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SPECIALTY SECTION
This article was submitted to
Environmental Economics and
Management, a section
of the journal
Frontiers in Environmental Science

RECEIVED 29 September 2022
ACCEPTED 02 November 2022
PUBLISHED 29 November 2022

CITATION
Chen Y and Zhao T (2022), Exploring the
role of technology innovation and
environmental regulation in
energy efficiency.
Front. Environ. Sci. 10:1056877.
doi: 10.3389/fenvs.2022.1056877

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Exploring the role of technology innovation and environmental regulation in energy efficiency

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This study adopts a relatively infrequent approach to explore the impact of environmental regulation and technological innovation on energy efficiency (EFF) based on the undesired superefficiency SBM and random Tobit model. To study the universal EFF, we establish the undesired superefficiency SBM model, which is composed of three input indexes such as energy, one expected output index, and three pollution emissions as the undesired output index, consider the EFF of the sample with an effective decision-making unit (DMU) value less than 1, and calculate with the MATLAB software, according to panel data of 30 Chinese provincial-level regions from 2001 to 2019. The empirical results show that the EFF has an N-type trend in the eastern, central, and western regions of China. When exploring the impact of environmental regulation and technological innovation on EFF, we conduct an empirical analysis of the eastern, central, and western regions with the random Tobit model. The regression results indicate that the impact of environmental regulation on EFF in the different regions varies significantly. Technological innovation has different impacts on EFF in different regions and is the main influencing factor of EFF. Moreover, we strive to analyze the impact of cross-term environmental regulation and technological innovation and find that the cross-term has a significant positive impact on EFF in each region. These results emphasize that environmental regulation and technological innovation have positive or negative impacts on EFF, and both impacts may exist simultaneously, which is a perfection of the EFF theory.

KEYWORDS

energy efficiency, technological innovation, environmental regulation, undesirable superefficiency SBM model, Tobit model

1 Introduction

In the past 20 years, China's economy has grown rapidly. This rapid growth requires the support of a large amount of energy consumption. Unfortunately, this large amount of energy consumption has also brought about problems of major social development. First, the degree of environmental contamination in China is getting higher. Large-scale haze weather has repeatedly appeared in China, indicating that the degree of industrial pollution has approached the limit of environmental carrying. According to the 2010 World Energy Statistical Yearbook, it is the largest energy consumer that China

has become in the world. A large amount of energy consumption will inevitably bring about air and serious water pollution (Liu et al., 2019). With China's economic development in the future, energy consumption is likely to increase (Feng and Wang, 2017), and balancing environmental protection and economic development has become an important factor affecting the sustainable development of China's economy and society (Zhang and Zhou, 2020). Therefore, reducing environmental pollution and improving energy efficiency (EFF) have become urgent in China. Second, it is difficult to achieve the goals of energy conservation, emission reduction, and EFF improvement simply by relying on the market; therefore, environmental regulations proposed by the government are needed to compensate for the market failure. The so-called "environmental regulation" refers to the direct intervention of the government in the utilization of environmental resources through non-market means (Zhao et al., 2009). China's environmental regulation is aimed at improving environmental quality and forcing enterprises to improve EFF (Zhang et al., 2019). However, any policy, like a coin, has two sides. Although environmental regulation can interfere with pollution emissions of enterprises, it is worth studying whether it can improve EFF. Third, the energy-saving effect of many emission reduction policies in China is unsatisfactory, and environmental pollution has not been alleviated from the root. However, there is no unified opinion on whether technological innovation, as the main factor of technological progress, can achieve EFF improvement and pollution reduction. It is generally believed that technological innovation can improve the level of the production process and is an effective way to improve energy utilization efficiency (Kemfert and Truong, 2007). However, not all innovations can improve EFF (Jia and Zhang, 2013). Whether environmental regulation and technological progress can affect EFF also needs further exploration. Therefore, studying the relationship between environmental regulation, technological innovation, and EFF, as well as how to reduce environmental pollution and improve EFF, has become an issue of great concern to academia, the Chinese government, and even the world. This is an important practical value to meet the era requirements of China's eco-efficient development economy.

The study on this issue has many meanings. First, it is beneficial to explore the impact mechanism of environmental regulation and technological innovation on EFF. Theoretically, the relationship is explored between environmental regulation and technological innovation to EFF to provide theoretical support for energy conservation and emission reduction in developing countries. The second aspect is helpful to clarify the differences in the impact of EFF among the three major regions of China in the process of economic development, which provides a reference for the balanced economic development of various regions in China. The third point is conducive to reducing pollution emissions and improving the environment, making the economy of various regions in China shift to the

green growth of low energy consumption and high output, and providing a certain reference for other countries when formulating energy policies.

This study has three main contributions: first, it explores the mechanism of environmental regulation and technological innovation on China's EFF. The impact of this mechanism on EFF of the three regions in China is quite different; the internal reasons for its impact on EFF are also different. This provides a theoretical reference for China to save energy, reduce emissions, and improve EFF in the process of economic development. Secondly, the cross-terms of environmental regulation and technological innovation have significant positive effects on EFF in different regions. However, the coefficients are different, and the impact coefficients are different at the same time. This indicates that part of technological innovation and part of environmental regulation are put into the production process of energy saving and efficiency improvement, which improved the EFF. This can further explain why scientific and technological innovation has a positive or negative impact on EFF in the literature. Thirdly, the EFF of the three regions is approximately N-shaped, and it is concluded that the EFF of the economically developed regions is sometimes lower than that of the undeveloped regions.

The idea of this study is divided into five parts. The first part is an introduction, which explains the research background, significance, and contributions. The second part is the literature review, which summarizes the impact of environmental regulation, technological innovation, and the two variables on EFF. The third part is the study design, which mainly introduces the undesired superefficiency SBM model, Tobit models, and variable setting. The fourth part is the analysis of empirical results. It includes whether the Tobit model needs to contain the cross-term, the selection of the random Tobit model, and the quantitative analysis of the influence on EFF of the three major regions and the whole country in the random Tobit model. The fifth part is the research conclusions and suggestions. Based on the measurement results and the existing research, this study sorts out the research conclusions and puts forward suggestions.

2 Literature review

EFF means that the actual energy input was optimal when the production output was fixed (Patterson, 1996). In the early research of EFF, the traditional DEA and SFA models were mostly applied. Such models did not consider the impact of undesired output, and the results of the models were difficult to reflect the true level of EFF. Therefore, some scholars began to use the superefficiency DEA method and build the SBM model that can deal with unwanted output to study EFF (Fan and Wang, 2013).

2.1 Impact of environmental regulation on EFF

At present, environmental regulation has made remarkable achievements in controlling environmental pollution, but there were differences in the research views on the impact of environmental regulation on EFF.

- (1) Environmental regulation had a negative impact on EFF “following costs” because environmental regulation increased pollution control costs of enterprises, which directly increased production costs. Thus, EFF can be reduced by environmental regulation. [Jorgenson and Wilcoxon \(1990\)](#) reported that environmental regulation led to the decline in the gross national product, through their empirical research on the economic growth of the United States through environmental regulation. [Levinsohn and Petrin \(2003\)](#) concluded that the high cost of pollution control in the US paper industry had a dampening effect on the productivity of the paper industry. [Li et al. \(2019\)](#) pointed out that the reduction of EFF had only become apparent when the intensity of environmental regulation increased to a certain extent.
- (2) Environmental regulation positively affects “innovation compensation” on EFF, which improves EFF. Environmental regulation forces enterprises to perform energy-saving technology innovation, which reduces the demand for energy under the condition of constant output, which improves the energy intensity. [Porter \(1991\)](#) proposed that environmental regulation, in an appropriate way, had offset the constraint of “compliance cost” and had improved the level of enterprise productivity. [Costantini and Crespi's \(2008\)](#)’ research showed that the dynamic impact of environmental regulation on the export of energy technology improved the efficiency under the background of international trade, which was in line with Porter’s hypothesis. [Mandal \(2010\)](#) conducted an empirical study on India’s cement industry and found that environmental regulation reduced pollution and improved EFF. [Bi et al. \(2014\)](#) suggested that limiting pollutant emissions improved EFF by comparing the change of total factor EFF in the thermal power generation industry, which was the idea of improving EFF that [Peng \(2020\)](#) also supported.
- (3) Environmental regulation may have a nonlinear effect on increasing or decreasing EFF. According to [Yang et al. \(2016\)](#), there was an inverted U-shaped relationship between environmental regulation and EFF. When environmental regulation reached certain conditions, per capita energy consumption was reduced. [Albrizio et al. \(2017\)](#) found that regulation intensity had different effects on the productivity growth of enterprises with different productivities. For enterprises with high productivity,

strict environmental regulations boosted their productivity, while for enterprises with low productivity, strict environmental regulation reduced their product productivity. [Hu et al. \(2019\)](#) believed that environmental regulation had a positive effect of U-shaped on the EFF and a lower environmental regulation, leading to reduced EFF.

2.2 Impact of technological innovation on EFF

It is almost common sense that technological innovation, as the main source of technological progress, contributes to EFF. However, there are two types of technological innovation ([Lee, 2010](#)). The first category is product innovation, which refers to technological innovation based on product design changes, and the second category is process innovation, which refers to technological changes in the production (service) process, which is an effective part of improving energy utilization. Although there are a lot of research achievements in the field of technological progress and EFF at home and abroad, most of the literature from unilateral or involving other factors. However, few studies directly describe the relationship between technological innovation and EFF ([Trianni et al., 2013](#)).

- (1) Technological innovation has a positive impact on EFF; it improves EFF by saving scarce production factors and changing the proportion of the marginal output of each factor. Technological progress was originally proposed by [Hicks \(1932\)](#), who believed that technological progress had been the use of abundant production factors to save scarce production factors and who divided it into capital-saving, labor-saving, and neutral technological progress. [Acemoglu \(2002\)](#) believed that technological progress had changed the proportion of the marginal output of each factor and the use ratio of energy factors to non-energy factors, thus improving EFF. [Bala Subrahmanya and Kumar \(2011\)](#) concluded from their study of SMEs in the Indian machine tool industry that technological innovation activities aimed at saving production costs contribute to improving EFF. [Ramirez-Portilla et al. \(2014\)](#) confirmed the positive correlation between innovation and EFF of enterprises. After their research on Italian foundry companies, [Cagno et al. \(2015\)](#) found that companies of high innovation activity preferred to use energy-saving technologies to improve EFF. [Herrerias et al. \(2016\)](#) supported that technological innovation had a significant co-directional impact on EFF.
- (2) Technological innovation has a negative or insignificant impact on EFF, which would reduce EFF. [Sun et al. \(2011\)](#) believed that due to the diversity of expenditure on technological innovation in the industry, EFF had a negative impact when technological expenditure was mainly used for product design rather than for the improvement of

production process efficiency. Luo et al. (2015) showed that technological innovation had no significant impact on EFF and sometimes had a negative impact. Wang and Wang (2020) used the exponential decomposition method and the regression method to prove that excessive investment in technological progress did not significantly improve EFF. The reason was caused by the diversity of the expenditure direction of technical funds and the great difference in the investment of technical funds in various industries.

2.3 Impact of environmental regulation and technological innovation on EFF

There were few studies on the relationship between environmental regulation, technological innovation, and EFF. In the long run, energy consumption was reduced only when the positive effect of “innovation compensation” was greater than the negative effect of “compliance cost” (Jaffe and Stavins, 1995; Liu et al., 2017). Managi et al. (2005) studied the natural gas and oil industry in the Gulf of Mexico and found that environmental regulation and technological innovation had a negative impact on the energy intensity in the current period, which had a positive impact on energy intensity in the lagged period. According to Yang and Zhu (2017), technological innovation in eastern and central China had no significant positive impact on EFF under environmental regulation. However, in western China, it had a significant negative impact.

In summary, most of the literature mainly studied the impact of environmental regulations on EFF of a certain enterprise from the micro-perspective and rarely considered the impact of environmental regulations under macro-policies. Regarding the relationship between technological innovation and EFF, the research literature based on Chinese data has not formed a consistent empirical conclusion. As for the views contrary to common sense, the formation mechanism behind them also lacked in-depth discussion in the relevant literature. Most of the literature on the relationship between the three aspects was qualitative judgment, which cannot quantitatively explain the impact of environmental regulation and technological innovation on industrial energy consumption. Based on the research of the above scholars and the provincial panel data of China from 2001 to 2019, this study used the undesired superefficiency SBM model to calculate the EFF with undesired output, which built the Tobit model of EFF on this basis. It further analyzed the magnitude and direction of the impact of environmental regulation and technological innovation on EFF in China's three major regions while discussing the impact of their cross-terms on EFF. This would provide a theoretical reference for the development of low-energy consumption and a green and sustainable economy in all regions of China. It also provided a reference for developing countries to

make energy policies. This was the innovation and unique value of this study.

3 Research methods and hypotheses

3.1 EFF measurement method

Currently, the superefficiency DEA model has been applied more in different fields, but there are not many related studies applying it to China's EFF evaluation. The research on energy and efficiency is not satisfied with the study of single-factor EFF, and the research on multi-factor EFF is the development tendency of future research in the field of EFF. Therefore, on the basis of relevant research at home and abroad, this study considers the following two aspects for improvement: first, carbon dioxide emissions and other pollution emissions are studied as unintended output indicators to examine the relationship between emission reduction and energy saving and EFF and second, the undesired superefficiency DEA model is used to study the EFF value of effective decision-making units and provides data basis for detailed research on improving EFF.

3.1.1 Selection of superefficiency DEA model

The DEA method is first proposed by Charnes and Cooper (1984). Up to now, the DEA model has been applied to mathematics, management science, and many other fields, but the original conventional DEA model is not applied to some fields of in-depth research with the research needs of scholars on DEA model, DEA model has also been further developed. When there is excessive input or insufficient output, the result of the decision-making unit (DMU) calculation will not conform to the objective reality. Therefore, to overcome the above problems, Tone (2001) created the measurement method of efficiency based on slack variables, that is, the SBM model.

The efficiency value calculated by the SBM model can be kept within the interval 0 to 1, and the efficient DMU takes the value of 1, whereas the DMU less than 1 is regarded as an invalid state. However, when quite a few DMUs are set to 1, we cannot compare efficient DMUs. Nevertheless, the efficiency value ρ is calculated by the superefficiency SBM model, which can be greater than or equal to 1, and which can perfectly compare the efficient DMUs in the SBM model. Modern production methods increase labor productivity, while industrial production inevitably generates a large amount of wastewater and gas (we call it undesirable output). Tone (2004), based on his own research, constructed an undesired superefficiency SBM model to calculate the true efficiency of the DMU.

Based on the research of Tone (2003) and Cheng (2014), this article constructed a non-radial and non-oriented SBM model with constant returns to scale (CRS) and non-expected

superefficiency. It used MATLAB software to calculate EFF to compare and analyze the efficiency.

The model assumed that there were n DMUs, and each DMU contained elements of input, desired output, and undesired output (e.g., carbon dioxide and wastewater), represented by three vectors X , Y , and Z , respectively. It was assumed that the DMU of the SBM model with undesired superefficiency in this study was (x_0, y_0, z_0) , and the formula was as follows:

$$\rho = \min \frac{1 + \frac{1}{m} \sum_{i=1}^m s_i^x / x_{i0}}{1 - 1/s1 + s2 \left(\sum_{k=1}^{s1} s_k^y / y_{k0} + \sum_{l=1}^{s2} s_l^z / z_{l0} \right)} \quad (1)$$

$$s.t. \begin{cases} \sum_{j=1, j \neq 0}^n x_j \lambda_j - s_i^x \leq x_{i0}, \forall i; \\ \sum_{j=1, j \neq 0}^n y_j \lambda_j - s_k^y \geq y_{k0}, \forall k; \\ \sum_{j=1, j \neq 0}^n z_j \lambda_j - s_l^z \leq z_{l0}, \forall l; \end{cases} \quad (2)$$

$$s.t. \left\{ 1 - \frac{1}{s1 + s2} \left(\sum_{k=1}^{s1} s_k^y / y_{k0} + \sum_{l=1}^{s2} s_l^z / z_{l0} \right) \right\} > 0 \quad (3)$$

$$s_i^x \geq 0, s_k^y \geq 0, s_l^z \geq 0, \lambda_j \geq 0, \forall i, j, l,$$

where $s^x \in s^m$ and $s^z \in s^2$ represent the excess of input and undesired output, respectively, and $s^y \in s^1$ represents the shortage of desired output. ρ stands for the efficiency value of the DMU. M , $S1$, and $S2$ stand for the number of variables for input, desired output, and undesired output. Eq. 1 satisfies constant returns to scale (CRS). If $\sum \lambda = 1$ is satisfied in Eq. 2, then Eq. 1 satisfies the case of variable returns to scale (VRS). Similar to the superefficient SBM model, the efficiency value ρ is calculated for the non-desired superefficient SBM model. When ρ is greater than or equal to 1, DMU is valid. On the contrary, it symbolizes that DMU is not effective and that there is room for improvement on DMU.

3.1.2 Variable selection and data sources

The undesired superefficiency SBM model of China's EFF in this study adopts three input indicators, one expected output index, and three unexpected output indicators. Among them, the input indicators include energy input and non-energy input (including capital input and labor input), and the EFF value is calculated by MATLAB software.

3.1.2.1 Variable choice

Energy is an avital input factor in the production process, which mainly includes coal, crude oil, natural gas, and other energy sources. Due to the differences in the energy consumption structure of each province, it is uniformly converted into "ten thousand tons of standard coal" and then summed up. The obtained total energy consumption is taken as the energy input (Tobin, 1958). In this study, all kinds of energy in each province

are converted into total energy consumption (Feng and Wang, 2015).

Capital input is represented by the fixed capital investment of each province after depreciation, and the depreciation rate of this study is calculated by the perpetual inventory method of Shan (2008):

$$K_t = K_{t-1} (1 - \delta_t) + I_t, \quad (4)$$

where K_t symbolizes the capital stock, I_t stands for the amount of investment, and δ_t represents the depreciation rate. The capital invested in this study is 10.28%, the average of 10.96% was estimated by Shan (2008), and 9.6% was estimated by Zhang et al. (2004), as the depreciation rate of each province in China.

Labor input, which is the best indicator to measure, is the labor time in the manufacturing process, but the data on labor time cannot be obtained. Therefore, referring to relevant literature, this study chooses to measure labor input by the "average number of employees in industrial enterprises above designated size" in each province (Ye and Li, 2022).

Desirable output, the pollutants emitted by energy consumption are mainly air pollution and water pollution. It is also the undesired output of energy consumption to the output of the environment. The existing literature mostly uses the gross product as the expected output, and the expected output of this study selects the adjusted GDP of each regional gross product index as the measurement index (Li and Li, 2018). To consider the year 2000 as the base period, divide the GDP of each region by the GDP deflator and get the real GDP, which is the expected output.

- Undesirable output, the pollutants emitted by energy consumption are chiefly air and water pollution. It is also the undesired output of energy consumption to the environment. By referring to the methods adopted by Managi and Kaneko (2006) and Watanabe and Tanaka (2007), the undesired output is measured by CO₂, SO₂, and industrial wastewater emissions, as shown in Table 1.

3.1.2.2 Data sources

According to the research purpose and data availability, this study considers 30 provinces, municipalities, and autonomous regions of China (hereinafter referred to as "provinces") as independent decision-making units and selects EFF panel data from 2001 to 2019, among which Tibet, Hong Kong, Macao, and Taiwan are not included due to missing data. According to the principle of combining economic development level and geographical location, China is divided into three major economic zones: eastern, central, and western. The eastern region includes Beijing, Hainan, and 11 other provinces. The central region includes eight provinces, such as Shanxi and Hunan. The western region includes 11 provinces, including Inner Mongolia and Xinjiang.

TABLE 1 Input–output variation table of the DEA model.

Name element	Variable name	Name of code	Meaning of variables	Units
Input factor	Total energy consumed	Energy	It is expressed by converting the total energy consumption of each province into “10,000 tons of standard coal”	Ten thousand tons
	Investment capital	Invest	Expressed as a fixed capital investment in each province (calculated by perpetual inventory method)	One hundred million yuan
	Labor input	Labor	Expressed by the average number of employees of industrial enterprises above the designated size in each province	thousands of people
Desirable output	GDP	GDP	Divide the GDP of each region by the GDP deflator (with 2,000 as the base period) to get the real GDP	One hundred million yuan
Undesirable output	Carbon emission	CO ₂	Total regional CO ₂ emissions	Ten thousand tons
	Industrial wastewater	Indus-Water	Total industrial wastewater discharge in the region	Ten thousand tons
	Waste gas	SO ₂	The total amount of SO ₂ emissions in the region	Ten thousand tons

TABLE 2 Average EFF of China's 30 provinces from 2001 to 2019 (unit, none).

ID	PROV	Mean	Max	Min	ID	PROV	Mean	Max	Min
1	Beijing	0.6486	1.2159	0.0384	18	Hubei	0.3143	1.1352	0.0036
2	Tianjin	0.3367	0.7148	0.0262	19	Hunan	0.3114	0.5666	0.0419
3	Hebei	0.2523	1.1482	0.0016	20	Inner Mongolia	0.2097	0.5453	0.0049
4	Liaoning	0.3639	1.1272	0.0030	21	Guangxi	0.5056	1.2205	0.0348
5	Shanghai	0.5391	1.1254	0.0043	22	Chongqing	0.4112	1.2037	0.0097
6	Jiangsu	0.2785	0.6283	0.0110	23	Sichuan	0.3481	1.0220	0.0258
7	Zhejiang	0.3167	1.1064	0.0014	24	Guizhou	0.2629	1.1416	0.0393
8	Fujian	0.4833	1.0452	0.0064	25	Yunnan	0.3369	1.3006	0.0072
9	Shandong	0.2300	0.5348	0.0155	26	Shanxi an	0.3759	1.1413	0.0367
10	Guangdong	0.4599	1.0669	0.0017	27	Gansu	0.4261	1.1469	0.0423
11	Hainan	0.9692	1.2111	0.0928	28	Qinghai	0.5325	1.2513	0.0333
12	Shanxi	0.1687	0.3601	0.0158	29	Ningxia	0.6739	1.2772	0.1774
13	Jilin	0.2607	0.5104	0.0397	30	Xinjiang	0.2558	1.0317	0.0062
14	Heilongjiang	0.4014	1.0251	0.0034	31	Nation	0.3824	0.5753	0.1730
15	Anhui	0.2388	0.4856	0.0317	32	East	0.4435	0.8337	0.0851
16	Jiangxi	0.3553	1.1152	0.0063	33	Central	0.2817	0.5257	0.0364
17	Henan	0.2032	0.4542	0.0051	34	West	0.3944	0.6130	0.2018

Among them, the data of each input variable are summarized from the data center of the National Bureau of Statistics of China and the statistical yearbooks of various provinces. The research data of expected and unexpected outputs are mainly summarized from the China Energy Statistical Yearbook, China Statistical Yearbook, and China Environmental Statistical Yearbook from 2001 to 2019.

3.1.2.3 Descriptive statistics of DEA model variables

In the process of calculating the EFF of China's 30 provinces by the DEA model, we not only study the overall EFF of China

but also divide China's 30 provinces into three regions and make a comparative analysis of the EFF of the three regions. Between 2001 and 2019, the average EFF in the east was 0.4435, the maximum value was 0.8337, and the minimum value was 0.0851. The mean value of EFF in the central region is 0.2817, the maximum value is 0.5257, and the minimum value is 0.0364. In the west, the mean value of EFF is 0.3944, the maximum value is 0.6130, and the minimum value is 0.2018. The national average EFF is 0.3824, the maximum is 0.5753, and the minimum is 0.1730. The order of EFF of the three economic zones from high to low is eastern, western, and central.

TABLE 3 EFF statistics of China’s eastern, central, western, and national regions from 2001 to 2019 (unit, none).

EFF	Nation	East	Central	West	EFF	Nation	East	Central	West
2001Y	0.5732	0.8337	0.5098	0.3589	2011Y	0.31	0.2361	0.0754	0.5546
2002Y	0.5675	0.8264	0.5088	0.3512	2012Y	0.173	0.0851	0.0899	0.3212
2003Y	0.5499	0.7875	0.4759	0.3662	2013Y	0.216	0.1444	0.1802	0.3137
2004Y	0.5623	0.8079	0.4864	0.3718	2014Y	0.3376	0.2328	0.17	0.5643
2005Y	0.5753	0.7995	0.5257	0.3873	2015Y	0.2363	0.1448	0.0479	0.4649
2006Y	0.565	0.8002	0.5192	0.363	2016Y	0.3048	0.1819	0.2578	0.4618
2007Y	0.5488	0.7862	0.501	0.3462	2017Y	0.2042	0.2304	0.1716	0.2018
2008Y	0.5486	0.7865	0.4965	0.3486	2018Y	0.3589	0.2395	0.1736	0.613
2009Y	0.183	0.2391	0.0413	0.2299	2019Y	0.2034	0.1491	0.0364	0.3792
2010Y	0.2468	0.1148	0.0853	0.4964	—	—	—	—	—

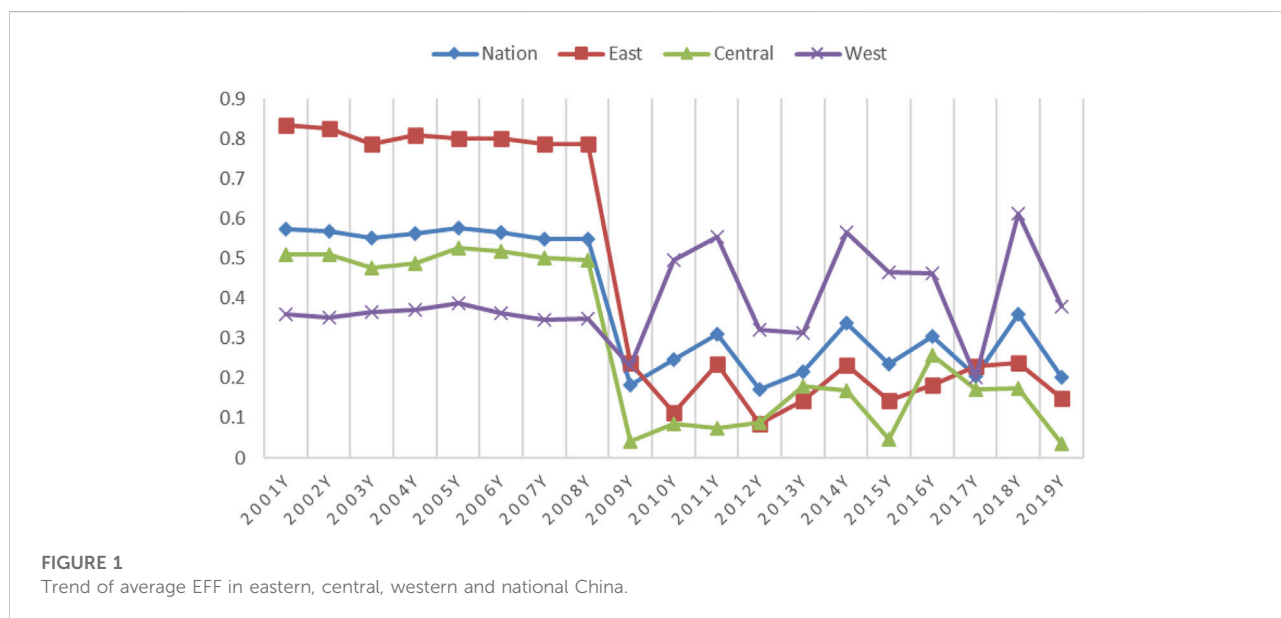


FIGURE 1 Trend of average EFF in eastern, central, western and national China.

Meanwhile, among the 11 eastern provinces, the average EFF of Hainan province is the highest (0.9692), and that of Shandong province is the lowest (0.2300). Among the 11 western provinces, the highest EFF is 0.6739 in Ningxia, and the lowest is 0.2097 in Inner Mongolia. Among the eight provinces in central China, Heilongjiang province has the highest average EFF of 0.4014, whereas Henan province has the lowest average EFF of 0.2032, as shown in Table 2.

From the average change trend (shown in Table 3), the EFF of each region is between 0 and 0.9. From 2001 to 2008, the EFF of the three major regions fluctuated slowly, and the order of EFF from high to low was the eastern, central, and western regions. The period 2008–2009 was a watershed in EFF from high to low, with a decline in EFF in all regions.

Between 2009 and 2019, the EFF of the eastern, central, and western regions of China all fluctuated greatly. The EFF of the western region jumped up and became the most energy-efficient region. Then, the eastern region was the second high and the lowest in the central region. The trend of EFF across the country is extremely similar to that of the eastern region, and the values for each year are the average of the EFF of the three major regions, as shown in Figure 1.

After comparing the EFF of the three regions, the average trend line of EFF in the west is the highest, the average trend line of EFF in the central is the second highest, and the average trend line of EFF in the east is the lowest. The EFF of the national average has a very similar trend to the average of the eastern region. There is a high possibility that this phenomenon is caused by the undesired output in the EFF model. In other words, in the

economic development of various regions in China, not only the economic output, but also the emissions of environmental pollution are concerned.

3.2 Analysis method of influencing factors of EFF

3.2.1 Tobit model construction

The classic Tobit model is a generalization of the Probit probability regression model in Tobin J's research, which is a regression model with limited dependent variables (Chen et al., 2022). Although the superefficiency DEA model in this study can calculate the EFF value of each DMU, it cannot estimate the magnitude and direction of the factors affecting EFF based on slack variables. Therefore, this study introduces the Tobit regression model and establishes a superefficiency DEA-Tobit two-stage model system to analyze the influencing factors of EFF.

The Tobit regression model criterion is defined as follows:

$$Y_i = \beta_i X_i + \mu_i, \mu_i \sim N(0, \sigma_{\mu_i}^2), i = 1, 2, \dots, n, \quad (5)$$

$$Y_i = Y_i, Y_i > 0; Y_i = 0, Y_i < 0;$$

where Y_i is the explained variable, namely, the EFF value of each province in China, X_i is the explanatory variable, namely, the influencing factor of each province, β_i is the required parameter vector, and μ_i is the random error vector. When Y_i is greater than 0, the actual EFF data value is taken, and when it is less than 0, the average value of EFF is 0.

This study assumes that the Tobit model of EFF is as follows:

$$EFF_{it} = \alpha_i + \beta_1 ER_{it} + \beta_2 TI_{it} + \beta_3 PGDP_{it} + \beta_4 IS_{it} + \beta_5 ENST_{it} + \beta_6 OPEN_{it} + \mu_{it}$$

$$\mu_{it} \sim N(0, \sigma_{\mu_{it}}^2), i, t = 1, 2, \dots, n$$

$$Y_{it} = Y_{it}, Y_{it} > 0; Y_{it} = 0, Y_{it} < 0. \quad (6)$$

Among them, EFF stands for EFF, ER is energy regulation, TI is technological innovation, PGDP stands for economic development, IS is industrial structure, ENST represents energy structure, OPEN represents the degree of opening to the outside world, i represents the cross-section of each province, and t represents the year.

In Eq. 7, M represents the cross-term of energy regulation and technological innovation that affects EFF simultaneously. The definitions of the remaining variables are the same as those in Eq. 6:

$$EFF_{it} = \alpha_i + \beta_1 ER_{it} + \beta_2 TI_{it} + \beta_3 M_{it} + \beta_4 PGDP_{it} + \beta_5 IS_{it} + \beta_6 OPEN_{it} + \beta_7 ENST_{it} + \mu_{it}$$

$$\mu_{it} \sim N(0, \sigma_{\mu_{it}}^2), i, t = 1, 2, \dots, n$$

$$Y_{it} = Y_{it}, Y_{it} > 0; Y_{it} = 0, Y_{it} < 0. \quad (7)$$

3.2.2 Variable selection and data sources

3.2.2.1 Variable selection

The Tobit model is calculated by STATA software. The model calculation mainly involves the following three types of

variables: explained variables, core explanatory variables, and control variables. As for the explained variable EFF, different scholars have different understandings of it and different methods for calculating EFF. This study uses the non-expected superefficiency SBM model to calculate the EFF of each province and takes the EFF of each province as the explained variable of the Tobit model.

The core explanatory variables of this study are the environmental regulation and technological innovation of each province, which is also the focus of this study. It should be noted that if the explanatory variables used for EFF are different, the conclusions may be inconsistent.

Environmental regulation (ER), according to the practice of most scholars, is expressed by the completion of the investment in industrial pollution control per thousand yuan of industrial added value (Wang and Zhong, 2015), that is, the actual amount of industrial pollution control investment in each province (hundred million yuan) divided by the actual value of industrial added value (hundred million yuan) and then multiplied by 1,000.

For technological innovation (TI), this study draws on Dong Huazhong to express the ratio of the research and experimental development expenditure (100 million yuan) of each province to the GDP of each province (Zhang et al., 2021). Many scholars use research and experimental development expenditures as technological innovations, but separate research and experimental development expenditures contain inflationary factors. Therefore, this study uses the ratio of it to provincial GDP to eliminate inflationary factors.

In order to avoid bias due to the omission of other variables in the EFF estimation, this study introduces four control variables: economic development level, industrial structure, energy structure, and degree of opening to the outside world.

- The level of economic development (PGDP) is expressed by the per capita GDP of each region, that is, PGDP, to measure the level of economic development (Dai and Fu, 2020; Wang, 2022). Industrial structure (IS) is caused by the different dependences of industries on labor and energy in different regions. Considering that the secondary industry is the main factor of energy consumption in China, this study adopts the proportion of the total output value of the secondary industry in each region as the ratio of the total industrial output value of each region as the industrial structure (Mu et al., 2022). Energy structure (ENST, is expressed by the proportion of coal consumption (converted to standard coal) in each province to the total energy consumption (converted to standard coal) of each province (Torrie et al., 2016). The degree of opening to the outside world (OPEN), usually the degree of openness of a country's economy, is related to the country's resource endowment, the size of the country, and the nature of its economic system. This study uses the ratio

TABLE 4 Explanatory variables and control variables in the Tobit model.

Types of variables	Variable name	Variable code	Variable connotation	Unit
Explanatory variables	Environmental regulation	ER	The completed investment in industrial pollution control per 1,000 yuan of industrial added value in each province	
	Technological innovation	TI	Ratio of provincial expenditure on research and experimental development to provincial GDP	
	The cross-term of environmental regulation and technological innovation	M	Equal to variable ER multiplied by variable TI	
Control variables	Economic development level	PGDP	Expressed by the per capita GDP of each region	Ten thousand yuan
	Industrial structure	IS	Use the ratio of the total output value of the secondary industry in each region to the total output value of the regional industry	
	Energy structure	ENST	The proportion of coal consumption (converted to standard coal) in each province to the total energy act consumption (converted to standard coal) of each province in the energy structure	
	Degree of openness	OPEN	It is calculated by the ratio of the total import and export volume of the region to the regional GDP	

TABLE 5 Statistics of Tobit variables.

Variable	Options	Mean	Std. Dev	Min	Max	Observations
EFF	Overall	0.382	0.377	0.0014	1.301	N = 570
	Between		0.169	0.169	0.969	n = 30
	Within		0.338	-0.494	1.346	T = 19
ER (%)	Overall	7.510	5.010	2.580	34.070	N = 570
	Between		4.619	2.907	22.257	n = 30
	Within		2.107	-1.543	25.597	T = 19
TI (%)	Overall	0.0142	0.011	0.001	0.063	N = 570
	Between		0.010	0.004	0.053	n = 30
	Within		0.004	-0.003	0.029	T = 19
M (M = ER*TI) (%)	Overall	0.100	0.087	0.011	0.491	N = 570
	Between		0.079	0.024	0.350	n = 30
	Within		0.039	-0.042	0.336	T = 19
PGDP (104 yuan)	Overall	2.156	1.410	0.294	8.462	N = 570
	Between		1.101	1.050	5.375	n = 30
	Within		0.903	-0.466	5.243	T = 19
IS (%)	Overall	0.429	0.081	0.160	0.620	N = 570
	Between		0.069	0.219	0.532	n = 30
	Within		0.043	0.242	0.535	T = 19
ENST (%)	Overall	0.458	0.164	0.012	0.868	N = 570
	Between		0.136	0.170	0.682	n = 30
	Within		0.094	0.202	0.798	T = 19
OPEN (%)	Overall	0.315	0.374	0.002	1.711	N = 570
	Between		0.360	0.006	1.264	n = 30
	Within		0.122	-0.170	0.863	T = 19

TABLE 6 Correlation test.

Variables	ER	TI	PGDP	IS	ENST	OPEN	M
(1) ER	1.000						
(2) TI	-0.130 (0.002)	1.000					
(3) PGDP	-0.192 (0.000)	0.793 (0.000)	1.000				
(4) IS	-0.210 (0.000)	-0.222 (0.000)	-0.228 (0.000)	1.000			
(5) ENST	0.097 (0.021)	-0.492 (0.000)	-0.671 (0.000)	0.344 (0.000)	1.000		
(6) OPEN	-0.203 (0.000)	0.607 (0.000)	0.570 (0.000)	-0.067 (0.108)	-0.527 (0.000)	1.000	
(7) M	0.546 (0.000)	0.727 (0.000)	0.489 (0.000)	-0.328 (0.000)	-0.339 (0.000)	0.345 (0.000)	1.000

of regional total import and export to regional GDP to measure. The unit of total import and export is US dollars, whereas the unit of regional GDP is RMB. Therefore the approximate conversion is made at the exchange rate of US dollars to RMB at the end of each year (Wu et al., 2017), as shown in Table 4.

3.2.2.2 Data sources

The data of the explained variables are derived from the calculation results of the undesired superefficiency SBM model in this study. The data of explanatory and control variables come from the 2001–2019 “China Energy Statistical Yearbook,” “China Statistical Yearbook,” “China Environmental Statistical Yearbook,” the data center of the National Bureau of Statistics, and the statistical yearbooks of various provinces.

3.2.2.3 Descriptive statistics of variables in the Tobit model

In the process of calculating the influence of variables on EFF by the Tobit model, there were 570 EFF samples of panel data in all provinces, among which the mean of EFF was 0.382, the maximum value was 1.301, the minimum value was 0.0014, and the standard deviation was 0.377.

The mean value of environmental regulation (ER) was 7.510, the maximum value was 34.070, the minimum value was 2.580, and the standard deviation was 0.377. The mean value of technological innovation (TI) was 0.014, the maximum value was 0.063, the minimum value was 0.001, and the standard deviation was 0.011. The mean value of the cross-term ($M = ER \times TI$) was 0.100, the maximum value was 0.491, the minimum value was 0.011, and the standard deviation was 0.087. The mean, maximum, and minimum values and standard deviation of the four control variables are recorded in detail in Table 5.

TABLE 7 Four model outputs without cross-terms: OLS, fixed effect, and Tobit model.

	LS	Fe	Tobit
ER	-0.0049 (0.0030)	-0.0303*** (0.0078)	-0.0168** (0.0059)
TI	-4.5461 (2.3575)	-30.2454*** (5.3905)	-15.5231*** (4.5898)
PGDP	-0.1297*** (0.0194)	-0.0152 (0.0303)	-0.0722* (0.0293)
IS	-0.8329*** (0.1946)	-0.5552 (0.4252)	-0.5706 (0.3111)
ENST	-0.3565** (0.1266)	0.1358 (0.2245)	-0.0077 (0.1925)
OPEN	0.4609*** (0.0510)	0.4751*** (0.1252)	0.5553*** (0.0773)
_cons	1.1372*** (0.1111)	1.0956*** (0.2831)	0.9567*** (0.2020)
sigma_u	3.0172	0.2915	0.2132*** (0.0382)
sigma_e	—	0.2996	0.3016*** (0.0094)
N	569	569	569

Standard errors in parentheses, * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (the * in the following table in this article has the same meaning).

The “overall” option represents the statistical description of the whole sample, “between” represents the statistical description of the 30 provinces, and “within” represents the statistical description of the 19 years in Table 5. These three options have different parameters in descriptive statistics except for the same mean value.

TABLE 8 Four model outputs with cross-terms: OLS, fixed effect, and Tobit model.

	LS	Fe	Tobit
ER	-0.0143 (0.0085)	-0.0702*** (0.0124)	-0.0525*** (0.0116)
TI	-10.7713 (5.8064)	-51.7000*** (7.4643)	-37.1713*** (7.4104)
PGDP	-0.1234*** (0.0201)	0.0053 (0.0303)	-0.0451 (0.0296)
IS	-0.8257*** (0.1946)	-0.4207 (0.4203)	-0.4653 (0.3220)
ENST	-0.3328** (0.1281)	0.3117 (0.2254)	0.1395 (0.1986)
OPEN	0.4664*** (0.0512)	0.4862*** (0.1234)	0.5588*** (0.0802)
M	0.8469 (0.7220)	3.4085*** (0.8330)	2.9437*** (0.8137)
_cons	1.1819*** (0.1175)	1.1742*** (0.2796)	1.0661*** (0.2128)
sigma_u	—	—	0.1967*** (0.0371)
sigma_e	—	—	0.2962*** (0.0092)
N	569	569	569

TABLE 9 Regression output of OLS, mixed OLS-Tobit, and random Tobit models.

	OLS	OLS-Tobit	Tobit
ER	-0.0702*** -0.0124	-0.0143 -0.0084	-0.0525*** -0.0116
TI	-51.7000*** -7.4643	-10.7713 -5.7655	-37.1713*** -7.4104
PGDP	0.0053 -0.0303	-0.1234*** -0.02	-0.0451 -0.0296
IS	-0.4207 -0.4203	-0.8257*** -0.1933	-0.4653 -0.322
ENST	0.3117 -0.2254	-0.3328** -0.1272	0.1395 -0.1986
OPEN	0.4862*** -0.1234	0.4664*** -0.0508	0.5588*** -0.0802
M	3.4085*** -0.833	0.8469 -0.7169	2.9437*** -0.8137
_cons	1.1742*** -0.2796	1.1819*** -0.1166	1.0661*** -0.2128
var (e.)	0.1089*** -0.0065	0.1086*** -0.0064	—
sigma_u	—	—	0.1967*** -0.0371
sigma_e	—	—	0.2962*** -0.0092
log-likelihood	—	-146.98	-149.41
Wald R2	—	—	154.35***
Pseudo R2	—	0.296	—
rho	—	—	0.3063
LR	—	49.4	55.15

4 Empirical process and results analysis

4.1 Correlation test

After the correlation analysis of all variables affecting EFF in the TOBIT model, the correlation coefficients between almost all explanatory and control variables were less than 0.3. Empirically, there is no correlation between them. Meanwhile, the values in parentheses are *p*-values, and most of the *p*-values are less than 0.05. Therefore, it can be judged that the variables are significantly uncorrelated. Detailed data are shown in Table 6. Therefore, it is necessary to further carry out regression or Tobit analysis on the data.

4.2 Selection of model

4.2.1 Selection of Tobit model and cross-term M

4.2.1.1 Comparison and selection of four models

For the energy panel data of 30 provinces in China, this study first performs OLS, random effects, fixed effects, and Tobit

regression on formula (5), and their output calculation results are shown in Table 7. At the same time, the regression model was tested by the Houseman test. The Houseman test result showed that the *p*-value was 0.00 and less than 0.05, which was significant. For this purpose, we chose the fixed effects model.

Secondly, after selecting the fixed effect model, it was compared with the output results of the OLS and Tobit regression model. In the output results of these models (see Table 7), we clearly found that the Tobit model has a better significance of the variables and the residual has better significance when compared with the other three models. Therefore Tobit's model is superior.

4.2.1.2 Comparative selection of models with or without the cross-term

Of course, Table 7 is the consequence of the model calculation without the cross-term (M). For Eq. 6 with cross-

TABLE 10 Multicollinearity test of OLS regression model for time series.

Variable	M	STP	ER	PGDP	ENST	OPEN	IS	Mean VIF
VIF	20.18	19.32	9.32	4.12	2.27	1.89	1.26	8.34

term (M), we conduct OLS, fixed effect, and Tobit regression calculation, and the results are shown in Table 8.

In the comparison between the Tobit model without and with cross-term M, this study has more significant variables and smaller residuals. Therefore, it is better to choose the Tobit model with cross-term M.

4.2.2 Comparison and selection of random Tobit models

After the selection of the Tobit model is determined, it is necessary to further determine the type of Tobit model to be selected. To this end, it is necessary to compare and analyze the three regression models of OLS, mixed OLS-Tobit, and stochastic Tobit for the EFF model. Then, we found that the number of significant variables in the stochastic Tobit model was more than that in other models, and the residual significance was also better than other models. Moreover, the Wald test results are significant, indicating that the hypothesis of individual effect exists; in other words, the mixed Tobit model is rejected. Finally, the LR test of the Tobit model is significant, indicating that the random Tobit model passes the overall test. Therefore, using the random Tobit model for the regression calculation in this study is appropriate. The specific calculation results are shown in Table 9.

4.2.3 Multicollinearity test of random TOBIT model

In time series data model, a multicollinearity test is usually performed, which is judged by the VIF of the value inflation factor. For example, if the panel data composed of provinces and time in this study are regarded as time series data, the VIF value can be calculated to judge whether the model in this study was multicollinearity. The data are shown in Table 10.

In Table 10, the VIF values of some variables are more than 10, indicating that there is collinearity in the Tobit model.

However, the model data in this study are panel data, and VIF values are generally not calculated for random Tobit models. When using STATA software to calculate, if there is complete multicollinearity in the Tobit model, STATA software will automatically omit collinearity variables. For incomplete multicollinearity, we can ignore it if we do not care about the specific regression coefficients and only care about the ability of the whole equation to predict the explained variable, or we can ignore it if we care about the specific regression coefficients. However, multicollinearity does not affect the significance of the variable of interest (Stock and

TABLE 11 Comparison of Tobit model results in the eastern, central, western, and national regions.

	East	Central	West	Nation
ER	-0.0599* (0.0283)	0.0228 (0.0200)	-0.0341 (0.0196)	-0.0495*** (0.0112)
TI	-28.6689** (8.8812)	4.6209 (16.4046)	-28.4623 (16.0901)	-34.6153*** (7.1354)
M	2.5583* (1.1471)	3.3219* (1.6875)	3.2898* (1.6662)	2.7473*** (0.7964)
PGDP	-0.1553*** (0.0277)	-0.1228* (0.0516)	0.0384 (0.0355)	-0.0622** (0.0224)
IS	-2.2788*** (0.4146)	—	0.7147 (0.7405)	-0.4563 (0.3184)
OPEN	0.6687*** (0.0788)	0.6608 (0.6109)	-0.6712 (0.3807)	0.5531*** (0.0764)
_cons	2.0791*** (0.3117)	0.4769** (0.1559)	0.4262 (0.3758)	1.1266*** (0.1864)
sigma_u	0.1164** (0.0400)	0.0991* (0.0403)	0.1541** (0.0503)	0.1894*** (0.0349)
sigma_e	0.2752*** (0.0140)	0.2230*** (0.0134)	0.3255*** (0.0166)	0.2972*** (0.0092)
log-likelihood	-35.04	6.148	-71.13	-149.69
Wald	222.16***	67.48***	7.55	173.95***
rho	0.151	0.164	0.183	0.288
LR	10.91***	6.89***	11.93***	61.11***
N	209	152	209	570

Watson, 2003). It is necessary to study whether multicollinearity causes insignificant results only if the coefficient of the core variable is insignificant.

As shown in the above description, incomplete multicollinearity exists in the Tobit model. When the core explanatory variables, environmental regulation (ER), technological innovation (TI), and cross-term (M), are put into the Tobit model together, the coefficients of these three variables are significant. When all the control variables are put into the model, the coefficients of several variables, including the core variables, are insignificant. However, when the ENST variable is removed, the coefficient significance of the core variable is greatly improved. When the IS variable is removed again, the coefficient significance of the core variable is little improved.

Therefore, according to Table 9 and the idea of the stepwise regression method, the insignificant variable ENST is deleted from the random Tobit model.

4.3 Analysis of results

According to the panel data of China's EFF, we divide panel data into four different regions: the eastern, central, western, and national regions. The Tobit models of the four regions were analyzed and compared. The model running results are shown in Table 11.

On the whole, the national and eastern models are very similar. In other words, the correlation coefficients of the explanatory variables of the national and the eastern models are inconsistent. However, the direction and significance of the correlation coefficients are the same except for "IS." In order to avoid repetition, the following mainly introduces the eastern, central, and western models.

The overall comparison of the eastern, central, and western models shows that the direction, magnitude, and significance of their correlation coefficients are quite different. In the Tobit models of EFF, the LR test of the EFF model is passed in the eastern, central, and western regions, and the model is significant. However, the LR test failed in the central model. In the eastern and national models, the core explanatory variables ER, TI, and the cross-term (M) passed the significance test. In the central and the western models, only the crossover variable M is significant, except for ER and TI.

4.3.1 The EFF shows large and regular fluctuations in eastern, central, and western regions after 2008

From the trend of mean value change (Figure 1), there is the watershed on EFF change of the three regions in 2008. Before 2008, the EFF of the first three regions fluctuated slowly, and the order of their EFF from high to low was eastern, central, and western regions, respectively. This was in line with the general perception that the EFF of economically developed regions was higher than that of underdeveloped regions. After 2008, the EFF of the three regions fluctuated greatly. The EFF has declined significantly in the eastern and central regions, whereas EFF has risen to a certain extent and has become the most energy-efficient in the western region. It would be concluded that the EFF of economically developed regions was sometimes lower than that of underdeveloped regions.

The EFF in the national region is the overall average of the three regions, and its fluctuation pattern is similar to that of the eastern region. However, the decline in the EFF is smaller in the national region after 2008, mainly due to increased EFF in the western region.

4.3.2 Environmental regulation has a linear effect on EFF

According to the output results in Table 11, the coefficients of environmental regulation (ER) variables are -0.0599^* , 0.0228 , -0.0341 , and -0.0495^{***} , in the eastern, central, western, and national models, respectively. In general, environmental regulation has a significant negative impact on EFF in the national model, but the impact of environmental regulation on EFF varies among the three major regions.

Environmental regulation in the eastern region has a significant negative linear impact on EFF, which has a negative impact on EFF of "following costs." The current environmental regulations are more inclined to end-of-production environmental pollution control in the eastern region. This kind of environmental pollution control expenditure will increase the production cost of enterprises and crowd out other technological investments in production while reducing corporate profits and EFF.

Environmental regulation in the central region has an insignificant positive impact of "innovation compensation" on EFF. Although the cost of pollution control has squeezed the production cost, it forces companies to innovate in energy-saving technologies and use the money invested in pollution control to reduce unwanted pollution emissions. Therefore, under the condition of constant expected output GDP, environmental regulation reduces the energy demand and improves EFF.

Environmental regulation has an insignificant negative impact on EFF in the western region. On the one hand, environmental regulation has a negative effect of "following costs" on EFF in the western region, and the pollution control costs squeeze the production costs, resulting in a decline in EFF. On the other hand, the western region is the source of China's water resources, so it has stricter requirements for environmental protection. The increase in the state's requirements for environmental regulation will inevitably make pollution control fees occupy more production costs of enterprises and reduce the EFF.

4.3.3 Technological innovation also has a linear effect on EFF

The results show that in the eastern, central, western, and national models, the coefficients of technological innovation (TI) are -28.6689^{**} , 4.6209 , -28.4623 , and -34.6153^{***} . Owing to the great impact of technological innovation on EFF, this also verified that technological progress is generally considered an important factor, or even a dominant factor, affecting EFF. For the whole country, increasing technological innovation is an important reason for the decline in EFF in China. However, the impact of technological innovation on EFF varies among the three regions.

Technological innovation has a significant negative impact on EFF in the eastern region. The main reasons are as follows. First, there is diversity in the direction of expenditures for

technological innovation, and the investment in technological innovation in the eastern region is mostly used for the design of product quality, not efficiency in the production process increase, resulting in a decrease in EFF. Second, there are technological innovations with high value-added output and increased energy input in technological innovation. This type of innovation still brings high-profit returns after deducting the cost of increasing energy input. For example, the eastern region is an export-intensive area of China's manufacturing industry, which faces fierce competition from overseas products. Companies may invest a lot of money in technological innovation with high-quality products and high returns to improve product competitiveness. Such technological innovations still require an increase in energy, resulting in a decrease in EFF.

Technological innovation has an insignificant positive impact on EFF in the central region because the technological innovation in the central region improves the use ratio of energy factors to non-energy factors in the production process, thereby improving EFF. For the central region, there is a large amount of old and high-energy-consuming equipment and energy is a scarce resource for them. Enterprises in the central region may be keen on technological innovations in energy conservation and emission reduction in the production process to reduce the emission of undesired pollutants in the production process. Under the condition that the expected output GDP remains unchanged, the enterprises in the central region reduce the energy demand, thereby improving EFF.

Technological innovation has an insignificant negative impact on EFF in the western region. There may be two reasons for this. First, there is diversity in the direction of expenditure on technological innovation. Some technological innovations may be mainly used for the design of product quality rather than the improvement of efficiency in the production process. Second, there is a shortage of scientific and technological talents in the western region. Although the western region invests a lot of money in technological innovation, technological innovation is finally implemented in the use of talents, and the shortage of scientific and technological talents may be the reason why this technological innovation is insignificant.

4.3.4 The cross-term has a significant positive linear relationship with EFF

The results show that in the models of the eastern, central, western, and national regions, the coefficients of the cross-terms (M) of environmental regulation and technological innovation on EFF are 2.5583*, 3.3219*, 3.2898*, and 2.7473***. On the whole, the cross-term has a significant positive impact on the national EFF. In terms of regions, the cross-terms also have significant positive impacts on the three major regions; however, only their coefficients are different.

The absolute value of the cross-term coefficient is greater than the coefficient of environmental regulation and smaller than

the coefficient of technological innovation, which indicates that the costs of some technological innovation and some environmental regulations are invested in technological innovation of energy conservation and emission reduction. This conclusion is not consistent with that of Yang (2017) because, under the requirement of the synergy between technological innovation and environmental regulation, the enterprises in the three major regions have improved the proportion of production scarce factors through their own technological innovation, which has greatly improved the production process. Output GDP has increased substantially. At the same time, the increased profits of enterprises far exceed the costs incurred by environmental regulations, thereby improving EFF.

4.3.5 Control variables have different effects on EFF in different regions

The influence coefficients of economic development (PGDP) on EFF in the eastern, central, western, and national areas are -0.1553^{***} , -0.1228^* , 0.0384 , and -0.0622^{**} , respectively. In other words, the impact of economic development on EFF in the eastern, central, and national regions is significantly negative, indicating that the economic development of the three regions significantly contributed to the reduction of regional EFF. The impact on EFF in the western region is insignificant in the positive direction.

The influence coefficients of industrial structure (IS) on EFF in the eastern, central, western, and national regions are -2.2788^{***} , -0.7147 , and -0.4563 , respectively. In other words, the impact of the industrial structure on EFF in the east is significantly negative but insignificant for regions excluding the east.

The influence coefficients of opening to the outside world (OPEN) on EFF of the eastern, central, western, and national regions are 0.6687^{***} , 0.6608 , -0.6712 , and 0.5531^{***} , respectively. In other words, the impacts of opening to the outside world on EFF in the eastern and national regions are significantly positive. The impact on EFF in the central region is insignificantly positive, which is insignificantly negative in the western region.

5 Conclusion and countermeasures

This study investigates the impact of environmental and technological innovations and their cross-terms on EFF using the undesired superefficiency SBM model and Tobit model. Its main conclusions are as follows:

- (1) Using the energy panel data of 30 provinces in China from 2001 to 2019, the article constructs an undesired superefficiency SBM model that includes both desired and undesired outputs. The results of the model showed that the

EFF of the three major regions in China was similar to an N-type trend and increased slowly before 2008, which was in line with the perception that the EFF of economically developed regions was higher than that of underdeveloped regions. From 2008 to 2009, EFF decreased rapidly and then slowly increased. The western region became the region with the highest EFF, so the EFF of economically developed regions was sometimes lower than that of less developed regions.

- (2) The impact of environmental regulation on EFF in different regions varies greatly. Environmental regulation has a “following cost” effect on EFF in the eastern, western, and national regions, which has a significant negative impact, resulting in a decline in EFF. It has an “innovative compensation” effect on EFF in the central region and an insignificant positive impact, increasing the EFF.
- (3) Technological innovation is the main factor affecting EFF, and its impact on EFF in different regions is also quite different. In the eastern and national regions, technological innovation has diversified expenditure directions, high added value, and high energy consumption, which has a significant negative impact on EFF of the eastern and national regions. Technological innovation has an insignificant positive impact on EFF in the central region. It also has an insignificant negative impact on the western region.
- (4) The cross-term has a significant positive impact on EFF in the three regions and the national region, indicating that part of technological innovation and environmental regulation costs is invested in the production innovation to improve the EFF.
- (5) The effects of control variables on EFF also differ in different regions. Economic development impacts on EFF in the eastern and central regions are significantly negative, the impact of industrial structure on EFF of the eastern region is significantly negative, and the impacts of opening in the eastern and national regions are significantly positive. In addition, the impacts of these variables on other regions are insignificant.

According to the above conclusions, in order to reduce environmental pollution, improve EFF, and make the economy of country grow steadily and continuously, the following suggestions are put forward:

- (1) Formulating unified environmental regulations to encourage energy-saving production in various regions.

Due to the cost effect of environmental regulation, if enterprises consider reducing such undesirable output emissions as waste gas and wastewater in production, it will indeed increase the cost of enterprises. Therefore, in places with stricter environmental regulations, some

enterprises withdraw from investment. In places where environmental regulations have been relaxed, some companies have increased production. In the long run, these will only divert China’s environmental pollution rather than reduce it. To this end, all parts of the country should formulate a unified environmental protection policy and treat all types of enterprises equally in implementing the policy. In addition, we must strictly check the approval of environmental regulations during the construction of enterprises and must not take the old road of pollution first and consider treatment later.

- (2) Encouraging technological innovation of enterprises in energy-saving production.

Technological innovation has the state of improving and reducing EFF, which is the choice of enterprises in market competition. Enterprises need more advanced production technology and equipment for energy-saving production and emission reduction and more energy-saving production emissions, which will increase the production cost of enterprises. However, the government can reduce the cost of enterprises through policies such as financing support and tax relief, encourage enterprises to carry out clean production, encourage enterprises to introduce advanced energy-saving technologies, and encourage enterprises to introduce efficient, clean production equipment.

- (3) Encouraging enterprises to use and innovate energy-saving technologies under environmental regulation and technological innovation

The government should design sound environmental regulation policies, and encourage enterprises to use energy-saving production technologies, and encourage enterprises to optimize resource allocation to improve their energy efficiency. On the one hand, the design and improvement of environmental regulation policies will stimulate enterprises to invest in clean technological innovation. On the other hand, the government will improve policies to encourage technological innovation and provide preferential tax policies for enterprises in the process of technological transformation and upgrading. Energy-saving production does indeed increase the cost of enterprises. However, the negative impact of “cost compliance” can still be partially or completely offset through the form of policy dividends to encourage enterprises to innovate in energy conservation and emission reduction. Therefore, through the innovation and application of green technology, the economic benefits of enterprises can be increased, and the sustainable development of enterprises can be led.

- (4) Improve the mechanisms for public participation and environmental protection.

We will focus on training a highly skilled labor force and high-level R&D personnel in enterprises and encourage the innovation and use of new energy technologies in society. Furthermore, we will strengthen the media publicity on energy saving and emission reduction and encourage the public to monitor the pollution behavior of enterprises.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization, validation, formal analysis, investigation, data curation, writing—original draft preparation, visualization, supervision, project administration, and funding acquisition: YC. Methodology, software, resources, writing—review and editing: TZ. All authors have read and agreed to the published version of the manuscript.

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Funding

This paper was supported by the Social Science Fund of Jiangsu Province in China (19GLD010): Research on the optimization of rural spatial structure in Jiangsu Province under the rural revitalization strategy (19GLD010).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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