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Influences of Technological Innovation on Energy Efficiency under Carbon Constraints

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Abstract

In this study, first, the influences of technological innovation on energy efficiency were theoretically analyzed. Second, CO2 emission was used as an unexpected output in the evaluation of total factor energy efficiency. On the basis of the data of some provinces, cities, and autonomous regions in China from 2011 to 2022, the regional energy under carbon emission constraints was investigated by constructing an SBM-Undesirable model. This study innovatively divided technological innovation into three dimensions of innovation environment, innovation investment, and innovation market. The effects of technological innovation on energy efficiency were evaluated comprehensively by grey relational analysis. Results show that, in view of energy utilization status, most provinces in China report a low efficiency of energy utilization under carbon emission constraints, presenting obvious spatial and geographic differences. The provincial administration regions in the first and second echelons mainly concentrate in East China, while the provincial administrative regions in the third echelon mainly concentrate in Central, West, and Northeast China. The efficiency of energy utilization declines from East China to Northeast China to Central China and then to West China. Technological innovation has significant influences on energy efficiency, and its indexes are highly related to total factor energy efficiency under carbon constraints.

Keywords: technological innovation; energy efficiency; SBM-Undesirable model; grey relational analysis; carbon constraint

Introduction

Most countries have entered into the industrialization process in the past century, which have brought rapid economic and social development and a quick increase in population. However, the global energy consumption has soared up accordingly, accompanied with intensifying environmental pollution. Natural capital refers to renewable and nonrenewable available natural resources that support human life. The Living Planet Report of 2016 stated that with the increase in human pressure, the reduction speed of natural capital is higher than the recovery rate. It emphasized that man's consumption of Earth resources has exceeded the sustainable supply capacity of the Earth since 1970s [1]. Therefore, countries in the world begin to discuss energy structural transformation to control the emission of greenhouse gases. Many countries and regions have proposed relevant measures. The World Energy Development Report of 2021 indicated that Japan will realize "net zero emission" of greenhouse gases by 2050. The South Korean government also proposed the goal of carbon neutralization before 2050 and determined renewable energy as a major type of energy source. The UK has determined clean energy growth as one of four industrial challenges, aiming to increase industrial energy efficiency by at least 20% by 2030 [2].

After China announced the goals of "carbon neutrality" and "carbon emission peak" in September 2020, these two goals have become an important topic in the energy industry [3]. In 2022, a report on the work of the government pointed out to "make an overall plan of steady growth, adjust the structure, promote reform, accelerate changes in development modes, and abandon extensive development." The agreement is to seek high-quality development by changing development mode, optimizing the layout of the energy industry, and accelerating the application of new green energy technologies [4]. Therefore, the increasing demands for energy management are an important part of environmental governance, and increasing the energy utilization is viewed as the optimal method with the highest cost efficiency to decrease the pollution caused by energy consumption. To increase the efficiency of energy utilization and decrease energy consumption intensity, our main goal is to realize energy saving and emission reduction. Technological progress and energy structural adjustment are essential bases [5]. To promote improvement of energy efficiency and realize the goal of "carbon emission peak" by 2030 and "carbon neutrality" by 2050, enterprises and government shall pay attention to increasing nonfossil energy utilization and strengthening technological innovation. This mission is not only conducive to guiding the development directions of enterprises but also has remarkable social significance.

Literature review

Studies on energy efficiency measurement mainly focus on a single-factor energy efficiency index. Xie et al. measured energy efficiency by using pure economic energy index, physical thermodynamic index, and economic thermodynamic index as single-factor indexes [6]. Hou et al. further analyzed energy efficiency in different regions through the ratio of gross national product to energy consumption [7]. These methods have simple calculations and can analyze and compare the energy efficiency of multiple regions quickly; however, they cannot consider the production process comprehensively, and single energy factors cannot be output effectively. Moreover, the influences of other supporting factors are ignored. Most Chinese scholars begin to use the new theory of estimation. On the basis of a previous analysis framework, Thompson et al. constructed a provincial regional calculation model by using data envelopment analysis (DEA) based on gross domestic product (GDP), capital, labor force, and energy input in provincial panel data. They displayed generally consistent results with previous analyses and better results [8]. Considering unexpected output, as well as scaled energy correlation factors and substitution effect under energy correlation, Liu et al. used the hyperefficiency DEA model and carried out an empirical study based on the panel data of 28 provinces in China to evaluate regional energy efficiency [9]. Martin et al. used the EBM model to estimate energy efficiency, involving the environmental pollution of undesirable output, carried out an empirical test on the relationship between economic agglomeration and energy efficiency in the government intervention background, and analyzed the influencing and action mechanism of energy efficiency [10].

Many studies on the influencing factors of energy efficiency have been reported. In the study on China's petroleum industry, Feng et al. attributed over 50% of the reduction in energy intensity to changes in the energy industrial structure [11]. Cheng et al. indicated that technological progress would increase energy efficiency, and changes in the driving force of energy needs in the fields of economic growth, industrial structure, economic system reform, and environmental and energy saving policies should be investigated [12]. Using the data of 20 developing countries, Lin et al. studied the relationship between foreign direct investment (FDI) and energy intensity and found that energy intensity decreased obviously with an increase in FDI. In addition, the improvement of FDI efficiency is the collaborative outcome of advanced management skills and modern technological factors [13]. Liu et al. studied large- and medium-sized enterprises in China and concluded that more than 50% of the reduction in energy intensity was due to industrial restructuring [14]. Wang et al. included knowledge stock into the production function and studied provincial energy efficiency from the perspective of market segmentation. They concluded that, in the energy clustering analysis, Sichuan, Hebei, and Shanxi were clustered as low-efficiency and high-input. This conclusion reflected that energy endowment restricted energy efficiency and the formation of scaled economy, thus hindering interindustrial development [15].

Wongsapai et al. suggested building an environmental DEA model with consideration to CO_2 emission in the industry. According to their empirical results, the improvement of the energy efficiency of China's industrial sectors was mainly promoted by technological progress [16]. Lin et al. discussed the simultaneous realization of regional economic growth and energy efficiency in Japan and investigated the relationship between Japan's manufacturing industry and energy efficiency. They concluded that energy efficiency was positively related to productivity. Agglomeration economy, a driving force of productivity growth, increased the energy efficiency of Japan's manufacturing industry. Furthermore, local economy can increase the energy efficiency of rural areas effectively through agglomeration of similar industries [17]. Liu et al. estimated environmental regulation intensity by establishing comprehensive evaluation indexes of three industrial wastes emissions and carried out an empirical test on the influences of environmental regulation and total factor energy efficiency through provincial panel data. They concluded that environmental regulation promoted countermeasures of energy efficiency [18]. Li et al. established total factor energy efficiency indexes covering environmental pollution and greenhouse gas, analyzed the influencing degrees of internal management factors and external factors, and proposed countermeasures to improve industrial energy efficiency [19]. On the basis of 30 enterprises in Latin America and the Caribbean, Yang et al. discussed the relations among energy efficiency, productivity, and export. According to an empirical analysis, they found that enterprise size and industrial sector vary in the relations of energy efficiency with productivity and export [19].

With respect to the influences of technological innovation on energy efficiency, the innovation theory of Joseph Alois Schumpeter demonstrates that innovation plays an important role in human social and economic development. After the industrial revolution, most countries in the world began to replace manual labors with machines. In this process, technological innovation can definitely improve mechanical efficiency. At present, although extensive opinions exist about the influences of technological innovation on energy efficiency, most scholars agree that technological innovation promotes energy efficiency. Yang et al. demonstrated that technological innovation drives green economic transformation and increases regional energy and ecological efficiency, with a stronger positive effect than industrial structure [20]. Shi et al. found a significantly positive correlation between technological innovation and energy ecological efficiency on the national and regional levels [21]. Wang et al. decomposed technological progress into scientific and technological progress index, pure technological efficiency index, and scaled efficiency index, analyzed their influences on energy efficiency through panel data measurement, and concluded that technological progress was the major contributor to the improvement of energy efficiency [22]. Cheng et al. studied energy ecological efficiency in the Yellow River region by using the SBM-Undesirable model and explored the action mechanism of technological innovation on energy ecological efficiency [23]. Li et al. demonstrated that technological innovation played a positive effect on the emission reduction in industrial SO_2 and wastewater. They recommended paying attention to the major role of innovation in reducing pollutant emissions and increasing energy efficiency [23]. Li et al. carried out the Granger causality test and a pulse response analysis based on PVAR model and conducted variance decomposition. They found that technological innovation could promote industrial production efficiency to some extent [24]. Gao et al. believed that product innovation and technological innovation could coordinate with energy efficiency to promote economic growth further. On this basis, they established a comprehensive system coordination model of technological innovation and energy efficiency. Through a study of the technological innovation and energy data of high and new technology industries in China, they determined a low degree of coordination between technological innovation and energy in such industries in China. They also stated that improving the coordination between technological innovation and energy efficiency would be the major task in the future [25].

To sum up, technological innovation could promote energy efficiency significantly. However, previous studies mainly viewed technological innovation as the mediating effect between energy efficiency and other factors and explored the action mechanisms of relevant influencing factors. Some scholars have discussed the influences of technological innovation on energy efficiency from its internal factors, but deeper discussions are needed.

Models and data source

SBM-Undesirable model

In the hyperefficiency SBM-Undesirable model, suppose n mutually independent provincial energy-efficient units exist, and each has m inputs ($x \in R^m$), k desirable outputs ($y \in R^k$), and one undesirable output ($b \in R^l$). The matrixes $X = [x_1, \ldots, x_n] \in R^{m \times n}$, $Y = [y_1, \ldots, y_n] \in R^{k \times n}$, and $B = [b_1, \ldots, b_n] \in R^{l \times n}$ were designed, where $X > 0, Y > 0, B > 0$. Each provincial unit pursues minimum input (X), maximum desirable output (Y), and maximum energy efficiency (B). The possibility set of production in this process is

$$P = \{(x, y, b) | x \geq X\lambda, y \leq Y\lambda, b \geq B\lambda, \lambda \geq 0\} \quad (1)$$

where $\lambda \in R^n$ is the weight vector, and λ ? 0 represents the constant returns to scale. $\sum \lambda = 1$ shows changing returns to scale. $x \geq X\lambda$ indicates that the actual input is higher than the optimal input, and y □ $Y\lambda$ shows that the actual desirable output is lower than the optimal desirable output. $b \geq B\lambda$ means that the actual undesirable output is higher than the optimal undesirable output. $\delta^* (0 < \delta^* \leq 1)$ was used to estimate the provincial energy efficiency of regions with an input–output state of (x_0, y_0, b_0). When $\delta^* = 1$, the provincial energy efficiency of such regions is high. s_i^-, s_r^+, s_v^- denote input redundancy, insufficient desirable output, and excessive undesirable input, respectively. They provide practice directions for provincial energy efficiency to further improve environmental technological efficiency. From Eq. (2), δ^* is not influenced by the data measurement unit. The slack variables of inputs and outputs decrease monotonously.

$$\delta^* = \min \delta = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{io}}{1 + \frac{1}{k+1}\left(\sum_{r=1}^{k} s_r^+ / y_{ro} + \sum_{v=1}^{l} s_v^- / b_{ro}\right)} \quad (2)$$

$$s.t. \quad x_{io} = X\lambda + s_i^-, \forall m; \quad (3)$$

$$y_{ro} = Y\lambda - s_r^+, \forall k; \quad (4)$$

$$b_{vo} = B\lambda + s_v^-, \forall l; \quad (5)$$

$$\lambda_j \geq 0, \forall n; s_i^- \geq 0, \forall m; s_r^+ \geq 0, \forall k; s_v^- \geq 0, \forall l. \quad (6)$$

In practical production, energy efficiency is usually sensitive to several environmental technological efficiency factors, which cannot be distinguished owing to the limitations of the SBM model setting. To address this issue, this study combined the hyperefficiency DEA and SBM models and proposed the hyperefficiency SBM model. On this basis, the hyperefficiency SBM-Undesirable model could be inferred to distinguish provinces with different environmental technology efficiency. In Eq. (3), w_i^-, w_r^+, w_v^- express the minimum input saving, minimum desirable output residues, and minimum undesirable output redundancy, respectively.

$$\delta^* = \min \delta = \frac{1 + \frac{1}{m}\sum_{i=1}^{m} w_i^- / x_{io}}{1 - \frac{1}{k+1}\left(\sum_{r=1}^{k} w_r^+ / y_{ro} + \sum_{v=1}^{l} w_v^- / b_{ro}\right)} \quad (7)$$

$$s.t. \quad x_{io} \ \square \ X\lambda - w_i^-, \forall m; \quad (8)$$

$$y_{ro} \ \square \ Y\lambda + w_r^+, \forall k; \quad (9)$$

$$b_{vo} \ \square \ B\lambda - w_v^-, \forall l; \quad (10)$$

$$\lambda_j \geq 0, \forall n; w_i^- \geq 0, \forall m; w_r^+ \geq 0, \forall k; w_v^- \geq 0, \forall l \quad (11)$$

In the tobit model, the provincial energy efficiency of all regions was measured higher than 0 in this study. The limited dependent variable model (Tobit) was used, and it can be expressed as follows:

$$E_i^* = \beta_0 + \beta_i X_i + \varepsilon_i, \varepsilon_i \in N\left(0, \sigma^2\right) \quad (12)$$

$$E_i = \max\left(0, E_i^*\right) \quad (13)$$

where E_i is the provincial energy efficiency of region *i*. E_i^* is the observation value in the interval $(0, +\infty)$. X_i is a series of characteristics that influence production environmental technological efficiency. β_i is a parameter vector, and ε_i is the independent random disturbance term. The marginal effect of estimation coefficient was further calculated for the convenience of interpreting the regression results.

Grey relational analysis

Grey relational analysis is to analyze the influencing degree of different factors on a research object by calculating the grey correlation coefficient among system factors. A reference sequence of data that reflect system behavioral characteristics is set, and data that influence such a reference sequence is called comparative sequence. The reference sequence is $\theta_0 = [\theta_0(1), \theta_0(2), \theta_0(3), \ldots, \theta_0(n)]$, and the comparative sequence is $\theta_i = [\theta_i(1), \theta_i(2), \theta_i(3), \ldots, \theta_i(n)]$, where $i = 1, 2, 3, \ldots, m$.

Dimensionless treatment of the reference and comparative sequences was implemented via a normalization method (Eq. (15)) or an initialization method (Eq. (16)).

$$\theta_i'(k) = \frac{\theta_i(k)}{\frac{1}{m}\sum_{k=1}^{m} \theta_i(k)} \quad (15)$$

$$\theta_i'(k) = \frac{\theta_i(k)}{\theta_i(1)} \quad (16)$$

The processed data can be expressed as $\theta_i' = \left[\theta_i'(1), \theta_i'(2), \theta_i'(3), \ldots, \theta_i'(n)\right], \quad i = 1, 2, 3, \ldots, m$.

Then, the difference sequence between the reference and comparative sequences was calculated in accordance with the following equation:

$$\Delta\theta_i(t) = \left|\theta_0'(t) - \theta_i'(t)\right|, 1 \leq t \leq n \quad (17)$$

The grey relational coefficient ($\xi\theta_i(t)$) of the reference and comparative sequences can be calculated as

$$\xi\theta_i(t) = \frac{\Delta(\min) + p\Delta(\max)}{\Delta\theta_i(t) + p\Delta(\max)} \quad (18)$$

where ρ is the resolution ratio, and it usually has a value from 0 to 1. The smaller the value of ρ, the better the resolution is; it is typically set to 0.5.

Finally, the correlation value could be calculated. Because the correlation coefficient results are relatively scattered, the mean of the correlation coefficient needs to be calculated. The calculation formula is

$$r\theta_i = \frac{1}{n}\sum_{i=1}^{n} \xi\theta_i(t) \quad (19)$$

A higher correlation value indicates a stronger correlation between the evaluation term and the reference sequence. Through calculation and ranking of correlation values, the ranking results of different evaluation terms could be gained.

Selection of indexes and data source

With consideration to the integrity and availability of data, energy efficiency was measured and evaluated on the basis of the data of 30 provinces, cities, and autonomous regions (hereinafter referred to as provinces) in China from 2011 to 2022. The Tibet Autonomous Region, Hong Kong, Macao, and Taiwan were excluded from the statistics because of the incomplete data or inconsistent statistical caliber of indexes.

Energy input was expressed by the total energy consumption (unit: 10,000 tons of standard coals) of provinces. The original data of electricity consumption (TWh) came from China Energy Statistical Yearbook. No regional statistics were available for 2022, such that provincial statistical yearbook data were used. Capital input was measured by the index of capital stock (unit: 100 million yuan), and its statistics used the "perpetual inventory method": $K_t = (1-\delta)K_{t-1} + I_t$, where K_t refers to the capital stock of phase t, K_{t-1} is the capital stock of phase t-1, δ is the fixed asset depreciation rate, and I_t denotes the actual fixed investments of year t. Younger's setting was applied in the estimation of interprovincial physical capital stock in China. It was subtracted on the basis of that in 2000, and the capital stocks of provinces in China from 2011 to 2022 were estimated. Specifically, the data of fixed investments came from China Statistical Yearbook from 2011 to 2022, and data after 2018 were calculated by percentage. Labor input was measured by the quantity of employment of provinces at the end of a year (unit: 10,000 people), and relevant data were from China Statistical Yearbook from 2011 to 2022. The desirable output was expressed by the actual GDP of provinces (unit: 100 million yuan). GDP was applied to convert nominal GDP from 2011 to 2022 into constant-price GDP in 2000 to keep consistent statistical caliber with capital stocks. Relevant data came from China Statistical Yearbook from 2011 to 2022. The undesirable output was expressed by the CO2 emissions of provinces (unit: 100 million tons of carbon dioxide equivalence). Data were from the CEADs database and checked by IPCC department laws. Data in 2020 were gained through linear interpolation.

Results

Energy efficiency measurement and analysis

Five input-output index data of some provinces in China from 2011 to 2022 were incorporated into SBM-Undesirable, and the energy efficiency values (ρ) of these provinces in these 11 years were calculated using MATLAB software. The results are shown in Table 1.

Table 1: Total factor energy efficiency values of some provinces in China from 2011 to 2022

Province	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Result
Beijing	1.000	0.924	1.000	1.000	1.000	0.999	1.000	0.945	0.966	1.000	1.000	0.912	0.979
Tianjin	0.834	0.948	0.842	0.855	0.847	0.926	0.936	0.905	0.851	0.963	0.922	0.992	0.902
Shanghai	0.994	1.000	1.000	1.000	1.000	1.000	0.966	0.946	1.000	1.000	1.000	1.000	0.992
Chongqing	0.447	0.522	0.582	0.561	0.417	0.519	0.438	0.545	0.437	0.463	0.413	0.535	0.490
Hebei	0.416	0.425	0.555	0.511	0.548	0.538	0.478	0.460	0.470	0.518	0.526	0.419	0.489
Shanxi	0.396	0.269	0.273	0.343	0.230	0.267	0.318	0.283	0.356	0.370	0.287	0.400	0.316
Liaoning	0.564	0.612	0.564	0.679	0.672	0.512	0.603	0.685	0.554	0.656	0.673	0.647	0.618
Jilin	0.621	0.667	0.621	0.534	0.507	0.552	0.594	0.611	0.581	0.679	0.679	0.699	0.612
Heilongjiang	0.685	0.556	0.628	0.550	0.636	0.550	0.663	0.536	0.592	0.593	0.575	0.565	0.594
Jiangsu	0.688	0.531	0.659	0.545	0.587	0.676	0.688	0.625	0.628	0.670	0.505	0.661	0.622
Zhejiang	0.673	0.661	0.619	0.633	0.664	0.611	0.678	0.577	0.521	0.623	0.645	0.639	0.629
Anhui	0.654	0.687	0.650	0.514	0.509	0.567	0.551	0.524	0.685	0.672	0.655	0.656	0.610
Fujian	0.679	0.546	0.531	0.526	0.577	0.551	0.684	0.527	0.531	0.629	0.582	0.691	0.588
Jiangxi	0.662	0.677	0.683	0.530	0.557	0.586	0.685	0.584	0.647	0.630	0.561	0.550	0.613
Shandong	0.502	0.542	0.525	0.647	0.527	0.572	0.537	0.562	0.625	0.691	0.590	0.614	0.578
Henan	0.529	0.655	0.513	0.502	0.699	0.546	0.513	0.559	0.693	0.536	0.677	0.500	0.577
Hubei	0.598	0.637	0.506	0.630	0.516	0.509	0.522	0.680	0.606	0.628	0.564	0.612	0.584
Hunan	0.597	0.580	0.526	0.665	0.507	0.510	0.656	0.614	0.656	0.511	0.508	0.596	0.577
Guangdong	1.000	0.932	0.840	0.824	0.893	1.000	0.920	0.937	0.887	1.000	0.815	0.961	0.917

Hainan	0.410	0.298	0.211	0.234	0.241	0.240	0.324	0.272	0.351	0.206	0.315	0.370	0.289
Sichuan	0.460	0.360	0.441	0.393	0.348	0.405	0.421	0.384	0.399	0.388	0.435	0.401	0.403
Guizhou	0.201	0.317	0.382	0.243	0.286	0.231	0.231	0.274	0.389	0.313	0.301	0.324	0.291
Yunnan	0.242	0.332	0.252	0.337	0.369	0.384	0.313	0.278	0.206	0.253	0.281	0.309	0.296
Shaanxi	0.281	0.219	0.295	0.224	0.281	0.283	0.273	0.300	0.251	0.300	0.288	0.299	0.274
Gansu	0.249	0.114	0.249	0.148	0.142	0.182	0.156	0.101	0.178	0.103	0.277	0.180	0.173
Qinghai	0.124	0.209	0.286	0.105	0.221	0.193	0.106	0.101	0.214	0.178	0.249	0.216	0.183
Neimenggu	0.394	0.372	0.259	0.284	0.365	0.317	0.354	0.300	0.318	0.267	0.362	0.286	0.323
Guangxi	0.248	0.230	0.296	0.202	0.327	0.265	0.246	0.314	0.217	0.339	0.276	0.351	0.276
Xizang	0.188	0.192	0.098	0.057	0.195	0.074	0.030	0.081	0.063	0.116	0.075	0.032	0.100
Ningxia	0.163	0.002	0.017	0.189	0.025	0.180	0.090	0.183	0.195	0.119	0.110	0.057	0.111
Xinjiang	0.191	0.271	0.210	0.215	0.236	0.284	0.147	0.245	0.263	0.279	0.162	0.164	0.222

The energy efficiency level of some provincial administrative units in China under the SBM-Undesirable model was divided. The spatial distributions of energy efficiency levels after grading in 2011, 2016, and 2022 were plotted using ArcGIS (Figure. 1–Figure. 3).

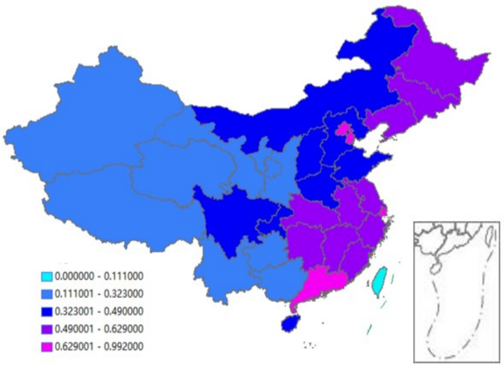

Figure 1: Spatial distribution of energy efficiency levels in 2011

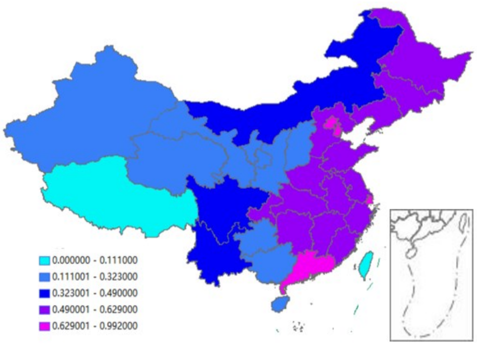

Figure 2: Spatial distribution of energy efficiency levels in 2016

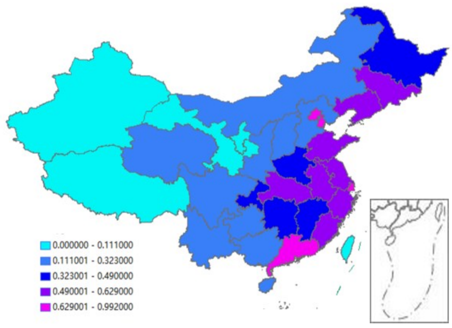

Figure 3: Spatial distribution of energy efficiency levels in 2022

Comparison of Fig .1 to Fig. 3 indicates that the total factor energy efficiency of China presents obvious spatial distribution characteristics. In particular, Shanghai, Beijing, Guangdong, and Tianjin in East China had been in the first echelon from 2011 to 2022. Chongqing and Sichuan in West China entered into the second echelon in 2016 and 2022.

In this study, the energy efficiency of some provincial administrative units in China under the SBM-Undesirable model was analyzed. The temporal variation trend of energy efficiency under carbon constraints was discussed. The average energy efficiency of some provincial administrative units in China from 2011 to 2022 was plotted using ArcGIS software (Fig. 4). The energy utilization of provinces in the sample period was not optimistic with regard to CO2 pollution. Considering that input and output had some hysteretic characteristics, the government and enterprises did their best in accordance with the carbon emission policies in the recent 2 years. With the continuous improvement of carbon transaction markets, the efficient energy utilization of some provincial administrative units in China under carbon constraints might be increased in some years in the future. In view of regions, the overall energy efficiency of West China is lower than those in eastern economic zones, central economic zones, and northeast regions of China. In Western China, Sichuan reported a high comprehensive evaluation, and its energy efficiency was higher than 0.4; however, it was still a province with low energy efficiency, and great improvement is needed. The energy efficiency of other provinces was at a low level. Governments and enterprises shall aim for excellent advancement. In Eastern China, the energy efficiency under carbon emission constraints was highest, significantly higher than those of Central China, West China, and Northeast China. The energy efficiency generally declined from East China to Northeast China to Central China and West China.

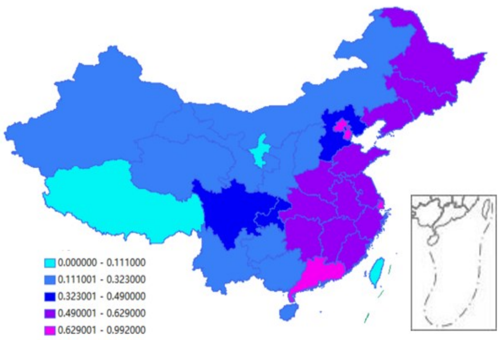

Figure 4: Average energy efficiency of some provincial administrative units in China from 2011 to 2022

Grey relational analysis results

In the energy field, innovation environment, innovation investment, and innovation market are closely related to energy industrial development. Hence, these three level-1 factors that influence energy efficiency were chosen. Each level-1 factor contains specific level-2 factors. With consideration to data availability, seven level-2 factors were selected. Specifically, the level-2 factors of innovation environment include government support (scientific and technological expenditure), technological innovation (number of patent approvals), and development level (regional GDP), which can reflect China's support to innovation environment. Level-2 factors of innovation investment comprise fund input (internal R&D inputs) and personnel input (R&D personnel full-time equivalence), which can indicate labor and financial inputs for technological innovation. Level-2 factors of innovation market include market transaction (sum of technological market transaction) and proportion of the industry (proportion of GDP of the secondary industry), which can show the technological innovation market conditions comprehensively. Major factors that influence the energy environments of provinces in China were recognized by studying the correlation degrees of three level-1 indexes and seven level-2 indexes with energy environmental efficiency.

Table 2: Correlation degrees between technological innovation factors and energy efficiency of some provinces in China

Provinces	Scientific and technological expenditure (100 million CNY)	Number of patent approvals (pcs)	Regional GDP (100 million CNY)	Internal R&D input (10,000 CNY)	R&D personnel full-time equivalence (people/year)	Sum of technological market transaction (100 million CNY)	GDP of the secondary industry (100 million CNY)
Beijing	0.786	0.777	0.843	0.883	0.762	0.803	0.928
Tianjin	0.846	0.848	0.920	0.790	0.770	0.921	0.827
Shanghai	0.822	0.823	0.872	0.930	0.794	0.947	0.782
Chongqing	0.885	0.769	0.769	0.793	0.844	0.853	0.805
Hebei	0.896	0.802	0.780	0.931	0.844	0.884	0.813

Shanxi	0.946	0.832	0.846	0.879	0.939	0.756	0.812
Liaoning	0.882	0.823	0.919	0.926	0.852	0.928	0.770
Jilin	0.819	0.925	0.852	0.923	0.817	0.947	0.872
Heilongjiang	0.878	0.779	0.944	0.827	0.907	0.883	0.882
Jiangsu	0.881	0.769	0.843	0.773	0.878	0.821	0.934
Zhejiang	0.760	0.907	0.794	0.783	0.796	0.874	0.834
Anhui	0.940	0.833	0.883	0.801	0.811	0.928	0.830
Fujian	0.775	0.830	0.759	0.918	0.944	0.932	0.799
Jiangxi	0.873	0.870	0.861	0.838	0.868	0.770	0.940
Shandong	0.913	0.898	0.838	0.759	0.887	0.788	0.769
Henan	0.752	0.881	0.787	0.760	0.776	0.828	0.887
Hubei	0.751	0.826	0.932	0.881	0.753	0.846	0.914
Hunan	0.923	0.863	0.942	0.911	0.927	0.821	0.790
Guangdong	0.898	0.939	0.767	0.912	0.864	0.828	0.878
Hainan	0.949	0.831	0.787	0.906	0.900	0.907	0.901
Sichuan	0.770	0.900	0.832	0.777	0.782	0.847	0.787
Guizhou	0.882	0.829	0.884	0.762	0.909	0.936	0.872
Yunnan	0.789	0.882	0.806	0.924	0.774	0.941	0.927
Shaanxi	0.886	0.896	0.817	0.896	0.812	0.768	0.821
Gansu	0.946	0.893	0.788	0.840	0.870	0.881	0.783
Qinghai	0.945	0.933	0.846	0.883	0.806	0.759	0.839
Neimenggu	0.897	0.788	0.854	0.945	0.906	0.804	0.795
Guangxi	0.824	0.782	0.810	0.841	0.881	0.840	0.921
Xizang	0.801	0.760	0.820	0.768	0.851	0.871	0.860
Ningxia	0.816	0.852	0.768	0.893	0.758	0.809	0.854
Xinjiang	0.914	0.895	0.938	0.783	0.926	0.801	0.890

In accordance with the grey correlation degrees between factors and energy efficiency of provinces in China in Table 2, the correlation degrees between factors and energy efficiency were defined by grey relational analysis method. Factors with a correlation degree ranging [0.9,1.0] were defined as extremely high-correlation factors, indicating their close relationships with energy efficiency. Factors with a correlation degree ranging [0.8,0.9] were defined as high-correlation factors. Factors with a correlation degree ranging [0.6,0.7] were defined as general-relevance factors. Factors with a correlation degree ranging [0.5, 0.6] were defined as relatively low-correlation factors. Factors with a correlation degree ranging [0.4,0.5] were defined as low-correlation factors. For the simplification of the table, factors were expressed in abbreviations: STE represents scientific and technological expenditures, NPA represents the number of patent approvals, GDP refers to regional GDP, R&D expenditure is the internal R&D input, R&D personnel represents R&D personnel full-time equivalence, Market transaction expresses the sum of technological market transaction, and TVSI represents the GDP of the secondary industry.

Discussions

Four provinces in China showed high energy efficiency, while 15 provinces were in the third echelon. This finding indicated fewer provinces with good input and output coordination under carbon emission constraints, except for some prominent ones. In view of efficiency, the comprehensive energy efficiency of 12 provincial administrative units in East China, Central China, and Northeast China was higher than 0.5, close to the grading standards of Shanghai, Beijing, Guangdong, and Tianjin in the first echelon. After the implementation of a series of CO2 emission reduction policies, the 12 provincial administrative units in the second echelon demonstrated the possibility of entering into the first echelon. East China comprised 4 provinces in the first echelon, 12 provinces in the second echelon, and 15 provinces in the third echelon. The energy efficiency of East China was 0.657, indicating its high-efficiency state. In view of regions, the energy efficiency of East China and Northeast China was relatively good, of which the energy efficiency of East China was better than that of Northeast China. Shanghai, Beijing, Guangdong, and Tianjin in East China achieved high-efficiency development, while the remaining provinces had different energy efficiency, indicating the imbalanced development among provinces in the region. In other words, a great gap existed among the provinces in East China, except for some prominent provinces. In Northeast China, Heilongjiang, Jilin, and Liaoning formed the second echelon, and the advantages of their coordinated development could be utilized. In Central China, the energy efficiency of provinces varied, but the overall energy efficiency was not very high. Only Sichuan was in the second echelon, while the rest were in the third echelon, implying poor energy efficiency. The energy quality and efficiency should be improved greatly.

Innovation environment, innovation investment, and innovation market showed a good development trend from 2011 to 2022. Scientific and technological expenditure, regional GDP, internal R&D input, R&D personnel full-time equivalence, and the sum of technological market transaction all achieved steady growth. Although FDI decreased slightly in 2015, 2018, and 2019, it still achieved steady growth in other years. China is accelerating the establishment of a new development pattern centered at the domestic general circulation and mutual promotion between domestic and overseas circulations, thus decreasing the dependence on foreign trade significantly. In this study, innovation environment, innovation investment, and innovation market were chosen as internal factors of technological innovation, and their correlation degrees with energy efficiency were calculated by grey relational analysis. Moreover, the correlation degrees of influencing factors and energy efficiency under grey relational analysis were defined. On this basis, the influencing factors of energy efficiency were analyzed by combining the statistical data of provinces. Research conclusions provide theoretical support to the proposal of improvement measures in the future.

Conclusions

This study focuses on the influences of technological innovation on China's energy efficiency, and it analyzes the relevant influencing mechanism. Data and development status of 31 provinces, cities, and autonomous regions in China from 2011 to 2022 were collected. An SBM-Undesirable model of the panel data of these 31 regions under CO2 emission constraints was established to measure the total factor energy efficiency. Regional energy efficiency was also discussed. On this basis, the influences of three dimensions of technological innovation, namely, innovation environment, innovation investment, and innovation market, on energy efficiency were evaluated comprehensively. The correlation degrees of seven indexes of these three dimensions and the energy efficiency of each region were estimated by grey relational analysis. The major conclusions are as follows:

First, the energy efficiency is not high in most provinces in China under carbon emission constraints, with obvious spatial and geographical differences. In view of grading, only four provincial administrative regions exist in the first echelon: Shanghai, Beijing, Guangdong, and Tianjin. The second echelon has 12 updating administrative units: Zhejiang, Jiangsu, Liaoning, Jiangxi, Jilin, Anhui, Heilongjiang, Fujian, Hubei, Shandong, Hunan, and Henan. The third echelon has 15 provincial administrative units, which induce substantial losses and wastes during energy production and utilization, implying considerable space for China to improve energy efficiency under carbon emission constraints. Provincial administrative regions in the first and second echelons concentrate in East China, while provincial administrative regions in the third and fourth echelons concentrate in Central China, West China, and Northeast China. Energy efficiency decreases from East China to Northeast China to Central China and then to

West China. This finding reflects that energy efficiency is closely related to regional development level. Given that regions develop and reform production technologies and optimize industrial structure after an improvement in economic development level, the energy efficiency of a region is influenced by imbalanced regional development to a large extent. In West China, specifically, the regional economic development level is low. In the future, it must develop the secondary industry with energy and raw materials. Resource-friendly development and regional migration of new technologies and new talents must be realized to decrease pollutant and carbon emissions and improve energy efficiency.

Second, technological innovation has significant influences on energy efficiency. All indexes of technological innovation are highly correlated to total factor energy efficiency under carbon constraints. Scientific and technological expenditure is an extremely high-correlation factor of energy efficiency in 70% of provincial administrative regions. This result reveals that energy technological innovation cannot be achieved without government inputs. R&D personnel full-time equivalence is also an extremely high-correlation factor of energy efficiency in 60% of provincial administrative regions, indicating that human capital input plays an important role in innovation investment. Innovation investment, innovation environment, and innovation market are highly correlated with energy efficiency. In particular, innovation investment shows the highest correlation degree with energy efficiency, followed by innovation environment and innovation market successively.

Third, CO2 redundancy rate is excessively high in most provinces in China, requiring long-term efforts to realize the goals of "carbon neutrality and carbon emission peak." Among the statistical samples of 31 provincial administrative regions, nearly half exceeded the redundancy rate by 50%. That is, development induces considerable CO2 emissions. To realize "carbon emission peak" by 2030 and "carbon neutrality" by 2060, China must focus on technological innovation to develop low-carbon and noncarbon energy sources and decrease the proportion of high-carbon energy, thus enabling to decrease carbon emissions effectively.

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