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Energy Utilization Efficiency of China Considering Carbon Emissions—Based on Provincial Panel Data

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Abstract: With the development of the economy, environmental pollution caused by energy consumption has become increasingly prominent. Improving the efficiency of energy utilization is an important way to solve this problem. Firstly, we used a data envelopment analysis (DEA) model to calculate the energy utilization efficiency of China's provinces and regions from the perspective of environmental constraints, including four inputs—labor force, capital stock, energy consumption and carbon emission—and one output, GDP. Secondly, an entity fixed effect model of panel data was built to investigate the influence of openness, urbanization, marketization and industrial structure on energy utilization efficiency in the process of economic structure change. The results indicate that China's energy efficiency shows a trend of first stabilizing and then declining from 2007 to 2017. Meanwhile, the comprehensive energy efficiency of all provinces and regions is not very ideal. Only Beijing, Shanghai and Guangdong constitute the forefront of China's energy efficiency. The lack of pure technical efficiency in most provinces is the main reason for the low comprehensive efficiency, but there are also obvious differences among provinces and regions. In addition, urbanization, openness and industrial structure have a negative impact on energy efficiency, while marketization has a significant positive impact on energy efficiency. Finally, based on the regional differences, some suggestions were put forward to improve China's energy utilization efficiency.

Keywords: DEA; regional difference; energy utilization efficiency; carbon emission

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1. Introduction

With the rapid development of the economy in recent years, China's energy production and consumption have been growing rapidly, but environmental pollution has also been significantly aggravated. Moreover, the restriction of energy on the economy and the environment is becoming more and more obvious, which has attracted the attention of many scholars. Therefore, in order to realize the coordinated development of energy–economy–environment, the 13th Five-Year Plan (2016–2020) has emphasized that China should adhere to the energy development strategy of "four revolutions and one cooperation" and deepen the energy revolution. In addition, energy consumption per unit of GDP and carbon dioxide emission are required to be reduced by 15% and 18%, respectively. Energy efficiency is generally measured by energy intensity (energy consumption per 10,000 yuan of GDP). The higher the energy intensity per unit of GDP, the lower the energy efficiency. As can be seen from Figure 1, since 1980, with the improvement of China's energy science and technology innovation ability, the rapid development of energy technology and equipment, and the optimization of the energy system driven by automation, intellectualization and digitization, China's energy efficiency has undergone great changes, and the energy intensity has generally declined. It can be seen that China's energy utilization efficiency drops sharply every 10 years, and the overall trend is a stepwise decline. However, the energy intensity dropped to 0.55 tons of standard coal per

10,000 yuan in 2018, which was not reduced by 15% on the basis of 2015. There, it is necessary to analyze China's energy efficiency in detail to develop more effective strategies for green development.

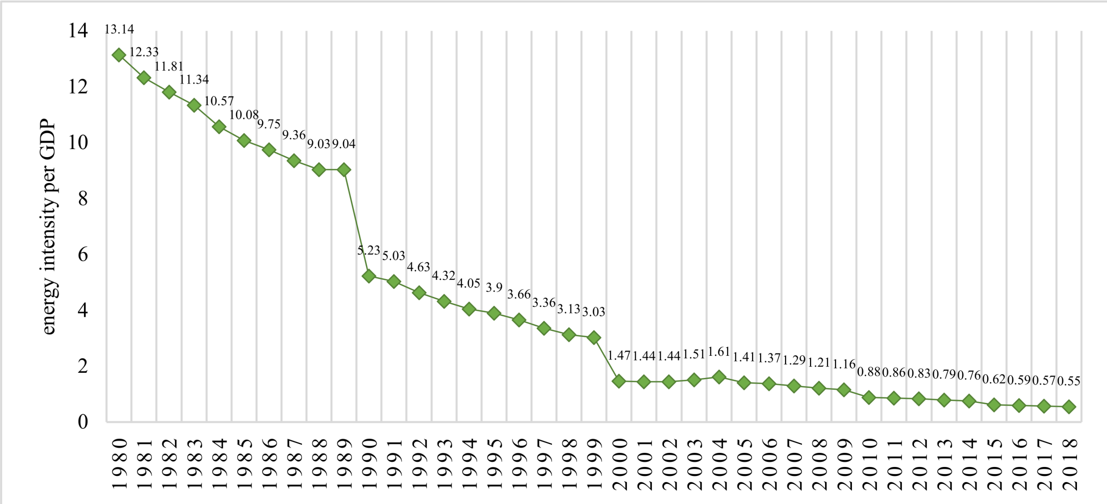

Figure 1. Energy intensity in China from 1980 to 2018. Data source: China economic network.

Many scholars have used various methods to study energy utilization efficiency. Patterson pointed out that energy efficiency itself is a general term [1], which can be measured by a variety of quantitative indicators The measuring methods can be divided into single-factor energy efficiency and total-factor energy efficiency. The former is the reciprocal of energy intensity. Compared with total-factor, the single-factor method is calculated in a simple way, and the alternative effects between various input elements are not taken into account. Total-factor energy efficiency considers the interaction between energy consumption and other factors of production and has more than one input and output indicator. Among various methods, data envelopment analysis (DEA) is widely used to calculate energy efficiency. George Halkos and Kleoniki Natalia Petrou analyzed the efficiency of the 28 EU member states in 2008, 2010, 2012 and 2014 using DEA and directional distance function, among which Germany, Ireland and the United Kingdom were the most efficient countries [2]. Zhongshan Yang, Xiaoxue Wei calculated the energy utilization efficiency of 26 major cities in China by building a multi input-output DEA model [3]. Tengfei Huo, Miaohan Tang et al. used the DEA model and the TFEE algorithm to calculate the actual total factor energy efficiency (TFEE) of the construction industry [4]. Cheng et al. measured the TFEE of 30 provinces in China from 1997 to 2016 based on the nonradial directional distance function of the DEA model and found that TFEE had significant regional heterogeneity [5]. The extended DEA method is also very common in the energy field. Geng et al. proposed a novel DEA model based on the affinity propagation (AP) clustering algorithm (AP-DEA) [6]. Iftikhar et al. used the network DEA method to measure the economic efficiency and distributive efficiency of major economies [7]. Fernández et al. evaluated the productivity and energy efficiency of existing industrial gases facilities through DEA and the Malmquist index [8]. Wen et al. combined a multiregional input-output model with DEA to evaluate the energy efficiency of China's construction industry at the provincial level [9].

From the above literature, it can be found that a variety of input and output factors should be considered when the DEA method is used to calculate energy utilization efficiency. In addition, we also need to pay attention to which social and environmental variables will affect the efficiency value. Scholars generally agree that technological progress and economic structure are two key factors. Zhu et al. held that the rationalization and advancement of industrial structure had a positive impact on the efficiency of green development [10]. The results of Wang et al. showed that the development of 21 industries would decrease the national carbon intensity in China's 28 industries [11]. Xiong, Ma and Ji supported that industrial structure efficiency was a determinative factor to provincial industrial energy efficiency [12]. In addition to industrial structure, openness, marketization and urbanization could also affect energy efficiency. Zhao and Lin constructed a simultaneous equation model and demonstrated positive feedback between foreign trade and energy efficiency in the textile industry [13]. Koengkan conducted a survey on the impact of trade openness on energy consumption in four Andean community countries, and found that economic growth and trade openness had a positive impact on energy consumption [14]. Peng et al. analyzed the overall textile industry energy efficiency gap between China and the United States, and argued that the main factors influencing the energy efficiency of the chemical fiber industry in China included economic structure, energy structure, industry scale and technology [15]. Wang, Shi and Zhang explored the influencing factors of energy efficiency using the Tobit regression model and found that market concentration and foreign direct investment had significantly positive effects on industrial energy efficiency [16]. Zhao et al. used a three-stage DEA model, and the results showed that economic and energy structure, urbanization rate and R&D investment would affect energy efficiency [17]. Morfeldt and Silveira believed that the government's behavior did not contribute to the improvement of the energy efficiency of the industry [18]. Li, Fang and He found that the overall impact of urbanization on energy efficiency was negative in China [19].

We find that previous studies cover countries, regions and industries, but lack analysis of regional differences. Meanwhile, most scholars only consider the economic output measured by GDP, and the choice of output indicators is often single. In addition, most studies focus on the relationship between technological progress, industrial structure and energy efficiency, with insufficient attention paid to openness, marketization and urbanization. This paper differs from the past researches as follows:

(1) We incorporate carbon emissions into the DEA model. In calculating the energy efficiency of regions and four major economic zones, it is considered an undesirable output to measure environmental pollution.
(2) Based on the provincial panel data from 2007 to 2017, the entity fixed effect models in China and its four major economic zones are constructed.
(3) We explore the impact of openness, marketization and urbanization on energy efficiency in the period of economic structure transformation, and put forward some suggestions to improve efficiency.

2. Energy Utilization Efficiency in China

2.1. DEA Method and Index Selection

DEA is proposed by Charnes [20], which is a non-parametric econometrics method based on operational research theory and linear programming technology. Many scholars have measured energy efficiency by the DEA method because of its distinct advantages in evaluating relative efficiency of decision-making units with multiple input and output indicators. The DEA model can be divided into two types: input-oriented and output-oriented. Due to the different situations in different provinces, we choose the input-oriented and changeable scale of the BCC model as the original DEA model (1) to calculate energy utilization efficiency, where n represents the number of decision-making units (DMU), U represents input, V represents output, and the relative efficiency of DMU_0 is a_0.

$$\min a_0 \text{S. t.} \begin{cases} \sum\limits_{i=1}^{n} \lambda_i x_{iu} \le a_0 x_{0u}, u = 1, 2, \cdots, U \\ \sum\limits_{i=1}^{n} \lambda_i y_{iv} \ge y_{0v}, v = 1, 2, \cdots, V \\ \lambda_1 + \lambda_2 + \cdots + \lambda_n = 1, i = 1, 2, \ldots n \\ \lambda_i \ge 0, i = 1, 2, \ldots n \end{cases} \tag{1}$$

In the previous studies, most scholars only considered expected output measured by GDP. However, the use of energy will inevitably bring undesirable outputs, such as environmental pollution, which should also be considered in efficiency evaluation. In this paper, we use carbon emissions to measure environmental pollution. For economic and environmental systems, carbon emissions are unexpected output. In the environmental efficiency evaluation model, there are many processing methods to deal with the undesirable outputs, among which "regarding unexpected output as input" is one of the main ideas. This measure conforms to the basic idea of the DEA model, that is, we expect to get more expected output with less input. Therefore, we regard carbon emissions as an input variable. In addition, under the framework of total-factor production function, labor, capital and energy consumption are regarded as input variables, and GDP is regarded as an output variable.

2.2. Data Sources and Processing

The panel data of 30 provinces in China from 2007 to 2017 are selected as the evaluation units for energy utilization efficiency (considering the availability and completeness of data, Shanxi, Guizhou and Tibet are not included, and the data of Chongqing are incorporated into Sichuan for accounting). The sources and processing of input and output data are as follows:

(1) **Energy consumption.** The total energy consumption of each province is used as the energy consumption index, and the data are from China Energy Statistical Yearbook in 2018.

(2) **Labor.** The number of employees in each province is selected to measure the labor input. The number of current employees = (the number of employees at the end of the previous period + the number of employees at the end of the current period)/2. The data are from CEInet Statistics Database.

(3) **Capital stock**. Perpetual inventory method is adopted to estimate the actual capital stock of each province every year. The calculation method is as follows: $K_{it} = K_{i,t-1}(1 - \delta_{it}) + I_{it}$, where K_{it} is the capital stock of province i in year t, I_{it} is the actual investment of province i in year t, δ is economic depreciation rate. I_{it} is calculated according to the total investment and the fixed asset investment price index of each province. The data are from China Statistical Yearbook, δ takes 5%. The initial value of capital stock $K_0 = \frac{I_0}{\delta+g}$ where I_0 is the actual fixed assets investment in initial year, g is the annual average growth rate of investment in sample period. All data are calculated according to the constant price in 2007.

(4) **Carbon emissions.** It is regarded as an unexpected environmental output indicator for measuring energy utilization efficiency. The energy consumption (coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil and natural gas) of each province is multiplied by the standard coal coefficient to obtain the standard consumption. Then multiply it by the carbon emission coefficient, and we can get the carbon emission of energy consumption in each province during 2007–2017. The data are from China Energy Statistics Yearbook 2018.

(5) **GDP.** It is used as an economic output index for measuring energy utilization efficiency. We get the GDP data (calculated by current price) of each province during 2007–2017 from China Statistical Yearbook. Meanwhile, we convert those data by the price in 2007.

2.3. Analysis of Energy Utilization Efficiency

2.3.1. Analysis of Provincial Energy Utilization Efficiency

We use DEAP2.1 software to calculate the energy efficiency of 30 provinces in China during 2007–2017. The results are shown in Table 1. The DEA model can be used to analyze the comprehensive efficiency, pure technical efficiency and scale efficiency. Pure technical efficiency (vrste) refers to the minimum factor cost of input under the maximum output of the same scale, which is calculated under the assumption of variable returns to scale. It can be used to measure the extent to which input factors are caused by pure technical inefficiency. Scale efficiency (scale) refers to the ratio between the output of technical efficiency on the production boundary and its optimal scale output under certain input conditions. The larger the scale efficiency is, the closer the production scale of the production unit is to the optimal production scale. Comprehensive efficiency (crste) refers to the minimum factor cost of required input under the maximum output, which is calculated under the assumption of constant return to scale. The quantitative relationship among them is that comprehensive efficiency = pure technical efficiency × scale efficiency.

First of all, according to Figure 2, the comprehensive energy utilization efficiency of provinces and cities in 2007–2017 is not very ideal. Only Beijing, Shanghai and Guangdong have a comprehensive efficiency value of 1, which constitutes the forefront of China's energy utilization efficiency. Secondly, the average energy efficiency of Tianjin, Zhejiang and Jiangsu reaches 0.8 in 2007–2017, which is relatively effective. Thirdly, the average energy efficiency of 12 provinces, such as Gansu, Yunnan, Ningxia and Qinghai, is below 0.6, so there is an urgent need to improve energy efficiency and find reasonable ways to save energy and reduce emissions. From a horizontal perspective, the energy utilization efficiency of all provinces and cities in China declined from 2007 to 2017. Improving energy efficiency is an urgent problem.

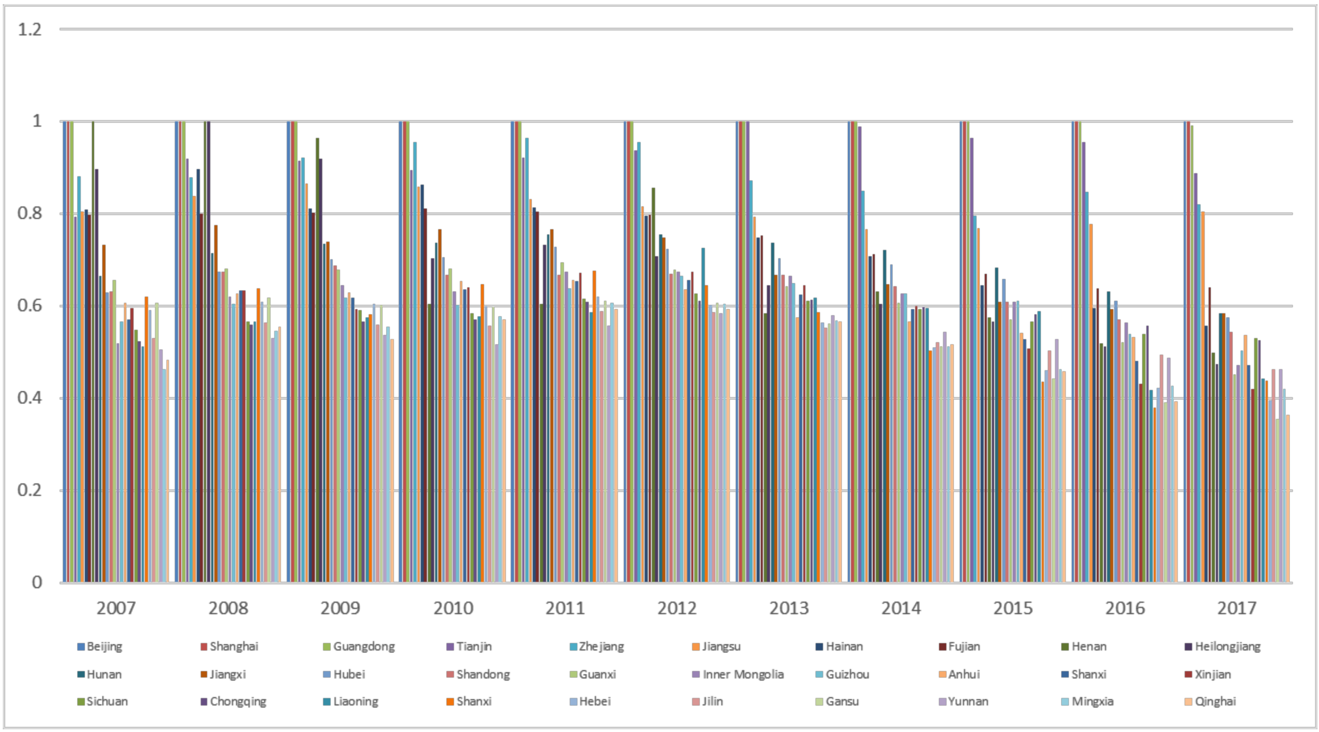

Figure 2. Comprehensive efficiency of China's regions during 2007–2017.

Table 1. Energy efficiency results of DEA in different provinces of China from 2007 to 2017.

		Beijing	Tianjing	Hebei	Shanxi	Inner Mon-golia	Liaoning	Jilin	Heilong jiang	Shanghai	Jiangsu	Zhejiang	Anhui	Fujian	Jiangxi	Shandong	Henan	Hubei	Hunan	Guang dong	Guangxi	Hainan	Chong qing	Sichuan	Guizhou	Yunnan	Shanxi	Gansu	Qinghai	Ningxia	Xinjiang	China
	crste	1.00	0.79	0.59	0.62	0.52	0.51	0.53	0.90	1.00	0.81	0.88	0.61	0.80	0.73	0.63	1.00	0.63	0.67	1.00	0.66	0.81	0.52	0.55	0.57	0.51	0.57	0.61	0.48	0.46	0.60	0.62
2007	vrste	1.00	0.93	0.59	0.65	0.52	0.63	0.53	0.93	1.00	0.90	0.89	0.62	0.80	0.74	0.75	1.00	0.64	0.68	1.00	0.67	1.00	0.53	0.55	0.62	0.53	0.58	0.67	1.00	0.96	0.65	1.00
	scale	1.00	0.85	1.00	0.95	1.00	0.81	0.99	0.97	1.00	0.89	1.00	0.98	1.00	0.99	0.84	1.00	0.98	0.98	1.00	0.98	0.81	0.99	0.99	0.92	0.96	0.99	0.91	0.48	0.48	0.92	0.62
	crste	1.00	0.92	0.61	0.64	0.62	0.57	0.56	1.00	1.00	0.84	0.88	0.63	0.80	0.77	0.67	1.00	0.67	0.72	1.00	0.68	0.90	0.56	0.57	0.61	0.53	0.63	0.62	0.55	0.55	0.63	0.65
2008	vrste	1.00	1.00	0.61	0.67	0.62	0.71	0.57	1.00	1.00	0.96	0.89	0.65	0.80	0.78	0.79	1.00	0.69	0.73	1.00	0.69	1.00	0.57	0.57	0.66	0.55	0.64	0.68	1.00	1.00	0.69	1.00
	scale	1.00	0.92	1.00	0.95	1.00	0.80	0.99	1.00	1.00	0.87	0.99	0.97	1.00	0.99	0.85	1.00	0.98	0.98	1.00	0.98	0.90	0.99	0.99	0.92	0.96	0.99	0.91	0.55	0.55	0.92	0.65
	crste	1.00	0.91	0.61	0.58	0.64	0.58	0.56	0.92	1.00	0.86	0.92	0.63	0.80	0.74	0.69	0.97	0.70	0.73	1.00	0.68	0.81	0.57	0.59	0.62	0.54	0.62	0.60	0.53	0.55	0.59	0.66
2009	vrste	1.00	1.00	0.61	0.61	0.66	0.73	0.57	0.93	1.00	1.00	0.94	0.66	0.80	0.75	0.82	0.98	0.71	0.75	1.00	0.69	1.00	0.57	0.60	0.67	0.56	0.63	0.66	1.00	0.90	0.64	1.00
	scale	1.00	0.91	1.00	0.96	0.98	0.79	0.99	0.99	1.00	0.86	0.98	0.95	1.00	0.99	0.84	0.98	0.98	0.98	1.00	0.98	0.81	0.99	0.99	0.92	0.97	0.99	0.91	0.53	0.62	0.92	0.66
	crste	1.00	0.90	0.60	0.65	0.63	0.58	0.56	0.70	1.00	0.86	0.95	0.65	0.81	0.77	0.67	0.61	0.71	0.74	1.00	0.68	0.86	0.57	0.59	0.60	0.52	0.64	0.60	0.57	0.58	0.64	0.66
2010	vrste	1.00	1.00	0.61	0.67	0.66	0.75	0.56	0.73	1.00	1.00	0.97	0.69	0.81	0.77	0.79	0.62	0.72	0.75	1.00	0.69	1.00	0.58	0.59	0.65	0.53	0.64	0.65	1.00	0.99	0.69	1.00
	scale	1.00	0.90	0.98	0.96	0.96	0.77	1.00	0.96	1.00	0.86	0.99	0.95	1.00	1.00	0.85	0.97	0.99	0.98	1.00	0.99	0.86	0.99	0.99	0.93	0.97	0.99	0.92	0.57	0.59	0.93	0.66
	crste	1.00	0.92	0.62	0.68	0.68	0.59	0.59	0.73	1.00	0.83	0.96	0.66	0.81	0.77	0.67	0.60	0.73	0.75	1.00	0.69	0.81	0.61	0.62	0.64	0.56	0.65	0.61	0.59	0.61	0.67	0.68
2011	vrste	1.00	1.00	0.64	0.70	0.72	0.77	0.59	0.76	1.00	1.00	0.98	0.72	0.81	0.77	0.78	0.63	0.74	0.77	1.00	0.71	1.00	0.62	0.62	0.69	0.58	0.66	0.67	1.00	0.90	0.72	1.00
	scale	1.00	0.92	0.97	0.96	0.94	0.76	1.00	0.96	1.00	0.83	0.98	0.92	1.00	1.00	0.85	0.96	0.99	0.98	1.00	0.99	0.81	0.98	0.99	0.92	0.97	0.99	0.92	0.59	0.67	0.93	0.68
	crste	1.00	0.94	0.60	0.65	0.67	0.73	0.59	0.71	1.00	0.82	0.96	0.64	0.80	0.75	0.67	0.86	0.72	0.76	1.00	0.68	0.80	0.61	0.63	0.67	0.59	0.66	0.61	0.59	0.60	0.68	0.68
2012	vrste	1.00	1.00	0.63	0.67	0.72	0.82	0.60	0.73	1.00	1.00	0.97	0.71	0.81	0.75	0.79	0.87	0.73	0.77	1.00	0.69	1.00	0.62	0.63	0.73	0.61	0.66	0.67	1.00	0.89	0.73	1.00
	scale	1.00	0.94	0.96	0.96	0.93	0.89	0.99	0.96	1.00	0.82	0.98	0.90	0.99	1.00	0.85	0.98	0.98	0.98	1.00	0.99	0.80	0.98	0.99	0.92	0.96	0.99	0.91	0.59	0.68	0.93	0.68
	crste	1.00	1.00	0.56	0.59	0.66	0.62	0.55	0.65	1.00	0.79	0.87	0.58	0.75	0.67	0.67	0.58	0.70	0.74	1.00	0.64	0.75	0.61	0.61	0.65	0.58	0.62	0.56	0.57	0.57	0.64	0.67
2013	vrste	1.00	1.00	0.61	0.61	0.72	0.77	0.57	0.67	1.00	1.00	0.89	0.67	0.78	0.69	0.80	0.65	0.71	0.74	1.00	0.65	1.00	0.62	0.61	0.72	0.61	0.63	0.63	1.00	0.89	0.69	1.00
	scale	1.00	1.00	0.93	0.97	0.92	0.80	0.97	0.97	1.00	0.79	0.98	0.86	0.96	0.96	0.84	0.89	0.99	0.99	1.00	0.99	0.75	0.99	1.00	0.91	0.95	0.99	0.89	0.57	0.64	0.93	0.67
	crste	1.00	0.99	0.51	0.50	0.63	0.60	0.52	0.60	1.00	0.77	0.85	0.57	0.71	0.65	0.64	0.63	0.69	0.72	1.00	0.61	0.71	0.60	0.59	0.63	0.54	0.59	0.51	0.52	0.51	0.60	0.64
2014	vrste	1.00	1.00	0.57	0.52	0.68	0.73	0.55	0.63	1.00	1.00	0.89	0.67	0.76	0.68	0.79	0.66	0.69	0.73	1.00	0.61	1.00	0.60	0.60	0.70	0.57	0.60	0.58	1.00	0.86	0.64	1.00
	scale	1.00	0.99	0.90	0.97	0.93	0.82	0.95	0.96	1.00	0.77	0.96	0.85	0.94	0.95	0.81	0.96	1.00	1.00	1.00	0.99	0.71	0.99	0.99	0.90	0.95	0.99	0.88	0.52	0.60	0.94	0.64
	crste	1.00	0.96	0.46	0.44	0.61	0.59	0.50	0.57	1.00	0.77	0.80	0.54	0.67	0.61	0.61	0.58	0.66	0.68	1.00	0.57	0.65	0.58	0.57	0.61	0.53	0.53	0.44	0.46	0.46	0.51	0.61
2015	vrste	1.00	1.00	0.53	0.44	0.65	0.70	0.54	0.57	1.00	1.00	0.88	0.64	0.76	0.65	0.77	0.64	0.69	0.70	1.00	0.58	1.00	0.59	0.59	0.65	0.54	0.55	0.49	1.00	0.87	0.53	1.00
	scale	1.00	0.96	0.86	1.00	0.94	0.84	0.94	0.99	1.00	0.77	0.91	0.84	0.88	0.93	0.79	0.89	0.96	0.97	1.00	0.99	0.65	0.99	0.96	0.93	0.98	0.96	0.91	0.46	0.54	0.96	0.61
	crste	1.00	0.92	0.62	0.68	0.68	0.59	0.59	0.73	1.00	0.83	0.96	0.66	0.81	0.77	0.67	0.60	0.73	0.75	1.00	0.69	0.81	0.61	0.62	0.64	0.56	0.65	0.61	0.59	0.61	0.67	0.68
2016	vrste	1.00	1.00	0.64	0.70	0.72	0.77	0.59	0.76	1.00	1.00	0.98	0.72	0.81	0.77	0.78	0.63	0.74	0.77	1.00	0.71	1.00	0.62	0.62	0.69	0.58	0.66	0.67	1.00	0.90	0.72	1.00
	scale	1.00	0.92	0.97	0.96	0.94	0.76	1.00	0.96	1.00	0.83	0.98	0.92	1.00	1.00	0.85	0.96	0.99	0.98	1.00	0.99	0.81	0.98	0.99	0.92	0.97	0.99	0.92	0.59	0.67	0.93	0.68
	crste	1.00	0.89	0.40	0.44	0.47	0.44	0.46	0.48	1.00	0.80	0.82	0.54	0.64	0.58	0.54	0.50	0.58	0.59	0.99	0.45	0.56	0.53	0.53	0.50	0.46	0.47	0.35	0.36	0.42	0.42	0.55
2017	vrste	1.00	0.98	0.50	0.45	0.48	0.50	0.48	0.48	1.00	1.00	0.94	0.65	0.77	0.63	0.76	0.67	0.68	0.68	1.00	0.51	1.00	0.58	0.61	0.51	0.47	0.54	0.38	1.00	0.88	0.43	1.00
	scale	1.00	0.91	0.79	0.98	0.98	0.89	0.96	0.99	1.00	0.80	0.88	0.83	0.83	0.92	0.72	0.74	0.85	0.86	0.99	0.88	0.56	0.91	0.88	0.99	0.99	0.87	0.93	0.36	0.48	0.98	0.55
	mean	1.00	0.92	0.56	0.59	0.62	0.58	0.55	0.73	1.00	0.82	0.90	0.61	0.76	0.71	0.65	0.72	0.68	0.71	1.00	0.64	0.77	0.58	0.59	0.61	0.54	0.60	0.56	0.53	0.54	0.60	0.64

We can divide the regions into five echelons according to the comprehensive energy utilization efficiency. The first echelon achieves DEA efficiency, including Beijing, Shanghai and Guangdong. The second echelon is the weak effective echelon, including Tianjin, Zhejiang and Jiangsu, which can strive to move closer to the first echelon. The third echelon includes Hainan, Fujian, Hunan, Jiangxi and Hubei. The comprehensive efficiency of this level is lower than 0.8 but higher than the national overall efficiency, which has promoted the national energy utilization efficiency for a long time. The energy efficiency of the fourth echelon is about the national overall efficiency, including Heilongjiang, Henan, Shandong and Guangxi. These provinces can improve energy efficiency through some structural adjustment. The fifth echelon includes 14 provinces, namely Inner Mongolia, Guizhou, Anhui, Xinjiang, Sichuan, Shanxi, Liaoning, Chongqing, Hebei, Gansu, Jilin, Ningxia, Yunnan and Qinghai. Their comprehensive efficiency has been lower than that of the whole country for a long time. To improve the overall energy utilization efficiency, the fifth echelon is the main target.

From the perspective of average comprehensive efficiency (Figure 3), the general characteristics of energy utilization comprehensive efficiency of 31 regions during 2007–2017 are as follows: the eastern region is larger than the central region, and the central region is larger than the western region. The reasons for the differences may come from three aspects: Firstly, from the perspective of capital stock and labor force, the capital investment in the eastern region is much higher than that in the central and western regions due to the differences in regional economic development level. Secondly, the central and western regions are located in the interior of China, and the development environment is relatively closed, which leads to the low level of input allocation of relevant factors and technology development. Finally, from the perspective of output, the large difference in output among the eastern, central and western regions directly affects the utilization efficiency of input factors.

Figure 3. Distribution of average comprehensive efficiency in China during 2007–2017.

2.3.2. Comparison of Energy Efficiency in Four Economic Zones

According to the standard of National Bureau of statistics, 30 regions are divided into four major economic zones, including eastern, central, western and northeastern regions. The eastern region includes 10 provinces: Beijing, Shanghai, Tianjin, Hebei, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The central region includes 6 provinces: Anhui, Jiangxi, Henan, Hubei, Shanxi and Hunan. The western region includes 11 provinces: Inner Mongolia, Guangxi, Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The Northeast region includes 3 provinces: Liaoning, Jilin and Heilongjiang. The energy efficiency of the four economic zones during 2007–2017 is shown in Table 2.

Table 2. Comprehensive efficiency in four major economic zones during 2007–2017.

	Eastern	**Central**	**Western**	**Northeastern**
2007	1	0.804	0.735	0.817
2008	1	0.831	0.778	0.868
2009	1	0.819	0.78	0.869
2010	1	0.829	0.78	0.885
2011	1	0.849	0.814	0.922
2012	1	0.84	0.822	0.924
2013	1	0.812	0.797	0.889
2014	1	0.796	0.774	0.848
2015	1	0.78	0.745	0.823
2016	1	0.783	0.718	0.681
2017	1	0.791	0.693	0.599

It can be seen from Table 2 that the average energy utilization efficiency in the eastern region is the highest, which has always been in the effective frontier. The comprehensive efficiency in the central region is basically above 0.8, which is weak effective. The efficiency in the western region is relatively weak, hovering around 0.7–0.8 for a long time, and has a downward trend. The efficiency in the northeast region has declined year by year in recent five years, and the efficiency in 2016 and 2017 was even lower than 0.7. From the perspective of scale efficiency and pure technical efficiency (Figure 4), the central region needs to improve scale efficiency and pure technical efficiency, and scale efficiency should be given more attention. The western region also needs to improve both, but the focus is on improving pure technological efficiency. The northeast region is obviously lacking in scale efficiency, but the pure technical efficiency is always in a good state.

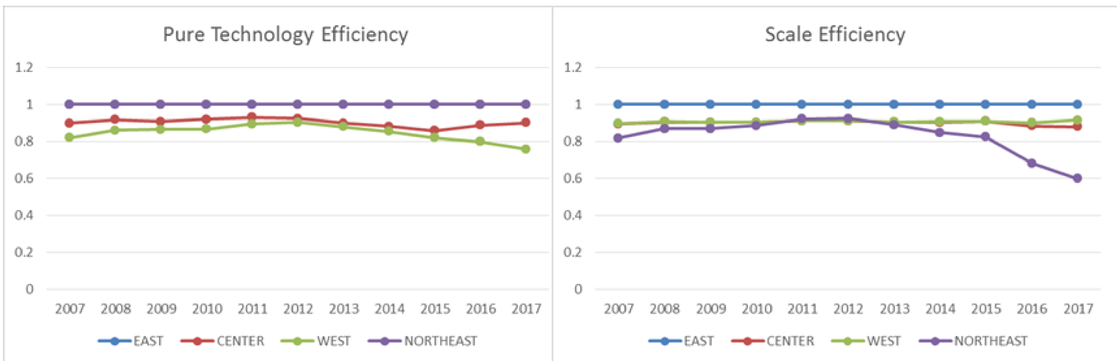

Figure 4. Pure technology efficiency and scale efficiency in four major economic zones.

The energy utilization efficiency in the four economic zones in China is basically in line with the actual economic situation. Compared with the inland areas, the eastern coastal areas have developed earlier and have great advantages in economic output, talent reserve and resource allocation. The economic development of the western region is relatively backward, and scientific and technological means should be adopted to improve energy utilization efficiency. There is still a big gap between Northeast China and Eastern China, and we should improve energy efficiency in terms of scale effect. In addition, there are significant improvements in energy efficiency in different regions compared to inter-provincial energy efficiency. That is to say, the overall energy efficiency difference of China's sub regions is gradually narrowing, but the energy efficiency within regions is extremely unbalanced, resulting in the huge energy efficiency differences among provinces.

3. The Relationship between Openness, Marketization, Urbanization and Energy Utilization Efficiency

3.1. The Definition of Variables

Due to the large gap in the resource status and economic development level of different regions, the time series model would ignore the individual differences among regions, while the cross-sectional data model cannot reflect the dynamic trend of economic change. In order to overcome these two shortcomings, this paper uses panel data model to analyze the impact of openness, marketization and urbanization on energy efficiency. The data are from China Statistical Yearbook and CEInet statistical database. The definition of variables is showed as follows:

(1) **Energy utilization efficiency (EE)**: The result of the DEA model in the previous section is energy efficiency.
(2) **Openness (OP)**: The proportion of total imports and exports in GDP is used to measure the degree of economic openness.
(3) **Marketization (MK)**: The marketization level is measured by (1- local fiscal expenditure/GDP). Generally speaking, the larger the proportion of government fiscal expenditure, the more government intervention, the lower the marketization degree.
(4) **Urbanization (UB)**: The urbanization level is measured by the proportion of urban population in the total population of regions.
(5) **Industrial structure (IS)**: It is measured by the proportion of added value of the tertiary industry in GDP.

3.2. Unit Root Test and Cointegration Test of Panel Data

In order to avoid spurious regression and guarantee the validity of estimation results, it is necessary to test the stability of panel data by a unit root test before regression. If the results of the unit root test have the same order among variables, the co-integration test can be used to study the long-term equilibrium relationship. If there is a long-term stable equilibrium relationship among variables, the regression residual of the equation is stable. On this basis, regression analysis will be more accurate.

There are many unit root test methods, including LLC, IPS, Breitung, Fisher-ADF, Fisher-PP test and so on. In this paper, we mainly use the common root test LLC and the different root tests Fisher-ADF and Fisher-PP. If they all reject the null hypothesis, the sequence is considered to be stationary. Otherwise, it is unstable. Then, the differential test is continued until it is stable. The unit root test result of panel data is shown in Table 3.

Table 3. The result of unit root test.

Methods / Variables	EE	ΔEE	OP	ΔOP	MK	ΔMK	UB	ΔUB	IS	ΔIS
LLC Test	−3.8587 **	−17.175 **	−12.010 **	−26.299 **	−7.4667 **	−13.495 **	−4.3202 **	−17.758 **	−3.7790 **	−21.562 **
Fisher-ADF Test	28.1527	132.902 **	116.860 **	206.809 **	68.4116	140.244 **	56.4507	150.582 **	41.6331	155.626 **
Fisher-PP Test	38.1522	150.277 **	124.424 **	213.927 **	77.1731	293.208 **	78.6062 *	208.198 **	62.1979	158.717 **

Note: **, * indicate that the variable is significant at the level of 1% and 5% respectively, the same below.

The results in Table 4 show that all variables are I (1) process. On this basis, the co-integration test is carried out to test whether there is a long-term stable equilibrium relationship between nonstationary sequences. The Pedroni method is used in this paper and the result is shown in Table 4.

Table 4. The result of co-integration test.

	Statistics	Prob.	Results
Panel v-Statistic	−2.319973	0.9898	Accept
Panel rho-Statistic	4.184402	1.0000	Accept
Panel PP-Statistic	−6.727107	0.0000	Reject
Panel ADF-Statistic	−4.357801	0.0000	Reject
Group rho-Statistic	6.557975	1.0000	Accept
Group PP-Statistic	−12.49921	0.0000	Reject
Group ADF-Statistic	−3.656433	0.0001	Reject

It can be seen from Table 4 that Panel v-Statistic, Panel rho-Statistic and Group rho-Statistic fail to pass the test at the significance level of 5%, indicating that they accept the null hypothesis and there is no co-integration relationship. However, the rest of the statistical data have passed the significance test. Panel ADF-Statistic and Group ADF-Statistic are more suitable for small sample data in the Pedroni test. Since the data used in this paper is relatively small (T < 20) and the above two statistics have passed the significance test, it can be concluded that there is a long-term stable equilibrium relationship among variables.

3.3. Estimation and Analysis of Panel Data Model

We take energy efficiency as a dependent variable, and openness, marketization, urbanization and industrial structure as independent variables to construct a panel data regression model. In this paper, the F test and Hausman test are used to determine the form of the model to avoid model setting errors and improve the effectiveness of parameter estimation.

From the results of F test in Table 5, the null hypothesis should be rejected. In other words, compared with a pooled regression model, we should establish an entity fixed effect model. Similarly, from the results of the Hausman test, an entity fixed effect model should be established compared with an entity random effect model. The model is as follows:

$$EE_{it} = C + \beta_1 OP_{it} + \beta_2 MK_{it} + \beta_3 UB_{it} + \beta_4 IS_{it} + D_1 + D_2 + \cdots D_{30} + u_{it} \tag{2}$$

Table 5. Results of F test and Hausman test.

	Statistics	Prob.
F test	24.573998	0.0000
Hausman test	180.561486	0.0000

The dummy $D_1, D_2, \cdots D_{30}$ variable is defined as:

$$D_i = \begin{cases} 1, (If\ it's\ the\ a-th\ individual) \\ 0, (others) \end{cases} \quad i = 1, 2, 3, \cdots 30;\ t = 2007, 2008, 2009, \cdots 2017$$

In this model, i represents province i and t stands for year t. EE, OP, MK, UB, IS, respectively represent the energy utilization efficiency, openness, marketization, urbanization and industrial structure variable. C is the public intercept; $D_1, D_2, \cdots D_{30}$ stands for individual difference; $\beta_1, \beta_2, \beta_3, \beta_4$ are corresponding coefficients; u_{it} is the random disturbance term.

To avoid heteroscedasticity and autocorrelation, the cross-section weights estimation method is adopted to estimate the entity fixed effects model of panel data. The results are shown in Table 6.

Table 6. Panel data model estimation results 1.

Variable	Coefficient	t-Statistic	Prob.
C	144.8916 **	16.66261	0.0000
OP	−0.182832 **	−10.49266	0.0000
MK	−0.151994 *	−1.978842	0.0488
UB	−0.26349 **	−3.573559	0.0004
IS	−1.071729 **	−16.27322	0.0000
Adj.R^2	0.971921	F-Statistic	310.4761
D-W	0.648526	Prob.(F-Statistic)	0.0000

** 5%, * 10%.

From Table 6, R^2 of this model is 0.9719 and the value of F-statistic is 310.4761. The regression equation is overall significant and its goodness of fit is very high. However, the explanatory variables OP, UB fail to pass the test at the significance level of 5%. The value of D-W statistic is 0.6540, which indicates that there is serious positive autocorrelation. To eliminate the autocorrelation, AR (1) is added to this model. The estimation results are shown in Table 7.

Table 7. Panel data model estimation results 2.

Variable	Coefficient	t-Statistic	Prob.
C	156.3528 **	15.47954	0.0000
OP	−0.04625 **	−4.768227	0.0000
MK	0.165401 *	1.757011	0.0401
UB	−1.268613 **	−9.512252	0.0000
IS	−0.649303 **	−10.03062	0.0000
AR(1)	0.686154 **	26.37959	0.0000
Adj.R^2	0.991604	F-Statistic	922.7332
D-W	1.737583	Prob.(F-Statistic)	0.0000

** 5%, * 10%.

From Table 7, R^2 of this model is 0.9916. Its goodness of fit is high and the value of F-statistic is 922.7332. The regression equation is overall significant. All explanatory variables pass the test at the significance level of 5%, and the value of D-W statistic is 1.7375, indicating that autocorrelation has been basically eliminated. Therefore, the final model is as follows:

$$\begin{cases} EE_{it} = 156.3528 - 0.0463OP_{it} + 0.1654MK_{it} - 1.2686UB_{it} - 0.6493IS_{it} \\ +97.0395D_1 + 66.6155D_2 + \cdots - 16.4617D_{29} - 24.9672D_{30} + u_{it} \\ u_{it} = 0.6862u_{it-1} + e_{it} \end{cases} \tag{3}$$

$$D_i = \begin{cases} 1, (If\ it's\ the\ a - th\ individual) \\ 0, (others) \end{cases}$$

$$i = 1, 2, 3, \cdots 30;\ t = 2007, 2008, 2009, \cdots 2017$$

According to the results of regression estimation, openness, marketization, urbanization and industrial structure are important factors affecting regional energy utilization efficiency. Openness has a significant negative impact on energy utilization efficiency, and its regression coefficient is −0.0463, which indicates that if the proportion of total imports and exports in GDP increases by 1%, China's energy efficiency will decrease by 0.0463%. Opening up is a double-edged sword. On the one hand, it can attract foreign advanced technology and experience. It can also produce technology spillovers, promote the transformation of the economic development mode, and improve the environment and efficiency. On the other hand, some high-polluting enterprises will flow into the country with the improvement of openness degree. They can cause serious environmental pollution and reduce energy efficiency. Generally speaking, the environmental pollution caused by economic opening partially offsets the technology spillover and affects the energy efficiency.

Marketization has a positive impact on energy efficiency. The regression coefficient of marketization is 0.1654, which passes the test at the significance level of 5%. If the proportion of local fiscal expenditure in GDP decreases by 1%, energy utilization efficiency in China will increase by 0.1654%. This shows that market-oriented reform is beneficial to the improvement of China's energy efficiency to some extent and promotes enterprises to increase independent innovation. However, the government should also play its role of macro-control and supervision to make up for the failure of the market in environmental governance and promote sustainable economic development.

Urbanization has the greatest negative impact on energy utilization efficiency, and its regression coefficient is −1.2686, indicating that every 1% increase in the urbanization rate will cause a 1.2686% decrease in energy utilization efficiency. It indicates that with the improvement of urbanization level, China's energy use efficiency has not improved, but decreased. The reason may be that the employment, infrastructure construction, transportation, capital and technology pressure brought by population aggregation make the urbanization quality of China's provinces not high. Moreover, many foreign-funded enterprises focus on the cheap labor force and broad market provided by China's urbanization, which is not conducive to the urbanization level to promote technological progress and improve energy utilization efficiency through the spillover effect of foreign-funded technologies.

Industrial structure has a significant negative influence on energy efficiency at the level of 1%. Its coefficient is −0.6493, which indicates that if the proportion of the added value of the tertiary industry in GDP increases by 1%, China's energy efficiency will decrease by 0.6493%. This is not consistent with expected results and conclusions of previous scholars. Why do we get this opposite conclusion? Although the proportion of the tertiary industry in China's industrial structure is increasing year by year, the proportion of the secondary industry is still high, with an average of 40.5%. Besides, energy-intensive industries occupy a large proportion in the secondary industry of China, which offset the improvement of energy utilization efficiency by the tertiary industry. Therefore, we conclude that the impact of industrial structure variables is negative.

In order to further investigate the influence of various factors on different regions, this paper not only carries out a regression analysis on the national panel data, but also makes a corresponding analysis on each region. The regression results of four major economic zones are shown in Table 8.

Table 8. Estimation results of four major economic zones.

Explanatory Variable	China	East	Central	West	Northeast
OP	−0.04625 **	−0.045487 *	−0.003827	0.101132	−0.347372
MK	0.165401 *	−0.015305	0.024308	0.117862 **	−1.372778 **
UB	−1.268613 **	−1.071398 **	−0.717434 **	−1.315832 **	−0.661520
IS	−0.649303 **	−0.797692 **	−0.894773 **	−0.557170 **	−1.495912 **
Adj. R^2	0.991604	0.976768	0.925243	0.924013	0.807909
D-W	1.737583	1.849916	2.090744	2.196564	1.925070

** 5%, * 10%.

As can be seen from Table 8, from a national perspective, openness, marketization, urbanization and industrial structure all have significant impacts on energy efficiency. However, from a regional perspective, their impacts are different and not entirely significant. The energy efficiency of the eastern region is the highest. Openness, urbanization and industrial structure all have a negative impact on its efficiency, while the impact of marketization on efficiency is not significant. Compared with other regions, the economic development level and opening-up degree are relatively high in the east. Meanwhile, by introducing and learning foreign advanced technology and experience, some enterprises with high pollution, high energy consumption and high emissions have flowed into China, which have a negative influence on the environment. For the eastern region, we should not blindly introduce foreign investment, but transfer from "quantity" to "quality". We should build a green and healthy urban environment while pursuing the speed of urbanization and improving infrastructure construction.

In western regions, urbanization and industrial structure have significant negative effects on energy efficiency, while marketization has a significant positive effect. However, the impact of openness is not significant. The high proportion of the secondary industry and energy-intensive industries in the western region offsets the improvement of energy utilization efficiency by the tertiary industry. Therefore, the government should strengthen its support and influence on the western region and promote the adjustment of economic structure and the transformation of the development mode. Meanwhile, it is of great importance to speed up the process of marketization and improve the quality of urbanization.

The impact of urbanization and industrial structure on energy efficiency in Central China is negative. The central region is an inland area, and there is a big gap between the central region and the eastern coastal area in terms of introducing foreign capital. Therefore, we should improve the economic openness degree and learn from foreign advanced technology and management experience. The urbanization process should also be controlled to avoid blind urban agglomeration. Otherwise, it will hinder the optimal allocation of resources and lead to the reduction of efficiency.

Marketization and industrial structure have a significant negative impact on the energy efficiency in Northeast China, with coefficients as high as -1.3728 and -1.4959, respectively, while other variables have no significant impact. As an old industrial base, the proportion of secondary industry in the northeast has been relatively high. There are a lot of energy-intensive industries, which offset the improvement of energy efficiency by tertiary industry and also make the influence of industrial structure negative. In order to improve the energy efficiency in Northeast China, we should not only pay attention to the adjustment of industrial structure, but also accelerate the transformation of the economic development mode and curb the excessive growth of energy-intensive industries.

4. Conclusions and Suggestions

Based on the analysis results, the following conclusions can be drawn:

(1) With the development of the economy and the progress of science and technology, energy utilization efficiency in China has not improved. There is a big gap in energy efficiency among the four major economic zones in China. How to improve energy utilization efficiency and find reasonable ways of energy conservation and emission reduction is extremely urgent.

(2) From the national perspective, the changes in economic structure, including openness, marketization and urbanization, are all important factors affecting energy utilization efficiency. From the regional perspective, the influence of openness, marketization, urbanization and industrial structure are different and not entirely significant. Therefore, regional differences must be fully taken into account when taking measures to improve energy efficiency.

Based on the above conclusions, we put forward the following suggestions for improving energy utilization efficiency in China:

(1) We should continue to take accelerating the transformation of the mode of economic development as a long-term and arduous task. China must strive to break the extensive growth mode of high input and low output, pay more attention to the quality of economic development, energy conservation and emission reduction, and realize the effective utilization of resources. In addition, energy conservation policies and objectives must take into account regional differences.

(2) The four major economic zones should encourage the rational flow of capital, technology, talent and resources, so as to promote the optimal allocation of resources, mutual exchange and cooperation. In order to improve the overall energy efficiency

of our country, the high-efficiency regions should ensure the stable improvement of efficiency and guide the low-efficiency areas to narrow the regional gap.

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References

1. Patterson, M.G. What is energy efficiency?: Concepts, indicators and methodological issues. *Energy Policy* **1996**, *24*, 377–390. [CrossRef]
2. Halkos, G.; Petrou, K.N. Assessing 28 EU member states' environmental efficiency in national waste generation with DEA. *J. Clean. Prod.* **2019**, *208*, 509–521. [CrossRef]
3. Yang, Z.; Wei, X. The measurement and influences of China's urban total factor energy efficiency under environmental pollution: Based on the game cross-efficiency DEA. *J. Clean Prod.* **2019**, *209*, 439–450. [CrossRef]
4. Huo, T.; Tang, M.; Cai, W.; Ren, H.; Liu, B.; Hu, X. Provincial total-factor energy efficiency considering floor space under construction: An empirical analysis of China's construction industry. *J. Clean. Prod.* **2020**, *244*, 118749. [CrossRef]
5. Cheng, Z.; Liu, J.; Li, L.; Gu, X. Research on meta-frontier total-factor energy efficiency and its spatial convergence in Chinese provinces. *Energ Econ.* **2020**, *86*, 104702. [CrossRef]
6. Geng, Z.; Zeng, R.; Han, Y.; Zhong, Y.; Fu, H. Energy efficiency evaluation and energy saving based on DEA integrated affinity propagation clustering: Case study of complex petrochemical industries. *Energy* **2019**, *179*, 863–875. [CrossRef]
7. Iftikhar, Y.; Wang, Z.; Zhang, B.; Wang, B. Energy and CO_2 emissions efficiency of major economies: A network DEA approach. *Energy* **2018**, *147*, 197–207. [CrossRef]
8. Fernández, D.; Pozo, C.; Folgado, R.; Jiménez, L.; Guillén-Gosálbez, G. Productivity and energy efficiency assessment of existing industrial gases facilities via data envelopment analysis and the Malmquist index. *Appl. Energy* **2018**, *212*, 1563–1577. [CrossRef]
9. Wen, Q.; Hong, J.; Liu, G.; Xu, P.; Tang, M.; Li, Z. Regional efficiency disparities in China's construction sector: A combination of multiregional input–output and data envelopment analyses. *Appl. Energy* **2020**, *257*, 113964. [CrossRef]
10. Zhu, B.; Zhang, M.; Zhou, Y.; Wang, P.; Sheng, J.; He, K.; Wei, Y.M.; Xie, R. Exploring the effect of industrial structure adjustment on interprovincial green development efficiency in China: A novel integrated approach. *Energy Policy.* **2019**, *134*, 110946. [CrossRef]
11. Wang, F.; Sun, X.; Reiner, D.M.; Wu, M. Changing trends of the elasticity of China's carbon emission intensity to industry structure and energy efficiency. *Energy Econ.* **2020**, *86*, 104679. [CrossRef]
12. Xiong, S.; Ma, X.; Ji, J. The impact of industrial structure efficiency on provincial industrial energy efficiency in China. *J. Clean Prod.* **2019**, *215*, 952–962. [CrossRef]
13. Zhao, H.; Lin, B. Impact of foreign trade on energy efficiency in China's textile industry. *J. Clean. Prod.* **2020**, *245*, 118878. [CrossRef]
14. Koengkan, M. The positive impact of trade openness on consumption of energy: Fresh evidence from Andean community countries. *Energy* **2018**, *158*, 936–943. [CrossRef]
15. Peng, L.; Zhang, Y.; Wang, Y.; Zeng, X.; Peng, N.; Yu, A. Energy efficiency and influencing factor analysis in the overall Chinese textile industry. *Energy* **2015**, *93*, 1222–1229. [CrossRef]
16. Wang, J.; Shi, Y.; Zhang, J. Energy efficiency and influencing factors analysis on Beijing industrial sectors. *J. Clean Prod.* **2017**, *167*, 653–664. [CrossRef]
17. Zhao, H.; Guo, S.; Zhao, H. Provincial energy efficiency of China quantified by three-stage data envelopment analysis. *Energy* **2019**, *166*, 96–107. [CrossRef]
18. Morfeldt, J.; Silveira, S. Capturing energy efficiency in European iron and steel production—comparing specific energy consumption and Malmquist productivity index. *Energy Effic.* **2014**, *7*, 955–972. [CrossRef]
19. Li, K.; Fang, L.; He, L. How urbanization affects China's energy efficiency: A spatial econometric analysis. *J. Clean. Prod.* **2018**, *200*, 1130–1141. [CrossRef]
20. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]