

Evaluation of Technological Innovation Efficiency of New Energy Enterprises in the Yangtze River Delta Region—Based on a Two-Stage DEA Optimization Model

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How to cite this paper: Jia, Y. C., Xie, R. J., & Yang, C. L. (2022). Evaluation of Technological Innovation Efficiency of New Energy Enterprises in the Yangtze River Delta Region—Based on a Two-Stage DEA Optimization Model. *Open Journal of Business and Management*, 10, 2026-2044. <https://doi.org/10.4236/ojbm.2022.104104>

Received: June 27, 2022

Accepted: July 25, 2022

Published: July 28, 2022

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Abstract

Because of the shortcomings of the traditional two-stage DEA model, on the basis that the output of the first stage is completely transformed into the second-stage input. The investment of scientific and technological personnel and capital is added to construct a two-stage DEA optimization model to evaluate innovation efficiency. The model is used to empirically measure the overall efficiency of technological innovation and the efficiency of each sub-stage of the 22 new energy-listed companies in the Yangtze River Delta from 2014 to 2019. An efficiency matrix is proposed. The empirical results show that the overall innovation efficiency of new energy companies in the Yangtze River Delta Region is above the medium level and that there are phenomena such as the incoordination of input and output ratios in the companies' innovation processes. The technological innovation efficiency of new energy companies has a two-stage nature, and efficiency gaps in different stages within each company are evident. The low efficiency of technology R&D is a key factor restricting the improvement of the overall innovation efficiency of new energy enterprises. The degree of economic transformation efficiency should be better to fit the overall efficiency.

Keywords

Two-Stage DEA Optimization Model, Efficiency Matrix, Technology Innovation Efficiency

1. Introduction

New energy has become a global economic growth factor, and the technological

innovation of new energy enterprises has become an important aspect in evaluating the comprehensive strength of a country. In terms of efficiency measurement and evaluation methods, the existing literature mainly adopts the parametric and nonparametric methods. The parametric method refers to stochastic frontier analysis (SFA). SFA constructs the production frontier by setting the production function, and the results are reliable and comparable.

However, this method is only applicable to multi-input and single unit output (Wang et al., 2018; Wang & Cai, 2020). The nonparametric method refers to data envelopment analysis (DEA), which solves the problem of multi-input and multi-output by constructing the traditional DEA model (Andriamasy et al., 2014; Sun, 2020). Many scholars combine the DEA model with the Malmquist index to analyze the changing trends in technological innovation efficiency from the static and dynamic perspectives, respectively (Luo et al., 2019; Wang et al., 2019a; Liu et al., 2019; Sue & Ma, 2018). They regard the innovation process as a whole and directly measure overall efficiency without considering the internal structure rate (Tseng, 2009). However, innovation is a relatively complex process. The traditional DEA model is not sufficiently accurate to measure overall efficiency. It cannot find the potential factors affecting low efficiency. Chen et al. open the “black box” of the technological innovation system and divide the innovation process into two stages (Chen et al., 2018). The research results show that the redundancy of intermediate products restricts improvements in overall efficiency and the efficiency of the economic transformation sub-stage. Liu et al. improve the DEA method, which measures technology R&D efficiency and achieves the transformation efficiency of the high-tech manufacturing industry in three provinces of Northeast China (Liu et al., 2020). It analyzes the impact of the efficiency of each sub-stage on the overall efficiency. In addition, many scholars have verified the applicability and effectiveness of DEA model (Cho et al., 2017; Zhang et al., 2019; Mohammad et al., 2018; Wang et al., 2019b). However, the literature on the technological innovation efficiency of new energy enterprises is relatively poor. Although scholars have begun to use the Two-stage DEA model to measure the overall efficiency and sub-stage efficiency of enterprises, they only take the output of the first stage as the input of the second stage, and few scholars consider that enterprises will invest in the second stage. In the second stage, the enterprise will use the output of the first stage to invest in research and development, so that intermediate products can be fully transformed and the conversion rate of technological achievements can be effectively improved. Therefore, starting from the value chain, this paper measures the overall and sub-stage innovation efficiency of 22 new energy-listed enterprises in the Yangtze River Delta through the improved Two-stage DEA model, and studies the influencing factors of technological innovation efficiency by using the two-stage Tobit regression model.

The rest of the paper has been structured as follows. Section II builds a two-stage DEA optimization evaluation model of the R&D innovation efficiency. Section III is the empirical analysis and results. And section IV is the conclusion

and policy implication aspects.

2. A Two-Stage DEA Optimization Evaluation Model of the R&D Innovation Efficiency of New Energy-Listed Enterprises in the Yangtze River Delta Region

2.1. Index Selection of New Energy Enterprises

In order to analyze the internal characteristics of the technological innovation process of an enterprise, based on Chen's research ideas, this paper decomposes the technological innovation process into the technology R&D stage and the economic transformation stage. The second stage introduces the indicators of scientific and technological capital and scientific and technological personnel input to measure the overall efficiency and sub-stage efficiency of new energy enterprises.

1) The input-output index selection of the technology R&D stage: This process considers the comparability of input-output indexes among enterprises. This paper selects the input indexes of the first stage as R&D personnel input intensity and R&D capital input intensity, respectively. And it selects the technology asset ratio as the output index of the technology R&D stage. In this paper, the technology asset ratio refers to the number of patent applications, new product development projects, and other assets with technology at the core (Huang et al., 2017).

2) The input-output index selection in the economic transformation stage: The technical asset ratio, the input intensity of the scientific and technological personnel, and the input intensity of the scientific and technological capital (Wu et al., 2017) are selected as the input indicators for the second stage. The profit rate of the main business and the return on assets (Huang et al., 2017; Wu et al., 2017) are selected as the output indicators. A two-stage innovation input-output chain is shown in Figure 1.

2.2. Construction of the Evaluation Model

There are 22 *DMUs* (Decision Making Units) in this paper, i.e., DMU_j and $j \in \{1, 2, \dots, 22\}$. They are 22 new energy enterprises in the Yangtze River Delta. For each DMU_j , there are I types of R&D investment denoted as x_i and $i \in \{1, 2, \dots, I\}$. There are R intermediate outputs (technical achievements) denoted as z_r and $r \in \{1, 2, \dots, R\}$. There are S economic transformation inputs denoted as w_s and $s \in \{1, 2, \dots, S\}$ in the stage of economic transformation. There are K final economic outputs denoted as y_k and $k \in \{1, 2, \dots, K\}$.

The production technology set is defined as follows:

$$T = \begin{cases} (x_i, z_r) : \text{Technology research and development} \\ \text{stage } x_i \text{ can produce } z_r \\ (w_s, z_r, y_k) : \text{In the stage of economic} \\ \text{transformation } z_r, w_s \text{ can produce } y_k \end{cases}$$

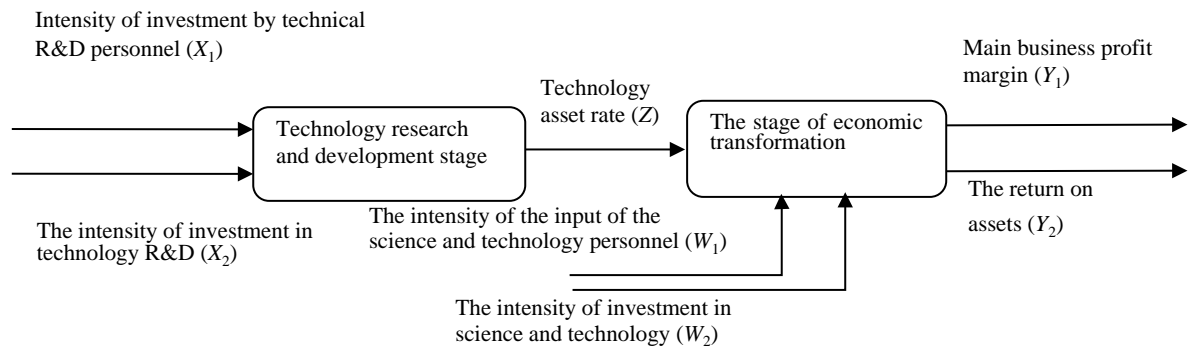


Figure 1. A two-stage innovation input-output chain.

Thus, the proposed model is established to calculate the overall efficiency of R&D innovation as follows:

$$\theta = (v_1 y_{10} + v_2 y_{20}) / (\mu_1 x_{10} + \mu_2 x_{20} + \mu_3 w_{10} + \mu_4 w_{10})$$

$$\text{s.t.} \begin{cases} (v_1 y_{1j} + v_2 y_{2j}) - (\mu_1 x_{1j} + \mu_2 x_{2j} + \mu_3 w_{1j} + \mu_4 w_{1j}) \leq 1 \\ v_1, v_2, \mu_1, \mu_2, \mu_3, \mu_4 \geq 0 \\ j \in \{1, 2, \dots, 22\} \end{cases} \quad (1)$$

where μ_1 and μ_2 are the first stage input weight coefficients. μ_3 and μ_4 are the second-stage input weight coefficients. v_1 and v_2 are the overall output weight coefficients. Equation (1) can be divided into a two-stage model. The first stage model is established as follows:

$$\theta_1 = mz_0 / (\mu_1 x_{10} + \mu_2 x_{20})$$

$$\text{s.t.} \begin{cases} mz_j - (\mu_1 x_{1j} + \mu_2 x_{2j}) \leq 1 \\ m, \mu_1, \mu_2 \geq 2 \\ j \in \{1, 2, \dots, 22\} \end{cases} \quad (2)$$

where m is the first stage output weight coefficient, $\mu_1 x_{10}$ and $\mu_2 x_{20}$ are input indexes, and mz_0 is the output index of the first stage. The second stage model is established as follows:

$$\theta_2 = (v_1 y_{10} + v_2 y_{20}) / (mz_0 + \mu_3 w_{10} + \mu_4 w_{20})$$

$$\text{s.t.} \begin{cases} v_1 y_{1j} + v_2 y_{2j} - (mz_j + \mu_3 w_{1j} + \mu_4 w_{2j}) \leq 1 \\ v_1, v_2, m, \mu_3, \mu_4 \geq 2 \\ j \in \{1, 2, \dots, 22\} \end{cases} \quad (3)$$

where $\mu_3 w_{10}$ and $\mu_4 w_{20}$ are the second-stage input indexes, respectively. And $v_1 y_{10}$ and $v_2 y_{20}$ are the output indexes of the second stage, respectively.

Based on the previous research literature, when constructing the total efficiency calculation model of the R&D innovation system, the internal sub-stage process of the R&D innovation system needs to be considered, which meets the two constraints mentioned in (Feng & Chen, 2014; Wang et al., 2020). Therefore, this paper constructs a model to measure the overall efficiency of chain DMU as follows:

$$\begin{aligned} \max \theta &= (\nu_1 y_{10} + \nu_2 y_{20}) / (\mu_1 x_{10} + \mu_2 x_{20} + \mu_3 w_{10} + \mu_4 w_{20}) \\ \text{s.t.} \quad &\begin{cases} \nu_1 y_{1j} + \nu_2 y_{2j} - (\mu_1 x_{1j} + \mu_2 x_{2j} + \mu_3 w_{1j} + \mu_4 w_{2j}) \leq 1 \\ mz_j - (\mu_1 x_{1j} + \mu_2 x_{2j}) \leq 1 \\ \nu_1 y_{1j} + \nu_2 y_{2j} - (mz_j + \mu_3 w_{1j} + \mu_4 w_{2j}) \leq 1 \\ \nu_1, \nu_2, \mu_1, \mu_2, \mu_3, \mu_4, m \geq 0 \\ j \in \{1, 2, \dots, 22\} \end{cases} \end{aligned} \tag{4}$$

The first constraint in Equation (4) is shown as follows:

$$\nu_1 y_{1j} + \nu_2 y_{2j} - (\mu_1 x_{1j} + \mu_2 x_{2j} + \mu_3 w_{1j} + \mu_4 w_{2j}) \leq 1 \tag{5}$$

The second constraint in Equation (4) is shown as follows:

$$mz_j - (\mu_1 x_{1j} + \mu_2 x_{2j}) \leq 1 \tag{6}$$

The third constraint in Equation (4) is shown as follows:

$$\nu_1 y_{1j} + \nu_2 y_{2j} - (mz_j + \mu_3 w_{1j} + \mu_4 w_{2j}) \leq 1 \tag{7}$$

It can be concluded that the sum of Equations (6) and (7) is equivalent to Equation (5). Therefore, Equation (4) can be simplified as follows:

$$\begin{aligned} \max \theta &= (\nu_1 y_{10} + \nu_2 y_{20}) / (\mu_1 x_{10} + \mu_2 x_{20} + \mu_3 w_{10} + \mu_4 w_{20}) \\ \text{s.t.} \quad &\begin{cases} mz_j - (\mu_1 x_{1j} + \mu_2 x_{2j}) \leq 1 \\ \nu_1 y_{1j} + \nu_2 y_{2j} - (mz_j + \mu_3 w_{1j} + \mu_4 w_{2j}) \leq 1 \\ \nu_1, \nu_2, \mu_1, \mu_2, \mu_3, \mu_4, m \geq 0 \\ j \in \{1, 2, \dots, 22\} \end{cases} \end{aligned} \tag{8}$$

Suppose that the optimal solution of Equation (8) is as follows: ν_1^* , ν_2^* , μ_1^* , μ_2^* , μ_3^* , μ_4^* , and m^* . Then, the overall efficiency of DMU is shown as follows:

$$\theta = (\nu_1^* y_{10} + \nu_2^* y_{20}) / (\mu_1^* x_{10} + \mu_2^* x_{20} + \mu_3^* w_{10} + \mu_4^* w_{20}) \tag{9}$$

The efficiency of the first stage is shown as follows:

$$\theta_1 = m^* z_0 / (\mu_1^* x_{10} + \mu_2^* x_{20}) \tag{10}$$

The efficiency of the second stage is shown as follows:

$$\theta_2 = (\nu_1^* y_{10} + \nu_2^* y_{20}) / (m^* z_0 + \mu_3^* w_{10} + \mu_4^* w_{20}) \tag{11}$$

Equation (8) is transformed into Equation (12) as follows:

$$\begin{aligned} \min \theta &= (\mu_1 x_{10} + \mu_2 x_{20} + \mu_3 w_{10} + \mu_4 w_{20}) / (\nu_1 y_{10} + \nu_2 y_{20}) \\ \text{s.t.} \quad &\begin{cases} mz_j - (\mu_1 x_{1j} + \mu_2 x_{2j}) \leq 1 \\ \nu_1 y_{1j} + \nu_2 y_{2j} - (mz_j + \mu_3 w_{1j} + \mu_4 w_{2j}) \leq 1 \\ j = 1, 2, \dots, 22 \end{cases} \end{aligned} \tag{12}$$

According to the Charnes Cooper transformation, Equation (12) can be transformed into a linear programming model as follows:

$$\begin{aligned}
 \min \theta &= \phi_1 x_{10} + \phi_2 x_{20} + \phi_3 w_{10} + \phi_4 w_{20} \\
 \text{s.t.} \quad & \begin{cases} \eta z_j - (\phi_1 x_{1j} + \phi_2 x_{2j}) \leq 1 \\ \varsigma_1 y_{1j} + \varsigma_2 y_{2j} - (\eta z_j + \phi_3 w_{1j} + \phi_4 w_{2j}) \leq 1 \\ \varsigma_1 y_{1j} + \varsigma_2 y_{2j} = 1 \\ \phi_1, \phi_2, \phi_3, \phi_4, \eta, \varsigma_1, \varsigma_2 \geq 0 \\ j \in \{1, 2, \dots, 22\} \end{cases} \quad (13)
 \end{aligned}$$

where η , ϕ_1 , ϕ_2 , ϕ_3 , ϕ_4 , ς_1 , and ς_2 are weight. These weights are derived from the DEA model, which is dynamic with different input-output index. Hence, the optimal solution can be obtained.

3. Empirical Analysis

3.1. Samples and Data

This paper selects the new energy enterprises listed on the Shanghai and Shenzhen stock markets in the Yangtze River Delta region from 2014 to 2018 as the research sample, excluding the stocks and enterprises with a negative net profit in 2014-2018. The total operating profit of the 22 selected enterprises accounts for two-thirds of the total operating profit of new energy enterprises in the Yangtze River Delta region. Therefore, the selected sample is representative. The relevant data of the 22 new energy-listed companies selected for this paper are taken from the CNKI and the annual reports of enterprises on the Shenzhen and Shanghai stock markets. The selected sample enterprises are shown in **Table 1**.

Table 1. Sample data selection.

Serial number	Corporate name	Stock code	Serial number	Corporate name	Stock code
1	Taisheng Wind Energy	300129	12	Zhengtai Electric	601877
2	Shanghai Electric	601727	13	Guodian Nari	600406
3	Space Rainbow	002389	14	Sinoma Technology	002080
4	Nandu Power Supply	300068	15	Tianshun Wind Energy	002531
5	The East Wind Rises Day by Day	300118	16	Aikang Technology	002610
6	Yijing Optoelectronics	600537	17	Huaguang Co., Ltd	600475
7	Shanshan Shares	600884	18	Jiangsu Shentong	002438
8	Hengdian Dongci	002056	19	GuoXuan Technology	002074
9	Jingsheng Electromechanical	300316	20	Zhonglai Shares	300393
10	Foster	603806	21	Zhongtian Technology	600522
11	Bowei Alloy	601137	22	Solar Power	300274

Source: CNKI and the annual reports of enterprises on the Shenzhen and Shanghai stock markets.

3.2. Descriptive Statistics of Main Input-Output Indicators

Descriptive statistics of the main input-output indicators. According to **Table 2**, the minimum profit margin of main business is 11.2%, the maximum is 50.0%, and the average is 24.522%; The minimum value of return on assets is 0.6%, the maximum value is 24.3%, and the average value is 4.9338%, indicating that there are certain differences in the economic returns of enterprises. The minimum value of technology asset ratio is 0.5%, the maximum value is 37.7%, and the average value is 3.779%, indicating that the ability of enterprises to develop new patents and new technologies is very different. The minimum input intensity of R&D personnel is 3.1%, the maximum is 39.9%, and the average is 7.336%. The minimum value of R&D capital investment intensity is 0.1%, the maximum value is 11.6%, and the average value is 3.999%. It can be seen that there are great differences in R & D investment among new energy enterprises. The specific descriptive statistical results are shown in **Table 2**.

3.3. Analysis of Innovation Efficiency of New Energy Enterprises in Yangtze River Delta Region

In line with the optimized two-stage DEA model, this paper uses MATLAB to calculate the efficiency of the two-stage input-output chain of technological innovation of new energy enterprises in the Yangtze River Delta region. It uses MATLAB and SPSS 24.0 to analyze the fitting relationship between the sub-stage efficiency and the comprehensive efficiency. It also analyzes the technological innovation efficiency matrix of enterprises, as follows.

3.3.1. Comparative Analysis of Comprehensive Efficiency

In this paper, the effectiveness of the improved model is verified, as compared with the case of not considering the intermediate input (i.e., $\mu_3 = 0$ and $\mu_4 = 0$) and $0 < \mu_3 \ \& \ \mu_4 \leq 1$. Then, using MATLAB to analyze the sample data of new energy enterprises in the Yangtze River Delta, the specific analysis is as follows.

Table 3 shows the comprehensive efficiency of the 22 new energy-listed companies in the Yangtze River Delta Region from 2014 to 2018. Compared with the traditional DEA model that does not consider intermediate input, the comprehensive efficiency and economic transformation efficiency measured by the proposed DEA model are significantly improved by 21.6% and 37.2%, respectively, indicating that the intermediate input level has a significant impact on the innovation efficiency of new energy enterprises. Overall, the average comprehensive efficiency of new energy enterprises in the Yangtze River Delta Region from 2014 to 2018 is 0.781, which is above the medium level.

There are 12 enterprises below the average level, accounting for 54.54% of the total sample. It indicates that the innovation efficiency of more than half of the new energy enterprises does not reach the average level for the Yangtze River Delta region. The variance is 0.027, which indicates that the average value of comprehensive efficiency of each enterprise is significantly different and that the

Table 2. Descriptive statistics of indicators.

Variable	Obs	Min	Max	Mean	Std. Dev.
Profit margin of main business (%)	132	11.2	53.2	25.162	8.5231
Technology asset ratio (%)	132	0.5	41.2	4.412	4.6112
Return on assets (%)	132	0.6	25.4	7.124	5.0892
R&d personnel input intensity (%)	132	3.1	42.8	15.374	7.6231
R&d capital investment intensity (%)	132	0.1	13.8	4.366	2.0683

Source: Computed by the author.

Table 3. The overall efficiency of new energy enterprises in the Yangtze River Delta region.

Enterprise	Traditional model ($\mu_3 = 0$ and $\mu_4 = 0$)			Improved model ($0 < \mu_3, \mu_4 \leq 1$)		
	θ	θ_1	θ_2	θ	θ_1	θ_2
Taisheng Wind Energy	0.525	0.634	0.081	0.728	0.634	0.556
Shanghai Electric	0.500	0.265	0.209	0.651	0.265	0.519
Space Rainbow	0.476	1.000	0.043	0.774	1.000	0.627
Nandu Power Supply	0.426	0.357	0.158	0.535	0.357	0.389
Sunrise in the East	0.351	0.141	0.386	0.572	0.141	0.582
Yijing Optoelectronics	0.291	0.172	0.195	0.500	0.172	0.449
Shanshan Shares	1.000	0.853	0.288	1.000	0.853	0.613
Hengdian Dongci	0.746	0.411	0.171	0.774	0.411	0.694
Jingsheng Electromechanical	0.462	0.198	0.253	0.980	0.198	0.979
Foster	0.886	0.207	0.467	0.951	0.207	0.938
Bowei Alloy	0.515	0.366	0.151	0.560	0.366	0.402
Zhengtai Electric	0.819	0.086	0.787	0.938	0.086	0.988
Guodian Nari	0.328	0.070	0.483	0.874	0.070	0.852
Sinoma Technology	0.449	0.337	0.122	0.651	0.337	0.546
Tianshun Wind Energy	0.468	0.171	0.285	0.729	0.171	0.697
Aikang Technology	1.000	0.512	0.278	1.000	0.512	0.520
Huaguang Co., Ltd.	0.417	0.173	0.382	0.700	0.173	0.641
Jiangsu Shentong	0.475	0.306	0.144	0.839	0.306	0.746
GuoXuan Technology	0.728	0.216	0.290	0.970	0.216	0.944
Zhonglai Shares	0.673	0.139	0.465	0.877	0.139	0.845
Zhongtian Technology	0.553	0.217	0.281	0.640	0.217	0.587
Solar power	0.351	0.040	1.000	0.929	0.040	1.000
Mean value	0.565	0.312	0.315	0.781	0.312	0.687
Variance	0.045	0.061	0.051	0.027	0.061	0.039

Source: Computed by the author.

development is unbalanced. From the perspective of enterprises, the average comprehensive efficiency of 10 enterprises, such as Shanshan Shares, is higher than the average overall efficiency, accounting for 45.45% of the total sample. The economic transformation efficiency of these enterprises is higher than the technology R&D efficiency. The comprehensive efficiency values of Nandu Power Supply, Dongfang Risheng, Yijing Optoelectronics, and Bowei Alloy are low, at 0.535, 0.572, 0.500, and 0.560, respectively. An analysis of the input-output sample data of these four enterprises shows that a low economic level of technological achievements and intermediate products leads to low innovation efficiency. We need to adjust the proportion of R&D investment so that the inputs can be fully transformed to improve the overall innovation efficiency.

3.3.2. Analysis of Sub-Stage Efficiency Level

Figure 2 and Figure 3 show that the average efficiency of new energy-listed enterprises in the Yangtze River Delta Region from 2014 to 2018 is 0.312, with eight enterprises having higher efficiency than the average, accounting for 36.4% of the total samples. The average efficiency of the economic transformation is 0.687, indicating that the economic transformation efficiency is above the medium level, with 10 enterprises operating at higher than the average efficiency level, accounting for 45.5% of the total sample. The economic transformation efficiency of the new energy-listed companies in the Yangtze River Delta Region is high, but the technology R&D efficiency is low.

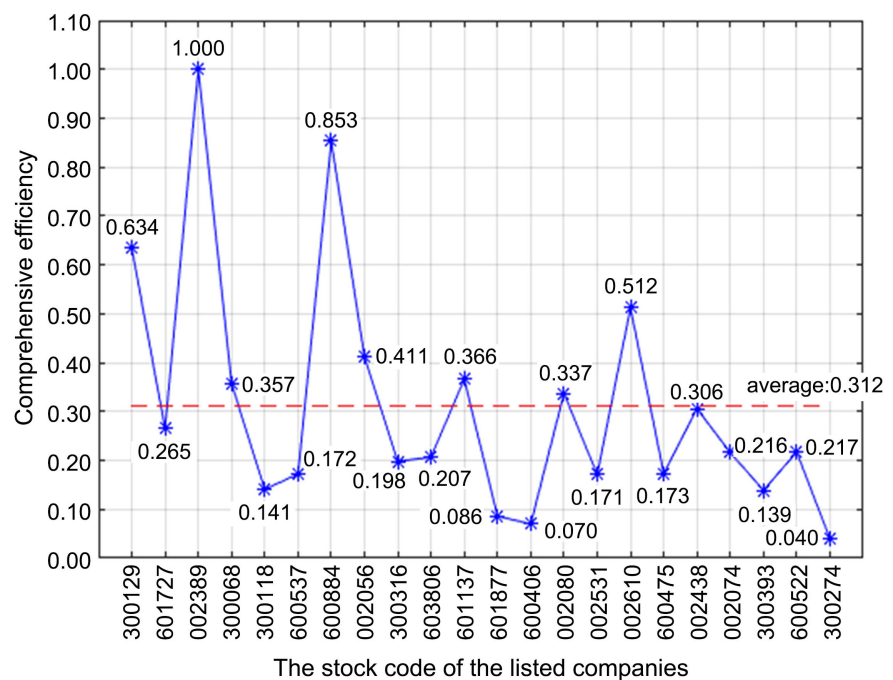


Figure 2. R&D efficiency and the average value of new energy-listed enterprises in the Yangtze River Delta Region. Source: Drawn by computer.

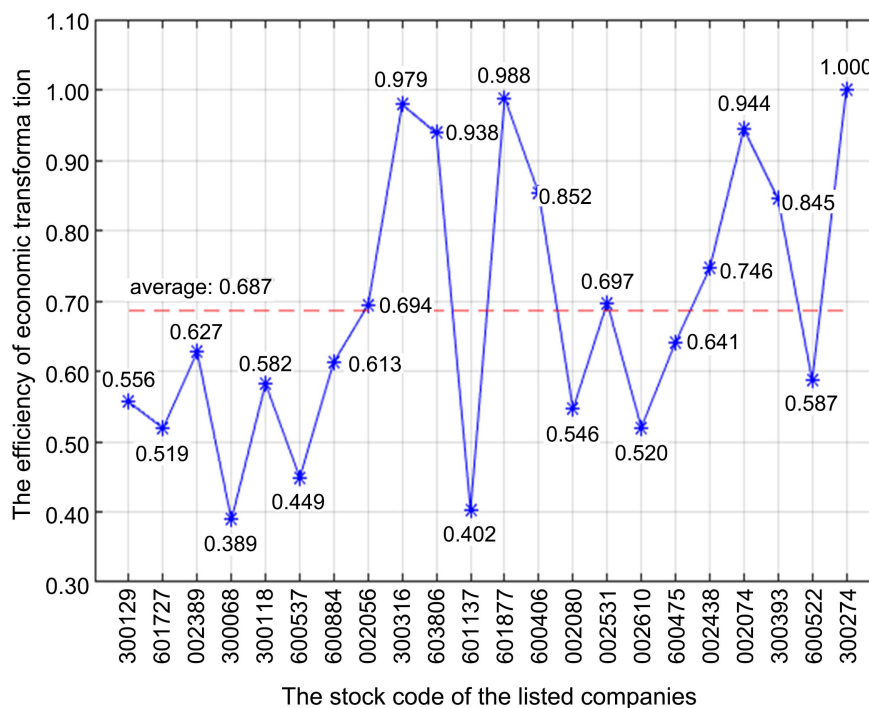


Figure 3. Economic transformation efficiency and the average value of new energy-listed enterprises in the Yangtze River Delta Region. Source: Drawn by computer.

The sub-stage efficiency in **Table 4** indicates that in the technology R&D stage, the R&D efficiency values of Zhengtai Electric, Guodian Nari, and Solar Power are ranked at the bottom for five consecutive years. In the technology R&D stage, they lack the ability to effectively transform the inputs into technological achievements, resulting in a low output rate of technological achievements. We need to optimize the input-output structure to avoid resource redundancy and to improve the efficiency of technology R&D.

In the stage of economic transformation, the average economic transformation efficiency of seven new energy enterprises, such as Jingsheng Electro mechanical is higher than 0.8 in 2014-2018. The analysis of the inputs and outputs for five consecutive years shows that the intermediate inputs such as technological achievements, scientific and technological funding, and the personnel of these enterprises are at the middle level, but the economic transformation efficiency is high. Therefore, the primary business profit margin and the return on assets are ranked in the third place in the long list in front of the corner.

Figure 4 shows that the average economic transformation efficiency of new energy-listed enterprises in the Yangtze River Delta region from 2014 to 2018 roughly presents an inverted “U” shape. From the perspective of the time sequence, the economic transformation efficiency shows an upward trend from 2014 to 2017 and reaches the highest value of 0.752 in 2017. This upward trend is related to the national policies to encourage the development of new energy industries in the 12th Five Year Plan. However, there has been a downward

trend since 2017, mainly due to the relentless expansion of investment in the excessive pursuit of economic benefits. This process results in a heavy financial burden and low-efficiency economic transformation. From 2014 to 2016, technology R&D efficiency shows a trend of slow decline followed by a rapid decline, reaching the lowest value of 0.162 in 2016. The analysis of enterprise input-output data indicates that due to the implementation of the new energy subsidy policy in 2016, enterprises invest too much in the economic transformation

Table 4. Technology R&D and economic transformation efficiency of new energy-listed enterprises in the Yangtze River Delta Region from 2014 to 2018.

Enterprise	Technology development stage					Stage of economic transformation						
	2014	2015	2016	2017	2018	mean value	2014	2015	2016	2017	2018	Mean value
Taisheng Wind Energy	0.789	0.698	0.239	0.684	0.761	0.634	0.419	0.655	0.676	0.662	0.369	0.556
Shanghai Electric	0.171	0.154	0.090	0.394	0.515	0.265	0.462	0.495	0.690	0.507	0.44	0.519
Space Rainbow	1.000	1.000	1.000	1.000	1.000	1.000	0.466	0.663	0.557	0.784	0.667	0.627
Nandu Power Supply	0.337	0.346	0.074	0.474	0.553	0.357	0.292	0.580	0.438	0.326	0.307	0.389
Sunrise in the East	0.168	0.128	0.041	0.088	0.281	0.141	0.434	0.549	0.787	0.688	0.454	0.582
Yijing Optoelectronics	0.199	0.203	0.055	0.194	0.208	0.172	0.431	0.494	0.591	0.349	0.382	0.449
Shanshan Shares	1.000	1.000	0.859	1.000	0.407	0.853	0.543	0.519	0.627	0.736	0.639	0.613
Hengdian Dongci	0.416	0.413	0.131	0.485	0.609	0.411	0.537	0.528	0.587	0.941	0.875	0.694
Jingsheng Electromechanical	0.319	0.323	0.049	0.123	0.177	0.198	0.901	1.000	0.996	1.000	1.000	0.979
Foster	0.177	0.207	0.063	0.299	0.289	0.207	0.753	0.937	1.000	1.000	1.000	0.938
Bowei Alloy	0.420	0.359	0.111	0.275	0.665	0.366	0.237	0.277	0.353	0.631	0.512	0.402
Zhengtai Electric	0.158	0.082	0.038	0.074	0.078	0.086	0.977	1.000	0.965	1.000	1.000	0.988
Guodian Nari	0.073	0.075	0.031	0.085	0.085	0.070	0.663	0.700	0.899	1.000	1.000	0.852
Sinoma Technology	0.306	0.361	0.116	0.402	0.500	0.337	0.332	0.580	0.525	0.677	0.616	0.546
Tianshun Wind Energy	0.241	0.166	0.042	0.187	0.217	0.171	0.462	0.707	0.929	0.695	0.694	0.697
Aikang Technology	0.709	0.542	0.153	0.607	0.551	0.512	0.397	0.498	0.582	0.563	0.560	0.520
Huaguang Co., Ltd	0.079	0.070	0.073	0.220	0.421	0.173	0.561	0.643	1.000	0.523	0.479	0.641
Jiangsu Shentong	0.293	0.496	0.132	0.291	0.319	0.306	0.694	0.684	0.791	0.847	0.714	0.746
GuoXuan Technology	0.299	0.287	0.115	0.153	0.227	0.216	1.000	1.000	1.000	0.985	0.735	0.944
Zhonglai Shares	0.152	0.204	0.064	0.078	0.199	0.139	1.000	1.000	0.875	0.781	0.571	0.845
Zhongtian Technology	0.277	0.226	0.075	0.187	0.321	0.217	0.471	0.446	0.539	0.847	0.631	0.587
Solar power	0.029	0.083	0.015	0.033	0.038	0.040	1.000	1.000	1.000	1.000	1.000	1.000
Mean value	0.346	0.337	0.162	0.333	0.383	0.312	0.592	0.680	0.746	0.752	0.666	0.687
variance	0.079	0.073	0.065	0.078	0.059	0.061	0.060	0.047	0.044	0.045	0.052	0.039

Source: Computed by the author.

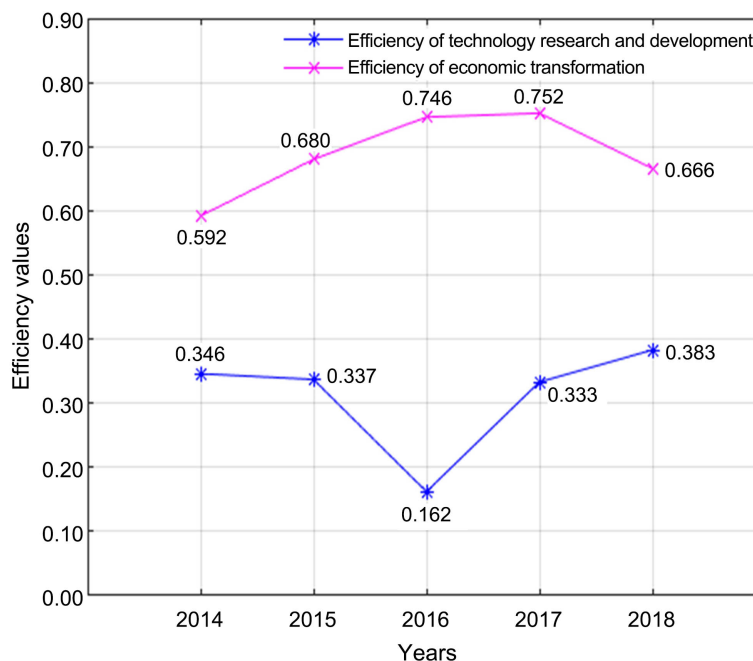


Figure 4. Change chart of technology R&D efficiency and economic transformation efficiency of new energy-listed enterprises in the Yangtze River Delta Region. Source: Drawn by the author.

stage, pay less attention to the technology R&D stage, and experience a certain lag in input-output, which lead to technology innovation. The output first shows as low and then a rapid decline. Since 2016, the trend of a rapid rise followed by a slower rise is related to the government's policy of supporting enterprises to achieve R&D innovation. Under government guidance, enterprises increase the introduction of advanced technology, cultivate high-quality R&D talent, and optimize the input-output structure to improve the ability of technology transformation.

3.3.3. Analysis of Fitting Relationship between Sub-Stage Efficiency and Comprehensive Efficiency

The results are shown in **Table 5**, **Figure 5** and **Figure 6**. R^2 is the Goodness of Fit, and the closer the R^2 is to 1, the better the model is. **Table 5** shows that the economic transformation efficiency R^2 is far greater than the technology R&D efficiency R^2 . The distribution of points near the line in **Figure 5** is relatively discrete, while the distribution of points near the line in **Figure 6** is uniform. This shows that the fitting degree of economic transformation efficiency to comprehensive efficiency is greater than that of technology R&D efficiency to comprehensive efficiency. Enterprises should coordinate the investment proportion of the two stages to promote overall efficiency. **Figure 6** shows that the 22 new energy enterprises are divided into four technological innovation modes: low R&D and high transformation, extensive low efficiency, high R&D and low transformation, and high R&D and high transformation.

Table 5. Main indicators of SPSS regression analysis.

Model	R ²	F	Standard coefficient (B)	The parameters were significant (<0.05)
Model 1 (θ^1)	0.014	0.278	0.117	0.603 (0.517)
Model 2 (θ^2)	0.518	21.531	0.720	0.000*** (0.00039)

Note: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Computed by the author.

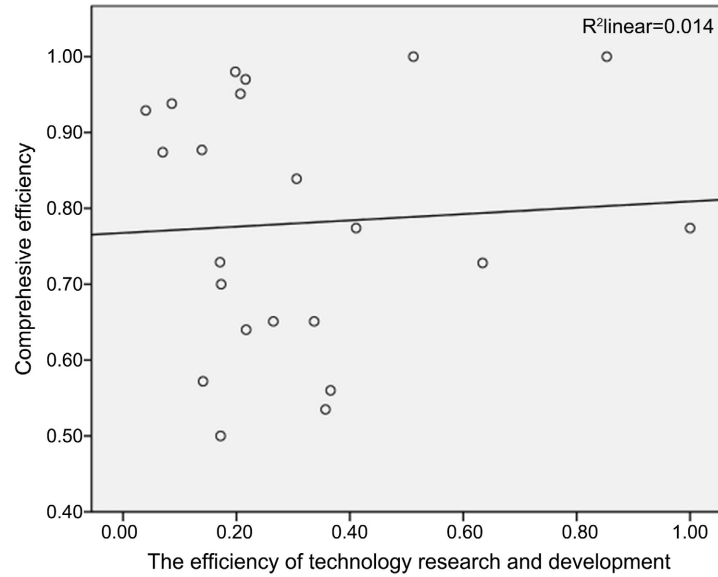


Figure 5. Goodness of Fit between technology R&D efficiency and comprehensive efficiency. Source: Drawn by the author.

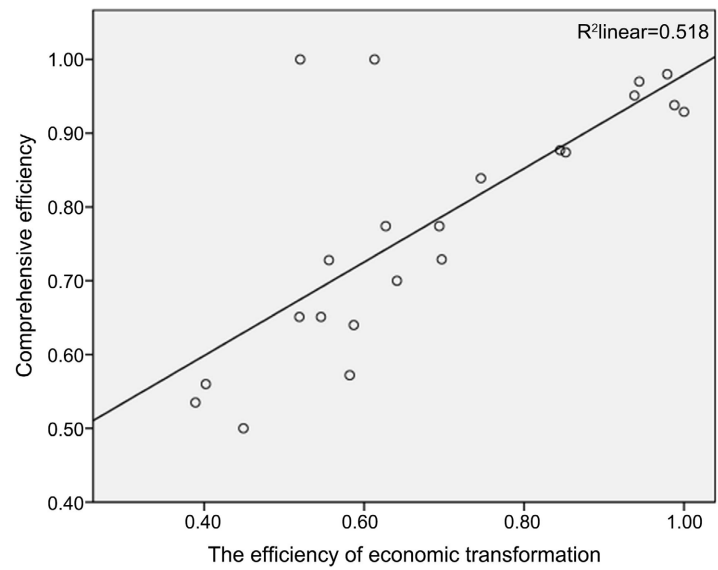


Figure 6. Goodness of fit between economic transformation efficiency and comprehensive efficiency. Source: Drawn by the author.

3.3.4. Matrix Analysis of Technological Innovation Efficiency of New Energy Enterprises in Yangtze River Delta Region Based on a Two-Stage DEA Optimization Model

According to the above analysis (Fathi, 2020; Henriques et al., 2020), the average value of the technology R&D and the economic transformation of new energy enterprises in the Yangtze River Delta Region is 0.312 and 0.687, respectively. To facilitate the graph Taisheng Wind Power, Shanghai Electric, Aerospace Rainbow, Nandu Power, Dongfang Risheng, Yijing Optoelectronics, Shanshan Shares Hengdian DongCi, Jingsheng Electromechanical, Foster, Bowei Alloy, Zhengtai Electric Guodian Nari, Sinoma Technology, Tianshun Wind Energy, Aikang Technology, Huaguang Co., Ltd., Jiangsu Shentong, GuoXuan Technology, Zhonglai Shares, Zhongtian Technology, and Sunshine Power Supply are selected. They are labeled as 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, and 22, respectively. The details are shown in **Figure 7**.

Based on the model and its experiments, there are four types of enterprises:

1) Type 1: Low R&D and high-transformation

Nine new energy enterprises, such as Jingsheng Electromechanical Co., Ltd., belong to Type 1, accounting for 40.9%. In the innovation process, there is the phenomenon of low R&D efficiency and high economic transformation efficiency. These enterprises have a strong ability to transform technological achievements into economic benefits, but they lack technology R&D ability. Therefore, enterprises need to pay attention to the investment of related resources at the technology stage. They need to introduce funds and talented personnel to optimize management methods and to find other ways to improve the technology R&D ability, to improve overall innovation efficiency.

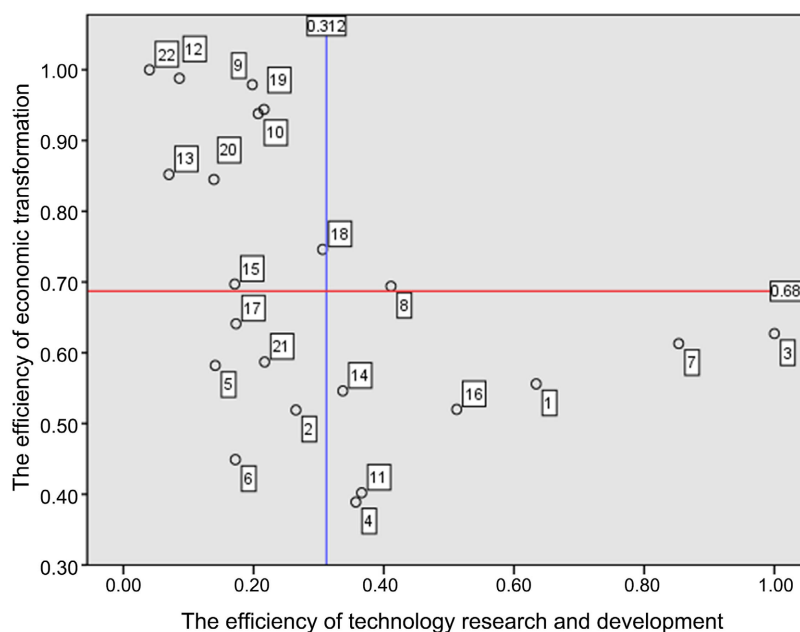


Figure 7. The efficiency matrix of “technology R&D economic transformation”. Source: Drawn by the author.

2) Type 2: Extensive low-efficiency

Shanghai Electric and the other five new energy enterprises belong to Type 2, accounting for 22.7%. The technology R&D efficiency and economic transformation efficiency of these enterprises are low, and there is redundancy in investment. When redundancy occurs, even if the investment of funds and personnel significantly increase, the output rate of technological achievements and economic benefits aren't improved correspondingly. Therefore, these enterprises should optimize their management structure. They should avoid resource redundancy and improve the efficiency of technology R&D and economic transformation.

3) Type 3: High R&D and low-transformation

Taisheng Wind Energy and seven other new energy enterprises belong to Type 3, accounting for 31.8%. These enterprises have high technology R&D ability but weak economic transformation ability. Enterprises can effectively transform resources into technology-based assets, such as patents and new product development projects. However, it is difficult to transform these intermediate products into economic benefits. Therefore, they should promote technology transformation and research. They should develop products according to market demand, avoid the disconnection between technology and markets, optimize enterprise operation, and improve economic benefits.

4) Type 4: High R&D and high-transformation

Only one new energy enterprise, Space Rainbow, belongs to Type 4, accounting for 4.6%. In this type, the efficiency of technology R&D and the efficiency of economic transformation are both high. Enterprises with high technology R&D ability and economic transformation ability can reasonably adjust the input-output ratio of the two-stage model, which has sufficient personnel training and optimize their policy. The efficiency of the enterprise is significantly ahead of other ones, which makes it a "benchmark" enterprise.

4. Conclusion

By constructing the improved two-stage DEA model, taking 22 new energy-listed companies in the Yangtze River Delta Region as the object, this paper studies the impact of the technology R&D stage, the economic transformation stage, and the intermediate investment on the overall innovation process. The results show that the average technological innovation efficiency of 22 new energy enterprises in the Yangtze River Delta selected in this paper from 2014 to 2018 is 0.781, which is at a medium level, and there is still room for improvement. From the variance of comprehensive efficiency, there are significant differences in the efficiency of technological innovation among enterprises. From the perspective of enterprise stage efficiency, the average technology R&D efficiency of new energy enterprises is 0.321, and the low pure technology efficiency is the main reason for the low technology R&D efficiency. In terms of sub-stages, more than 80% of the new energy enterprises in the sample have low-efficiency

values in the first stage, indicating that the utilization rate of human, material and capital as R&D investment resources in the first stage is not high, the utilization rate of enterprise resources is low, and the efficiency of economic transformation presents an inverted “U” feature. Compared with the efficiency of technology research and development stage, the conversion rate of technological achievements in the second stage is better, which to some extent shows that the low efficiency of technology research and development restricts the improvement of the overall efficiency of technological innovation of new energy enterprises. The lack of key core technologies and the unreasonable allocation of input factors are the biggest obstacles in the process of technological innovation and development of enterprises. Fitting analysis shows that the level of economic transformation efficiency is consistent with the overall innovation efficiency, but there is a certain upper limit. According to the two-stage efficiency value of each enterprise, the technological innovation mode can be divided into low R&D, high transformation and extensive low efficiency.

Based on the above conclusions, this paper puts forward the following strategic suggestions.

1) Give play to the exemplary role and strengthen the flow of innovation resources

For enterprises with low technology R&D efficiency, learn from typical demonstration enterprises, improve investment factors and quickly adapt to many consumer needs in the market. Strengthen the flow of innovation resources among regions, actively build a collaborative innovation platform for industry, university and research, formulate a training mechanism for scientific and technological talents, give full play to the role of scientific and technological talents, stimulate the innovation vitality of enterprise employees, and provide sustainable driving force for R&D and innovation, so as to improve the efficiency of technological R&D and drive the improvement of the overall innovation efficiency.

2) Optimize the operation environment and improve the management level

Give full play to the incentive effect of government subsidies on the technical efficiency of new energy enterprises, ensure the production of products that meet the needs of consumers and improve economic benefits by optimizing the operating environment. For enterprises with low efficiency of economic transformation, it is necessary to improve the management level, develop products according to market demand, strengthen the supervision of innovation funds, give full play to the role of market laws, make special funds for special purposes, avoid the disconnection between technology and market, resulting in redundancy of intermediate products such as technology patents, and achieve the goal of improving innovation input and output.

3) Rationally allocate input factors and pay attention to the optimal allocation of resources

For double low enterprises, it is necessary to reasonably allocate investment

factors in technology R&D stage and economic transformation stage, optimize redundancy mechanism and avoid resource waste. For enterprises with sufficient resources, we can optimize the resource allocation in the technology R&D stage and the economic transformation stage at the same time. For enterprises with limited resources, they can give priority to improving the efficiency of technological R&D or economic transformation, use the high-efficiency stage to drive the low-efficiency stage, build and improve the collaborative innovation supervision system, adhere to promoting scientific and technological innovation and system innovation, adhere to endogenous reform, avoid capital and human redundancy, improve the transformation rate of technological innovation achievements, and improve the overall efficiency.

In future related research work, we plan to compare the innovation efficiency of new energy enterprises in the Yangtze River Delta with that in other developed regions of China, such as Beijing, Tianjin, Hebei and the Pearl River Delta. Through comparative analysis, evaluate the advantages and disadvantages of the new energy industry in the Yangtze River Delta, and put forward reasonable suggestions for the development of the new energy industry in the Yangtze River Delta according to the development mode of the new energy industry in other regions.

Data Availability

The data used to support the finding of this study is available from the corresponding author upon request.

Funding Statement

The work was supported by National Natural Science Foundation of China under Grant No. 61872006 and 71701002; National Social Science Foundation of China under Grant No. 16bgl201.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

- Andriamasy, L., Barros, C. P., & Liang, Q. (2014). Technical Efficiency of French Nuclear Energy Plants. *Applied Economics*, *46*, 2119-2126. <https://doi.org/10.1080/00036846.2014.892199>
- Chen, Y. W., Wang, M. Q., Chen, Y. Y., & Geng, J. G. (2018). Research on R&D Innovation Efficiency of China's High-Tech Industry Based on Improved Two-Stage DEA. *Soft Science*, *32*, 14-18.
- Cho, C., Sun, Y. P., Son, J. K., & Lee, S. (2017). Comparative Analysis of R&D-Based Innovation Capabilities in SMEs to Design Innovation Policy. *Science & Public Policy*, *44*, 403-416. <https://doi.org/10.1093/scipol/scw073>

- Fathi, B. (2020). Environmental, and Economic Efficiency in Fossil Fuel Exporting Countries: A Modified Data Envelopment Analysis Approach. *Sustainable Production and Consumption*, 26, 588-596. <https://doi.org/10.1016/j.spc.2020.12.030>
- Feng, Z. J., & Chen, W. (2014). Research on R&D Innovation Efficiency of China's High Tech Industry—A New Perspective Based on Resource-Constrained Two-Stage DEA Model. *Systems Engineering Theory and Practice*, 34, 1202-1212.
- Henriques, I. C., Sobreiro, V. A., & Kimura, H. (2020). Two-Stage DEA in Banks: Terminological Controversies and Future Directions. *Expert Systems with Applications*, 161, Article ID: 113632. <https://doi.org/10.1016/j.eswa.2020.113632>
- Huang, J., Yang, Z. R., Yin, L. M., Zhang, W. W., & Qin, Y. (2017). Research on R&D Efficiency Evaluation and Influencing Factors of Domestic Robot Enterprises Based on DEA Tobit Two-Stage Analysis Method. *Scientific and Technological Progress and Countermeasures*, 34, 101-106.
- Liu, F. C., Zhang, N., & Zhao, L. S. (2020). Research on Innovation Efficiency Evaluation of High Tech Manufacturing Industry in Northeast China Based on Two-Stage Network DEA Model. *Management Review*, 32, 90-103.
- Liu, T., Gao, Q., & Wu, F. (2019). Research on Spatial Differentiation of Technological Innovation Efficiency of Enterprise Based on the Super-Efficiency DEA-Malmquist Model. In *Proceedings of the 2nd International Conference on Economy, Management and Entrepreneurship (ICOEME 2019)* (pp. 676-683). <https://doi.org/10.2991/icoeme-19.2019.127>
- Luo, Q. L., Miao, C. L., Sun, L. Y., Meng, X. N., & Duan, M. M. (2019). Efficiency Evaluation of Green Technology Innovation of China's Strategic Emerging Industries: An Empirical Analysis Based on Malmquist-Data Envelopment Analysis Index. *Journal of Cleaner Production*, 238, Article ID: 117782. <https://doi.org/10.1016/j.jclepro.2019.117782>
- Mohammad, I., Madjid, T., Debora, D. C., & Francisco, J. S. (2018). A Novel Two-Stage DEA Production Model with Freely Distributed Initial Inputs and Shared Intermediate Outputs. *Expert Systems with Applications*, 99, 213-230. <https://doi.org/10.1016/j.eswa.2017.11.005>
- Sue, Z. G., & Ma, Z. X. (2018). Evaluation of Technological Innovation Efficiency of Key Provinces and Enterprises in the "Belt and Road"—An Empirical Analysis Based on Generalized DEA Model. *Scientific Management Research*, 36, 90-93.
- Sun, T. (2020). Research on the Efficiency Evaluation of Scientific and Technological Achievements Transformation in China's Old Industrial Bases—A Case Study of Northeast China. *China Soft Science*, 1, 164-170.
- Tseng, F. M., Chiu, Y. J., & Chen, J. S. (2009). Measuring Business Performance in the High-Tech Manufacturing Industry: A Case Study of Taiwan's Large-Sized TFT-LCD Panel Companies. *Omega*, 37, 686-697. <https://doi.org/10.1016/j.omega.2007.07.004>
- Wang, C. L., & Cai, Y. Y. (2020). Research on the Efficiency of Three Stages of Industrial R&D under the Global Value Chain: A Case Study of China's Equipment Manufacturing Industry. *China Soft Science*, 3, 46-56.
- Wang, Q. Q., Wu, Z. B., & Chen, X. (2019a). Decomposition Weights and Overall Efficiency in a Two-Stage DEA Model with Shared Resources. *Computers Industrial Engineering*, 136, 135-148. <https://doi.org/10.1016/j.cie.2019.07.014>
- Wang, Y. Q., Zhu, Z. W., & Liu, Z. B. (2019b). Evaluation of Technological Innovation Efficiency of Petroleum Companies Based on BCC-Malmquist Index Model. *Journal of Petroleum Exploration and Production Technology*, 9, 2405-2416.

<https://doi.org/10.1007/s13202-019-0618-9>

Wang, Y., Pan, J. F., Pei, R. M., Yi, B. W., & Yang, L. (2020). Assessing the Technological Innovation Efficiency of China's High-Tech Industries with a Two-Stage Network DEA Approach. *Socio-Economic Planning Sciences*, 71, Article ID: 100810.

<https://doi.org/10.1016/j.seps.2020.100810>

Wang, Y., Wang, Z. Q., & Liu, B. F. (2018). Development of Producer Services, R&D Agglomeration and R&D Efficiency of High Tech Industry: An Empirical Study Based on Stochastic Frontier Model. *Soft Science*, 32, 1-4, 15.

Wu, C. Q., Huang, L., & Wen, C. H. (2017). Research on Technological Innovation Efficiency and Its Influencing Factors in Yangtze River Economic Belt. *China Soft Science*, 5, 160-170.

Zhang, J. J., Wu, Q., & Zhou, Z. X. (2019). A Two-Stage DEA Model for Resource Allocation in Industrial Pollution Treatment and Its Application in China. *Journal of Cleaner Production*, 228, 29-39. <https://doi.org/10.1016/j.jclepro.2019.04.141>