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Threshold Effects of Environmental Regulation on Total Factor Energy Efficiency in China

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Abstract: This paper examines the threshold effects of environmental regulation on China's total factor energy efficiency (TFEE) using technological innovation (as measured by patents) as a threshold variable. Using the Slacks-based measure-undesirable (SBM-undesirable) output model, we first estimate TFEEs in 30 Chinese provinces from 2000 to 2011 under the constraints of energy conservation and emissions reduction. We then analyze the impact of environmental regulation on TFEE based on the panel threshold regression model. The results show that the average TFEE in China from 2000 to 2011 is 0.503, indicating that this measure can be significantly improved. However, environmental regulation has threshold effects on TFEE. Stringent environmental regulation can only improve TFEEs in provinces with technological innovation levels between the first and second threshold values. When technological innovation levels are below the first or above the second threshold value, tighter environmental regulation would lower TFEE. The results suggest that environmental regulation does not always enhance TFEE and that the positive effect of environmental regulation on TFEE must fall within a range of threshold values. In addition, improving the technological innovation level and adjusting the industrial structure have positive effects on TFEE, while the irrational energy consumption structure has a negative effect on TFEE.

Keywords: Environmental regulation, technological innovation, threshold effects, total factor energy efficiency.

1. INTRODUCTION

As the world's largest energy consumer in 2012, China's primary energy consumption accounted for 21.9% of total global energy consumption. This rate may increase to 26.6% in 2035 according to British Petroleum's "Energy Outlook 2035". In the same year, Yale University and Columbia University launched the annual global Environmental Performance Index (EPI), which includes 178 countries and regions, and China ranked 118th. The increasing energy consumption and worsening ecological environment indicate that China's traditional pattern of economic development has seriously affected and restricted the country's economic and social sustainability. Ensuring sustainable economic growth under the premise of energy conservation and pollution abatement has become a major issue in China. Recently, the Chinese government has gradually increased the intensity of environmental regulation to encourage companies to explore technological innovations and improve TFEE through energy conservation and emissions reduction. However, how can TFEE be measured effectively? Can intensifying environment-tal regulation improve TFEE? Is the impact of environmental regulation on TFEE linear?

This study aims to find answers to these questions. We use the SBM-undesirable model to estimate TFEEs in China's 30 provinces from 2000 to 2011 using the chemical oxygen demand (COD) of wastewater, sulfur dioxide emissions and carbon dioxide emissions from exhaust gases as unexpected output. In addition, we propose a panel threshold model to analyze the impacts of environmental regulation on TFEE using technological innovation as the threshold variable. These analyses were conducted in the context of energy conservation and emissions reduction. Using careful empirical examinations, we hope to yield useful suggestions for governmental regulation and policy making, as well as for future research studies concerning the relationship between environmental regulation and TFEE.

The next section provides a brief literature review of the relationship between environmental regulation and energy efficiency. Then, we describe and evaluate the econometric model and data resources. Next, the empirical results and relative tests are presented and explained. Finally, we conclude with some policy implications and future research challenges and opportunities.

2. LITERATURE REVIEW

Early economists held that environmental regulation would increase the cost of production, thus reducing production efficiency. For instance, Gollop and Roberts [1] (1983) analyzed the SO_2 emission controls in the United States from 1973 to 1979 and found that environmental regulation decreased the industrial production efficiency. Gray (1987) [2] estimated the effect of environmental regulation on the manufacturing productivity in the United States and found that regulation reduced the industrial productivity by 30% from 1958-1978. However, some recent studies have shown effects that are more positive. Now

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known as "Porter Hypothesis", Porter (1995) [3] argued that a well-designed environmental regulation can trigger technological innovation that may offset the cost of regulatory compliance due to cost reduction, thereby improving the industry productivity. Berman and Bui (2001) [4] and Sabuj (2010) [5] also reported that environmental regulation can improve industrial energy efficiency. Bi (2013) [6] analyzed the relationship between fossil fuel consumption and the environmental regulation of China's thermal power generation, finding that decreasing the discharge of major pollutants can significantly improve the energy performance and efficiency.

From the above studies, we conclude that no consensus exists as to whether environmental regulation can promote energy efficiency. This lack of consensus is due to multiple reasons. First, the methods for measuring energy efficiency vary. Some scholars use single factors to measure energy efficiency, while others use total factors. Furthermore, some measurement methods are based on radial or oriented functions that do not consider slack problems associated with inputs and outputs. Therefore, the energy efficiency is biased. Additionally, the effect of environmental regulation on TFEE may be nonlinear. Whether environmental regulation can improve TFEE may be largely determined by the level of technological innovation. Namely, the effective size and direction of the environmental regulation on TFEE may be different due to different technological innovation levels.

3. MODELS AND DATA

3.1. SBM-Undesirable Model

The SBM model was originally proposed by Tone (2001) [7]. The model effectively solved the slack problems associated with inputs and outputs. However, the traditional SBM model neglected the environmental impacts of undesirable outputs when assessing TFEE. Tone (2004) [8] proposed the SBM-undesirable model, adding undesirable outputs into the traditional SBM model. This paper adopts Tone's SBM-undesirable model to evaluate China's regional TFEE under the restrictions of energy conservation and emissions reduction. Assuming that there are *n* decision making units (DMU) at point *t*, each unit has *m* types of input *X*, *s* types of good (desirable) output *Y* and *t* types of bad (undesirable) output *B,* the production possibility set(P) is defined as follows:

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

where $\lambda\in \mathrm{R}^{n}$ is the intensity vector. Note that the above definition corresponds to the constant returns to scale technology. In accordance with the above-mentioned production technology, Cooper *et al.* (2007) [9] proposed the CRS-SBM model with undesirable outputs to calculate the technical efficiency of a production system. The CRS-SBM model with undesirable outputs for the i^{th} decision-making unit at phase t is as follows:

$$\min\rho=\frac{1-\frac{1}{m}\sum_{j=1}^{m}\frac{s_j^-}{x_{j0}}}{1+\frac{1}{s+t}\left(\sum_{r=1}^{s}\frac{s_r^+}{y_{r0}}+\sum_{p=1}^{t}\frac{s_p^+}{b_{p0}}\right)}$$

$$s.t.\sum_{i=1}^{n}\lambda_i x_{ji}+s_j^-=X_0, j=1,2...m$$

$$\sum_{i=1}^{n}\lambda_i y_{ri}-s_r^+=Y_0, r=1,2...s$$

$$\sum_{i=1}^{n}\lambda_i b_{pi}+s_p^+=B_0, p=1,2...t$$

$$s_j^-\geq 0, s_r^+\geq 0, s_p^+\geq 0, \lambda_i\geq 0. \tag{2}$$

where s_i^- , s_r^+ and s_p^+ represent input redundancy, expected output redundancy and unexpected output redundancy, respectively. λ_{i} is a nonnegative multiplier vector for technology construction. In this study, the good output contains regional GDP, while CO_2 and COD are the bad outputs. The input vectors contain capital, labor and energy consumption. ρ is defined as TFEE. If $\rho=1$, which indicates that all the slack variables are 0, the TFEE of the province is efficient in the presence of undesirable outputs.

3.2. Panel Threshold Model Of Environmental Regulation on TFEE

The Porter Hypothesis posits that a well-designed environmental regulation can spur technological innovation that may reduce production cost, and thus enhance industry-based productivity. Therefore, the ability of environmental regulation to promote productivity depends on the effects of technological innovation and the costs of environmental regulation. When a government increases the intensity of environmental regulation, firms generally decrease their pollution levels to the new standard in one of two ways. They may increase inputs to pollution abatement, which would produce a cost of regulation and increase the production cost, thereby reducing TFEE under the restrictions of energy conservation and emissions reduction. However, firms may increase their energy efficiencies by adopting technological innovations to optimize resources allocation, leading to a “win-win” situation that reduces pollution and to improve the level of output and TFEE under the restrictions of energy conservation and emissions reduction. This is the so-called innovation offset effect. In regions with low levels of technological innovation, the cost is relatively low if firms adopt the first environmental regulation approach, as opposed to choosing technological innovation. Therefore, firms tend to adopt the first approach to meet the emissions reduction standard. In this manner, more intense environmental regulation would reduce TFEE under the restrictions of energy conservation and emissions reduction. However, in areas with high levels of technological innovation, the cost is relatively high if firms adopt the first approach, while the cost of technological innovation is lower. Thus, firms prefer the second approach to meet the standard. In this manner, the more intense environmental regulation will increase TFEE. As a result, the effect of environmental regulation on TFEE has a threshold. This paper uses the panel threshold regression mode proposed by Hansen (1999) [9] to empirically analyze the threshold effect of environmental regulation on TFEE. The Panel threshold model is expressed as follows:

$$\begin{aligned} EE_{it} = {} & \beta_0 + \beta_{11} ER_{it} * I(INNIO_{it} \le \gamma_1) + \\ & \beta_{12} ER_{it} * I(\gamma_1 \le INNIO_{it} \le \gamma_2) \\ & + ... \beta_{1n} ER_{it} * I(\gamma_n \le INNIO_{it}) + \beta_2 ER_{it-1} \\ & + \beta_3 INNO_{it} + \beta_4 IS_{it} + \beta_5 ECS_{it} + \varepsilon_{it} \end{aligned} \quad (3)$$

where i and t denote the region and year, respectively; EE_{it} represents TFEE under the restrictions of energy conservation and emissions reduction; $INNO_{it}$ represents technological innovation; ER_{it-1} denotes the first-lagged period of environmental regulation; I (*) is the indicator function; $INNO_{it}$ is a threshold variable; $\gamma_1, \gamma_2 \cdots \gamma_n$ is the threshold value; and $\beta_{11}, \beta_{12} \cdots \beta_{1n}$ is the effect of the intense environmental regulation on TFEE under the restrictions of energy conservation and emissions reduction within different levels of innovation. Relevant test methods refer to the test methods proposed by Hansen (1999) [10].

3.3. Variables and Data Sources

This paper uses panel data from China's 30 provinces from 2000 to 2011 as samples, excluding Hong Kong, Macao, Taiwan and Tibet, for which corresponding statistics are not available. The input indicators are as follows: labor, taking the current employment as the labor input, i.e., the mean employment of the current year and previous year; capital stock, using gross fixed capital formation as capital stock index to calculate the capital stocks of 30 provinces in China from 2000 to 2011 with a depreciation rate of 10.96%; and energy consumption, setting each province's total energy consumption as the energy consumption index. The output indicators are as follows: the expected output, which is the real GDP based on the period (2000); and the unexpected output, which includes the chemical oxygen demand (COD) of wastewater, sulfur dioxide emissions and carbon dioxide emissions from exhaust gases. Because there are no official CO_2 emissions statistics, we calculate the CO_2 emissions using the IPCC methodology (2006). The formulation is

$$EC = \sum_{i=1}^{7} E_i \times EF_i ,$$

where EC denotes the estimated value of total CO_2 emissions from all types of energy consumption; i represents the energy consumption categories, which include coal, coke, gasoline, kerosene, diesel oil, fuel oil and natural gas; and E_i denotes the total energy consumption of the i^{th} energy. EF_i is the carbon dioxide emission coefficient of the i^{th} energy type, and coal, coke, gasoline, kerosene, diesel oil, fuel oil and natural gas carbon dioxide emission coefficients are 1.647 tons CO_2/ton, 2.848 tons CO_2/ton, 3.045 tons CO_2/ton, 3.174 tons CO_2/ton, 3.150 tons CO_2/ton, 3.064 tons CO_2/tons and 21.670 tons CO_2/cubic meter.

The control factors affecting TFEE are as follows: (1) environmental regulation ER_{it}, is based on the ratio of the industrial pollution control investment to the industrial output. The higher the ER_{it} value, the greater the intensity of the environmental regulation. TFEE exhibits a lag effect with the impact of environmental regulation. The first-lagged period of environmental regulation is taken as an explanatory variable; (2) technological innovation $INNO_{it}$ is based on the number of patents granted, providing a proxy indicator of the technological innovation output; (3) industrial structure IS_{it} is the ratio of the added value of the second industry to GDP based on the Industrial Structure index; (4) energy consumption structure ECS_{it} is the rate of coal consumption compared to the total energy consumption, providing an indicator of the energy consumption structure.

The data resources used in this study include the China statistical yearbook, China environment yearbook, China statistical yearbook on science and technology, China's environmental statistics yearbook and all provincial statistical yearbooks.

4. TESTS AND RESULTS

4.1. TFEE Under the Restrictions of Energy Conservation and Emissions Reduction

According to the SBM-undesirable model, we calculate TFEE under the restrictions of energy conservation and emissions reduction using the data from China's 30 provinces from 2000 to 2011.

Table 1. Mean values of the provincial TFEEs from 2000 to 2011.

Provinces	Energy efficiency	Provinces	Energy efficiency
Yunnan	0.966	Shandong	0.450
Fujian	0.927	Guangxi	0.447
Liaoning	0.800	Hubei	0.431
Guangdong	0.777	Jilin	0.421
Hainan	0.716	Henan	0.367
Tianjin	0.705	Hebei	0.364
Zhejiang	0.696	Shanxi	0.341
Anhui	0.687	Shaanxi	0.337
Beijing	0.658	Jiangxi	0.327
Shanghai	0.593	Xinjiang	0.315
Jiangsu	0.558	Inner Mongolia	0.290
Sichuan	0.505	Qinghai	0.257
Heilongjiang	0.502	Ningxia	0.256
Hunan	0.488	Guizhou	0.240
Chongqing	0.469	Gansu	0.207

From Table **1**, we conclude that the mean Chinese TFEE from 2000 to 2011 is 0.503. The highest energy efficiency score exhibited in Yunnan province, reaching 0.966, while the lowest score is exhibited in Gansu province at only 0.207. According to the level of energy efficiency, we divide the areas into three groups: areas with high energy efficiency (Yunnan, Fujian, Liaoning, Guangdong, Tianjin, Hainan, Zhejiang, Anhui, Beijing and Shanghai); areas with moderate energy efficiency (Jiangsu, Sichuan, Heilongjiang, Hunan, Chongqing, Shandong, Guangxi, Hubei, Jilin and Hebei); areas with low energy efficiency (Henan, Jiangxi, Shanxi, Shaanxi, Xinjiang, Inner Mongolia, Qinghai, Ningxia, Guizhou and Gansu).

4.2. Empirical Analysis of the Impact of Environmental Regulation on TFEE

According to the empirical analysis and tests using the model (3), we first must determine the number of thresholds. The results show that the threshold of the technological innovation variable has two threshold values, as shown in Table **2**.

Table 2. Threshold effect bootstrap test of the threshold the technological innovation variable.

Threshold number	F-value	P-value	1%	5%	10%
1	21.764**	0.015	24.603	14.983	10.955
2	34.395***	0.000	16.138	6.784	1.777
3	6.285	0.207	28.214	17.061	10.965

Note: * * *, * * and *, significant at 1%, 5% and 10%, respectively. The numbers in brackets are the LM test statistics determined by the "sampling method" (the bootstrap) repeated 1000 times.

Table 3. Threshold estimation and confidence interval.

Threshold variable	Threshold number	Threshold estimation	95% confidence interval
Technological innovation	Threshold 1	1.066	[0.662,1.440]
	Threshold 2	12.388	[11.934,13.838]

Table 4. Threshold value and its distribution.

Threshold value interval	Provinces (2011)
INNO<1.066	Qinghai, Ningxia, Guizhou, Hainan, Inner Mongolia, Gansu, Xinjiang, Yunnan, Guangxi, Jiangxi, Jilin, Shanxi
1.066<INNO<12.388	Hebei, Shanxi, Heilongjiang, Tianjin, Chongqing, Hunan, Hubei, Liaoning, Anhui, Henan, Fujian, Sichuan, Beijing, Shanghai, Shandong
INNO>12.388	Guangdong, Zhejiang, Jiangsu

From Table **3** and Table **4**, we conclude that the threshold estimations of technological innovation are 1.066 and 12.388. Twelve provinces' technological innovation levels are below the first threshold value in 2011, including Qinghai, Ningxia, Guizhou, Hainan, Inner Mongolia, Gansu, Xinjiang, Yunnan, Guangxi, Jiangxi, Jilin and Shanxi. Fifteen provinces' technological innovation levels are between the first and second threshold, including Hebei, Shanxi, Heilongjiang, Tianjin, Chongqing, Hunan, Hubei, Liaoning, Anhui, Henan, Fujian, Sichuan, Beijing, Shanghai and Shandong. Three provinces' technological innovation levels are above the second threshold, including Guangdong, Zhejiang and Jiangsu.

Table 5. Panel threshold model regression estimation.

Variable	Coefficient	P value
INNO	0.047***	0.000
IS	0.005***	0.000
ECS	-0.096***	0.001
ER_{t-1}	-0.049***	0.003
ER_1 (INNO<1.066)	-0.059***	0.001
ER_2(1.066<INNO<12.388)	0.120**	0.016
ER_3 (12.388> INNO)	-2.939***	0.000
_cons	0.347***	0.000

Note: * * *, * * and * represents significance at 1%, 5% and 10%, respectively.

Based on the regression results in Table **5**, if the technological innovation level is below the first threshold value, the significant effect of environmental regulation on energy efficiency is negative, and the estimated coefficient is -0.059. Thus, more intense environmental regulation would reduce TFEE. For the provinces with technological innovation levels above the first threshold value, the significant effect of environmental regulation on energy efficiency is positive, and the estimated coefficient is 0.120. In 2011, the technological innovation level of most developed eastern and some central provinces fell between the first and second threshold values. More stringent but properly designed environmental regulations can improve TFEEs in these regions. For the 3 provinces whose technological innovation levels are above the second threshold, the effect of environmental regulation on TFEE is negative. Thus, decreasing environmental regulation in these areas can improve their TFEE.

CONCLUSION

This paper estimates China's provincial TFEEs under the restrictions of energy conservation and emissions reduction using data from 30 provinces from 2000 to 2011. We then discuss the threshold effects of environmental regulation on TFEE based on the empirical data. The results show that the average value of China's TFEE from 2000 to 2011 is 0.503. The relationship between environmental regulation and TFEE is nonlinear, which is determined by the technological innovation level. When the region's technological innovation level is below the first or above the second threshold value, more intense environmental regulation reduces the region's TFEEs. When the level of technological innovation is between the first and second thresholds, stringent environmental regulation can improve the region's TFEEs. Improving the technological innovation level and adjusting the industrial structure can enhance TFEEs, while the irrational energy consumption structure hinders TFEEs.

These results may have important implications for Chinese environmental policies. First, China's average TFEE under the restrictions of energy conservation and emissions reduction can be significantly improved. Second, understanding how different levels of technological innovation and environmental regulation influence TFEE can help policy makers formulate the most appropriate level of environmental regulation based on their regional innovation level. The findings of this study suggest that environmental policy makers should adopt different environmental regulatory policies based on the level of innovation. In the Midwestern provinces of China with low levels of technological innovation, corresponding to provinces with fewer than 10660 patents granted, policy-makers should focus on developing technological innovation through accelerating independent innovation and importing advanced technologies from eastern China and abroad. In central and eastern provinces with technological innovation levels between the first and second threshold values, policy-makers should focus on adopting stricter environmental regulation. In the 3 provinces (Guangdong, Zhejiang, Jiangsu) whose technological innovation levels are above the second threshold value, policy-makers should decrease environmental regulation appropriately. In addition, simultaneously optimizing and upgrading the industrial structure, and decreasing the proportion of coal in the total energy consumption can also improve TFEE.

Ideally, firm and global level data sets could be used to examine the threshold effects of environmental regulation on TFEE in future research. In addition, the impacts of various environmental regulation strategies on TFEE should be evaluated in the future.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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