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*Original Research*

# Efficiency and Influencing Factors of Energy Conservation and Emission Reduction in High-Energy-Consuming Industries Driven by Technological Innovation

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## Abstract

High-energy-consuming industries (HECI) are the main sectors of energy consumption and carbon emissions. Technological innovation (TI) driving the energy conservation and emission reduction (ECER) of HECI is critical to achieving carbon neutrality. Using a system theory perspective, this study decomposed the system of ECER of HECI driven by TI into two stages, TI and ECER. Based on panel data of 30 provinces in China from 2015-2020, the network weighted stochastic block model (WSBM) and panel Tobit models were used to measure the efficiency of ECER of HECI driven by TI; the spatial and temporal differences and influencing factors were analyzed. The overall efficiency exhibited a V-shaped pattern of falling, then rising. From a regional perspective, the Northeast region shows a breakthrough growth from a low point to a high point. The East, Central and West regions show similar trends to the national overall, with the total efficiency of the East slightly higher than the West and a lower total efficiency in the Central region. In terms of two-stage efficiency, the efficiency of the ECER stage was higher than that of the TI stage. The rationalization level of industrial structure, green finance development level, and investment in education were the main forces enabling TI to drive the efficiency improvement of ECER in HECI.

**Keywords**: technological innovation, high-energy-consuming industries, energy conservation and emission reduction, network weighted stochastic block model, efficiency, influencing factor

## Introduction

In recent years, due to the intensification of the greenhouse effect, natural disasters have been occurring frequently around the world. To combat this, countries worldwide are exploring energy conservation and emission reduction (ECER) solutions in line with their own sustainable economic development [1]. The $CO_2$ emissions of China, a major carbon emitter, reached 18.18 billion tons in 2021, ranking first in the world [2]. Furthermore, China is also the major country leading global carbon emission reduction and plays a key role

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in global climate and environment governance [3]. China committed to the goal of reducing greenhouse gas emissions in "The Paris Agreement" and promised that its $CO_2$ emissions per unit of gross domestic product (GDP) would be reduced by 60-65% from 2005 levels by 2030, and the share of non-fossil energy would be increased to around 20% of total energy [4]. At the United Nations General Assembly in 2020, China announced that it would strive to achieve peak $CO_2$ emissions by 2030 and carbon neutrality by 2060, further enhancing China's determination to reduce emissions [5]. China's carbon neutrality commitment indicates that it will adopt stricter policies and measures to become more proactive in Global Climate Governance [6,7].

The industrial sector is the most significant contributor to China's GDP and the largest $CO_2$ producer. High-energy-consuming industry (HECI) is a typical representative of the industrial sector [8, 9] and is responsible for a high proportion of the carbon emissions of the whole industrial system [10]. In 2006, the European Commission defined HECI as industries with an energy consumption per unit output value higher than the average level of all corresponding industries in the same period. In "The National Economic and Social Development Statistics Report in 2010", China's National Bureau of Statistics defined six industries as HECI: manufacture of chemical raw materials and chemical products, non-metallic mineral products, ferrous metal smelting and rolling, non-ferrous metal smelting and rolling processing industry, petroleum processing coking and nuclear fuel processing industry, and electric power and heat production and supply [11]. In recent years, China's six HECI accounted for approximately 30% of the industrial output above the designated size. In contrast, energy consumption accounted for up to 75% of the industrial energy consumption above the designated size [12], and was accompanied by high carbon emissions, which requires high carbon emissions to produce unit value [13], which has seriously restricted energy conservation and emission reduction.

Due to its high energy consumption, high emission, and high pollution, HECI has concerned scholars. For the sake of rapid development, developing countries like China have invested heavily in HECI, which has led to sharp increases in carbon emissions [14]. Reduction of $CO_2$ emissions in developed countries, such as the United States and Australia, has been largely due to transformation from HECI to service and information intensive industries [15]. In Malaysia, the rubber production industry is a HECI, and many energy-saving strategies have been applied in this industry to achieve ECER targets [16]. Thailand proposed an ECER scheme to promote sustainable design of the construction industry and improve the distribution process, aiming at the power industry with high energy consumption [17]. Some researchers have shown that more than 90% of manufacturing industry's energy consumption in China and more than 50% of the $CO_2$ emissions generated by energy consumption come from HECI, and the $CO_2$ emissions of HECI are increasing at an annual rate of 7.8% [18]. Some studies discussed the characteristics of ECER in different sectors of HECI [19-21]. Among them, the energy consumption of the electricity and heat production industry was the highest, followed by those of the petrochemical and metal smelting industries [22].

China is currently experiencing rapid development of heavy industries as the primary characteristic of the late stage of industrialization and the industrial structure, which is dominated by heavy chemical industries with high consumption, low efficiency, and heavy pollution, cannot be changed in the short term [13]. Therefore, without changing the background of China's industrial development, a technological innovation (TI)-oriented approach should be explored to change the traditional high-carbon development model of HECI. Achieving low-carbon development model with low energy consumption, emissions, and pollution would be a significant breakthrough. Therefore, important theoretical and practical implications should follow from taking TI as the driving force for the ECER of HECI, examining the process effect of energy conservation and emission reduction of HECI under the guidance of TI, and promoting a better low-carbon transformation of the industry.

At the same time, due to the rapid development of China, there are regional imbalances in TI [23], which are bound to cause regional differences in the process of ECER in HECI. Scientifically measuring the efficiency of ECER in HECI driven by TI and exploring the spatial and temporal differentiation of efficiency between regions and the influencing factors is important and will help the country to enhance the understanding of the ECER level of HECI in different regions to make targeted strategic arrangements.

Since the innovation-driven development strategy was proposed, it has attracted the attention of scholars within and outside of China. Scholars generally believe that TI is the key to industrial green production [24] and low-carbon, green, and energy technology innovation can effectively reduce carbon emissions [25-28]. Most scholars focus on promoting ECER in the manufacturing industry. The key to carbon emission reduction in the manufacturing industry is the low-carbon development of HECI. Cheng et al. showed that from the perspective of sustainable development, HECIs need to transform their development mode through the improvement of TI capacity [29]. Cao et al. systematically compared the effects of ECER among six industries with high energy consumption and predicted that the use of standard oil could be reduced at least 1.231 million tons by 2025 under the application of ECER technology [30]. Yuan & Zhao proposed the technology coefficient elasticity to determine the transactions between economic sectors that have an impact on carbon emission reduction in HECI and the results showed that TI effectively promoted ECER in HECI [31]. Using the method of system dynamics, Hu & Zhang explained that the improvement of the level of technology is the fundamental guarantee for low-carbon transformation of HECI [32]. Li et al. further proposed that capacity and technological progress were two important driving factors for ECER in the iron and steel industry [33].

At present, frontier analysis method occupies the mainstream among methods of efficiency evaluation [34]. Frontier analysis is divided into stochastic frontier analysis (SFA) and data envelope analysis (DEA) [35]. The former ensures the accuracy of estimation by using an econometric method to measure efficiency. It has strict restrictions on the choice of functions, and the disadvantage that the output is single indicator [36, 37]. Stochastic frontier analysis has been widely used in hospitals and the catering and cultural industries, as well as others [38, 39]. Data envelope analysis is a deterministic method of estimating efficiency based on linear programming [40]. It is not limited by choice of functions and can avoid the influence of subjective setting of the production function. Thus, it is suitable for complex systems with multiple inputs and outputs, which has advantages in dealing with efficiency measures of multiple outputs [41]. The network WSBM model is a data envelope analysis method that considers the weight of slack variables, which makes the efficiency value measurement more accurate. Few scholars have used the network WSBM model to empirically analyze the efficiency of ECER in HECI driven by TI and even fewer scholars divided the system of ECER in HECI driven by TI into two stages to solve the intermediate input problem.

Therefore, in this study, we divided the complex system of ECER in HECI driven by TI into two stages: TI and ECER, based on innovation theory and system dynamics. We built a concept model and index system of ECER in HECI driven by TI. Next, we established a two-stage efficiency network WSBM model considering the relaxation variable weight, effectively solving the problem of intermediate input. Finally, we measured the efficiency and space-time differences of ECER in HECI driven by TI between regions in the 30 provinces and explored the influencing factors. The outcomes are intended to strengthen the innovation-driven development strategies of all regions, implement the concept of green and low-carbon development, and play a leading role of ECER in HECI driven by TI.

## Materials and Methods

### Conceptual Model

Innovation promoting ECER is a complex dynamic system [42]. From the initial input of innovation elements to the final realization of ECER, the industry needs to go through a series of stages. The input of innovation elements is the basis of the whole system. After development and research, TI results are formed and the application of the innovation results to the process of industry production and creation is the key to ECER in the industry. However, the output of innovation results is not enough to drive the transformation of real productivity of HECI. Therefore, in addition to the output of the first stage serving as the input of the second stage, this output should also be combined with other production factors, namely, the intermediate input links [43], to transform and apply the innovation results, form new products and new technologies, and finally achieve the goal of ECER. According to this dynamic process, the complex system of TI driving ECER in HECI is composed of two stages (Fig. 1), i.e., (1) A TI subsystem, consisting of innovation element input, development and research, and innovation achievement output; (2) An ECER subsystem, consisting of innovation achievement output (as the input of ECER subsystem), intermediate input, transformation and application, and final output. The TI subsystem provides a power guarantee for the ECER subsystem and, in turn, the high benefits brought by the ECER of the industry provide material support for the

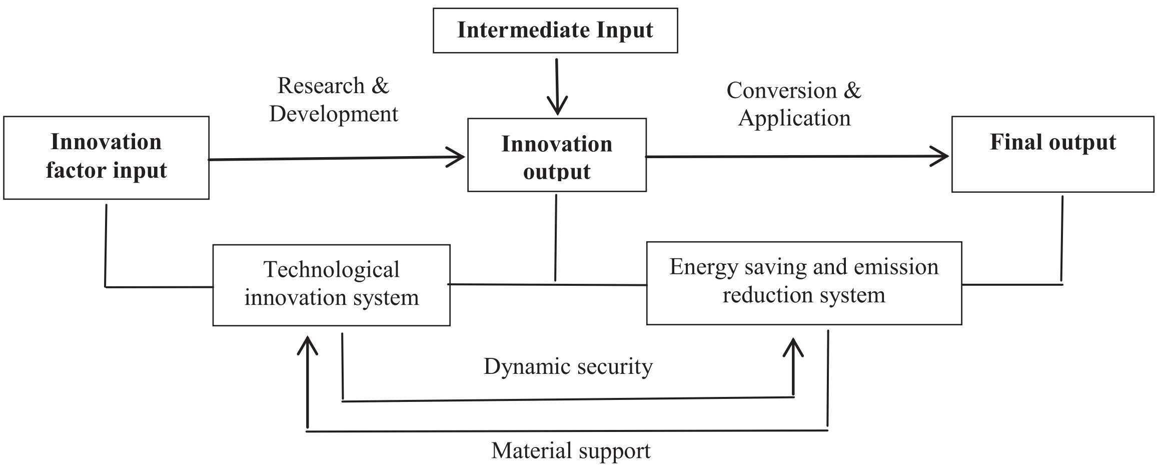


Fig. 1. Conceptual model of ECER in the HECI driven by TI.

TI subsystem. The two systems are closely related and together constitute a complete system.

## Index Construction

Combined with the research of most scholars, the input in TI constructed indicators from three aspects: human, material, and financial resources. Considering the characteristics of high emissions and high pollution in HECI, this study added important green indicators. The full-time equivalent of research and development (R&D) personnel was taken as the human element [44], the proportion of new fixed assets in technical services and the scientific research industry as the material element, and the internal expenditure of R&D funds as the financial element [45, 46]. The innovation output of the first stage adopted three outcome indicators: the number of scientific and technological papers, indicating the status of regional scientific research activities; number of green invention patents granted, indicating the active state of low-carbon TI; and technology market turnover, indicating the transfer, diffusion, and application of TI achievements.

The input index of the second stage added the level of green financial support and technology service on the basis of the innovation achievement output in the first stage [47]. Specifically, green financial support was measured using the interest expenditure of HECI as a percentage of total industrial interest expenditure; the technology services were measured by the number of science and technology business incubators.

The key to the efficient evaluation of ECER of HECI driven by TI lies in the measurement of ECER of the industry. Currently, several studies have interpreted ECER and proposed some ECER evaluation indicators. Qu & Liu considered more per capita carbon emissions and the urban green rate when evaluating urban ECER [48]. Ye et al. assessed the development of a regional low-carbon circular economy in Sichuan Province, China, and the selection of indicators included three aspects: Development of the economy, progress of society, and energy consumption [49]. Liang et al. proposed the construction of ECER indicators for the logistics industry considering environmental variables, density of logistics, level of urbanization, and logistics specialization level [50]. Wang et al. constructed comprehensive indicators for the green development of the coal industry from three aspects: Energy consumption, environment, and resource utilization [51]. Dong et al. chose industrial added value as the expected output and $CO_2$ emissions as the non-desired output to construct indicators for green development in the industrial sector [52].

To summarize, the academic community has carried out ECER evaluations of different research objects. However, the selection of specific indicators has been diverse. In this study, considering existing literature and the applicability of ECER indicators of various HECI, we added industrial value generated per unit of carbon emissions, ratio of carbon emission intensity between industry and country [53], and ratio of industrial output to energy consumption as the three indicators for the final output of industrial ECER of the second stage. The industrial added value generated per unit of carbon generation reflects the industrial production capacity. The ratio of the industrial carbon emission intensity to the national carbon emission intensity demonstrates the competitiveness of the low carbon development of the industry. The energy efficiency of an enterprise is reflected by the ratio of industrial output to energy consumption. The specific efficiency evaluation indicators used in this study are shown in Table 1.

## Entropy Value Method

Utilizing the DEA efficiency evaluation method, the weight of the index is as objective as possible. The entropy value method is a weighting method that only depends on the discreteness of data itself to determine the index weight objectively [54]. It was first introduced into information theory by the American mathematician C.E. Hannon [55] and has been widely used. Therefore, this study adopted the entropy value method to assign objective weights to each index. The procedures of the entropy method are as follows:

(1) Normalize the data. To solve the problem of different measurement units of each index, it is necessary to normalize them.

For positive indicators:

$$x_{ij} = 0.998 \frac{x_{ij} - \min\left\{x_{1j}, \cdots x_{nj}\right\}}{\max\left\{x_{1j}, \cdots x_{nj}\right\} - \min\left\{x_{1j}, \cdots x_{nj}\right\}} + 0.002 \tag{1}$$

For negative indicators:

$$x_{ij} = 0.998 \frac{\max\left\{x_{1j}, \cdots x_{nj}\right\} - x_{ij}}{\max\left\{x_{1j}, \cdots x_{nj}\right\} - \min\left\{x_{1j}, \cdots x_{nj}\right\}} + 0.002 \tag{2}$$

(2) The proportion $P_{ij}$ of the index value of the scheme $i$ under the item $j$ is calculated as follows:

$$\mathbf{P}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}} (j = 1, 2, \cdots, m) \tag{3}$$

(3) The information entropy value $e_j$ of the $j$-item is calculated as follows:

$$\mathrm{e}_j = -k \sum_{i=1}^{n} p_{ij} \ln p_{ij} \tag{4}$$

Among them, $k = 1/\ln(n)$, meet $e>0$.

(4) The information entropy redundancy is calculated as follows:

Table 1. Efficiency evaluation index system of ECER of HECI driven by TI.

| Stage | First-level indicator | | Secondary indicators | Indicator direction |
|---|---|---|---|---|
| Technological Innovation | Innovation input | | Full-time equivalent of R&D personnel | + |
| | | | Internal expenditure of R&D funds | + |
| | | | Proportion of new fixed assets in the technical services and scientific research industry | + |
| | Innovation output | | No. of scientific papers among 10,000 people | + |
| | | | No. of green invention patents among 10,000 people | + |
| | | | Technology market turnover among 10,000 people | + |
| Energy conservation and emission reduction | Second input | Innovation output | No. of scientific papers among 10,000 people | + |
| | | | No. of green invention patents among 10,000 people | + |
| | | Intermediate input | Technology market turnover among 10,000 people | + |
| | | | Green finance support | + |
| | | | Science and technology service | + |
| | Final output | | Industrial added value per unit of carbon emissions | + |
| | | | Ratio of industry carbon emission intensity to national carbon emission intensity | – |
| | | | Ratio of industrial output to energy consumption | + |

$$g_j = 1 - e_j \tag{5}$$

(5) The weight of each index is calculated as follows:

$$W_j = \frac{g_j}{\sum_{j=1}^{m} g} \tag{6}$$

## Network WSBM

Data envelope analysis is a mathematical method used to evaluate the relative effectiveness of decision-making units (DMU) based on input and output [56]. The traditional DEA model regards each DMU as a camera obscura without considering its internal structure [57]. It cannot view the relaxation of input and output, which measures the efficiency value inaccurate. The network DEA model disintegrates the black box, divides the DMU into a sub-decision-making unit (sub-DMU) according to the actual production process, and calculates both its DMU and its sub-DMU efficiency value. To measure the efficiency value more accurately, Tone constructed the SBM model, which is a DEA analysis method that considers relaxation variables and measures them in a non-radial and non-angular manner [58]. The advantage of this method is the efficiency value decreases strictly monotonically with the alternation of input and output slack degree. The SBM model has more substantial resolving power than the traditional DEA model. To reflect the importance of slack variables, we should consider giving them different weights, i.e., as in the WSBM. The extended two-stage network DEA model has since been presented [59]. That is, all the output of the first stage is used as the input of the second stage, and there can be other additional inputs. This study also divided the ECER of HECI driven by TI into two sets. It built a network WSBM to measure the two stages and the overall efficiency of ECER of HECI driven by TI. The model settings are as follows:

It is assumed that $DMU_k(k = 1, ..., n)$ consists of two stages: $x_{ik}(i = 1, 2, ..., m)$ is the $i$th input of the $k$th DMU in the first stage and $z_{gk}$(g = 1, 2, ..., $G$) is the $g$th production of the $k$th DMU in the first stage and an input factor in the second stage. $y_{rk}$(r = 1, 2, ..., $s_1$) is the $r$th expected output of the $k$th DMU in the second stage and $u_{bk}(b = 1, 2, ..., s_2)$ is the $b$th unexpected output of the $k$th DMU in the second stage. The specific expression formula of the two-stage input-output is as follows:

First stage:

$$\min \rho_1^* = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} w_{io} s_i^- / x_{io}}{1 + \frac{1}{g}\sum_{g=1}^{G} w_{go} s_g^+ / z_{go}},$$
$$s.t.\quad x_{io} = \sum_{j=1}^{n} \lambda_j x_{ik} + s_i^-,$$
$$z_{go} = \sum_{j=1}^{n} \lambda_j z_{gk} - s_g^+,$$
$$\sum_{i}^{m} w_{io} = 1; \sum_{g}^{G} w_{go} = 1,$$
$$\lambda_j \geq 0, s_i^- \geq 0, s_g^+ \geq 0, x_{ik} \in R^{m\times n}, z_{gk} \in R^{G\times n} \tag{7}$$

In the above formula (8), $s_i^-$ and $s_g^+$ represent relaxation variables of input and output of the model, respectively, and $w_{io}$, $w_{go}$ are weights of input and output of the first stage, respectively.

Second stage:

$$\min \rho_2^* = \frac{1-\frac{1}{g}\sum_{i=1}^{m} w_{go}s_i^- / z_{go}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} w_{ro}s_r^+ / y_{ro} + \sum_{b=1}^{s_2} w_{bo}s_b^+ / u_{bo}\right)},$$

$$s.t.\ z_{go} = \sum_{j=1}^{n} \lambda_j x_{gj} + s_g^-,$$

$$y_{ro} = \sum_{j=1}^{n} \lambda_j y_{rk} - s_r^+,$$

$$u_{bo} = \sum_{j=1}^{n} \lambda_j u_{bk} + s_b^k,$$

$$\sum_{r}^{s_1} w_{ro} + \sum_{b}^{s_2} w_{bo} = 1, \sum_{g}^{G} w_{go} = 1,$$

$$\lambda_j \geq 0, s_g^- \geq 0, s_r^+ \geq 0, s_b^k \geq 0, z_{gk} \in R^{G\times n}, y_{rk} \in R^{s_1\times n}, u_{bk} \in R^{s_2\times n}. \tag{8}$$

Since Equations (8) do not distinguish the relative importance between desired and undesired outputs, $\sum_{r}^{s_1} W_{ro} + \sum_{b}^{s_2} W_{bo} = 1$ is set. $\rho_1^*$ and $\rho_2^*$ represent the efficiency of the region's TI and ECER $k(k = 1, 2, ..., n)$, respectively. For the measurement of the final efficiency of the two-stage approach, the efficiency $\rho^*$ of the whole system is represented by the geometric mean of two stages. When $\rho^* = 1$, it suggests that the evaluation unit is effective as a whole, and when $\rho^*<1$, it indicates that the evaluation unit is invalid.

## Data Sources

Consider the science and availability of the data, this study took HECI (including data on six high-energy-consuming industries) in 30 provinces (including autonomous regions and municipalities directly under the Central Government) in China from 2015 to 2020 as the research subjects. The HECI are subject to the six major energy-intensive industries proposed by the National Bureau of Statistics. The data were obtained from the 2013-2020 "China Venture Capital Development Report", "China Science and Technology Statistical Yearbook", "China Energy Statistical Yearbook", and the "Statistical Yearbook" of 30 provinces. The ECER of HECI driven by TI is a phased value transformation process and there is a specific time lag between factor input and output. Therefore, it was assumed that the time interval between factor input and output at each stage was 1 year. The descriptive statistical analysis of the specific index data is shown in Table 2.

## Results

Based on the network WSBM in this paper, with variable returns to scale and unexpected outputs, MaxDEA software was used to measure the performance of ECER in HECI driven by TI. The 30 provinces were grouped into four regions: East, Central, Northeast, and West (see reference [60] for classification criteria). The empirical results of total efficiency and two-stage efficiency in each province are shown in Table 3. The spatial and temporal differentiation characteristics of total efficiency, two-stage efficiency evolution characteristics, and two-stage efficiency matrix were analyzed. The efficiency level of ECER

Table 2. Descriptive statistical analyses.

| Variable | Maximum | Minimum | Mean | Standard deviation |
|---|---|---|---|---|
| Full-time equivalent of R&D personnel | 872238 | 4007.7 | 144882.4 | 165715.9 |
| Internal expenditure of R&D funds | 34798833 | 115842.7 | 6313709.1 | 7048915.3 |
| The proportion of new fixed assets in the technical services and scientific research industry | 0.256 | 0.111 | 0.181 | 0.03 |
| Number of scientific papers per 10,000 people | 59.87 | 3.92 | 11.27 | 10.78 |
| Number of green invention patents per 10,000 people | 10.18 | 0.19 | 1.39 | 1.61 |
| Technology market turnover per 10,000 people | 4.31 | 0.01 | 0.29 | 0.59 |
| Green finance support | 0.91 | 0.001 | 0.51 | 0.16 |
| Science and technology service | 1079 | 4 | 142.73 | 186.07 |
| Industrial added value per unit of carbon emissions | 1524516 | 2684.48 | 198578 | 261897.6 |
| Ratio of industry carbon emission intensity to national carbon emission intensity | 11.64 | 0.02 | 1.40 | 1.84 |
| Ratio of industrial output to energy consumption | 22886518 | 295445 | 3286251 | 3462799 |

driven by TI was not balanced in the 30 provinces studied and the gap was large. This is consistent with the conclusion on energy efficiency in China from the research by Zhu et al. [61].

## Space-Time Evolution Features of Total Efficiency

### *Time Series Analysis*

The characteristics of evolution of regional total efficiency from 2015 to 2020 are shown in Fig. 2. The efficiency of ECER in HECI driven by TI fluctuated little across the 30 provinces; however, there was a brief low point in 2018. This result corroborates the fact that global carbon emissions increased significantly in 2018 as published in the 2019 BP World Energy Statistics Yearbook. In terms of regions, the East, Central, and West show a similar trend to the national overall, with the total efficiency of the East slightly higher than that of the West, while the total efficiency of the Central region is lower. The northeast region showed a breakthrough growth trend from low to high.

This observed efficiency pattern has both historical causes and practical effects. As an old industrial base of China, Northeast China is rich in energy resources and has a wide distribution of HECI. However, HECI in Northeast China still use production equipment from the past and the energy consumption is dominated by coal, which leads to high carbon emissions in the early years. In addition, the regional economy is not developed, resulting in brain drain. As a result, the efficiency of ECER in Northeast China was low in the early years. However, with the promotion of initiatives to revitalize the old industrial bases in Northeast China, the HECI in the three Northeastern provinces have gradually improved their efficiency

Table 3. The efficiency of ECER of HECI driven by TI.

| Area | Province | 2015 | | | 2016 | | | 2017 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Subphase | | TE | Subphase | | TE | Subphase | | TE |
| | | TI | ECER | | TI | ECER | | TI | ECER | |
| East | Beijing | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Tianjin | 0.140 | 0.275 | 0.311 | 0.155 | 0.342 | 0.378 | 0.287 | 0.576 | 0.644 |
| | Hebei | 0.148 | 1 | 0.344 | 0.118 | 1 | 0.295 | 0.146 | 1 | 0.298 |
| | Shanghai | 1 | 1 | 1 | 0.275 | 0.537 | 0.503 | 0.189 | 0.354 | 0.390 |
| | Jiangsu | 0.236 | 0.963 | 0.402 | 0.149 | 0.821 | 0.361 | 0.104 | 0.555 | 0.326 |
| | Zhejiang | 0.636 | 1 | 0.812 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Fujian | 0.132 | 0.682 | 0.337 | 0.112 | 0.798 | 0.326 | 0.139 | 1 | 0.350 |
| | Shandong | 0.157 | 1 | 0.367 | 0.132 | 1 | 0.378 | 0.124 | 1 | 0.374 |
| | Guangdong | 0.221 | 1 | 0.392 | 0.163 | 1 | 0.373 | 0.130 | 0.926 | 0.350 |
| | Hainan | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Central | Shanxi | 1 | 1 | 1 | 0.371 | 1 | 0.685 | 0.378 | 1 | 0.689 |
| | Anhui | 0.585 | 1 | 0.757 | 0.585 | 1 | 0.792 | 0.614 | 1 | 0.807 |
| | Jiangxi | 0.185 | 1 | 0.411 | 0.151 | 1 | 0.453 | 0.166 | 1 | 0.476 |
| | Henan | 0.130 | 1 | 0.339 | 0.118 | 1 | 0.332 | 0.138 | 1 | 0.350 |
| | Hubei | 0.166 | 0.464 | 0.363 | 0.117 | 0.542 | 0.360 | 0.142 | 0.530 | 0.323 |
| | Hunan | 0.174 | 0.904 | 0.432 | 0.148 | 1 | 0.425 | 0.179 | 1 | 0.432 |
| Northeast | Liaoning | 0.251 | 0.513 | 0.374 | 0.213 | 0.620 | 0.369 | 0.314 | 0.705 | 0.458 |
| | Jilin | 0.261 | 0.975 | 0.453 | 0.264 | 0.854 | 0.408 | 0.355 | 0.783 | 0.469 |
| | Heilongjiang | 0.309 | 0.652 | 0.431 | 0.295 | 0.737 | 0.399 | 0.642 | 0.746 | 0.567 |
| West | Chongqing | 0.263 | 0.616 | 0.466 | 0.205 | 0.567 | 0.448 | 0.252 | 0.943 | 0.546 |
| | Sichuan | 0.158 | 0.649 | 0.324 | 0.143 | 0.757 | 0.302 | 0.187 | 0.810 | 0.313 |
| | Guizhou | 0.287 | 1 | 0.403 | 0.249 | 1 | 0.420 | 0.300 | 1 | 0.465 |
| | Yunnan | 0.124 | 1 | 0.393 | 0.131 | 1 | 0.394 | 0.233 | 1 | 0.405 |
| | Shaanxi | 0.158 | 0.449 | 0.390 | 0.129 | 0.478 | 0.348 | 0.166 | 0.512 | 0.358 |
| | Gansu | 0.131 | 0.821 | 0.351 | 0.252 | 0.839 | 0.342 | 0.325 | 0.981 | 0.401 |
| | Qinghai | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Inner Mongolia | 0.286 | 0.932 | 0.447 | 0.369 | 1 | 0.488 | 0.669 | 1 | 0.681 |
| | Guangxi | 0.210 | 1 | 0.373 | 0.188 | 1 | 0.414 | 0.224 | 1 | 0.412 |
| | Ningxia | 0.693 | 0.977 | 0.733 | 0.661 | 0.999 | 0.719 | 0.661 | 0.876 | 0.735 |
| | Xinjiang | 0.356 | 0.888 | 0.540 | 0.315 | 1 | 0.524 | 0.522 | 1 | 0.592 |
| All | Mean | 0.380 | 0.859 | 0.531 | 0.334 | 0.862 | 0.508 | 0.386 | 0.877 | 0.540 |

Table 3. Continued.

| Area | Province | 2018 | | | 2019 | | | 2020 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Subphase | | TE | Subphase | | TE | Subphase | | TE |
| | | TI | ECER | | TI | ECER | | TI | ECER | |
| East | Beijing | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Tianjin | 0.199 | 0.313 | 0.345 | 0.169 | 0.405 | 0.473 | 0.153 | 0.405 | 0.466 |
| | Hebei | 0.184 | 1 | 0.167 | 0.118 | 1 | 0.302 | 0.139 | 1 | 0.312 |
| | Shanghai | 0.182 | 0.183 | 0.213 | 0.609 | 0.892 | 0.648 | 0.599 | 0.894 | 0.678 |
| | Jiangsu | 0.084 | 0.248 | 0.122 | 0.132 | 0.761 | 0.382 | 0.168 | 0.761 | 0.400 |
| | Zhejiang | 0.093 | 0.417 | 0.208 | 0.344 | 1 | 0.582 | 0.507 | 1 | 0.574 |
| | Fujian | 0.134 | 0.830 | 0.214 | 0.090 | 0.771 | 0.384 | 0.103 | 0.786 | 0.392 |
| | Shandong | 0.100 | 0.495 | 0.131 | 0.068 | 0.612 | 0.277 | 0.080 | 0.614 | 0.283 |
| | Guangdong | 0.070 | 0.351 | 0.123 | 0.105 | 0.968 | 0.351 | 0.153 | 1 | 0.359 |
| | Hainan | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Central | Shanxi | 0.364 | 1 | 0.682 | 0.438 | 1 | 0.719 | 0.411 | 1 | 0.705 |
| | Anhui | 0.138 | 0.841 | 0.207 | 0.145 | 1 | 0.457 | 0.242 | 1 | 0.471 |
| | Jiangxi | 0.208 | 0.850 | 0.392 | 0.158 | 1 | 0.576 | 0.661 | 1 | 0.830 |
| | Henan | 0.148 | 1 | 0.184 | 0.096 | 1 | 0.346 | 0.115 | 1 | 0.355 |
| | Hubei | 0.160 | 0.394 | 0.186 | 0.118 | 0.556 | 0.381 | 0.134 | 0.518 | 0.389 |
| | Hunan | 0.180 | 1 | 0.302 | 0.117 | 0.859 | 0.453 | 0.148 | 0.875 | 0.471 |
| Northeast | Liaoning | 0.360 | 0.536 | 0.403 | 0.297 | 0.618 | 0.463 | 0.317 | 0.617 | 0.474 |
| | Jilin | 0.515 | 0.559 | 0.399 | 0.363 | 0.681 | 0.577 | 0.371 | 0.680 | 0.581 |
| | Heilongjiang | 0.874 | 0.588 | 0.593 | 1 | 1 | 1 | 1 | 1 | 1 |
| West | Chongqing | 0.239 | 0.595 | 0.365 | 0.158 | 0.876 | 0.504 | 0.184 | 0.899 | 0.517 |
| | Sichuan | 0.200 | 0.465 | 0.213 | 0.125 | 0.621 | 0.335 | 0.157 | 0.621 | 0.351 |
| | Guizhou | 0.273 | 0.925 | 0.379 | 0.241 | 1 | 0.400 | 0.231 | 1 | 0.397 |
| | Yunnan | 0.287 | 0.810 | 0.358 | 0.226 | 1 | 0.368 | 0.207 | 1 | 0.360 |
| | Shaanxi | 0.195 | 0.455 | 0.331 | 0.132 | 0.471 | 0.376 | 0.149 | 0.471 | 0.385 |
| | Gansu | 0.458 | 0.560 | 0.419 | 0.347 | 0.828 | 0.414 | 0.363 | 0.828 | 0.423 |
| | Qinghai | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | Inner Mongolia | 1 | 0.807 | 0.759 | 0.501 | 1 | 0.597 | 1 | 0.862 | 0.828 |
| | Guangxi | 0.337 | 1 | 0.339 | 0.222 | 1 | 0.403 | 0.226 | 1 | 0.406 |
| | Ningxia | 0.625 | 0.702 | 0.696 | 0.512 | 0.981 | 0.713 | 0.518 | 0.991 | 0.717 |
| | Xinjiang | 0.525 | 1 | 0.528 | 0.421 | 1 | 0.565 | 0.355 | 1 | 0.534 |
| All | Mean | 0.371 | 0.698 | 0.409 | 0.342 | 0.863 | 0.536 | 0.390 | 0.861 | 0.555 |

Note: "ECER" stands for energy saving and emission reduction; "TI" stands for technological innovation; "TE" stands for total efficiency.

in ECER driven by TI. Compared with Northeast China, the development and construction of HECI in the Eastern and Central regions started later, so the production and manufacturing level was relatively high. Driven by TI, the ECER effect of these industries was relatively good. Although the economy of the Western region is relatively undeveloped, the TI level of HECI in the region is still at the forefront of the country because of the national support for construction and preferential talent attraction policies provided by the regional government. Therefore, the ECER efficiency of HECI driven by TI in the Western region can reach the national average.

*Spatial Evolution Analysis*

To further analyze the spatial differences of total efficiency, 2015, 2017 and 2020 were selected as representatives and ArcGIS was used to analyze the spatial evolution of total efficiency in 30 provinces (Fig. 3). The average value of the annual total efficiency was taken as the node value. According to the node value, the provinces were divided into three states: high effectiveness (red area), moderate effectiveness (blue area), and low effectiveness (yellow area). In 2015, five of the 30 provinces (Beijing, Shanxi, Qinghai, Shanghai, and Hainan) were highly effective, and four provinces were moderately effective (Anhui, Zhejiang, Ningxia, and Xinjiang). The remaining 21 provinces fell in the low effectiveness state. The levels differ substantially and there is a large gap in the efficiency values of ECER in HECI driven by TI among regions, showing an obvious spatial pattern. Since 2016, because of the introduction of several national opinions on the comprehensive revitalization of the old industrial bases in Northeast China, the total efficiency of the Northeast

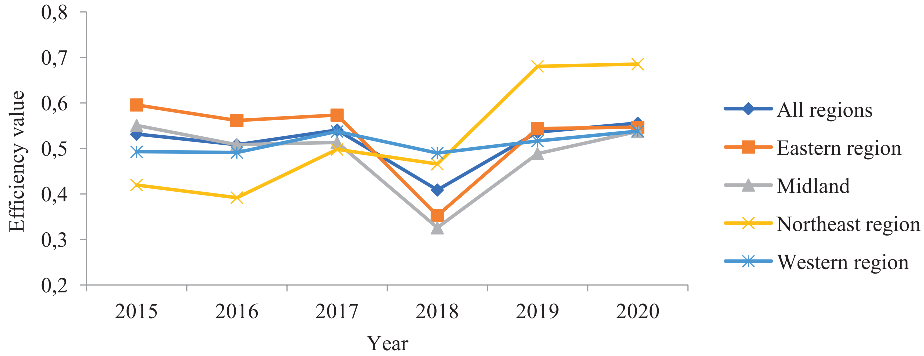


Fig. 2. Regional total efficiency evolution characteristics (2015-2020).

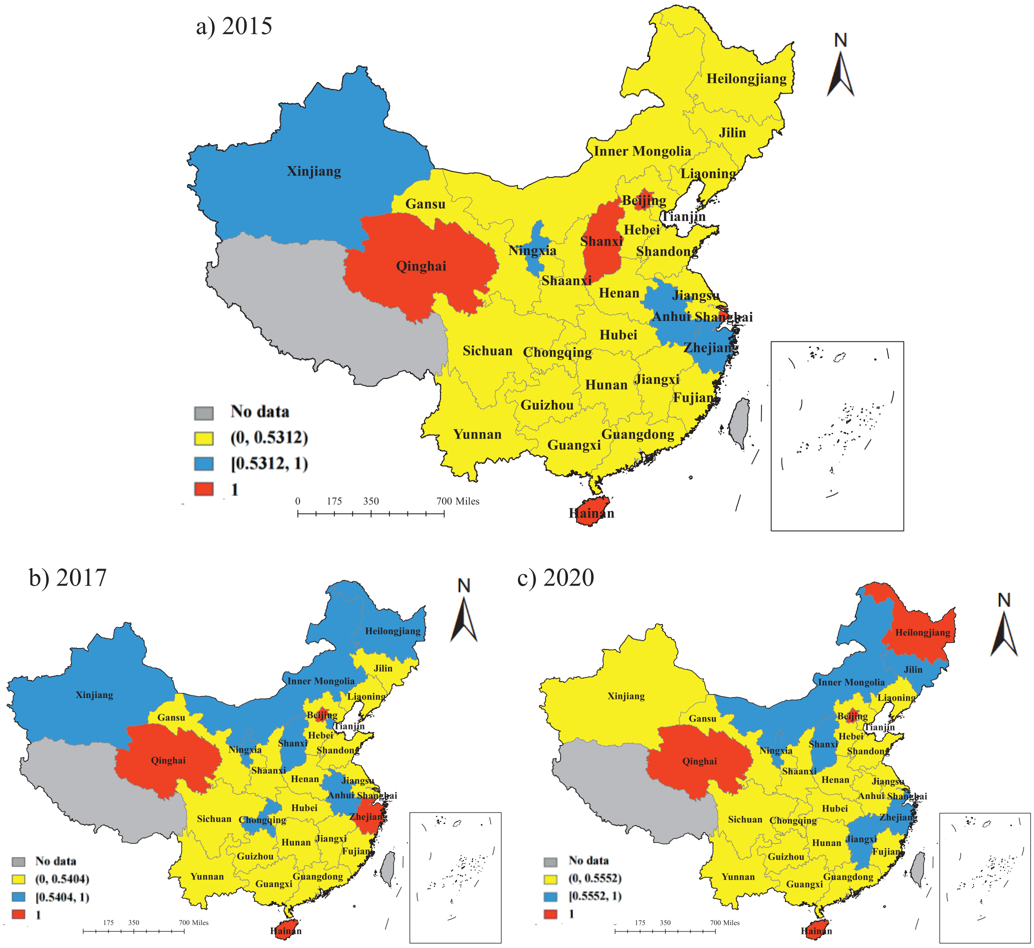


Fig. 3. Spatial evolution characteristics of total efficiency in 30 provinces.

region has changed significantly. The total efficiency of all three northeastern provinces was in the low effective state in 2015, and in 2017, Heilongjiang and Jilin crossed to a moderate effective state. Heilongjiang is even in 2020 to reach the effective frontier surface, its ECER of HECI driven by TI jumped to the forefront of the country, the growth momentum is remarkable. In this research area, the total efficiency values of Beijing, Qinghai and Hainan were always in the effective frontier state. Benefiting from its advantages as a capital city, Beijing has high-quality educational resources, rich TI resources, and gradual relocation of HECI. The remaining HECI is bound to be a model of ECER development. Qinghai and Hainan are geographically remote, have a good ecological foundation, are not dense in HECI, and their TI can be quickly popularized. In the eastern region, the provinces located in the Yangtze River Delta region show a state of agglomeration leadership, but the Jiangsu province has always been in a low degree of effective state, and the future of HECI to save energy and reduce emissions is still a serious problem in this area. Influenced by the

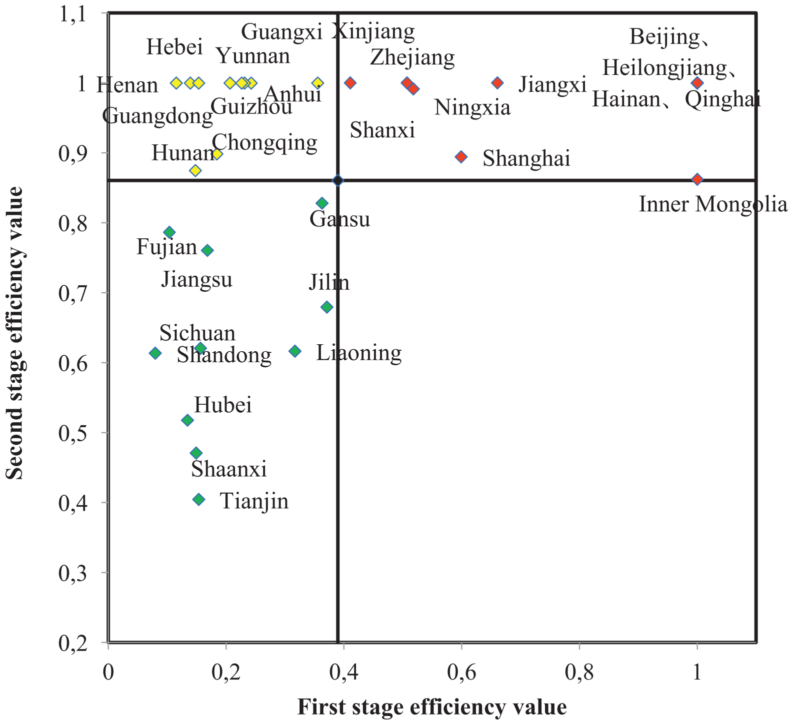


Fig. 4. Two-phase efficiency matrix plot in Fig in 2020.

technology spillover effect of the Yangtze River Delta region, the neighboring provinces of Anhui and Jiangxi have seen varying degrees of improvement in efficiency. Compared to the western region, the central region has a concentrated population, a secondary industry representing an important pillar of local economic development, a dense HECI, high environmental costs, and poor TI to drive the efficiency of ECER in HECI. It will take more time for TI to drive the ECER of HECI in these regions.

## Two-Stage Efficiency Evolution Characteristics

### *Technology Innovation Stage*

The average value of the 30 provinces in 2015-2020 shows a shallow "W" shape with no significant fluctuations. The six-years average is 0.36703, which is similar to the results measured by Qiao & Wang using the three-stage DEA [62], indicating that the efficiency of the TI stage was not high. Efficiencies in 11 provinces were above the average, accounting for 36.7%. Only Beijing, Hainan, and Qinghai reached the effective frontier, and their efficiency of technological innovation is in the first echelon of the country. There are 10 provinces with TI efficiency higher than the national average for the year 2020, which is two additional provinces compared to 2015. The efficiency of technological innovation in Jiangxi Province has increased significantly, from 0.1851 in 2015 to 0.6606 in 2020. While Shanxi Province's TI efficiency remained 1 in 2015, at the effective frontier, it has dropped to 0.4105 by 2020. This may be because the more efficient Beijing, Hainan, and Qinghai, among other places, have increased their innovation input and output over the years, while Shanxi Province maintained the status quo, failing to keep the pace, and was therefore left behind. By region, the efficiency of TI in the eastern, central, northeastern, and western regions in 2020 is higher than the national average by 40%, 33.3%, 33.3%, and 36.4% respectively, demonstrating that the eastern and western regions are better than the central and northeastern regions. Future efforts to narrow the differences in local TI levels and enhance the flow of innovation factors between regions are crucial.

### *Energy Conservation and Emission Reduction Stage*

Over the past six years, the average efficiency of the 30 provinces has been high with a six-year average of 0.8607, indicating that the efficiency of ECER in HECI is generally high. Twenty of the 30 provinces have higher-than-average efficiency for ECER in HECI, accounting for 66.7%. Table 3 shows that provinces below the national average are less effective in driving TI. Thus, more innovation support is needed in the future, and the main task should be to strengthen the transformation of innovation results in the ECER of HECI.

### *Two-Stage Efficiency Matrix Analysis*

The average efficiency of the two stages in 30 provinces (according to the results for 2020 shown in Table 3) was taken as the dividing line to make a scatter plot (Fig. 4). The 30 provinces were distributed in the first, second, and third quadrants. The first quadrant includes 10 provinces: Beijing, Heilongjiang, Hainan, Qinghai, Inner Mongolia, Zhejiang, Ningxia, Jiangxi, Shanxi, and Shanghai. The two-stage efficiency values of these 10 provinces are higher than the national average, and the efficiency of ECER in HECI driven by TI is at the forefront of the country. Among them, Beijing, Heilongjiang, Hainan, and Qinghai all reached the two-stage DEA validity. Their technology innovation resource allocation mechanism and innovation driving mechanism perform well and TI drives the ECER of the HECI intensively and effectively.

The 10 provinces located in the second quadrant are Henan, Hebei, Guangdong, Hunan, Chongqing, Guizhou, Anhui, Xinjiang, Guangxi, and Yunnan. The common feature of these provinces is an HECI with high efficiency in ECER, but low efficiency in TI. Except Chongqing and Hunan, the other eight provinces have reached the effective frontier of ECER efficiency. The outstanding performance of these provinces for ECER in HECI is closely related to the role of the functional supervision departments of the government. For example, in 2017, Henan Province issued the "Thirteenth Five-Year Plan for Energy Conservation and Low Carbon Development in Henan Province," which clearly sets out the goal of effectively controlling the province's total energy consumption and significantly improving the energy efficiency of the industry. Hunan Province formulated a five-year action plan in 2016 to implement low-carbon development and improve the groundwork for establishing carbon emissions trading. Some provinces in the central and western regions, where TI is less efficient and the region's innovation capacity is weaker, have achieved effectiveness in the ECER development phase. Possible reasons for this are related to the fact that these regions are actively exploring effective modes for transforming TI results, and the ECER phase in HECI is more extensively utilized for innovation outputs. For example, Anhui Province, Hefei City, University of Science and Technology of China and Chinese Academy of Sciences jointly built a collaborative innovation platform; Hebei Province promoted the establishment of a Beijing-Tianjin-Hebei science and technology information data sharing platform; and Yunnan Province pioneered the "science and innovation loan + risk pool" model to minimize the financing difficulties of science and innovation enterprises, among other problems. This series of initiatives has driven the region's innovative output to translate into ECER targets more quickly for HECI.

In the third quadrant, there are ten provinces: Gansu, Fujian, Jiangsu, Jilin, Sichuan, Shandong, Liaoning, Hubei, Shaanxi, and Tianjin. The efficiency of the two stages in this quadrant is lower than the average levels. Statistics show that the investment in TI in these provinces is significantly insufficient compared to the first quadrant provinces. Except for Gansu, Jilin and Liaoning, the limited innovation resources invested by the other seven provinces in the R&D process are not fully utilized, resulting in low efficiency of TI. The main reason for the low efficiency of ECER for HECI in this quadrant is also due to the apparent lack of TI drivers.

## Influencing Factors of TI Driving ECER in HECI

### *Main Influencing Factors*

ECER in HECI driven by TI is a complex system influenced by a variety of factors. To further improve the efficiency of ECER, it is necessary to deeply analyze the influencing factors. The quality of labor (LAB), industrial structure rationalization index (ISR), marketization level (MAR), green finance index (GF), energy consumption structure (ECS), education investment (EI), venture capital (VC), R&D investment (RD) and green invention patents (GIP) were selected for the impact effect analysis. Labor quality was measured by the proportion of employees with college degree or above, industrial structure was represented by the industrial structure rationalization index constructed by Shao et al. [63], marketization level was measured by the results of Wang Xiaolu and Fan Gang's calculation of the marketization process in various regions of China, a green finance index adopted the measurement method of Wang et al. [64], energy consumption structure was represented by the proportion of coal in energy consumption, and education input was represented by the proportion of education expenditure in financial expenditure.

### *Tobit Model*

Considering that the DEA method is used to measure efficiency, the efficiency value is limited to values between 0 and 1. For the explained variables with limited value, using the Tobit model based on the maximum likelihood method for regression analysis can more scientifically examine the principal factors that cause the variations in the explained variables [65]. Given this, the panel Tobit model was selected to analyze the influencing factors. The Tobit model takes the following form:

Table 4. Tobit likelihood ratio test results.

| | (10) | (11) | (12) |
|---|---|---|---|
| Chi-square | 155.585 | 91.094 | 138.373 |
| AIC value | 47.499 | 134.555 | 18.406 |
| BIC value | 82.622 | 169.678 | 16.716 |
| P value | 0.000 | 0.000 | 0.000 |

$$y_i = \begin{cases} c_1, \text{ if } y_i^* \le c_1 \\ x_i\beta + \varepsilon_i, \text{ if } c_1 \le y_i^* \le c_2 \\ c_2, \text{ if } y_i^* \le c_2 \end{cases} , \quad (9)$$

where $\beta$ is the regression parameter vector, $x_i$ is the explanatory variable vector, $y_i^*$ is the explained variable vector, and $y_i$ is the explained variable value vector. The typical form of the Tobit model is to set $c_1$ to 0 and $c_2$ to positive infinity. $\varepsilon_i$ is the error term that is assumed to be normally distributed with mean zero and constant variance [66].

LAB, ISR, MAR, GF, ECS, EI, VC, RD, and GIP were taken as explanatory variables, and the efficiency value of technological innovation stage, efficiency value of energy conservation and emission reduction stage and total efficiency value (TE) were taken as explanatory variables to analyze the impact effect.

The Tobit regression model is constructed as follows:

$$TIE_{it} = c + \beta_1 LAB_{it} + \beta_2 ISR_{it} + \beta_3 MAR_{it} + \beta_4 GF_{it} + \beta_5 ECS_{it} + \beta_6 EI_{it} + \beta_7 VC_{it} + \beta_8 RD_{it} + \beta_9 GIP_{it} + \varepsilon_{it} , \quad (10)$$

$$ECERE_{it} = c + \beta_1 LAB_{it} + \beta_2 ISR_{it} + \beta_3 MAR_{it} + \beta_4 GF_{it} + \beta_5 ECS_{it} + \beta_6 EI_{it} + \beta_7 VC_{it} + \beta_8 RD_{it} + \beta_9 GIP_{it} + \varepsilon_{it} , \quad (11)$$

$$TE_{it} = c + \beta_1 LAB_{it} + \beta_2 ISR_{it} + \beta_3 MAR_{it} + \beta_4 GF_{it} + \beta_5 ECS_{it} + \beta_6 EI_{it} + \beta_7 VC_{it} + \beta_8 RD_{it} + \beta_9 GIP_{it} + \varepsilon_{it} . \quad (12)$$

In the formula (Equations (10), (11) and (12)), i represents the 30 provinces studied, and t (2015, ..., 2020) is the period.

### *Tobit Regression Likelihood Ratio Test*

To ensure the reliability of the model used, the Tobit regression model was tested for likelihood ratio, and the test results are shown in Table 4. According to the results, the p-values of the likelihood ratio tests for the constructed models (10), (11), and (12) are all 0.000 less than 0.01; thus, the explanatory variables in the model are helpful for the model, i.e., the model is meaningful.

### *Analysis of Empirical Results*

The regression analysis results of all factors are shown in Table 5.

Table 5 shows that in the TI stage, the industrial structure rationalization index, marketization level, green finance index, energy consumption structure, investment in education, and R&D investment significantly influenced the efficiency of TI. However, labor quality, number of green invention patents, and venture capital had no significant impact. Among them, investment in education had the most substantial impacts in promoting the efficiency of TI and had influence coefficients greater than 1; Education is the foundation of a strong country and regional investment in education will ultimately be reflected in the output of talents, which will greatly promote the efficiency of regional innovation. The marketization level and energy consumption structure had a conspicuous negative impact on the efficiency of TI, which reflects the unreasonable problems existing in the marketization construction in China.

In the ECER stage, in addition to the quality of labor, R&D investment, and a number of green invention patents, other influencing factors had a conspicuous influence on efficiency. The rationalization of the industrial structure, progress of green finance, and increase in the education investment conspicuously promoted the efficiency of ECER, and the coefficients were all >1. The increase in venture capital also slightly improved the efficiency of ECER. As for the stage, the grade of marketization and energy consumption structure also negatively influenced the ECER efficiency of the industry. Unlike the first stage, venture capital had a conspicuous positive influence on the efficiency of ECER of HECI. Venture capital usually invests in enterprises with high and new technologies, which have unknown but high risk, so it has a lower coefficient and a lower degree of impact on ECER.

Among the possible influencing factors of the total efficiency, there is a significant relationship between the total efficiency and all the other factors except for the quality of workers, venture capital, R&D investment, and the number of green invention patents. The industrial structure rationalization index, green finance index, and education investment had significant positive relationships with the total and two-stage efficiency. These are the three key factors for TI to drive the ECER of HECI. The level of marketization also had a conspicuous negative correlation with the total efficiency, which appeared to indicate that China's marketization construction gives considerable attention to high-speed economic growth while ignoring the need for ECER of the industry and that the market-oriented development does not correspond with the green development needs. The relationship between R&D funding input and total efficiency is not significant, probably because there is investment redundancy in research funding. Excessive investment in R&D funding may lead to inefficiency in research, and the mismatch between input and output leads to an insignificant impact relationship.

### *Robustness Test*

To enhance the robustness of Tobit regression results, we performed robustness tests by replacing proxy variables. In addition to the common use of the proportion of workers with college degrees and above to

Table 5. Regression results of influencing factors. Values are coefficients.

| Explanatory variable | Technological innovation stage | Energy conservation and emission reduction stage | Total efficiency |
|---|---|---|---|
| Constant term | 2.224*** | 2.097*** | 1.704*** |
| Labor quality (LAB) | -0.005 | -0.054 | 0.010 |
| Industrial structure rationalization index (RIS) | 0.952*** | 1.709*** | 0.831*** |
| Marketability level (MAR) | -0.131*** | -0.211*** | -0.102** |
| Green finance index (GF) | 0.851* | 1.266* | 0.940** |
| Energy consumption structure (ECS) | -0.644*** | -0.692** | -0.375** |
| Educational investment (EI) | 2.746*** | 5.781*** | 1.792** |
| Venture capital (VC) | 0.001 | 0.001** | 0.001 |
| R&D investment (RD) | 0.001* | 0.002 | 0.001 |
| Green invention patents (GIP) | 0.001 | 0.001 | 0.001 |

Note: *, **, and *** represent significance at the significance levels of 10%, 5%, and 1% respectively.

Table 6. Robustness test results. Values are coefficients.

| Explanatory variable | Technological innovation stage | Energy conservation and emission reduction stage | Total efficiency |
|---|---|---|---|
| Constant term | 2.166*** | 1.692*** | 1.702*** |
| Labor quality (LAB) | 0.001 | -0.005 | 0.004 |
| Industrial structure rationalization index (RIS) | 0.940*** | 1.691*** | 0.807*** |
| Marketability level (MAR) | -0.131*** | -0.219*** | -0.099** |
| Green finance index (GF) | 0.794* | 1.297* | 0.725** |
| Energy consumption structure (ECS) | -0.648*** | -0.694** | -0.388** |
| Educational investment (EI) | 2.670*** | 5.902*** | 1.559** |
| Venture capital (VC) | 0.001 | 0.001** | 0.001 |
| R&D investment (RD) | 0.001* | 0.002 | 0.001 |
| Green invention patents (GIP) | 0.001 | 0.001 | 0.001 |

Note: *, **, and *** represent significance at the significance levels of 10%, 5%, and 1% respectively.

measure the quality of the labor force, the average years of education of employed workers can also be a good measure of the quality of the labor force. Therefore, in this section, we use the average years of education of employed persons as a proxy variable for the quality of the workforce in the context of robustness testing. The regression results are shown in Table 6. We focus on the coefficients' values of the explanatory variables and their significance. It can be seen that the coefficients sign's direction of the explanatory variables remains the same and the level of significance does not change in the regression of the efficiency values. This suggests that the findings in the influencing factors section remain the same even when the proxies for the explanatory variables are replaced.

## Discussion

### Spatial and Temporal Differentiation Analysis

Regional differences were observed in China's HECI, as also reported by previous studies [67]. Previous studies have shown that from 2005 to 2015, the efficiency of ECER gradually decreased from east to west [68]. However, under different spatial and temporal conditions and limited research objects, the ECER of regional HECI will vary [69]. In this study, the ECER efficiency of HECI in China, driven by TI from 2015–2020, shows a significant difference, with higher improvement in the northeast and no significant improvement in other regions. The lower starting value of energy efficiency in energy-intensive industries driven by technological innovation demonstrated in the Northeast is consistent with the lower economic efficiency of urbanization in the Northeast in 2015 measured by Cao et al [70]. To some extent, the quality of economic benefits affects the drive of TI to ECER in regional HECI. In recent years, the industrial structure in the Northeast region has been upgraded continuously [71], which has greatly promoted the ECER efficiency of HECI in the Northeast Region and promoted the sustainable development of the region.

### Influencing Factors Analysis

In order to further improve the efficiency of ECER in HECI and achieve sustainable development, it is necessary to study the influence of various factors on the efficiency of ECER. Since China's accession to the WTO, the manufacturing industry (including six HECI) has gradually expanded, and China has quickly become a manufacturing power [72]. Since then, HECI have grown rapidly, making China gradually become a major carbon emitter while developing its economy [73]. At present, the key to achieving the goal of ECER is the upgrading of industrial structure [74]. Qinghai's industrial structure rationalization index is in the forefront, which is the main key to Qinghai's leading position in ECER efficiency of HECI. Green finance provides financial support for industrial ECER. In particular, green credit is an effective tool for ECER in the industrial field [75]. Among the influencing factors of this study, the strong promoting effect of green finance on ECER efficiency in HECI was once again confirmed. Policies aiming to foster the development of science and technology should pay attention to the cultivation of talents. This paper has confirmed the positive impact of education investment on the realization of sustainable development goals of HECI. In previous studies, most scholars found that the level of marketization had a significant positive impact on the improvement of energy efficiency [76]. In particular, R&D investment has a greater impact on the reduction of energy intensity in HECI [77]. However, the level of marketization and R&D investment had significant negative impacts on the economic benefits of HECI in the current study. In recent years, China's marketization level and R&D development investment entered a key turning point. In the past, simply carrying out market-oriented development and increasing R&D investment no longer met the sustainable development and construction of HECI. Sustainable development and construction of HECI requires a more reasonable combination to achieve optimal ECER in HECI.

## Conclusions and Police Implications

To monitor progress towards the Sustainable Development Goals, this study used system theory decomposed the complex process of ECER of HECI driven by TI into two stages: TI and ECER. We constructed a conceptual model and index system for ECER of HECI driven by TI. The model established a two-stage network WSBM considering relaxation variable weight based on DEA. Then, we calculated the efficiency levels of ECER of HECI driven by TI in 30 provinces in China. The spatial and temporal evolution of the total efficiency and the characteristics of the two-stage efficiency were analyzed. An efficiency matrix was constructed based on the two-stage efficiency in 2020 and the 30 provincial-level regions were divided into three quadrants. The panel Tobit model was used to analyze the factors that influenced total efficiency and two-stage efficiency.

The research found that: (1) from 2015-2020, the overall performance level of ECER of HECI driven by TI in 30 provinces first decreased and then rose. 2018 was a turning point and efficiency peaked at 0.555 in 2020. The efficiency of the 30 provinces is uneven with large disparities between them. (2) By region, the Northeast region shows a breakthrough growth trend from low to high. The East, Central and West show similar trends to the national overall, with the total efficiency slightly higher in the East than in the West and lower in the Central region, which has a clear pattern of spatial and temporal differences. The main reasons for those differences are the high environmental cost of resource-based industries, weak TI ability, low degree of technology marketization, insufficient investment in TI, low proportion of TI personnel, inadequate utilization of scientific and technological resources, and policy deviation in various provinces. (3) Considering two-stage efficiency revealed that the efficiency of ECER stage of HECI was above that of the TI stage. (4) Panel Tobit regression analysis revealed that the industrial structure rationalization index, green finance index, and education investment significantly affected the total efficiency and two-stage efficiency, showing a positive relationship. The marketization had an apparent negative correlation with total and two-stage efficiencies.

The above conclusions indicate that differentiated development policies should be adopted according to regional advantages and national development strategies: (1) The Northeast should focus on continuing to strengthen the industrial advancement of HECI and the construction of TI systems. In the face of a brain drain in Northeast China, relevant departments should actively introduce preferential policies for talent. (2) The Eastern region will continue to play a pioneering role in innovation-driven development. For example, Beijing should make full use of the advantages of regional TI levels, actively carry out research and development of relevant major scientific research projects, promote the combination of technology research and development with the low-carbon demand of HECI, and strengthen the connection between innovation and industrial chains. (3) Central regions such as Anhui, Hubei, and Henan have lower efficiency of technological innovation and lower level of industrial structure rationalization. In future, education investment, green financial support, and other relevant measures should be strengthened to enhance clean and sustainable production of HECI in the region. (4) The efficiency of ECER in HECI has undergone subversive changes, benefiting from the support of relevant national strategies such as "Western Development," and the clean production level of HECI is at the forefront. The concept of "cooperation and shared development" has already brought great results. In the future, Xinjiang, for example, needs to enhance its own development potential and improve the level of education, funding, and other relevant factors. (5) Regional governments should actively promote the flow and integration of relevant factors, strengthen regional cooperation, and achieve complementary advantages in accordance with the development goals of ECER in HECI. In addition, the government should also provide green innovation and financial support for sustainable production in HECI.

## Contributions

This study makes the following key contributions: (1) The network WSBM model incorporates the slack variables, considering their weights, into the objective function, and has stronger discrimination ability than the traditional DEA model; few scholars used the Network WSBM model to carry out this research; (2) The complex system of TI-driven ECER in HECI is divided into two stages for empirical research, effectively solving the problem of intermediate input; (3) The spatial and temporal differentiation characteristics of 30 provinces and cities are analyzed from the perspective of overall efficiency and two-stage efficiency; (4) A panel Tobit model is established to test the influencing factors of ECER efficiency in TI-driven HECI. Important improvements needed in ECER of HECI were highlighted. This is very important for reducing carbon emissions and achieving greenhouse gas emission reduction targets and has important theoretical significance and reference value.

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## Conflicts of Interest

The authors declare no conflict of interest.

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