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Analysis of Total Factor Energy Efficiency and Its Influencing Factors on Key Energy-Intensive Industries in the Beijing-Tianjin-Hebei Region

Jinchao Li [1,2,*], Yuwei Xiang [1], Huanyu Jia [1] and Lin Chen [1]

1 School of Economics and Management, North China Electric Power University, Beijing 102206, China; xyw@ncepu.edu.cn (Y.X.); 13261692355@163.com (H.J.); 1121320104@ncepu.edu.cn (L.C.)
2 Beijing Key Laboratory of New Energy and Low-Carbon Development, North China Electric Power University, Beijing 102206, China
* Correspondence: lijc@ncepu.edu.cn

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Abstract: In order to realize the synergistic optimization management of energy efficiency in the key energy-intensive industries of the Beijing-Tianjin-Hebei (Jing-Jin-Ji) region, this paper calculates the total factor energy efficiency (TFEE) of 27 industries in the Jing-Jin-Ji region. We discover that the manufacturing of raw chemical materials and chemical products, the smelting and processing of ferrous metals, and the production and supply of electric power and heat power are key industries, considering their economic output ratio, energy consumption ratio, and energy efficiency. Then, the Malmquist index is used to decompose the TFEE of key energy-intensive industries. The results show that the TFEE changes in the three major industries in the Jing-Jin-Ji region are caused by technological progress. Hebei has the highest total factor average energy efficiency in the production and supply of electric power and heat power industry, the main reason for this being the spillover effect from Beijing enterprises that have led to significant technological changes in Hebei. Due to similar technological advancements, Tianjin has the highest total factor average energy efficiency in the manufacturing of raw chemical materials and chemical products and the smelting and processing of ferrous metals. Therefore, the Jing-Jin-Ji region should work to increase its technological innovation and enhance its core competitiveness. We should optimize the allocation of resources in specific industries to improve the scale efficiency.

Keywords: Beijing-Tianjin-Hebei region; industrial industries; TFP; DEA; Malmquist index

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1. Introduction

The Jing-Jin-Ji region is part of China's capital region and, as such, holds an important strategic position. At the end of 2015, the total population of the region exceeded 100 million, accounting for 8.11% of the total Chinese population. Total energy consumption reached 452.58 million tons of standard coal, accounting for 10.95% of the national total energy consumption, and the regional gross domestic product (GDP) reached 6935.889 billion Renminbi (RMB), accounting for 9.60% of China's GDP. Moreover, during the 12th Five Year Plan (FYP) period, the economy of the Jing-Jin-Ji region was strong, with an average GDP growth rate of 7.4%, while total energy consumption growth slowed down to an average growth rate of 0.68%. However, due to the large total consumption of energy, there is still a significant impact on the ecological environment. In 2015, the Jing-Jin-Ji region accounted for nine out of 10 of the cities with the most severe smog and haze occurrences in China. While the environment is deteriorating, the energy shortage in the Jing-Jin-Ji region is still unresolved. In 2015, primary energy production accounted for only 17.79% of total consumption. Faced with the dual challenges of energy shortage and environmental pollution, energy efficiency management has become an important solution. At present, the Beijing, Tianjin, and Hebei provinces have great differences in the effectiveness of their energy efficiency management. In 2015, the energy consumption reduction rate per 10,000 RMB gross regional product in the Beijing, Tianjin, and Hebei provinces was 6.17% (Beijing), 7.21% (Tianjin), and 6.14% (Hebei). The differences between the three industries' reduction rates of 10,000-yuan industrial added value of energy consumption were even more striking, with rates of 8.16%, 13.25%, and 6.02%, respectively. Therefore, identifying the differences in energy efficiency between the three provinces and exchanging energy utilization experience will be conducive to lessening the industry energy efficiency differences in the Jing-Jin-Ji region. This should improve the overall energy efficiency of the Jing-Jin-Ji region and achieve coordinated development. Meanwhile, there were some changes of industrial energy consumption proportion in Beijing, Tianjin, and Hebei between 2005 and 2015. The detailed proportions are shown in Figure 1. The internal ring shows the industrial energy consumption of 27 industries in the Beijing-Tianjin-Hebei (BTH) area in 2005, while the outer ring shows the industrial energy consumption of 27 industries in the BTH area in 2015. Several signs indicate the trend of many Beijing factories being relocated to the city boundary, especially to Hebei Province. For example, the proportion of energy consumption by the manufacture of raw chemical materials and chemical products in Beijing declined from 7.81% in 2005 to 5.28% in 2015. However, this proportion in Tianjin rose to 32.08% in 2015 from 23.63% in 2005, and the proportion in Hebei reached 8.10% in 2015, an increase of 1.32% over 2005. We aim to analyze whether this shift in industry location is beneficial to the industrial total factor energy efficiency. Thus, in this paper we present a study of the total factor energy efficiency and its influencing factors in many key energy-intensive industries in the Beijing-Tianjin-Hebei region.

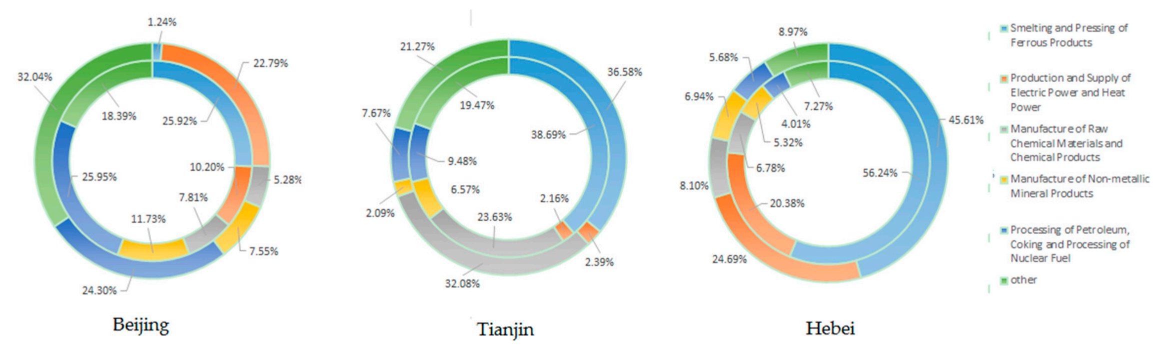

Figure 1. The change of industrial energy consumption proportions.

The second part of this paper serves as a literature review, summarizing existing research methods and measurement indicators. The third part introduces the technical route and the total factor energy efficiency indicators' calculation methods and models. The fourth part measures the total factor energy efficiency (TFEE) of 27 industries in the Jing-Jin-Ji region. In the fifth part, three key industries are selected and the Malmquist index is used to decompose the energy efficiency of the Jing-Jin-Ji region. Finally, the sixth part offers conclusions and policy suggestions.

2. Literature Review

Energy efficiency has been extensively researched by academics, both internationally and domestically. Energy intensity is a single factor efficiency index, which has some apparent flaws. TFEE appears more advantageous, particularly in certain circumstances such as revealing the impact of regional resource endowments on energy efficiency. Accordingly, in recent years, scholars have turned more towards energy efficiency research under a total factor framework. The most common method of TFEE is data envelopment analysis. Specific examples in the literature are shown in Table 1.

Table 1. Research on total factor energy efficiency.

Authors	Evaluation Object	Indexes	Method
Zhang et al. (2011) [1]	Yangtze River Delta	Energy, Labor, Capital Stock, GDP, Exhaust gas	Super Efficiency–Data Envelopment Analysis (SE-DEA), Malmquist-Luenberger (ML) productivity index
Feng et al. (2015) [2]	Beijing-Tianjin-Hebei metropolitan region	Energy, Labor, Capital Stock, GDP, CO_2, SO_2, Inhalable particles	Slack Based Model (SBM model), Tobit model
Ma et al. (2011) [3]	Yangtze River Delta, Peral River Delta, Bohai Zone	Energy, Labor, Capital Stock, Number of patent authorizations, GDP	SE-DEA, ML productivity index
Zhao et al. (2013) [4]	29 provinces in China	Energy, Labor, Capital Stock, GDP	Stochastic Frontier Analysis (SFA) model
Wang et al. (2014) [5]	Industrial sector of 30 Chinese major cities	Energy, Labor, Capital Stock, Value-added of industrial enterprises, CO_2, SO_2	Data Envelopment Analysis
Zhang and Choi (2013) [6]	30 provinces in China	Energy, Labor, Capital Stock, GDP, CO_2, SO_2, COD	SBM-DEA
Apergis et al. (2015) [7]	20 Organization For Economic Cooperation And Development (OECD) countries	Productive capital stock, Labor, Renewable and non-renewable energy	SBM model
Wu et al. (2014) [8]	China's industry	Fixed assets of industry, Electricity, GRP in industry, NO_2	Data Envelopment Analysis
Wang et al. (2013) [9]	30 regions in China	Energy, Labor, Capital Stock, GDP, CO_2	Range Adjusted Measure–Data Envelopment Analysis (RAM-DEA)
Long et al. (2013) [10]	31 provinces in China	Capital, Labor, Coal, GRP, SO_2	Directional distance function
Wang and Chen (2010) [11]	25 industries in China	Energy, Labor, Capital Stock, Value-added of industrial	DEA, Tobit model
Chen(2014) [12]	30 industries in China	Coal, Electricity, Oil, Labor, Capital Stock, Value-added of industrial	Stochastic frontier analysis (SFA)
Huang et al. (2014) [13]	30 provinces in China	Energy, Labor, Capital Stock, Land input, GDP, Environment pollutants	Undesirable output, super efficiency and SBM (US-SBM)
Fan et al. (2015) [14]	32 industrial sub-sectors in Shanghai	Energy consumption, Labor force, Capital stock, Gross industrial output, CO_2	Geography Markup Language (GML) index
Rohdina et al. (2007) [15]	The Swedish foundry industry	Capital, Technical risk, Long-term energy strategy, People with real ambition et al.	A case study, a questionnaire
Saygin et al. (2012) [16]	The German basic chemical industry	Energy coverage, Energy efficiency improvements,	The Process Industries–Inventory Energy Use Plus model (PIE-Plus)
Wu et al. (2007) [17]	The steel industry of Taiwan	Process equipment, Operation method, Energy category, Raw material, System management, Energy saving activity, Utilization of production capability	Taylor series expansion
Hassan et al. (2017) [18]	Small and medium-sized manufacturing enterprises in Pakistan	Access to capital, Risk and hidden cost, Government and state policies	Semi-structured questionnaires and interviews
Honma et al. (2014) [19]	The industries in Japan and 14 developed countries	Labor, Capital stock, Energy and non-energy intermediate inputs	DEA methodology, Sensitivity analyses
Zhou et al. (2010) [20]	18 top CO_2 emitters of the world	Energy, Labor, Capital stock, GDP, CO_2	Malmquist CO_2 Emission Performance Index (MCPI) index, Bootstrapping MCPI index, DEA
Sueyoshi et al. (2017) [21]	30 municipalities and provinces in China	GRP, CO_2, SO_2, Dust, Waste water, Ammonia nitrogen, Energy, Labor, Capital	DEA ML Productivity index
Zhang et al. (2015) [22]	CO_2 emission in Chinese transportation industry	Energy, Labor, Capital Stock, GDP, CO_2	Non-Radial Malmquist CO_2 Emission Performance Index (NMCPI) Bootstrapping approach
Zhou et al. (2012) [23]	OECD countries	Capital stock, Labor force, Energy, GDP	DEA, SFA
Sueyoshi et al. (2017) [24]	30 industries in China	GRP, CO_2, SO_2, Smoke and Dust, Waste Water, COD, Ammonia Nitrogen, Capital, Labor, Energy	DEA, Radial approach non-radial approach
Sueyoshi et al. (2016) [25]	30 municipalities and provinces	GRP, Primary industry, Secondary industry, Tertiary industry, PM_{10}, SO_2, NO_2, Investment, Coal, Oil, Natural gas, Electricity	Radial model: Returns to Damage (RTD) and Damages to Return (DTR) under congestions

3. Model and Estimation Methods

3.1. Research Route

The technical route is shown in Figure 2.

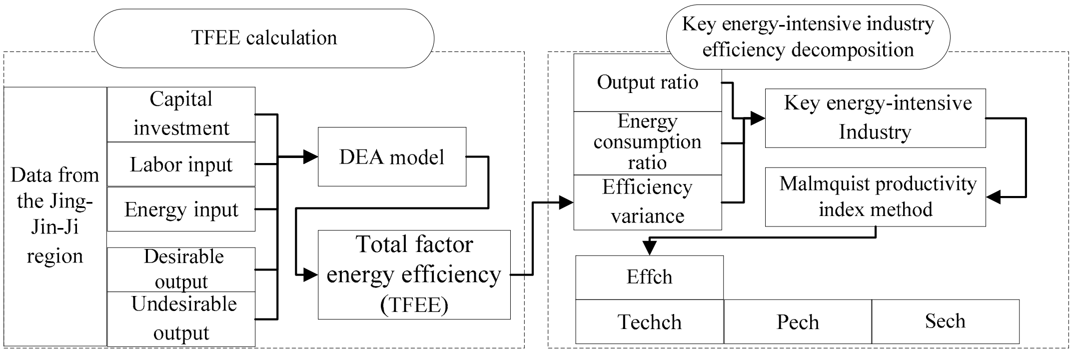

Figure 2. Research technical route.

3.2. Model Method

3.2.1. Total-Factor Energy Efficiency

Hu and Wang [26] defined total-factor energy efficiency (TFEE) since the index is established based on the viewpoint of total factor productivity. Index TFEE is also employed to analyze energy efficiency in an industry; Industry α's TFEE at time t is:

$$\text{TFEE}(\alpha) = \frac{\sum \text{Target Energy Input}(t)}{\sum \text{Actual Energy Input}(t)} \tag{1}$$

Here, Equation (1) shows that the TFEE in an industry is calculated by dividing the summation of target energy inputs by the total actual energy inputs of the industry.

3.2.2. DEA Model

Data envelopment analysis (DEA) was proposed by American operational researchers Charnes, Cooper, and Rhodes in 1978; accordingly named the CCR model, it uses mathematical programming and statistical data to identify the relatively efficient production frontier. The decision-making unit is projected onto the production frontier and then their relative validity is evaluated by comparing the extent to which decision-making units deviate from the production frontier. The DEA method has its unique advantages. Firstly, it is suitable for evaluating the validity of multiple-input and multiple-output. Secondly, there is no need for non-dimensional data processing when applying this method. Finally, it eliminates many subjective factors without any weight assumption.

The CCR model is the most classic DEA model and is based on the assumption of constant returns to scale, although this assumption does not match reality. To this end, Banker et al. (1984) added variable returns to the scale based on the CCR model and proposed the Banker, Charnes, and Cooper (BCC) model. Not only is this model more in line with the actual production experience, but it can examine the technical efficiency and scale effectiveness of decision-making units. Its specific form is:

$$\begin{aligned} & Min\theta \\ s.t. \quad & \sum_{j=1}^{n} \lambda_j x_j \leq \theta x_0 \\ & \sum_{j=1}^{n} \lambda_j y_j \geq y_0 \\ & \sum \lambda_j = 1; \lambda_j \geq 0, j = 1, \ldots, n \end{aligned} \tag{2}$$

where θ is the effective value of the evaluation unit, s^+ and s^- are the slack variables, λ_j is the combination ratio of the original decision unit, and the corresponding reconstructed decision unit.

The efficiency value (TIE) calculated by the CCR model can be decomposed into the product of the scale efficiency (SE) and pure technical efficiency (PTE), namely, technical efficiency = pure technical efficiency $\times$ scale efficiency, and pure technical efficiency is the efficiency value required for the BCC model. Then we can determine the returns to scale of decision-making units according to the value of $\sum\lambda_j$:$\sum\lambda_j > 1$, which indicates a diminishing returns to scale. $\sum\lambda_j = 1$ means the returns to scale reaches the best point of return, while $\sum\lambda_j < 1$ indicates an increasing returns to scale.

3.2.3. Unified Efficiency DEA Model

To deal with the undesirable outputs in assessing the operational and environmental performance of energy firms, Fare [27] proposed the following directional distance function:

$$Max\{\theta \big| (G + \beta\zeta_g, B - \beta\zeta_b) \in P(X)\} \tag{3}$$

Here, $P(X)$ = {(G, B): X can produce (G, B)}. The $P(X)$ indicates a production possibility set, which has a column vector of inputs (X) that can produce not only a column vector of desirable outputs (G) but also a column vector of undesirable outputs (B). $\zeta = (\zeta_g, -\zeta_b)$ is suggested as (1, 1, ..., 1, −1, −1, . . . , $-1)^T$, which contains $s + h$ components.

Mandal and Madheswaran [28] assumed that if the firm's objective is to simultaneously expand the desirable outputs and reduce the undesirable ones by the same proportion without increasing the inputs, the directional technology distance function becomes:

$$\vec{D}_T(x, y, b; 0, y, -b) = \sup[\beta : [(1+\beta)y, (1-\beta)b] \in P(x)] \tag{4}$$

The value β represents technical inefficiency. The direction vector $g = (g_x, g_y, -g_b) = (0, y, -b)$ determines the direction in which efficiency is measured. Given the technology and direction vector, the directional distance function measures the maximum feasible expansion of desirable output and the directional distance function β is zero. The directional distance function β is obtained by solving the maximization problem in Model (5).

$$\begin{aligned}
& Max\beta \\
s.t. \quad & \sum_{j=1}^{n} x_{ij}\lambda_j \le x_{ik} \qquad (i = 1, \ldots.) \\
& \sum_{j=1}^{n} g_{rj}\lambda_j \ge grk + \beta g_{rk} \quad (r = 1, \ldots.) \\
& \sum_{j=1}^{n} b_{fj}\lambda_j \le b_{fk} - \beta b_{fk} \quad (f = 1, \ldots.) \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& \beta \ge 0, \lambda_j \ge 0 \quad (j = 1, \ldots.)
\end{aligned} \tag{5}$$

Here, the outputs regarding the jth decision making unit (DMU) are separated into desirable outputs (g_{rk}) and undesirable outputs (b_{fk}). This model can measure the efficiency by $\theta = 1 - \beta$, where β is obtained from the optimality of Model (5).

In addition to Model (5), Zhou and Ang [29] proposed the following model to measure the unified efficiency of the energy firms:

$$\begin{aligned}
& Min\theta \\
s.t.\ & \sum_{j=1}^{n} x_{ij}\lambda_j \le x_{ik} \quad (i = 1, \ldots.) \\
& \sum_{j=1}^{n} e_{qj}\lambda_j \le \theta e_{qk} \quad (q = 1, \ldots.) \\
& \sum_{j=1}^{n} g_{rj}\lambda_j \ge g_{rk} \quad (r = 1, \ldots.) \\
& \sum_{j=1}^{n} b_{fj}\lambda_j = b_{fk} \quad (f = 1, \ldots.) \\
& \theta \ge 0 and \lambda_j \ge 0 \quad (j = 1, \ldots.)
\end{aligned} \tag{6}$$

Here, inputs regarding the *j*th DMU are separated into non-energy (x_{ij}: $i = 1$) and energy-related inputs (e_{ij}: $q = 1, \ldots$). Model (6) can be considered as an extension of CCR (Charnes-Cooper-Rhods) and the production possibility set of Model (6) is shaped by constant RTS (returns to scale).

3.2.4. Clustering Analysis

Clustering analysis is a kind of statistical method used to classify the research objects corresponding to the data. Through clustering analysis, we can measure the distance between different combinations, adopt different measuring distance methods, combine the two closest combinations in all combinations into one, and repeat the operation. Therefore, the final result will show the most similar samples gathered together; this plays an important role in statistical analysis.

3.2.5. Principal Component Analysis

Principal component analysis is a statistical analysis method that simplifies multiple indicators into a small number of comprehensive indicators, using a small number of variables to reflect as much of the original variable's information as possible while ensuring that the original information loss is small. Suppose $X = (X_1, X_2, \ldots, X_P)'$ is a p-dimensional random vector whose linear variation is as follows:

$$\begin{gathered}
PC_1 = \alpha'_1 X = \alpha_{11}X_1 + \alpha_{21}X_2 + \ldots + \alpha_{p1}X_p \\
PC_2 = \alpha'_2 X = \alpha_{12}X_1 + \alpha_{22}X_2 + \ldots + \alpha_{p2}X_p \\
\cdots\cdots\cdots \\
PC_p = \alpha'_p X = \alpha_{1p}X_1 + \alpha_{2p}X_p + \ldots + \alpha_{pp}X_p
\end{gathered}$$

Using the new variable PC_1 to replace the original p variables, $X_1, X_2, \ldots, X_P$, PC_1 should reflect the original variable information as much as possible. If the first principal component is not enough to represent most of the information of the original variable, consider introducing the second principal component PC_2, and so on. The main purpose of principal component analysis is to simplify the data. Therefore, in practical application we will not take p main components; rather, we will usually use m ($m < p$) principal components. Number m of the principal component is finally determined according to the cumulative variance contribution rate of each principal component.

$$\text{Cumulative variance contribution rate} = \sum_{k=1}^{m} \lambda_k / \sum_{i=1}^{p} \lambda_i$$

where λ is the corresponding eigenvalue of each principal component; k is the selected principal component fraction; and i is number of the total principal components.

3.2.6. Malmquist Index

The Malmquist productivity index, originally proposed by Sten Malmquist, constructs the total factor productivity (TFP) index from period t to t + 1. In 1992, Fare combined the DEA model solution with the Malmquist index calculation. The Malmquist productivity index (TFPCH) can be decomposed into the technical efficiency change index (EFFCH) and the technical change index (TECHCH). The transformation of the Malmquist index is as follows:

$$\mathrm{M}(x^{t+1},y^{t+1},x^t,y^t) = \frac{D^{t+1}(x^{t+1},y^{t+1})}{D^t(x^t,y^t)} \times \left[\frac{D^t(x^{t+1},y^{t+1})}{D^{t+1}(x^{t+1},y^{t+1})} \times \frac{D^t(x^t,y^t)}{D^{t+1}(x^t,y^t)}\right] = \mathrm{EFFCH} \times \mathrm{TECHCH} \quad (7)$$

When the returns to scale change, the technical efficiency change index can be further decomposed into pure technical efficiency change (PECH) and scale efficiency change (SECH).

$$\frac{D^{t+1}(x^{t+1},y^{t+1})}{D^t(x^t,y^t)} = \frac{D^{t+1}(x^{t+1},y^{t+1}/V)}{D^t(x^t,y^t/V)} \times \frac{S^{t+1}(x^{t+1},y^{t+1})}{S^t(x^t,y^t)} = \mathrm{PECH} \times \mathrm{SECH} \quad (8)$$

The final transformation of the Malmquist index is as follows:

$$\mathrm{M}(x^{t+1},y^{t+1},x^t,y^t) = \mathrm{EFFCH} \times \mathrm{TECHCH} = \mathrm{PECH} \times \mathrm{SECH} \times \mathrm{TECHCH} \quad (9)$$

$\mathrm{M}(x^{t+1},y^{t+1},x^t,y^t)$ represents the variation of the TFP level. If EFFCH > 1, it indicates that the relative technical efficiency of t and $t + 1$ period is increased, whereas, in the contrary, it is the reverse. If TECHCH > 1, it indicates that $t + 1$ period has technological progress compared to t period, whereas, in the contrary, it is the reverse. PECH indicates whether the technology is fully utilized; if it is larger than 1, it indicates that the resource allocation is reasonable, whereas, in the contrary, it is the reverse. SECH expresses the index of the change of scale efficiency in two periods; if it is larger than 1, it means that the scale efficiency is optimized, whereas, in the contrary, it is the reverse.

4. Jing-Jin-Ji Region Key Energy-Intensive Industries Analysis

4.1. Jing-Jin-Ji Region Industrial Industries TFP Measurement

This paper selects the industrial energy input and output indicators of the 27 industries above designated size in the Jing-Jin-Ji region from 2005 to 2015. The indicators are defined as follows:

Capital investment. Capital investment is expressed as the "total fixed investment" of the industries above the designated size in the Jing-Jin-Ji region, and the actual value of the corresponding year is reduced by the fixed-asset investment price index (2005 = 100).

Labor input. Select the Jing-Jin-Ji region above the designated size industrial "average number of years of employment" as a labor input index.

Energy input. Select the Jing-Jin-Ji region above the designated size industrial energy total consumption as the energy input.

Desirable output. Select the Jing-Jin-Ji region above the designated size total industrial output as the desirable output, and the actual value of the corresponding year is reduced by the industrial production price index (2005 = 100).

Undesirable output. Calculate the CO_2 emissions of 27 industries in 2005–2015 according to the 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories. The above data is sourced from the Beijing Statistical Yearbook, Tianjin Statistical Yearbook, Hebei Economic Yearbook, China Industrial Economy Yearbook, and China Population and Employment Statistics Yearbook from 2006 to 2016 calendar years.

Descriptive statistics of TFEE measurement indicators are shown in Table 2.

Table 2. Descriptive statistics of TFEE measurement indicators of the Jing-Jin-Ji region.

Variables	Unit	Quantity	Expected Value	Variance	Maximum Value	Minimum Value
Capital	10,000 yuan Renminbi (RMB)	891	1,925,008.5	1006.227	48,598,069	719.7662
Labor	10,000 people	891	4.27	5.12	42.8	0.25
Energy	10,000 tons of standard coal	891	251.4162	1003.602	10,765.11	0.32
Desirable output	10,000 yuan RMB	891	5,135,763.6	9,995,731.7	119,232,787	17,693.821
Undesirable output	10,000 tons	891	648.7856	2474.223	26,446.65	0.029884

4.2. TFEE Measurement Results

The DEA model is used to calculate the TFEE results of the Jing-Jin-Ji region in 27 industries in Beijing, Tianjin, and Hebei from 2005 to 2015. The descriptive statistics of the TFEE results are shown in Table 3.

Table 3. TFEE measurement results of the Jing-Jin-Ji region.

Number	Industrial Industries	Beijing		Tianjin		Hebei	
		Average	Median	Average	Median	Average	Median
1	Processing of Food from Agricultural Products	0.526	0.244	0.449	0.119	0.381	1.000
2	Manufacture of Foods	0.291	0.149	0.310	0.074	0.298	0.064
3	Manufacture of Beverages	0.270	0.188	0.203	0.035	0.247	0.047
4	Manufacture of Textile	0.343	0.110	0.168	0.023	0.310	0.985
5	Manufacture of Textile Wearing Apparel and Accessories	0.410	0.103	0.651	0.207	0.729	0.100
6	Manufacture of Leather, Fur, Feathers, and Related Products	0.713	0.151	0.379	0.136	0.763	0.198
7	Manufacture of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products	0.226	0.151	0.325	0.083	0.319	0.065
8	Manufacture of Furniture	0.338	0.121	0.325	0.064	0.371	0.061
9	Manufacture of Paper and Paper Products	0.340	0.233	0.166	0.039	0.212	0.059
10	Printing and Reproduction of Recording Media	0.189	0.115	0.251	0.040	0.425	0.064
11	Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment activities	0.357	0.066	0.551	0.088	0.627	0.084
12	Processing of Petroleum, Coking and Processing of Nuclear Fuel	0.908	0.841	0.307	1.000	0.203	0.525
13	Manufacture of Raw Chemical Materials and Chemical Products	0.338	0.279	0.170	1.000	0.181	1.000
14	Manufacture of Medicines	0.348	0.242	0.263	0.040	0.206	0.064
15	Manufacture of Rubber and Plastic Products	0.268	0.141	0.264	0.043	0.285	0.130
16	Manufacture of Non-Metallic Mineral Products	0.281	0.214	0.181	0.043	0.173	1.000
17	Smelting and Pressing of Ferrous Products	0.473	0.400	0.280	1.000	0.265	1.000
18	Smelting and Pressing of Non-Ferrous Products	0.591	0.344	0.713	0.170	0.422	0.058
19	Manufacture of Metal Products	0.368	0.203	0.389	0.295	0.470	0.696
20	Manufacture of General Purpose Machinery	0.424	0.247	0.398	0.122	0.378	0.690
21	Manufacture of Special Purpose Machinery	0.435	0.226	0.377	0.080	0.389	0.058
22	Manufacture of Railway, Ship, Aerospace, and Other Transport Equipment	0.593	0.554	0.522	1.000	0.526	1.000
23	Manufacture of Electrical Machinery and Apparatus	0.656	0.403	0.564	0.138	0.606	0.550
24	Manufacture of Computers, Communication, and Other Electronic Equipment	0.835	0.745	0.975	0.569	0.519	0.071
25	Production and Supply of Electric Power and Heat Power	0.830	0.780	0.230	1.000	0.068	1.000
26	Production and Supply of Gas	0.359	0.412	0.597	0.274	0.389	0.061
27	Production and Supply of Water	0.210	0.095	0.154	0.049	0.142	0.015

The definition and information of these 27 industries can be found in national bureau of statistics of China.

4.3. TFEE Measurement Results and Information Statistics

The DEA model, data of TFEE, average TFEE, variance, proportion of energy consumption in various industrial industries, and economy output ratio in 27 industries in Beijing, Tianjin, and Hebei from 2005 to 2015 are used. The descriptive statistics of upper indicators are shown in Table 4.

Table 4. Descriptive statistics of industry data in the Jing-Jin-Ji region.

Number	Industrial Industries	TFEE Variance	Energy Consumption Ratio	Economy Output Ratio
1	Processing of Food from Agricultural Products	0.219	0.012	0.041
2	Manufacture of Foods	0.162	0.009	0.031
3	Manufacture of Beverages	0.072	0.003	0.010
4	Manufacture of Textile	0.261	0.005	0.022
5	Manufacture of Textile Wearing Apparel and Accessories	0.014	0.001	0.011
6	Manufacture of Leather, Fur, Feathers, and Related Products	0.092	0.001	0.017
7	Manufacture of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products	0.046	0.002	0.004
8	Manufacture of Furniture	0.044	0.001	0.006
9	Manufacture of Paper and Paper Products	0.090	0.006	0.009
10	Printing and Reproduction of Recording Media	0.033	0.002	0.006
11	Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment activities	0.027	0.001	0.012
12	Processing of Petroleum, Coking and Processing of Nuclear Fuel	0.200	0.060	0.042
13	Manufacture of Raw Chemical Materials and Chemical Products	0.328	0.107	0.051
14	Manufacture of Medicines	0.148	0.007	0.026
15	Manufacture of Rubber and Plastic Products	0.100	0.006	0.024
16	Manufacture of Non-Metallic Mineral Products	0.262	0.050	0.033
17	Smelting and Pressing of Ferrous Products	0.147	0.493	0.174
18	Smelting and Pressing of Non-Ferrous Products	0.096	0.003	0.018
19	Manufacture of Metal Products	0.114	0.012	0.052
20	Manufacture of General Purpose Machinery	0.123	0.005	0.036
21	Manufacture of Special Purpose Machinery	0.048	0.007	0.036
22	Manufacture of Railway, Ship, Aerospace, and Other Transport Equipment	0.175	0.013	0.133
23	Manufacture of Electrical Machinery and Apparatus	0.198	0.007	0.045
24	Manufacture of Computers, Communication, and Other Electronic Equipment	0.288	0.003	0.061
25	Production and Supply of Electric Power and Heat Power	0.109	0.177	0.091
26	Production and Supply of Gas	0.093	0.005	0.008
27	Production and Supply of Water	0.070	0.002	0.002

4.4. Analysis of Key Energy-Intensive Industry in the Jing-Jin-Ji Region

4.4.1. Clustering Analysis Result

The clustering analysis of 27 industrial industries in Beijing, Tianjin, and Hebei is conducted by using the method of system clustering analysis, according to the three indicators of energy consumption ratio, economy output ratio, and energy efficiency fluctuation. The calculation results are shown in Figure 3.

Through Figure 3, we find that the 27 industries are divided into three categories. The first category is the production and supply of electric power and heat power, raw chemical materials and chemical products, the smelting and processing of ferrous metals, and the oil and gas mining industry. The second category is petroleum processing, the coking and nuclear fuel processing industry, the manufacturing of computers, communication, and other electronic equipment, and the manufacturing of railways, ships, aerospace equipment, and other transport equipment. Finally, the third category is comprised of the remaining industries.

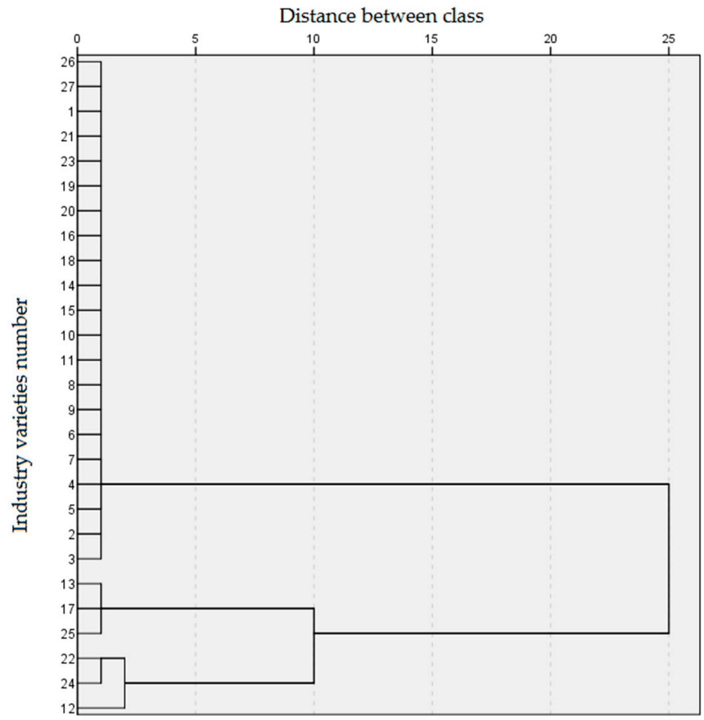

Figure 3. System clustering figure.

4.4.2. Principal Component Analysis Result

Through principal component analysis, we reduce the number of variables, while minimizing the original information loss, to make the research clearer and the categorization more intuitive. The specific results are shown in Figure 4.

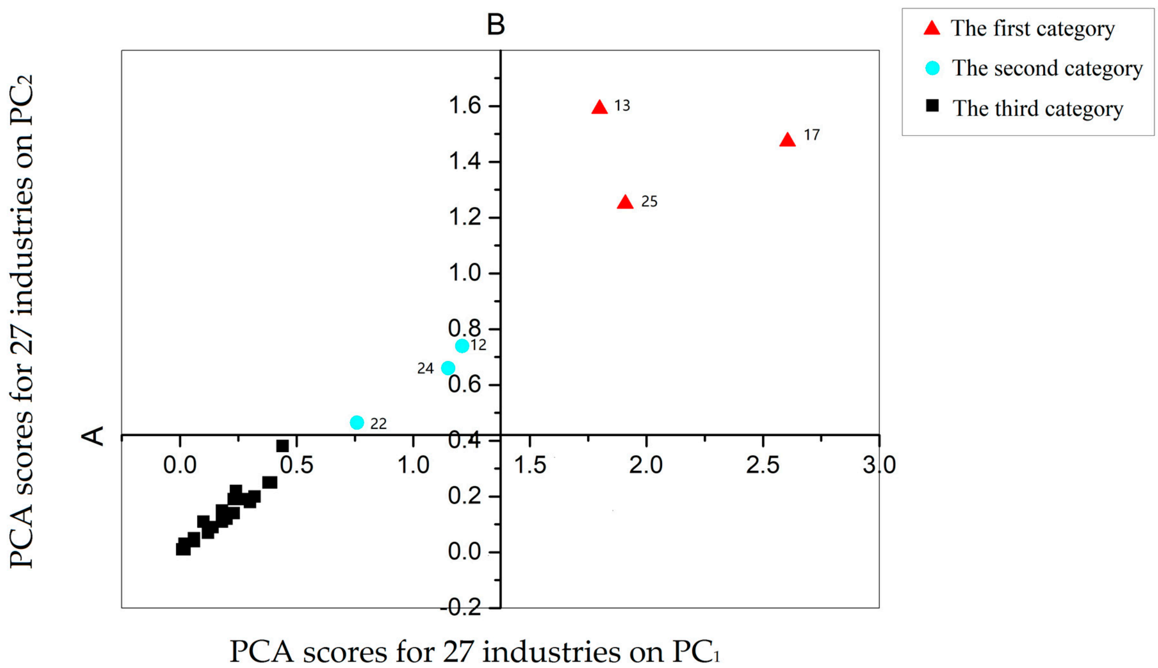

Figure 4. Principal component analysis.

Two principal components are selected. The first principal component predominately reflects the energy consumption information, while the second principal component mainly reflects the output value information. The cumulative variance contribution rate is 97.7%, which is greater than the threshold value of 85%. We find that the production and supply of electric power and heat power, raw chemical materials and chemical products, smelting, and the processing of ferrous metals fall in the positive direction of the first principal component and the second principal component. This indicates that the three industries account for a large proportion of the energy consumption ratio and economic output ratio. The petroleum processing, coking and nuclear fuel processing industry, the manufacturing of computers, communication, and other electronic equipment, and the manufacturing of railways, ships, aerospace equipment, and other transport equipment fall in the second quadrant of the first principal component and the second principal component. This indicates that the three industries account for a larger proportion of output, but a smaller proportion of energy consumption. The remaining industries in the third quadrant indicate low energy consumption and low output.

4.4.3. The Results of Analysis of Key Energy-Intensive Industries in the Jing-Jin-Ji Region

Based on the two methods above, we conduct the following classification system. The specific results are shown in Table 5.

Table 5. Industry classification table.

Classification	Industrial Industries
The first category	Raw Chemical Materials and Chemical Products, Smelting and Processing of Ferrous Metals, Production and Supply of Electric Power and Heat Power
The second category	Petroleum Processing, Coking and Nuclear Fuel Processing Industry, Manufacturing of Computers, Communication, and Other Electronic Equipment, Manufacturing of Railway, Ship, Aerospace, and Other Transport Equipment
The third category	The rest of the department

The above categorization is useful according to clustering analysis and principal component analysis. The industries are classified into three types. The first type has a high GDP, a large amount of energy consumption, and a large difference in energy efficiency between the three provinces. The second type has a relatively high GDP, relatively low energy consumption, and a relatively large difference in energy efficiency between the three provinces. The third type has a small GDP and energy consumption, with energy efficiency differences between the three provinces also proving small. We select the first type of industries as the focus of this study.

5. Analysis of Influencing Factors of the TFEE in Key Energy-Intensive Industries

5.1. Production and Supply of Electric Power and Heat Power

From the overall integrated efficiency change, the average value of the production and supply of electric power and heat power in the Jing-Jin-Ji region is 1.065, of which the average of technical progress changes is 1.090, while the average of comprehensive technical efficiency changes is 1.038. Judging from its decomposition, the pure technical efficiency change index average value is 1.083, and the scale efficiency change index is 0.985. This shows that the Jing-Jin-Ji region has made remarkable achievements in technological innovation. The reason for the low efficiency of integrated technology is the change in scale efficiency, indicating that the optimal industrial scale has not yet been reached.

In terms of differences, Beijing's TFP has been on a downward trend since 2009 and is much lower than that of Tianjin and Hebei in 2015. By contrast, the TFP of industry in Hebei Province is greater than 1 each year, indicating that the industry in Hebei Province has been showing a positive progressive change. At 9%, it has the highest average annual rate of change among the three provinces.

In Tianjin, the average annual rate of change is 6.7% in the industry, but in a few years the TFP changes predict negative growth. The change curves of TFP in the production and supply of electric power and heat power in the Jing-Jin-Ji region are shown in Figure 5.

The average scale efficiency of the industry in Beijing is 0.839, which is lower than the values of 1.005 in Tianjin and 0.965 in Hebei. This is the predominate reason why the TFP of the industry in Beijing is low. The technological progress of the industry in Hebei is 1.1078, higher than the values of 1.0914 in Beijing and 1.0703 in Hebei, which is the primary reason why the TFP of this industry in Hebei Province is the highest among the three provinces. The detailed data of average Malmquist index in the production and supply of electric power and heat power in the Jing-Jin-Ji region, 2005–2015 are shown in Table 6.

In Beijing, in order to realize its overall planning, much of the industry's enterprise had to relocate. Since 2010, Beijing has shut down its original coal-fired thermal power plant represented by the four coal-fired cogeneration plants. Although the city has reduced its consumption of coal by 9.2 million tons, the scale efficiency of the industry in Beijing remains low. Hebei Province, in part, accepts the relocation of Beijing's enterprises from the city. The spillover effect from Beijing enterprises has led to significant technological change in industries in the Hebei Province. At the same time, the efficiency of scale change in the Hebei Province is 0.965, which is not optimal. If the scale benefits are increased and industrial structure changed, the overall technical efficiency of the province can be improved.

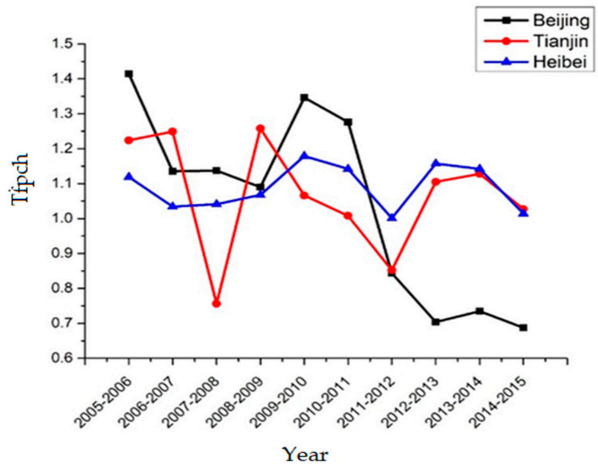

Figure 5. Dynamic change of TFP in the production and supply of electric power and heat power in the Jing-Jin-Ji region, 2005–2015.

Table 6. The average Malmquist index in the production and supply of electric power and heat power in the Jing-Jin-Ji region, 2005–2015.

	Beijing	Tianjin	Hebei
TFPCH	1.036696	1.0673	1.0897
SECH	0.83945	1.0052	0.9649
PECH	1.110767	1.0419	1.1458
TECHCH	1.0914	1.0703	1.1078
EFFCH	0.969428	1.0675	1.0767

5.2. Smelting and Processing of Ferrous Metals

From the overall integrated efficiency change, the average value of ferrous metal smelting and rolling processing industry in the Jing-Jin-Ji region is 1.103, showing progress with the average technical progress changes at 1.144, while the average comprehensive technical efficiency changes are at 0.993. Judging from its decomposition, the pure technical efficiency change index average value is 1.058, while the scale efficiency change index is 0.949. This shows that the Jing-Jin-Ji region has made remarkable progress in technological innovation. The reason for the low efficiency of integrated technology is the change in scale efficiency, indicating that the optimal industrial scale has not yet been reached. The change curves of TFP in the smelting and processing of ferrous metals in the Jing-Jin-Ji region are shown in Figure 6.

In terms of differences, Beijing's TFP presents a sharp decline, followed by a trend of ascending and descending since 2008. In Tianjin, the TFP of the industry shows an upward trend in 2008 or so, followed by a decline and then an increase. Meanwhile, Hebei Province has seen a sharp rise in the industry in 2008, since followed by a declining trend.

In Hebei Province, the average scale efficiency change is rather low at 0.848, compared with 1.054 in Beijing and 0.944 in Tianjin, leading to the conclusion that Hebei's TFP for the industry is low. The average pure technical efficiency change in Tianjin is 1.114, higher than the values of 0.983 in Beijing and 1.077 in Hebei. This is the primary reason why the TFP of the industry in Tianjin is the highest of the three regions. The detailed data of average Malmquist index in the smelting and processing of ferrous metals in the Jing-Jin-Ji region, 2005–2015 are shown in Table 7.

In Beijing, in order to realize its overall planning and undertake the Green Olympics, a number of large-scale enterprises headed by the Beijing ShouGang Group moved out of Beijing in 2008, causing the TFP of the industry in Beijing to plunge. At this time, the surrounding areas of Tianjin and Hebei accepted these enterprises, making the TFP of the surrounding areas rise. As a port city, Tianjin's economy is vulnerable to international trade. In 2011, the impact of the global financial crisis on Tianjin caused the industry to show a downward trend; however, it then rebounded rapidly. Beijing and Hebei provinces should actively study Tianjin's advanced management methods and technical experience in the industry.

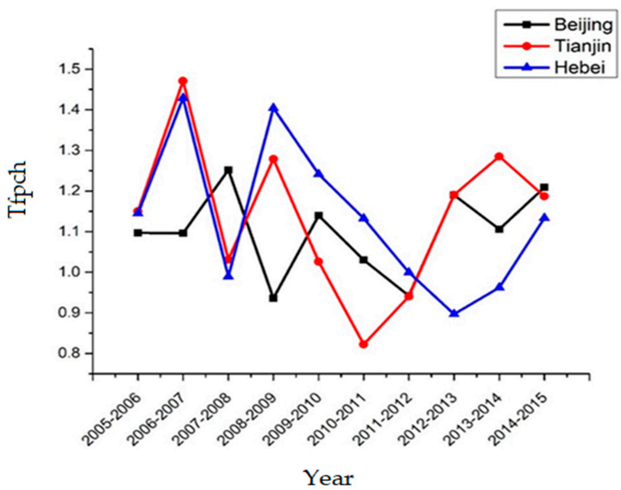

Figure 6. Dynamic change of total factor productivity (TFP) in the smelting and processing of ferrous metals in the Jing-Jin-Ji region, 2005–2015.

Table 7. The average Malmquist index in the smelting and processing of ferrous metals in the Jing-Jin-Ji region, 2005–2015.

	Beijing	Tianjin	Hebei
TFPCH	1.100	1.138	1.098
SECH	1.054	0.944	0.868
PECH	0.983	1.114	1.077
TECHCH	1.091	1.103	1.188
EFFCH	1.015	1.053	0.935

5.3. Manufacture of Raw Chemical Materials and Chemical Products

From the overall integrated efficiency change, the average value of raw chemical materials and chemical products manufactured in the Jing-Jin-Ji region is 1.096, of which the average technical progress changes are 1.062, while the average comprehensive technical efficiency changes are 1.048. Judging from its decomposition, the pure technical efficiency change index average value is 1.060, while the scale efficiency change index is 0.994. This shows that the Jing-Jin-Ji region has made notable achievements in technological innovation. The reason for the low efficiency of integrated technology is the change in scale efficiency, indicating that the optimal industrial scale has not yet been reached.

In terms of differences, the growth of Beijing's industry in 2005–2011 is relatively slow compared with that of Tianjin and Hebei. By 2010, the industry in Beijing dropped sharply, while the industry in Tianjin and Hebei increased during the same period. In Tianjin, in addition to the TFP being less than 1 from 2009–2011, significant progress has also been made in subsequent years. Since 2009, Hebei has shown significant and progressive changes. The change curves of TFP in the manufacturing of raw chemical materials and chemical products in the Jing-Jin-Ji region are shown in Figure 7.

The average TFP of Tianjin in this industry is 1.140, which is considerably higher than the values of 1.062 in Beijing and 1.085 in Hebei. The predominant reason for this is that the technical progress of Tianjin in this industry is 1.132, a figure that is significantly higher than the equivalent 1.023 in Beijing and 1.030 in Hebei. The detailed data of average Malmquist index in the manufacturing of raw chemical materials and chemical products in the Jing-Jin-Ji region, 2005–2015 are shown in Table 8.

In 2005, a fire broke out in Beijing Chemical Plant No. 2, causing an explosion. After the accident, the Beijing government decided to relocate all polluting enterprises, including chemical plants and coking plants, beyond the Fifth Ring Road, while Beijing Chemical Plant No. 2 immediately stopped production. Additionally, 22 enterprises in this industry relocated out of Beijing around 2010, causing the TFP of the industry to decline. At this time, Tianjin and Hebei's peripheral regions accepted these enterprises, resulting in an increase in the TFP in the surrounding areas. Tianjin, as a city with frequent international trade, was hit by the financial crisis in 2008, causing its growth to slow down.

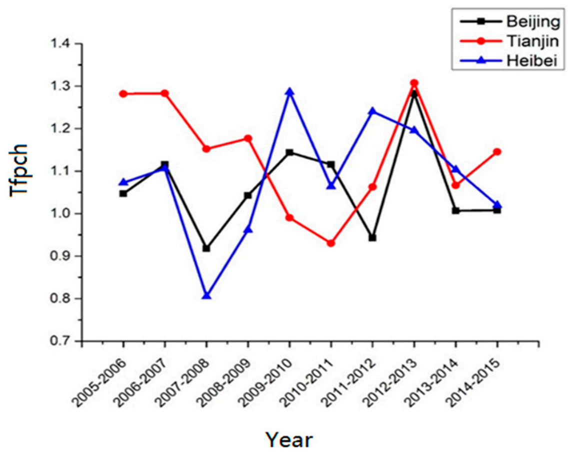

Figure 7. Dynamic change of TFP in the manufacturing of raw chemical materials and chemical products in the Jing-Jin-Ji region, 2005–2015.

Table 8. The average Malmquist index in the manufacturing of raw chemical materials and chemical products in the Jing-Jin-Ji region, 2005–2015.

	Beijing	**Tianjin**	**Hebei**
TFPCH	1.062	1.140	1.086
SECH	0.990	1.004	0.989
PECH	1.066	1.031	1.084
TECHCH	1.023	1.132	1.030
EFFCH	1.060	1.020	1.063

6. Conclusions

This paper first uses the DEA model to compare the average efficiency of the 27 industrial industries in Beijing, Tianjin, and Hebei from 2005 to 2015, and highlights three industries with considerable differences in their efficiency and energy consumption. Subsequently, we employ the Malmquist index analysis, which shows that the manufacturing of raw chemical materials and chemical products, the smelting and processing of ferrous metals, and the production and supply of electric power and heat power are rising steadily. However, the efficiency of technological changes in these three major industries is generally low, so the Jing-Jin-Ji region should improve its technological innovation and enhance its core competitiveness. At the same time, the scale efficiency is insufficient, which is reflected in the inefficiency of the allocation of resources. We should optimize the allocation of these resources in specific industries to improve the scale efficiency.

The average value of the overall efficiency change of the three key industries in Beijing, Tianjin, and Hebei is 1.09, which, on the whole, shows a progressive change. The primary reason for this is that the technical changes in the three industries are 1.10, and this is because the three industries themselves have considerable economic strength and a strong ability to import and develop technologies.

We also find that Beijing industries have a tendency to relocate towards the region's peripheries, especially to Hebei Province. By 2015, Beijing had transferred more than 80 industrial projects to Hebei, with a total investment exceeding 120 billion yuan RMB and generating a capacity of 250 billion yuan RMB. Beijing can make use of this opportunity to ease its non-capital function, adjust its economic structure and spatial structure, explore a model for optimizing the intensive development of a densely populated area, and promote harmonious regional development. Hebei Province can take advantage of this opportunity to accelerate the optimization and adjustment of its economic structure and industrial institutions by promoting the upgrade of industrial enterprises equipment and forming a large-scale industry, thereby enhancing industrial energy efficiency.

Thus far, Tianjin is the only free trade zone in the north and has the opportunity of building the "Belt and Road". Tianjin should focus on promoting the international nature of its industries and work to constantly improve its international competitiveness. At the same time, it must also make good use of the opportunity of building a "national advanced manufacturing research and development base" and strive to enhance research and development capability so as to create a well-structured and distinctive industrial system, improve industrial clusters, and build a gathering place with high-end industry, advanced technology, and innovation elements.

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