The green total factor productivity and convergence in China

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Abstract
The green total factor productivity (GTFP) has become an important index of balancing the energy consumptions, economic development, and environmental protections. This study extends the slacks-based directional distance function (SDDF) of Fare and Grosskopf into the framework of the Malmquist–Luenberger productivity index to estimate the slack-based GTFP. This SDDF can allow decision-making units to explore the optimal direction and measure a more precise productivity index. For the empirical study, we employ the new model to measure the slack-based GTFP for Chinese 30 provinces over the period of 2005–2017. Furthermore, we investigate the effect of the regional differences on the GTFP and the convergence of the Chinese GTFP with $\beta$-converge and $\sigma$-convergence. Our results show that there is a rapid improvement in the GTFP in China, which is attributed to the technical change. However, there exists a significant difference in GTFP for three regions of China. The eastern region performs significantly better than the others. Finally, we find there is a strong convergence in China, and the eastern region has a faster convergence than the other regions.

KEYWORDS
China, convergence, green total factor productivity, regional difference, slack-based directional distance function

1 | INTRODUCTION

As for China, it is well known that there has been an average 9.5% annual growth in GDP since the late 1970s due to the reformation. However, depending on large-scale factor input and government-leading investment, the economic growth of China mainly relies on, and its extensive growth model also leads to excessive consumption of a lot of natural resources and environmental pollution. To break through the “bottleneck” of resources and environment during its economic development, the Chinese government has rolled out an increasing number of policies and proposed that economic development should comply with four types of development: innovative, coordinated, green, open, and shared. This indicates that green development has been promoted to a new height. Therefore, the goal of sustainable development has been faced with the urgent problem of dealing with the relationship between the resources, environment, and economic development.

Total factor productivity (TFP) exerts a significant influence on the transformation of economic development...
modes. Consequently, it further plays an essential role in sustainable development. However, the environmental and energy constraints for economic growth can influence TFP through enterprise costs, market access mechanisms, technological innovation, and other ways. TFP can also be affected by structural adjustment, international trade, Foreign Direct Investment, and other ways. Based on several factors of production (labor, capital, energy, etc.), a higher TFP might be attained by changing the proportion of inputs and outputs. To take environmental performances into account and minimize negative environmental impacts, the green total factor productivity (GTFP) index can introduce variables related to the environment into the original TFP to evaluate the economy’s ability to produce some outputs from several certain inputs. Chambers et al. and Chung et al. first came up with the DDF method, and then most studies employ DDF to construct an ML indicator to access the growth of green productivity by incorporating undesirable outputs.

Nevertheless, Fare and Lovell discussed that measurements of efficiency under an isoquant may give rise to the misidentification of a DMU as being technically valid. Since calculations of nonradial efficiency can promote the discriminative ability in estimating the efficiency scores of DMUs, some scholars report that nonradial DEA method seems to effectively evaluate the efficiency performance of the industry. Fare and Grosskopf introduce a DDF-based recapitulation of the slacks-based measure (SBM). Applying the summation of DDF as a foundation, this method can reflect the condition in which inputs are overused and the extent of underproduction of outputs. Only the DMU is under efficiency measure based on directional slack-based distance functions (DSBD), they pointed out the SBM proposed by Tone is a special case that a DMU is SBM efficient. In the DSBD, the optimal direction is accessed by measuring the inefficiency maximization of DMUs over the directional vector, and it can also measure a more realistic rate of inefficiency due to the directional choice depending on the real data. Chang and Hu and Arabi et al. point out that this DSBD method is not an arbitrary direction of deployment, but by finding an optimal direction, it rather makes the DMU in the best state.

In this study, we attempt to solve the following problems. What was the GTFP growth during 2005–2017 in China? What are the driving factors of this GTFP growth? Has there been a significant difference between GTFP and its decomposed components among three Chinese regions (eastern, central, and western regions)? Finally, is there any evidence that GTFP is converging to peer group clusters?

Therefore, we measure and investigate the GTFP of China for the period 2005–2017. First, we extend the slacks-based DDF (DDF) of Fare and Grosskopf to consider the undesirable output, which shows the path of reducing the bad outputs and expanding the good outputs; the direction will be optimal, depending on the real data, so that it can better represent the adjustment of the variables according to all outputs. Second, we employ the proposed SDDF to introduce the slacks-based ML productivity index, which can be defined as GTFP. Moreover, the ML index can decompose GTFP into a change in technology and efficiency improvement. The former represents the change in the production frontier and the latter represents the movement toward the frontier. Third, this paper utilized the β convergence and σ convergence concepts from the related studies to analyze the convergence state of GTFP. From the results of the proposed models, this paper uses 30 Chinese provinces to measure the GTFP during 2005–2017. The estimated results present that the GTFP increased significantly during the given period in China, particularly in eastern China. Apart from that, the main drivers of GTFP growth convergence are identified.

The rest of the content is structured as follows. Section 2 introduces the slack-based DDF and ML productivity index. Section 3 presents the sample and the estimated results. Section 4 discusses policy implications. Finally, we issue our conclusions in Section 5.

2 | METHODOLOGY

2.1 | The production set

We set k (k = 1, 2, ..., K) DMUs based on the panel data and make the assumptions that each DMU can utilized N inputs x ∈ Rₙ with generate M good outputs y ∈ Rₘ and H bad outputs b ∈ Rₜ in one period. For DMUₖ, we apply y, b, and x in one period for the input and output vectors. We also define the production technology S as where is producible with x. Non-void, convex, and closed is the feature of production technology in our assumption. Adhering to the methods from Chung et al., we define the DDF with the undesirable output as

where 0 indicates the changing ratio of two types of outputs and g is a vector of directions which is defined as g = (y, −b). This function also allows good outputs to be added and bad outputs reduced. Therefore, weak
disposability means: \((y^i, b^i) \in S^t\) and \(0 \leq \theta \leq 1\) implies \((\partial y^i, \partial b^i) \in S^t\).

Refer to the method from Chung et al.,\(^3\) it is able to reconstruct \(S^t\) as follows:

\[
S^t = \{(y^i, b^i) : \sum_{k=1}^{K} \lambda^t_{nk} x^i_{nk} \leq x^i_{nk} \quad n = 1, 2, ..., N; \quad \sum_{k=1}^{K} \lambda^t_{nk} y^i_{mk} \leq y^i_{mk} + \theta y^i_{mk} \quad m = 1, 2, ..., M; \quad \sum_{k=1}^{K} \lambda^t_{nk} b^i_{hk} \leq b^i_{hk} + \theta b^i_{hk} \quad h = 1, 2, ..., H; \quad \lambda \geq 0 \}.
\]

The above equation also can be reorganized as

\[
\begin{align*}
\vec{D}^t(x^i, y^i, b^i; g) &= \max \theta \\
\sum_{k=1}^{K} \lambda^t_{nk} x^i_{nk} &\leq x^i_{nk} \quad n = 1, 2, ..., N \\
\sum_{k=1}^{K} \lambda^t_{nk} b^i_{hk} &\leq b^i_{hk} - \theta b^i_{hk} \quad h = 1, 2, ..., H \\
\sum_{k=1}^{K} \lambda^t_{nk} b^i_{hk} &\leq b^i_{hk} - \theta b^i_{hk} \quad h = 1, 2, ..., H \\
k = 1, 2, ..., K; \quad \lambda \geq 0,
\end{align*}
\]

where \(g\) equals \((b^i, y^i)\).

When there are nonzero slacks in the measurement of efficiency, Zhou et al.\(^{14}\) pointed out that the original DDF approach can promote the inaccuracy of the efficiency scores. Therefore, Fukuyama and Matousek\(^{21}\) further came up with a new nonradial DDF models to deal with the problem above, and this new method has been successfully applied in various kinds of studies about DEA.\(^{22}\) Additionally, a number of studies in the different field have applied these models to estimate efficiency, such as agricultural efficiency,\(^{23}\) energy efficiency,\(^{24}\) Bank operating efficiency.\(^{25}\)

Tone\(^{26}\) introduced the SBM of inefficiency and Tone and Tsutsui\(^{26}\) deployed the SBM and its changes to calculate several factors related to productivity. However, Färe and Grosskopf\(^{27}\) highlight the shortage of the SBM approach and introduce a Slack-based DDF approach as\(^3\)

\[
\begin{align*}
\vec{D}^t'(x^i, y^i) &= \max \alpha^t e^i_1 + ... + \alpha^t e^i_N + \beta^t e^i_m + \beta^t e^i_{m+1} + ... + \beta^t e^i_{m+M} \\
\sum_{k=1}^{K} \lambda^t_{nk} y^i_{mk} &\geq y^i_{mk} + \theta y^i_{mk} \quad m = 1, ..., M \\
\sum_{k=1}^{K} \lambda^t_{nk} b^i_{hk} &\geq b^i_{hk} - \alpha^t e^i_n \quad n = 1, ..., N \\
\lambda^t_k &\geq 0, \quad \beta^t_m \geq 0, \quad \alpha^t_n \geq 0; \quad k = 1, ..., K.
\end{align*}
\]

We extend this directional distance function to include the undesirable output, as below:

\[
\begin{align*}
\vec{D}^t(x^i, y^i, b^i; g) &= \max \gamma^t_1 e^i_1 + ... + \gamma^t_N e^i_N + \beta^t e^i_m + \beta^t e^i_{m+1} + ... + \beta^t e^i_{m+M} \\
\sum_{k=1}^{K} \lambda^t_{nk} y^i_{mk} &\geq y^i_{mk} + \theta y^i_{mk} \quad m = 1, ..., M \\
\sum_{k=1}^{K} \lambda^t_{nk} b^i_{hk} &\geq b^i_{hk} - \gamma^t_k \gamma^t e^i_n \quad n = 1, ..., N \\
\lambda^t_k &\geq 0, \quad \beta^t_m \geq 0, \quad \gamma^t_n \geq 0; \quad k = 1, ..., K.
\end{align*}
\]

This directional SBM introduces new advantages for measuring technical inefficiency. The direction will not be chosen as before, and it is estimated endogenously. This means that the measure of efficiency will depend more on real data.\(^{28}\) This new directional slack-based distance function can measure the inefficiency by choosing an optimal direction. It means that an inefficient DMU at the farthest edge of the frontier is looking for peers or benchmarks on the frontier. Therefore, DMUs can have a more realistic rate of inefficiency due to the realistic choice of the benchmark. Therefore, by using this directional slack-based distance function, DMUs can reach an efficient point (benchmark) with the goal of profit.

However, there will be an infeasible issue in directional distance measure in the mix period, namely, the DMU falls beyond the production possibility set. We follow Arabii et al.\(^{8}\) to measure the efficiency level for the DMU which above the frontier. This study defines the measure model for these DMUS as

\[
\begin{align*}
\vec{D}^t'(x^i, y^i, b^i; g) &= \min \gamma^t_1 e^i_1 + ... + \gamma^t_N e^i_N + \beta^t e^i_m + \beta^t e^i_{m+1} + ... + \beta^t e^i_{m+M} \\
\sum_{k=1}^{K} \lambda^t_{nk} y^i_{mk} &\geq y^i_{mk} - \beta^t M e^i_m \quad m = 1, ..., M \\
\sum_{k=1}^{K} \lambda^t_{nk} x^i_{kn} &\geq x^i_{kn} \quad n = 1, ..., N \\
\sum_{k=1}^{K} \lambda^t_k b^i_{hk} &\leq b^i_{hk} - \gamma^t_k \gamma^t e^i_n \quad h = 1, ..., H \\
\lambda^t_k &\geq 0, \quad \beta^t_m \geq 0, \quad \gamma^t_n \geq 0; \quad k = 1, ..., K.
\end{align*}
\]

This efficiency measure presents a minimum decrease of both good and undesirable outputs, which can project the DMU to the production frontier. Under this measure, the DMU seeks for the nearest direction toward frontier, since the DMUs below and above the frontier follows different paradigms. For the DMUs located below the frontier, those closer to the frontier are evaluated as being more efficient, however for the DMUs above the frontier regarded as being less efficient. In other words, in this case the DMU located furthest away from the frontier is the most efficient.

\(^1\)In Fare and Grosskopf,\(^{16}\) although they set the \(e^i_m = 1\), other specifications can be set.
2.2 Malmquist–Luenberger Index

In terms of the Malmquist productivity index (MI), Chung et al. further came up with the ML. The ML can be used to access the productivity, including undesirable outputs. Also, it can be divided into efficiency change (EC) and technical change (TC) which is similar to the decomposition of the MI during the given period.

We define the MLI with the new directional distance function as follows:

\[
ML_{t}^{1+1} = \left[ \frac{(1 + \vec{D}(x^t, y^t, b^t, y^t, -b^t))}{(1 + \vec{D}(x^{t+1}, y^{t+1}, b^{t+1}, y^{t+1}, -b^{t+1}))} \right]^{1/2}.
\] (7)

On the basis of the DDF, the MLI is used to access the productivity which attempts to find out the highest possible promotion in inputs and decrease in outputs. The value of the MLI is positive, which means that the productivity grows; if the value is negative, this indicates a decline in productivity.

The ML can be decomposed in the same way as the Malmquist productivity index:

\[
ML_{t}^{1+1} = \frac{(1 + \vec{D}(x^t, y^t, b^t, y^t, -b^t))}{(1 + \vec{D}(x^{t+1}, y^{t+1}, b^{t+1}, y^{t+1}, -b^{t+1}))} \frac{(1 + \vec{D}(x^t, y^t, b^t, y^t, -b^t))}{(1 + \vec{D}(x^{t+1}, y^{t+1}, b^{t+1}, y^{t+1}, -b^{t+1}))}^{1/2},
\] (8)

EC reflects the efficiency change of outputs between the consecutive periods. TC measures the changes of production technology in all outputs; a value greater than 1 means technological progress, and a value less than 1 indicates technological regression.29,30

2.3 β-convergence and σ-convergence

In terms of methods developed from Barro and Sala-Martin, this section shows the estimated results that we obtain from the tests of β-convergence and σ-convergence. Based on the original level, we use β-convergence to regress the growth convergence rate of Malmquist–Luenberger GTFP. If the value of coefficient is less than zero and at a significant level, this signifies convergence. Conversely, a coefficient that is positive and statistically significant indicates divergence. The explanation for the β-convergence is that provinces with lower TFP have faster growth than do provinces with higher initial TFP. The formula of β-convergence is presented in the following equation:

\[
\ln GTFP_{jt} - \ln GTFP_{jt-1} = \alpha + \beta \ln GTFP_{jt-1} + \varepsilon,
\] (9)

where \(GTFP_{jt}\) represents the ML for \(j\) province in \(t\) year and \(GTFP_{jt-1}\) represents the ML for \(j\) province in \(t-1\) year. \(\alpha\) is a parameter and \(\beta\) is the coefficient that we need to measure. \(\varepsilon\) is the error term.

According to Degl’Innocenti et al., the σ-convergence is utilized to evaluate how quickly the Malmquist–Luenberger productivity of each province changes when converging to the average Malmquist–Luenberger productivity. The formula of σ-convergence is shown in the following equation:

\[
\Delta \left( \ln GTFP_{jt} - \ln GTFP \right) = \alpha + \beta \left( \ln GTFP_{jt-1} - \ln GTFP \right),
\] (10)

where \(\Delta (\ln GTFP_{jt} - \ln GTFP)\) represents the first difference for \(j\) province in \(t\) year. The interpretation of \(\beta\) is similar with that of coefficient in β-convergence. Therefore, we use these two formulas to investigate the convergence results of GTFP.

3 VARIABLES AND DATA SOURCES

Following previous studies, we use capital stock, labor and energy consumption as inputs. A sample period from 2005 to 2017 is selected in this study. We utilize the total employment to characterize the variable of labor in each province. So far as capital stock is concerned, most previous studies used Goldsmith’s perpetual inventory to estimate the value of capital stock. Price indices should be considered in this...
estimation to strip out the effects of inflation. Adopting the approach of previous studies, as the performance of the fixed assets' formation is better than that of the fixed assets' investment, we use the former to assess capital stock. As the depreciation plays a significant role in the measurement of capital stock, we set 10.96% as the value of the depreciation rate, which has been the usual method in previous studies.

Total energy consumption of official statistics is used as the variable of energy consumption.

As output can be divided into two types, most studies use GDP as the desirable output variable. Moreover, here we use three main types of industrial wastes as the undesirable output variables in accordance with the strategies of environmental protection in the 13th Five-Year Plan. The total number of COD and ammonia nitrogen emissions is used to characterize the waste water. The sum of SO2 and soot emissions is used to characterize the waste gas. The industrial solid waste of each province is used to characterize the solid waste. The definitions of the variables are shown in Table 1, and the data sources of each variable are presented in Table A1.

Based on the documents issued by the State Council, China can be divided into eastern, central, and western regions, which is displayed in Table A2. Considering the incomplete statistics of the Tibet, Hongkong, Taiwan, and Macao, the tested provinces do not include Tibet.

In Table 2, we present the descriptive statistics of each variable. By and large, the eastern region has better economic development and performance due to higher average GDP with the value of 21,926,210 hundred million Yuan compared to the descriptive information.

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**Table 1 Variables and definition.**

| Variable        | Type          | Unit        | Definition                                                   |
|-----------------|---------------|-------------|--------------------------------------------------------------|
| Labor           | Input         | 10^4 Person | Total employment at the end of year                         |
| Capital stock   | Input         | Hundred million yuan | Calculated by the Goldsmith’s perpetual inventory       |
| Energy consumption | Input   | 10^4 tce    | Energy consumed in production and living                   |
| GDP             | Desirable output | Hundred million yuan | Price indices are used to strip out inflation     |
| Waste water     | Undesirable output | 10^4 tons  | The sum of COD and ammonia nitrogen emissions |
| Waste gas       | Undesirable output | 10^4 tons  | The sum of SO2 and soot emissions                              |
| Solid waste     | Undesirable output | 10^4 tons  | Industrial solid waste at the end of year                   |

**Table 2 Descriptive statistics of variables.**

| Region | Labor | Capital stock | Energy consumption | GDP | Waste water | Waste gas | Solid waste |
|--------|-------|---------------|---------------------|-----|-------------|-----------|-------------|
|        | Mean  | 2960          | 64,407              | 16,884 | 21,926      | 68.3      | 110.1       | 8,920       |
|        | Max   | 6650          | 176,825             | 38,899 | 69,943      | 216.5     | 299.5       | 45,576      |
|        | Min   | 379.3         | 3756                | 822.0 | 919.8       | 8.7       | 3.5         | 127.0       |
|        | Stdv  | 1985          | 39,854              | 10,466 | 15,681      | 53.1      | 89.4        | 10,369      |
|        | Mean  | 3173          | 40,215              | 12,835 | 12,355      | 77.6      | 133.2       | 9626        |
| Central| Max   | 6766          | 136,515             | 23,647 | 35,735      | 167.3     | 333.3       | 34,162      |
|        | Min   | 1239          | 17,887              | 4,286  | 3620        | 19.8      | 36.2        | 2457        |
|        | Stdv  | 1514          | 22,552              | 4,968  | 6567        | 37.4      | 69.6        | 6656        |
|        | Mean  | 1839          | 25,363              | 9,168  | 6893        | 45.1      | 108.8       | 7625        |
| Western| Max   | 4907          | 73,993              | 20,874 | 27,235      | 145.6     | 269.0       | 27,953      |
|        | Min   | 291.0         | 3,641               | 1,670  | 543.3       | 6.5       | 22.2        | 649.0       |
|        | Stdv  | 1226          | 16,697              | 4,829  | 5272        | 32.2      | 57.2        | 5540        |

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https://test/test/2008-03/24/content_927136.htm and http://test/gongbao/content/2001/content_60854.htm.
between other two regions. The eastern provinces have developed rapidly, and they have more capital stock to put into the production process. Moreover, the energy consumption of the central and western regions is less than that of the eastern region, with average values of 128,350,000 and 91,680,000 tce, respectively. In terms of labor input, the total employment of the central region is slightly higher than that of eastern region, and the average total employment of the western region is only 18,388,680 persons during 2005–2017 which is consistent with the fact that the population is concentrated in the eastern region and central region.

As for the average value of industrial wastes the central region is the highest emitter of the three undesirable outputs, with values of 776,000, 1,332,000, and 96,260,000 tons, respectively. Although the eastern region has higher economic development, the emissions of three undesirable outputs are lower than in the central region, indicating that it has done better in terms of environmental protection from 2005 to 2017. The western region has the smallest average for all indicators, but this does not directly reflect the change in its TFP. In the eastern region, compared with other provinces, Hainan has the minimum values of these variables. In the central region, the variable values of Jiangxi and Anhui are smaller than are those of other provinces. The variable values of Qinghai province are smaller than are those of other provinces in the western region.

4 | GTFP ANALYSIS

4.1 | Predicted adjustment range

In this section, we present the predicted adjustment range estimated by the new slacks-based measure of directional distance function. In Table 3, B1 is the predicted adjustment proportion of waste water for each province. B2 is the predicted adjustment proportion of waste gas, B3 is the predicted adjustment proportion of solid waste and G1 is the predicted adjustment proportion of GDP. Each province can strengthen control over the discharge of pollutants and stimulate the economy according to the value given in Table 3. For B1, B2, and B3, provinces should reduce the emissions of waste water, waste gas and solid waste and increase GDP by the percent in Table 3 to optimize energy efficiency and GTFP.

As is seen above, the predicted adjustment proportion of five provinces are 0, such as Beijing, Shanghai, Guangdong, Hainan and Qinghai. These provinces should maintain the current level of environmental protection and economic development, they do not need to make significant adjustment, which indicates that they have the best energy efficiency. In the eastern region, in addition to Beijing, Shanghai, Guangdong and Hainan, Tianjin also did well in energy efficiency during the period of 2005–2017, for it only need to reduce the waste gas and solid waste by 0.1% and 0.4%. The energy efficiency of Jiangsu, Zhejiang and Shandong also

| Region | Province | B1 | B2 | B3 | G1 |
|--------|----------|----|----|----|----|
| Beijing | 0.000    | 0.000 | 0.000 | 0.000 |
| Tianjin | 0.000    | 0.0001 | 0.004  | 0.000 |
| Hebei   | 0.594    | 0.840 | 0.925 | 0.000 |
| Liaoning| 0.697    | 0.844 | 0.913 | 0.000 |
| Shanghai| 0.000    | 0.000 | 0.000 | 0.000 |

| Eastern | Jiangsu  | 0.033 | 0.098 | 0.210 | 0.000 |
|         | Zhejiang | 0.080 | 0.330 | 0.292 | 0.000 |
|         | Fujian   | 0.596 | 0.655 | 0.761 | 0.000 |
|         | Shandong | 0.080 | 0.241 | 0.283 | 0.000 |
|         | Guangdong| 0.000 | 0.000 | 0.000 | 0.000 |
|         | Hainan   | 0.000 | 0.000 | 0.000 | 0.000 |
|         | Mean     | 0.189 | 0.274 | 0.308 | 0.000 |
|         | Shanxi   | 0.644 | 0.942 | 0.955 | 0.296 |
|         | Jilin    | 0.714 | 0.823 | 0.782 | 0.373 |
|         | Heilongjiang | 0.572 | 0.686 | 0.694 | 0.043 |

| Central | Anhui     | 0.729 | 0.836 | 0.883 | 0.079 |
|         | Jiangxi   | 0.776 | 0.880 | 0.919 | 0.057 |
|         | Henan     | 0.508 | 0.755 | 0.798 | 0.000 |
|         | Hubei     | 0.764 | 0.788 | 0.788 | 0.000 |
|         | Hunan     | 0.770 | 0.812 | 0.764 | 0.000 |
|         | Mean      | 0.685 | 0.815 | 0.823 | 0.106 |
|         | Inner Mongolia | 0.626 | 0.896 | 0.910 | 0.495 |
|         | Guangxi   | 0.791 | 0.838 | 0.844 | 0.364 |
|         | Chongqing | 0.589 | 0.865 | 0.695 | 0.094 |
|         | Sichuan   | 0.776 | 0.798 | 0.846 | 0.000 |
|         | Guizhou   | 0.509 | 0.942 | 0.923 | 0.234 |

| Western | Yunnan    | 0.651 | 0.873 | 0.924 | 0.322 |
|         | Shaanxi   | 0.655 | 0.889 | 0.864 | 0.236 |
|         | Gansu     | 0.468 | 0.904 | 0.889 | 0.108 |
|         | Qinghai   | 0.000 | 0.000 | 0.000 | 0.000 |
|         | Ningxia   | 0.120 | 0.146 | 0.035 | 0.257 |
|         | Xinjiang  | 0.653 | 0.906 | 0.814 | 0.415 |
|         | Mean      | 0.531 | 0.732 | 0.704 | 0.229 |
performed well. Jiangsu should mainly reduce the emission of solid waste by 21%, and slightly reduce the emissions of waste water and waste gas. Zhejiang should reduce the emissions of waste gas and solid waste by 33% and 29.2%, respectively. The predicted adjustment range of Shandong is basically similar to that of Zhejiang. For all their adjustment proportion of undesirable outputs is greater than 50%, Hebei, Liaoning and Fujian have large room to strengthen their energy conservation and emission reduction.

In central region, all provinces should make large adjustment to reduce the emissions of waste water, waste gas and solid waste, for most adjustment ranges are greater than 60 percent. Shanxi should mainly focus on reducing the emissions of waste gas and solid by 94.2% and 95.5%, implying that it still emits too much waste gas and solid waste. The same situation also exists in western region. Most provinces in western region should further strengthen the emissions controls of pollutions. The eastern region has the lowest average of waste water, waste gas and solid waste among these three regions, indicating that provinces in the eastern region have done better in saving energy and reducing emissions during the period of 2005–2017. So far as the central region and western region are concerned, provinces in these two regions should improve environmental protection and take effective measures to reduce the emissions of waste water, waste gas and solid waste. The sums of B1, B2, B3, and G1 in Shanxi, Inner Mongolia, and Guangxi are the bottom three among 30 tested provinces, implying that they need to make drastic adjustment to reduce the emissions of pollutions and stimulate the economy.

Through the results of G1 in Table 3, the average value of G1 in eastern region is 0, signifying that the economic development of eastern region performed better than the other two regions from 2005 to 2017. The eastern region has obvious coastal advantages and the overall economic strength is very strong, so the provinces in eastern region can achieve optimal energy efficiency mainly by reducing the emissions of waste water, waste gas and solid waste. The average G1 of central region is 0.106, which is slightly lower than the 0.229 in the western region. This means that central and western region need economic stimulus to accelerate the economic development and improve the energy efficiency.

### 4.2 GTFP and its decompositions

In this study, the GTFP is estimated by the new SBM of DDF and it can be divided into two sub-formulas: GEC and GTC. GEC is the efficiency change and GTC is the technical change over the given period. The value of GEC > 1 indicates the improvement of efficiency. The value <1 means regression of efficiency. If the value of GTC > 1, it signifies the improvement of production technology. If the value of GTC < 1, it indicates the regression of production technology. Table 4 shows the cumulative GTFP and its decompositions over these

| Year        | Eastern GTFP | GEC  | GTC  | Central GTFP | GEC  | GTC  | Western GTFP | GEC  | GTC  |
|-------------|--------------|------|------|--------------|------|------|--------------|------|------|
| 2005–2006   | 1.152        | 0.991| 1.163| 1.101        | 0.990| 1.112| 1.033        | 1.002| 1.031|
| 2006–2007   | 1.160        | 1.004| 1.156| 1.044        | 0.865| 1.206| 1.078        | 1.055| 1.021|
| 2007–2008   | 1.176        | 1.012| 1.162| 1.051        | 0.997| 1.055| 1.022        | 0.996| 1.026|
| 2008–2009   | 1.163        | 0.991| 1.173| 1.035        | 0.984| 1.052| 0.994        | 0.933| 1.065|
| 2009–2010   | 1.160        | 1.045| 1.110| 1.041        | 0.994| 1.047| 1.004        | 0.980| 1.024|
| 2010–2011   | 0.937        | 0.921| 1.018| 0.949        | 0.978| 0.971| 0.971        | 1.076| 0.902|
| 2011–2012   | 1.124        | 1.000| 1.124| 1.028        | 1.001| 1.027| 1.039        | 0.998| 1.041|
| 2012–2013   | 1.109        | 0.999| 1.110| 1.017        | 0.989| 1.028| 1.040        | 0.994| 1.046|
| 2013–2014   | 1.058        | 0.997| 1.061| 1.011        | 0.990| 1.021| 1.029        | 0.992| 1.036|
| 2014–2015   | 1.122        | 0.994| 1.129| 1.020        | 0.985| 1.036| 1.041        | 0.986| 1.056|
| 2015–2016   | 1.251        | 1.105| 1.133| 1.154        | 1.032| 1.119| 1.112        | 1.000| 1.112|
| 2016–2017   | 1.057        | 1.006| 1.051| 1.049        | 1.002| 1.047| 1.048        | 0.993| 1.056|
| Mean        | 1.120        | 1.005| 1.115| 1.041        | 0.983| 1.059| 1.034        | 1.000| 1.034|

**Abbreviations:** GEC, green efficiency change; GTC, green technical change; GTFP, green total factor productivity.
three regions to analyze the change characteristic of GTFP.

As Figure 1 shows, we first present the overall cumulative GTFP, GEC, and GTC from 2005 to 2017. By and large, the overall GTFP shows a gradually rising trend, in addition to a trend of GTC. The GTFP rises steadily since 2006 and 1.480 in 2009, with a cumulative 7.1% improvement annually in GTFP. In 2010, after China's environmental protection work conference, new emission reduction targets were issued. Government asked enterprises whose pollution had risen above an acceptable level to either pay for environmental maintenance or stop production. Therefore, the cumulative GTFP decreased slightly, to 1.410, in 2010. Most enterprises further strengthened their reduction of emissions of industrial wastes during 2010–2011, and the value of GTFP increased to 1.503 in 2011. The cumulative GTFP maintained an upward trend, and the cumulative value of GEC remained between 0.923 and 0.995 from 2011 to 2017, implying that technology of production had been significantly improved and directly increased the GTFP. However, the production efficiency had not been improved sufficiently, and it fell slightly in some years.

Table 4 depicts the change of GTFP and its decompositions over three regions during 2005–2017. As mentioned, if the values of GTFP, GEC, and GTC are greater than 1, this implies improvement. If the values are less than 1, this implies deterioration. If the value is equal to 1, this implies constancy. From the results in Table 4, the values of these three indexes of the eastern China are higher than that of other two regions. From the perspective of the mean value, only the eastern region performed well in respect of GTFP and its decomposition in the research period, their average values were all greater than 1. The GTFP and GTC of the central region showed a significant improvement, but the GEC decreased slightly. However, the GEC of the western region did not improve significantly and, on average, it tended to remain the same. The GTFP and GTC improved in all three regions.

Figure 2 shows the cumulative GTFP, GEC, and GTC change of the eastern region from 2005 to 2017. On the whole, the cumulative GTFP shows a gradual upward trend, implying that the GTFP of the eastern region continued to improve and maintained positive growth in the research period, with the exception of 2010. The cumulative GTFP was 2.120 in 2009, and it decreased slightly to 1.987 in 2010 due to the stricter regulation of emissions of industrial wastes. The growth trend of GTC was smoother, and even in 2010 there was no decline in the cumulative GTC. As for the changing trend of GEC, its performance was very stable during 2005–2017, being maintained at approximately 1.057. New emissions’ reduction targets and stricter regulations caused a slight decline in cumulative GEC in 2010, leading to the reduction of cumulative GTFP. Hence, technical progress can be viewed as the major driven force of GTFP’s growth.

Figure 3 shows the changing trend of cumulative GTFP, GEC, and GTC in the central China. The annual improvement of GTFP in the central region is relatively small compared to the improvement of GTFP in the eastern region. Nevertheless, generally speaking, the GTFP of the central region presents an upward growth trend. The average values of cumulative GTFP and GTC in the eastern region are 2.178 and 2.193, respectively, which are higher than in the central region, with mean of 1.292 and 1.548, respectively. So far as the GTFP and technological progress are concerned, the central region is slightly weaker than the eastern region.
The GEC of the central region did not perform well during 2005–2017. The cumulative GEC was 0.990 in 2005. After that, the value of the GEC began to decrease gradually until it reached 0.788 in 2014. From 2015, the GEC began to increase slowly. The promotion of GTFP in the central region is also significantly stimulated by the GTC, because its trend is similar to the situation in the eastern region.

As Figure 4 shows, the trend of GTFP, GEC, and GTC of western region is different from that of other two regions. The cumulative GTFP remained between 1.130 and 1.137 during 2007–2009. The major driven factor for this situation is that the GTC shows an increasing trend, whereas the GEC shows a decreasing trend. Since 2010, the cumulative GTFP has gradually increased, and the GTC has shown an upward trend similar to that of GTFP. In contrast, the GEC started to decline slightly year by year from 2010. The average values of cumulative GTFP and GTC are 1.192 and 1.175, respectively, in the research period, which is the smallest average among these three regions. This means that the GTFP and production technology in the western region have improved, but they still lag behind those in other two regions. However, the average value of GEC in the
western China is 1.000, implying that the GEC of the western region remained unchanged until 2017.

The Wilcoxon–Mann–Whitney test is used to analyze whether there are differences between these three regions. In terms of the estimated results in Table 5 and the average values in Table 4, the GTFP of the eastern region is 1.120, which is higher than the values of the central (1.041) and western (1.034) regions. For the average values of GEC among these three regions, the eastern region performed best during the research period, with a value of 1.005. As for the results of GTC, the value of the eastern region is 1.115, and it is also much higher than are the values of other two regions. The differences in the GTFP, GEC, and GTC between the eastern and central regions are statistically significant at 1%. Furthermore, the differences between eastern and western regions are also statistically significant at 1%. Nevertheless, only the difference in GTC between the central and western regions is statistically significant at 10%, which means that the gaps in GTFP, GEC, and GTC between the central and western region are very small. In conclusion, the eastern region outperforms in terms of GTFP, GEC, and GTC compared to the other two regions. Only the eastern region showed significant improvements in GTFP, GEC, and GTC from 2005 to 2017.

### 4.3 Tests of convergence

Table 6 presents the regression results of \( \beta \)-convergence and \( \sigma \)-convergence on the basis of GTFP among these three regions during the period 2005–2017. The coefficients of the \( \beta \)-convergence are all negative and statistically significant at 0.01, which indicates that GTFP has converged across the provinces from 2005 to 2017. It can be viewed as a great support for the hypothesis about convergence among 30 provinces.

Meanwhile, Table 6 shows the measurements of \( \sigma \)-convergence over the sample period. Similar to the results of \( \beta \)-convergence, all coefficients of \( \sigma \)-convergence are less than zero and statistically significant at 0.01 level. The coefficient of \( \sigma \)-convergence represents the rate of convergence of GTFP in one province toward the average GTFP of 30 tested provinces. Therefore, if the coefficient is negative and its absolute values is larger, which means that the GTFP of this province converges to the average GTFP of 30 tested provinces. However, if the coefficient is positive and its absolute values is smaller, which means that the GTFP of this province converges to the average GTFP of 30 tested provinces. Therefore, if the coefficient is negative and its absolute values is larger, which means that the GTFP of this province converges to the average GTFP of 30 tested provinces. Therefore, if the coefficient is negative and its absolute values is larger, which means that the GTFP of this province converges to the average GTFP of 30 tested provinces. Therefore, if the coefficient is negative and its absolute values is larger, which means that the GTFP of this province converges to the average GTFP of 30 tested provinces.
region. Compared to the values of central (−0.590) and western (−0.704) China, the converged speed is faster in the eastern region, with the σ-convergence coefficient values of −0.826 in the given period.

The convergence of GTFP is mainly due to the adoption of technical progress, specifically core production technology. The major reason for the faster convergence rate of provinces in the eastern region is the more developed economy compared to other two regions, which enables enterprises in the eastern region to have more sufficient funds to develop more advanced technologies and improve the management methods of production so as to promote the technical efficiency. The provinces in the eastern region have a stronger technical support than provinces in other two regions which need to gradually adapt to technological advances. As a result, the eastern region converges faster than other two regions.

5 | CONCLUSION AND POLICY IMPLICATIONS

A new SBM of DDF is utilized in this paper to access the GTFP and its decompositions in 30 tested provinces and then estimate the average adjustment range of all outputs in each province during 2005–2017. We divide 30 tested provinces into three different regions, and compare GTFP, and its decompositions. The estimated results of a Wilcoxon–Mann–Whitney test show the eastern region has the best performance according to the results of GTFP, green efficiency change (GEC), and green technical change (GTC) among these three regions. β-convergence and σ-convergence are used to show the results of convergence among these three regions.

From the empirical evidence, it can be concluded that Tianjin, Guangdong, Beijing, Shanghai, Guangdong, Qinghai, and Hainan perform best in energy conservation and environmental protection as benchmarks among 30 provinces from 2005 to 2017. We also find that the GTFPs of three regions all show a gradually incremental trend during the sample period, similar to the changing trends of GTC, indicating that GTC is the main driven force give rise to the increase of GTFP. This result is similar to Tao et al. and Oh, who suggested that technological progress was a major contributor to GTFP. Only the eastern region shows a slight increase in GEC, whereas the GEC of the central region has fallen slightly and that of the western region remains unchanged. The results of coefficients in β-convergence and σ-convergence present that there is GTFP growth convergence for the overall period, indicating that GTFP has grown faster in provinces with low GTFP than in
provinces with high GTFP and the GTFP values in all provinces have gradually converged.

To achieve higher green productivity, it is necessary to further limit and reduce the emissions of pollutants, and there needs to be a major focus on the treatment of solid waste discharges. For the provinces in the eastern region, the local governments can fine-tune the policies of energy-saving and pollution reduction. Moreover, provincial governments should further strengthen the regulation of pollutant discharge. Stricter environmental regulations will help improve China’s productivity level. Under the condition of having sufficient financial funds, local governments not only should continue to strengthen support for energy saving and high technologies but also should require enterprises to upgrade and reform their production processes to improve production efficiency. The research of Li and Wu also pointed out that developed cities should optimize their industrial structure, encourage enterprises to innovate, and improve social welfare. Lin and Chen encouraged to increase the degree of freedom in the factor market and further promote enterprise innovation.

As for the central and western regions, they need to make big adjustments and strengthen environmental protection. While increasing the financial funds on science and technology, the provinces in the central region should note the structure and investment in energy science and technology, which should maximize the effective role of the investment in improving GTFP. Provinces in the central region can also optimize their industrial structure, avoid as far as possible the transfer of high energy consumption industries to their own areas, and vigorously develop local energy-consuming industries. These suggestions are consistent with the conclusions of Tao et al., Wang et al., and Chen and Golley. With a vast territory and a large population, the western region lags behind the other two regions in development phase, and its infrastructure, capital construction, and comprehensive development all need to be greatly strengthened. Abundant labor resources and low costs will help the western region to attract capital, introduce advanced technology, and develop the regional economy. Li and Wu, Wang et al. also suggested that underdeveloped regions in the central and western regions should pay more attention to the balance between economic growth and energy intensity.

Additionally, local governments in all provinces should require enterprises to improve the training and personal skills of their employees, and they can also issue preferential policies to attract talents. All provinces should emphasize the importance of enterprises gradually switching from fossil energy to renewable energy in their industrial production. To sum up, these three regions can improve their GTFP through the measures mentioned above.

ACKNOWLEDGMENTS
This paper is supported by Youth Foundation of Social Science and Humanity, China Ministry of Education (No. 21YJCZH149) and Zhejiang Provincial Natural Science Foundation of China under Grant No. LQ21G010006.

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**How to cite this article:** Zhuang W, Wang Y, Lu C-C, Chen X. The green total factor productivity and convergence in China. *Energy Sci Eng.* 2022;10:2794-2807. doi:10.1002/ese3.1168
APPENDIX A
See (Tables A1 and A2).

TABLE A1  Data sources of variables.

| Variables         | Data sources                                      |
|-------------------|---------------------------------------------------|
| Labor             | China Labor Statistical Yearbook                  |
| Capital stock     | China Statistical Yearbook                        |
| Energy consumption| China Energy Statistical Yearbook                  |
| GDP               | China Statistical Yearbook                        |
| Waste water       | China Energy Yearbook and China Environmental Statistical Yearbook |
| Waste gas         | China Energy Yearbook and China Environmental Statistical Yearbook |
| Solid waste       | China Energy Yearbook and China Environmental Statistical Yearbook |

TABLE A2  Division of areas.

| Area    | Provinces and municipalities                      |
|---------|---------------------------------------------------|
| Eastern | Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan |
| Central | Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan |
| Western | Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang |