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Research Article

Measuring the Total-Factor Green Efficiency in China's Industrial Sectors: A Parametric Approach

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At present, China's industrial economy is facing a severe problem of green transformation, so the measurement of total-factor green efficiency has become one of the research hot spots. Combining Shephard's distance function and metafrontier model, this study constructs a parametric total-factor green efficiency model in consideration of technology heterogeneity. Stochastic metafrontier analysis, which controls individual effects, is used to estimate metafrontier green efficiency. This study calculates the green efficiency of Chinese industrial sectors. Results show that there are significant differences in metafrontier green efficiency between high- and low-emission groups, and the efficiency level of the low-emission group is systematically higher than that of the high-emission group. Compared with pooled green efficiency and existing studies without considering technology heterogeneity, the metafrontier green efficiency is more intuitive and realistic. In order to achieve green industrial growth, this study suggests that the government should implement heterogeneous energy conservation and emission reduction policies for high- and low-emission groups, especially to encourage carbon-intensive industries to improve the use of existing group technologies, and to promote technology diffusion and spillover between high- and low-emission groups. Based on the reliable measurement of green efficiency, green productivity might be reliably explored as well in the future.

1. Introduction

In the past four decades of reform and opening up, China has made remarkable achievements in economic development. At the same time, the industrial economy has also achieved unprecedented development. China has not only become the "world factory" covering the whole industrial chain but also increased its industrial added-value production by nearly 60 times compared with 1978, with an average annual growth rate of 14.5% [1]. China's economic growth miracle has dramatically improved the welfare of its people and eliminated absolute poverty across the country by 2020. However, decades of rapid growth have also brought enormous environmental pressure, resulting in the frequent haze, extreme weather, and environmental degradation across the country in recent years, which is largely due to the traditional extensive mode of growth. This type of growth is characterized by "high input, high consumption, and high emissions" and is also the main culprit of various environmental and climate change problems. For this reason, since the 11th Five-Year Plan [2], energy conservation and emission reduction have become a mandatory target of the government's national economic plan and have been well implemented. At present, energy conservation and emission reduction have become the international consensus to deal with global warming. At the 75th Session of the United Nations General Assembly recently, the Chinese government stated that China will strive to achieve the carbon emission peak by 2030 and achieve carbon neutrality by 2060. On the other hand, economic growth has its inherent regularity. Since 2012, China's economic growth has been under great downward pressure and entered the "new normal" of medium-high growth [3]. Therefore, how to ensure the sound and steady growth of China's economy and solving the problems of environment and climate change has become one of the core issues of China's sustainable economic growth in the new era.

Under this background, green growth has become a new economic growth model that attracts much attention [4]. Although there is no universally recognized and unified definition, its basic connotation is to achieve sustainable economic growth with minimum resource consumption and minimum environmental cost [5]. In other words, green growth is an environmentally inclusive growth model that ensures environmental friendliness while achieving economic growth. It is an alternative to the "pollution first, treatment later" model and a feasible solution to environmental and climate change issues. Studies have shown that industrial activities are the main source of environmental and climate change problems, and the green development of China's economy largely depends on the green transformation of the industrial economy.

There are two main lines of research on measuring green growth. One is to construct a comprehensive evaluation indicator system, and the other is to construct relevant indexes of green growth under the input-output framework [5]. This study adopts the second research route, in which green growth is often expressed by green total-factor productivity or total-factor green efficiency. Chambers et al. [6] proposed an environmental regulation behavior analysis model based on directional distance function (DDF), which can asymmetrically deal with outputs and/or inputs. However, the directional distance function requires that the inputs or outputs vary in the same proportion (radial) and that input- and output-based choices (angular) are required for efficiency measurement. In order to overcome the above two defects, Chuang et al. [7]; Oh et al. [8]; and Du et al. [9] combined DDF to construct Malmquist-Luenberger total-factor productivity index by taking undesirable output as an output variable to measure the green total-factor productivity that takes environmental factors into account. However, this method is carried out in a nonparametric framework and has two main shortcomings: (i) mathematical programming is nonlinear except in the case of constant return to scale; (ii) the model is deterministic, and statistical inference cannot be made unless bootstrapping is used [10].

On the other hand, Fare et al. [11] introduced a hyperbolic distance function to measure production performance through the ability to expand output and shrink input in a balanced way. In this case, the traditional radial distance function, which expands output or contracts input, is a special case of the hyperbolic distance function. Fare et al. [12] used the linear programming technique to construct a parametric (quadratic) directional distance function to assess the ability of firms to improve environmental efficiency by simultaneously increasing good output and reducing bad output, but this model is still affected by the second shortcoming of the nonparametric approach described above. Cuesta et al. [13] developed a stochastic hyperbolic distance function model, which utilized the transcendental logarithmic production function proposed by Christensen et al. [14]. Zhang and Ye [15] extended the hyperbolic distance function module of Cuesta et al. [13] to include the use of an elastic time-varying framework to capture neutral technical changes using technology (t) rather than time dummy variables. Duman and Kasman [16] applied the enhanced hyperbolic distance function proposed by Cuesta et al. [13] to investigate the environmental efficiency of EU members and candidate countries and analyzed its convergence. However, the hyperbolic distance function still needs to expand and decrease the good and bad outputs in equal proportion. Zhou et al. [17] proposed the carbon emission distance function under the DEA framework, which can investigate the maximum emission reduction potential of carbon emissions under the condition that other inputs and technologies remain unchanged, so as to flexibly measure carbon emission efficiency or green efficiency more. Lin and Du [18] proposed the green efficiency based on the carbon emission distance function under the SFA framework and investigated the green efficiency and productivity of each province in China. The SFA framework for green efficiency measurement gained many attention because it could provide statistical inference while the DEA framework generally does not. For example, Tan et al. [19] estimated the green efficiency of 36 industrial subsectors in China from 2001 to 2015. Lv et al. [20] used the SFA framework to evaluate the green productivity of 30 provinces in China from 1997 to 2017.

A common assumption in the above studies is that all DMUs share the same production technology, which may lead to biased measurement results because there may be inherent differences between different technology groups. Hayami and Ruttan [21] first proposed the concept of metafrontier to solve the problem of noncomparability of production performance of different groups. Battese and Rao [22] developed the stochastic metafrontier method (SMFA) by combining the coproduction concept with the SFA framework, but the method had problems with the data generation process (DGP). Battese et al. [23] proposed a different definition of the metafrontier function to solve the above DGP problem. They also proposed a two-step standard estimation procedure, that is, the first step uses SFA to estimate the group frontier, and the second step uses linear or quadratic programming techniques to estimate the metafrontier. O 'Donnell et al. [24] further extended this method to the distance function and the DEA model. Based on the development of the metafrontier function and due to the advantage of providing statistical inference of SFA, Lin and Du [25] used the SMFA method to measure the total-factor energy efficiency of 30 regions in China from 1997 to 2010. Along this line, Lin and Du [18] used the fixed-effects SMFA model to estimate the total-factor carbon emission efficiency and Malmquist carbon emission performance of 30 provinces in China during 2000–2010. Bai et al. [26] used the SMFA to measure the environmental performance and carbon emission reduction potential of 39 industrial sectors in China from 2005 to 2011. Zheng et al. [27] estimated the total-factor water efficiency of 30 provinces in China from 2001 to 2016 using the SFMA. All the above studies adopted the two-step method proposed by Battese et al. [23] and O 'Donnell et al. [24]. However, Huang et al. [28] pointed out that the statistical properties of the metafrontier estimated by the second step of the above two-step mixed approach are not clear, because the estimated results obtained from programming techniques may be "contaminated" by random disturbances. They then proposed a two-step stochastic frontier approach that uses SFA estimation in both the first and second steps to address the limitations mentioned above. The two-step stochastic frontier approach attracted many attention and was applied in a wide range of efficiency studies. For example, Safiullah and Shamsuddin [29] applied the two-step stochastic frontier approach to measure the Islamic banks' cost efficiency and Alem et al. [30] evaluated Norwegian dairy farms' technical efficiency using this approach. In the field of energy and environmental studies, Lu et al. [31] used the two-step stochastic frontier approach to assess the environmental efficiency of China's 273 cities from 2002 to 2016. Zhang et al. [32] estimated the energy efficiency of Chinese cities from 2005 to 2015 using the two-step stochastic frontier approach. However, these studies seldom considered individual heterogeneity, which might cause biased results [18].

Therefore, this study aims to provide a new parametric framework of total-factor green efficiency, based on the carbon emission distance function proposed by Zhou et al. [17] and Lin and Du [18] and the two-step stochastic frontier approach proposed by Huang et al. [28]. The new method can deal with both individual heterogeneity and technology heterogeneity, which has been seldom carried out in literature, especially in the measurement of green efficiency. Moreover, there are numerous studies assessing the energy or green efficiency in China from the province perspective while those from the industry perspective are very limited. Thus, using this method, this study calculates the total-factor metafrontier green efficiency of China's 34 industrial sectors from 2000 to 2016, and the results show that the green efficiency is more reasonable and accurate after considering the technology heterogeneity and individual heterogeneity.

This study is arranged as follows: in section 2, the method of total-factor green efficiency considering technology heterogeneity is given, and the data source and parametric estimation are given. Section 3 is the analysis of the green efficiency of the Chinese industry. Section 4 is the conclusion.

2. Research Methodology

2.1. Method. Zhou [17] proposed the Shephard emission distance function under the DEA framework. This function measures the largest reduction of bad output (carbon emissions) given good output. Lin and Du [18] parameterized this function and proposed a parametric measurement framework of total-factor green efficiency. Based on Lin and Du [18], this study will construct the total-factor green efficiency in consideration of technology heterogeneity among different groups of industrial sectors. Under the concept of metafrontier, there are two different kinds of environmental technologies: one is group technology, which is heterogeneous among different groups; the other is the metafrontier technology, which is the envelope function of different group technologies.

An environmental technology that produces good output (Y) and bad output of carbon dioxide (C) is considered by putting in capital (K) and labor (L). The reason why energy input is not considered here is that China's industrial energy consumption structure is relatively stable, which has a very high correlation with carbon emissions and thus affects the effect of econometric analysis [18]. In this study, China's industrial sectors are divided into groups, and the group environmental technology is defined by the following:

$$P^j = \left\{\left(K^j, L^j, Y^j, C^j\right):\ \left(K^j, L^j\right) \text{can produce} \left(Y^j, C^j\right)\right\}, \quad (1)$$

where $j = 1, 2, \ldots, J$ denotes sectors, and P^j stands for the group environmental technology.

Accordingly, the metafrontier environmental technology is defined by the following:

$$P^* = \{(K, L, Y, C):\ (K, L) \text{can produce} (Y, C)\}, \quad (2)$$

where P^* stands and the metafrontier environmental technology.

Referring to Zhou et al. [17] and Lin and Du [18], the Shephard emission distance function corresponding to group environmental technology and metafrontier environmental technology is given by the following:

$$\begin{aligned} D_C^j\left(K^j, L^j, Y^j, C^j\right) &= \sup\left\{\theta \middle| \left(K^j, L^j, Y^j, \frac{C^j}{\theta}\right) \in P^j\right\}, \\ D_C^*(K, L, Y, C) &= \sup\left\{\theta \middle| \left(K, L, Y, \frac{C}{\theta}\right) \in P^*\right\}, \end{aligned} \quad (3)$$

where $\theta \geq 1$ reflects the maximum reduction potential of carbon emissions given by the capital stock, labor, and technology. The group green efficiency (GGE) is defined by the following:

$$GGE = \frac{1}{D_C^j\left(K^j, L^j, Y^j, {}^j_C\right)}. \quad (4)$$

The metafrontier green efficiency (MGE) is defined by the following:

$$MGE = \frac{1}{D_C^*(K, L, Y, C)}. \quad (5)$$

Since the metafrontier is an envelope function of the group frontiers, it can be obtained as follows:

$$D_C^*(K, L, Y, C) \geq D_C^j(K, L, Y, C). \quad (6)$$

In other words, we get the following:

$$MGE \leq GGE. \quad (7)$$

O 'Donnell et al. [24] constructed a metafrontier ratio (MTR) to capture the potential gap between group frontier and metafrontier as follows:

$$\begin{aligned} MTR &= \frac{D_C^*(K, L, Y, C)}{D_C^j(K, L, Y, C)} \\ &= \frac{MGE}{GGE}. \end{aligned} \quad (8)$$

Thus, the metafrontier green efficiency can be regarded as the product of group green efficiency and metafrontier ratio as follows:

$$MGE = GGE \times PGE. \tag{9}$$

Equation (9) reveals that for any decision-making unit, its green efficiency relative to the metafrontier consists of two parts: one is within the group, namely, group green efficiency (GGE), and the other is between groups, namely, metafrontier ratio (MTR). Accordingly, there are two basic ways to improve green efficiency. One is to approach the leaders of green efficiency within the group by tapping their own potential, such as management, innovation, and energy-saving investment. The other is to improve the group's overall potential green efficiency by improving the economic environment and conditions, such as infrastructure investment, environmental regulation, and technology diffusion. The above discussion shows that under the concept of metafrontier, the improvement of green efficiency requires not only the contribution of a single individual but also the joint efforts of its group.

Following Huang et al. [28] and Wang [33], this study first describes the carbon emission distance function in the translogarithmic function because of its flexibility, ease of calculation, and homogeneity [18, 34]. In order to control individual effects, we adopt the fixed-effects SFA method proposed by Greene [35]. The group emission distance function is then given by the following:

$$\begin{aligned}\ln D_{it}^{j} = {} & \alpha_i + \alpha_k \ln K_{it}^{j} + \alpha_l \ln L_{it}^{j} + \alpha_t t + 0.5\alpha_{kk}\left(\ln K_{it}^{j}\right)^2 \\ & + 0.5\alpha_{ll}\left(\ln L_{it}^{j}\right)^2 + 0.5\alpha_{tt}t^2 \\ & + \alpha_{kl}\ln K_{it}^{j}\ln L_{it}^{j} + \alpha_{tk}t\ \ln K_{it}^{j} + \alpha_{tl}t\ \ln L_{it}^{j} \\ & + \beta_y \ln Y_{it}^{j} + 0.5\beta_{yy}\left(\ln Y_{it}^{j}\right)^2 \\ & + \beta_c \ln C_{it}^{j} + 0.5\beta_{cc}\left(\ln C_{it}^{j}\right)^2 + \beta_{yc}\ln Y_{it}^{j}\ln C_{it}^{j} \\ & + \gamma_{ky}\ln K_{it}^{j}\ln Y_{it}^{j} + \gamma_{ly}\ln L_{it}^{j}\ln Y_{it}^{j} + \gamma_{ty}t\ \ln Y_{it}^{j} \\ & + \delta_{kc}\ln K_{it}^{j}\ln C_{it}^{j} + \delta_{lc}\ln L_{it}^{j}\ln C_{it}^{j} \\ & + \delta_{tco_2}t\ \ln C_{it}^{j} + \varepsilon_{it}^{j},\end{aligned} \tag{10}$$

where α_i measures the individual effects; D_{it}^{j} is the distance function of industry i at time t; t is also a technical variable; and ε_{it}^{j} is a random term and satisfies $\varepsilon_{it}^{j} \sim N(0, \sigma_{\varepsilon j}^{2})$. For the convenience of expression, equation (10) is rewritten as follows:

$$\ln D_{it}^{j} = TL\left(K^j, L^j, t, Y^j, C^j\right) + \varepsilon_{it}^{j}. \tag{11}$$

Since the carbon emission distance function is linearly homogeneous to carbon emission, it can be obtained as follows:

$$\ln D_{C,it}^{j}\left(K_{it}^{j}, L_{it}^{j}, t, Y_{it}^{j}, C_{it}^{j}\right) = \ln C_{it}^{j} + \ln D_{H,it}^{j}\left(K_{it}^{j}, L_{it}^{j}, t, Y_{it}^{j}, 1\right). \tag{12}$$

Table 1: China's industrial sectors and group codes.

Code	Sectors
H01	Coal mining and washing
H02	Oil and natural gas extracting
H03	Ferrous metal mining
H04	Nonmetal mining
H05	Paper industry
H06	Oil processing and coking
H07	Chemical materials and products
H08	Nonmetallic mineral products
H09	Ferrous metal smelting and pressing
H10	Nonferrous metal pressing
H11	Electricity production
H12	Gas production
L13	Nonferrous metal mining
L14	Food processing
L15	Food manufacturing
L16	Beverage manufacturing
L17	Tobacco manufacturing
L18	Textile industry
L19	Leather manufacturing
L20	Timber and wood processing
L21	Furniture manufacturing
L22	Printing and intermediary replication
L23	Culture, education, and sport activities
L24	Medicine manufacturing
L25	Chemical fiber manufacturing
L26	Rubber and plastic manufacturing
L27	Metal product manufacturing
L28	General-purpose manufacturing
L29	Special-purpose manufacturing
L30	Transport equipment manufacturing
L31	Electrical machinery and equipment
L32	Communication equipment manufacturing
L33	Measuring instrument manufacturing
L34	Water production

Note: *H* and *L* denote high-emission and low-emission groups, respectively.

After rearranging, we get the following:

$$\begin{aligned}-\ln C_{it}^{j} = {} & \alpha_i + \alpha_k \ln K_{it}^{j} + \alpha_l \ln L_{it}^{j} + \alpha_t t + 0.5\alpha_{kk}\left(\ln K_{it}^{j}\right)^2 \\ & + 0.5\alpha_{ll}\left(\ln L_{it}^{j}\right)^2 \\ & + 0.5\alpha_{tt}t^2 + \alpha_{kl}\ln K_{it}^{j}\ln L_{it}^{j} + \alpha_{tk}t\ \ln K_{it}^{j} \\ & + \alpha_{tl}t\ \ln L_{it}^{j} + \beta_y \ln Y_{it}^{j} + 0.5\beta_{yy}\left(\ln Y_{it}^{j}\right)^2 \\ & + \gamma_{ky}\ln K_{it}^{j}\ln Y_{it}^{j} \\ & + \gamma_{ly}\ln L_{it}^{j}\ln Y_{it}^{j} + \gamma_{ty}t\ \ln Y_{it}^{j} + \varepsilon_{it}^{j} - u_{it}^{j},\end{aligned} \tag{13}$$

where $u_{it}^{j} = \ln D_{C,it}^{j}(K_{it}^{j}, L_{it}^{j}, t, Y_{it}^{j}, C_{it}^{j}) > 0$ is defined as the inefficiency term in stochastic frontier analysis and satisfies $u_{it}^{j} \sim N^{+}(0, \sigma_u^{2j})$.

Then, the group green efficiency can be estimated as follows:

$$\widehat{GGE}_{it} = E\left\{\exp\left(-u_{it}^{j}\right) | \hat{\varepsilon}_{it}^{j}\right\}. \tag{14}$$

Table 2: Statistical description of main variables.

Variable	Unit	High-emission group			Low-emission group		
		Observations	Mean	Standard deviation	Observations	Mean	Standard deviation
Y	10^8 yuan	204	1419.15	1580.14	374	2426.98	3737.28
K	10^8 yuan	204	15648.84	23092.15	374	5401.28	6579.41
L	10^4 persons	204	297.49	237.93	374	346.02	337.35
E	PJ	204	5849.65	9835.75	374	323.48	304.07
C	10^4 tons	204	40414.37	77756.41	374	1316.99	1339.65
CI	Ton/10^4 yuan	204	23.83	34.68	374	1.00	0.86

Table 3: Estimated results of different stochastic frontier functions.

Model	(1) High-emission group		(2) Low-emission group		(3) Metafrontier		(4) Pooled	
Methods	MLE		MLE		QMLE		MLE	
lnK	−2.717***	(0.713)	3.308***	(0.737)	3.275***	(0.025)	0.815**	(0.413)
lnL	0.402	(0.914)	−1.020 *	(0.616)	−0.988***	(0.023)	−1.492***	(0.462)
lnY	1.473 *	(0.767)	−0.728	(0.726)	−0.896***	(0.027)	−0.409	(0.399)
t	0.191#	(0.127)	−0.529***	(0.092)	−0.511***	(0.002)	−0.144**	(0.057)
lnK2	−0.216**	(0.106)	−0.295**	(0.118)	−0.318***	(0.007)	−0.108#	(0.066)
lnL2	−0.232	(0.269)	−0.098	(0.103)	−0.093***	(0.003)	0.079	(0.087)
lnY2	−0.174#	(0.118)	0.195***	(0.069)	0.200***	(0.003)	0.031	(0.054)
t2	0.008***	(0.003)	−0.002	(0.002)	−0.002***	(0.000)	0.006***	(0.001)
lnKL	0.628***	(0.218)	0.409**	(0.186)	0.430***	(0.006)	0.117	(0.113)
lnKY	0.400***	(0.153)	−0.242**	(0.102)	−0.208***	(0.008)	−0.037	(0.070)
lnLY	−0.452	(0.392)	−0.125	(0.128)	−0.156***	(0.006)	−0.014	(0.097)
tlnK	0.023	(0.029)	0.094***	(0.024)	0.096***	(0.001)	0.024#	(0.014)
tlnL	−0.052	(0.045)	−0.062***	(0.018)	−0.061***	(0.000)	−0.034***	(0.012)
tlnY	−0.036#	(0.025)	0.026 *	(0.014)	0.022***	(0.001)	0.013 *	(0.008)
σ_u								
lnCI	0.843***	(0.264)	2.905#	(1.799)	2.583***	(0.121)	0.392***	(0.065)
_Cons	−5.460***	(0.939)	−6.340***	(2.174)	−6.229***	(0.104)	−2.526***	(0.174)
σ_v								
_Cons	−3.872***	(0.356)	−3.572***	(0.084)	−14.387***	(0.518)	−4.675***	(0.317)
σ_u	0.678***	(0.195)	0.942***	(0.345)	1.839 *	(1.089)	0.137***	(0.039)
σ_v	0.005***	(0.000)	0.001***	(0.000)	0.008***	(0.001)	0.002***	(0.000)
Likelihood	51.93		129.43		917.36		91.40	
LR test			179.92 (P−value = 0.000)					
Observations	578		204		374		578	

Note: (1) #, *, **, and *** represent statistical significance of 15%, 10%, 5%, and 1%, respectively. (2) The numbers in brackets are standard deviations.

The second step is to estimate the metafrontier ratio (MTR). Referring to Huang et al. [28], it can be derived that:

$$-\ln\left(TL_{it}^{j}\right) = -\ln\left(TL_{it}^{*}\right) - u_{it}^{j*}, \tag{15}$$

$$\begin{aligned} -\ln\left(Y_{it}^{j}\right) &= -\ln\left(TL_{it}^{j}\right) + \varepsilon_{it}^{j}, \\ &= -\ln\left(\hat{TL}_{it}^{j}\right) + \hat{\varepsilon}_{it}^{j}. \end{aligned} \tag{16}$$

Equation (15) is substituted into equation (17) to get the following:

$$-\ln\left(\hat{TL}_{it}^{j}\right) = \ln\left(TL_{it}^{*}\right) + \varepsilon_{it}^{j*}, \tag{17}$$

where $\varepsilon_{it}^{j*} = v_{it}^{j*} - u_{it}^{j*}$ and $v_{it}^{j*} = \varepsilon_{it}^{j} - \hat{\varepsilon}_{it}^{j}$.

Referring to Huang et al. [28], the non-negative inefficiency term can be assumed as i.i.d. $u_{it}^{j*} \sim N\left(\mu, \sigma_{uj*}^{2}\right)$; v_{t}^{ij*} can also reasonably be assumed to be an asymptotically normal distribution with zero mean, but it may not be an independent normal distribution because of the inclusion of ε_{t}^{ij}. To solve this problem, a quasi-maximum likelihood estimator (QMLE) can be used. Therefore, MTR can be predicted as follows:

$$\hat{MTR}_{it} = E\left\{\exp\left(-u_{it}^{j*}\right) | \hat{\varepsilon}_{it}^{j*}\right\}. \tag{18}$$

Finally, the metafrontier green efficiency (MGE) can be calculated according to equation (9) given equations (14) and (18).

2.2. Data. The sample period of this study is 2000–2016. During this period, the National Industry Classification Standard (NSIC) was revised twice (2002 and 2011). In order to ensure the consistency of statistical coverage, we finally select 34 industrial sectors with good continuity of industry connotation for empirical analysis, as shown in Table 1. The capital stock and labor data of China's industrial sectors

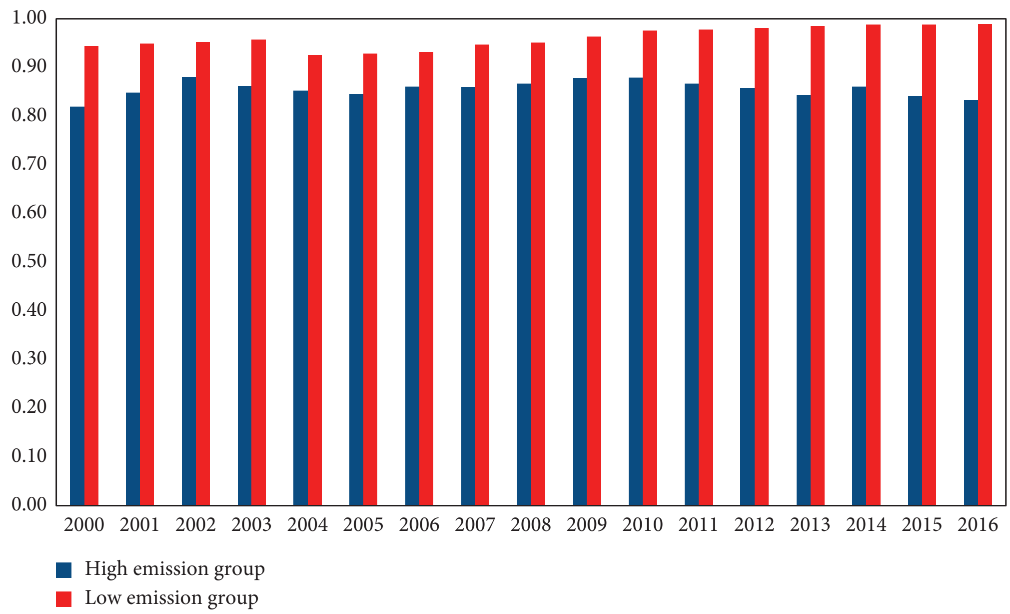

Figure 1: Trends in group green efficiency of different groups.

Table 4: Group green efficiency of China's industrial sectors.

Code	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
H01	0.823	0.849	0.866	0.804	0.932	0.929	0.920	0.913	0.926	0.798	0.861	0.820	0.795	0.789	0.950	0.941	0.931	0.873
H02	0.602	0.720	0.822	0.794	0.853	0.908	0.896	0.934	0.865	0.917	0.883	0.930	0.898	0.839	0.893	0.803	0.861	0.848
H03	0.912	0.920	0.941	0.935	0.895	0.906	0.910	0.923	0.909	0.936	0.809	0.909	0.925	0.902	0.905	0.922	0.919	0.911
H04	0.951	0.952	0.952	0.923	0.895	0.808	0.806	0.806	0.858	0.870	0.914	0.932	0.900	0.943	0.941	0.935	0.921	0.900
H05	0.832	0.870	0.865	0.891	0.835	0.839	0.867	0.889	0.882	0.885	0.932	0.928	0.945	0.955	0.962	0.962	0.957	0.900
H06	0.898	0.939	0.938	0.888	0.823	0.878	0.891	0.839	0.825	0.870	0.812	0.705	0.692	0.650	0.653	0.537	0.560	0.788
H07	0.877	0.909	0.904	0.908	0.850	0.829	0.839	0.863	0.898	0.911	0.937	0.914	0.917	0.920	0.912	0.874	0.881	0.891
H08	0.820	0.844	0.867	0.809	0.675	0.684	0.767	0.825	0.864	0.882	0.917	0.870	0.868	0.911	0.917	0.912	0.910	0.844
H09	0.892	0.906	0.923	0.910	0.911	0.844	0.844	0.824	0.845	0.794	0.816	0.779	0.752	0.747	0.722	0.726	0.659	0.817
H10	0.891	0.929	0.918	0.921	0.910	0.900	0.876	0.882	0.896	0.906	0.933	0.929	0.933	0.942	0.936	0.933	0.930	0.916
H11	0.727	0.818	0.850	0.862	0.829	0.847	0.832	0.829	0.849	0.831	0.786	0.736	0.697	0.601	0.584	0.600	0.541	0.754
H12	0.615	0.531	0.725	0.699	0.823	0.771	0.875	0.791	0.789	0.943	0.949	0.958	0.966	0.916	0.958	0.953	0.922	0.834
L13	0.940	0.944	0.934	0.917	0.838	0.855	0.839	0.920	0.944	0.958	0.974	0.967	0.973	0.980	0.981	0.982	0.987	0.937
L14	0.897	0.898	0.903	0.930	0.757	0.779	0.806	0.782	0.783	0.867	0.941	0.956	0.964	0.970	0.965	0.957	0.956	0.889
L15	0.807	0.841	0.877	0.911	0.803	0.819	0.816	0.864	0.859	0.880	0.933	0.936	0.958	0.961	0.967	0.970	0.964	0.892
L16	0.947	0.953	0.950	0.947	0.774	0.774	0.810	0.840	0.852	0.897	0.968	0.971	0.973	0.974	0.975	0.978	0.980	0.916
L17	0.991	0.992	0.992	0.993	0.996	0.996	0.997	0.998	0.999	0.999	0.999	0.999	0.999	0.999	1.000	1.000	1.000	0.997
L18	0.931	0.935	0.936	0.935	0.874	0.887	0.913	0.930	0.942	0.953	0.963	0.960	0.972	0.979	0.987	0.988	0.989	0.946
L19	0.969	0.978	0.980	0.982	0.970	0.975	0.952	0.966	0.974	0.980	0.988	0.990	0.989	0.992	0.994	0.995	0.995	0.981
L20	0.905	0.931	0.932	0.917	0.810	0.831	0.874	0.915	0.926	0.940	0.965	0.965	0.972	0.981	0.987	0.989	0.994	0.931
L21	0.955	0.965	0.967	0.967	0.991	0.991	0.982	0.984	0.984	0.987	0.990	0.992	0.994	0.995	0.996	0.996	0.997	0.984
L22	0.973	0.979	0.980	0.980	0.989	0.990	0.985	0.988	0.988	0.991	0.992	0.995	0.996	0.996	0.995	0.995	0.996	0.989
L23	0.987	0.988	0.989	0.990	0.987	0.990	0.984	0.988	0.990	0.992	0.993	0.996	0.986	0.988	0.987	0.989	0.988	0.989
L24	0.977	0.982	0.982	0.983	0.973	0.976	0.973	0.974	0.976	0.984	0.986	0.986	0.987	0.990	0.993	0.994	0.995	0.983
L25	0.892	0.834	0.839	0.912	0.896	0.885	0.922	0.940	0.949	0.963	0.968	0.957	0.958	0.966	0.976	0.976	0.973	0.930
L26	0.964	0.971	0.976	0.976	0.959	0.958	0.950	0.962	0.963	0.973	0.980	0.983	0.987	0.990	0.993	0.994	0.995	0.975
L27	0.918	0.931	0.938	0.953	0.961	0.965	0.953	0.960	0.963	0.972	0.981	0.985	0.979	0.981	0.988	0.989	0.990	0.965
L28	0.943	0.951	0.953	0.964	0.957	0.944	0.941	0.946	0.947	0.954	0.967	0.940	0.980	0.986	0.988	0.988	0.989	0.961
L29	0.900	0.921	0.944	0.942	0.958	0.962	0.961	0.969	0.975	0.979	0.979	0.986	0.991	0.992	0.992	0.994	0.995	0.967
L30	0.959	0.971	0.976	0.986	0.985	0.983	0.983	0.987	0.987	0.990	0.992	0.993	0.993	0.994	0.996	0.997	0.998	0.987
L31	0.992	0.994	0.994	0.995	0.993	0.994	0.992	0.994	0.995	0.996	0.997	0.997	0.998	0.998	0.999	0.999	0.999	0.996
L32	0.998	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999
L33	0.989	0.991	0.991	0.992	0.996	0.997	0.997	0.997	0.998	0.998	0.998	0.999	0.999	0.999	0.999	1.000	1.000	0.997
L34	0.931	0.938	0.923	0.896	0.894	0.884	0.874	0.935	0.935	0.946	0.906	0.962	0.934	0.965	0.980	0.975	0.977	0.933
High	0.820	0.849	0.881	0.862	0.853	0.845	0.860	0.860	0.867	0.879	0.879	0.867	0.857	0.843	0.861	0.842	0.833	0.856
Low	0.944	0.949	0.952	0.958	0.926	0.929	0.932	0.947	0.951	0.964	0.975	0.978	0.981	0.985	0.988	0.988	0.989	0.961
All	0.900	0.914	0.927	0.924	0.900	0.899	0.907	0.916	0.922	0.934	0.941	0.939	0.937	0.935	0.943	0.937	0.934	0.924

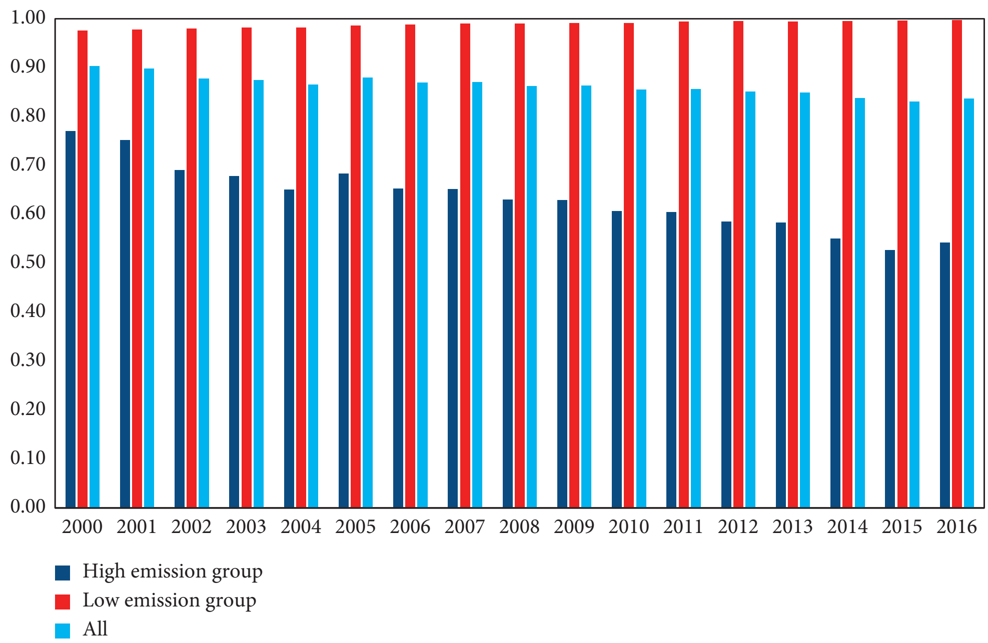

Figure 2: Trends in metafrontier ratio of different groups.

from 2000 to 2008 are quoted by Chen [36]. The data from 2009 to 2016 are extrapolated according to Chen's method, and the original data required are from China Statistical Yearbook and China Industry Statistical Yearbook. All nominal values are deflated at 1990 constant price. Referring to Shan et al. [37], the carbon emissions are calculated by the following:

$$C_{ij} = AD_{ij} \times NCV_j \times CC_j \times O_{ij} \times \frac{44}{12}, \tag{19}$$

where C_{ij} represents the carbon emissions; AD_{ij} represents energy consumption; NCV_j is the net caloric value; CC_j is carbon content; and O_{ij} stands for the oxidation rate. It should be noted that the first two variables on the right-hand side of equation (19) measure the standard quantity of energy consumption. Since this study directly uses the final energy consumption of industrial sectors provided by China Energy Statistical Yearbook, there is no need to repeat the calculation. The coefficients of carbon content (CC_j) and oxidation rate (O_{ij}) are referred to Shan et al. [37].

Industrial sectors need to be grouped to reflect technology heterogeneity. We calculate carbon emission intensity first and then rank the sectors in terms of the annual average levels between 2000 and 2016. Together with the classification of light and heavy industries, the industries with more than 4 tons per10000 yuan are classified as the high-emission group, while those with less than 4 tons per 10000 yuan are classified as the low-emission group. The high- and low-emission groups consist of 12 and 22 industrial sectors, respectively. Table 2 presents the statistical description of variables in the high- and low-emission groups, respectively. Notice that the average carbon intensity of two groups (CI) is quite different, which to a certain extent supports the rationality of the use of carbon intensity as a grouping variable.

2.3. Estimation. Table 3 reports the estimation results of four different stochastic frontiers, in which models (1), (2), and (4) adopt the MLE estimation, and model (3) adopts the QMLE estimation. Models (1) and (2) are group estimates, model (3) is a metafrontier estimate, and model (4) is a pooled estimate. Here, the logarithmic likelihood ratio (LR) is used to test whether group heterogeneity is statistically significant, i.e., $\lambda = -2\{\ln[L(H_0) - L(H_1)]\}$, ln[L(H)0)] represents the likelihood ratio value of the null hypothesis that all groups face the same frontier; Ln [L(H_1)] represents the likelihood ratio value of the alternative hypothesis, that is, the sum of the logarithmic likelihood values of the high-emission group and the low-emission group. As shown in Table 3, the logarithmic likelihood ratio test rejects the null hypothesis, indicating that the high- and low-group frontiers are statistically heterogeneous. In addition, the standard deviations of inefficiency (σ_u) and random disturbance (σ_v) in models (1)–(4) have a statistical significance of 1%–10%, indicating that the two-step stochastic metafrontier method is appropriate. In particular, lnCI, which measures inefficiency variables, was positive in each model. This is consistent with theoretical expectations, indicating the reliability of the model.

3. Results and Discussion

3.1. Group Green Efficiency. With estimation results in Table 3, we calculate the group green efficiency of 12 sectors in the high-emission group and 22 sectors in the low-emission group. Figure 1 shows the trend of average group green efficiency of high- and low-emission groups. As defined, they are not comparable between groups. So, we analyze their individual trends here. In the high-emission group, the group green efficiency experienced a fluctuating process, with an increase during 2000 and 2002 but a decrease during

Table 5: Metafrontier ratio of China's industrial sectors.

Code	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
H01	0.742	0.772	0.791	0.783	0.801	0.831	0.839	0.878	0.882	0.947	0.929	0.981	0.997	0.983	0.954	0.914	0.886	0.877
H02	0.987	0.715	0.529	0.414	0.363	0.344	0.289	0.241	0.244	0.220	0.192	0.170	0.166	0.156	0.133	0.142	0.126	0.319
H03	0.894	0.999	0.643	0.629	0.475	0.409	0.427	0.398	0.377	0.403	0.336	0.334	0.351	0.359	0.359	0.358	0.394	0.479
H04	0.347	0.355	0.366	0.442	0.561	0.999	0.743	0.826	0.734	0.757	0.748	0.714	0.683	0.666	0.628	0.692	0.817	0.652
H05	0.997	0.987	0.984	0.962	0.913	0.956	0.924	0.901	0.842	0.804	0.768	0.775	0.745	0.714	0.685	0.670	0.662	0.841
H06	0.994	0.930	0.948	0.867	0.728	0.601	0.544	0.563	0.526	0.463	0.467	0.462	0.451	0.445	0.436	0.443	0.452	0.607
H07	0.995	0.982	0.952	0.885	0.770	0.812	0.820	0.734	0.641	0.671	0.611	0.606	0.611	0.588	0.544	0.545	0.475	0.720
H08	0.995	0.865	0.832	0.816	0.810	0.798	0.755	0.690	0.639	0.656	0.602	0.609	0.630	0.560	0.507	0.492	0.455	0.689
H09	0.890	0.894	0.799	0.851	0.828	0.921	0.981	0.984	0.897	0.936	0.840	0.740	0.694	0.609	0.530	0.456	0.425	0.781
H10	0.997	0.991	0.959	0.972	0.928	0.938	0.933	0.907	0.857	0.867	0.844	0.807	0.797	0.750	0.729	0.710	0.680	0.863
H11	0.271	0.293	0.304	0.307	0.403	0.298	0.305	0.313	0.283	0.261	0.238	0.216	0.190	0.168	0.151	0.146	0.137	0.252
H12	0.140	0.240	0.177	0.213	0.233	0.298	0.268	0.384	0.635	0.571	0.706	0.838	0.705	0.998	0.944	0.757	0.998	0.536
L13	0.943	0.941	0.935	0.931	0.933	0.942	0.950	0.955	0.967	0.975	0.979	0.981	0.985	0.987	0.993	0.995	0.999	0.964
L14	0.970	0.969	0.971	0.974	0.974	0.978	0.980	0.982	0.981	0.989	0.989	0.994	0.996	0.998	0.997	0.998	0.997	0.985
L15	0.968	0.969	0.976	0.973	0.975	0.980	0.983	0.986	0.985	0.988	0.987	0.990	0.991	0.989	0.990	0.998	0.998	0.984
L16	0.986	0.986	0.989	0.990	0.987	0.990	0.991	0.994	0.994	0.995	0.994	0.995	0.995	0.995	0.994	0.997	0.998	0.992
L17	0.999	0.999	0.998	0.998	0.999	0.999	0.998	0.997	0.997	0.999	0.999	0.998	0.999	0.998	0.999	1.000	1.000	0.999
L18	0.991	0.991	0.991	0.992	0.987	0.991	0.992	0.992	0.991	0.992	0.992	0.996	0.998	0.997	0.995	0.997	0.998	0.993
L19	0.996	0.999	0.997	0.999	0.987	0.993	0.993	0.995	0.994	0.995	0.995	0.998	0.998	0.996	0.992	0.990	0.990	0.994
L20	0.958	0.965	0.965	0.961	0.963	0.971	0.974	0.979	0.981	0.985	0.988	0.995	0.997	0.998	0.999	0.997	0.996	0.981
L21	0.959	0.964	0.967	0.972	0.978	0.985	0.989	0.994	0.990	0.991	0.991	0.995	0.999	0.999	0.998	0.998	0.996	0.986
L22	0.980	0.994	0.993	0.997	0.996	0.999	0.999	0.999	0.996	0.995	0.993	0.992	0.994	0.991	0.991	0.991	0.990	0.994
L23	0.995	0.998	0.999	0.997	0.987	0.991	0.990	0.993	0.994	0.994	0.993	0.996	0.997	0.996	0.999	0.998	0.995	0.995
L24	0.975	0.978	0.983	0.985	0.988	0.993	0.992	0.993	0.992	0.993	0.992	0.992	0.993	0.994	0.995	0.999	0.999	0.990
L25	0.997	0.977	0.980	0.978	0.983	0.993	0.994	0.995	0.990	0.985	0.982	0.990	0.990	0.987	0.988	0.992	0.998	0.988
L26	0.989	0.988	0.991	0.992	0.991	0.992	0.992	0.993	0.991	0.992	0.991	0.996	0.996	0.997	0.996	0.998	0.999	0.993
L27	0.970	0.974	0.975	0.973	0.969	0.974	0.976	0.980	0.978	0.982	0.982	0.988	0.994	0.993	0.999	0.991	0.992	0.982
L28	0.969	0.973	0.976	0.981	0.981	0.985	0.987	0.989	0.989	0.991	0.992	0.995	0.998	0.997	0.997	0.999	0.998	0.988
L29	0.960	0.963	0.968	0.974	0.974	0.979	0.982	0.984	0.985	0.988	0.989	0.994	0.997	0.997	0.998	0.998	0.998	0.984
L30	0.978	0.982	0.986	0.988	0.988	0.993	0.994	0.995	0.994	0.996	0.993	0.995	0.996	0.995	0.993	0.998	0.999	0.992
L31	0.992	0.994	0.995	0.997	0.995	0.997	0.997	0.997	0.996	0.997	0.996	0.998	0.999	0.998	0.998	0.999	1.000	0.997
L32	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.999	1.000	0.999	1.000	1.000	1.000	1.000	1.000	1.000	0.999
L33	0.969	0.970	0.971	0.988	0.988	0.994	0.996	0.998	0.998	0.996	0.998	0.999	0.999	0.999	0.999	0.999	1.000	0.992
L34	0.925	0.938	0.958	0.966	0.978	0.970	0.988	0.994	0.988	0.989	0.984	0.987	0.986	0.979	0.974	0.988	0.999	0.976
High	0.771	0.752	0.690	0.678	0.651	0.684	0.652	0.652	0.630	0.630	0.607	0.604	0.585	0.583	0.550	0.527	0.542	0.635
Low	0.976	0.978	0.980	0.982	0.982	0.986	0.988	0.990	0.990	0.991	0.991	0.994	0.995	0.994	0.995	0.996	0.997	0.989
All	0.903	0.898	0.878	0.875	0.865	0.879	0.870	0.871	0.863	0.864	0.855	0.856	0.850	0.849	0.838	0.831	0.837	0.864

Table 6: Comparison between group green efficiency and metafrontier ratio.

Group	Top and bottom industries	Grouped green efficiency		Common frontier ratio	
High-emission group	Top three	Nonferrous metal pressing H10	0.916	Coal mining and washing H01	0.877
		Ferrous metal mining H03	0.911	Nonferrous metal pressing H10	0.863
		Nonmetal mining H04	0.900	Paper industry H05	0.841
	Bottom three	Electricity production H11	0.754	Electricity production H11	0.252
		Oil processing and coking H06	0.788	Oil and natural gas extracting H02	0.319
		Ferrous metal smelting and pressing H09	0.817	Ferrous metal mining H03	0.479
Low-emission group	Top three	Communication manufacturing L32	0.999	Communication equipment manufacturing L32	0.999
		Tobacco manufacturing L17	0.997	Tobacco manufacturing L17	0.999
		Measuring instrument manufacturing 33	0.997	Electrical machinery and equipment L31	0.997
	Bottom three	Food processing L14	0.889	Nonferrous metal mining L13	0.964
		Food manufacturing L15	0.892	Water production L34	0.976
		Beverage manufacturing L16	0.916	Timber and wood processing L20	0.981

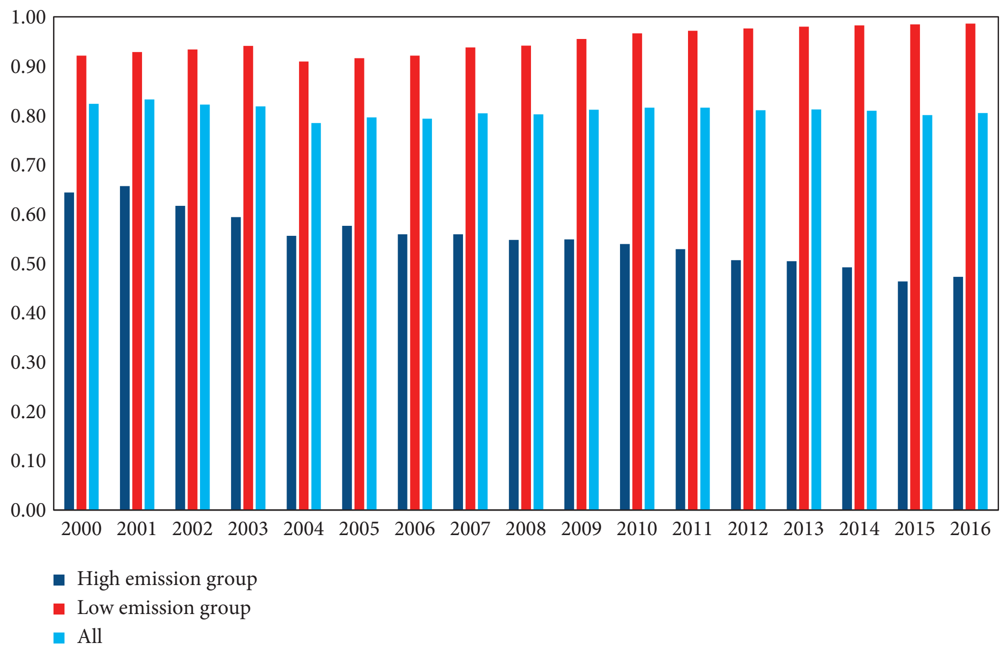

Figure 3: Trends in the metafrontier green efficiency of different groups.

2003 and 2005. This is because the heavy industrialization process occurred during this period, resulting in a large amount of energy consumption and pollution discharge. The energy conservation and emission reduction have become a mandatory target of the government's 11th Five-Year Plan, so the group green efficiency has undergone an improvement since 2006. However, the group green efficiency of the high-emission group deteriorated from 2011 to 2013, which may be related to the four-trillion stimulus measures taken in response to the global financial crisis. Large-scale investment flowed to the heavy industry, resulting in the deterioration of group green efficiency of the high-emission group. At the same time, it may also be related to the transition of China's economic growth rate, because during this period China entered the "new normal" stage characterized by medium-high speed. The traditional model of supporting high-speed growth could not be sustained, while the new growth mode was being shaped. In 2014, the group green efficiency showed a temporary improvement but then entered the decline range, because the long-term heavy industrialization and high investment in response to the financial crisis accumulated a large amount of excess capacity. The deterioration of economic efficiency led to the deterioration of group green efficiency. Comparatively, the low-emission group witnessed an increase-decrease-increase trend, which is relatively smooth.

Table 4 reports the group green efficiency of China's industrial sectors. Since there is no comparability between high- and low-emission groups, we investigate sectoral performance within each group. On the one hand, in the high-emission group, H10 has the highest green efficiency, with an average value of 0.916. Meanwhile, H11 has the lowest group green efficiency of 0.754. In the low-emission group, the top three sectors are L32, L17, and L33, with average group green efficiency of 0.999, 0.997, and 0.997, respectively. The bottom three are L14, L15, and L16, with average group green efficiency of 0.889, 0.892, and 0.916, respectively.

3.2. Metafrontier Ratio. The metafrontier ratio measures the gap between group frontier and metafrontier. It is the key indicator to transform the noncomparable group green efficiency into comparable metafrontier green efficiency. Figure 2 shows the trend of the metafrontier ratio of the high- and low-emission groups from 2000 to 2016. In the high-emission group, except for a transient increase in 2005 and 2016, the rest years show a continuous decline. In the low-emission group, with the exception of a few years (2004, 2008, 2010, and 2013), the metafrontier has been growing on. This means that the low-emission group is gradually shrinking the gap to the metafrontier. From the perspective of comparison, the metafrontier of the low-emission group is systematically higher than that of the high-emission group. That is to say, the low-emission group is closer to the metafrontier. This conclusion is consistent with the reality that the low-emission group or light industry is generally considered to be more efficient in carbon emission. In other words, carbon-intensive sectors need to make more effective use of technology spillover mechanisms, such as stricter regulations and technology diffusion reservoirs, to shrink the technology gap to the metafrontier.

Table 5 shows the metafrontier ratios of China's industrial sectors. Since the metafrontier ratios of the different groups are comparable, we can analyze them from a global view of point. Comparisons can be made from the perspective of the entire industrial sector. In terms of individual sectors, the three industries with the highest metafrontier ratios are L32, L17, and L31, with values of 0.9993, 0.9985, and 0.9968, respectively. We observe that they belong to the

Table 7: Metafrontier green efficiency of China's industrial sectors.

Code	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
H01	0.610	0.656	0.685	0.630	0.746	0.772	0.772	0.802	0.817	0.756	0.800	0.805	0.792	0.776	0.907	0.860	0.825	0.765
H02	0.594	0.515	0.435	0.329	0.309	0.313	0.259	0.226	0.211	0.202	0.169	0.158	0.149	0.131	0.118	0.114	0.108	0.255
H03	0.815	0.919	0.605	0.588	0.426	0.370	0.388	0.367	0.343	0.377	0.272	0.303	0.324	0.324	0.325	0.330	0.362	0.438
H04	0.330	0.338	0.348	0.408	0.502	0.807	0.599	0.666	0.630	0.658	0.683	0.665	0.614	0.628	0.591	0.647	0.753	0.580
H05	0.830	0.858	0.851	0.857	0.763	0.802	0.801	0.801	0.743	0.712	0.716	0.719	0.704	0.681	0.659	0.644	0.633	0.751
H06	0.892	0.873	0.889	0.770	0.599	0.528	0.485	0.472	0.434	0.403	0.379	0.326	0.312	0.289	0.285	0.238	0.253	0.496
H07	0.873	0.893	0.861	0.804	0.655	0.673	0.688	0.634	0.575	0.611	0.573	0.553	0.560	0.542	0.496	0.476	0.419	0.640
H08	0.816	0.731	0.722	0.660	0.546	0.546	0.579	0.569	0.552	0.579	0.552	0.530	0.547	0.510	0.465	0.449	0.414	0.574
H09	0.794	0.809	0.737	0.774	0.755	0.778	0.829	0.811	0.757	0.743	0.686	0.576	0.522	0.455	0.383	0.331	0.280	0.648
H10	0.888	0.920	0.880	0.895	0.845	0.844	0.817	0.800	0.768	0.786	0.788	0.750	0.743	0.706	0.683	0.662	0.633	0.789
H11	0.197	0.240	0.259	0.264	0.334	0.252	0.254	0.259	0.240	0.216	0.187	0.159	0.132	0.101	0.088	0.087	0.074	0.197
H12	0.086	0.127	0.128	0.149	0.192	0.230	0.235	0.304	0.501	0.539	0.669	0.803	0.681	0.914	0.904	0.722	0.920	0.477
L13	0.886	0.889	0.873	0.854	0.782	0.806	0.797	0.879	0.912	0.934	0.953	0.948	0.959	0.967	0.974	0.977	0.985	0.904
L14	0.870	0.871	0.877	0.906	0.738	0.762	0.790	0.768	0.769	0.857	0.931	0.950	0.961	0.968	0.962	0.955	0.953	0.876
L15	0.781	0.815	0.855	0.886	0.783	0.803	0.802	0.852	0.846	0.869	0.921	0.926	0.949	0.951	0.957	0.969	0.962	0.878
L16	0.934	0.940	0.939	0.937	0.764	0.766	0.803	0.834	0.846	0.893	0.962	0.966	0.969	0.969	0.969	0.976	0.977	0.909
L17	0.990	0.991	0.990	0.991	0.995	0.995	0.995	0.995	0.995	0.998	0.998	0.997	0.998	0.997	0.999	0.999	0.999	0.996
L18	0.922	0.927	0.928	0.927	0.863	0.879	0.905	0.923	0.934	0.946	0.955	0.956	0.970	0.975	0.982	0.985	0.988	0.939
L19	0.965	0.977	0.977	0.981	0.957	0.968	0.944	0.961	0.968	0.975	0.984	0.988	0.987	0.988	0.986	0.985	0.985	0.975
L20	0.867	0.898	0.899	0.881	0.781	0.807	0.851	0.897	0.908	0.925	0.953	0.960	0.969	0.978	0.986	0.987	0.989	0.914
L21	0.916	0.931	0.936	0.940	0.969	0.976	0.970	0.978	0.974	0.978	0.981	0.987	0.993	0.994	0.994	0.995	0.993	0.971
L22	0.954	0.973	0.972	0.978	0.985	0.989	0.984	0.987	0.984	0.986	0.986	0.987	0.990	0.986	0.986	0.987	0.986	0.982
L23	0.981	0.987	0.988	0.986	0.974	0.981	0.974	0.980	0.984	0.986	0.986	0.993	0.983	0.984	0.986	0.986	0.983	0.984
L24	0.953	0.961	0.965	0.969	0.961	0.969	0.966	0.967	0.968	0.977	0.978	0.978	0.980	0.985	0.988	0.992	0.993	0.974
L25	0.890	0.815	0.823	0.891	0.881	0.879	0.917	0.936	0.939	0.948	0.951	0.947	0.949	0.953	0.964	0.968	0.971	0.919
L26	0.954	0.960	0.967	0.968	0.950	0.951	0.943	0.955	0.953	0.965	0.971	0.978	0.983	0.987	0.989	0.992	0.994	0.968
L27	0.890	0.907	0.914	0.928	0.931	0.940	0.930	0.940	0.942	0.954	0.963	0.973	0.973	0.974	0.986	0.980	0.982	0.947
L28	0.913	0.925	0.930	0.946	0.939	0.930	0.928	0.936	0.937	0.945	0.959	0.935	0.977	0.983	0.985	0.987	0.987	0.950
L29	0.864	0.887	0.914	0.918	0.933	0.941	0.944	0.954	0.961	0.967	0.969	0.980	0.988	0.989	0.991	0.992	0.993	0.952
L30	0.938	0.954	0.963	0.975	0.973	0.976	0.978	0.983	0.982	0.986	0.986	0.988	0.989	0.989	0.989	0.995	0.997	0.979
L31	0.984	0.988	0.989	0.992	0.988	0.990	0.988	0.991	0.991	0.993	0.993	0.996	0.997	0.997	0.997	0.998	0.999	0.993
L32	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.999	0.999	0.999	1.000	1.000	1.000	1.000	1.000	1.000	0.999
L33	0.959	0.962	0.962	0.980	0.985	0.991	0.993	0.996	0.996	0.994	0.996	0.998	0.998	0.999	0.999	0.999	0.999	0.988
L34	0.861	0.879	0.885	0.866	0.875	0.858	0.864	0.929	0.923	0.935	0.892	0.950	0.921	0.944	0.954	0.963	0.976	0.910
High	0.644	0.657	0.617	0.594	0.556	0.576	0.559	0.559	0.548	0.548	0.540	0.529	0.507	0.505	0.492	0.463	0.473	0.551
Low	0.921	0.929	0.934	0.941	0.909	0.916	0.921	0.938	0.941	0.955	0.967	0.972	0.977	0.980	0.983	0.985	0.986	0.950
All	0.823	0.833	0.822	0.818	0.785	0.796	0.793	0.804	0.802	0.812	0.816	0.816	0.811	0.812	0.810	0.801	0.805	0.809

low-emission group. The three industries with the lowest metafrontier ratios are H11, H02, and H03, which belong to the high-emission group.

We also observe that group green efficiency and metafrontier ratio are not always consistent. As shown in Table 6, H03 in the high-emission group appears in the top three for highest green efficiency and the bottom three for lowest metafrontier ratio. More generally, there is a big discrepancy between the top and bottom sectors in terms of group green efficiency and metafrontier ratio. In fact, this shows the difference between group technologies and metatechnology, which implies different possibilities for efficiency catch-up. That is, sectors with low group green efficiency may get a free ride on technology spillover and environmental regulation of the group to improve the metafrontier ratio. On the other hand, some sectors with higher group green efficiency may deviate from the metafrontier if they do not effectively utilize technology spillover. In short, in order to improve the overall green efficiency, it is necessary not only to improve its own group green efficiency but also to promote the technological progress of this group and make comprehensive use of the technology spillover.

3.3. Metafrontier Green Efficiency. As discussed above, the metafrontier green efficiency is comparable from a global view of point. In Figure 3, the overall metafrontier green efficiency suffered a general declining trend from 2000 to 2004, a rising trend during 2005–2011, and a slightly declining trend after 2012. This periodic shift is in line with those studies that considered the technology heterogeneity, e.g., Li and Lin [38]; Cheng et al. [39]; and Cheng and Jin [40]. However, this periodic shift is not very in line with those studies that either did not consider technology heterogeneity or did not consider individual heterogeneity, e.g., Sun and Huang [41]; Ouyang et al. [42]; and Luo et al. [43]. Moreover, the high-emission group witnessed a general declining trend of metafrontier

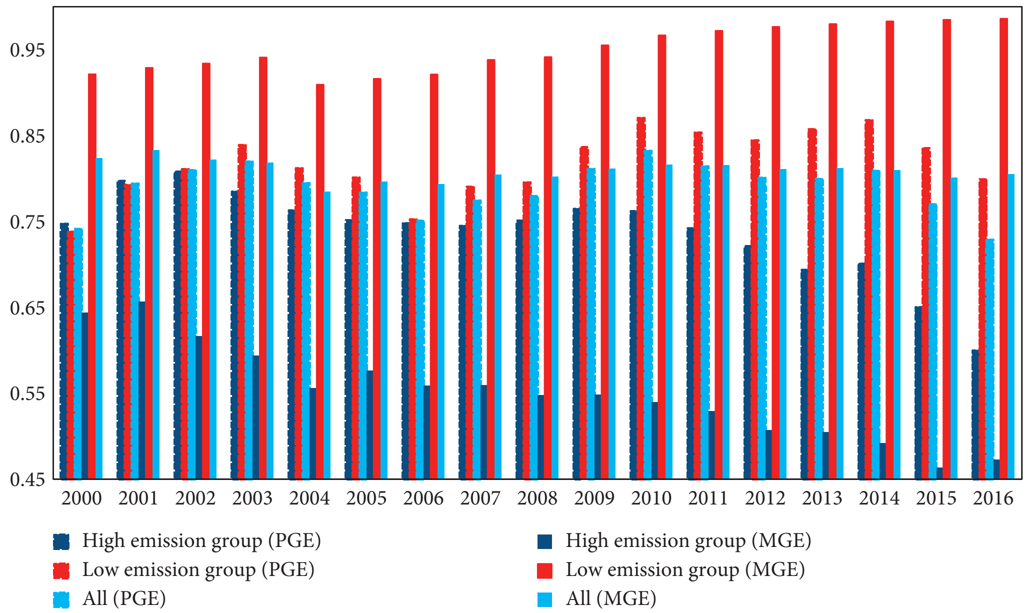

Figure 4: Comparison of metafrontier and pooled green efficiency in different groups.

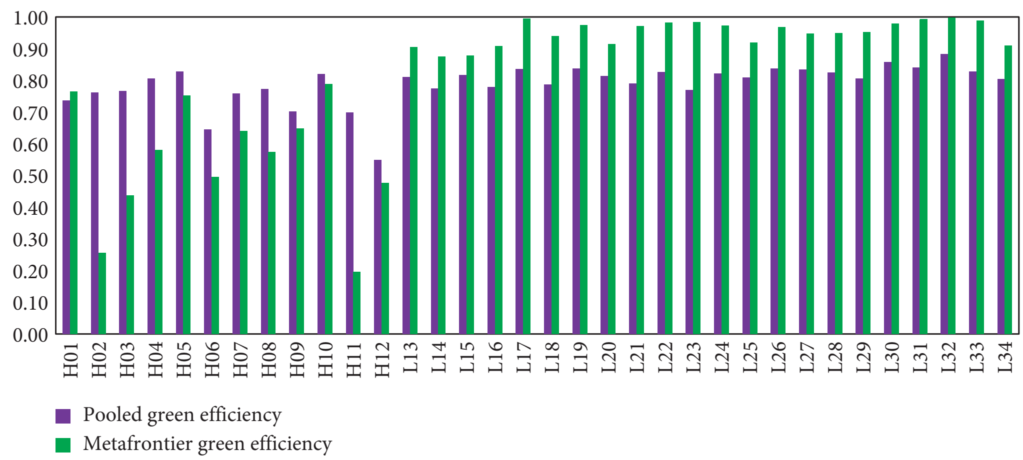

Figure 5: Comparison of metafrontier and pooled green efficiency in different sectors.

green efficiency while the low-emission group experienced an increasing trend. These results are in line with the existing literature, e.g., Li and Lin [38]; Kang et al. [44]; and Liu et al. [45].

Table 7 reports the metafrontier green efficiency of China's industrial sectors. Among different industrial sectors, the top three sectors of metafrontier green efficiency are L32 (Communication equipment manufacturing), L17 (Tobacco manufacturing), and L31 (Electrical machinery and equipment), with values of 0.9988, 0.9955, and 0.9925, respectively. The bottom three sectors of metafrontier green efficiency are H11 (Electricity production), H02 (Oil and natural gas extracting), and H03 (Ferrous metal mining), with values of 0.197, 0.255, and 0.438, respectively. This is consistent with the metafrontier ratio, because the metafrontier ratio has more difference than group green efficiency between the high- and low-emission groups. Therefore, the metafrontier ratio has a greater weight than group green efficiency in the calculation of metafrontier green efficiency. From the perspective of the industry distribution of best and worst metafrontier green efficiency, the calculation results in this study are reliable and follow the practical observations. Comparatively, those studies that did not consider technology heterogeneity and/or individual heterogeneity might suffer bias. For example, in Li and Cheng [46], the top three sectors of green efficiency include Communication equipment manufacturing (L32), Oil processing and coking (H06), and Leather manufacturing (L19). However, the Oil processing and coking (H06) is known as the high-emission and low green efficiency sector [38]. Printing and intermediary replication (L22) and Paper industry (H05) are the bottom two sectors in their study,

Table 8: Comparison of rankings of metafrontier and pooled green efficiency.

Sectors	MGE	MGE rank	PGE	PGE rank	Difference of rank
H01	0.765	24	0.736	30	6
H02	0.255	33	0.762	28	−5
H03	0.438	32	0.766	27	−5
H04	0.580	28	0.805	19	−9
H05	0.751	25	0.828	8	−17
H06	0.496	30	0.645	33	3
H07	0.640	27	0.759	29	2
H08	0.574	29	0.773	25	−4
H09	0.648	26	0.702	31	5
H10	0.789	23	0.819	13	−10
H11	0.197	34	0.699	32	−2
H12	0.477	31	0.548	34	3
L13	0.904	20	0.810	16	−4
L14	0.876	22	0.774	24	2
L15	0.878	21	0.816	14	−7
L16	0.909	19	0.779	23	4
L17	0.996	2	0.835	6	4
L18	0.939	15	0.787	22	7
L19	0.975	8	0.837	5	−3
L20	0.914	17	0.813	15	−2
L21	0.971	10	0.791	21	11
L22	0.982	6	0.826	10	4
L23	0.984	5	0.769	26	21
L24	0.974	9	0.822	12	3
L25	0.919	16	0.809	17	1
L26	0.968	11	0.837	4	−7
L27	0.947	14	0.834	7	−7
L28	0.950	13	0.825	11	−2
L29	0.952	12	0.806	18	6
L30	0.979	7	0.859	2	−5
L31	0.993	3	0.841	3	0
L32	0.999	1	0.883	1	0
L33	0.988	4	0.828	9	5
L34	0.910	18	0.804	20	2

Note: ranking differences are calculated with reference to metafrontier green efficiency.

which is also anti-intuitive because none of them belong to the six high-emission industries recognized by the Chinese government [47].

3.4. Comparison between Metafrontier and Pooled Green Efficiency. Figure 4 shows the average pooled green efficiency and metafrontier green efficiency from 2000 to 2016. For the high-emission group, the pooled green efficiency is obviously higher than the metafrontier green efficiency, while for the low-emission group the pooled green efficiency is systematically lower than the metafrontier green efficiency. Nevertheless, from the global perspective, the average pooled green efficiency is very close to the metafrontier green efficiency. These results indicate that the pooled green efficiency overestimates the efficiency level of the high-emission group and underestimates the efficiency level of the low-emission group when technological heterogeneity is not considered.

Figure 5 provides a further comparison at the sector level. Consistent with the situation of the high- and low-emission groups in Figure 4, in the high-emission group, the pooled green efficiency of each sector (except H01) is systematically higher than the metafrontier green efficiency, which is consistent with Figure 4. In the low-emission group, the metafrontier green efficiency of each sector is systematically higher than the pooled green efficiency, which is also consistent with Figure 4.

Finally, we provide Table 8 to compare the rankings of sectors between the metafrontier green efficiency and the pooled green efficiency. As shown, the rankings of metafrontier green efficiency among sectors and those of the pooled green efficiency are quite different. There are only two sectors that have the same ranking, i.e., L31 and L32, both of which belong to the top three sectors of green efficiency. The biggest ranking difference appears in H05, which ranks 25th in the metafrontier green efficiency while ranks 8th in pooled green efficiency ranked. Since H05 ranks 11th in terms of carbon intensity (from high to low), we believe that the ranking of metafrontier green efficiency is more reliable than that of pooled green efficiency. Overall, there are 13 sectors with ranking differences within 3 while more than 60% of sectors have ranking differences greater than 3. Compared with existing studies that did not consider technology heterogeneity and/or individual heterogeneity (e.g., [45, 46]), we find that their rankings of green efficiency are quite different from ours. Take the six high-emission sectors as an example, they are ranked the 34th (Electricity production, H11), 30th (Oil processing and coking, H06), 29th (Nonmetallic mineral products, H08), 27th (Chemical materials and products, H07), 26th (Ferrous metal smelting and pressing, H09), and 23rd (Nonferrous metal pressing, H10). In other words, all of them belong to the bottom group of sectors in terms of green efficiency. However, in Li and Cheng [46], only Chemical materials and products (H07) and Nonmetallic mineral products (H08) belong to the bottom group while Ferrous metal smelting and pressing (H09) belong to the middle group and Non-ferrous metal pressing (H10) and Oil processing and coking (H06) even belong to the top group. This indicates that technology heterogeneity should be considered to get a better understanding of individual sectors' green efficiency performance.

4. Conclusions

In this study, we propose a new parametric measurement framework for total-factor green efficiency by combining the Shephard distance function [18] and the two-step stochastic frontier approach [28]. The new approach can not only flexibly evaluate green efficiency but also deal with both technology heterogeneity and individual heterogeneity. Using the comprehensive approach, we measure the metafrontier green efficiency of 34 industrial sectors in China.

It is found that the metafrontier green efficiency in China's industrial sectors has experienced a fluctuating change, with an overall trend of decline-increase-decline. At the same time, the metafrontier green efficiency levels of the high- and low-emission groups are significantly different. Moreover, the efficiency level of the low-emission group is systematically higher than that of the high-emission group.

Compared with pooled green efficiency without considering technology heterogeneity, the metafrontier green efficiency is more intuitive and realistic both at the group average level and at the sector level. Moreover, compared with those studies that did not consider technology heterogeneity and/or individual heterogeneity, this study produces more reliable green efficiency of industrial sectors, which also follows the common economic sense. The results indicate that, in order to achieve green growth, the government needs to implement heterogeneous energy conservation and emission reduction policies for high- and low-emission groups. In particular, carbon-intensive industries should be encouraged to effectively improve the utilization of existing group technologies and to promote technology diffusion and spillover between groups.

Overall, the new approach proposed in this study produces a reliable measurement of green efficiency, which is supported by various comparisons. Nevertheless, there are some limitations of this study. For example, the high-emission and low-emission groups are equally divided on the basis of carbon intensity. In the future, a new grouping criterion that asymmetrically divides the industrial sectors into groups may be found with additional information. Besides, this study only considers the metafrontier green efficiency. In the future, green productivity based on the reliable measurement of green efficiency can be explored.

Data Availability

The data that support the findings of this study are openly available in China Statistical Yearbook and China Industry Statistical Yearbook.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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