can promote energy conservation and carbon reduction in industry. Both energy consumption structure and energy technology level have a negative effect on industrial energy efficiency, because coal is low thermal energy and high carbon emission energy, while the development of industrial coal consumption in the Yangtze River Delta is large, and the heavy coal energy consumption structure means that energy technology innovation is insufficient, which is not conducive to the efficient use of energy.

5. Policy Recommendations

Based on the previous research results of industrial energy efficiency measurement and its driving factors in the Yangtze River Delta, the following recommendations are put forward:

Strengthen the regulation of carbon emission reduction policies. Governments at all levels uphold the concept of sustainable development, attach importance to macroeconomic regulation and control of industrial development, build a standardized industrial carbon emission reduction environmental regulation policy system, strengthen the pollution control of high-input and high-polluting industrial enterprises, and implement the production constraint system of low-carbon environmental protection.

Carry out large-scale reform of green production. Deeply excavate the key problems in industrial large-scale production such as waste of input, low output efficiency and serious pollution discharge, promote the scale of green production links such as waste reuse and factor utilization rate improvement, and establish an intensive industrial production system from point to area.

Optimize the energy consumption structure. Industry enterprises should increase investment in scientific and technological research and development, break the coal dependence path, introduce clean energy with high efficiency and low emissions, and build a diversified energy utilization system. The government takes the lead in promoting the introduction of new energy, maintaining the information symmetry of new energy supply and demand, and introducing policies to improve the energy trading market to smooth the flow of new energy elements.

Transform energy-dependent industrial production mode. Accelerate the introduction of advanced digital and intelligent production methods, break dependence on energy, labor and other traditional factors of production, and strengthen the use of science and technology, knowledge and information. Through financial support and a sound legal system, the government has taken multiple measures at the same time to curb the market monopoly of digital information and intelligent technology factors, unblock the market-oriented circulation of production factors of the digital economy, build a new input system of industrial factors, and guide the accelerated development of industrial digitalization.

6. Conclusion

This paper deeply analyzes the severe situation of industrial economic growth in the Yangtze River Delta and believes that the development of low-carbon industry in the Yangtze River Delta is imperative. We creatively regard carbon emissions as unintended output, scientifically measure industrial energy efficiency and explore its spatiotemporal distribution and evolution characteristics, and then comprehensively trace the driving factors of industrial energy efficiency through panel regression model, and summarize the problems that need to be paid attention to in promoting industrial low-carbon production in the Yangtze River Delta with a view to accurate and effective implementation. However, the industrial development level of three provinces and one city has typical differentiation characteristics. Whether there is spatial interaction effect in industrial energy efficiency and its deep internal cause exploration are the focus of the next research work.

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