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Green Total Factor Energy Efficiency in China and Its Influencing Factors

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ABSTRACT

In this paper, the green total factor energy efficiencies (GTFEEs) of 30 Chinese provincial administrative regions (provinces) are evaluated by the slack-based measure (SBM) model with undesirable output based on the panel data in 2000-2017. On this basis, the Tobit model was adopted to empirically analyze the factors affecting the GTFEE. The results show that most provinces in China had a low GTFEE, leaving an ample room for improvement; there were significant provincial differences in GTFEE: most provinces in East China had high GTFEEs, but the provinces in Central and West China did not achieve satisfactory GTFEEs; the regional difference in GTFEE was also obvious: East China had the highest GTFEE, followed in turn by Central China and West China; the GTFEEs of China and all three regions are affected by economic growth, industrial structure, property right structure, technological progress, opening-up, energy structure, and environmental regulation; the GTFEEs of China and all three regions were significantly suppressed by property right structure, and significantly promoted by opening-up; meanwhile, economic growth, industrial structure, technological progress, energy structure, and environmental regulation each exerted varied impacts on the GTFEEs of China and all three regions.

1. INTRODUCTION

In the last four decades, the Chinese economy has been the envy of the world. Currently, China's GDP is only smaller than that of the US, and nearly three times of Japan, the third largest economy in the world. However, there is a cloud in every silver-lining. The economic wealth of China is created at the cost of energy and environment.

For a long time, the fast-growing economy of China has consumed a huge amount of energy and emitted a mind-boggling amount of pollutants. In 2016, China contributed 14.2% of world's total economic output, while consuming 22.9% of the world's energy. To create each unit of GDP, China needs to consume 6 times more energy than Japan, 5 times more than the US, and 1.8 times more than India. Also in 2016, nearly 1/3 of greenhouse gases (GHGs) and 28.5% of pollutant gases (SO_2 and NO_X) were emitted in China.

What is worse, the energy structure of China is very irrational, as evidenced by the heavy reliance on imported oil, and the excessively low proportion of clean energy. In 2014, China imported 308 million tons of oil, about 59.5% of the oil consumed in that year. In 2017, coal accounted for 60.4% of the total energy consumption, while primary power and other renewable energy sources accounted for only 13.8%.

Therefore, China is under an enormous pressure to save energy, lower consumption, and reduce pollution. On the UN Climate Change Conference 2009 in Copenhagen, China promised to increase the proportion of non-fossil energies in its energy structure to 20%. Against this backdrop, it is of great practical significance to study how to improve the green total factor energy efficiency (GTFEE) in China.

Energy efficiency has attracted a growing attention from the academia, for the economic development is bottlenecked by energy depletion and environmental pollution. Early studies on energy efficiency are limited to single factor energy efficiencies, such as energy intensity, energy productivity, and energy technology efficiency [1-2]. Despite the simplicity in calculation, single-factor energy efficiencies cannot be combined with other factors, making them less practical. Since the emergence of total factor energy efficiency (TFEE), single-factor energy efficiencies have been gradually abandoned [3].

Later, many scholars have compared the TFEEs between countries and regions. For example, Hu and Kao [4], Mukheijee [5], Zhang et al. [6], and Simsek [7] measured and compared the TFEEs of different countries, revealing the sharp TFEE difference between countries. Moreover, Honma and Hu [8] conducted data envelopment analysis (DEA) on the TFEEs of 47 first-level administrative regions in Japan, and compared the results between these regions. Bai et al. [9] evaluated and compared the TFEEs of provinces (municipalities) in western China.

In addition, the influencing factors of the TFEE are another research hotspot. Studies have confirmed that the TFEE could be affected by the following factors: industrial structure [10], technological progress [11], energy structure [12], energy price [13], environmental regulation [14], to name but a few.

To sum up, multi-faceted research has been done on the energy efficiency, yield fruitful results. However, there are two weaknesses in the existing studies: (1) The undesirable output of environmental pollution has not been included in most TFEE research frameworks, causing large errors in the measurement of energy efficiency. (2) The influencing factors of energy efficiency are mostly investigated on the global scale. Few scholars have probed into the regional difference of these factors.

Through the above analysis, this paper establishes a slack-based measure (SBM) model with undesirable output, and then measures the GTFEEs of 30 provincial administrative regions (hereinafter referred to as provinces) in China, according to the panel data of these provinces in 2000-2017. On this basis, the authors identified the factors affecting the nationwide GTFEE, and the GTFEEs of East, Central, and West China. The research results provide a good reference for China to speed up the construction of a clean, low-carbon, safe, and efficient energy structure.

2. METHODOLOGY

2.1 SBM model with undesirable output

This paper measures the GTFEE in China through the DEA. Since its birth, this popular nonparametric method has been constantly improved. The earliest DEA models are Chames-Cooper-Rhodes (CCR) model and Banker-Chames-Cooper (BCC) model. The two models have been widely applied to efficiency evaluation of economy, ecology, energy, and many other fields. However, neither of them can effectively handle the undesirable output.

Traditionally, the undesirable output is converted into desirable output for efficiency evaluation. This practice clearly goes against the reality, and brings large errors in the evaluation results. To solve the problem, Tone [15] put forward the SBM model in 2001. Besides handling undesirable output, the SBM model can calculate the slack values of input and output indices, turning inefficiency to efficiency [16]. In general, the GTFEE measured by SBM model falls within [0, 1]. The principle of the SBM model is as follows:

Suppose there is a production system consisting of n decision-making units (DMUs), and each decision is a complete production flow. The production system can convert m units of production input into s_1 units of desirable output and s_2 units of undesirable output. More intuitively, the input, desirable output, and undesirable output are expressed as vectors $X=(x_1, x_2 \ldots, x_n) \in R_+^{mxn}$, $Y^g=(y_1^g, y_2^g, \ldots, y_n^g) \in R_+^{s_1 \times n}$, and $Y^b=(y_1^b, y_2^b, \ldots, y_n^b) \in R_+^{s_2 \times n}$, respectively. Let $DMU_0 = (x_0, y_0^g, y_0^b)$ be each DMU. Then, the SBM model with undesirable output can be expressed as:

$$
\begin{aligned}
\min \rho &= \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^{x-}/x_{io}}{1+\frac{1}{s_d+s_u}\left(\sum_{d=1}^{d}\frac{s_d^{y+}}{y_{do}}+\sum_{u=1}^{u}\frac{s_u^{b-}}{b_{uo}}\right)} \\
\text{s.t. } x_0 &= \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{x-}, i = 1,2,\ldots,m \\
y_0 &= \sum_{j=1}^{n} \lambda_j y_{dj} - s_d^{y+}, d = 1,2,\ldots,d \\
b_0 &= \sum_{j=1}^{n} \lambda_j b_{uj} + s_u^{b-}, u = 1,2,\ldots,u \\
\lambda &\geq 0, s_i^{x-} \geq 0, s_d^{y+} \geq 0, s_u^{b-} \geq 0
\end{aligned}
\tag{1}
$$

where, $s^{x-} \in R^m$, $s^{y+} \in R^d$, and $s^{b-} \in R^u$ are the slack terms of input, desirable output, and undesirable outputs (if s^{x-}, s^{y+} or s^{b-} is nonzero, then the input is excessive, the desirable output is insufficient, and the undesirable output is excessive, respectively; $0 < \rho \leq 1$ is the ratio of inefficiency input (fewer input is needed to improve the efficiency) to inefficient output (more desirable output and fewer undesirable output are needed to improve the efficiency).

If $\rho = 1$, the DMU_0 has an efficiency of 1. In this case, the DMU_0 is in the optimal state, without needing to improve the input and output variables; if $\rho<1$, the entire DMU_0 is inefficient. In this case, the slack terms of input and outputs must be eliminated, making the inefficient DMU efficient.

Formula (1) shows that the basic form of our SBM model is a linear programming model. It can be seen that the SBM model has some important features, namely, the null jointless and joint weakly disposability of desirable and undesirable outputs [17].

2.2 GTFEE evaluation index system

As the evaluation target, the GTFEE is a concept involving multiple factors, including labor, capital, and energy. It can be understood as the economic efficiency of energy under the constraints of environmental variables.

Referring to the findings of Hao et al. [18], this paper defines the GTFEE as the ratio of the maximum desirable output to the minimum undesirable output at the minimal inputs of labor, capital, and energy. Mathematically, the GTFEE is described as the ratio of the target energy input (i.e. the minimal energy input) to the actual energy input. Hence, the GTFEE of region i at time t can be expressed as:

$$
GTFEE_{it} = \frac{target\ energy\ input}{actual\ energy\ input} \tag{2}
$$

Formula (2) shows that the GTFEE falls within the value range of [0,1]. The result of formula (2) is positively correlated with the GTFEE. By the above definition, a GTFEE evaluation index system was set up based on the input-output relationship and the results of Zhang et al. [19] and Li and Hu [20]. As shown in Table 1, the evaluation indices in the system cover three input indices, a desirable output index, and an undesirable output index.

(1) Labor input: Labor input is indispensable to the evaluation index system. Labor is the key element of economic growth. Without labor input, the production equipment in enterprises cannot operate, making it impossible to tap the value of energy.

(2) Capital input: Capital is another essential input index of the evaluation index system. Labor alone cannot support the economic growth of the entire region, unless backed up by sufficient capital. The production activities of enterprises, the basic production units in national economy, determine the economic competitiveness of a region. In the absence of sufficient capital, an enterprise will not be able to purchase advanced production equipment or hire more workers, not to mention expanded reproduction. In this case, the energy cannot be utilized efficiently, and the economy will lose an important growth engine.

(3) Energy input: Energy input is the core input index of the evaluation index system, for our research aims to evaluate China's GTFEE.

(4) Gross domestic product (GDP) (desirable output): Desirable output is the good output of energy utilization. GDP has long been recognized as the best indicator of regional economy [21].

(5) SO_2 (undesirable output): Undesirable output is the bad output of energy utilization. The utilization of energy often produces various pollutants, posing a serious threat to the eco-environment. Since China has made SO_2 the main target of pollutant control, SO_2 was taken as the undesirable output of the evaluation index system.

Table 1. The evaluation index system of GTFEE

Type	Name	Meaning
Input indices	Labor input	The labor input is the year-end number of employees of each province in the sample period (unit: 10,000 persons).
	Capital input	The capital input is the actual capital stock of each province in the sample period (unit: 100 million yuan). Since the relevant data are not available in statistical yearbooks, the nominal capital stock of each province was estimated by permanent inventory method (PIM): $k_{i,t}=I_{i,t}+(1-\delta)K_{i,t-1}$, where, $k_{i,t}$ and $I_{i,t}$ are the capital stock, and fixed capital formation of province i in time t, respectively; δ =10.96% is the capital depreciation rate. To eliminate the distortion caused by price factors, the nominal capital stock was converted into actual capital stock with 2000 as the base period.
	Energy input	The energy input is the energy consumption of each province in the sample period (unit: 10,000 TCE). Note that the total energy consumption includes various energies like coal, coke, crude oil, diesel, gasoline, and natural gas. For simplicity, the consumptions of different energies converted and totaled by the standard coal coefficients (unit: 10,000 TCE).
Output indices	GDP (desirable output)	The GDP is the actual GDP of each province in the sample period; The statistical yearbooks only provide nominal GDP that contains price factors. To prevent inflation induced by price factors, the nominal GDP was deflated into actual GDP with 2000 as the base period, using the GDP index.
	SO_2 (undesirable output)	The SO_2 is the SO_2 emissions of each province in the sample period (unit: 10,000 tons).

2.3 Tobit model

In addition to GTFEE evaluation, this research attempts to identify and analyze the factors affecting the GTFEE in China, laying the basis for preparing energy policies that fit the situation of China. For this purpose, it is necessary to select a suitable metering model.

Since the GTFEE measured by the SBM model falls in [0, 1], the GTFEE as the explained variable in the metering model must be controlled between 0 and 1. If the model is regressed by the traditional ordinary least squares (OLS) method, the model result will skew to zero rather than reflect the actual situation [22]. In other words, the OLS method is not a desirable metering model for our research.

The above problem can be solved by the Tobit model, which was proposed by Tobit in 1958. Also known as the censored regression model, the Tobit model limits the explained variable between the upper bound of 1 and lower bound of 0 before regression analysis. Thus, the Tobit model adapts well to the empirical analysis of our research.

Drawing on the relevant literature Copeland and Talyer [23] and Xie et al. [24], this paper decides to discuss the influencing factors of the GTFEE from the aspects of economy, resource, institution, and technology. The effect mechanism of each influencing factor is summarized below:

(1) Economic growth (EG): The economic growth of a region is closely related to the intensity of energy consumption. On the one hand, the continuous growth of regional economy intensifies energy consumption, and pushes up pollutant emissions. On the other hand, economic growth promotes industrial upgrading and the awareness of environmental protection, and thereby suppresses the intensity of energy consumption and reduces pollutant emissions [25]. It is very meaningful to explore the exact impact of economic growth of the GTFEE.

(2) Industrial structure (IS): The industrial sector can be divided into primary, secondary, and tertiary industries. The secondary industry, which is mainly composed of manufacturing, consumes more energy, and produces more pollutants (SO_2) than the other two industries [26]. Still a developing country, China is being quickly industrialized. The secondary industry occupies a large portion of the national economy. This is obviously detrimental to the GTFEE.

(3) Property right structure (PS): The production activities of enterprises with different property rights are incentivized under different mechanisms. In general, the production activities of state-owned or state-controlled enterprises are affected by national policies. These enterprises tend to have a low production efficiency, and pay little attention to energy conservation. Meanwhile, most profit-seeking small and medium-sized enterprises focus on reducing costs (e.g. energy cost), and improve production efficiency. Their property right structure is conducive to the improvement of GTFEE.

(4) Technological progress (TP): Technological progress is an important driver for regional energy conservation and emission reduction. Normally, technological progress promotes enterprises to upgrade equipment, reduce input of factors (e.g. energy), and improve the energy efficiency. Moreover, technological progress also motivates enterprises to purchase advanced emission reduction equipment, reducing the level of pollutant emissions. These two mechanisms work together to promote the GTFEE.

(5) Opening-up (OU): China has been sticking to the opening-up policy. The degree of opening-up is mirrored by foreign direct investment (FDI). Over the past four decades, China has actively encouraged foreign investment. The influx of foreign capital provides the funds needed for regional economic development, speeding up economic growth. Furthermore, the FDI is accompanied by the entry of advanced production technologies, management experience, and environmental standards from foreign countries. All of these helps reduce regional energy intensity and slash pollutant emissions [27].

(6) Energy structure (ES): Energy is the core variable in the evaluation of the GTFEE. Thus, the energy structure can have a direct impact on GTFEE. Due to energy endowments, China has an energy system dominated by traditional fossil energies. Unlike bioenergy, wind power, and biomass energy, coal and other fossil energies are unclean. The utilization of unclean energies will produce a huge amount of SO_2. Till now, China remains as large producer and consumer of coal. The coal-dominated energy structure suppresses the GTFEE.

(7) Environmental regulation (ER): Studies have shown that environmental regulation could force enterprises to reduce emissions or cause the green paradox [28]. If a region has a high level of environmental regulation, e.g. the government imposes severe administrative penalties and charge pollution fees, the enterprises will be forced to optimize their energy structure and improve energy efficiency. If a region has a low level of environmental regulation, e.g. the government does not generously subsidize the use of clean energy, the enterprises will choose the profitable high-pollution

production model over the attractiveness of the clean energy subsidy, resulting in the green paradox. The exact effect of environmental regulation on the GTFEE remains to be unveiled.

Based on the above effect mechanism, a Tobit model was constructed with GTFEE as the explained variable, and EG, IS, PS, TP, OU, ES and ER as the explanatory variables:

$$\begin{gathered} GTFEE_{it}^{*} = \alpha + \beta_1 EG_{it} + \beta_2 IS_{it} + \beta_3 PS_{it} + \\ \beta_4 TP_{it} + \beta_5 OU_{it} + \beta_6 ES_{\mathrm{it}} + \beta_7 ER_{\mathrm{it}} + \varepsilon \\ \begin{cases} GTFEE_{it} = GTFEE_{it}^{*} & (if\ GTFEE_{it}^{*} < 1) \\ GTFEE_{it} = 1 & (\text{if}\ GTFEE_{it}^{*} \geq 1) \end{cases} \end{gathered} \tag{3}$$

where, $GTFEE_{it}^{*}$ is the GTFEE, the explained variable of the model; EG_{it} is economic growth measured by per-capita GDP (to eliminate the effect of collinearity, the natural logarithm of per-capita GDP is used in the model); IS_{it} is the industry structure measured by the output of secondary industry as a proportion of GDP; PS_{it} is the property right structure measured by the industrial output of state-owned or state-controlled enterprises as a proportion of the total industrial output; TP_{it} is technical progress measured by the research and development (R&D) expenditure as a proportion of GDP; OU_{it} is opening-up measured by the actual FDI as a proportion of GDP (the USD is converted into RMB at the mean exchange rate); ES_{it} is energy structure measured by the coal consumption as a proportion of total energy consumption; ER_{it} is environmental regulation measured by the industrial pollution investment as a proportion of the total industrial output.

2.4 Data sources

Considering the data availability and completeness of all variables in the SBM model and the Tobit model, the panel data (2000-2017) of 30 Chinese provinces were selected for our research. Tibet, Hong Kong, Macao, and Taiwan were excluded, for the incompleteness of their data. The data on GDP, per-capita GDP, output of secondary industry, year-end number of employees, total energy consumption, coal consumption, fixed asset formation, SO_2, FDI, and R&D expenditure were extracted from *China Statistical Yearbooks*, *China Energy Statistical Yearbooks*, *China Statistical Yearbooks on Environment*, *China Science and Technology Statistical Yearbooks*, *China Industry Statistical Yearbooks*, local statistical yearbooks, and the website of the National Bureau of Statistics of China. The few missing items in the panel data were supplemented by moving average method.

3. RESULTS

3.1 Measurement results of GTFEE

Based on the GTFEE evaluation index system, the data on labor input, capital input, energy input, GDP, and SO_2 were imported to maxDEA to measure the GTFEEs of 30 Chinese provinces, using the SBM model with undesirable output. For simplicity, the mean GTFEEs of the 30 provinces in 2000-2017 are presented in Figure 1.

As shown in Figure 1, there were significant provincial differences in the GTFEE in China during the sample period. The mean GTFEEs of Shanghai, Fujian, and Yunnan remained at 1 throughout the sample period, reaching the efficient frontier, while those of the other provinces were far smaller than 1, leaving a room for improvement.

By the mean GTFEE, the 30 provinces can be allocated to three clusters: high-efficiency cluster (GTFEE=0.9-1), medium efficiency cluster (GTFEE=0.5-0.9), and low-efficiency cluster (GTFEE<0.5).

Seven provinces belong to the high-efficiency cluster, including include Shanghai, Fujian, Yunnan, Hainan, Tianjin, Liaoning, and Beijing. All of them are located in East China, except Yunnan, which lies in West China.

Nine provinces belong to the medium efficiency cluster, including Anhui, Guangdong, Zhejiang, Jiangsu, Heilongjiang, Hubei, Sichuan, Hunan, and Shandong. Among them, Guangdong, Shandong, Zhejiang, and Jiangsu are located in East China, and the others exist in Central and West China.

Fourteen provinces belong to the low-efficiency cluster, including Chongqing, Jilin, Guangxi, Hebei, Henan, Jiangxi, Xinjiang, Inner Mongolia, Shaanxi, Qinghai, Shanxi, Guizhou, Gansu, and Ningxia. Among them, only Hebei is located in East China, while all the others exist in Central and West China. The members of the low-efficiency cluster had low GTFEEs, leaving an ample room for improvement.

In summary, China's GTFEE exhibited strong provincial differences. Most of the provinces with relatively high GTFEE are located in East China, while most of the provinces with relatively low GTFEE are part of Central and West China. In addition, 23 (76.77%) of all samples belong to medium and low-GTFEE clusters, indicating that most provinces in China have a low GTFEE. Therefore, China is facing a huge pressure on energy saving and emission reduction.

China boasts a vast territory. The resource endowments vary greatly from region to region. According to official documents, geography, and economic level, the country can be divided into three regions: East China, Central China, and West China. To disclose the regional difference in GTFEE, the mean GTFEE trends of China and its three regions are displayed in Figure 2.

As shown in Figure 2, the nationwide mean GTFEE and the mean GTFEEs of Central and West China exhibited roughly the same trend: the mean GTFEEs declined significantly from 2000 to 2001, and slowly increased from 2002 to 2017. The opposite trend was observed for the mean GTFEE of East China, which increased before 2015 and decreased thereafter.

The three regions differed sharply in the mean GTFEE. During the sample period, the mean GTFEE (0.8259) of East China was much higher than the national average of 0.5861; that (0.5147) of Central China was close to the national average; that (0.3900) of West China was below the national average.

Overall, East China had the highest GTFEE, followed in turn by Central China and West China. Therefore, the future energy policies of China must consider the regional difference in energy efficiency, and adapt to the local conditions.

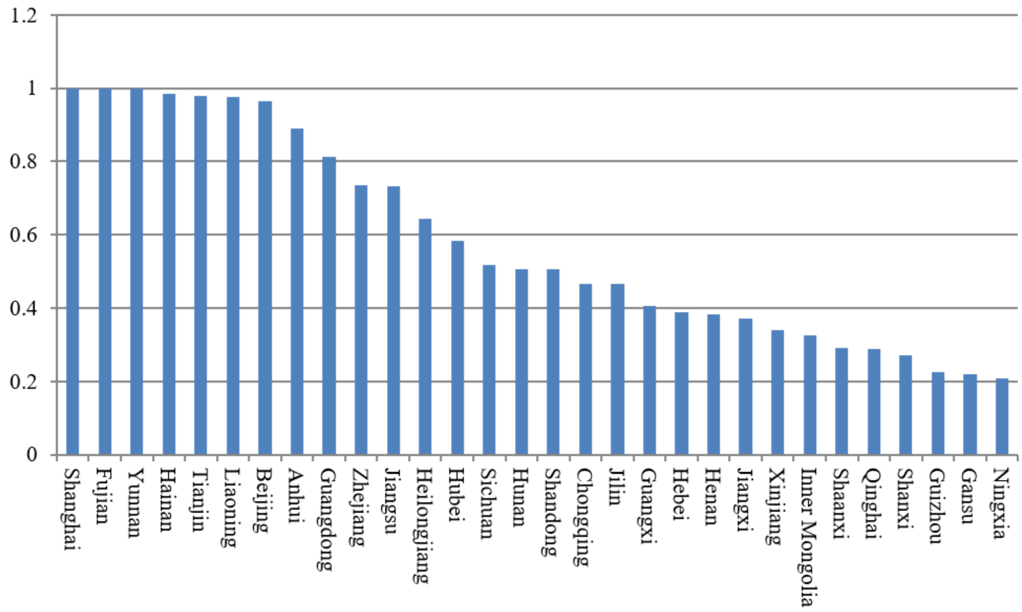

Figure 1. The mean GTFEEs of 30 Chinese provinces

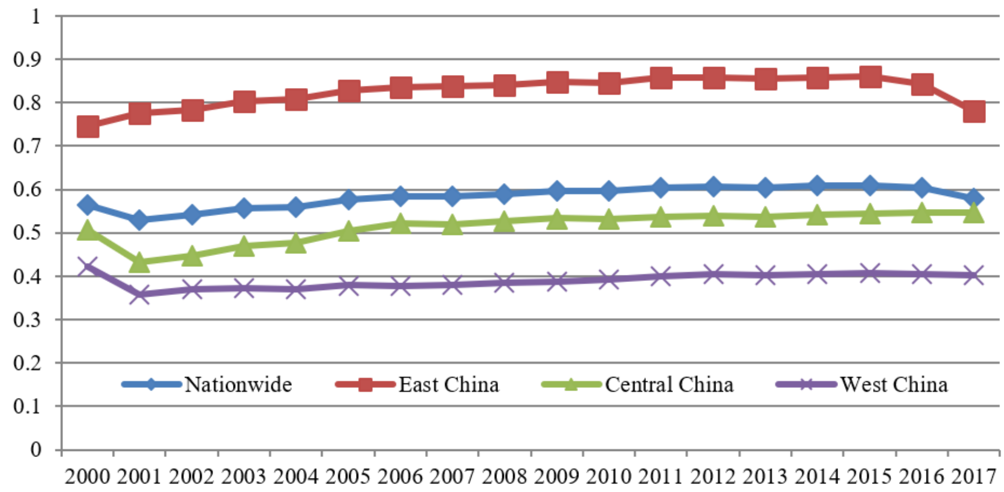

Figure 2. Mean GTFEE trends of China and its three regions

3.2 Results of Tobit model

By formula (3), the influencing factors of China's GTFEE were regressed on Tobit model, using Stata 12.0. Table 2 presents the empirical results on the panel data of China and its three regions.

Table 2. Regression results of Tobit model

Variable	Nationwide	East China	Central China	West China
EG	0.0690***	0.3278***	-0.1204***	0.0097
	(3.47)	(6.30)	(-4.13)	(0.37)
IS	-1.1238***	-0.4493	-0.1436	-0.9450***
	(-6.26)	(-1.22)	(-0.64)	(-2.57)
PS	-0.0731	1.0137***	0.1218	-0.1405
	(0.96)	(4.54)	(1.27)	(-1.17)
TP	4.2330***	-9.9072***	45.2615***	-3.6765
	(2.64)	(-3.98)	(8.64)	(-1.32)
OU	7.4294***	5.6035***	2.4209*	2.8985*
	(11.62)	(5.93)	(1.66)	(1.82)
ES	-0.2198***	-0.9177***	0.1517*	-0.1583***
	(-4.10)	(-4.68)	(1.88)	(-2.56)
ER	-0.7604	38.5086***	-27.8407***	-6.6733*
	(-0.21)	(3.60)	(6.3241)	(-1.60)
Log-likelihood	-118.1511	-34.6016	43.7418	-9.4698

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

As shown in Table 2, economic growth exerted a significant positive impact on nationwide GTFEE and the GTFEE of East China on the 1% level, an insignificant positive impact on the GTFEE of West China, and a significant negative impact on the GTFEE of Central China. These results prove the validity of the Environmental Kuznets Curve (EKC) in China: the correlation between environmental pollution and per-capita GDP is positive in the early phase of economic development, and negative in the latter phase. East China is much more developed than Central and West China. As a result, the growing per-capita GDP in East China is conducive to the GTFEE. On the contrary, the growing per-capita GDP in Central and West China either greatly inhibits or slightly promotes the GTFEE.

Industrial structure exerted a significant negative impact on nationwide GTFEE and the GTFEE of West China on the 1% level, and an insignificant negative impact on the GTFEEs of East and Central China. The possible reason is that China has vigorously advocated the green transform of industries in recent years. The enterprises are encouraged to use clean energy on a large scale, and required to reduce pollutant emissions. Moreover, the manufacturers in the secondary industry must further cut down excess capacity. In these respects, East and Central China do better than West China. In 2017, 38.36% of the GDP in East China came from secondary industry, 3% higher than that in West China.

Property right structure exerted an insignificant negative impact on nationwide GTFEE and the GTFEE of West China, a significant positive impact on the GTFEE of East China on the 1% level, and an insignificant positive impact on the GTFEE on Central China. The impact of property rights structure on GTFEE varies from region to region, owing to the regional difference in property right structure. As mentioned before, if a region owns many small and medium-sized enterprises, the enterprises in that region will have a relatively high production efficiency, and make intensive use of energy. Therefore, it is difficult to increase the GTFEE if a great proportion of the total industrial output is realized by state-owned or state-controlled enterprises. In 2017, that proportion was 26.48% in East China, 27.92% in Central China, and as high as 43.30% in West China. Hence, East and Central China have a much higher degree of marketization than West China.

Technological progress exerted a significant positive impact on nationwide GTFEE and the GTFEE of Central China on the level of 1%, a significant negative impact on the GTFEE of East China, and an insignificant negative impact on the GTFEE of West China. The regional differences mainly result from the varied orientations of technical innovations. According to Acemoglu et al. [29], technical innovations could lead to clean technologies or polluting technologies. If an enterprise is initially engaged in polluting technologies, its R&D activities could only create more pollutants, instead of curbing emissions. Owing to resource endowments, the R&D of enterprises in East and West China emphasizes on profitable polluting technologies, while that in Central China pursues environmental-friendly clean technologies.

Opening-up exerted a significant positive impact on the GTFEE of China and its three regions. This is consistent with the prediction in the previous sections. As China further opens to the world, more and more foreign investment has been attracted. From 2000 to 2017, the FDI in China increased by 2.21 times from USD 59.356 billion to USD 131.135 billion. The continuous influx of the FDI has enhanced China's ability to save energy and reduce emissions.

Energy structure exerted a significant negative impact on nationwide GTFEE, and the GTFEEs of East and West China, and a significant positive impact on the GTFEE of Central China. The possible reason is that most provinces in Central China, which used to be big coal consumers, have been actively replacing coal with clean energies. However, the coal consumption has not decline significantly in provinces of East and West China.

Environmental regulation exerted an insignificant negative impact on nationwide GTFEE, a significant negative impact on the GTFEEs in Central and West China, and a significant positive impact on the GTFEE in East China. These results echo with our previous expectation, that is, strict environmental regulation makes enterprises to save energy and reduce emissions, while relaxed environmental regulation causes the green paradox to the production activities of enterprises. In 2017, East China spent 37.063 billion yuan to control industrial pollution, while Central and West China only invested 18.278 billion yuan and 12.805 billion yuan in this field, respectively. Thus, East China is much stricter with environmental regulation than the other two regions.

4. CONCLUSIONS

Based on the panel data (2000-2017) on 30 Chinese provinces, this paper sets up an evaluation index system for the GTFEE, measures China's GTFEE with an SBM model with undesirable output, and analyzes the influencing factors of GTFEE with Tobit model. The main conclusions are as follows:

(1) Most provinces in China had a low GTFEE, leaving an ample room for improvement.

(2) There were significant provincial differences in GTFEE. Most of the provinces with relatively high GTFEE are located in East China, while most of the provinces with relatively low GTFEE are part of Central and West China.

(3) The nationwide mean GTFEE and the mean GTFEEs of Central and West China exhibited roughly the same trend: declining before rising; the opposite trend was observed for the mean GTFEE of East China.

(4) In terms of regional difference, East China had the highest GTFEE, followed in turn by Central China and West China.

(5) The empirical results of Tobit model show that the GTFEEs of China and all three regions were significantly suppressed by property right structure, and significantly promoted by opening-up. Meanwhile, economic growth, industrial structure, technological progress, energy structure, and environmental regulation each exerted varied impacts on the GTFEEs of China and all three regions.

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