

Original Research

Research on the Measurement and Convergence of Technological Innovation Efficiency of New Energy Enterprises under the Target of “Double Carbon”

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Abstract

The new energy industry helps to meet the challenges of energy exhaustion and environmental pollution. Based on the panel data from 2015 to 2021, this paper uses the BCC model and Tobit model to construct the empirical measurement of technology innovation efficiency of listed new energy enterprises with three-stage DEA technology and uses the convergence model to test the efficiency difference. The results show that: (1) Using the traditional BCC model, the technical innovation level of new energy enterprises is insufficient, and the overall comprehensive efficiency and pure technical efficiency are 0.220 and 0.302 respectively, which need to be improved. (2) The three-stage DEA model was used to control environmental factors and statistical errors, and the overall efficiency of technological innovation of new energy enterprises increased. The comprehensive efficiency and scale efficiency increased to 0.541 and 0.896 respectively. (3) The technological innovation efficiency of new energy enterprises presents temporal and spatial heterogeneity.

The coefficient of variation of technological innovation efficiency of new energy enterprises ranged from 0.084 to 1.000 with significant differences. The technological innovation efficiency of new energy enterprises in eastern, central and western China shows a U-shaped fluctuation.

Keywords: double carbon, new energy, technological innovation, three stage model, model of convergence

Introduction

Traditional energy consumption leads to increased carbon emissions and environmental pollution. The energy structure that is highly dependent on traditional petrochemical raw materials has forced the development of new energy industries to become a key direction for the transformation and upgrading of industrial structures. Coal as the main fuel of the energy model has led to the growth of carbon dioxide emissions, posing a challenge to climate governance. The Chinese government attaches great importance to the issue of carbon emissions. In 2022, President Xi Jinping proposed the goals of “carbon peaking by 2030” and “carbon neutrality by 2060” at the 75th session of the United Nations General Assembly. At present, the problem of global warming is becoming more and more serious, which has become a common concern of people all over the world. China has a high proportion of traditional fossil fuels, and by 2026, the proportion of non-fossil energy sources is projected to be as high as 21% [1]. The proposal of the “double carbon” goal is a medium - and long-term national strategy put forward by China to cope with the changing environment [2]. In order to achieve this goal, both new energy development and energy conservation and emission reduction need full attention. In order to reduce the high production cost of new energy, the government should promote scale, provide financial support to enterprises and encourage them to carry out technological innovation. Compared with traditional energy, new energy has the advantages of large reserves, small pollution and wide distribution [3]. New energy enterprises refer to enterprises that use renewable resources such as water energy, electric energy and solar energy for industrial production. At present, common new energy enterprises include new energy vehicles, new energy power plants, and electronic enterprises that produce intelligent products such as photovoltaic and lithium batteries [4]. The “low carbon” caused by global climate change is gradually affecting the decision-making of various enterprises.

The new energy enterprises started late and developed slowly, so the new energy enterprises should improve their innovation enthusiasm and take the initiative to shoulder social responsibility. For new energy companies, the challenge they face is the lack of access to institutional funding; the price of renewable energy technologies; lack of skilled labor; underdeveloped physical infrastructure and logistics; the incumbents are not dominant enough; insufficient government or policy support [5]. In this context, new energy enterprises should establish a diversified new energy technology supply system in the future, based on diversified supply security, vigorously promote the application of new energy technologies, and combine other high and new technologies with new energy application technologies in a green and low-carbon oriented manner. On the other hand, international

cooperation should be strengthened to realize energy sharing under open conditions [6].

Innovation is an important symbol of a country's core competitiveness [7]. Innovation is the first source of power for the development of the country, nation and province, and the innovation capacity determines the country's ability to cope with sudden changes. Especially after the “double carbon” goal was put forward, our demand for innovation is increasing [8]. Since 2008, new energy enterprises have been developing rapidly with the support of national policies. According to the analysis of China Energy News, the operating revenue of China's new energy enterprises now accounts for 63.41%, indicating that the innovative development of new energy enterprises has made some achievements. Since the 21st century, our economy has realized leap-forward development and achieved remarkable achievements, the GDP grew from 10,028 billion yuan in 2000 to 11,43669 billion yuan in 2021, but this extensive economic model led to the problem of environmental pollution. According to statistics, China's CO₂ emissions increased from 4.025 billion tons in 2000 to 11.71 billion tons in 2018, putting great pressure on emission reduction [9].

Innovation efficiency is an indicator of the excellence of a company's modernization investments and the efficiency of converting innovation inputs into outputs in technological activities. Domestic and foreign scholars have made rich achievements in innovation efficiency evaluation, providing technical support for the subsequent innovation and development of enterprises [10]. The estimation models of innovation efficiency include the data envelopment model (DEA), stochastic Frontier model (SFA) [11]. The advantage of using the SFA model is to evaluate the influence of related factors on volume efficiency by constructing production functions. However, the method of the parametric function model has the risk of model hypothesis error. Once the model hypothesis is wrong, not only the estimated results are different from the expected results, but even the conclusions are meaningless. Therefore, since then, more researchers choose non-parametric methods, such as the DEA analysis method, to measure individual innovation efficiency. DEA is a non-parametric method and an effective method to evaluate the relative efficiency of the decision-making unit (DMU) [12]. To a certain extent, this method can improve the accuracy of research results and solve the problems existing in the traditional DEA model. Fried published two papers in a series to discuss the use of the DEA model to estimate efficiency [13]. The DEA analysis method can fundamentally avoid the wrong results caused by the wrong model selection. Meanwhile, the weight of indicators is automatically calculated from the input-output data, which makes the whole research process more objective [14]. To sum up, the DEA method has been promoted and applied in the measurement of innovation efficiency.

Although the classical DEA method overcomes the deviation of parameter estimation, it ignores the influence of external environmental factors and random bias. DEA's three-stage method innovatively integrates the advantages of the two models, excludes the influence of external factors and random factors, and obtains more objective results.

Schumpeter's innovation theory is of monumental significance. In addition to the research on how to innovate, the technical requirements for innovation, the needs for its realization, and the innovation cycle, research on the efficiency of innovation has been added. The research on innovation efficiency is not only related to the development of enterprises, but also directly affects the technological innovation and economic development of a country. MENG and XU (2021) estimated the innovation efficiency of China's provinces and territories by examining data. After excluding the external environmental factors, the results showed that the innovation efficiency of China's central and western regions was lower than that of the eastern regions [15]. On the whole, the innovation efficiency of China was still in slow development. At the same time, the research of innovation efficiency also has many limitations, such as environmental constraints, capital input, marketization degree and so on [16]. Some scholars studied the innovation efficiency of China's high-tech zones in 2012 and found that the environment was an important factor restricting the improvement of innovation efficiency in the central and western regions. Hu found through empirical research that industrial structure and enterprise scale have a significant influence on technological innovation efficiency, but the influence factors of enterprise systems are not significant enough. In addition, the research also found that regional higher education also has a significant impact on the efficiency of regional technological innovation [17].

Different from the classic one-stage DEA model, the three-stage DEA model can eliminate the interference of environmental factors and attract attention. Domestic and foreign scholars have used the three-stage DEA model to study the tourism ecological efficiency of China's coastal cities [18] and the resource allocation efficiency of elderly care services [19]. Through the construction of the DEA three-stage model, this paper measures the innovation efficiency of national and regional new energy enterprises by setting environment variables and random factors, integrating and processing corresponding data.

To sum up, the DEA model is an effective method to evaluate innovation efficiency. Referring to relevant domestic and foreign achievements, this paper mainly selects panel data of new energy enterprises to analyze their technological innovation efficiency. The innovation of this paper is shown as follows: on the one hand, the application scope of the DEA model is expanded, and the three-stage innovation efficiency estimation of China's new energy enterprises is

constructed. By smoothing out the interference of the external environment and random bias, the accuracy of innovation efficiency evaluation can be improved. On the other hand, the convergence model is introduced to discuss the convergence distribution of innovation efficiency of new energy enterprises.

Material and Methods

Model Construction

Since the three-stage DEA model proposed by Fried effectively avoids the influence of environmental factors and random errors on the efficiency value, and is combined with the characteristics of new energy enterprises, this paper adopts the three-stage DEA model when measuring the innovation efficiency of new energy enterprises. In the first stage, the input-oriented BCC model is selected. Different from the classical three-stage model, considering that the efficiency value of the BCC model is no more than 1, it has the property of truncation. Therefore, the Tobit regression model is used in the second stage of this paper.

(1) The first stage: initial calculation of BCC model

In terms of enterprise innovation efficiency, the innovation of new energy enterprises is uncertain. Input variables are variables determined by enterprises themselves and can be controlled, while it is difficult for enterprises to determine or accurately predict output variables. In addition, CCR model can only show comprehensive efficiency, while BCC model can respectively show comprehensive efficiency, pure technical efficiency and scale efficiency. Therefore, when measuring the innovation efficiency of new energy enterprises, this paper uses the input-oriented BCC model in the first stage, and its model scale returns are variable. According to Charnes' research, the general expression of BCC model can be obtained as follows [20]:

$$\begin{aligned}
 & \min_{\theta, \lambda} \rho - \varepsilon(e^t s^+ + e^t s^-) \\
 & s.t. \quad \sum_{i=1}^n \gamma_i x_{ir} + s^+ = \rho x_{0j}, \\
 & \quad \quad \sum_{i=1}^n \gamma_i y_{ir} - s^- = y_{0r}, \\
 & \quad \quad \sum_{i=1}^n \gamma_i = 1, \\
 & \quad \quad \gamma_i \geq 0, \\
 & \quad \quad s^+ \geq 0, \\
 & \quad \quad s^- \geq 0
 \end{aligned} \tag{1}$$

In the above equation, ρ represents the target value of the decision unit. $x_{ij} (j = 1, 2, \dots, k)$ represents the input

factors, $y_{ir}(j = 1, 2, \dots, s)$ represents the output factors, where in $i = 1, 2, \dots, n, j = 1, 2, \dots, m, r = 1, 2, \dots, s$. n represents the number of decision-making units, k represents the number of decision-making unit input, s represents the number of decision-making unit output.

The efficiency value of BCC model is comprehensive technical efficiency (TE), which can be decomposed into the product of scale efficiency (SE) and pure technical efficiency (PTE).

$$TE = SE \times PTE \tag{2}$$

(2) The second stage: adjust the input-output data

In the first stage, the efficiency value ρ can be obtained by substituting the original input $x_{ij}(j = 1, 2, \dots, k)$ and output $y_{ir}(j = 1, 2, \dots, s)$ of the j th decision-making unit into the BCC model. The relaxation variables $s_{ij}^{-*}(j = 1, 2, \dots, k)$ and $s_{ij}^{+*}(i = 1, 2, \dots, s)$ of both input and output are obtained.

Assume that the environment variable of the i th input factor is Z_p , and the environment variable of the RTH output variable is Z_r , the corresponding influence coefficients are α_i and α_r respectively, and the random disturbance terms are μ_{ij} and μ_{rj} respectively.

At the same time, it is assumed that the coefficients of variation of environmental variables of all decision-making units are consistent, namely α_i and α_r , which is conducive to maintaining the consistency of evaluation [21].

With reference to relevant domestic studies, the following adjustment relationships can be obtained:

$$s_{ij}^{-*} = g^-(Z_i, \alpha_i, \mu_{ij}), i = 1, 2, \dots, k; j = 1, 2, \dots, n \tag{3}$$

$$s_{ij}^{+*} = g^+(Z_r, \alpha_r, \mu_{rj}), i = 1, 2, \dots, s; j = 1, 2, \dots, n \tag{4}$$

$$g^-(Z_i, \alpha_i, \mu_{ij}) = \alpha_0^- + \alpha_i z_i + \mu_{ij} \tag{5}$$

$$g^+(Z_r, \alpha_r, \mu_{rj}) = \alpha_0^+ + \beta_r z_r + \mu_{rj} \tag{6}$$

The above model calculates the linear relationship between input-output and environmental factors based on the Tobit model.

Meanwhile, the parameter estimators of hypothesis α_i and α_r are respectively $\hat{\alpha}_i$ and $\hat{\alpha}_r$. Then the adjusted input-output variables can be obtained:

$$x_{ij}^a = x_{ij} - \hat{\alpha}_i Z_i, i = 1, 2, \dots, k; j = 1, 2, \dots, n \tag{7}$$

$$y_{ij}^a = y_{ij} + \hat{\alpha}_r Z_r, i = 1, 2, \dots, s; j = 1, 2, \dots, n \tag{8}$$

(3) The third stage: DEA efficiency of input and output variables after adjustment

Using the adjusted input-output data to substitute into the BCC model, a new efficiency value ρ' can be obtained. That is, $x_{ij}^a = x_{ij} - \hat{\alpha}_i Z_i, i = 1, 2, \dots, k, j = 1,$

$2, \dots, n$ and $y_{ij}^a = y_{ij} + \hat{\alpha}_r Z_r, i = 1, 2, \dots, s, j = 1, 2, \dots, m$ were substituted into the BCC model as the adjusted input and output variables to get a new set of efficiency values.

Suppose $EG = \frac{\rho'}{\rho}$, when $EG > 1$, it means that the

adjusted efficiency is higher than the original efficiency value. When $EG = 1$, it indicates that environmental factors have no influence on the efficiency value of DMU; When $EG < 1$, the adjusted efficiency value is lower than the original efficiency value.

Model Construction of δ Convergence Analysis

In order to deeply explore the differences in technological innovation efficiency and their sources, Dagum Gini coefficient method was introduced in this study. With reference to relevant studies [22], Dagum Gini coefficient is calculated as follows:

$$G = \frac{\sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{2\mu n^2} \tag{9}$$

In Formula (9), k represents the total number of regions under investigation, j and h are the regional subscripts, n represents the number of enterprises under investigation, i and r are the enterprise subscripts. n_j and n_h are the number of enterprises in area $j(h)$, y_{ji} is the enterprise in the $j(h)$ region, G is innovation efficiency measure value, μ represents the mean value of innovation efficiency of all enterprises under investigation.

In order to analyze the distribution position and shape of variables, this paper introduces Gaussian kernel function.

The density function of random variable x is set as $f(x)$, where N, X_i and $k(x)$ are the number of observed values, independent identically distributed observed values, bandwidth and kernel function respectively. See Equation (10-11) for the calculation method.

$$f(x) = (1/Nh) \sum_{i=1}^N K[(X_i - x)/h] \tag{10}$$

$$K(x) = (1/\sqrt{2\pi}) \exp(-x^2/2) \tag{11}$$

Through the convergence test of the above equations, the evolution of technological innovation efficiency gap of new energy enterprises in different regions can be verified. Therefore, the δ convergence analysis of technological innovation efficiency can be conducted according to Equations (9) and (10). Common convergence studies include α convergence, δ convergence and club convergence. δ convergence represents the process of sample deviation decreasing

over time, which is described by coefficient of variation (*cv*) in this study, as shown in Equation (12). Where, *i* and *j* are the subscripts of regions and enterprises respectively, *n_i* is the number of enterprises in area *j*, \bar{F}_{ij} is the mean value of innovation efficiency in region *j*.

$$K(x) = (1/\sqrt{2\pi}) \exp(-x^2/2) \tag{11}$$

$$\sigma = \frac{\sqrt{\sum_i^{n_j} F_{ij} - \bar{F}_{ij} / n_j}}{\bar{F}_{ij}} \tag{12}$$

Variable Selection and Data Sources

(1) Input and output index selection:

The construction of an indicator system is an important method for quantitative research and an important basis for selecting indicator variables that fit the research object. In this regard, the strengths and weaknesses of the indexes and their relevance to the target population can be obtained through the screening of a large amount of literature and the comparative analysis of the selected indexes. According to the above ideas, the literatures with high citation volume of related topics in CNKI and some English literature [23] were retrieved and their index variables were sorted out. Referring to the research base of domestic scholars [24, 25], most studies are based on the C-D production function theory. The selected input indicators mainly include: labor, capital stock and energy output, etc. Based on the availability, science and rationality of data, and considering the specific situation of the new

energy industry, the input indicators selected in this paper are the number of R&D personnel and R&D input respectively, and the output indicators are the number of patents and net profit.

(2) Selection of environment variables:

Technological innovation efficiency refers to the input-output ratio of technological innovation resources. Before that, most of the existing literature and research only considered the efficiency value of input and output, and only analyzed the environmental factors affecting the efficiency of technological innovation, but did not control or treat the environmental factors to calculate the efficiency of technological innovation. The research results are not rigorous enough. Different degrees of environmental regulation have different impacts on technological innovation [26]. In this paper, the total export trade of the location of an enterprise is used as an indicator to measure the degree of external development. There is a certain relationship between the economic development difference of China's eight economic regions and the regional difference of technological innovation efficiency of enterprises. Per capita GDP is used to evaluate the regional economic level. With the exception of factors such as physical capital and human capital, technology market has a significant influence on innovation [27]. Therefore, the turnover of technology market in the region where the company is located is taken as an indicator to measure the technology market environment. The definitions of all the variables are shown in Fig. 1.

(3) Data source:

The data studied in this paper are mainly from China Statistical Yearbook, State Intellectual Property Office, RESSE Reisi Financial Database, etc.

In terms of sample selection, selecting listed companies that meet the requirements based on the new

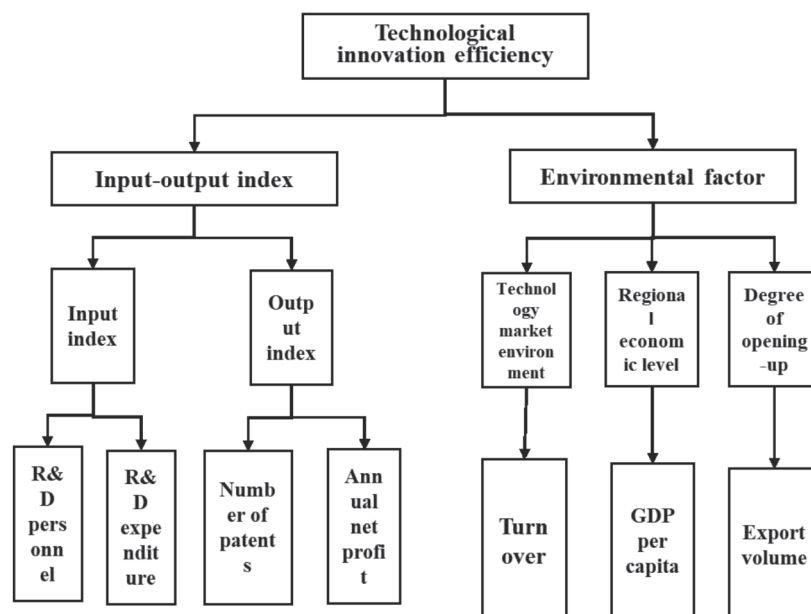


Fig. 1. Input-output index system.

energy concept sector in Huaxi Securities (including the new energy concept of the main board and the small and medium-sized board). In order to ensure the continuity of the research, the time span selected in this paper is 2015-2021. Considering the stability of the model, companies with serious data deficiency, such as Silver Star Energy, Bowei Alloy and Zhongmin Energy, were excluded. Finally, after data screening and cleaning, 72 new energy listed companies were collated. When partial data of individual samples were missing, the linear difference method was used to complete the values.

Results and Discussion

According to the idea and principle of three-stage DEA model, DEAP2.1 software is used in the first stage and the third stage, and STATA software is used in the second stage to realize data processing and analysis.

Analysis of DEA Model Results in the First Stage

In the first stage, the DEA-BBC model was used to measure the panel data of 72 listed new energy enterprises from 2015 to 2021.

As can be seen from Table 1 the overall technical efficiency value of the sample is between 0.013 and 1.000, and the overall difference is large. Among them, only 3% enterprises (Beixin building materials, energy-saving wind power) have comprehensive innovation efficiency equal to 1, and their innovation efficiency and management efficiency are relatively effective, while the rest enterprises have no efficiency in technological innovation. Among the research objects, 49 enterprises' technological innovation efficiency value is lower than the average, and 23 enterprises' technological innovation efficiency value is higher than the average. Under the interference of environmental factors and random errors, the average comprehensive innovation efficiency, pure technical efficiency and scale efficiency

Table 1. Measurement results of DEA model in the first stage.

Name	Crste	Vrste	Scale		Name	Crste	Vrste	Scale	
Sinochem International	0.04	0.23	0.245	Drs	Ikang Technology	0.181	0.192	0.953	Irs
TVB electrician	0.304	0.874	0.382	Drs	Top of the line	0.074	0.085	0.919	Irs
Guodian Nanrui	0.398	0.871	0.524	Drs	Star Technology	0.212	0.225	0.932	Drs
Tiancheng	0.353	0.369	0.961	Drs	Ultra quick order	0.382	0.432	0.854	Drs
Tongwei Shares	0.168	0.333	0.584	Drs	Maoso power supply	0.362	0.375	0.955	-
Yuanxing Energy	0.135	0.309	0.607	Drs	Kehua data	0.043	0.047	0.956	Drs
Guancheng Chase	0.15	0.205	0.762	Irs	Tianwo Technology	0.1	0.101	0.991	Irs
Huayin Electric Power	0.532	0.62	0.868	Irs	GCL integration	0.546	0.571	0.919	Irs
Baoan, China	0.025	0.057	0.608	Drs	Zhongli Group	0.061	0.063	0.915	-
World science and technology	0.134	0.177	0.74	Drs	Sun Sun Shares	0.488	0.543	0.892	Drs
Aerospace mechanical and electrical	0.282	0.283	0.995	-	Expand daily new energy	0.409	0.415	0.987	-
Beixin Building Materials	1	1	1	-	Wall new material	0.826	0.842	0.979	Drs
Nordisk Shares	0.127	0.13	0.974	Irs	Solar energy	0.294	0.397	0.752	Drs
Cofco Science and Technology	0.066	0.085	0.89	Drs	Taihao Technology	0.134	0.146	0.903	-
South Bo A	0.899	0.928	0.963	-	Buddha Plastic Technology	0.091	0.091	0.99	-
Shanghai Electric Power Company	0.255	0.813	0.376	Irs	CNPC Technology	0.13	0.133	0.975	Irs
Yingfeng environment	0.02	0.048	0.615	Drs	Fang Large Group	0.046	0.082	0.718	-
Junzheng Group	0.041	0.473	0.161	Drs	Auspicious Electric Company	0.149	0.196	0.835	Drs
Fortis Information	0.092	0.095	0.974	Irs	Wolong electric drive	0.013	0.024	0.608	Drs
Great Wall Electrician	0.037	0.038	0.976	Irs	Antai Technology	0.267	0.295	0.892	Drs
Cheng Zhi Shares	0.045	0.056	0.842	Drs	Energy-saving wind power	1	1	1	-
Entrepreneurship Environmental protection	0.23	0.336	0.735	Drs	Coriyuan	0.35	0.355	0.963	-
Cisodium shares	0.058	0.06	0.968	Irs	Shanghai Electric Company	0.147	0.833	0.251	Drs

Table 1. Continued.

Hong Xun Technology	0.161	0.168	0.963	Drs	Changhong Meiling	0.132	0.133	0.993	Drs
North International	0.161	0.214	0.807	Irs	Merrycloud	0.601	0.612	0.98	Drs
Power of navigation	0.083	0.108	0.638	Drs	Datang power generation	0.057	0.859	0.082	Irs
Hongfa Shares	0.014	0.041	0.364	Drs	Jia Hua Energy	0.083	0.254	0.383	Drs
Research new materials	0.068	0.069	0.981	Irs	Avic Heavy Machinery	0.044	0.046	0.965	Drs
Zhongtian Technology	0.152	0.195	0.765	-	Qibin Group	0.021	0.094	0.364	Drs
Enn Shares	0.027	0.365	0.27	Drs	Beijing Express	0.151	0.153	0.979	Drs
Desai battery	0.079	0.086	0.92	Drs	Golden Crystal Technology	0.066	0.073	0.946	Drs
Xemc Corporation	0.024	0.025	0.939	Irs	Variety Entertainment Shares	0.197	0.202	0.976	Irs
Innovation Technology	0.028	0.028	0.982	-	Dongxu Optoelectric	0.371	0.426	0.821	-
Lin Yang Energy	0.089	0.119	0.735	Drs	Constant change electrical	0.344	0.348	0.987	-
ST Wah Yee	0.215	0.219	0.982	Irs	New Sai Shares	0.835	0.84	0.986	-
Mingtai Aluminum Industry	0.09	0.136	0.746	Drs	Blue stone reload	0.076	0.087	0.89	Irs
The mean						0.22	0.302	0.796	

(Crste: comprehensive technical efficiency Vrste: pure technical efficiency Scale: scale efficiency)

of the samples from 2015 to 2021 are 0.220, 0.302 and 0.796 respectively. The comprehensive innovation efficiency of listed new energy enterprises is generally not high, indicating that the input-output results in the innovative use of new energy are relatively low return, and development needs to be strengthened.

Combined with Fig. 2, the innovation efficiency of new energy enterprises is on a slow rising trend, and the change trend of pure technical efficiency is very similar to the trend of innovation efficiency. Scale efficiency is in a relatively stable state, and compared with scale efficiency, pure technical efficiency is at a lower level. However, due to the influence of environmental

factors and random errors, the results of traditional BCC model can not accurately display the technical innovation efficiency level of Chinese new energy listed enterprises, so it is necessary to further analyze.

Analysis of Technological Innovation Efficiency of New Energy Enterprises in Different Regions

In order to further explore the technological innovation efficiency level of sample enterprises as representatives of various provinces in China, the distribution Fig. 3 of new energy technology innovation efficiency in 2015, 2017, 2019 and 2021 was drawn

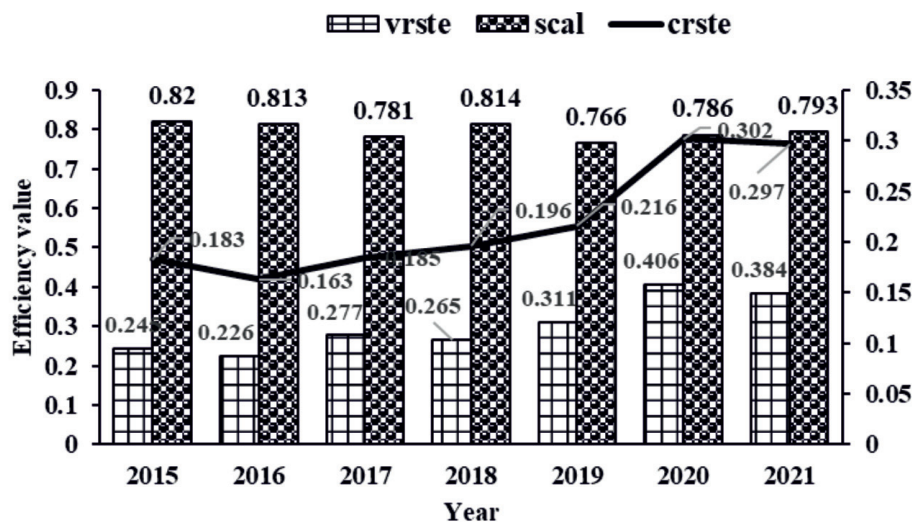


Fig. 2. Innovation efficiency of new energy enterprises and its decomposition.

respectively. As can be seen from Fig. 3, after adjusting environmental variables, the technological innovation efficiency of Xinjiang and other provinces with relatively backward market environment is higher, indicating that their enterprises have strong technological innovation ability.

The technological innovation efficiency performance of listed new energy enterprises in the 9 provinces and cities in the eastern China covered in this paper can be divided into four types: (1) dual-optimal type, that is, provinces where both pure technical efficiency and scale efficiency are above 0.9. This is represented by Hebei Province, which has new energy enterprises represented by Great Wall Motor and others. (2) Optimal-low type, which is represented by Jiangsu Province, has a high scale efficiency of 0.92 and a pure technical efficiency of 0.386. (3) Medium-low type. Taking Zhejiang as the representative, the scale efficiency level is 0.84 and the pure technical efficiency is only 0.39, indicating that the development focus of new energy enterprises in Zhejiang Province is to enhance their own technological innovation ability and improve the pure technical efficiency. (4) Double medium-sized. Its pure technical efficiency and scale efficiency is above 0.65. Taking Shanghai as the representative, these provinces and cities should both expand the scale of enterprises and focus on improving their technical innovation capacity in the subsequent development. The above analysis shows that the current situation of

new energy enterprises in the eastern provinces is that the pure technical efficiency is low, leading to a low comprehensive efficiency level.

The new energy innovation efficiency of the six provinces in western China can be divided into three types: (1) Dual-optimal type, that is, the provinces with pure technology innovation efficiency and scale efficiency are both above 0.9, including two provinces at the technological frontier (Xinjiang and Ningxia) and Guizhou and Gansu. The new energy technology innovation efficiency of these provinces needs less improvement. (2) Double-medium, that is, pure technology innovation efficiency and scale efficiency are both above 0.7, including Sichuan Province and Chongqing Province. (3) The medium-low type, represented by Shaanxi Province, has a low pure technical efficiency (0.431) and a high scale efficiency (0.88). The above analysis shows that all provinces and cities have a good momentum of new energy technology innovation development, but there is room for further optimization.

Analysis of Tobit Regression Model Results in the Second Stage

In this paper, the technology market environment, the degree of regional openness to the outside world and the level of regional economy are taken as

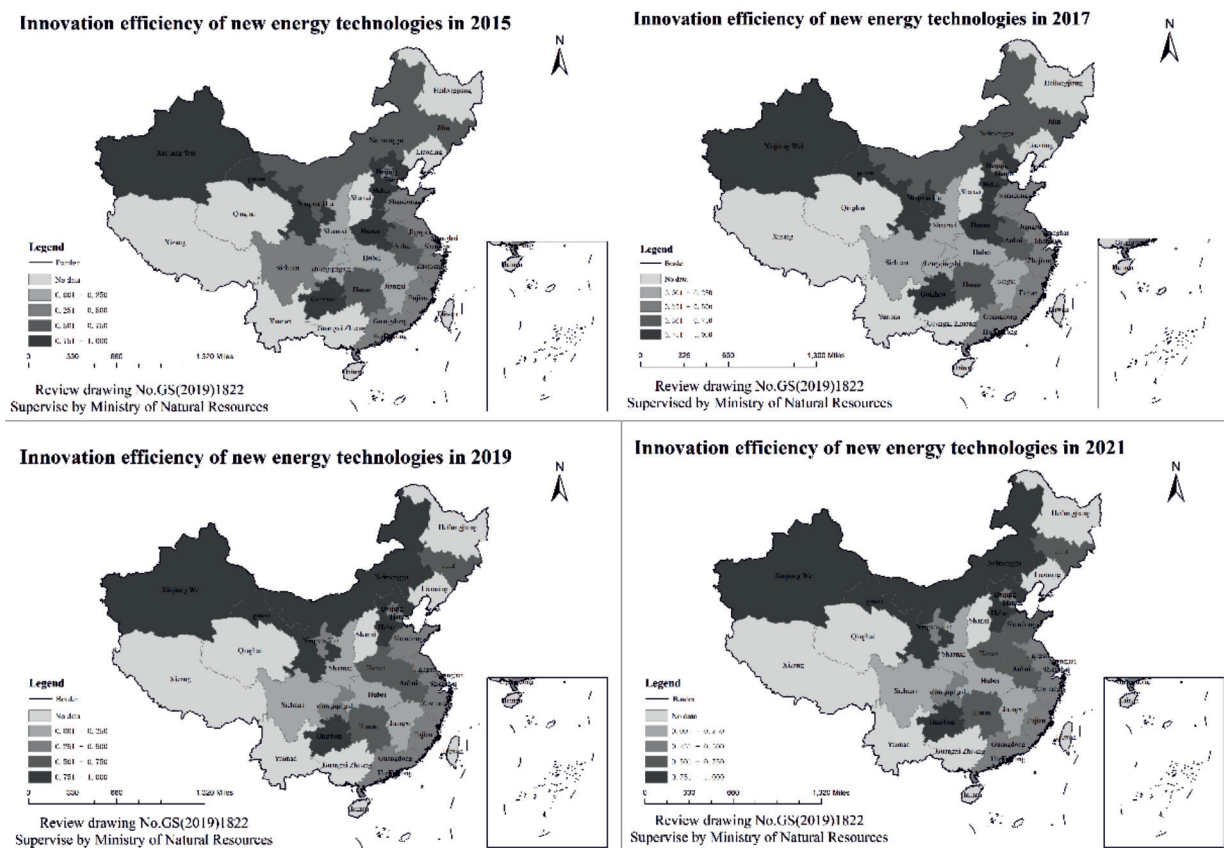


Fig. 3. Distribution of new energy technology innovation efficiency.

Table 2. Results of Tobit model.

	Coefficient of regression	T-value	P values
Technology market	0.0724	5.24	0.000
Degree of opening up	0.1735	1.02	0.382
Regional economic level	0.0932	1.47	0.497
Constant (constant)	0.1900	3.61	0.090
Sigma_u	0.2450	10.99	0.000
Sigma_e	0.1380	28.31	0.000
Mean dependent var	0.2200	SD dependent var	0.266
Number of obs	504	Chi-square	49.522

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

environmental variables to establish the Tobit model. Thus, Tobit model is adopted to explain the influencing factors of enterprise technological innovation efficiency, and relevant results are shown in Table 2.

As can be seen from Table 2, the regression coefficient value of the technology market is 0.0724, showing a significance level of 0.01 ($z = 5.24$), indicating that the technology market has a significant impact on efficiency. In other words, with the increasing development and improvement of the technology market in which new energy enterprises are located, the technological innovation efficiency of new energy enterprises shows a trend of gradual improvement. The higher the development level of technology market, the more intensive technology trading, which is conducive to the technological innovation of enterprises.

At the level of 1%, the degree of external openness has a significant promoting effect on efficiency, indicating that the higher the degree of external openness, the higher the efficiency of technological innovation of enterprises. This may be because the higher the degree of external openness, the more opportunities for enterprises to introduce more advanced technologies and capital.

The regional economic level has a negative influence on the technological innovation efficiency of new energy enterprises at the 1% level, indicating that the

regional economic level inhibits the technological innovation efficiency of new energy enterprises, indicating that the improvement of the regional economic level does not improve the technological innovation efficiency of new energy enterprises. The reason may be that the main objectives of the enterprise and the region are not consistent. Enterprises carry out technological innovation in order to form patents and finally obtain economic value, that is, to obtain corporate profits.

The above results show that the influence of environmental factors on decision-making units is not completely consistent. Next, we apply equation (4) to form a new environmental factor and add it as a new input variable, so as to control the impact of environmental factors.

Analysis of the Results after Adjustment of Input in the Third Stage

Table 3 shows the efficiency results of the re-measurement. As can be seen from the table, the adjusted comprehensive innovation efficiency, pure technology efficiency and scale efficiency are 0.541, 0.606 and 0.896, respectively. Among them, the overall technological innovation efficiency is between 0.120 and 1.000. Compared with before adjustment, the comprehensive

Table 3. Measurement results of DEA model in the third stage.

Name	Crste	Vrste	Scale		Name	Crste	Vrste	Scale	
Sinochem International	0.229	0.401	0.632	Drs	Ikang Technology	0.372	0.385	0.963	Drs
TVB electrician	1	1	1	-	Top of the line	0.275	0.308	0.912	-
Guodian Nanrui	0.986	1	0.986	Drs	Star Technology	0.798	0.81	0.985	Drs
*ST Tiancheng	0.917	0.953	0.963	Drs	Ultra quick order	0.478	0.487	0.984	Drs
Tongwei Shares	0.699	0.79	0.874	Drs	Maoso power supply	0.445	0.455	0.982	Drs
Yuanxing Energy	0.749	0.84	0.904	-	Kehua data	0.411	0.423	0.973	-
Guancheng Chase	0.464	0.686	0.706	Irs	Tianwo Technology	0.246	0.253	0.971	Irs

Table 3. Continued.

Huayin Electric Power	0.878	0.902	0.974	Irs	GCL integration	0.673	0.694	0.964	Irs
Baoan, China	0.167	0.223	0.798	Irs	Zhongli Group	0.203	0.216	0.939	Irs
World science and technology	0.304	0.353	0.876	Drs	Sun Sun Shares	0.679	0.712	0.964	Drs
Aerospace mechanical and electrical	0.423	0.428	0.988	Drs	Expand daily new energy	0.493	0.501	0.988	Drs
Beixin Building Materials	1	1	1	-	Wall new material	0.89	0.897	0.992	-
Nordisk Shares	0.628	0.66	0.953	Irs	Solar energy	0.777	0.879	0.888	Drs
Cofco Science and Technology	0.579	0.639	0.913	Irs	Taihao Technology	0.333	0.34	0.979	Drs
South Bo A	0.951	0.968	0.981	-	Buddha Plastic Technology	0.254	0.261	0.966	Drs
Shanghai Electric Power Company	0.498	0.875	0.604	Irs	CNPC Technology	0.289	0.311	0.927	Drs
Yingfeng environment	0.26	0.339	0.802	Irs	Fang Large Group	0.189	0.314	0.714	-
Junzheng Group	0.743	0.927	0.807	Irs	Auspicious Electric Company	0.673	0.779	0.881	Irs
Fortis Information	0.291	0.301	0.964	Irs	Wolong electric drive	0.253	0.274	0.926	Irs
Great Wall Electrician	0.967	0.977	0.989	Irs	Antai Technology	0.305	0.312	0.979	Drs
Cheng Zhi Shares	0.734	0.789	0.933	Irs	Energy-saving wind power	1	1	1	-
Entrepreneurship Environmental protection	0.474	0.723	0.682	Drs	Coriyuan	0.783	0.795	0.984	-
Cisodium shares	0.168	0.187	0.916	-	Shanghai Electric Company	0.67	0.936	0.729	Drs
Hong Xun Technology	0.332	0.353	0.944	Drs	Changhong Meiling	0.711	0.748	0.955	Drs
North International	0.325	0.44	0.784	Drs	Merrycloud	1	1	1	-
Power of navigation	0.378	0.431	0.88	Drs	Datang power generation	0.12	0.869	0.142	Irs
Hongfa Shares	0.287	0.344	0.852	Irs	Jia Hua Energy	0.294	0.572	0.568	Drs
Research new materials	0.157	0.167	0.93	Drs	Avic Heavy Machinery	0.871	0.883	0.985	Irs
Zhongtian Technology	0.429	0.477	0.906	Drs	Qibin Group	0.584	0.649	0.91	Irs
Enn Shares	0.748	0.889	0.846	Drs	Beijing Express	0.267	0.309	0.835	Drs
Desai battery	0.207	0.246	0.842	Drs	Golden Crystal Technology	0.31	0.325	0.952	Drs
Xemc Corporation	0.521	0.546	0.952	Irs	Variety Entertainment Shares	0.359	0.396	0.916	Drs
Innovation Technology	0.189	0.2	0.947	Irs	Dongxu Optoelectric	1	1	1	-
Lin Yang Energy	0.241	0.36	0.679	Drs	Constant change electrical	0.952	0.973	0.979	Drs
ST Wah Yee	0.38	0.389	0.973	Irs	New Sai Shares	1	1	1	-
Mingtai Aluminum Industry	0.694	0.756	0.922	Irs	Blue stone reload	0.986	1	0.986	Irs
The mean						0.541	0.606	0.896	

Crste: comprehensive technical efficiency Vrste: pure technical efficiency Scale: scale efficiency

technical efficiency, scale efficiency and pure technical efficiency have been improved to different degrees. The number of enterprises at the forefront of technological innovation has increased from 2 (Beishin

Building Materials, energy-saving wind power) to 6 (Tebean Electrician, Beishin Building Materials, energy-saving wind power, Meili Cloud, Dongxu Optoelectronics, and XinsaiStock), and the efficiency

indicators of other enterprises have changed. Among them, the technological innovation efficiency of only 23 enterprises was higher than the overall average value of the first stage (0.220), and that of 33 enterprises was higher than the overall average value of the third stage (0.541). This also shows that environmental factors have different impacts on enterprise efficiency.

Convergence Analysis of Technological Innovation Efficiency of New Energy Enterprises

In order to explore the difference of technological innovation efficiency, δ convergence test was used. The main purpose is to explore the effect and change trend of the above new energy enterprises' technology innovation efficiency into practical engineering applications.

Convergence theory originated from neoclassical growth theory. In fact, it is easy to understand that in a relatively closed and closed economic system, backward or underdeveloped countries or regions have a faster and higher economic growth rate. The purpose is to catch up with the relatively developed economic regions and countries faster, that is, to reach the mean value and constantly try to narrow the gap. In the mathematical sense, it is reflected as convergence, convergence to the average level. Finally, it approaches to a stable state of economic development. Otherwise, the growing gap between regions will pose a challenge to social stability and rapid development of society.

In general, δ convergence refers to the fact that the dispersion of the distribution of per capita income or salary between countries or regions with different economic development will decrease over time. In short, people's income intervals will no longer disperse to a large extent, but tend to the mean, that is, converge to the mean. Next, a new test method of δ convergence is introduced: by tracking the dispersion degree of per capita income in a country and region, and analyzing the changes of the coefficient of variation of income over time, the convergence can be measured

more appropriately and the correlation test can be conducted. This method is known as the Friedman test.

The Friedman test applied in this paper, while choosing three dimensions, namely overall level, regional level and time for different levels and regions in China, including national level, central, western and eastern parts of the country to do δ convergence analysis on the efficiency of technological innovation of new energy enterprises. Factorial δ convergence is one of the methods to evaluate the technological innovation efficiency of new energy enterprises.

In this paper, according to the relevant method of convergence model, the δ convergence results of technological innovation efficiency are obtained according to the geographical location of new energy enterprises, as shown in Table 4. The results show that during 2015-2021, the δ convergence and variation coefficient of eastern, central and western regions are all lower than 0.4, and the variation coefficient is lower than 0.6, with significant differences among regions.

According to the convergence analysis, the coefficient of variation is between 0.084 and 1.000, indicating that there are significant differences in technological innovation efficiency among Chinese new energy enterprises.

As shown in Table 5, δ convergence analysis is carried out for the four aspects respectively, and it is found that there is no obvious δ convergence in the whole country, central, western and eastern parts. On the whole, the technological innovation efficiency level of the national sample is not high, and there is still a large room for improvement, and the development and innovation gap between enterprises in the eastern region is large. The variation coefficient of the whole country presents an upward trend. Meanwhile, the coefficient of variation in the eastern region is significantly higher than that in the other regions, while the coefficient of variation in the western region is relatively small. In the middle and west regions show a good upward trend after going downward.

Table 4. δ coefficient and variation coefficient of different regions.

Year	The national		In the east		In the middle		In the west	
	Coefficient of δ	Coefficient of variation	Coefficient of δ	Coefficient of variation	Coefficient of δ	Coefficient of variation	Coefficient of δ	Coefficient of variation
2015	0.2886	0.4700	0.2883	0.5459	0.1624	0.2294	0.2051	0.2284
2016	0.2892	0.4718	0.2791	0.5441	0.1710	0.2292	0.1833	0.2021
2017	0.2953	0.4764	0.2909	0.5584	0.1595	0.2101	0.1894	0.2091
2018	0.2978	0.4906	0.2852	0.5693	0.1809	0.2358	0.1868	0.2085
2019	0.2942	0.4872	0.2925	0.5724	0.1822	0.2509	0.1878	0.2137
2020	0.3124	0.5113	0.3178	0.6052	0.2249	0.3167	0.1753	0.1977
2021	0.3184	0.5576	0.3194	0.6668	0.2144	0.3172	0.2002	0.2309

Table 5. Technology innovation efficiency zones of new energy enterprises.

Technological innovation efficiency value	Enterprise technology innovation efficiency level	The number of
0.8 or higher	Higher	23
0.6 or higher	Medium	13
< 0.6	The lower	36

Conclusions

In order to analyze the technological innovation efficiency of listed new energy enterprises, this paper takes 72 listed new energy enterprises as the research object, uses the panel data from 2015 to 2021, builds the three-stage DEA model and convergence analysis model, and empirically tests the technological innovation efficiency of listed new energy enterprises.

The results show that if environmental factors are not controlled, the average value of enterprise technological innovation efficiency measured by the classical DEA model is 0.220. If environmental factors are controlled, the technological innovation efficiency of listed new energy enterprises measured by the three-stage DEA increases to 0.541. However, the overall average technological innovation level is still low, and there is still a large room for improvement. The lack of pure technical efficiency is the key constraint. This indicates that the development of technological innovation of new energy enterprises in China mainly depends on technological innovation capability, not simply by virtue of the scale effect.

There are significant differences between the measured results of the classical DEA model and the three-stage DEA model, indicating that the environmental variables affect the technological innovation efficiency of new energy enterprises, and the regional economic level of the environmental variables is not conducive to reducing the redundancy of human and financial investment in the technological innovation process of new energy enterprises. Since the pure technical efficiency of most listed new energy enterprises in this paper is low, enterprises need to focus on improving their technical innovation ability by increasing R&D investment and increasing the proportion of technical talents.

Finally, through the convergence analysis of the technological innovation efficiency of new energy enterprises in different regions, it is found that the innovation gap of enterprises in the eastern region is large, and the innovation efficiency among enterprises is uneven, while the gap is small in the western region, and the regional technological innovation efficiency shows obvious temporal and spatial heterogeneity.

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Conflict of Interest

The authors declare no conflict of interest.

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