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Do Factor Market Distortions and Carbon Dioxide Emissions Distort Energy Industry Chain Technical Efficiency? A Heterogeneous Stochastic Frontier Analysis

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Abstract: China's high-quality economic development is hampered by market distortions, and promises to achieve peak carbon emissions by 2030, meaning that its economic growth faces serious environmental constraints. We use a heterogeneous stochastic frontier model to analyze the impact of factor market distortions and carbon dioxide emissions on economic growth, and to evaluate the Chinese energy industry's chain technical efficiency under the influence of factor distortions and carbon dioxide emissions. Finally, the counterfactual measurement method is used to calculate the factor market distortions and loss of the energy industry chain technology efficiency as a result of carbon dioxide emissions. The main research results show that China's energy technology efficiency is 0.959, and the average energy industry chain technical efficiency for each region from the highest to the lowest is east (0.961), center (0.957), northeast (0.955), and west (0.950). The space for efficiency improvement is 3.6377%, 4.5151%, 4.7669%, and 5.2521%, respectively. Factor market distortion and carbon dioxide emissions are the main sources of losses of energy industry chain technical efficiency. Although the energy industry chain technical efficiency is subject to market factors, the structural factors caused by sustainable efficiency are more obvious. In the case of factor market distortions and carbon dioxide emissions, China's energy industry chain technical efficiency slowly increased from 0.952 in 2000 to 0.964 in 2016. By reducing the degree of factor market distortion, China's average energy industry chain technical efficiency will rise to 0.9651 from 0.9649, representing an improvement of 3.6162%.

Keywords: factor market distortion; energy industry chain; technological effect; carbon dioxide emission; stochastic frontier analysis of heterogeneity; counterfactual method



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1. Introduction

At present, China's economy is in a critical period of high-quality economic development. Maintaining high-quality economic development necessitates improving the efficiency of resource allocation, deepening economic restructuring and increasing the proportion of economic growth accounted for by green growth. Traditionally, a mode of economic growth that involves high energy consumption, high pollution, and high input is gradually restricted by environmental protection, carbon dioxide emissions, and a shortage of energy resources. At the same time, problems such as resource mismatch in the factor market also plague high-quality economic development [1,2]. The existing research results show that there are widespread distortions in the factor market in China, and the marketization process of the factor market lags behind the marketization process of the product market. Additionally, the marketization process of factor markets is inconsistent between different regions [3,4]. Some scholars, such as Lin and Du (2013) [2], believe that

China's factor market distortion inhibits the improvement of energy efficiency to a certain extent, but is this in line with China's current factor market goals? Compared with the single-index energy efficiency of the ratio of energy consumption to total economic output, is the impact of factor distortion on multi-index energy technology efficiency consistent?

According to World Bank estimates, China's energy intensity (energy industry chain consumption per unit of GDP) was reduced by 19.1% (the goal was 20% in "The Eleventh Five-Year Plan") ("The Twelfth Five-Year Plan" was mainly the twelfth five-year plan outline formulated by the Chinese government for economic and social development. It was a grand blueprint for China's economic and social development from 2011 to 2015. "The Eleventh Five-Year Plan" period was from 2006 to 2010, "The Tenth Five-Year Plan" period was from 2001 to 2005, and "The Thirteenth Five-Year Plan" period was from 2016 to 2020.) and 18.2% (the goal was 16% in "The Twelfth Five-Year Plan"), respectively, during "The Eleventh Five-Year Plan" and "The Twelfth Five-Year Plan", while the government has set an energy intensity target of 15% in "The Thirteenth Five-Year Plan" (2016–2020). At the same time, China has pledged to achieve peak carbon emissions by 2030, which requires China to pay attention to environmental pollution issues such as carbon dioxide emissions, while deepening the reformation of the market economic system and promoting economic development.

Therefore, this study focuses on the impact of factor market distortions on energy technology efficiency, and the impact of carbon emissions on heterogeneity. The clarification of the above problems will aid our understanding of factor market distortions and the relationship between carbon dioxide emissions and energy technology efficiency in the context of China's commitment to achieving peak carbon emissions by 2030. Additionally, reducing factor distortions and carbon dioxide emissions to achieve high-quality economic development has important theoretical and practical significance. In view of this, this paper will discuss the far-reaching impact of resource allocation as represented by factor distortions, and environmental protection as represented by carbon dioxide emissions from the perspective of energy industry chain technical efficiency.

2. Literature Review

The energy industry chain technical efficiency (TE) is a measure of the relationship between the actual and potential economic output in the energy industry chain, and involves energy exploitation, energy processing, energy supply, etc. [5–10]. Its economic definition is: how much energy input can be saved if the output remains unchanged; or under the condition of constant input, how much economic output can be increased? Energy technical efficiency puts the whole industrial chain in an "input–output" framework to evaluate the technical efficiency of the whole industrial chain [11,12]. Beatrice and Simone (2017) [3] called for the expansion of traditional energy efficiency research to industrial and supply chains in future research, and also pointed out that the original efficiency evaluation methods are still applicable in industrial chain efficiency analysis, but the analysis needs to be deeper. However, for now, this kind of research is scarce. One example is the work of Dong et al. (2021) [13], which applied a three-stage DEA method to evaluate the efficiency of the upstream, middle, and downstream areas of China's wind power industry chain.

In view of this, we need to find theoretical and methodological references from a large number of energy technology efficiency studies. The pioneering contribution to the study of technical efficiency should be attributed to Farrell (1957) [14], while the research and analysis of energy technical efficiency comes from Hoffmann (1982) [15] and Bengtson (1983) [16]. The existing studies on energy technology efficiency are mainly divided into the following categories:

The first kind studies the spatiotemporal differentiation characteristics and evolution law of technical energy efficiency. This kind of study mainly combines different individuals in different industries and regions. For example, from the existing literature on energy efficiency, the overall energy efficiency estimated by some scholars is about 60% to 70% [17]. Additionally, an "inverted U-shaped" trend has been observed [18]. Most scholars believe

that there are obvious regional differences in energy efficiency in China, which are characterized by regional imbalances [8,17–20], and there are also large inter-provincial energy efficiency differences in China [20]. Although the DEA model has the advantage of not considering the production function, it does not consider the error. When estimating the operating efficiency of an energy industry chain with a heterogeneous production mode, not considering the error may cause obvious measurement errors [21]. Therefore, the SFA model is favored in the research on energy efficiency estimation. Hu and Honma (2014) [22] estimated total-factor energy efficiency (TFEE) scores for 10 industries in 14 developed countries for the period 1995–2005 using the stochastic frontier analysis (SFA) technique. They found that most of the OECD industries have much room for improvement in terms of their total-factor energy efficiency. Haider and Mishra (2021) [23] estimated the energy efficiency, and quantified the energy-saving potential of Indian iron and steel firms. The results show that energy efficiency slightly declined over time. The SFA method has been widely used in energy efficiency evaluation and has the advantage of paying attention to statistical errors. From the perspective of the industrial chain, the error problem exists objectively, and must be paid attention to, which is why the original intention of this study was to measure energy efficiency via the SFA method.

The second category sorts out the factors that affect the energy technology efficiency. The first is institutional heterogeneity, which involves opening to the outside world and environmental regulation. Representative studies include those by Wei and Shen (2007) [24], Mandal (2010) [25], and Bi et al. (2014) [26]. Opening to the outside world can introduce relevant technology from developed countries, especially through innovation that improves the level of energy technology and management methods, to improve energy technical efficiency [27]. Its mechanism involves the introduction of foreign capital, and the positive spillover effect in the management system and technical level can improve energy efficiency. However, due to the existence of a “pollution paradise”, the level of opening may aggravate the consumption of energy resources [26], subsequently reducing energy efficiency; that is, opening to the outside world has a negative impact on China’s energy efficiency [24,27]. Environmental regulation mainly means that the government gives full play to the “promising government” and the “visible hand”, which aim to target the shortcomings of a market economy, such as negative externalities and information asymmetry, and limit unreasonable energy consumption by controlling environmental pollution so as to improve and enhance energy technology efficiency [25,26]. The second is the market structure. The existing literature believes that the market structure is an important factor affecting energy technology efficiency [27–29]. Market structure factors mainly affect energy technology efficiency in two ways: on the one hand, by expanding investment in the energy industry, and then increasing resources and energy consumption, which may lead to more serious pollution problems [8,9]; on the other hand, by increasing energy consumption through changes in the industrial economic structure and the reallocation of resources and factor demand, which makes use of technological innovation to have a positive effect. Wei and Zheng (2017) [30] found that market segmentation suppresses energy efficiency by affecting technical efficiency, scale efficiency, and allocation efficiency. The third is factor distortion. Lin and Du (2013) [2] used Wang and Ho’s (2010) [31] stochastic frontier fixed effect model to analyze the impact of factor market distortions on energy efficiency in China from 1997 to 2009. The results show that factor market distortions had a significant negative impact on China’s energy efficiency; eliminating factor market distortions can improve energy efficiency by an average of 10% per year. The fourth is environmental pollution. Li and Zhang (2019) [32] proposed that air pollution increases enterprise environmental costs and enterprise production costs, distorts factor redistribution efficiency [1,27], and reduces productivity. In addition, environmental pollution crowds out the R&D expenditure of enterprises and reduces the level of R&D [33], which is not conducive to improving technical efficiency. The fifth is other factors. For example, Fu et al. (2021) [34] and Chen (2018) [35] analyzed the impact of government size, added value of secondary industry, urbanization rate, and openness on China’s energy consumption and output efficiency.

By combing the relevant literature, we found that the existing research on the impact of factor distortion on energy technology efficiency has made some progress, and that systematic research has led to a certain consensus. However, the model assumptions used in the current energy technical efficiency analysis literature are based on the optimal production scale. Due to the problems of market information asymmetry, imperfect competition and resource and environmental constraints, the assumption of an optimal production scale cannot be established completely, so there is room for improvement in the research model. In addition, there is still no consensus on whether reducing the degree of factor market distortion can improve energy efficiency or energy technology efficiency, especially in the context of carbon dioxide emission restrictions. It is worth noting that some authors face deficiencies when discussing how to reduce the degree of factor distortion and improve efficiency. Lin and Du (2013) [2] took Shanghai as the benchmark, and set the degree of factor market development in all regions and at all times to the level of factor market development in Shanghai—that is, there is no relative distortion in the factor market—and then set the value of the factor market distortion variable to 0. Although this method can help us to analyze the counterfactual impact of factor distortion to a certain extent, it is also subject to its factor market hypothesis. In addition, there are few studies on the interpretation of energy technology efficiency from the perspective of industrial chains.

In general, there are some areas where further research on the SFA model needs to be done, including: (1) The lack of heterogeneity factors. Although different variables are considered in the existing literature, they are only considered as general variables in the practical application of the model. In this study, a heterogeneous stochastic frontier model is introduced to construct an analytical framework. (2) The heterogeneous SFA model is more suitable for the problems of incomplete competition and resource and environmental constraints, and deeply decomposes the chain technical efficiency of the energy industry. The main innovations of this study include the following: (1) Based on the fact that there are widespread distortions in China's regional factor markets and that the marketization process of factor markets in different regions is very inconsistent, the Greene (2005) [36] panel heterogeneity stochastic frontier model is used to empirically study the relationship between factor market distortion, carbon dioxide emissions and energy technology efficiency, and to deeply decompose the energy technology efficiency, which broadens the research scope. It is a useful supplement to the existing research. (2) The counterfactual analysis method of Chernozhukov et al. (2016) [37] is introduced to analyze the counterfactual impact of factor distortions and carbon dioxide emissions on China's energy technology efficiency, without setting specific values of factor market distortions and carbon dioxide emissions.

3. Methods

3.1. Research Model Design

3.1.1. Definition of Energy Industry Chain Technical Efficiency

We assume that the regional economy takes labor (*LAB*), capital (*CAP*), and energy (*ENE*) as factor inputs, and regional *GDP* (*GDP*) as the economic output (see Zhou et al. (2012)) [38] to define the production boundary of energy and industrial chain technical efficiency:

$$D_k(LAB, CAP, ENE, GDP) = \text{sub}\{\theta | (LAB, CAP, ENE/\theta, GDP) \in T\} \quad (1)$$

Zhou et al. (2012) [38] defined the related properties of the production boundary of energy technical efficiency $D_k \geq 1$, which was a linear homogeneous function of the input of energy factors into *ENE*. Therefore, referring to Zhou's definition of energy technology efficiency, the mathematical expression of energy technology efficiency is defined here:

$$TE = \frac{1}{D_k(LAB, CAP, ENE, GDP)} \quad (2)$$

It can be seen from Equation (2) that the actual energy input is equal to the optimal input when $\frac{1}{D_k} = 1$, at which point the production activity is energy-efficient; the more the actual production activity deviates from the optimal energy input when $\frac{1}{D_k} < 1$, the more ineffective the energy input. Therefore, $1 - \frac{1}{D_k}$ is approximately expressed as the loss of regional energy technology efficiency.

3.1.2. Stochastic Frontier Analysis Model of Heterogeneity

Stochastic frontier analysis models (SFAs) based on fixed effect estimation are usually subject to outliers [36], so it is impossible to effectively and accurately estimate the heterogeneity and inefficiency in the output. The existing literature has pointed out that confusing heterogeneity with inefficiency may seriously distort the efficiency change of the research object [31,39,40]. Therefore, ideally, modeling inefficiency and heterogeneity in the same model to separate heterogeneity and inefficiency is helpful to the analysis of energy industry chain technical efficiency. Referring to the stochastic frontier analysis model of heterogeneity proposed by Greene (2005) [36], we discuss the effects of factor distortion and carbon dioxide emissions on energy industry chain technical efficiency. The main setting models are:

$$y_{it} = f(x_{it}, z_i) + v_{it} \pm u_{it} = \alpha + \beta'x_{it} + \tau'z_i + v_{it} \pm u_{it}, u_{it} \geq 0 \quad (3)$$

where y_{it} is the output representation of decision making units (DMU) i ($i = 1, \dots, N$) in the period t ($t = 1, \dots, T$), such as profit, cost, etc.; x_{it} is the input factor price vector; and z_i is the control variable vector. The $v_{it} \pm u_{it}$ symbol depends on whether the boundary describes cost (positive) or production or profit (negative), and is distributed as follows:

$$v_{it} \sim N[0, \sigma_v^2] \quad (4)$$

$$u_{it} = |U_{it}|, U_{it} \sim N[0, \sigma_u^2] \perp v_{it} \quad (5)$$

In this paper, the production boundary of energy TE is set, and the production function needs to be selected in the stochastic frontier analysis model. Although the Cobb–Douglas production function has many advantages, it does not have generality [41,42]. Therefore, this paper uses the transcendental logarithmic production function model (Trans-log). The transcendental logarithmic production function can be used as the second-order approximation of the general function, and the specific form is as follows:

$$\ln y_{it} = \alpha_0 + \sum_{j=1}^3 \beta_j x_{j,it} + \sum_{j=1}^3 \sum_{n=1}^3 \theta_{jn} x_{j,it} \times x_{n,it} + \alpha_i + \epsilon_{it} \quad (6)$$

where $\alpha_0 = \alpha_0^* - E(\eta_i) - E(u_{it})$, $\alpha_i = \mu_i - \eta_i + E(\eta_i)$, and $\epsilon_{it} = v_{it} - u_{it} + E(u_{it})$.

The loss equation of heterogeneous energy industry chain technical efficiency is as follows:

$$u_{it} = u_{it}^* h_{it}, h_{it} = \exp(FAC_{it}\delta + CO2_{it}\gamma + z'_{it}\tau) \quad (7)$$

Through the estimation of the model's parameters, the change in China's energy TE can be estimated using the following Equation:

$$TE_{it} = \exp(-u_{it}^*), u_{it}^* = E[u_{it} | \epsilon_{it}] \quad (8)$$

Although the literature has mainly analyzed the TE of DMU and its impact, an analysis of the influencing factors based on TE estimation is still unable to distinguish the clear impact of DMU [43], especially in the analysis of energy TE under the serious influence of random factors. Most studies only estimate the overall energy TE of DMU objects and evaluate the input–output management practices of DMU according to these values. For example, in the existing literature, the decomposition methods of energy

technical efficiency are divided into growth effects (changes in the level of economic activity), structural effects (changes in the share of different industries), and efficiency effects (energy consumption per unit of value added in industry and the service industry). In addition, the *TE* can be decomposed based on the introduction of other variables by the Dirichlet average index method. According to the available literature [43,44], *TE* can be used to understand the potential improvements in overall production, which can be achieved by reducing the input of radial production factors or expanding radial production [8,9,41]. Furthermore, *TE* may be composed of structural changes related to structural factors (continuous efficiency, persistent efficiency, *PTE*) and technological residual empirical information factors that change over time (residual efficiency, *RTE*) [39,40]. Ignoring *PTE* and *RTE* in the assessment of output management practices may affect the efficiency. By referring to the decomposition model of Manevska-Tasevska et al. (2017) [43] and Agasisti and Gralka (2019) [44], this paper further quantitatively calculates and analyzes the contribution of residual empirical information factors and structural factors causing changes in energy industry chain technical efficiency in different regions. Based on this, in the evaluation of energy industry chain technical efficiency, the distinction between *PTE* and *RTE* can more clearly assess the impact of structural factors or residual empirical information factors. Among them, *TE* and its decomposition can be expressed as follows:

$$RTE = \exp(-u_{it}|\epsilon_{it}) \quad (9)$$

$$PTE = \exp(-\eta_i) \quad (10)$$

$$TE = RTE \times PTE \quad (11)$$

PTE may persist over time and change only when management practices change profoundly [40]. Therefore, *PTE* reflects the impact of persistence conditions on DMU, and these structural conditions predetermine that DMU operates at a specific level of efficiency. On the other hand, *RTE* changes over time, which may be caused by random factors such as weather, market and policy changes, or by empirical information [40]. Therefore, we can consider *RTE* to reflect the change in conditions over time.

3.2. Variables and Data Description

Based on the above research model design, the variables mainly include input, output, and influencing factors for measuring the energy industry chain technical efficiency across 29 provinces and cities in China (except Tibet, Hong Kong, Taiwan, and Macao). Among these provinces and cities, the input variables needed to exceed the logarithmic production function mainly include labor, capital, and energy consumption for energy exploitation, energy processing, and energy supply; the output is the regional *GDP*; and the core explanatory variables are factor market distortion and carbon dioxide emissions.

3.2.1. Input Variables

By referring to the relevant literature, the input variables selected include labor force, capital stock, and energy input. Firstly, the total employment population at the end of the year is selected to characterize *LAB*. Secondly, the calculation of capital stock (*CAP*) is conducted according to the method described by Peng et al. (2019) [8], combined with Peng's (2020) [9] fixed capital stock calculation method. We use the equation $K(t) = \Delta K(t) + (1 - \delta)K(t - 1)$, where $K(t)$ is the actual capital stock of period t , $K(t - 1)$ is the capital stock of period $t - 1$; and δ is the depreciation rate, which is generally set at 5%. The total amount of regional energy consumption represents the input of energy elements into *ENE*.

3.2.2. Output Variables

Due to the wide application of data envelopment analysis (DEA), output is generally divided into single output and multi-output, and expected output and non-expected output, in the existing literature on efficiency evaluation. Peng et al. (2019, 2020) [8,9] chose the

actual regional *GDP* as the measure of regional comprehensive output, mainly because although industry is the main output of energy consumption, with the development of science and technology, social progress, increased levels of urbanization, and an increase in the proportion of the tertiary industry, the regional *GDP* is still the most appropriate index to reflect output.

3.2.3. Core Variables

Factor market distortions (*FAC*). The existing literature points out that factor market distortions cannot be measured by a direct method because Yang et al. (2018) [7] believed that the process of product marketization is faster than that of factor market, and there are significant differences in the degree of factor development among regions [2]. Therefore, it is a common practice to characterize factor market distortion via an indirect method, such as measuring factor market distortion by introducing factor price and measuring the degree of relative distortion. This paper considers inter-regional heterogeneity and structural factors, and draws lessons from the research methods of Lin and Du (2013) [2]. We refer to the factor market development index published to measure the degree of regional factor market distortion (The marketization index published by Fan Gang and others includes total score, government–market relationship score, non-state-owned economic development score, product market development score, factor market development score, and market intermediary and legal environment score. this paper chooses a score that can measure the development of the factor market. As the factor market development index comes from the “China marketization process Index report”, the report mainly covers the period from 1997 to 2016. This paper selects the period 2000–2016 for the factor market distortion index).

Carbon dioxide (*CO*₂). This paper estimates the carbon dioxide emissions of various provinces and cities in China according to the carbon emission coefficient and carbon oxidation factor published by the Intergovernmental Panel on Climate change (IPCC).

3.2.4. Control Variables

In order to control the influence of other factors, the relevant control variables are set as follows: Firstly, the regional average years of education representing human capital (*EDU*) reflects the current situation of human capital in different regions. Secondly, the regional education expenditure (*EDR*) calculates government education expenditure, which reflects the degree of government intervention in education. Thirdly, the regional public financial expenditure (*FIN*) reflects the financial expenditure of the government for economic development. Fourth, the R&D expenditure (*RD*) is expressed by the internal R&D expenditure. Fifth, the total regional population (*POP*) reflects the level and scale of regional economic activity. Sixth, the total regional trade (*TRA*) is expressed by the total volume of regional import and export trade, which is used to reflect the degree of opening to the outside world.

3.2.5. Data Description

Based on the availability of data, the sample period of this study is 2000–2016. The balance panel data mainly comes from statistical databases, such as the EPS regional economic database, the CSMAR database, and so on. Because this paper mainly uses the transcendental logarithmic function to calculate the relevant results, the main variables are logarithmically treated. The descriptive statistical results and the correlation of the main variables are shown in Tables 1 and 2.

Table 1. Descriptive statistical summary of variables.

Variables	(Vars)	Unit	Obs	Mean	SD	Min	Max
regional GDP	GDP	100 million yuan	493	8.042	0.886	6	10
labor	LAB	person	493	7.552	0.836	6	9
capital	CAP	100 million yuan	493	9.404	1.042	7	12
energy consumption	ENE	bcm	493	9.342	0.865	6	11
labor squared	LABsq	/	493	57.736	12.182	32	78
capital squared	CAPsq	/	493	89.512	19.402	44	138
energy consumption squared	ENEsq	/	493	88.026	15.637	37	124
interaction between labor and capital	LABC	/	493	71.600	14.020	37	103
interaction between labor and energy consumption	LABE	/	493	71.054	12.743	35	98
interaction between capital and energy consumption	CAPE	/	493	88.578	16.605	44	131
factor market development degree score	FAC	/	493	4.845	2.459	0	14
regional CO2 emissions	CO2	ton	493	10.023	0.896	6	12
average years of education	EDU	person	493	2.123	0.126	2	3
regional education expenditure	EDR	100 million yuan	493	14.562	1.154	11	17
regional public financial expenditure	FIN	100 million yuan	493	16.398	1.091	13	19
R&D expenditure	RD	100 million yuan	493	13.511	1.633	9	17
district population	POP	person	493	8.158	0.771	6	9
total regional trade	TRA	100 million yuan	493	5.259	1.764	1	9

Table 2. Summary of correlation coefficients between variables.

Vars	GDP	LAB	CAP	ENE	FAC	CO2	EDU	EDR	FIN	RD
GDP	1	0.79 ***	0.81 ***	0.69 ***	0.58 ***	0.68 ***	0.32 ***	0.62 ***	0.61 ***	0.79 ***
LAB	0.85 ***	1	0.61 ***	0.62 ***	0.23 ***	0.62 ***	−0.09 **	0.52 ***	0.47 ***	0.52 ***
CAP	0.84 ***	0.67 ***	1	0.775 ***	0.68 ***	0.77 ***	0.59 ***	0.92 ***	0.92 ***	0.92 ***
ENE	0.75 ***	0.69 ***	0.81 ***	1	0.36 ***	0.99 ***	0.39 ***	0.72 ***	0.72 ***	0.67 ***
FAC	0.49 ***	0.15 ***	0.60 ***	0.29 ***	1	0.36 ***	0.61 ***	0.59 ***	0.59 ***	0.76 ***
CO2	0.76 ***	0.69 ***	0.79 ***	0.99 ***	0.28 ***	1	0.39 ***	0.71 ***	0.71 ***	0.66 ***
EDU	0.36 ***	−0.05	0.57 ***	0.36 ***	0.66 ***	0.34 ***	1	0.57 ***	0.61 ***	0.67 ***
EDR	0.68 ***	0.57 ***	0.93 ***	0.76 ***	0.52 ***	0.75 ***	0.55 ***	1	0.99 ***	0.85 ***
FIN	0.65 ***	0.53 ***	0.92 ***	0.75 ***	0.53 ***	0.74 ***	0.58 ***	0.99 ***	1	0.85 ***
RD	0.82 ***	0.59 ***	0.93 ***	0.73 ***	0.7 ***	0.72 ***	0.66 ***	0.87 ***	0.87 ***	1
POP	0.85 ***	0.99 ***	0.64 ***	0.69 ***	0.13 **	0.7 ***	−0.05	0.53 ***	0.49 ***	0.55 ***
TRA	0.82 ***	0.48 ***	0.84 ***	0.63 ***	0.74 ***	0.62 ***	0.66 ***	0.74 ***	0.73 ***	0.87 ***

Note: the lower triangle reports the Pearson's correlation value, and the upper triangle reports the Spearman's correlation value; *** $p < 0.01$, ** $p < 0.05$.

4. Results

According to the index system, we comprehensively use Greene's (2005) [36] heterogeneous stochastic frontier model to measure the changes in China's energy industry chain technical efficiency under the influence of factor market distortion and carbon dioxide emissions, and analyze the counterfactual characteristics of the impact of factor market distortion and carbon dioxide emissions on *TE*. We calculate the *TE* using STATA software, the results of which are discussed below.

4.1. Analysis of Regression Results

According to the setting of the heterogeneous stochastic frontier model and the consideration of the robustness of the model, this paper will impose different constraints on the parameters and estimate models (1)–(8) in turn (see Table 3). Table 3 takes the actual GDP as the explained variable. Models (1)–(5) are the results of transcendental logarithmic function estimation and models (6)–(8) are estimated and compared by the Cobb–Douglas production function. Model (1) is estimated by the OLS method, while models (2) and

(3) use the fixed effect and random effect estimation methods of panel regression (refer to Schmidt and Sichles (1984) [45]), respectively. Model (4) uses the stochastic frontier analysis method with maximum likelihood MLE estimation, and model 5 uses the stochastic frontier analysis with the real fixed effect model (refer to the heterogeneous stochastic frontier model of Greene (2005) [36]). Model (6) adopts a maximum likelihood estimation for stochastic frontier analysis; model (7) adopts Battese and Coelli's (1992) [29] general panel stochastic frontier analysis model; model (8) adopts the heterogeneous stochastic frontier analysis model of Greene (2005) [36]. Model (5) and model (8) calculate the estimated results of energy technical efficiency loss under two different production functions.

Table 3. Comparison of the effects of factor distortions and carbon dioxide emissions on energy industrial chain technology efficiency.

Function	Trans-Log				Cobb–Douglas			
	(1) OLS	(2) FE	(3) RE	(4) SFA	(5) SFA	(6) SFA	(7) SFA	(8) SFA
LAB	−0.0043 (0.381)	1.261 *** (0.309)	0.872 ** (0.371)	1.129 *** (0.348)	0.876 *** (0.290)	−0.0329 (0.0378)	−0.0326 (0.0405)	−0.0664 * (0.0384)
CAP	2.430 *** (0.342)	0.602 *** (0.0765)	0.770 *** (0.112)	0.616 *** (0.0778)	0.424 *** (0.0700)	0.106 *** (0.00889)	0.0852 *** (0.0102)	0.101 *** (0.00763)
ENE	−0.474 (0.340)	−0.232 *** (0.0822)	−0.244 ** (0.122)	−0.223 *** (0.0826)	−0.187 *** (0.0706)	0.214 *** (0.0131)	0.188 *** (0.0141)	0.179 *** (0.0110)
LABsq	−0.120 *** (0.0434)	−0.134 *** (0.0260)	−0.102 *** (0.0317)	−0.123 *** (0.0291)	−0.101 *** (0.0256)			
CAPsq	−0.0882 *** (0.0336)	−0.0479 *** (0.00715)	−0.0827 *** (0.0101)	−0.0502 *** (0.00712)	−0.0218 *** (0.00841)			
ENEsq	−0.0180 (0.0443)	0.0839 *** (0.0109)	0.0730 *** (0.0162)	0.0838 *** (0.0108)	0.0915 *** (0.0130)			
LABC	0.0494 (0.0571)	0.150 *** (0.0142)	0.189 *** (0.0200)	0.153 *** (0.0146)	0.128 *** (0.0159)			
LABE	0.202 *** (0.0647)	−0.0607 *** (0.0175)	−0.0637 ** (0.0258)	−0.0633 *** (0.0176)	−0.0569 *** (0.0173)			
CAPE	−0.0779 (0.0617)	−0.0765 *** (0.0130)	−0.0568 *** (0.0194)	−0.0756 *** (0.0128)	−0.0960 *** (0.0185)			
Energy industrial chain technology efficiency loss function estimation								
FAC					0.519 *** (0.132)			0.479 *** (0.115)
CO2					2.246 *** (0.402)			1.470 *** (0.283)
EDU					−1.541 (2.221)			2.874 ** (1.430)
EDR					−2.961 ** (1.150)			−0.575 (0.937)
FIN					0.764 (1.011)			−0.830 (0.881)
RD					1.152 *** (0.321)			0.581 ** (0.226)
POP					−0.764 ** (0.383)			−0.479 (0.301)
TRA					−1.510 *** (0.307)			−1.498 *** (0.278)
Cons	−4.947 *** (1.227)	0.0155 (0.929)	−0.597 (1.131)	1.367 (1.017)	−6.833 *** (0.851)	0.662 ** (0.277)	(0.273) (0.312)	6.425 *** (0.209)
Obs	493	493	493	493	493	493	493	493

Note: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As can be seen from the estimated results in Table 3, the estimated results of model (5) show the impact of the frontier on the energy industry chain technical efficiency. Whether in the constraint equation or the unconstrained equation, the elasticity coefficient values of

the quadratic and interactive terms of the selected labor, capital, and energy input factor endowment variables are significant at the level of at least 1%. Among them, the labor force and capital stock play the most important role in promoting the energy technology production boundary of each province and city, and their elastic coefficient values are 0.876, 0.424 and -0.187 , respectively. This shows that the demand of energy technology production for labor and capital-intensive factors is increasing with China's economic growth, and the accumulation of labor and capital can effectively stimulate and expand the boundary of energy technology production. The sum of the three elastic coefficients is greater than 1, indicating that the production function is of increasing scale.

In the selection of the model setting, according to the results of the likelihood ratio test, $LR1 = 136.03$. Referring to the statistical significance level of Kodde and Palm (1986) [46], the results reject the original hypothesis at the 1% significance level and indicate that the model that accounts for inefficiency is more effective; that is, the energy technical efficiency loss estimated by the Greene (2005) [36] model is effective, and the SFA model of maximum likelihood estimation is rejected (model 1). The fact that $LR2 = 38.41206$ shows that the alternative hypothesis is accepted at the level of 1% significance; that is, it has its own heterogeneity and fluctuating heterogeneity in terms of inefficiency. Therefore, when combining the two kinds of test results, it is shown that the stochastic frontier model with complete heterogeneity shows the best estimation of the impact of the loss of energy industry chain technical efficiency. The estimated results of the loss of energy technical efficiency are as follows.

For the core variables, the factor market distortion is significantly positive at the level of 1% for the regression coefficient of inefficiency, which shows that although the factor market distortion positively affects the loose part of the energy industry chain technical efficiency, it is not significantly conducive to the improvement of energy industry chain technical efficiency. This is similar to the research results of Lin and Du (2013) [2]; that is, the greater the factor market distortion, the more disadvantageous the improvement of energy industry chain technical efficiency. However, the parameter coefficient of factor market distortion is significantly higher than the 0.006 estimated by Lin and Du (2013) [2]. Although Wang and Ho's (2010) [31] panel-fixed effect estimation has many advantages, stochastic frontier analysis models through fixed effect estimation are usually subject to outliers [36], so it is impossible to effectively and accurately estimate the heterogeneity and inefficiency in the output. Carbon dioxide emissions pass the test at a significant level of 1%; that is, an increase in carbon dioxide emissions is not conducive to the improvement of energy industry chain technical efficiency. The expenditure on education, the size of the population, and the total volume of regional trade significantly promote the efficiency of energy technology. On the one hand, the government provides knowledge reserves for the development of energy technology through education, and on the other hand, it promotes energy technology through regional trade. We can use trade to transfer and introduce new energy technologies. In terms of the loss of energy technical efficiency, the estimated results of the average years of education and public financial expenditure are not significant, and the estimated conclusions do not have statistical significance.

The Cobb–Douglas production function is adopted in model (8), and the conclusion of the regression of the core variables of the loss of energy technical efficiency is consistent with the estimation of the transcendental logarithmic production function. Therefore, the distortion of factor market and carbon dioxide emissions inhibit the improvement of energy industry chain technical efficiency; at the present stage, the non-synchronization of the marketization process of the regional factor market is an important reason for the difference in energy industry chain technical efficiency between regions [34]; increasing investment in education and government investment in public finance to promote the popularization of educational knowledge will help to improve energy industry chain technical efficiency; regional trade will help to improve China's energy industry chain technical efficiency.

4.2. The Evolution of Energy TE

4.2.1. Overall Change

According to the heterogeneous stochastic frontier model of Greene (2005) [36], the overall estimated energy technical efficiency in China is 0.959; that is, when the input factors remain unchanged, the total economic growth rate is 4.2318%, indicating that although China's overall energy technical efficiency is higher than the results calculated by Lin et al. (2013), it does not reach the production boundary of energy technology, and thus there is still much room for growth. As is shown in Table 3 with the comparison of energy industry chain technical efficiency in different regions, the average energy industry chain technical efficiency in China from high to low is found in the east (0.961), center (0.957), northeast (0.955), and west (0.950). The average TE is 0.965 in the east region, indicating that if the east used potential energy technology boundary technology for production, efficiency improvement could be 3.6377% higher. The center, northeast, and west could improve their efficiency by 4.5151%, 4.7669%, and 5.2521%, respectively. This shows that the energy technical efficiency is close to 1 in the center, west, and northeast, and the use of energy is relatively extensive and insufficient for effective utilization in these three regions. There may be a certain amount of "energy waste" at the same time, and there is also the problem of insufficient energy investment. Through further calculation, Table 4 reports the energy technical efficiency variance of the four regions during the sample period, which is 0.029 (east), 0.046 (center), 0.049 (west), and 0.038 (northeast). The average for all provinces and cities included in the study is 0.0179. This shows that (1) during the sample period, the improvement of energy industry chain technical efficiency is relatively slow in different provinces and cities in different regions, and there is little space for improvement. (2) Although the energy industry chain technical efficiency in some provinces and cities in some areas has been improved during the sample period, it has been wiped out by the decline in energy industry chain technical efficiency in other provinces and cities in other regions. The next part of this article explains in detail the possible reasons for the results mentioned above.

Table 4. Statistical description of regional energy technical efficiency.

Region	Mean	S.D.	Mix	Q1	Q3	Max
The east	0.961	0.029	0.8124	0.9727	0.9914	0.9985
The central	0.957	0.046	0.7735	0.9481	0.9847	0.9960
The west	0.950	0.049	0.7359	0.9329	0.9876	0.9974
The northeast	0.955	0.038	0.8444	0.9421	0.9810	0.9883

Note: Q1 represents the first quartile; Q3 represents the third quartile.

4.2.2. Time Trend Change

According to the heterogeneous stochastic frontier model, the estimated change and convergence trend of China's energy industry chain technical efficiency and its regional energy industry chain technical efficiency are shown in Figure 1.

Figure 1A is a report on the measurement and zoning results of China's energy industry chain technical efficiency from 2000 to 2016. As can be seen from the chart, for the national energy industry chain technical efficiency, *TE* maintained an overall upward trend from 2000 to 2016, which is generally consistent with the annual change trend of energy efficiency calculated by Lin et al. (2013) and Bai and Meng (2017). In terms of the value of China's energy industry chain technical efficiency, the lowest value was 0.925 (in 2003), which increased slightly from 2004 to 2008, but decreased to 0.965 in 2009. After that, it continued to rise, reaching a maximum of 0.988 in 2011. Over the period 2011–2016, it continued to decline. This shows that if the input factors remain unchanged in 2005, the energy technical efficiency can be increased by 8.1081%. In 2011, the energy technology efficiency can be reduced by about 1.2146% while keeping the energy industry chain technical efficiency unchanged, or the energy industry chain technical efficiency can be improved by about 1.2146%, while keeping the input factors unchanged. This shows that China's energy

utilization potential is far from being brought into full play during the sample period, and there is still a large space for energy conservation. Figure 1B assesses the variation trend of the coefficient of variation of China's energy industry chain technical efficiency to characterize σ convergence. As can be seen from Figure 1B, the coefficient of variation of China's energy industry chain technical efficiency showed a downward trend from 2000 to 2016, reaching a peak and valley in 2003, then declined sharply, and re-bounded slightly in 2011. The above trends show that there is a σ convergence trend in energy industry chain technical efficiency; that is, the gap of energy industry chain technical efficiency among regions is gradually narrowing in China.

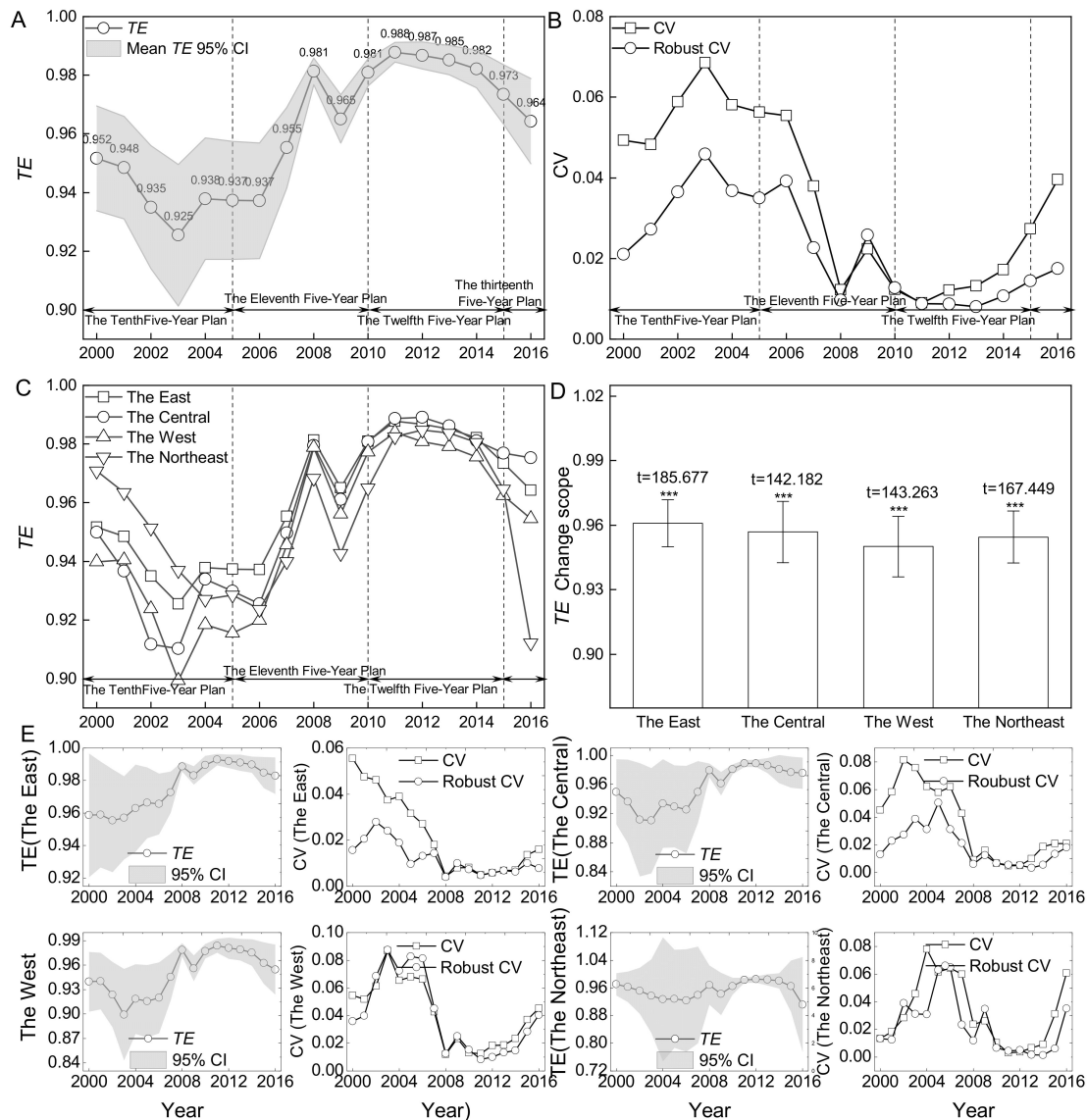


Figure 1. Annual mean trend and coefficient of variation of energy TE under the influence of factor distortion and carbon dioxide emissions. Note: CI 95% is 95% confidence interval; (A) China energy industrial chain technology efficiency annual change trend and 95% confidence interval; (B) China energy industrial chain technology efficiency annual average coefficient of variation and robust coefficient of variation trend; (C) China eastern, central, western and northeast energy industrial chain technology efficiency annual change trend; (D) China eastern, central, western and northeast mean one-sided t -test and 95% error analysis; (E) the coefficient of variation, robust coefficient of variation and 95% confidence interval of TE in different regions. *** means the t -test value pass the statistical test.

While analyzing the time evolution characteristics of China's overall energy industry chain technical efficiency, we also measured the energy industry chain technical efficiency of each region (Figure 1C), which reflects the efficiency level of the use of factor resources in each region. Figure 1C shows that the energy technical efficiency of the four regions shows a trend of first declining, then gradually increasing, and then slightly declining, but the decline range is different. Among them, the TE of the eastern, central, and western regions decreased in 2000–2003 and 2011–2016, and the troughs were 2003 and 2016, respectively. The TE of the above three regions began to increase to a certain extent at the end of “The Twelfth Five-Year Plan” period, and showed an overall increasing trend during “The Eleventh Five-Year Plan” period, while the TE value decreased during “The Twelfth Five-Year Plan” period. The range of TE decreased from 2000 to 2006 and from 2013 to 2016 in the northeast, and the trough shows a certain upward trend at the beginning of “The Eleventh Five-Year Plan” period in 2006 and 2016, respectively, but began to decline at the end of the twelfth five-year plan. The TE value of the four major regions basically showed a trend of declining from the end of “The Twelfth Five-Year Plan” period, an increase at the beginning of “The Eleventh Five-Year Plan” period, and then a slight decline during “The Twelfth Five-Year Plan” period. Thus, we found that the implementation of energy-saving measures through fiscal policy during “The Eleventh Five-Year Plan” period has achieved certain results and improved energy technical efficiency, but due to the shortcomings of fiscal policy, the lag brought by administrative means is more obvious. This led to a decline in energy technical efficiency during “The Twelfth Five-Year Plan” period. Figure 1D tests the heterogeneity of the energy industry chain technical efficiency in different regions via unilateral *t*-test, and the *t* statistics obtained are 185.677 (east), 142.182 (center), 143.263 (west), and 167.449 (northeast). The corresponding *p* values are 0.000, 0.000, 0.000, and 0.000, respectively. All reject the original hypothesis of the energy industry chain technical efficiency value at the 99% confidence level. This shows that heterogeneity of energy technology does exist among the four regions. Based on this, the following article makes a detailed analysis of the evolution law of energy technical efficiency of the provinces and cities in the four regions.

4.2.3. TE Changes in Provinces and Cities

Table 4 shows that the inter-regional energy technical efficiency shows obvious gradient characteristics during the sample period; that is, the eastern region is higher than the central region, the central region is higher than the northeastern region, and the northeastern region is higher than the western region. Specifically, within the central and eastern regions (Table 5), Guangdong (0.994) and Hainan (0.992) were at the forefront during the sample period, which is basically consistent with the results calculated by Wang (2018). Other provinces and cities basically maintain high energy industry chain technical efficiency. Comparatively speaking, in the sample period, the energy technical efficiency of Shanxi (0.897) and Ningxia (0.895) is not only obviously at a lower level in terms of absolute value, but it also shows a certain gap compared with the national average level. This suggests a serious loss of energy technical efficiency.

Table 5. The changing trend of China's energy industrial chain technology efficiency under the influence of factor distortion and carbon dioxide emissions.

Provinces	2000	2005	①	2006	2010	②	2011	2015	③	2016	Mean
Beijing	0.812	0.885	0.854	0.900	0.977	0.954	0.988	0.988	0.988	0.989	0.931↑
Tianjin	0.946	0.975	0.941	0.965	0.977	0.971	0.983	0.952	0.973	0.943	0.959↓
Hebei	0.975	0.963	0.965	0.951	0.986	0.974	0.991	0.980	0.986	0.983	0.975↑
Shanghai	0.966	0.968	0.953	0.975	0.987	0.982	0.990	0.981	0.987	0.986	0.973↑
Jiangsu	0.976	0.977	0.973	0.973	0.995	0.987	0.996	0.994	0.995	0.993	0.985↑
Zhejiang	0.964	0.966	0.970	0.962	0.996	0.981	0.997	0.994	0.996	0.992	0.982↑

Table 5. Cont.

Provinces	2000	2005	①	2006	2010	②	2011	2015	③	2016	Mean
Fujian	0.991	0.978	0.986	0.978	0.996	0.986	0.997	0.989	0.995	0.981	0.988↓
Shandong	0.990	0.967	0.981	0.971	0.987	0.980	0.992	0.980	0.987	0.973	0.982↓
Guangdong	0.985	0.991	0.989	0.991	0.998	0.995	0.999	0.998	0.998	0.998	0.994↑
Hainan	0.982	0.995	0.988	0.991	0.996	0.992	0.997	0.995	0.996	0.992	0.992↑
Shanxi	0.867	0.835	0.821	0.822	0.977	0.915	0.986	0.939	0.964	0.939	0.897↑
Anhui	0.970	0.972	0.968	0.965	0.985	0.974	0.992	0.974	0.987	0.966	0.975↓
Jiangxi	0.973	0.958	0.963	0.967	0.991	0.982	0.996	0.994	0.995	0.993	0.980↑
Henan	0.981	0.979	0.974	0.968	0.976	0.975	0.984	0.992	0.989	0.993	0.980↑
Hubei	0.943	0.908	0.906	0.903	0.974	0.947	0.984	0.976	0.983	0.978	0.945↑
Hunan	0.967	0.926	0.941	0.930	0.983	0.964	0.990	0.987	0.990	0.984	0.965↑
Inner Mongolia	0.987	0.882	0.951	0.885	0.960	0.932	0.959	0.889	0.932	0.855	0.934↓
Guangxi	0.988	0.990	0.989	0.992	0.994	0.994	0.996	0.996	0.995	0.995	0.993↑
Sichuan	0.957	0.936	0.939	0.928	0.975	0.956	0.989	0.988	0.990	0.988	0.962↑
Guizhou	0.890	0.875	0.885	0.862	0.966	0.933	0.982	0.992	0.987	0.990	0.935↑
Yunnan	0.982	0.957	0.967	0.961	0.983	0.977	0.990	0.991	0.992	0.989	0.978↓
Shaanxi	0.897	0.938	0.892	0.943	0.968	0.958	0.983	0.930	0.966	0.923	0.935↑
Gansu	0.984	0.936	0.951	0.955	0.987	0.972	0.990	0.951	0.979	0.947	0.965↓
Qinghai	0.857	0.867	0.847	0.882	0.978	0.938	0.987	0.963	0.977	0.936	0.917↑
Ningxia	0.885	0.789	0.830	0.802	0.966	0.906	0.967	0.935	0.951	0.952	0.895↓
Xinjiang	0.972	0.987	0.978	0.988	0.997	0.992	0.997	0.989	0.995	0.972	0.987↑
Liaoning	0.959	0.867	0.905	0.859	0.957	0.910	0.980	0.984	0.984	0.870	0.928↓
Jilin	0.968	0.939	0.955	0.935	0.976	0.964	0.986	0.980	0.986	0.975	0.968↑
Heilongjiang	0.985	0.979	0.979	0.976	0.962	0.970	0.983	0.930	0.968	0.891	0.968↓
The east	0.952	0.937	0.939	0.937	0.981	0.964	0.988	0.973	0.983	0.964	0.961↑
The central	0.950	0.930	0.929	0.926	0.981	0.959	0.989	0.977	0.984	0.975	0.957↑
The west	0.940	0.916	0.923	0.920	0.977	0.956	0.984	0.962	0.976	0.955	0.950↑
The northeast	0.971	0.929	0.946	0.924	0.965	0.948	0.983	0.965	0.979	0.912	0.955↓

Note: ① is the “The Tenth Five-Year Plan” period, ② is “The Eleventh Five-Year Plan” period, ③ is “The Twelfth Five-Year Plan” period; ↑ indicates that the energy technical efficiency of the province and city shows an overall growth trend during the sample period, ↓ indicates an overall downward trend during the sample period. In total, 19 provinces and cities rose, while 10 provinces and cities declined as a whole.

Zhao and Shi (2006) believe that the energy technical efficiency of DMUs mainly depends on the appropriateness of resource allocation, while whether resource allocation can promote energy consumption and conservation also depends on DMUs’ own production enthusiasm and external policy environment. It is well known that the eastern region was the pilot area for the reform and opening up, and DMUs mainly carry out production and operation activities in accordance with the laws of a market economy, so the level of marketization in the eastern region is higher than that in other regions, while trade activities such as reform and opening up have effectively introduced new technologies for energy development and effectively improved the efficiency of energy technology. The corresponding eastern regions, such as Guangdong (0.994), Hainan, Jiangsu, Zhejiang, Fujian, and other places, have higher energy industry chain technical efficiency. The energy industry chain technical efficiency of Shanxi (in the central region) is lower than the average central level, ranking second to last in the country (0.897), but the energy industry chain technical efficiency in the central region is still higher than that in the western region. One possible explanation is that activities such as energy technology diffusion or energy technology innovation are carried out according to economic or geographical gradients. Specifically, the eastern region has a relatively high degree of market economy development, and in terms of the total amount of economic development, it is the forerunner. It belongs to a high-gradient region of the economy, which enjoys more policy dividends through reform and the level of opening, so it has more advanced energy technology and energy enterprise management and organizational forms. On the other hand, the development degree of the market economy in the central region is lower than that in the eastern region, but it is geographically closer to the eastern region under the action of externalities such as

capital flow, technology flow, and trade flow in the energy field. This makes it possible for the region to receive energy technology diffusion or energy innovation products, thus improving the level of energy industry chain technical efficiency in the region to a certain extent, which is higher than that in the western region. Although Heilongjiang, Jilin, and Liaoning provinces are closer to the Beijing–Tianjin–Hebei urban agglomeration around the Bohai Sea, due to their proximity to the northern coastal areas, the degree of development of their market economies is not higher than that of the central region. Due to the economic inertia and energy depletion of the northeast region, its traditional form of energy economy development as the main body is slightly weak, so the energy technical efficiency of the three northeastern provinces is lower than that of the central region. As for the western provinces and cities, although the average energy industry chain technical efficiency of Guangxi ranks second (0.993) and those of Xinjiang, Gansu, and other places rank first, in terms of the overall ranking, it is at the bottom. Despite policies to support the large-scale development of the western region, the introduction of energy exploitation and production technology and equipment itself lags behind the eastern and central regions, and is deeply influenced by heterogeneity and structural factors such as history and geographical location, and the level of energy innovation in the western region is not high. The level of marketization is relatively low [19], and the above comprehensive factors have led to a lack of necessary hardware facilities such as energy extraction and production, as well as soft power such as energy enterprise management capacity and internal incentives in the western region [28]. This has led to a relatively low level of energy technical efficiency, resulting in a large gap between the established input and the maximum output.

4.2.4. Energy Technical Efficiency Decomposition and Robustness Analysis

Next, this paper examines energy technology residual efficiency (RTE) and sustainable efficiency (PTE) to characterize the evolution trend by describing the change in nuclear density. Figure 2 shows the nuclear density distribution of China's energy technologies *TE*, *RTE*, and *PTE*. It can be seen that the dynamic evolution of China's energy industry chain technical efficiency shows two main characteristics: (1) As the quantile increases, the *TE* nuclear density peak is located on the left side and the density distribution decreases, and the nuclear density change in *PTE* is similar, but the nuclear density value is significantly smaller than that of *TE*. (2) The opening of the *RTE* nuclear density curve shrinks; that is, the gap between the low-efficiency level and the high-efficiency level represented by the two ends of the nuclear density curve is gradually narrowed, so that the distribution of China's energy technology residual efficiency tends to be dispersed. It can also be seen from Figure 2 that China's energy *TE* and its decomposition index *RTE* and *PTE* densities are all greater than 0. Thus, there is a great difference in energy utilization between different years during the sample period, and the difference tends to expand in different stages. At the same time, China's energy technical efficiency is mainly restricted by *RTE*; that is, market factors represent the main factor in energy utilization, while sustainable efficiency obviously "drags" *TE*.

As for the residual efficiency of energy technology, it can be seen that the overall level of energy technology residual efficiency has been maintained at a high level during the sample period (Figure 2E, the value is higher), which indicates that if we reduce the traditional adverse factors in energy use, such as coal-based electricity consumption, power structure, and other unfavorable factors such as (*PTE*), then the energy industrial chain technology efficiency may be improved. This is because, under the dual effects of the distortion of the factor market and the tightening of environmental constraints, provinces and cities are unable to effectively produce in accordance with the endowment of energy resources and the comparative advantages of energy technology. Under the guidance of the signal mechanism of incomplete market information transmission, resource allocation leads to the convergence of energy industry structure and energy consumption.

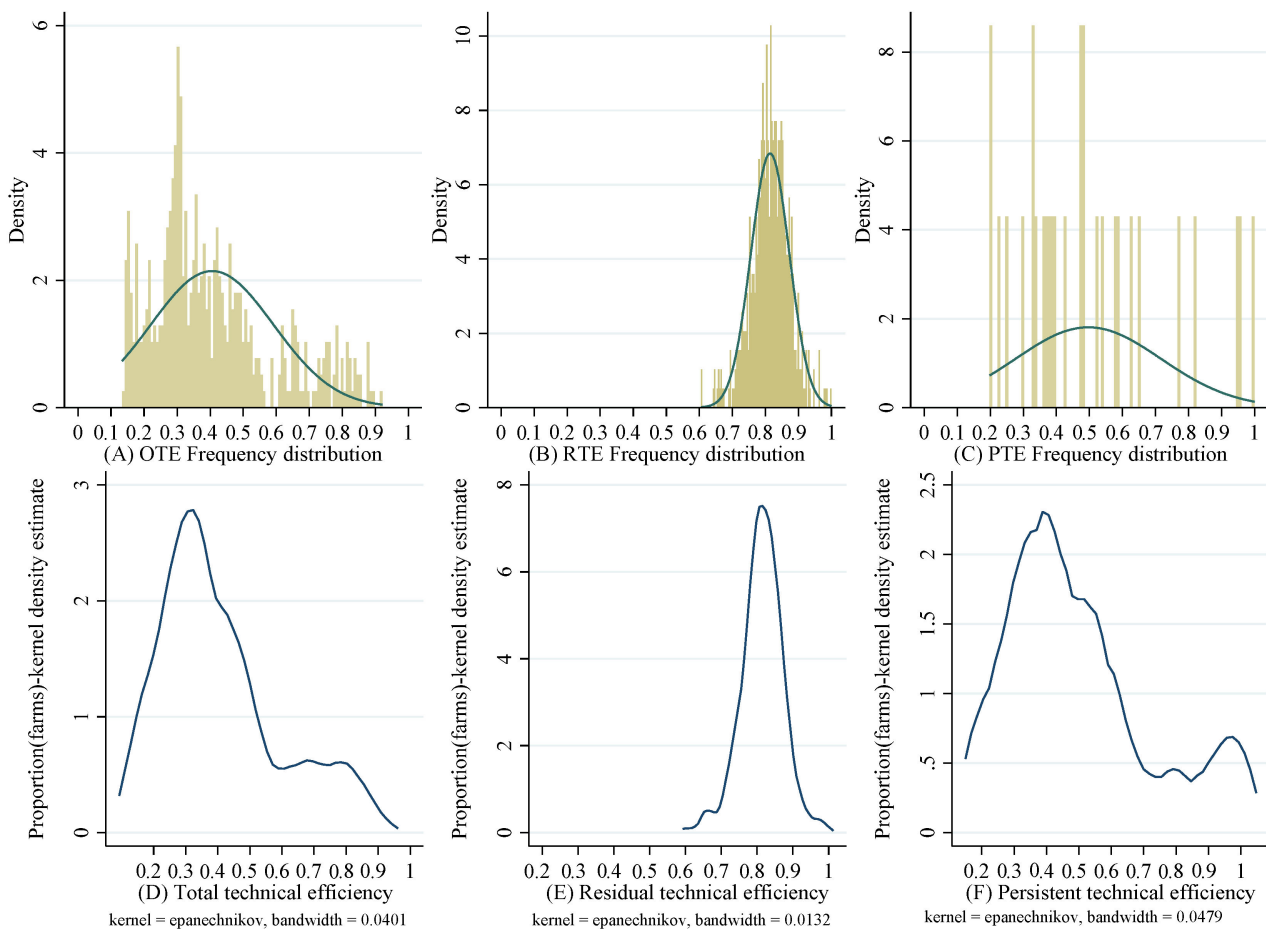


Figure 2. The model used in this paper to estimate China’s energy industrial chain technology efficiency TE and its decomposition efficiency RTE and PTE. Note: OTE = TE (A), RTE (B), and PTE (C) denote quantile frequency change and data distribution; OTE (D), RTE (E), and PTE (F) denote nuclear density change.

4.3. Counterfactual Analysis

The counterfactual analysis of “benchmarking” (This approach is the core “strategic approach” of management consulting companies such as McKinsey. Lin and Du (2013) [2] introduced this method to the counterfactual estimation of the distortion of factor markets, and compared the provinces and cities with a higher degree of factor market development, making follow-up improvements.) [2] and the synthetic control method are limited to the distorting of factor market, and the limitation of carbon dioxide emissions in different provinces and cities. Therefore, the traditional “counterfactual” analysis method is not suitable for the evaluation object of this paper. Through the heterogeneity stochastic frontier analysis model, it is verified that the current factor market distortion and carbon dioxide emissions are important factors affecting the improvement of energy industry chain technical efficiency. This paper attempts to measure the effect of energy industry chain technical efficiency loss through Chernozhukov et al.’s (2013) [37] quantile counterfactual analysis. Figure 3 shows the scatter chart changes and energy industry chain technical efficiency, and there are obvious agglomeration characteristics.

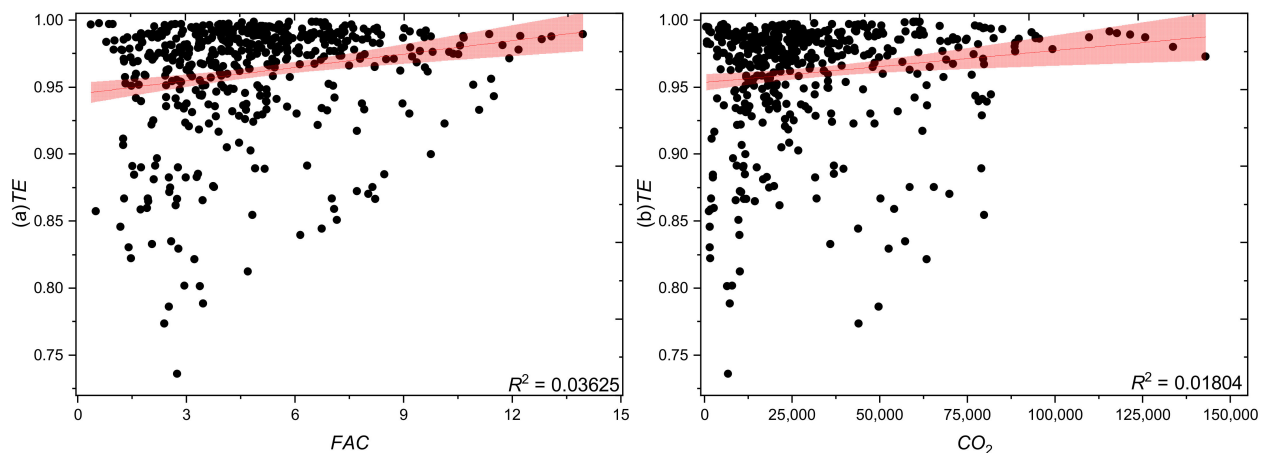


Figure 3. Changes in factor market distortions, carbon dioxide emissions and TE scatter chart.

In contrast to the “benchmarking” counterfactual analysis method proposed by Lin and Du (2013) [2], this paper attempts to use the Chernozhukov et al. (2013) [37] quantile counterfactual analysis method to study the effects of factor market distortion and carbon dioxide emissions on energy industry chain technical efficiency. Referring to the counterfactual model of Chernozhukov et al. (2013) [37], this paper sets the counterfactual model of energy technical efficiency, as shown below. First of all, the energy technical efficiency structure function $F_{TE|j|k}(TE)$, factor market distortion, and carbon dioxide emission combination function are defined as $F_{FAC,CO_2k}(FAC, CO_2)$, where $k \in \{0, 1\}$, $j \in \{0, 1\}$ represent the actual observation and counterfactual estimation of the control group and the treat group, respectively.

$$F_{TE|j|k}(TE) = \int F_{TE_j}(TE|FAC, CO_2) dF_{FAC,CO_2k}(FAC, CO_2) \quad (12)$$

The distribution effect is defined as:

$$\Delta^{DE}(TE) = F_{TE0|1}(TE) - F_{TE0|0}(TE) \quad (13)$$

Because the quantile model changes following random analysis, this paper uses the quantile counterfactual analysis model to test the counterfactual effects of factor market distortion and carbon dioxide emissions, and defines:

$$Q_{TE|j|k}(\tau) = \inf \{ TE : F_{TE|j|k}(TE) \geq u \}, 0 < \tau < 1 \quad (14)$$

The quantile counterfactual effect is:

$$\Delta^{QE}(\tau) = Q_{TE0|1}(\tau) - Q_{TE0|0}(\tau) \quad (15)$$

4.3.1. Counterfactual Result

Through the one-sided t -test of (D) in Figure 1, this paper considers that there is heterogeneity among different regions, so the eastern, central, western, and northeastern regions are set as the control group, and the counterfactual results estimated by STATA are shown in Figures 4 and 5. The 95% confidence interval results of Figure 4 show that the TE counterfactual estimations in the eastern, central, and northeastern regions have obvious statistical differences, while the counterfactual estimation results in the western region obviously do not change within the 95% confidence interval. Combined with the comparative changes in Figure 5, this paper holds that, first, although “The Eleventh Five-Year Plan” fiscal policy plays an effective role, the distortion of factor market and the negative impact of carbon dioxide emissions may smooth out the positive role of fiscal

policy. Second, factor market distortion and carbon dioxide emissions are of obvious significance to the improvement of energy industry chain technical efficiency in the eastern, central, and northeastern regions, but the counterfactual analysis in the western region is the opposite. This shows that the economic impact of the development of a factor market and the degree of environmental constraints in the western region are obviously small.

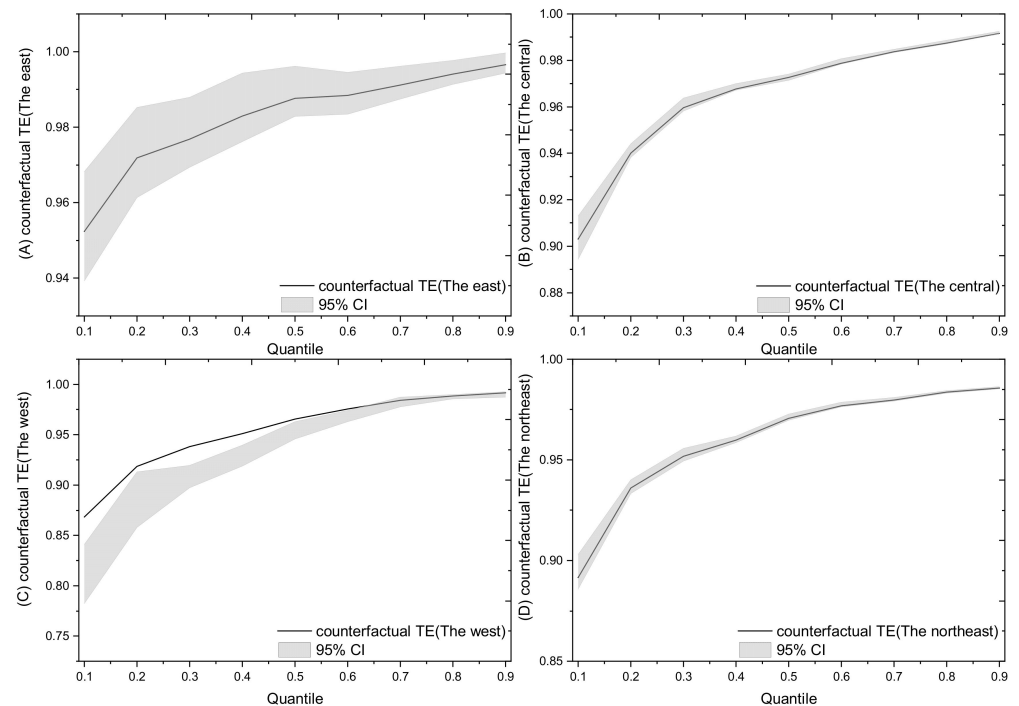


Figure 4. Counterfactual estimated TE changes in the east, the central, the west and the northeast with 95% confidence intervals.

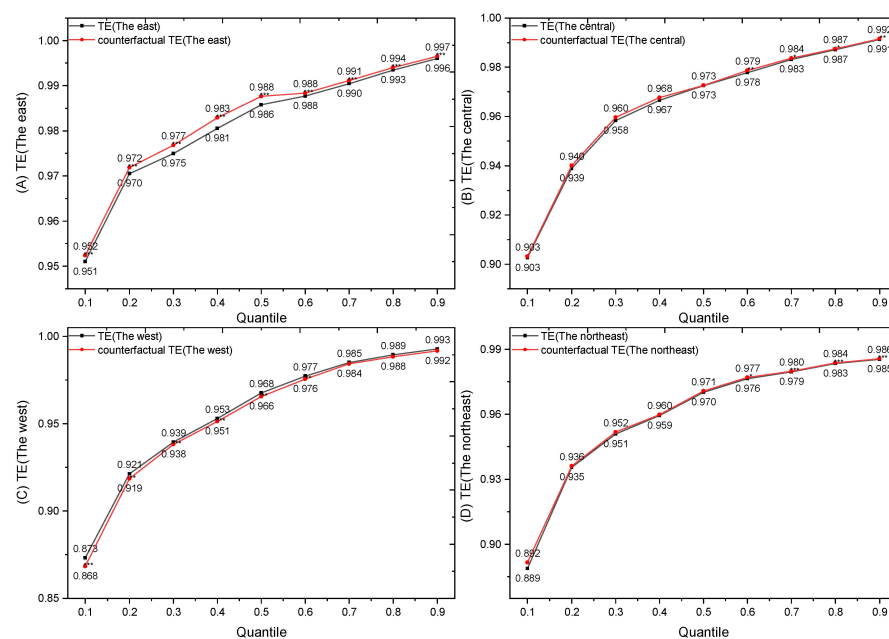


Figure 5. Comparison between the energy industrial chain technology efficiency measured in this paper and the counterfactual estimation of energy industrial chain technology efficiency. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.2. Counterfactual Test

Via the relevant commands, this paper examines the statistical significance of counterfactual results, and the results are shown in Table 6. The test results of counterfactual estimates show that factor market distortions and carbon dioxide emissions have significant negative effects on the counterfactual estimates of TE in the eastern, central and northeast regions.

Table 6. Bootstrap test results of quantile counterfactual estimation.

Null-Hypothesis	The East		The Central		The West		The Northeast	
	KS	CMS	KS	CMS	KS	CMS	KS	CMS
Correct specification of the parametric 0	0.69	0.77	0.27	0.63	0.45	0.51	0.59	0.72
Correct specification of the parametric 1	0.57	0.58	0.16	0.59	0.17	0.6	0.71	0.71
Differences between the observable distributions								
No effect: $QE(\tau) = 0$	0.00	0.00	0.16	0.08	0.00	0.00	0.00	0.00
Constant effect: $QE(\tau) = QE(0.5)$	0.68	0.89	0.94	0.97	0.00	0.00	0.68	0.89
Stochastic dominance: $QE(\tau) > 0$	0.88	0.88	0.97	0.97	0.95	0.95	0.88	0.88
Stochastic dominance: $QE(\tau) < 0$	0.00	0.00	0.11	0.05	0.00	0.00	0.00	0.00
Effects of characteristics								
No effect: $QE(\tau) = 0$	0.67	0.58	0.55	0.39	0.25	0.14	0.67	0.58
Constant effect: $QE(\tau) = QE(0.5)$	0.92	0.92	0.67	0.73	0.46	0.59	0.92	0.92
Stochastic dominance: $QE(\tau) > 0$	0.50	0.27	0.43	0.32	0.89	0.89	0.50	0.27
Stochastic dominance: $QE(\tau) < 0$	0.93	0.93	0.96	0.96	0.19	0.08	0.93	0.93
Effects of coefficients								
No effect: $QE(\tau) = 0$	0.00	0.00	0.13	0.04	0.00	0.00	0.00	0.00
Constant effect: $QE(\tau) = QE(0.5)$	0.68	0.86	0.83	0.95	0.00	0.00	0.68	0.86
Stochastic dominance: $QE(\tau) > 0$	0.86	0.86	0.96	0.96	0.91	0.95	0.86	0.86
Stochastic dominance: $QE(\tau) < 0$	0.00	0.00	0.08	0.03	0.00	0.00	0.00	0.00

Note: the value is *p*-values in Table 6.

5. Conclusions and Policy Implications

There is a basic consensus that the process of factor marketization lags behind the process of product marketization in China, and that the agreement to achieve peak carbon emissions by 2030 means that economic growth will face serious environmental constraints. This paper briefly analyzed the impact of factor market distortion and carbon dioxide emissions on economic growth using Greene's (2005) [36] heterogeneity stochastic frontier analysis model. Then, we evaluated China's energy industry chain technical efficiency under the influence of factor distortion and carbon dioxide emissions. Finally, the counterfactual measurement method was used to calculate the factor market distortion and the energy industry chain technical efficiency loss of carbon dioxide emissions. The main conclusions include the following: (1) Factor market distortion and carbon dioxide emissions are indeed the main sources of energy industry chain technical efficiency loss. (2) The overall energy technical efficiency is 0.959 in China, and the average value of energy technical efficiency by region from highest to lowest is east (0.961), central (0.957), northeast (0.955), and west (0.950). Among them, the space for efficiency improvement is 3.6377%, 4.5151%, 4.7669% and 5.2521%, respectively. (3) Although energy technical efficiency is subject to market factors, the structural factors caused by sustainable efficiency are more obvious. (4) In the situation of factor market distortion and carbon dioxide emissions, China's energy industry chain technical efficiency slowly increased from 0.952 in 2000 to 0.964 in 2016. By reducing the degree of factor market distortion, China's average energy industry chain technical efficiency could increase to 0.9651 from 0.9649, showing an improvement of 3.6162%.

From the perspective of the evolution of energy technical efficiency, this paper confirms that the implementation of energy-saving measures through fiscal policy during "The Eleventh Five-Year Plan" period improved the energy technical efficiency in this period to a certain extent, but there is an obvious lag in fiscal policy. As a result, the energy

technical efficiency began to decline during “The Twelfth Five-Year Plan” period. This shows that in addition to playing the role of the “promising government” and “visible hand” in improving energy technical efficiency during “The Thirteenth Five-Year Plan” period, it is also necessary to speed up the market-oriented construction of factors and improve the allocation of factor resources. Specifically, we should first carry out the network reform of the main body of the energy market, carry out the reform of the whole industry chain from the upper and lower reaches of the energy market, deepen the reform plan of the oil and gas system, and speed up the flow and reallocation of factors; secondly, in the case of limited carbon dioxide emissions, we should consider regional heterogeneity and then divide the carbon emission quotas of the different main bodies of the energy market to avoid the excessive gradient transfer of the energy market and the excessive convergence of the energy industry. Then, based on the regional heterogeneity, especially the characteristic facts of energy resource endowment and factor market development in different regions [8], we should develop a set of timely and feasible dynamic mechanisms to mobilize the enthusiasm for factor flow and adjust the adverse impact of carbon dioxide emissions on the development of the energy industry. In this way, we can reduce the inequality between economies and energy entities caused by distorted factors, and carbon dioxide emissions in different regions.

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