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# Impact of Environmental Regulation on Total-Factor Energy Efficiency from the Perspective of Energy Consumption Structure

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***Abstract –*** *In order to explore whether the interregional differences in environmental regulations affect the improvement of energy efficiency incorporating undesirable outputs, the total-factor energy efficiency of 30 province-level divisions in China are evaluated by the slack-based DEA model (SBM). A panel smooth transition regression (PSTR) is made to analyze the impact of environmental regulations on the total-factor energy efficiency. This impact performs different with different energy consumption structure. The empirical results show that the proportion of clean energy in the energy consumption in Zhejiang, Guangdong, Beijing and Fujian has exceeded the threshold value successively. Environmental regulation has a significant enhancing effect on the total-factor energy efficiency in these regions. Whereas, in those regions with low proportion of clean energy, the estimated impact coefficient of environmental regulation on the total-factor energy efficiency performs negative. Great pressure on environmental regulation should be matched up with energy-saving technical innovation and new energy usage stimulus. The positive promoting effect of environmental regulation on the total-factor energy efficiency needs a better energy consumption structure.*

***Keywords –*** economic sustainable development, energy consumption structure, environmental regulation, total-factor energy efficiency.

## 1. INTRODUCTION

Since reform and opening up in 1978, China has made remarkable economic achievements in the process of industrialization and urbanization. However, the Environmental Performance Index(EPI) of China ranked next-to-last in the Environmental Performance Index Report released by Yale University in the year of 2016 [1]. In recent years, the haze containing lots of fine particulate matter less than 2.5 microns wide (PM2.5) occurs frequently in China and the scope of the outbreak is getting broader. Because of the serious pollution brought by the extensive economy, environmental protection has become China's national policy. It is reasonable to presume that China would introduce stricter environmental regulations. PM2.5 is mainly generated by the burning of fossil fuels such as coal. Coal is still the dominant energy variety in china accounting for 50% of total energy consumption in 2015 [2]. In China, a resource-based province like Shanxi had almost the same gross regional product as Yunnan in 2015, but spent much more energy than Yunnan. The investment in industrial pollution of Shanxi was also higher than Yunnan. However, the $SO_2$ emission of Shanxi was nearly twice that of Yunnan in the year of 2015. This instance gives us an intuitive feel that strict environmental regulation will not necessarily lead to high performance of regional energy efficiency. It may depend on the regional energy consumption structure. Therefore, the research from perspective of energy consumption structure is in line with China's national conditions.

Energy is the material basis for economic sustainable development and plays an important role in economic life. Both energy efficiency and energy consumption are of obvious geographical characteristics [3]. Since major environmental policies are usually made at the central level and implemented by provincial and municipal governments in China [4], a better understanding of environmental regulation' role will help to devise appropriate policies for realizing sustainable development. Sustainable development focuses on economic development, social development and environmental protection for future generation. Energy consumption is inevitably combined with other inputs to produce an economic output, and substitution effects exist between energy and other input factors such as labor and capital stock [5]. The total-factor energy efficiency (TFEE) is a more comprehensive indicator than other partial-factor energy efficiency. Besides, there will be a lot of undesirable outputs such as carbon dioxide, sulfur dioxide and so on arising from the production process or other economic activities. It is essential to introduce the undesirable output into our analyzing framework to examine the environmental impact of energy consumption. The TFEE calculated by the SBM model can explain the level of economic sustainable development [6].

This paper argues that the impact of environmental regulations depends on the energy consumption structure. If both the total fossil fuel consumption and the proportion of fossil fuel are at a low level, environmental regulations will have a great up-regulated impact on the TFEE.

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## 2. LITERATURE REVIEW

### *2.1. Environmental Regulation and Total-Factor Energy Efficiency (TFEE)*

At present, there has been a long debate in academia on the impact of environmental regulation on the TFEE. On one hand, environmental regulation may raise the production cost and thus bring down the TFEE; on the other hand, environmental regulation may also force companies to develop efficient technologies of using energy or substitute the fossil fuel with non-fossil fuel and thus promote the TFEE. One view is that environmental regulation can have a positive effect on the TFEE through reducing environmental negative externalities [7]. The resulting economic benefits will be greater than the cost of environmental regulation [8]. Another view is that environmental regulation may have a negative effect on the TFEE because of the productivity losses, as demonstrated in the Research on the Mexico’s 1990 Clean Air Act amendments [9]. The impact of environmental regulation on the TFEE presents obvious “polarized” and “agglomeration” effect in China [10]. In our opinion, the environmental regulation can have some positive effect on the enhancement of TFEE under certain circumstances, for example a cleaner energy consumption structure.

### *2.2. Environmental Regulation and Energy Consumption Structure*

Most scholars hold that environmental regulation can improve the energy consumption structure and reduce the total fossil energy consumption [11], [12]. There is a significant negative correlation between environmental regulation intensity and the coal consumption [13]. China’s stringent environmental regulation would send the proportion of coal used in primary energy consumption down to 47% or so by 2030 under the energy supply constraints [14]. In contrast, firms could increase the exploitation or consumption of fossil fuels for short-term benefits, worsening energy consumption structures under strict environmental regulation. This contradiction is called the “green paradox” in environmental management [15], [16]. Environmental regulation has a threshold effect on energy consumption structure. When environmental regulation stringency is lower than a certain level, it is not able to improve the energy consumption structure, and may even exacerbate the ecological deterioration of the environment; but when above this threshold, energy consumption structure will be improved as environmental regulation gets stricter [17]. However, the mediating role of energy consumption structure played in the impact of environmental regulations on the TFEE has not been researched from the above studies.

### *2.3. Energy Consumption Structure and Total-factor Energy Efficiency (TFEE)*

It is generally accepted that the improvement of energy consumption structure can raise TFEE [18], [19]. Taking the proportion of coal consumption as a structural factor, TFEE will decrease when the proportion of coal consumption in industry increases based on data development analysis [20]. According to the empirical results in China, energy efficiency is more relevant to structure of primary energy consumption than to that of final energy consumption [21]. Coal refining, storage and transportation technologies are also important to the improvement of energy efficiency [22]. Taking the total coal consumption as a structural factor, more coal consumption will lead to less TFEE based on the stochastic frontier approach [23]. It is vital to replace fossil fuels such as coal with non-fossil fuels to reduce the negative externalities of coal consumption [24], thus increasing the natural optimization of non-fossil energy use [25]. Based on the above discussion, we can infer that cleaner energy consumption structures would lead to higher TFEE. But the methods used to calculate the energy consumption structure and the TFEE are also vital to the research results.

In the study, we calculate the total energy consumption by 17 types of energy and CO2 emissions with 13 types of fossil fuels. Then we measure the TFEE. In addition, we interpret energy consumption structure from two aspects: scale and ratio. A nonlinear model is also used to study the impact of environmental regulations on the TFEE.

## 3. EMPIRICAL MODEL

### *3.1. Impact Mechanism*

How does the environmental regulation effect the TFEE in the transition of energy consumption from fossil fuels to cleaner energy sources? The answer has been given in Figure 1. It is called high fossil energy consumption system when the fossil fuel is the dominant energy consumption in our economy. Oppositely, it is called low fossil energy consumption system when the cleaner energy source is the dominant energy consumption in our economy.

#### *3.1.1. Mechanism under the System of High Fossil Energy Consumption*

Dependence on fossil fuels induces great environmental problems: (1) The human and material resources spent on the execution of environmental regulation will increase the social burden and reduce the social net welfare [26], [27]; (2) According to the announcement effect in the green paradox theory, if stringent environmental regulation in the foreseeable future is predicted by manufacturers, the drop in the fossil fuel prices will stimulate the demand for fossil fuels, leading to a rise in greenhouse gas and pollution emissions [28]; (3) if this enterprise consumes fossil fuels dominantly, the transition cost will be enormous, because the cleaner energy sources need to be combined with new device or new skilled workers to push the production. The TFEE will be fall [29], [30]. The mechanism is labeled “System 1” in Figure 1.

#### *3.1.2. Mechanism under the System of Low Fossil Energy Consumption*

Although the green paradox effect still exists, the impact on the TFEE can be offset by positive effects if the cost of environmental regulation can be well controlled.

Enterprises' internal costs can be compensated by technological innovation in the long term [31]. Besides, if these enterprises are consuming cleaner energy sources dominantly, environmental regulation's negative impact on enterprises will be relatively small. The mechanism is labelled "System 2" in Figure 1.

The nonlinear effect of environmental regulation on the TFEE is generated by the dynamic interaction of external social costs, the announcement effect in green paradox and the internalization cost of enterprises.

### *3.2. Slack-based Measurement (SBM) Directional Distance Function*

The Slack-Based Measurement is a mature and objective method for accurately estimating total-factor energy efficiency [32]. Many scholars use SBM model to measure the TFEE of regions in China [33]. Unlike traditional DEA models, the directional distance function takes environmental factors into consideration. The directional distance function introduces slack variable $\vec{S}=(s_{eo}\ ,s_{xm}\ ,s_{yr},\ s_{uk})$ in the linear constraint and estimates the productivity of production units in the Pareto optimal production frontier. For the sake of accuracy, objectivity and data availability, this paper adopts the approach of converting 17 types of energy into total energy input and estimating CO2 emissions with 13 types of fossil fuels. The total-factor energy efficiency is calculated by reference to Cooper [34]. The SBM with undesirable outputs could be specified as:

$$\rho^*=\min\left\{\frac{1-\frac{1}{M}\sum_{m=1}^{M}\frac{s_{mo}^{x}}{x_{mo}}}{1+\frac{1}{R+J}\left(\sum_{r=1}^{R}\frac{s_{mo}^{y}}{y_{ro}}+\sum_{j=1}^{J}\frac{s_{jo}^{b}}{b_{jo}}\right)}\right\}$$

$$s.t.\ \sum_{n=1}^{N}\lambda_n x_{mn}=x_{mo}-s_{mo}^{x} \qquad (1)$$

$$\sum_{n=1}^{N}\lambda_n y_{rn}=y_{ro}+s_{mo}^{y}$$

$$\sum_{n=1}^{N}\lambda_n b_{jn}=b_{jo}-s_{jo}^{b}$$

$$s_{mo}^{x}\geq 0, s_{mo}^{y}\geq 0, s_{jo}^{b}\geq 0, \lambda_n\geq 0$$

Where $o$ is the decision-making unit (DMU) to be assessed, and denote slack variables of inputs, desirable outputs and undesirable outputs, respectively.

### *3.3. Panel Smooth Transition Regression (PSTR) Model*

Most existing studies use panel threshold regression (PTR) and panel smooth transition regression (PSTR) models to research the nonlinear effects of panel data. The PTR model implies that the different groups of observations can be clearly distinguished from each other based on the value of the threshold variable alone, with sharp borders or thresholds separating the groups, while the PSTR model allows the regression coefficients to change gradually when moving from one group to another [35] – [36]. We use the PSTR model to research the nonlinear effect of environmental regulation on the TFEE. The general form of the PSTR model with r transition functions is

$$TFEE=u_i+\beta_0 x_{it}+\sum_{j}^{r}\beta_j x_{it} g(q_{it},\gamma_j,c_j)+\varepsilon_{it} \qquad (2)$$
$$i=1,2,\cdots,N;\quad t=1,2,\cdots,T$$

Where the transition function $g(q_{it},\gamma_j,c_j)$ is a continuous function of the transition variable $q_{it}$ .It is in the form of the logistic function. The slope parameter $\gamma$ determines the smoothness of the transition, and $c_j(j=1,2,3...,m)$ is an m-dimensional vector of location parameters. As $c_j$ and $q_{it}$ change continuously, $g(q_{it},\gamma_j,c_j)$ is normalized to be bounded between 0 and 1, resulting in a smooth transition from group $\beta_0$ to $\beta_0$ + $\sum_{j}^{r}\beta_j$ .

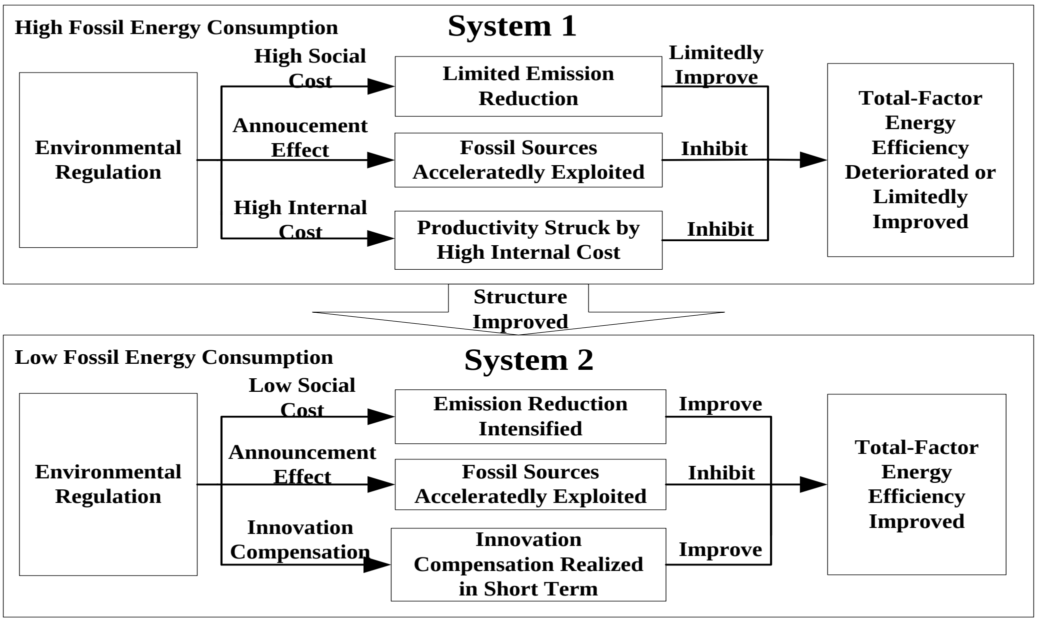


**Fig. 1. Impact mechanism of environmental regulation on TFEE.**

**Table 1. Input and output variables to estimate the TFEE.**

| | Variable | Indicator | Description |
|---|---|---|---|
| Input | Physical capital | Physical capital stock | By perpetual inventory method, benchmark at 2000 |
| | Labor force | Labor force | Year-end payrolls |
| | Energy consumption | Energy consumption | Total consumption of seventeen kinds of energy sources |
| Output | Desirable: Economic growth | Provincial gross district product | Use the GDP index in the past years to convert, benchmark at 2000 |
| | Undesirable: environmental pollution | $SO_2$ | Major environmental pollutants |
| | | $CO^2$ | Major greenhouse gas |
| | | Industrial waste water discharged | The total industrial waste water discharged |

*Note: 30 provinces or municipalities except Tibet are selected as the samples. The data comes from the China Statistical Yearbook and China Energy Data.*

## 4. DATA SOURCE AND PROCESSING

### *4.1. Data Source and Processing for the TFEE*

The panel data in 30 provinces of China from 2004 to 2014 was used to estimate the total-factor energy efficiency. The data comes from China Statistical Yearbook, China Labor Statistical Yearbook, China Energy Statistical Yearbook, and China Statistical Yearbook on Environment. The input factors include physical capital, labor force and energy consumption. The output factors include desirable outputs and undesirable outputs. The indicators are shown in the Table 1.

As proposed by Zhang [37], the Capital stock calculated by the perpetual inventory method as the indicator of capital input, taking the year of 1992 as the base period was adopted. The depreciation rate comes from Data of Gross Domestic Product of China 1952-2004.

As for the carbon dioxide emissions, the "top-down" computing method in 2006 Intergovernmental Panel on Climate Change (IPCC) Guidelines for National Greenhouse Gas Inventories was adopted

$$CO_2 = \sum_{i=1}^{n}(CO_2)_i = \sum_{i=1}^{n} E_i \times CEF_i \times NCV_i \times COF_i \times (44/12) \quad (3)$$

$E_i$ refers to the total consumption of energy source $i$ in the Energy Balance Sheet. $NCV_i$ refers to the average net calorific value, $CEF_i$ refers to the carbon emission factor, and $COF_i$ refers to the carbon oxidation factor. The coefficients of CO2 emissions are shown in Table 2.

### *4.2. Data Source and Processing for the PSTR*

#### *4.2.1. The PSTR Model with Transition Variable of the Ratio $q_1$ of the Fossil Energy Consumption*

In consideration of the differences in time-invariant factors such as factor endowment, policy space, culture, consumption customs, a fixed individual effect test is necessary for the model setting. Testing with mixed effect regarded as the null hypothesis and fixed effect regarded as the alternative hypothesis, the F statistic is 6.83, which rejects the null hypothesis at the significance level of 1%. Moreover, in the Hausman test, the Wald statistic is 20.94, also rejecting the null hypothesis at the significance level of 1%. Consequently, whether it is based on economics or on statistical tests, building the PSTR model with fixed effect is undoubtedly correct.

Before the PSTR model is established, we perform a nonlinear effect test on proportion of fossil energy consumption. Imposing $H_0: \gamma = 0$ , the LM statistic rejects the null hypothesis at the 5% significance level, indicating that the nonlinear characteristics of heterogeneity exist in the model, the accuracy of using fossil energy consumption proportion is verified. Setting $m = 3$, we determine the number of transition functions by the homogeneity test and non- remaining nonlinear effect test. The results show there is only one transition function in the model, that is, $r = 1$. Then, to determine $m$ , the number of thresholds, we impose in sequence null hypothesis $H_{03}: \beta_3 = 0;$ $H_{02}:\beta_2 = 0|\beta_3 = 0;$ $H_{01}:\beta_1 = 0|\beta_2 = 0\beta_3 = 0$ . The results of the $LM$ and $LM_f$ tests show that the null hypothesis $H_{03}$ is accepted up to the 0.01% significance level. Therefore, we determine that $m = 2$ . In the model, there is one transition function with tow thresholds. The results of the homogeneity test and no remaining heterogeneity test are as shown in Table 3, and the test for determining the number of thresholds is shown in Table 4.

**Table 2. Coefficients of $CO_2$ emissions.**

| Energy Source | Raw Coal | Cleaned Coal | Other Washed Coal | Coke | Coke Oven Gas | Crude Oil | Gasoline |
|---|---|---|---|---|---|---|---|
| Quantity | 1.903 | 2.4953 | 0.7922 | 2.8623 | 7.6976 | 3.0208 | 2.9256 |
| Unit | $kgCO_2/kg$ | $kgCO_2/kg$ | $kgCO_2/kg$ | $kgCO_2/kg$ | $10^4 tCO_2/10^8 m^3$ | $kgCO_2/kg$ | $kgCO_2/kg$ |
| Energy Source | Kerosene | Diesel Oil | Fuel Oil | LPG | Refinery Gas | Natural Gas | |
| Quantity | 3.0334 | 3.0959 | 3.1705 | 3.1013 | 3.0119 | 21.6219 | |
| Unit | $kgCO_2/kg$ | $kgCO_2/kg$ | $kgCO_2/kg$ | $kgCO_2/kg$ | $kgCO_2/kg$ | $10^4 tCO_2/10^8 m^3$ | |

**Table 3. Test for homogeneity and for determining the number of transition functions r.**

| | LM | $LM_F$ |
|---|---|---|
| $H_0$: r=0 vs. $H_1$: r=1 | 10.240** (0.017) | 3.170** (0.025) |
| $H_0$: r=1 vs. $H_1$: r=2 | 1.499 (0.683) | 0.449 (0.718) |

**Table 4. Test for determining the number of thresholds m.**

| | $H_0$ | $H_{03}$ | $H_{02}$ | $H_{01}$ |
|---|---|---|---|---|
| LM | 10.240** | 1.423 | 8.130*** | 0.744 |
| P-value | 0.017 | 0.233 | 0.004 | 0.388 |
| $LM_F$ | 3.170** | 1.286 | 7.527*** | 0.675 |
| P-value | 0.025 | 0.258 | 0.006 | 0.412 |

*Notes: t-statistics in () and *, **, *** respectively at 10, 5, and 1% significance level.*

Therefore, taking the proportion of fossil energy as our transition variable, we establish the one-transition-function ($r = 1$) and the two-threshold ($m = 2$) PSTR model with fixed effect:

$$TFEE = u_i + \beta_0 ER_{it} + \beta_1 ER_{it} \times \frac{1}{\left[1 + e^{-\gamma(q_{1it} - c_1)\times(q_{1it} - c_2)}\right]} + \varepsilon_{it} \tag{4}$$

where $ER_i$ represents the level of environmental regulation. We refer to the Ying and Zhou [38], evaluating the level of environmental regulation by standardizing and adding together investment in the treatment of waste water, waste gas and solid waste.

$$ER_i = \sum_j \frac{E_{ij}}{\sum_i E_{ij}} / \frac{O_i}{\sum O_i} (j = 1, 2, 3; i = 1, 2, 3...n) \quad (5)$$

$E_{ij}$ represents the investment in the treatment of waste $j$ in province $i$, and $O_i$ represents the gross product of province $i$. We calculate $ER_i$ by dividing the ratio of investment in the treatment of wastes of province $i$ to that of the nation by the ratio of gross product of province $i$ to that of the nation, and adding together according to the category of wastes. Data of investment in the treatment of waste water, waste gas and solid waste are from the China Statistical Year book on Environment.

#### *4.2.2. The PSTR Model taking both Ratio $q_1$ and Scale $q_2$ as transition variables*

In our study, the energy consumption structure does not only refer to the relative concept of the ratio of fossil fuel in the structure of primary energy consumption, but also involves the absolute concept of total fossil fuel consumption in the total energy consumption. Therefore, we introduce both the ratio and the scale of fossil energy consumption into our empirical model.

We conduct a redundant variables nonlinear effect test on the total fossil energy consumption in the empirical model taking the ratio $q_1$ of fossil energy consumption as transition variable. Since the absolute value of the total fossil energy consumption is out of range, we choose the logarithm of the total fossil energy consumption, which is represented by $q_2$, as the proxy indicator to facilitate parameter searching. Among the rest, $q_2 = \ln(cfe)$ and the "$cfe$" refers to the absolute value of the total fossil energy consumption. Its unit is ten thousand tons. We set the reduction factor τ to be 0.5 to correct the significant level. As is shown in Table 5, the Lagrange Multiplier (LM) statistic is 16.890, rejecting the null hypothesis at the 1% significance level.

Therefore, establish a PSTR model with fixed effect, taking $q_1$ and $q_2$ as transition variables:

$$TFEE = u_i + \beta_0' ER_{it} \times \frac{1}{[1 + e^{-\gamma(q_{1it} - c_1) \times (q_{1it} - c_2)}]} + \beta_2' ER_{it} \times \frac{1}{[1 + e^{-\gamma_2 (q_{2it} - c_3)}]} + \varepsilon_{it} \quad (5)$$

The transition function is $g_2 = (1+\exp(-\gamma_2(q_2 - c_3)))^{-1}$, where $q_2$ is the logarithmic form of total consumption of fossil energy. The redundant variable nonlinear effect is significant in the PSTR model with both transition variable $q_1$ and $q_2$. There are two transition functions ($r = 2$), and one threshold ($m = 1$) $c_3$ in the transition function $g_2$.

## 5. EMIPIRICAL RESULTS

### *5.1 Calculation Results of TFEE*

Unlike the output indicators and calculating method in the study of Weiguo and Dan [39], this study involved three undesirable outputs to estimate the TFEE. The results do not show a significant upward or downward trend. Yuan *et al.* [40] hold that the TFEE of central China was the lowest, while in our empirical study, the lowest TFEE lies in the West China. The TFEEs for 30 regions in 2014 are shown in Table 6.

**Table 5. Homogeneity test for the model with transition variable of $q_2$.**

| | $H_0$ | $H_{03}$ | $H_{02}$ | $H_{01}$ |
|---|---|---|---|---|
| LM | 16.890*** | 0.7855 | 7.667*** | 8.678*** |
| p | 0.001 | 0.3755 | 0.006 | 0.003 |
| $LM_F$ | 5.304*** | 0.7087 | 3.508* | 7.994*** |
| p | 0.001 | 0.4006 | 0.062 | 0.005 |

*Notes: t-statistics in () and *, **, *** respectively at 10, 5, and 1% significance level.*

**Table 6. The TFEEs for 30 regions in 2014.**

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Beijing | Tianjin | Hebei | Shanxi | Neimeng | Liaoning | Jinin | Heilongjiang | Shanghai | Jiangsu |
| 1.0000 | 1.0000 | 0.8633 | 0.8223 | 0.8420 | 0.8802 | 0.8921 | 0.8880 | 1.0000 | 0.9359 |
| Zhejiang | Anhui | Fujian | Jiangxi | Shandong | Henan | Hubei | Hunan | Guangdong | Guangxi |
| 0.9397 | 0.8860 | 0.9549 | 0.9200 | 0.8829 | 0.8857 | 0.9202 | 0.9314 | 1.0000 | 0.9083 |
| Hainan | Chongqing | Sichuan | Guizhou | Yunnan | Shanxi | Gansu | Qinghai | Ningxia | Xinjiang |
| 0.8825 | 0.9342 | 0.9123 | 0.8469 | 0.8880 | 0.8557 | 0.8593 | 0.8502 | 0.8247 | 0.8371 |

### *5.2 Estimation Results of PSTR with transition variable $q_1$*

The $q_1$ is the proportion of fossil energy in the total energy consumption. The slope coefficient $\gamma$ and location parameters $c_1$ and $c_2$ in the PSTR model can be obtained by the nonlinear least square method (NLS). With the minimum objective function of sum of squared residuals, the minimum value of residual convergence is obtained by grid search after times of iteration. The estimation results are shown in Table 7.

It can be seen that the impact of environmental regulation on the TFEE has significant characteristics of double thresholds, which are $c_1 = 0.0864$ and $c_2 = 0.9276$, when taking fossil energy consumption proportion as transition variable. When the domain of $q_1$ is (0, 1), the transition function $g_1$ is asymmetric. Especially if $0.8864 < q_1 < 0.9276$, the model is in the middle regime, and environmental regulation's impact on the TFEE is negative. The number of sample observations in the middle regime is 125, accounting for 37.88%.

The transition function curve of environmental regulation's impact on the TFEE is shown in Figure 2.

As we can see in the figure, the blue segment represents the positive effect and the red segment represents the negative effect. Environmental regulation has a significant nonlinear effect on the TFEE in the two-regime model with proportion of fossil energy consumption $q_1$ as a transition variable.

**Table 7. Results of PSTR model with transition variable of fossil energy consumption ratio.**

| Γ | c1 | c2 | β0 | β1 | SSR | AIC | BIC | F |
|---|---|---|---|---|---|---|---|---|
| 0.2000 | 0.8864 | 0.9276 | -45.282*** (-3.23) | 90.482*** (3.23) | 0.0511 | -1954.68 | -1947.08 | 6.830*** |

*Notes: t-statistics in () and *, **, *** respectively at 10, 5, and 1% significance level.*

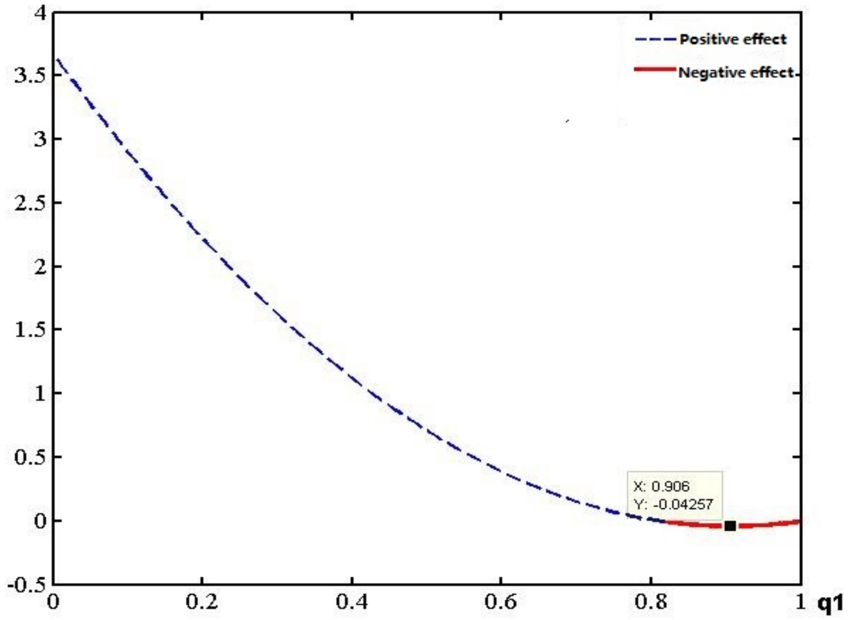


**Fig. 2. Effect coefficients in the model with $q_1$ as transition variable.**

**Table 8. Estimation results of PSTR model with transition variable of $q_1$ and $q_2$.**

| Parameter | Estimation | Parameter | Estimation |
|---|---|---|---|
| $\gamma_1$ | 0.2004 | $\beta_1$ | 73.50 *** |
| $c_1$ | 0.8866 | | (3.75) |
| $c_2$ | 0.9253 | $\beta_2$ | -1.66*** |
| $\gamma_2$ | 5.6461 | | (-9.67) |
| $c_3$ | 1.9390 | SSR | 0.0487 |
| $\beta_0$ | -35.13*** | AIC | -1967.96 |
| | (-3.58) | F | 37.01*** |

*Notes: t-statistics in () and *, **, *** respectively at 10, 5, and 1% significance level.*

### 5.3. Estimation Results of PSTR with transition variables both $q_1$ and $q_2$

The estimation results are obtained by the nonlinear least square method and extreme value grid search method. The results are shown in Table 8.

According to the estimation results, taking both the ratio $q_1$ of fossil fuel consumption in the primary energy structure and the logarithm $q_2$ of the total fossil energy consumption as transition variables, the impact of environmental regulation on the TFEE presents significant and clear non-linear effect. In our empirical model, $g_1$ is a three-regime logistic function containing two outer regimes and one middle regime. The outer regimes are $q_1 \in [0, 0.8866] \cup [0.9253, 1]$, while $g_2$ is a two-regime logistic function, where the system of low fossil energy consumption corresponds to $q_2 \in [-\infty, 1.9390]$ and the system of high fossil energy consumption corresponds to $q_2 \in [1.9390, +\infty]$. Therefore, we can identify four regimes according to the significance level of environmental regulation's nonlinear effect on the TFEE. Thereinto, the regime with the most significantly up-regulating effect is a union set of the outer regime of transition function $g_1$ and the high regime of transition function $g_2$, which is $\{(q_1, q_2) \mid q_1 \in [0, 0.8866] \cup [0.9253, 1], q_2 \in [-\infty, 1.9390]\}$.

#### 5.3.1. The results of PSTR with $q_1$ invariant and $q_2$ changeable

In the model with transition variables of both $q_1$ and $q_2$, there is also a nonlinear effect. The effect function of environmental regulations' impact on the TFEE $\beta'(q_1, q_2) = \beta'_0 + \beta'_1(q_1) + \beta'_2(q_2)$ is a three-dimensional continuous surface of both $q_1$ and $q_2$. According to the counter lien of zero in the surface, the effect function $\beta'(q_1, q_2)$ has areas of positive and negative effects (the grey area in Figure 3). As the color gets darker, the negative effect gets larger. Empirical results show that 83.64% of the sample observations are associated with a negative effect while 16.36% of them are in area of positive effect. With the popularization of cleaner energy sources such as nuclear, wind and solar energy, the nonlinear effect values of environmental regulation on the TFEE in Peking, Zhejiang and Guangdong are transiting from the negative zone to the positive zone.

#### 5.3.2. The results of PSTR with both $q_1$ and $q_2$ changeable

The impact of environmental regulation on the TFEE is changing with transformation in energy consumption structures, which consists of proportion factor $q_1$ and scale factor $q_2$. According to the contour plots in Figure 3 (right), intensifying environmental regulation does not always improve the TFEE. In area of negative effect (the shadow in Figure 3, right), where both proportion and scale of fossil energy consumption are relatively high, intensifying environmental regulation leads to a deterioration of the TFEE. As previously mentioned, environmental regulation may result in productivity loss in a fossil-energy-intensive economy and bring about a decline of the TFEE. Moreover, the contour plots in the three-dimensional surface (Figure 3, left) shows that the effect coefficient $\beta'(q_1, q_2)$ presents the gradual step-up trend when both the proportion factor $q_1$ and the scale factor $q_2$ are decreasing together.

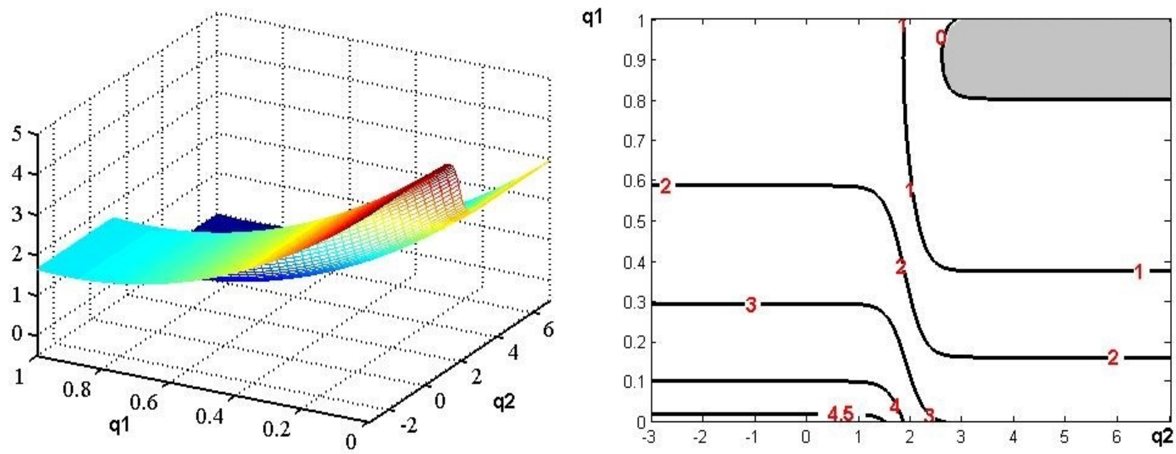


**Fig. 3. Effect coefficients in the model with $q_1$ and $q_2$ as transition variables.**

## 6. CONCLUSIONS AND POLICY IMPLICATIONS

In this study, in order to figure out the impact of environmental regulation on the TFEE and the mediating role of energy consumption structure, we provided a concrete diagram of its influence path. The TFEE for 30 regions in China are also measured by

SBM model. In addition, we implemented the PSTR to examine this impact of environmental regulation on the TFEE, based on the panel data for 30 provinces in China during the period 2004-2014.

The PSTR verification results show that stringent environmental regulation will enhance the TFEE if both the ratio and scale of fossil energy consumption are at a low level. If the ratio of fossil energy consumption goes down while the scale is still at a high level, environmental regulation's up-regulated effect on the TFEE won't reach the best. Similarly, if the scales of fossil energy consumption declines while the ratio fossil energy is still at a high level, environmental regulation will not enhance the TFEE to the optimum level.

The energy consumption structures for province-level divisions in China are quite different from each other. Most of the provinces are dominant by fossil fuels, while some developed municipalities directly under central government are popular with electricity. The region with cleaner energy consumption structure tends to perform better in TFEE. Environmental regulation will reduce the pollution emission at the price of economic decline in the region with cleaner energy consumption structure. Energy consumption structure is the main limiting factor for effectiveness of environmental regulation on the TFEE. Therefore, environmental regulations should be matched up with suitable energy management policies to improve energy consumption structure. As in the following, the environmental regulation can help realize the goal of building environment-friendly and resource-saving society adequately.

Recently, China has written a series of energy targets into the Energy 13$^{th}$ Five-year Plan, such as, to increase the share of non-fossil energy consumption to more than 15%, to reduce coal consumption to 58% and to increase the consumption of natural gas to 10%. Total energy consumption should be controlled under five billion metric tons by 2020.

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