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Research on the Heterogeneity of Green Biased Technology Progress in Chinese Industries: Decomposition Index Analysis Based on the Slacks-based measure integrating

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ABSTRACT

Green-biased technological progress takes into account the influence of energy input and pollution emissions, which is of great significance to China's green development. This paper decomposes technological progress into two categories: green input-biased technological progress (IBTC) and green output-biased technological progress (OBTC), using the Slacks-based measure integrating (SBM) model. The factor bias in technological progress is determined based on data from 34 industries in China from 2000 to 2015. The results show that green-biased technological progress exists significantly in the industry, and most of it promotes the growth of green total factor productivity. IBTC first tends to consume energy to pursue capital between capital input and energy input, while it tends to save energy after the Eleventh Five-Year Plan. Between labor input and energy input, it is biased towards saving labor and consuming resources. OBTC is biased towards promoting industrial growth and curbing pollution emissions. Medium and light-polluting industries are biased toward promoting industrial growth and curbing pollution emissions, while heavy-polluting industries are biased towards emitting more pollution.

KEYWORDS

Green input biased technological progress; Green output biased technological progress; Slacks-based measure integrating; Factor bias; Total Factor Productivity

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1. Introduction

Under the background of China's economic pursuit of high quality, coordinating the relationship between economic growth and environmental protection, and promoting green development has become an important problem that the Chinese government needs to urgently solve (Xia et al., 2020). According to the China National Environmental Analysis report, China had three of the world's top ten most polluted cities in 2012, and air pollution's annual economic loss accounts for 1.2-3.8% of GDP (Xu et al., 2019). Industrial energy consumption-caused air pollution has led to the continuous occurrence of haze weather in Beijing and other regions, which was even called "Haze China" by the public (Huang et al., 2017). According to the report released by the International Energy Agency (IEA), global carbon dioxide emissions hit a record high of 33 billion tons in 2018 (Padhan et al., 2022). Global coal consumption rose by 1.4 percent, double the average growth rate of the past decade, with the majority of coal consumption growth coming from India (36 million tons of oil equivalent) and China (16 million tons of oil equivalent) (Feng et al., 2020). It can be seen that the rapid development of China's economy has come at the expense of resources and the environment. Therefore, controlling environmental pollution has become a crucial problem faced by the whole world. The Chinese government has formulated corresponding policies to solve this problem (Zheng & Shi, 2017). The report of the 19th National Congress calls for promoting green technology innovation, vigorously developing green technology, improving the utilization rate of resources, and reducing waste emissions, to realize green development (Du & Li, 2019). In 2019, the "Two Sessions" adhered to the principle of "giving priority to ecology and leading green development through technological progress" as an important strategy to achieve high-quality economic development in China and proposed that only continuous innovation and improvement of environmental technology can ultimately achieve a virtuous economic cycle[1]. Therefore, as an industrial country, the Chinese government has realized that green transformation under the new normal needs technological progress as the main means (Li and Lin, 2018). In the early economic growth theory, it was assumed that technological progress was neutral, but technological progress has a bias in reality, which may be resource-conserving or resource-consuming (Li et al., 2019). The bias of technological progress directly affects the result of the production process on the environment. Therefore, identifying the specific factor bias of green input-biased technological progress (IBTC) or green output-biased technological progress (OBTC) has crucial practical and theoretical significance for reasonably guiding energy conservation and emission reduction and optimizing resource allocation. At the same time, it is expected to provide experience and policy inspiration for further promoting China's technological progress.

The rest of this paper is arranged as follows. In Section 2, the literature review is introduced. In Section 3, the model construction, index measurement, and data explanation are fully explained. In Section 4, the measurement and factor bias of green input and output biased technological progress are provided. In Section 5, conclusions and policy recommendations are given. The research framework is shown in Figure 1.

2. Literature review

Biased technological progress was first proposed by Hicks (1963), who pointed out that technological progress has a bias towards the use of factors, thus saving factors that become expensive. This thought was further developed in the 1960s and formed the inducing technological innovation theory, which was further verified by Drandakis and Phelps (1966) and Samuelson (1965). Kennedy (1964) indicated that the income share brought by the factor of innovation development remains unchanged in an economy in equilibrium because it is restricted by the frontier of innovation possibilities. Later, European and American scholars such as Romer (1990) expanded on this theory. Since the late 1990s, scholars represented by Acemoglu (1998) have systematically studied Hicks' biased

[1] The National People's Congress (NPC) and the Chinese People's Political Consultative Conference (CPCC).

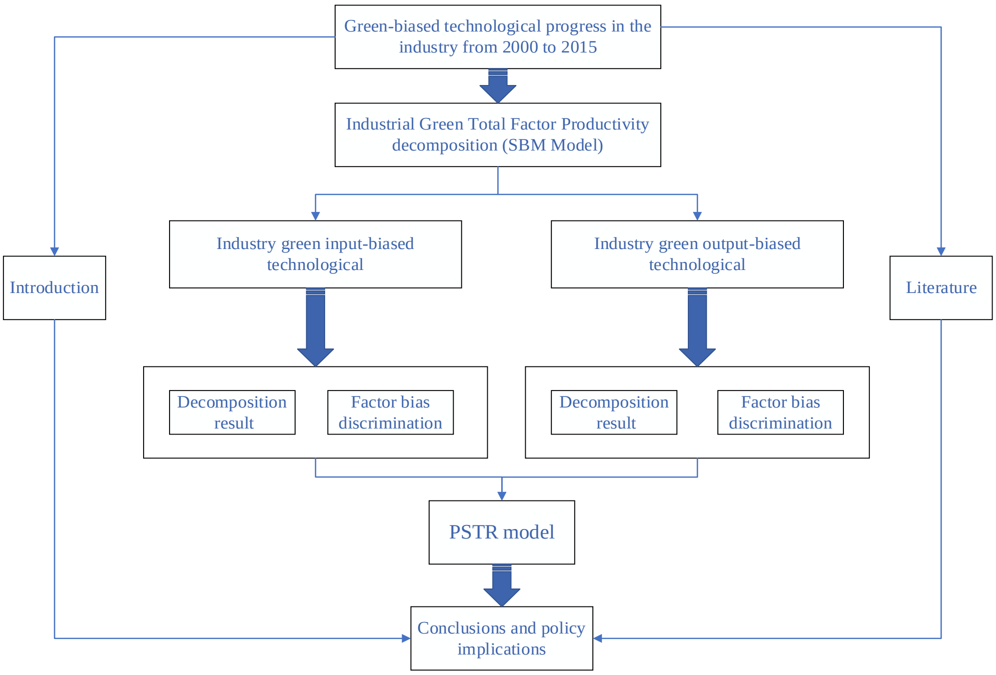

Figure 1. Research structure.

technology progress theory within the research framework of endogenous technology progress theory. They have proposed the biased technology progress theory systematically. Based on the endogenous economic growth model of vertical technological innovation, Acemoglu depicts the influencing factors and endogenous process of biased technological progress for the first time and finds that the bias of technological progress is jointly determined by factor substitution elasticity, price effect, and market scale effect. In the paper "Attention-seeking Technology Change," Acemoglu (2007) describes the endogenous mechanism of biased technological progress in "Directed Technology Change" and proposes two sources of promoting biased technology progress: pricing effect and market scale effect. In recent years, economists represented by Acemoglu and other scholars have reshaped the theory of biased technological progress and gradually developed it into the field of the relationship between the improvement of resources and the environmental and economic growth (Acemoglu, 2012). They concluded that the continuous progress of various technologies in the process of economic development is biased, which provides the corresponding theoretical basis for the further development of technological progress.

The proposal of the theoretical framework of biased technological progress has attracted a group of scholars to discuss its empirical aspects (Kiley, 1999). At present, domestic and foreign scholars' empirical research on biased technological progress has formed three main opinions. One is the measurement method of bias in technological progress. The mainstream method is the stochastic frontier analysis method (Estache, 2004; Shu, 2011), which measures TFP based on the DEA index and further decomposes technological change. It can decompose IBTC, OBTC, and MATC from technological change. Besides, another mainstream method is the standardized supply surface system method (Managi & Karemera, 2004). In the CES production function, capital, labor, energy, and other factors are introduced to build a multi-factor model, and factor elasticity is estimated to judge the bias of technological progress. The second category studies the sources and influencing factors of biased technological progress. Some studies have analyzed the influencing factors of biased technological progress and concluded that trade liberalization (Harrigan, 2015), energy intensity (Kratena, 2007; Wang et al., 2014; Wei et al., 2019), capital deepening (Conte, 2007; Conte, 2011; Chongvilaivan, 2012), economic growth (Galor & Moav, 2000; Barros and Weber, 2009; Goos et al., 2014), labor share (Luo & Zhang, 2010; Elsby et al., 2013; Karabarbounis, 2014), agricultural finance (Jaumotte et al., 2013; Abate et al., 2016), and other factors have different degrees of influence on biased technological progress. Some scholars also conducted a series of measurement and empirical studies on environmental total factor productivity (Hoang & Coelli, 2011; Li & Wu, 2017; Shen, 2019) from different perspectives, but these studies were not carried out from the perspective of biased technological progress and have a relative lack of theoretical basis. The third category is to study various types of biased technological advances. For example, agricultural biased technological progress is measured by adding factors of pesticide pollution, pesticides, chemical fertilizer, polluting energy, and other factors from the perspective of agriculture (Shao et al., 2016; Olusegun et al., 2019). Innovation-biased technological progress is measured by adding variables such as innovation output, innovation capital input, and innovation personnel (Coakes et al., 2011; Song et al., 2019). The land conservation-biased technological progress takes into account such factors as the price of industrial land, the area of industrial land, and the number of employees per unit in industrial towns (Song et al., 2018). Different kinds of biased technological progress are calculated by adding relevant variables according to their characteristics.

By reviewing the previous literature, we can find that current research has not included the pollution emission index from an industry perspective. Therefore, it cannot calculate biased technological progress that considers both energy and pollution emissions. Moreover, most of the calculated biased technological progress is IBTC, which does not consider the output perspective. Thus, the research direction of biased technological progress is too narrow. Additionally, most of the calculation methods adopt parametric methods, but since there is a variety of technological production in reality, the production function calculated by the parametric method cannot yield robust results. Given the above-stated limitations, we use the directional distance function model to estimate the green total factor productivity of 34 industries in China from 2000 to 2015. We consider both energy input and pollution emission and obtain OBTC and IBTC through further decomposition. We then divide the industries into severe, moderate, and mild pollution industries based on the pollution intensity to judge the bias of green technology progress in the Chinese industry more precisely. This will guide the direction of technological progress and optimize the path of industrial development more purposefully, and provide some references for the sustainable development of the Chinese economy.

3. Model construction and variable selection

3.1. Model construction

DEA method can fully account for the diversity of production technologies in the economy and the fact that the bias of technological progress is easily affected by various factors and can effectively avoid the inaccuracy or unstable results caused by pre-set models (Barros et al., 2009; Yu et al., 2020). Therefore, we have chosen the DEA model for directional distance functions. On the one hand, the directional distance function is a kind of frontier production function that can well describe the production technology when expected and non-expected outputs exist simultaneously. At the same time, it can capture the behavior that pollution emissions also decrease when expected output increases. On the other hand, compared to the DEA method, the parametric method must assume a production function, which is more complex (Barros et al., 2010; Bagchi et al., 2019). In summary, this paper has selected the DEA model of the directional distance function to calculate the total factor productivity of 34 industries in China and decompose it to obtain the growth rate change caused by efficiency change and technological progress, respectively. Among them, the change in the distance between the input-output combination and the production front is measured by efficiency change (EC). Changes in the production frontier are measured by technological progress (TC). Then, referring to Fare (1997), this paper further decomposed the technological changes brought about by technological progress into output-biased technological progress (OBTC), input-biased technological progress (IBTC), and neutral technological progress (MATC).

3.2. Model construction of green biased technological progress

3.2.1. Measurement of biased technological progress

Suppose that the production system has N decision making units (DMUs), there are three kinds of input and output vectors of DMU $i = 1, \dots, N$ at time period $t = 1, \dots, T$, i.e. input vector $x_i^t = (x_{1i}^t, \dots, x_{Mi}^t) \in R_M$, desirable output vector $y_i^t = (y_{1i}^t, \dots, y_{Ji}^t) \in R_J$ and undesirable output vector $b_i^t = (b_{1i}^t, \dots, b_{Li}^t) \in R_L$.

Assuming that $PPS^t = \{(x^t, y^t, b^t) | x^t can\ product\ both\ y^t\ and\ b^t)\}$ is the production possibility set in time t, to calculate the technical efficiency of DMU in t time in proportion to the frontier of the t time under the constant returns to scale (CRS), we can use the following model:

$$D^t(x_0^t, y_0^t, b_0^t) = min \frac{1 - \frac{1}{M}\left(\sum_{m=1}^{M} \frac{S_m^t}{x_{m0}}\right)}{1 + \frac{1}{J+L}\left(\sum_{j=1}^{J} \frac{\tau_j^t}{y_{j0}} + \sum_{l=1}^{L} \frac{\nu_l^t}{b_{l0}}\right)}$$
$$s.t. \begin{cases} \sum_{i=1}^{n} \lambda_i^t x_{mi}^t + s_m^t = x_{m0}^t \\ \sum_{i=1}^{n} \lambda_i^t y_{ji}^t - \tau_j^t = y_{j0}^t \\ \sum_{i=1}^{n} \lambda_i^t b_{li}^t + \nu_l^t = b_{l0}^t \\ \lambda_k \geq 0, s_m^t \geq 0, \tau_j^t \geq 0, \nu_l^t \geq 0 \end{cases} \tag{1}$$

So MI is calculated by the following formula (Fare et al., 1994):

$$MI = \sqrt{\frac{D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D^{t+1}(x^t, y^t, b^t)}} \times \sqrt{\frac{D^t(x^{t+1}, y^{t+1}, b^{t+1})}{D^t(x^t, y^t, b^t)}} \tag{2}$$

Then, MI is further decomposed into technical efficiency index and technical change index:

$$MI = \sqrt{\frac{D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D^{t+1}(x^t, y^t, b^t)} \times \frac{D^t(x^t, y^t, b^t)}{D^t(x^{t+1}, y^{t+1}, b^{t+1})}} \times \left[\frac{D^t(x^{t+1}, y^{t+1}, b^{t+1})}{D^t(x^t, y^t, b^t)}\right] = TECH \times EFFCH \tag{3}$$

Fare (2001) decomposed technological progress into input-biased technological progress (IBTC), output-biased technological progress (OBTC), and a technology-scale progress index (MATC), where the technology-scale change index refers to neutral technological progress.

$$MATC = \frac{D^t(x^t, y^t, b^t)}{D^{t+1}(x^t, y^t, b^t)} \tag{4}$$

$$OBTC = \sqrt{\frac{D^t(x^{t+1}, y^{t+1}, b^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \frac{D^{t+1}(x^{t+1}, y^t, b^t)}{D^t(x^{t+1}, y^t, b^t)}} \tag{5}$$

$$IBTC = \sqrt{\frac{D^{t+1}(x^t, y^t, b^t)}{D^t(x^t, y^t, b^t)} \times \frac{D^t(x^{t+1}, y^t, b^t)}{D^{t+1}(x^{t+1}, y^t, b^t)}} \tag{6}$$

3.2.2. Judgment of the biased of green technology progress

OBTC and IBTC cannot reflect the bias between the input and output factors of biased technological progress. Therefore, by analyzing the calculated index, cross-period changes, and the ratio of factor input to output results, we can determine the factor bias of China's industrial green technology progress (Weber & Domazlicky, 1999).

Based on Table 1, if $x_2^{t+1}/x_1^{t+1}<x_2^t/x_1^t$, then IBTC>1 indicates that technological progress is made using X1, while IBTC<1 indicates that the technological progress is made using X2. If $x_2^{t+1}/x_1^{t+1}>x_2^t/x_1^t$, then IBTC>1 indicates that the technological progress is using X2, while IBTC<1 indicates that the technological progress is using X1. However, when IBTC=1, it indicates that the technological progress has neutral utility.

Table 1. Method for determining the direction of technological progress with input bias.

Input portfolio	IBTC>1	IBTC=1	IBTC<1
$x_2^{t+1}/x_1^{t+1}< x_2^t/x_1^t$	Save x_2， use x_1	Neutral	Save x_1， use x_2
$x_2^{t+1}/x_1^{t+1}>x_2^t/x_1^t$	Save x_1， use x_2	Neutral	Save x_2， use x_1

According to Table 2, when $x_2^{t+1}/x_1^{t+1}< x_2^t/x_1^t$, OBTC > 1 means that technological progress tends to increase unexpected output, OBTC < 1 indicates that technological progress tends to promote expected output. When $x_2^{t+1}/x_1^{t+1}>x_2^t/x_1^t$, OBTC > 1 represents that technological progress tends to promote desired output, OBTC < 1 indicates that technological progress increases the expected output. When OBTC=1, technological progress is neutral..

Table 2. Method for determining the direction of technological progress with output bias.

Output portfolio	OBTC>1	OBTC=1	OBTC<1
$x_2^{t+1}/x_1^{t+1}< x_2^t/x_1^t$	Save x_2， use x_1	Neutral	Save x_1， use x_2
$x_2^{t+1}/x_1^{t+1}>x_2^t/x_1^t$	Save x_1， use x_2	Neutral	Save x_2， use x_1

3.2.3. Data sources

China's industrial panel data was used to study the bias of technological progress and explore whether industrial green technology progress is biased towards saving energy input or reducing pollution emissions from 2000 to 2015. The relaxed directional distance function (SBM) was used to measure the green total factor productivity of the industry, and it was decomposed into IBTC, OBTC, and MATC. The industries were selected according to the China Industry Statistics Yearbook. Since the "Rubber Products industry" and "Plastic Products Industry" were merged into the same category of "Rubber and Plastic Products Industry" in 2011, the "Rubber Products Industry" and "Plastic Products Industry" from the years before 2011 were merged into "Rubber and Plastic Products Industry"[2]. The data mainly came from the China Statistical Yearbook, China Industrial Statistical Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, and China Environmental Yearbook.

(1) Capital input (K). This paper uses the perpetual inventory method (PIM) to measure the capital stock (Zhang, 2008). The model is set as follows:

$$K_t = I_t + (1-\delta_t)K_{t-1} \tag{7}$$

[2] Since the beginning of 2011, the "transportation equipment manufacturing industry" was divided into "automobile manufacturing industry", "railway, ship, aerospace, and other transportation equipment manufacturing industry", so the "automobile manufacturing industry", "railway, ship, aerospace, and other transportation equipment manufacturing industry" were merged into "transportation equipment manufacturing industry" after 2011. However, due to the lack of data, "comprehensive utilization of waste gas resources", "water production and supply industry", "mining auxiliary activities", and “other manufacturing industries” were deleted.

Where K_t represents the capital stock in t years; K_{t-1} denotes the capital stock in the t-1 year; I_t indicates the new investment in t year; δ_t represents the depreciation rate in year t. For the depreciation rate, China's Industrial Economic Statistics Yearbook provides the current year depreciation and the original value of fixed assets in industrial sub-industries above the scale from 2001 to 2008. The ratio of depreciation in the current year and the original value of fixed assets in the previous year can be used to construct the depreciation rate of fixed assets in this region. This paper estimates the original value and net value of fixed assets of the industry from 2009 to 2015, so as to infer the depreciation rate of the industry in that year. Accumulated depreciation is equal to the original value of the fixed assets minus the net value of the fixed assets. Current year depreciation is equal to accumulated depreciation minus accumulated depreciation from the previous year. The depreciation rate is equal to the current year depreciation and the previously fixed assets of the original value of the ratio. The capital stock in the base period is based on 1990, which is used as the starting capital stock for 2000-2015.

(2) Labor input (L): According to the research of Jorgenson (2007), this paper measures labor input by employment in 34 industries.

(3) Energy input (E): Referring to Wang and Wei (2016), Energy input is measured by total energy consumption.

(4) Expected output (Y): We measured the industrial added value of 34 industries from 2000 to 2015 based on the 1990 period (Shao et al., 2014). Since the industry added value data is only up to 2008, the data after 2008 are estimated by the product of the industrial added value of the previous year, the growth rate of this year in December (cumulative), and the producer price index of industrial products in different industries.

(5) Undesired output: Referring to Molinos-Senante's research (2014), this paper takes the industrial wastewater emissions (S) and industrial waste gas emissions (Q) from 34 industries as undesired output outputs.

4. Result and Discussion

4.1. Decomposition of industrial green total factor Productivity

The green total factor productivity (MI) of 34 industries was measured from 2000 to 2015 based on the biased technological progress model. Green total factor productivity is decomposed into efficiency change (EC) and technological progress (TC). Technological progress (TC) is then decomposed into green output biased technological progress (OBTC), green input biased technological progress (IBTC), and neutral technological progress (MATC). Additionally, the factor bias of green technological progress is judged based on the inter-temporal proportion of input-output, and the distribution characteristics of green total factor productivity and IBTC in the industry during the "tenth five-year Plan period," "eleventh Five-Year Plan period," "twelfth five-year Plan period," and the whole period from 2000 to 2015 are analyzed.

From Figure 2, it can be seen that the TC index and EC index are more consistent with the trend of MI from the perspective of the changing trend of the TC index, indicating that technological progress will improve the green total factor productivity in the industry. For most years, the MI index is greater than 1, indicating that the overall green total factor productivity of the industry is increasing year by year, although the increase is unstable. In 2008, the MI index was 0.9526, suggesting that the environmental efficiency of China's industry may have been affected by the global financial crisis, resulting in a decline in green total factor productivity. In 2010, 2012, and 2014, the MI index was also less than 1, indicating that green total factor productivity was in a state of decline, and the industry was affected by the country's "new normal" development model, which required the industry to undergo transformation and upgrading. The production process needed to be integrated and optimized, and the enterprise was still in the debugging period. The large fluctuation range of the TC index indicates that technological progress may deviate due to policy and other reasons (Goos, 2018). During the transition period from "The Tenth Five-Year Plan" to "the

Eleventh Five-Year Plan" and "the Twelfth Five-Year Plan", the growth rate of green total factor productivity in the industry fluctuated greatly. It can also be observed that the green production efficiency of the industry changes with economic development, and the growth of green total factor is supported by technological changes. The value of IBTC fluctuates around 1, and its influence on green total factor productivity improvement gradually slows down. Moreover, OBTC is in a state of fluctuation, indicating that the environmental regulation or comprehensive reform policies implemented in different periods are changing when weighing the policy objectives of increasing or reducing the expected output.

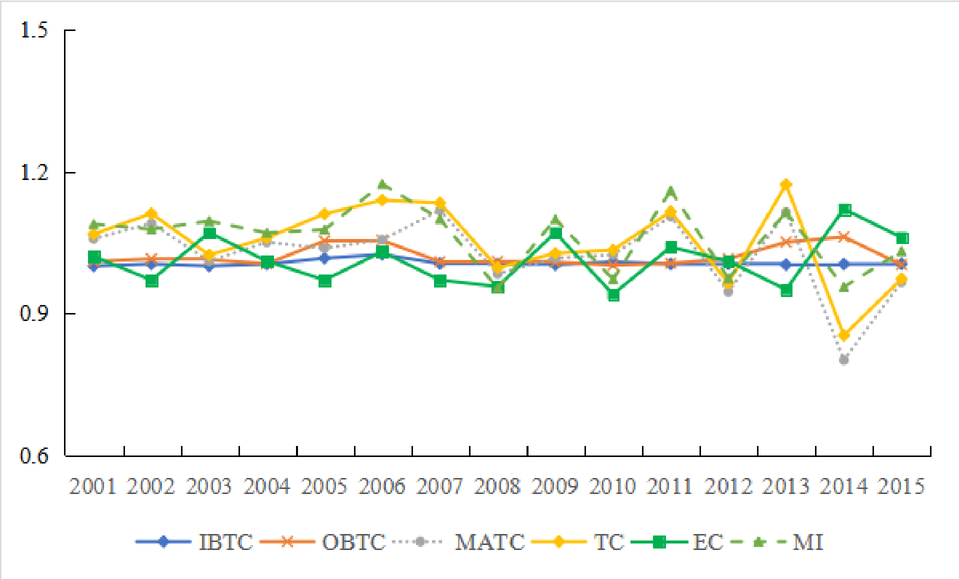

Figure 2. MI index and its decomposition index trend.

4.2. Calculation and discrimination of IBTC in the industry

4.2.1. Calculation of IBTC in the industry

We further decompose green total factor productivity into IBTC. Table 3 shows that in most of the 34 industries, the IBTC was greater than 1 from 2000 to 2015 and during different periods, indicating that the IBTC promoted the improvement of green total factor productivity overall. During "the Tenth Five-year Plan period", "the Eleventh Five-Year Plan", and "the Twelfth Five-Year Plan", the fluctuations of IBTC increased first and then decreased. The possible reason is that China's infrastructure construction is not perfect, and environmental pollution cannot be taken into account while pursuing economic development. This results in the ineffectiveness of green investment-oriented technological progress during the Tenth Five-Year Plan period. However, IBTC increased during the Eleventh Five-Year Plan period because various industries gradually became aware of the environmental problems brought by fast economic growth. China also introduced relevant environmental protection policies to control air, water, and solid waste pollution, resulting in relatively lower energy consumption and reduced waste and abuse of resources. The IBTC decreased again during "The Twelfth Five-Year Plan period." This may be because the opening up of China's foreign economy caused capital to flood into China, and the implementation of relevant environmental protection policies failed to keep pace with the pace of environmental governance as scheduled. Environmental governance was not vigorous enough, and the more complete implementation effects were lacking. In general, IBTC is growing and greater than 1, which can improve green total factor productivity in the industry.

4.2.2. Discrimination of the bias of IBTC in industry

Table 3. Industry as a whole and phased IBTC from 2000 to 2015.

Industry	The Tenth Five-Year Plan	The Eleventh Five-Year Plan	The Twelfth Five-Year Plan	2001 to 2015
H01	1.000258	1.001473	1.001119	1.000950
H02	0.999310	1.000080	1.000 480	0.999956
H03	1.003899	1.021954	1.015667	1.013840
H04	0.990016	1.021570	1.018450	1.010012
H05	0.997487	1.002138	0.998331	0.999319
H06	1.000384	1.000509	1.000063	1.000319
H07	0.999802	1.000334	0.999739	0.999958
H08	1.000883	1.000706	0.999582	1.000390
H09	1.005777	1.013996	1.037240	1.019004
H10	1.001138	1.000388	1.000151	1.000559
H11	1.000188	1.000665	0.999910	1.000254
H12	1.000408	1.000407	0.998729	0.999848
H13	1.000041	1.002411	1.000915	1.001122
H14	0.996174	0.999740	0.999703	0.998539
H15	1.020124	1.010399	1.013557	1.014693
H16	1.000244	1.000213	1.000803	1.000420
H17	1.000785	1.000892	1.001972	1.001217
H18	1.000334	1.001921	1.001179	1.001145
H19	0.999100	0.999802	0.999842	0.999581
H20	0.999642	1.016978	1.000147	1.005589
H21	1.012971	1.000775	1.004667	1.006138
H22	0.998262	1.002406	1.001695	1.000787
H23	1.072233	1.106906	1.005089	1.061410
H24	0.988833	1.001437	1.006252	0.998840
H25	0.996447	0.999099	1.001127	0.998891
H26	1.000436	0.999674	1.001460	1.000523
H27	1.000258	1.000813	1.000940	1.000670
H28	0.999485	1.000540	1.000650	1.000225
H29	1.000029	1.000403	1.000295	1.000242
H30	1.000876	1.000608	1.000653	1.000712
H31	1.024444	1.026641	1.000466	1.017183
H32	1.044461	1.043296	1.000328	1.029362
H33	1.008990	1.017203	1.016276	1.014156
H34	0.996930	1.003959	1.000231	1.000373
Mean	1.004474	1.008405	1.003622	1.005538

This paper mainly involves three input factors, including energy input (E), capital input (K), and labor input (L). We compare the above three coefficients to identify biased technological progress. Table 4 shows that from 2000 to 2015, capital input and energy input tended to save energy, while labor input and energy input tended to save labor but consume energy. To further verify the bias of technological progress in different periods, we divided the time into three periods: "the Tenth Five-Year Plan", "the Eleventh Five-Year Plan", and "the Twelfth Five-Year Plan". Among them, in terms of capital input and energy input, the technological progress during "the Tenth Five-Year Plan" was more inclined to pursue capital and consume energy excessively, while the technological progress during "the Eleventh Five-Year Plan" and "the Twelfth Five-Year Plan" was more inclined to save energy. However, labor input and energy input tended to save labor and consume energy at any time. Since "the Eleventh Five-Year Plan", the Chinese government has paid more attention to sustainable green development, and energy-saving environmental protection industries have been listed as the first of strategic emerging industries. In 2013, China implemented "the Action Plan for the Prevention and Control of Air Pollution" and "the Action Plan for the

Prevention and Control of Water Pollution". China took the "total quantity control" system as the starting point, promoted the emission reduction of major pollutants, and made positive progress so that environmental governance entered a new stage of priority development.

Table 4. Factors biased in China industry during different periods.

Year	IBTC	$\frac{(E/K)_{t+1}}{(E/K)_t}$	$\frac{(E/L)_{t+1}}{(E/L)_t}$	Factor savings from biased technological progress	
				E vs K	E vs L
2001	0.999671	1.028780	1.049773	K	L
2002	1.003939	1.086754	1.091802	K	L
2003	0.999971	0.984654	0.987311	E	E
2004	1.003598	1.055955	1.085452	K	L
2005	1.015747	1.234614	1.297856	K	L
2006	1.052720	0.952896	0.998405	E	E
2007	1.005001	0.872994	0.940388	E	E
2008	1.003704	0.929039	1.023328	E	L
2009	1.002323	0.858068	0.993322	E	E
2010	1.008343	0.971564	1.094264	E	L
2011	1.003751	0.925239	1.025348	E	L
2012	1.00425	1.024967	1.090507	K	L
2013	1.002371	0.902971	0.997907	E	E
2014	1.003767	0.936595	1.011286	E	L
The Tenth Five-Year Plan	1.004585	1.078152	1.102439	K	L
The Eleventh Five-Year Plan	1.008585	0.916912	1.009941	E	L
The Twelfth Five-Year Plan	1.003651	0.950	1.031262	E	L
2001 to 2014	1.005607	0.981688	1.049068	E	L

Due to the different characteristics of the 34 industries, this paper divides them into heavily polluting industries, moderately polluted industries, and lightly polluted industries according to their pollution emission intensity and analyzes the factor bias of China's industrial technological progress in more detail. The specific method is as follows:

We calculate the pollutant emission values per unit in each of the 34 industries:

$$UE_{ij} = \frac{E_{ij}}{O_i} \tag{8}$$

E_{ij} represents industry $i(i = 1,2,\cdots,m)$ Emissions of main pollutant $j(j = 1,2,\cdots,n)$, O_i denotes the total industrial output value of each industry.

Standardized treatment of pollutant emissions by 34 industry units:

$$UE_{ij}^{s} = \frac{\left[UE_{ij} - min\left(UE_j\right)\right]}{\left[max\left(UE_j\right) - min\left(UE_j\right)\right]} \tag{9}$$

Where, UE_{ij}^{s} is the value of standardized processing. max (UE_j) and min (UE_j) respectively represent the maximum and minimum values of wastewater and waste gas in 34 industries.

Calculated average score by weighting and doing average for wastewater and waste gas:

$$NEU_{ij} = \frac{\sum_{j=1}^{n} UE_{ij}^{s}}{n} \tag{10}$$

The average score was summarized to obtain the pollution emission intensity coefficient A for the 34 industries. The industries were then classified based on their A values: if A > 0.2034, the industry is classified as heavily polluting; if 0.0354 < A < 0.2034, the industry belongs to the moderately polluting category; if A < 0.0354, the industry is classified as lightly polluting.

Table 5. Factors bias in the technological progress of IBTC.

Industry		The Tenth Five-Year Plan		The Eleventh Five-Year Plan		The Twelfth Five-Year Plan		2001 to 2015	
		E vs K	E vs L	E vs K	E vs L	E vs K	E vs L	E vs K	E vs L
Heavily polluting industries	H01	K	L	E	L	E	L	E	L
	H02	E	E	E	E	E	L	E	L
	H03	K	L	E	L	E	E	E	L
	H04	K	L	E	L	E	L	E	L
	H05	K	L	E	L	E	L	E	L
	H08	K	L	E	E	E	L	E	L
	H10	K	L	E	L	E	L	K	L
	H15	K	L	E	E	E	L	E	L
	H18	K	L	E	L	Y	L	K	L
	H19	K	L	E	L	E	L	E	L
	H21	E	E	E	E	E	L	E	E
	H23	K	L	E	E	E	L	K	L
	H24	K	L	E	L	E	L	E	L
	H25	K	L	E	L	E	L	E	L
	H33	E	L	E	L	E	E	E	L
	H34	E	L	E	E	E	E	E	E
Moderately polluting industries	H06	K	L	E	E	E	L	E	L
	H07	K	L	E	E	E	E	E	E
	H11	K	L	E	L	E	L	E	L
	H12	K	E	E	E	Y	L	E	L
	H17	E	E	E	L	E	E	E	E
	H20	E	L	E	E	E	L	E	L
	H22	K	L	E	L	E	L	E	L
	H26	K	L	E	L	E	L	E	L
Lightly polluting industries	H09	E	L	E	E	E	E	E	E
	H13	K	L	E	E	E	L	E	L
	H14	E	E	E	L	Y	L	E	L
	H16	K	L	E	L	E	E	E	L
	H27	K	L	E	L	E	E	E	L
	H28	K	L	E	E	E	E	E	L
	H29	E	L	E	L	E	E	E	L
	H30	K	L	E	L	E	L	E	L
	H31	K	E	E	E	E	L	E	E
	H32	E	E	E	E	E	L	E	E

Both heavily polluting industries and lightly polluted industries show that technological progress tends to save capital and consume energy in terms of energy and capital input during the Tenth Five-Year Plan (Table 5). In terms of energy and labor input, technological progress tends to save labor and consume resources. It is not difficult to understand that the Chinese government attached little importance to environmental protection in the early stages of economic development. Economic development was not combined with environmental protection, and it was developed on the premise of resource waste. During the Eleventh Five-Year Plan and the Twelfth Five-Year Plan, among the two factors of energy input and capital input, technological progress tends to save energy. Regarding labor and energy, the technological progress of heavily polluting industries and moderately polluting industries tends to save labor and consume energy, while lightly polluting industries tend to save energy. This is because heavily polluting industries are dominated by a large number of manufacturing industries that emit large amounts of pollutants. Since the "Eleventh Five-Year Plan", the state's policy orientation and the development of economic industries have not been based on the premise of environmental damage, and the state has formulated many environmental protection policies, leading to the preference of factor input for energy conservation. However, many high-tech or tourism industries cannot emit too much pollution, leading to technological progress in favor of energy conservation in lightly polluting industries.

4.3. Calculation and discrimination of OBTC

4.3.1. Calculation of OBTC in the industry

Table 6. Industry overall and phased OBTC 2005-2006.

Industry	The Tenth Five-Year Plan	The Eleventh Five-Year Plan	The Twelfth Five-Year Plan	2001 to 2015
H01	1.043 850	1.027 030	1.002 705	1.024 528
H02	1.001 848	0.997 155	1.069 329	1.022 778
H03	1.335 127	1.129 239	1.233 780	1.232 715
H04	1.078 473	1.137 615	1.190 568	1.135 552
H05	1.009 689	1.005 680	1.022 958	1.012 776
H06	1.003 404	1.003 874	1.014 162	1.007 147
H07	1.001 727	1.000 322	1.001 479	1.001 176
H08	1.001 794	0.995 379	0.995 279	0.997 484
H09	1.012 824	1.001 425	0.993 202	1.002 484
H10	1.004 632	0.999 241	1.001 142	1.001 671
H11	0.997 583	1.004 394	1.000 834	1.000 937
H12	1.007 029	1.000 392	0.997 152	1.001 525
H13	1.012 490	1.006 203	0.994 336	1.004 343
H14	1.020 488	1.013 210	1.002 739	1.012 146
H15	1.007 090	1.018 453	1.073 019	1.032 854
H16	1.001 741	1.002 571	1.000 239	1.001 517
H17	1.002 233	0.999 745	1.003 646	1.001 875
H18	1.003 518	1.000 698	0.991 600	0.998 605
H19	1.006 001	1.000 657	1.029 501	1.012 053
H20	0.998 134	0.989 910	1.013 975	1.000 673
H21	1.009 905	1.016 825	1.004 210	1.010 313
H22	1.001 627	0.999 803	0.997 738	0.999 723
H23	1.004 307	1.037 826	1.009 189	1.017 108
H24	1.040 283	1.019 379	1.187 298	1.082 320
H25	0.997 152	1.027 499	1.032 642	1.019 097
H26	1.007 625	0.994 973	1.001 706	1.001 435
H27	1.007 111	1.001 936	1.002 725	1.003 924
H28	0.997 606	1.006 892	0.998 762	1.001 087
H29	1.002 870	0.999 781	0.999 191	1.000 614
H30	1.009 469	1.000 814	0.997 705	1.002 663
H31	0.996 697	1.035 167	1.041 095	1.024 320
H32	0.969 150	1.035 791	0.991 054	0.998 665
H33	1.027 143	1.032 302	1.012 657	1.024 034
H34	1.016 473	1.010 059	1.004 689	1.010 407
Mean	1.017 289	1.015 479	1.024 619	1.019 345

Green total factor productivity can be decomposed to obtain OBTC. Depending on the proportion of different outputs, technological progress may promote either good or bad output. Therefore, OBTC should be judged based on the factor bias to determine whether it has a positive or negative impact on the industry. As shown in Table 6, during the period from 2000 to 2015, the biased technological progress in most industries was greater than 1. During "the Tenth Five-Year Plan", "the Eleventh Five-Year Plan", and "the Twelfth Five-Year Plan", the OBTC showed a trend of first decreasing and then increasing.

4.3.2. Discrimination of OBTC

As shown in Table 7, the estimation of green total factor productivity reveals that the output factors of 34 industries include wastewater discharge (S), industrial added value (Y), and waste gas discharge (Q). From 2000 to 2015, the increase in industrial added value was more inclined to be associated with an increase in wastewater discharge, while the increase in industrial added value was more inclined to be associated with an increase in waste gas discharge. To further analyze the bias of technological progress in different periods, the time period was divided into three periods: "the Tenth Five-Year Plan", "the Eleventh Five-Year Plan", and "the Twelfth Five-Year Plan". In terms of industrial added value and wastewater discharge, technological progress during "the Tenth Five-Year Plan" was more inclined to increase industrial added value. Technological progress during "the Eleventh Five-Year Plan" and "the Twelfth Five-Year Plan" was also more inclined to increase industrial added value. In terms of industrial added value and exhaust emissions, technological progress in all three stages was more inclined to increase industrial added value than to increase pollution emissions. With the continuous diffusion and transfer of technology, technological progress has gradually become more inclined to increase industrial added value and reduce pollutant emissions.

Table 7. The factor bias of OBTC by year.

Year	OBTC	$\frac{(Y/S)_{t+1}}{(Y/S)_t}$	$\frac{(Y/Q)_{t+1}}{(Y/Q)_t}$	The promotion of factors by biased technological progress	
				Y vs S	Y vs Q
2001	1.009299	1.144734	1.136221	Y	Y
2002	1.014867	1.516852	1.098959	Y	Y
2003	1.012814	1.478777	1.498078	Y	Y
2004	1.004681	1.243479	1.198233	Y	Y
2005	1.051549	1.193216	1.070377	Y	Y
2006	1.052720	1.237744	1.194537	Y	Y
2007	1.008614	1.216245	1.134980	Y	Y
2008	1.009208	1.117767	1.116095	Y	Y
2009	1.007696	1.126166	1.116126	Y	Y
2010	1.001470	1.365071	1.148575	Y	Y
2011	1.005139	1.304823	1.149348	Y	Y
2012	1.014751	1.100664	1.292608	Y	Y
2013	1.048650	0.982057	1.210757	S	Y
2014	1.059450	2.993832	1.046224	Y	Y
The Tenth Five-Year Plan	1.018642	1.315411	1.200373	Y	Y
The Eleventh Five-Year Plan	1.015942	1.212599	1.142062	Y	Y
The Twelfth Five-Year Plan	1.026115	1.488645	1.146798	Y	Y
2001 to 2014	1.020233	1.338885	1.163078	Y	Y

We divided the industries according to the different intensity of pollution (Table 8). Heavy polluting industries made technological progress during "the Tenth Five-Year Plan" period to promote the discharge of wastewater. The technological progress of the "non-metallic mineral extraction industry", "petroleum processing, coking, and nuclear fuel processing industry", and "non-ferrous metal smelting and rolling processing industry" tended to promote exhaust emissions. Technological progress in the rest of the industry is biased towards boosting industrial added value. During the "the Eleventh Five-Year Plan" period, although the overall technological progress was biased towards promoting industrial added value, the number of industries favoring waste gas and wastewater discharge increased, indicating that although the whole industry promoted industrial added value on the premise of promoting economic development, it could not solve the environmental problems caused by the increase of waste gas and wastewater discharge. Until "the Twelfth Five-Year Plan", the number of polluting industries with technological progress tending to discharge waste gas and wastewater has decreased, indicating that the pollution control policies issued by the government have achieved corresponding results.

Table 8. Factors bias in the technological progress of OBTC in different industries.

Industry		The Tenth Five-Year Plan		The Eleventh Five-Year Plan		The Twelfth Five-Year Plan		2001 to 2015	
		Y vs S	Y vs Q	Y vs S	Y vs Q	Y vs S	Y vs Q	Y vs S	Y vs Q
Heavily Polluting industries	H01	Y	Y	Y	Y	Y	Y	Y	Y
	H02	Y	Y	S	Q	S	Y	Y	Y
	H03	Y	Y	Y	Y	Y	Y	Y	Y
	H04	Y	Y	Y	Y	Y	Y	Y	Y
	H05	Y	Q	Y	Y	Y	Y	Y	Y
	H08	Y	Y	S	Q	S	Q	S	Y
	H10	Y	Y	S	Q	S	Y	Y	Y
	H15	Y	Y	Y	Y	Y	Y	Y	Y
	H18	Y	Q	Y	Q	Y	Q	S	Y
	H19	Y	Y	Y	Y	Y	Y	Y	Y
	H21	Y	Y	Y	Y	Y	Y	Y	Y
	H23	Y	Y	Y	Y	Y	Y	Y	Y
	H24	Y	Y	Y	Q	Y	Y	Y	Y
	H25	S	Q	Y	Y	Y	Y	Y	Y
	H33	Y	Y	Y	Q	Y	Y	Y	Y
	H34	Y	Y	Y	Y	Y	Y	Y	Y
Moderately polluting industries	H06	Y	Y	Y	Y	Y	Y	Y	Y
	H07	Y	Y	Y	Q	Y	Y	Y	Y
	H11	S	Q	Y	Y	Y	Y	Y	Y
	H12	Y	Y	Y	Y	Y	Y	Y	Y
	H17	Y	Y	S	Q	S	Q	Y	Y
	H20	S	Q	S	Q	S	Y	Y	Y
	H22	Y	Y	S	Q	S	Q	S	Y
	H26	Y	Y	S	Q	S	Y	Y	Y
Lightly polluting industries	H09	Y	Y	Y	Y	Y	Q	Y	Y
	H13	Y	Y	Y	Y	Y	Y	Y	Y
	H14	Y	Y	Y	Y	Y	Y	Y	Y
	H16	Y	Y	Y	Y	Y	Q	Y	Y
	H27	Y	Y	Y	Y	Y	Y	Y	Y
	H28	S	Q	Y	Y	Y	Q	Y	Y
	H29	Y	Y	S	Q	S	Y	Y	Y
	H30	Y	Y	Y	Y	Y	Y	Y	Y
	H31	Y	Q	Y	Q	Y	Y	Y	Y
	H32	Y	Q	Y	Y	Y	Q	S	Y

On the whole, the technological progress of moderately polluting industries tends to promote industrial added value, and the amount of waste gas and wastewater discharged during "the Tenth Five-Year Plan", "the Eleventh Five-Year Plan", and "the Twelfth Five-Year Plan" period is less than that of heavily polluting industries. This may be because moderately polluting industries generally emit less pollution than heavily polluting industries, and moderately polluting industries such as "pharmaceutical manufacturing", "rubber and plastic products" and "metal products" emit more waste gas and waste, leading to technological progress in these industries in favor of pollution emissions. For light pollution industries, both overall and phased technological progress tends to promote industrial added value, which may be due to a large number of high-tech or service industries in light pollution industries. There is no manufacturing or heavy industry to cause a lot of pollution and profit-making mode, so technological progress tends to promote industrial added value.

5. Conclusion

In this paper, the relaxed directional distance function (SBM) model is employed to measure the IBTC and OBTC of the industry based on 34 industry panel data from 2000 to 2015 in China. Then, the factor bias is judged by the change of the proportion of factors. The influencing factors of GBTC are also investigated. The results show that China's green total factor productivity is in a state of continuous growth. The growth is mainly contributed to by technological progress, which is further subdivided into IBTC, OBTC, and technological scale change. Among them, technological scale change contributes the most to technological progress. Between capital input and energy input, IBTC first tends to pursue capital and energy consumption, but after the "Eleventh Five-Year Plan" period, it tends to save energy. But between labor input and energy input, it tends to save labor and consume resources. Green output technology advances tend to promote industrial growth and curb pollution emissions. The bias of the industries with high pollution emission, moderate pollution, and light pollution is consistent with the overall industry, but the influence of the industries with moderate pollution and light pollution is not significant.

Given the above findings, the following recommendations are proposed: First, each industry should seize the opportunities brought by economic development based on their factor endowments and bias, understand their stage, and increase investment in certain elements. Policymakers should regulate labour, capital, and other investments and the ratio of industrial added value and "three wastes" emissions to promote GBTC, improve green total factor productivity, and realize economic sustainable development. Second, policymakers should take measures to improve productivity without damaging the environment as the premise and try to avoid the cost of repairing the environment after environmental damage to control pollution from the source and save costs to increase industrial added value and improve green total factor productivity. Third, environmental regulation should focus on industries with high pollution emission, increase investment in environmental protection, enrich and refine environmental regulation laws and regulations, and include a variety of pollutants in the content of environmental regulation. For moderately and lightly polluted industries, policymakers can improve GBTC through technological innovation and other technological upgrades. Under the constraint of energy and pollution emission, this article analyses the input and output biased technological progress of the industry and takes into account the differences of the industry and the influence of policies. It provides a new perspective for the quantitative measurement of biased technological progress and also provides policy inspiration for the green development of the Chinese industry.

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Declaration of Competing Interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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