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Analysis of green total factor productivity in OECD and BRICS countries: based on the Super-SBM model

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ABSTRACT

To address the conflict between environmental constraints and fast economic growth, as well as to coordinate green growth strategies between developing and developed countries, improving green total factor productivity (GTFP) is an important way to accelerate the green and low-carbon transformation and get rid of the problems of environment and resources. Therefore, it is significant to analyze and compare the GTFP of Organization for Economic Cooperation and Development (OECD) and BRICS (i.e. Brazil, Russia, India, China and South Africa) countries. By applying the Super-SBM model, our study analyzes the distribution characteristics and the evolving trend of GTFP. The empirical results indicate that: (1) The GTFP of BRICS countries has significantly improved, but there is still a significant gap compared with OECD countries. (2) Brazil, Luxembourg and Norway's GTFP values are higher than others. (3) Among the BRICS countries, Brazil exhibits the highest value and China has the minimum value, which was far ahead in energy consumption and PM2.5. (4) In the analysis of OECD countries, Hungary displays the lowest average value and Luxembourg has the highest average value. As such, some policy implications improve green and low-carbon development.

Key words: BRICS, green total factor productivity, OECD, PM2.5, Super-SBM model

HIGHLIGHTS

- This study uses the Super-SBM model considering undesirable outputs to estimate the green total factor productivity (GTFP).
- The GTFP of OECD countries is higher than that of BRICS countries as a whole.
- Hungary displays the lowest average value and Luxembourg has the highest average value.
- Brazil exhibits the highest value and China has the minimum value, which was far ahead in energy consumption and PM2.5.

1. INTRODUCTION

Based on the development stage and characteristics, the economic development of the developing countries is the primary task and follows the development path of 'pollution first, then treatment'. Developed countries have adopted modern production technology to make industrial production more attractive and efficient, achieving energy conservation, emission reduction and green development. However, efforts to stimulate economic growth by increasing blind expansion of production are damaging the natural environmental quality of the economy. Therefore, developing countries face more and more environmental challenges (Nawaz *et al.* 2021). In this context, improving green total factor productivity (GTFP) has become the only way for developed and developing countries to get rid of the pressure of global climate change and carbon emission reduction.

The Organization for Economic Cooperation and Development (OECD) and BRICS (i.e. Brazil, Russia, India, China and South Africa) are the world's major economies and sources of emissions (Xie *et al.* 2014). The BRICS countries account for about 42% of the world population and 26% of the world territory. The total economic volume of BRICS countries has accounted for 21% of the global economy, and its contribution to global economic growth has exceeded 50% in the past decade. The OECD is an intergovernmental international economic organization, which aims to jointly meet the economic, social and governmental challenges brought about by globalization. Historically, the OECD countries are the largest energy-consuming economies (Camioto *et al.* 2016). Therefore, while realizing the coordinated economic development of various countries, we also need to take into account resource investment and environmental carrying capacity. How to realize the green economic growth mode has become a real problem for all countries. Changing the mode of economic development is crucial to green development. Therefore, GTFP is regarded as a key indicator and is widely used to judge whether a country is transforming to green development.

GTFP adds resources and environment into the total factor productivity (TFP) analysis framework and pays attention to the quality of economic growth (Wang *et al.* 2020). GTFP considers the role of energy consumption and pollution emissions as undesired outputs for economic growth, and it is widely used as a measure of green economic efficiency (Wang *et al.* 2018; Chen *et al.* 2019). GTFP extends the meaning of the TFP and takes the ecological environment as one of the criteria. In order to build a world economy with efficient use of resources, it is very important to evaluate and estimate the GTFP of countries. In addition to contributing to the sustainable development of countries affecting the world economy, this analysis can also provide useful information for energy and environmental policies.

As a core issue in the age of green growth, there are many studies including qualitative and quantitative analyses on GTFP (Xia & Xu 2020; Zhang *et al.* 2021). Many studies have discussed the influencing factors of GTFP, such as green finance, environmental regulation, technological innovation and so on (Li & Wu 2017; Wang *et al.* 2021; Lee & Lee 2022). Although some literatures analyze the GTFP of individual countries such as China or industries, such as agricultural GTFP (Chen *et al.* 2021; Li & Chen 2021). However, few studies have compared the GTFP and long-term sustainable green development of developed and developing countries from the perspective of global comparison. There are great differences between developed and developing countries in the process of industrialization, economic development, technological innovation capacity, etc., and their perceptions and policies on the global environmental crisis are also different. The comparative analysis of GTFP between developed and developing countries is helpful to coordinate the policy coordination of countries at different stages of global green development in the future. To this end, we have identified cutting-edge research and knowledge gaps in GTFP.

Our study tries to measure GTFP using the Super-SBM model with undesirable outputs for 2 groups including 30 OECD countries and 4 BRICS countries over the period of 2003–2012. Our study pays more attention to the distribution characteristics and the evolving trend of GTFP among them. Meanwhile, the investigation of comparison was performed between the OECD and BRICS countries. We attempt to provide a benchmark for evaluating the environmental efficiency from the perspective of global comparison.

The study's main contribution can be concluded as follows: first, because energy consumption produces more environmental pollution, scholars usually select different environmental pollution indicators based on research purposes and use the SBM model to calculate the industrial or regional total factor energy efficiency. The calculation results are different. The SBM model may have multiple decisions effective at the same time, which is not convenient to distinguish and sort these decision-making units (DMUs). Therefore, this study sets that if multiple DMUs are effective at the same time in the SBM calculation results, the Super-SBM model is used to calculate the GTFP, so as to improve the accuracy of the calculation results. Second, PM2.5 is regarded as an undesirable output, and interference is eliminated to reveal the real GTFP of this paper, which provides a new theoretical perspective for the research of GTFP and fills the blank index of theoretical research on green development strategy. In addition, for practical implications, the assessment of GTFP is not only conducive to a more reliable assessment of the sustainability of green development but also can summarize the models of green development in developing and developed countries, reveal the green efficiency of different types of countries in the world and provide diverse solutions for the global green development strategy.

The remainder of the study is arranged as follows: Section 2 reviews the available literature. Section 3 shows the research methods used in the study. Section 4 analyzes the variable selection and descriptive statistics. Section 5–6 discusses the empirical results. Finally, conclusions are summarized.

2. LITERATURE REVIEW

Generally speaking, in the social production process, inputs are accompanied by outputs. However, outputs include not only desirable outputs but also undesirable outputs (e.g., pollution emissions). With the development of social economy, people's demand for environmental quality is getting higher and higher, and people pay more and more attention to the balance between environmental protection and economic development (El Kasri *et al.* 2021; Hang 2022). Some recent studies have discussed the environmental and economic problems caused by urbanization and COVID-19 (Okeke *et al.* 2020; Qerimi *et al.* 2020; Golmohammadi & Fazelabdolabadi 2021; Mehmood & Lal 2021). TFP, which is obtained by calculating the transformation ratio of total inputs into outputs, is used to measure productivity growth or the quality of growth (Feng *et al.* 2018). Traditional TFP only focuses on input factors and desirable outputs (Coelli & Rao 2005; Chen *et al.* 2008). However, the traditional TFP indicator neglects environmental constraints and undesirable outputs, which may lead to errors in the evaluation of production efficiency and sustainable economic development (Chen & Golley 2014; Li & Lin 2015; Mao *et al.* 2022).

Concerns about environmental protection have led a growing number of scholars to assess GTFP, taking into account undesirable outputs (Song *et al.* 2012; Emrouznejad & Yang 2017; Tao *et al.* 2017; Liu *et al.* 2021). For example, taking the industrial output and carbon dioxide (CO_2) as a desirable output and an undesirable output, Feng *et al.* (2018) evaluated the GTFP of China's regional metal industry. Kumar (2006) incorporated commercial energy consumption and carbon dioxide (CO_2) into the TFP framework to estimate the GTFP of 41 countries. Yaisawarng & Klein (1994) explored GTFP by taking sulfur and SO_2 emissions into consideration. Zhang *et al.* (2011) treated an integrated environmental factor as an undesirable output to measure GTFP using the Data Envelopment Analysis (DEA)-based Malmquist–Luenberger index. Mahlberg *et al.* (2011) analyzed the GTFP changes in 14 EU countries by incorporating greenhouse gas into the framework. Zhu *et al.* (2018) investigated the green TFP of China's mining and quarrying industry. You & Xiao (2022) measured the green TFP using the three-stage DEA. Lee *et al.* (2022) calculated the green TFP using the GML model.

Some literatures have studied the assessment of green development in OECD and BRICS countries. Färe *et al.* (1994) explored the productivity growth of 17 OECD countries using a non-parametric approach during 1979–1988. Hoang & Coelli (2011) analyzed the agricultural TFP incorporating environmental factors among 30 OECD countries and found that the growth rate of environmental TFP is slower than that of traditional TFP. Mahlberg & Sahoo (2011) estimated the environmental productivity of 22 OECD countries. Using the DEA approach and the Malmquist productivity index, Woo *et al.* (2015) also evaluated the environmental efficiency of renewable energy in 31 OECD countries and indicated that there are geographical differences in the environmental efficiency in OECD. For the BRICS countries, Song *et al.* (2013) analyzed the energy efficiency based on bootstrap-DEA. The slacks-based measure model was used to measure the total factor energy efficiency index of the BRICS group and the G7 group. Chang (2015) also compared the room for improvements in the low-carbon economies of the G7 group and the BRICS group.

In recent decades, there has been a proliferation of research on environmental efficiency and productivity. Studies have proposed various methods and models to assess the TFP. There are two methods used to measure GTFP in the existing literature, one is the parametric method (e.g., stochastic frontier analysis – SFA) and the other is a non-parametric method (e.g., DEA). They assume that all the DMUs operate under the same production or cost technology for the estimation of efficiency. Zhou *et al.* (2012), Lin & Long (2015), and Ouyang *et al.* (2021) applied the SFA to estimate energy efficiency. Chen *et al.* (2017) discussed the productive efficiency using SFA. DEA is a non-parametric mathematical programming method. It is first used to evaluate the relative efficiency of DMU. The DEA model is widely used in efficiency evaluation (Lu *et al.* 2013; Wang *et al.* 2020; Mohsin *et al.* 2021). For example, Khoshnevisan *et al.* (2013) estimated the energy efficiency based on the DEA approach. Dai *et al.* (2016) used the super-efficiency DEA model to evaluate the industrial eco-efficiency in east China. Compared to the parametric method, DEA does not require pre-set function form, so it is more suitable to measure the TFP or efficiency of DMUs with multiple inputs and outputs.

A new DEA model, which is called slacks-based measure DEA, was introduced. The difference between the SBM model and traditional CR and BCC models is that slack variables are added directly to the objective function. The SBM method solves both the problem of input–output slacks and efficiency evaluation. In addition, the SBM model belonging to the DEA model has non-radial characteristics. Non-directional measurement avoids radial and directional deviations and is superior to any other model in solving the defects of the traditional DEA model and evaluating the reflection efficiency (Li *et al.* 2013). Subsequently, Tone & Saoo (2003) proposed a new measurement efficiency model based on the SBM model with an undesirable output to better handle the undesirable output. Therefore, we can evaluate the GTFP of DMU by using the Super-SBM method with an undesirable output and put forward suggestions to improve the efficiency of DMU according to slacks variables.

To the best of our knowledge, few studies and comparisons of GTFP in OECD and BRICS countries have been made in the existing literature. What is more, as reviewed above, there may be multiple efficient DMUs simultaneously equal to 1 in the SBM model. In this case, the model fails to rank efficient DMUs. Therefore, this study develops the Super-SBM model with undesirable outputs for estimating the GTFP. It should be noted that some literature neglects the undesirable outputs (such as carbon emissions) in the production process, especially PM2.5, which is ignored by most literatures. The purpose of our study is to fill the research gap in the Super-SBM model by taking CO_2 emission and PM2.5 as undesirable outputs.

3. METHODOLOGY

In this part, the Super-SBM model, which is called a slacks-based measure DEA considering undesirable outputs, is proposed. It solves the slackness problems of inputs and outputs caused by the radial and angular choices.

We assume the LCE production system with n DMUs. Each unit (DMU) has three factors: inputs, desirable outputs and undesirable outputs (pollution emission, for example, carbon dioxide, etc.). Each unit (DMU) makes use of m input factors and produces s_1 desirable outputs and s_2 undesirable outputs. Three vectors are defined: $x \in R^m$, $y^d \in R^{s_1}$ and $y^{ud} \in R^{s_2}$ and the matrices X, Y^d and Y^{ud} are defined as follows:

$$X = [x_1, x_2, \cdots, x_n] \in R^{m \times n}$$

$$Y^d = [y_1^d, y_2^d, \cdots, y_n^d] \in R^{s_1 \times n}$$

$$Y^{ud} = [y_1^{ub}, y_2^{ub}, \cdots, y_n^{ub}] \in R^{s_2 \times n}$$

Then, the production possibility set (PPS) is defined as follows:

$$P(x) = \left\{ (y^d, y^{ud}) \middle| x \text{ produce } (y^d, y^{ud}), x \geq X\lambda, y^d \leq Y^d\lambda, y^{ud} \geq Y^{ud}\lambda, \lambda \geq 0 \right\}$$

where λ is the intensity vector, and the three inequalities in the P function stand for when, respectively, the actual input level is greater than the frontier investment level, actual desirable output levels are below the frontier desirable output level and the actual undesirable output is greater than the leading edge of the undesirable output level. Based on Tone (2001), the SBM model dealing with undesirable outputs is described as follows:

$$\beta = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^d}{y_{r0}^d} + \sum_{t=1}^{s_2}\frac{s_t^{ud}}{y_{t0}^{ud}}\right)} \tag{1}$$

$$\text{s.t. } x_0 = X\lambda + s^-$$

$$y_0^d = Y^d\lambda - s^d$$

$$y_0^{ud} = Y^{ud}\lambda + s^{ud}$$

$$s^- \geq 0, s^d \geq 0, s^{ud} \geq 0, \lambda \geq 0$$

where the vector s^d represents the loss of desirable outputs, s^- represents the slacks in inputs and s^{ud} represents the slacks in undesirable outputs. In the model, subscript 0 represents the evaluated DMU. The target function value of β is the efficiency value of each unit (DMU); m stands for the number of factors for inputs, and s_1 and s_2 represent the desirable outputs and undesirable outputs, respectively. The DMU is SBM-efficient considering undesirable outputs if $\beta = 1$ and $s^- = s^d = s^{ud} = 0$. The DMU is inefficient if $\beta < 1$, which means the inputs and outputs need to be further optimized.

The efficiency of the solution by Equation (1) is between 0 and 1. To further rank DMUs with efficiency value of 1, this paper calculates the efficiency of an effective DMU by using the Super-SBM model including the non-desirable output.

A finite PPS excluding a DMU (x_0, y_0^d, y_0^{ud}) is defined.

$$P(\bar{x})\ (y_0^d, y_0^{ud}) = \left\{ (\bar{y}^d, \bar{y}^{ud}) \middle| \bar{x} \text{ produce } (\bar{y}^d, \bar{y}^{ud}),\ \bar{x} \geq \sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j x_j,\ 0 \leq \bar{y}^d \leq \sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j y_j^d,\ \bar{y}^{ud} \geq \sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j y_j^{ud},\ 1 \leq e\lambda \leq u,\ \lambda \geq 0 \right\}$$

$$\beta_{SE} = \min_{(\lambda, \bar{x}, \bar{y}^d, \bar{y}^{ud})} \left\{ \frac{\dfrac{1}{m + s_2} \left(\sum_{i=1}^{m} \dfrac{\overline{X}_i}{X_{i0}} + \sum_{t=1}^{s_2} \dfrac{\overline{y}_k^{ud}}{y_{t0}^{ud}} \right)}{\dfrac{1}{s_1} \left(\sum_{r=1}^{s_1} \dfrac{\overline{y}_d^r}{y_{r0}^d} \right)} \right\} \tag{2}$$

$$s.t.\ \bar{x} \geq \sum_{\substack{j=1, \\ j \neq 0}}^{n} \lambda_j x_j$$

$$\bar{y}_d \leq \sum_{\substack{j=1 \\ j \neq o}}^{n} \lambda_j y_j^d$$

$$\bar{y}^{ud} \geq \sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j y_j^{ud}$$

$$\bar{x} \geq x_0,\ \bar{y}^d \leq y_0^d,\ \bar{y}^{ud} \geq y_0^{ud}$$

$$\bar{y}^d \geq 0,\ \bar{y}^{ud} \geq 0,\ 1 \leq e\lambda \leq u,\ \lambda > 0$$

where β_{SE} is the efficiency value measured by the Super-SBM model with the undesirable output. The Super-SBM model with the undesirable output has three characteristics. First, the slackness of input and output is effectively solved. Second, the problem of undesirable output is fully considered and effectively solved (Zhou *et al.* 2006). Third, it effectively solves the ranking problem when multiple DMUs are effective at the same time. Overall, compared with other DEA models, the Super-SBM model with undesirable outputs can better reflect the core of efficiency evaluation.

4. VARIABLE SELECTION AND DESCRIPTIVE STATISTICS

We evaluate the GTFP of 30 OECD countries (except the Slovak Republic, Korea and the Czech Republic because of the lack of available data) and 4 BRICS (Russia is not included) over the period of 2003–2012. GTFP is an important indicator of sustainable economic development. Based on the existing literature, capital and labor are the two basic production input factors (Zhang *et al.* 2017). Hailu & Veeman (2001) chose production labor, administration labor, energy, wood residue and so on as inputs. Chung *et al.* (1997) selected labor, capital stock, energy and wood fiber as inputs. For outputs, the GDP, CO_2 emission, integrated environmental factors, biological oxygen demand, chemical oxygen demand and suspended solids are selected as outputs (Ahmed 2012).

In general, the selection of input–output factors depends on the availability of data and research objectives (Feng *et al.* 2017). From the existing literature, labor force, capital stock and energy consumption are commonly selected as inputs; gross output and CO_2 emission are desirable and undesirable outputs (Li & Lin 2016). The objective of this study is to evaluate the GTFP in OECD countries. Considering the availability of data and the selection of index parameters for the literature study, we choose the capital stock, labor force and energy consumption as the inputs; real GDP, total lighting as the desirable outputs; CO_2 emission and PM2.5 as undesirable outputs. Table 1 shows the input–output indicators of GTFP based on the Super-SBM method. The data are collected from the Energy Statistics Database of the United Nations, IEA (the International Energy Agency) database, Energy Statistics of OECD Countries, and Energy Statistics of Non-OECD Countries.

Our study pays more attention to the distribution characteristics and the evolving trend of GTFP in the OECD and BRICS countries. Hence, these data cover 30 OECD countries and 4 BRICS countries including Brazil, India, China and South Africa. Thirty OECD countries can be divided into three groups during 2003–2012: OECD Americas (Canada, Chile,

Table 1 | Input and output indicators of green total factor productivity

	Category	Specific indicators	Measurement
Input indicators	Labor input	Labor force	Total labor force
	Capital input	Capital stock	Total fixed capital formation
	Resource input	Energy consumption	Total oil equivalent
Output indicators	Desirable output	GDP	Real GDP
		Total lighting	Total lighting
	Undesirable outputs	CO_2	Carbon dioxide emissions
		PM2.5	PM2.5 emissions

Mexico and the United States), OECD Asia-Oceania (Australia, Israel, Japan and New Zealand) and OECD Europe (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, Turkey and the United Kingdom). Because of the unavailability of data, Slovak Republic, Korea, Czech Republic and Russia are not included.

Table 2 presents the average annual growth rate of inputs and outputs. According to Table 1, the OECD Americas maintains a high average annual growth rate of 1.24% in labor force input and the low average growth rate of labor force input in the OECD Asia-Oceania is 0.22%. BRICS has a high average annual growth rate in capital stock, while OECD Asia-Oceania displays a low average annual growth rate. The average annual energy consumption in OECD Asia-Oceania declined by an average of up to 0.51% and by a minimum of 0.35% in the OECD Americas. The average annual growth rate of energy consumption was highest in BRICS. We also find that the highest annual real GDP growth rate was 8.29% of the BRICS and the lowest was 1.15% of OECD Asia-Oceania. The highest average annual growth rate of PM2.5 is 0.45%, and the lowest is −1.48%. The highest annual average growth rate of carbon dioxide emissions is 8.31% of the BRICS, and the lowest annual average growth rate is −1.07% of OECD Europe.

In the evaluation of GTFP, the input indicators generally include capital stock, labor force and energy consumption. The average annual growth rates of inputs are displayed in Figures 1–3, respectively. In Figure 1, our empirical results show the average annual growth rates of labor force. We find that OECD Asia-Oceania has the lowest growth rate of labor force input, whereas OECD Americas exhibit the highest growth rate. Among them, labor force input in the OECD Americas increased by 1.76% in 2006; labor force input in the OECD Asia-Oceania decreased by −1.11% in 2011. Figure 2 indicates the average annual growth rates of capital stock. The results illustrate that capital stock growth rate of BRICS countries is significantly higher than that of OECD countries. Among them, capital stock input in the BRICS increased by 16.31% in 2009; capital stock input in the OECD Americas decreased by −12.68% in 2009. Figure 3 shows the average annual growth rates of energy consumption. The results suggest that BRICS countries have the highest energy consumption compared with other OECD countries. Among them, energy consumption input in the BRICS increased by 11.73% in 2004 and energy consumption input in the OECD Americas decreased by –4.85% in 2009.

Among all the output indicators, we focus on two indicators: CO_2 emission and PM2.5. The average annual growth rates of outputs are reported in Figures 4 and 5, respectively. Figure 4 shows the average annual growth rates of CO_2 emission. The empirical results suggest that BRICS countries exhibit the highest CO_2 emission compared with other OECD countries. Among them, carbon dioxide emission decreased by −7.02% in OECD Europe in 2009, while carbon dioxide emission

Table 2 | The average annual growth rates of inputs and outputs

Regions	Labor force (%)	Capital stock (%)	Energy consumption (%)	Rgdp (%)	Total lighting (%)	PM2.5 (%)	CO_2 (%)
OECD Americas	1.24	1.19	−0.35	1.75	3.32	−0.77	−0.89
OECD Asia-Oceania	0.22	0.65	−0.51	1.15	3.49	0.45	0.30
OECD Europe	0.91	0.86	−0.37	1.33	6.66	−1.48	−1.07
Total OECD	0.79	0.90	−0.41	1.41	4.49	−0.60	−0.55
BRICS	0.83	11.55	6.74	8.29	−0.89	−0.89	8.31

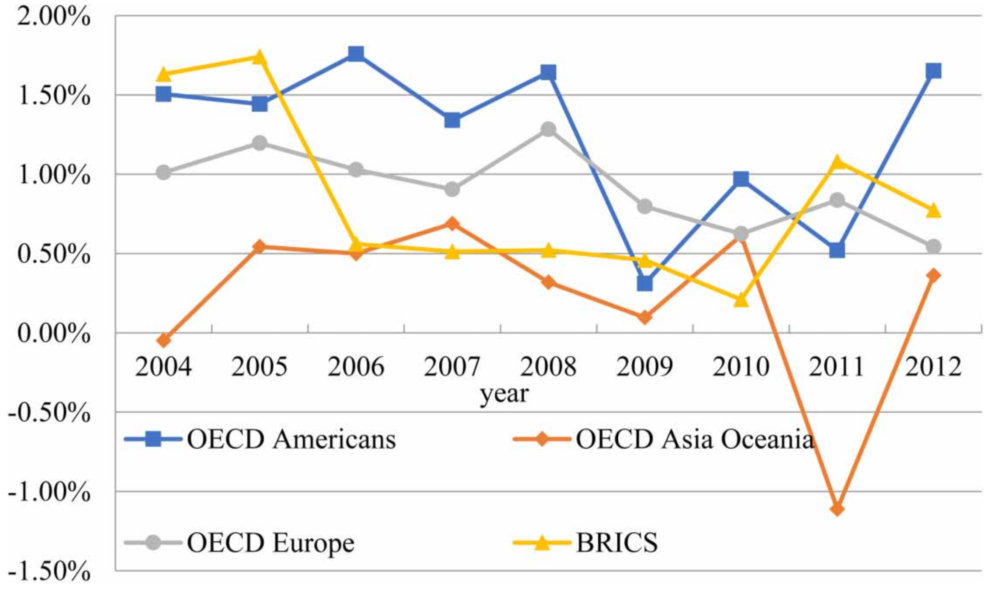

Figure 1 | The average annual growth rates of labor force during 2004–2012.

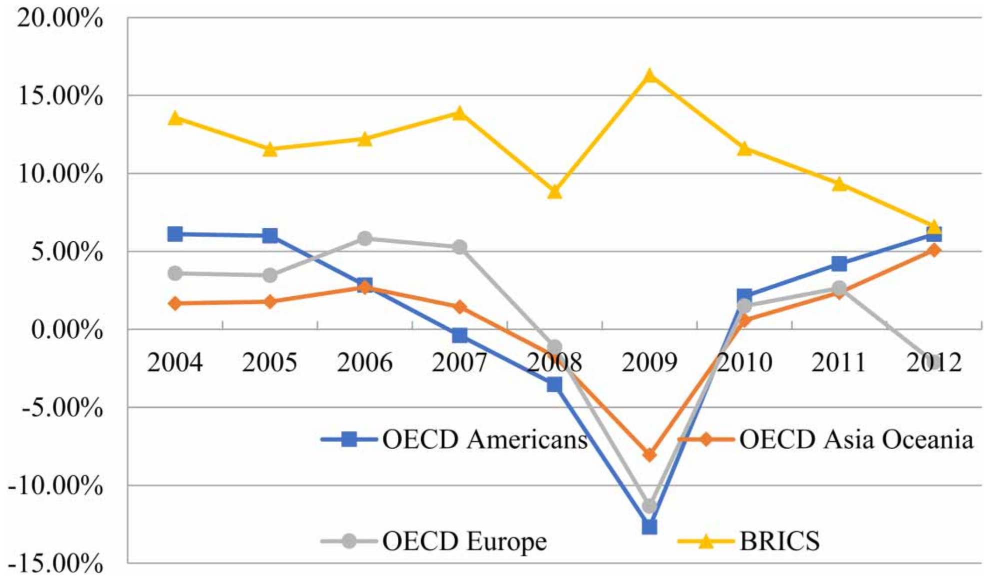

Figure 2 | The average annual growth rates of capital stock during 2004–2012.

increased by 13.85% in 2003. Figure 5 indicates the average annual growth rates of PM2.5. The results illustrate that OECD Americans' PM2.5 increased by 31.48% in 2006, while PM2.5 output decreased by –39.30% in 2007.

5. EMPIRICAL ANALYSIS

In this section, we use the Super-SBM model to measure the GTFP of OECD and BRICS countries from 2003 to 2012 and analyze the performance and development trend of GTFP in different countries.

The OECD and BRICS countries' GTFP are shown in Figure 6. According to Figure 6, the empirical results directly present the GTFP of each country from 2003 to 2012. On the whole, Brazil, Luxembourg, Norway, Japan, Italy and France's GTFP are higher than others, which are closely related to the economy, society, pollution emission and environmental protection.

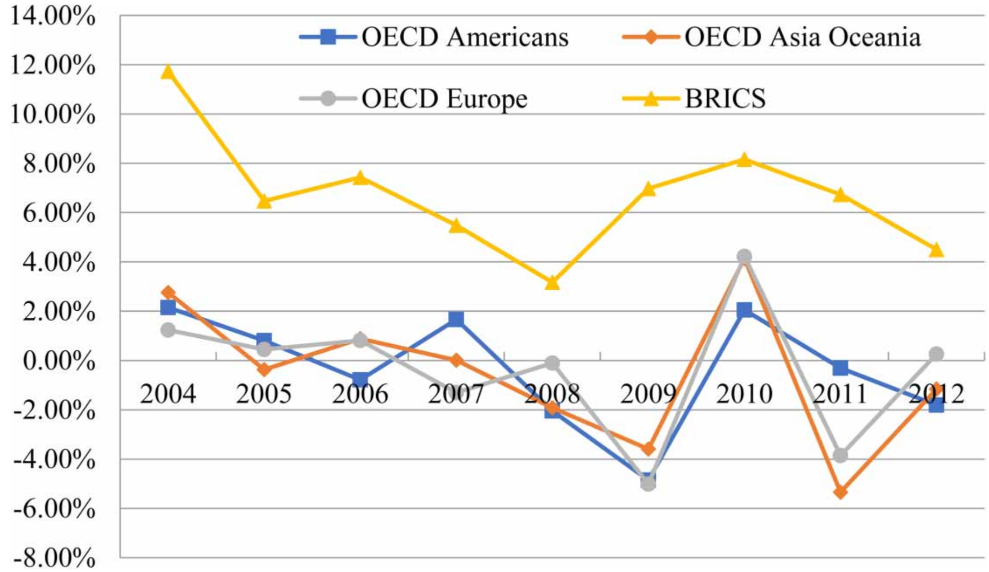

Figure 3 | The average annual growth rates of energy consumption during 2004–2012.

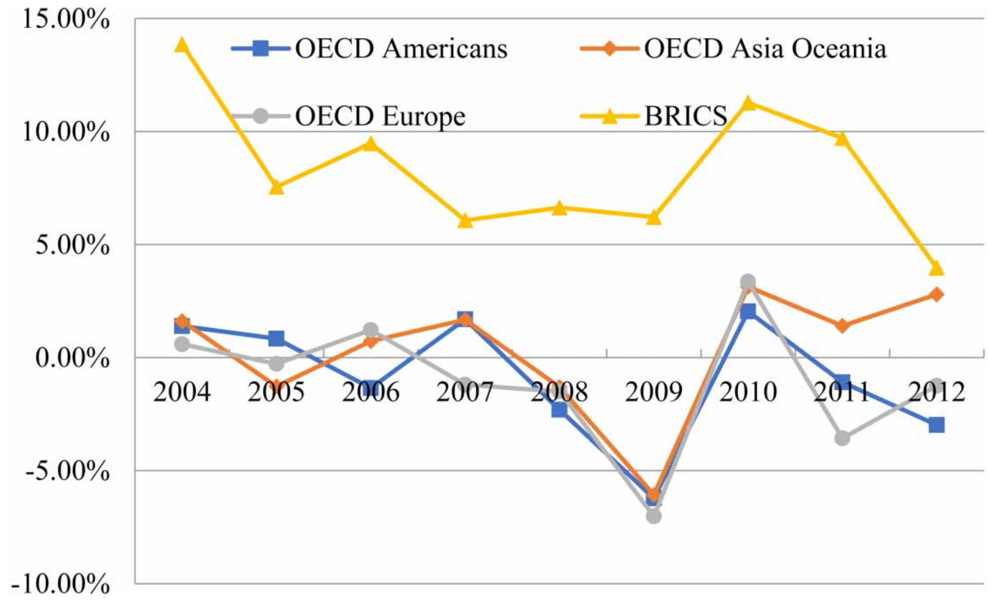

Figure 4 | The average annual growth rates of CO_2 emission during 2004–2012.

Among them, the maximum GTFP is 1.0846 in Luxembourg in 2010; the minimum value is 0.2092 in China in 2005. Further analysis of input–output factors reveals that China's energy consumption and carbon dioxide emissions achieve their highest point in 2012. Meanwhile, China's PM2.5 reached its maximum in 2010. The overall GTFP of BRICS ranges from 0.2092 to 1.0235. The average GTFP of BRICS during the period of 2003–2012 is 0.4642. Among the four countries, Brazil exhibits the highest value of GTFP, which is due to the restructuring of the energy sector and the improvement of renewable energy, and China has the minimum value of the GTFP, which was far ahead in energy consumption and PM2.5. In the analysis of the OECD countries, the GTFP in OECD countries ranges from 0.2891 to 1.0846, with Luxembourg as the country which had the highest average GTFP. The average GTFP of OECD during the period of 2003–2012 is 0.6557.

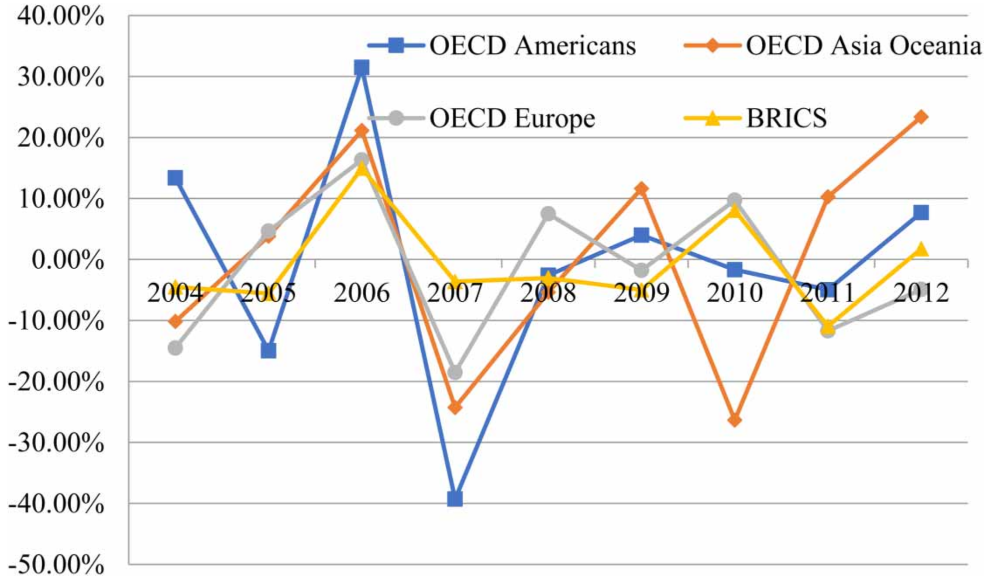

Figure 5 | The average annual growth rates of PM2.5 during 2004–2012.

GTFP is important progress in productivity research. GTFP is an important indicator to measure the coordination of resources and environmental and economic development. As described in Section 3, the Super-SBM model with undesirable outputs is used to measure the GTFP. We obtain the dynamic GTFP of the listed countries from 2003 to 2012. Table 3 shows the green TFP of the OECD of 30 countries in 2003 and 2012. As per the results illustrated in Table 2, we find that Canada has the highest GTFP, while Mexico exhibits the lowest value of 0.3632 in the OECD Americas in 2003. In 2012, the value of GTFP declined in Canada and the value in the United States ascended to the highest, whereas the value of Chile is found to be the worst, with the lowest value of 0.3106 for the OECD Americas. For the OECD Asia-Oceania, Israel has the highest value of 0.7556, while New Zealand has the lowest value of 0.2918 in 2003; Japan exhibits the highest GTFP, while New Zealand maintained the lowest value in 2012. For the OECD Europe, Norway revealed the highest value of 1.0147, while Hungary had the lowest value of 0.3162 in 2003; Greece exhibited the highest value, while Hungary was still the lowest in 2012. For BRICS countries, Brazil exhibits the highest value of 1.0043, while China has the lowest value of 0.2097 in 2003. In 2012, Brazil was still the highest and China was also still the lowest. This is consistent with the evidence that Brazil's energy consumption was only 254 million tons of oil equivalents, and China became the world's largest primary energy consumer economy in 2010. In general, Portugal has had the largest GTFP over the period.

We further compare GTFP between OECD and BRICS countries. Figure 7 shows the average annual growth rate of green TFP measured by Super-SBM with undesirable outputs during 2003–2012. As shown in Figure 7, the average annual growth rate of OECD remained around 0.6 from 2003 to 2009. Subsequently, the average annual growth rate rose to a peak of 0.86 in 2010. Then, the average annual growth rate dropped to 0.72 in 2011. Finally, the average annual growth rate of OECD slowly increased to 0.78 in 2012. In general, the average annual growth rate of OECD shows an encouragingly upward trend during 2003–2012. The average annual growth rate of BRICS slightly decreased during 2003–2009 and then rose rapidly to 0.6438 in 2010. In 2011, the average annual growth rate dropped to 0.4584. Then, there was a slight increase in 2012. Comparing the two curves, we find that the GTFP of OECD countries is significantly higher than that of BRICS countries.

This section reveals the changing trends and sub-sample differences between the OECD and BRICS countries, which provides insights into the evolution of the GTFP. Using the Super-SBM with the undesirable outputs, we calculate the average annual growth rate of green TFP of the sub-sample (OECD Americas, OECD Asia-Oceania, and OECD Europe) from 2003 to 2012. The changing trend of the average annual growth rate is shown in Figure 8.

As shown in Figure 8, the average annual growth rate of GTFP in OECD Asia-Oceania is higher than that in OECD Americas and OECD Europe from 2004 to 2006, while the average annual growth rate of GTFP in OECD Europe is much higher than that in Asia-Oceania and OECD Americas. Among them, the maximum value of OECD Europe reached 0.92. Analysis

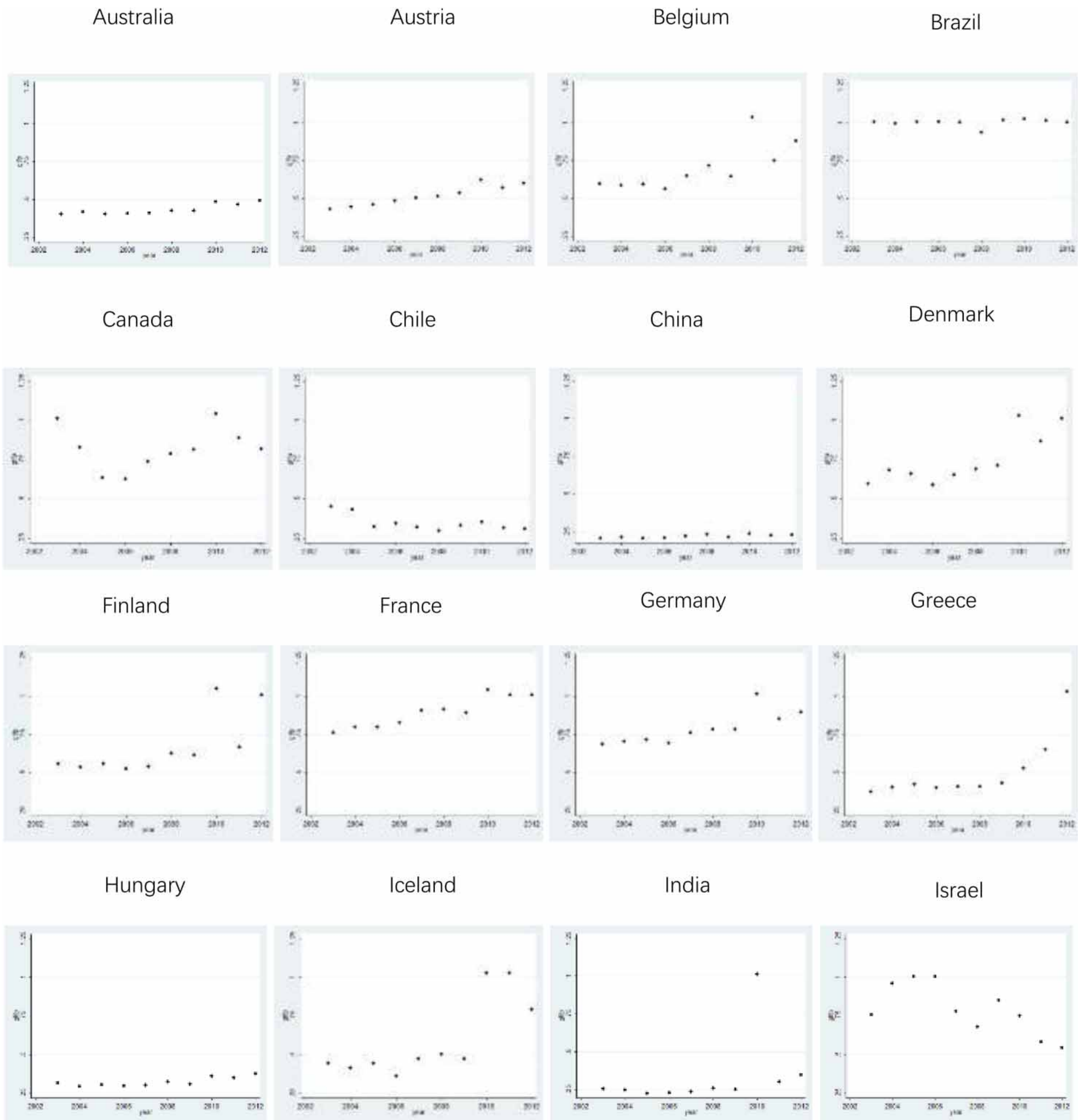

Figure 6 | Trends of GTFP in OECD and BRICS countries from 2003 to 2012. (*continued.*).

of input and output indicators of the sub-sample reveals that average energy consumption and carbon dioxide emissions are the lowest in OECD Americas. Average energy consumption is the highest in OECD Asia-Oceania.

The results also indicate that the average annual growth rate of the OECD displays an increasing trend because the OECD Europe has made a greater contribution. From these four curves, the GTFP of BRICS countries was still at the lowest level. The OECD countries also exhibit the highest value which may be the result of mechanisms by the government to reduce pollution emissions in OECD countries.

Comparing the GTFP of BRICS countries with OECD countries, we find that the OECD countries' GTFP is higher than BRICS countries as a whole, which may be the result of mechanisms by the government to reduce pollution emissions in

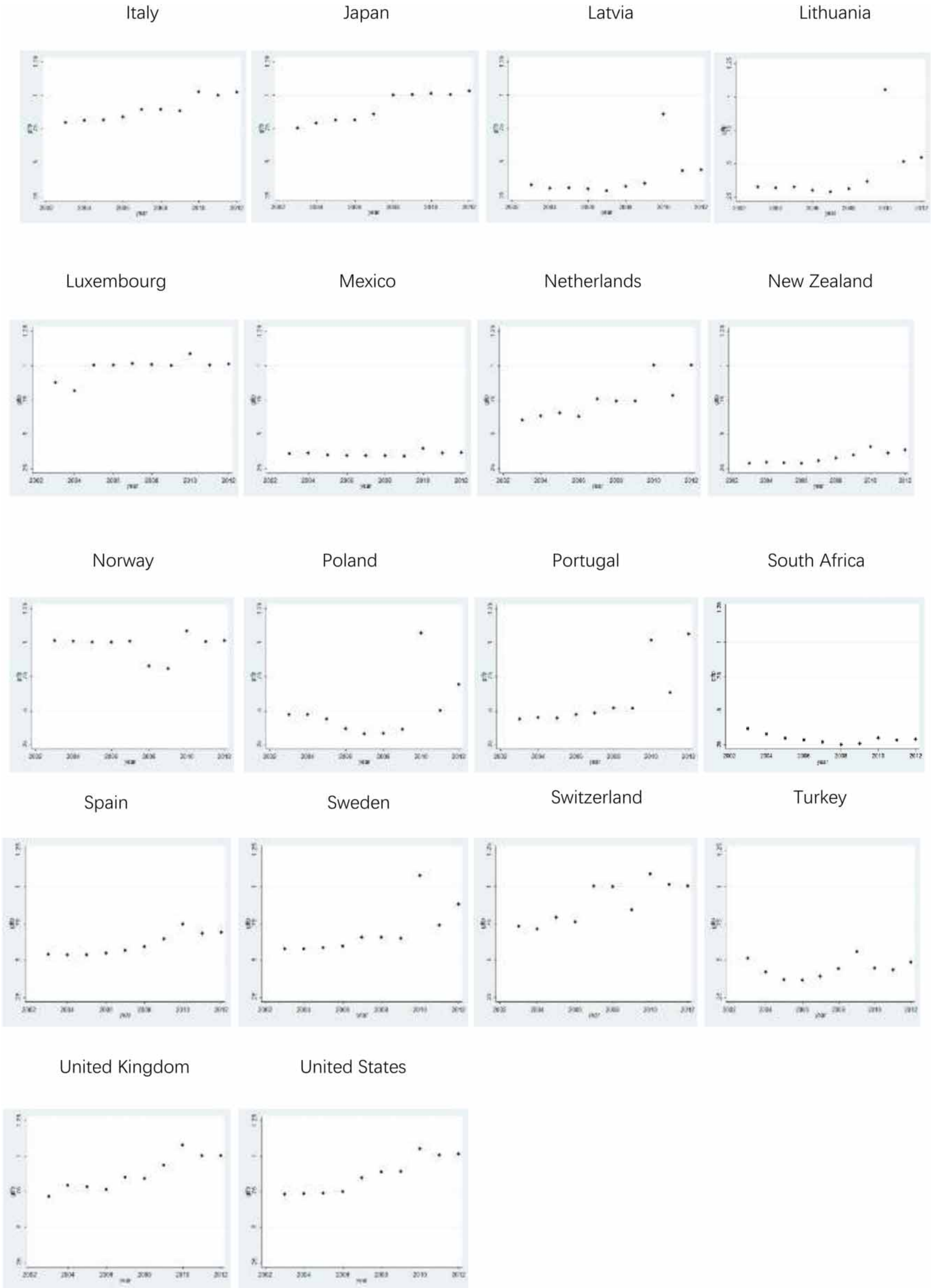

Figure 6 | Continued.

Table 3 | The green TFP of OECD and BRICS countries in 2003 and 2012

Country	2003	Country	2003	Country	2012	Country	2012
OECD Americas							
Canada	1.0111	Mexico	0.3632	Canada	0.8145	Mexico	0.3684
Chile	0.4495	United States	0.7319	Chile	0.3106	United States	1.0131
OECD Asia-Oceania							
Australia	0.4042	Israel	0.7556	Australia	0.4940	Israel	0.5429
Japan	0.7519	New Zealand	0.2918	Japan	1.0301	New Zealand	0.3876
OECD Europe							
Netherlands	0.6035	Latvia	0.3322	Netherlands	1.0033	Latvia	0.4435
Austria	0.4291	Lithuania	0.3237	Austria	0.6002	Lithuania	0.5430
Belgium	0.5952	Luxembourg	0.8762	Belgium	0.8780	Luxembourg	1.0095
Denmark	0.5961	Turkey	0.5142	Denmark	1.0100	Turkey	0.4900
Finland	0.5581	Norway	1.0147	Finland	1.0069	Norway	1.0138
France	0.7618	Poland	0.4721	France	1.0070	Poland	0.6951
Germany	0.6861	Portugal	0.4415	Germany	0.8958	Portugal	1.0622
Greece	0.3756	Spain	0.5400	Greece	1.0294	Spain	0.6912
Hungary	0.3162	Sweden	0.5777	Hungary	0.3773	Sweden	0.8793
Iceland	0.4431	Switzerland	0.7292	Iceland	0.7905	Switzerland	1.0038
Italy	0.7960	United Kingdom	0.7140	Italy	1.0221	United Kingdom	1.0019
BRICS							
South Africa	0.3688	China	0.2097	South Africa	0.2913	China	0.2338
India	0.2597	Brazil	1.0043	India	0.3498	Brazil	1.0028

OECD countries. Thus, based on the results indicated, benchmark countries can be identified in terms of GTFP, so that Brazil and OECD Europe can serve as good references for sustainable development. Other countries should pay more attention to improving environmental protection in order to reduce energy consumption without damaging economic growth. Therefore,

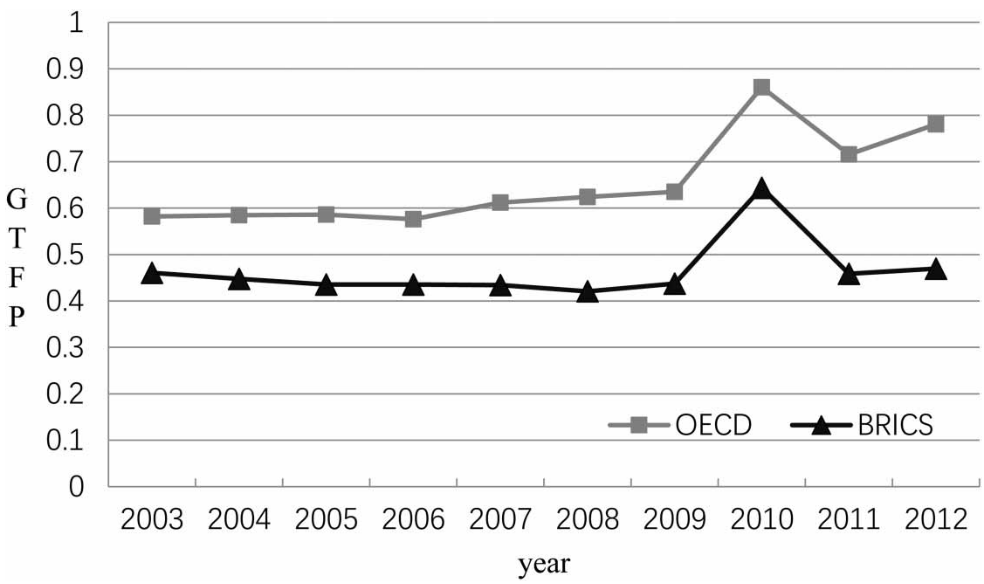

Figure 7 | The average annual growth rate of TFP during 2003–2012.

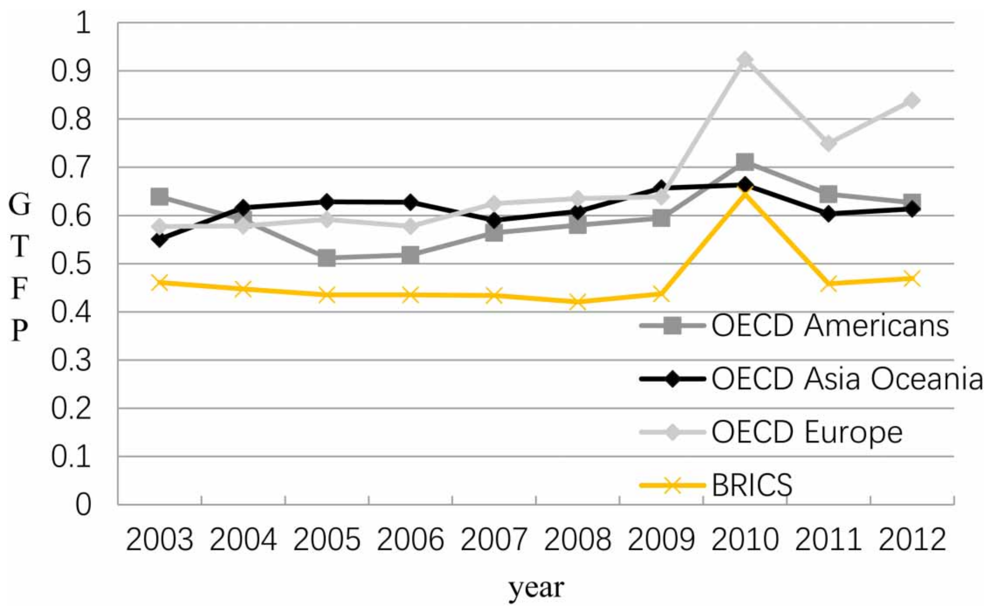

Figure 8 | The average annual growth rate of GTFP in sub-sample during 2003–2012.

in these countries, it is possible to guide government resources and focus on policy incentives to implement measures to reduce pollution emissions.

6. MORE DISCUSSIONS: COMPARATIVE ANALYSIS

In this part, we discuss the comparison between our empirical results and other similar results. Zhang *et al.* (2019) calculated the GTFP, technical change (TC) and technical efficiency change (TEC) of 33 countries along the Belt and Road. The average annual growth rate of GTFP in 33 countries along the Belt and Road is 1.4%. Among them, GTFP showed a negative growth trend in 1995, 1997, 2001 and 2009. Baležentis *et al.* (2021) calculated the total environmental factor productivity of the agricultural sector in European countries and found that there was a trend of convergence in the total environmental factor productivity of various countries. Ates & Derinkuyu (2021) discussed the green growth performance of OECD countries and found that Sweden, Luxembourg, Norway and Denmark had a better green performance. Although some studies discussed the green growth performance or GTFP of OECD countries and countries along the Belt and Road, they have not clearly evaluated and compared the GTFP of OECD and BRICS countries. Developing countries and countries with economies in transition are likely to suffer from statistical noise and economic instability. Therefore, we use the comparison of GTFP between OECD and BRICS countries to provide a reference for the green strategies of developing and developed countries.

7. CONCLUSIONS

In the context of global attention to environmental issues, the purpose of this paper is to explore the GTFP of OECD and BRICS countries, as well as the spatial distribution and dynamic changes after eliminating external influences, so as to fill the gap in the existing literature that only adopts the DEA model and considers the research of green environmental performance and find a sustainable development path to balance the environment and economy. Therefore, this study adopts the Super-SBM model to evaluate the actual GTFP of OECD and BRICS countries in combination with the unexpected output.

The main conclusions of this research draw as follows: There are differences in GTFP between OECD and BRICS countries. The GTFP of BRICS countries has significantly improved, but there is still a significant gap compared with OECD countries. From the results of GTFP calculated directly by the Super-SBM model with undesirable outputs, the overall GTFP of BRICS is on the low side, which ranges from 0.2092 to 1.0235. The average GTFP of BRICS during the period of 2003–2012 is 0.4642. Among the four countries, Brazil exhibits the highest value of GTFP, which is due to the restructuring of the energy sector and the improvement of renewable energy; China has the minimum value of GTFP, which was far ahead in energy consumption. In addition, to better analyze the results of the GTFP, an analysis of the slacks of inputs and outputs was performed. The results show that variables of carbon dioxide emissions and energy consumption are the highest on average in China. Average carbon dioxide emissions are the lowest in Brazil. Although BRICS countries have a significant growth trend in 2010 compared to the value during 2003–2009, which shows the achievements and efforts of government in environmental protection, there is still much room for improvement. This result may indicate that BRICS countries need to invest more in renewable energy and improve the GTFP, such as more efficient technologies or processes to reduce pollution emissions.

Overall, the GTFP of OECD countries is higher than that of BRICS countries. In the analysis of OECD countries, GTFP in OECD countries ranges from 0.2891 to 1.0846, with Luxembourg as the country which had the highest average GTFP. The average GTFP of OECD during the period of 2003–2012 is 0.6557. The empirical results also illustrate that Hungary exhibits the lowest average GTFP. In addition, we analyze the slacks of inputs and outputs to better understand the results of the GTFP. The empirical results indicate that average energy consumption and carbon dioxide emissions are the lowest in OECD Americas. Average energy consumption is the highest in OECD Asia-Oceania.

According to the above research conclusions, the following policy recommendations are put forward. The OECD countries have strong economic strength and technological advantages and have the ability and advantages to effectively repair the atmosphere and treat environmental problems. OECD should actively assume its due green responsibility, provide financial support for technological development conducive to environmental protection, build a green economic development measurement system and contribute the wisdom of developed countries to promote green sustainable development. The BRICS countries should carry out information exchange and cooperation in the fields of clean energy, low-carbon technology, sustainable and resilient infrastructure construction, carbon market, adaptation to climate change, jointly promote green and low-carbon development policy research, technical cooperation and demonstration projects, promote the transformation and upgrading of energy resources, industrial structure and consumption structure driven by scientific and technological innovation, and jointly explore a low-carbon, green and sustainable development path. Through the sharing, exchange, promotion and application of green technology in BRICS countries, we will contribute ecological and environmental protection solutions to developing countries and even countries around the world.

Finally, it is worth noting that our research has certain limitations: (1) due to the lack of data, the estimation of GTFP in this study only considers CO_2 and PM2.5 emissions and does not comprehensively consider other unexpected outputs. (2) Considering the limitations of variable acquisition, this study did not further explore the influencing factors of GTFP, which is a blank to be filled in future research.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Ahmed, E. M. 2012 Green TFP intensity impact on sustainable East Asian productivity growth. *Econ. Anal. Policy* **42** (1), 67–78.

Ates, S. A. & Derinkuyu, K. 2021 Green growth and OECD countries: measurement of country performances through distance-based analysis (DBA). *Environ. Dev. Sustainable* **23** (10), 15062–15073.

Baležentis, T., Blancard, S., Shen, Z. & Streimikiene, D. 2021 Analysis of environmental total factor productivity evolution in European agricultural sector. *Decis. Sci.* **52** (2), 483–511.

Camioto, F., Moralles, H. F., Mariano, E. B. & Rebelatto, D. 2016 Energy efficiency analysis of G7 and BRICS considering total-factor structure. *J. Cleaner Prod.* **122**, 67–77.

Chang, M. C. 2015 Room for improvement in low carbon economies of G7 and BRICS countries based on the analysis of energy efficiency and environmental Kuznets curves. *J. Cleaner Prod.* **99**, 140–151.

Chen, S. & Golley, J. 2014 'Green' productivity growth in China's industrial economy. *Energy Econ.* **44**, 89–98.
Chen, P. C., Ming-Miin, Y. U., Chang, C. C. & Shih-Hsun, H. S. U. 2008 Total factor productivity growth in China's agricultural sector. *China Econ. Rev.* **19** (4), 580–593.
Chen, J., Wu, Y., Song, M. & Zhu, Z. 2017 Stochastic frontier analysis of productive efficiency in China's forestry industry. *J. For Econ.* **28**, 87–95.
Chen, L., Zhang, X., He, F. & Yuan, R. 2019 Regional green development level and its spatial relationship under the constraints of haze in China. *J. Cleaner Prod.* **210**, 376–387.
Chen, Y., Miao, J. & Zhu, Z. 2021 Measuring green total factor productivity of China's agricultural sector: a three-stage SBM-DEA model with non-point source pollution and CO_2 emissions. *J. Cleaner Prod.* **318**, 128543.
Chung, Y. H. H., Färe, R. & Grosskopf, S. 1997 Productivity and undesirable outputs: a directional distance function approach. *Microecon* **51** (3), 229–240.
Coelli, T. J. & Rao, D. S. P. 2005 Total factor productivity growth in agriculture: a Malmquist index analysis of 93 countries,1980–2000. *Agric. Econ.* **32**, 115–134.
Dai, Z., Guo, L. & Jiang, Z. 2016 Study on the industrial Eco-Efficiency in East China based on the super efficiency DEA model: an example of the 2003–2013 panel data. *Appl. Econ.* **48** (59), 5779–5785.
El Kasri, J., Lahmili, A., Soussi, H., Jaouda, I. & Bentaher, M. 2021 Trend analysis of meteorological variables: rainfall and temperature. *Civ. Eng. J.* **7** (11), 1868–1879.
Emrouznejad, A. & Yang, G. L. 2017 A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio Econ. Plann. Sci.* **61**, 4–8.
Färe, R., Grosskopf, S., Norris, M. & Zhang, Z. 1994 Productivity growth, technical progress, and efficiency change in industrialized countries. *Am. Econ. Rev.* **84** (5), 1040–1044.
Feng, C., Zhang, H. & Huang, J. B. 2017 The approach to realizing the potential of emissions reduction in China: an implication from data envelopment analysis. *Renew. Sustain. Energy Rev.* **71**, 859–872.
Feng, C., Huang, J. B. & Wang, M. 2018 Analysis of green total-factor productivity in China's regional metal industry: a meta-frontier approach. *Resour. Policy* **58**, 219–229.
Golmohammadi, S. & Fazelabdolabadi, B. 2021 COVID-19: a game-changer to equity markets? *J. Hum. Earth Future* **2** (1), 46–81.
Hailu, A. & Veeman, T. S. 2001 Non-parametric productivity analysis with undesirable outputs: an application to the Canadian pulp and paper industry. *Am. J. Agric. Econ.* **83** (3), 605–616.
Hang, N. P. T. 2022 Policy implications for the green bank development in the context of global climate change. *Emerg. Sci. J.* **6** (4), 817–833.
Hoang, V. N. & Coelli, T. 2011 Measurement of agricultural total factor productivity growth incorporating environmental factors: a nutrients balance approach. *J. Environ. Econ. Manage.* **62** (3), 462–474.
Khoshnevisan, B., Rafiee, S., Omid, M. & Mousazadeh, H. 2013 Reduction of CO_2 emission by improving energy use efficiency of greenhouse cucumber production using DEA approach. *Energy* **55** (1), 676–682.
Kumar, S. 2006 Environmentally sensitive productivity growth: a global analysis using Malmquist- Luenberger index. *Ecol. Econ.* **56**, 280–293.
Lee, C. C. & Lee, C. C. 2022 How does green finance affect green total factor productivity? Evidence from China. *Energy Econ.* **107**, 105863.
Lee, C. C., Zeng, M. & Wang, C. 2022 Environmental regulation, innovation capability, and green total factor productivity: new evidence from China. *Environ. Sci. Pollut. Res.* **29** (26), 39384–39399.
Li, Y. & Chen, Y. 2021 Development of an SBM-ML model for the measurement of green total factor productivity: the case of pearl river delta urban agglomeration. *Renew. Sustain. Energy Rev.* **145**, 111131.
Li, K. & Lin, B. 2015 Measuring green productivity growth of Chinese industrial sectors during 1998–2011. *China Econ. Rev.* **36**, 279–295.
Li, K. & Lin, B. 2016 Impact of energy conservation policies on the green productivity in China's manufacturing sector: evidence from a three-stage DEA model. *Appl. Energy* **168**, 351–363.
Li, B. & Wu, S. 2017 Effects of local and civil environmental regulation on green total factor productivity in China: a spatial Durbin econometric analysis. *J. Cleaner Prod.* **153**, 342–353.
Li, H., Fang, K., Yang, W., Wang, D. & Hong, X. 2013 Regional environmental efficiency evaluation in China: analysis based on the Super-SBM model with undesirable outputs. *Math. Comput. Modell.* **58**, 1018–1031.
Lin, B. & Long, H. 2015 A stochastic frontier analysis of energy efficiency of China's chemical industry. *J. Cleaner Prod.* **87**, 235–244.
Liu, D., Zhu, X. & Wang, Y. 2021 China's agricultural green total factor productivity based on carbon emission: an analysis of evolution trend and influencing factors. *J. Cleaner Prod.* **278** (123692), 1–12.
Lu, C. C., Chiu, Y. H., Shyu, M. K. & Lee, J. H. 2013 Measuring CO_2 emission efficiency in OECD countries: application of the hybrid efficiency model. *Econ. Modell.* **32**, 130–135.
Mahlberg, B. & Sahoo, B. K. 2011 Radial and non-radial decompositions of Luenberger productivity indicator with an illustrative application. *Int. J. Prod. Econ.* **131** (2), 721–726.
Mahlberg, B., Luptacik, M. & Sahoo, B. K. 2011 Examining the drivers of total factor productivity change with an illustrative example of 14 EU countries. *Ecol. Econ.* **72**, 60–69.
Mao, J., Wu, Q., Zhu, M. & Lu, C. 2022 Effects of environmental regulation on green total factor productivity: an evidence from the Yellow River Basin, China. *Sustainability* **14** (4), 2015.

Mehmood, R. & Lal, I. 2021 Human capital, urbanization and dynamics of economic growth and development. *Urban. Dyn. Econ. Growth Dev.* **4** (2), 382–394.

Mohsin, M., Hanif, I., Taghizadeh-Hesary, F., Abbas, Q. & Iqbal, W. 2021 Nexus between energy efficiency and electricity reforms: a DEA-based way forward for clean power development. *Energy Policy* **149**, 112052.

Nawaz, M. A., Hussain, M. S., Kamran, H. W., Ehsanullah, S., Maheen, R. & Shair, F. 2021 Trilemma association of energy consumption, carbon emission, and economic growth of BRICS and OECD regions: quantile regression estimation. *Environ. Sci. Pollut. R* **28** (13), 16014–16028.

Okeke, F. O., Eziyi, I. O., Udeh, C. A. & Ezema, E. 2020 City as habitat: assembling the fragile city. *Civ. Eng. J.* **6** (6), 1143–1154.

Ouyang, X., Chen, J. & Du, K. 2021 Energy efficiency performance of the industrial sector: from the perspective of technological gap in different regions in China. *Energy* **214**, 118865.

Qerimi, D., Dimitrieska, C., Vasilevska, S. & Rrecaj, A. A. 2020 Modeling of the solar thermal energy use in urban areas. *Civ. Eng. J.* **6** (7), 1349–1367.

Song, M., An, Q., Zhang, W., Wang, Z. & Wu, J. 2012 Environmental efficiency evaluation based on data envelopment analysis: a review. *Renew. Sustain. Energy Rev.* **16** (7), 4465–4469.

Song, M., Zhang, L., An, Q., Wang, Z. & Li, Z. 2013 Statistical analysis and combination forecasting of environmental efficiency and its influential factors since China entered the WTO: 2002–2010–2012. *J. Cleaner Prod.* **42**, 42–51.

Tao, F., Zhang, H., Hu, Y. & Duncan, A. A. 2017 Growth of green total factor productivity and its determinants of cities in China: a spatial econometric approach. *Emerg. Mark Financ. Tr.* **53**, 2123–2140.

Tone, K. 2001 A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **130** (3), 498–509.

Tone, K. & Sahoo, B. K. 2003 Scale, indivisibilities and production function in data envelopment analysis. *Int. J. Prod. Econ.* **84** (2), 165–192.

Wang, K., Wei, Y.-M. & Huang, Z. 2018 Environmental efficiency and abatement efficiency measurements of China's thermal power industry: a data envelopment analysis based materials balance approach. *Eur. J. Oper. Res.* **269** (1), 35–50.

Wang, K. L., Pang, S. Q., Ding, L. L. & Miao, Z. 2020 Combining the biennial Malmquist–Luenberger index and panel quantile regression to analyze the green total factor productivity of the industrial sector in China. *Sci. Total Environ.* **739**, 140280.

Wang, H., Cui, H. & Zhao, Q. 2021 Effect of green technology innovation on green total factor productivity in China: evidence from spatial Durbin model analysis. *J. Cleaner Prod.* **288**, 125624.

Woo, C., Chung, Y., Chun, D., Seo, H. & Hong, S. 2015 The static and dynamic environmental efficiency of renewable energy: a Malmquist index analysis of OECD countries. *Renewable Sustainable Energy Rev.* **47**, 367–376.

Xia, F. & Xu, J. 2020 Green total factor productivity: a re-examination of quality of growth for provinces in China. *China Econ. Rev.* **62**, 101454.

Xie, B. C., Shang, L. F., Yang, S. B. & Yi, B. W. 2014 Dynamic environmental efficiency evaluation of electric power industries: evidence from OECD (Organization for economic cooperation and development) and BRIC (Brazil, Russia, India and China) countries. *Energy* **74**, 147–157.

Yaisawarng, S. & Klein, J. D. 1994 The effects of sulfur dioxide controls on productivity change in the U.S. electric power industry. *Rev. Econ. Stat.* **76** (3), 447–460.

You, J. & Xiao, H. 2022 Can FDI facilitate green total factor productivity in China? Evidence from regional diversity. *Environ. Sci. Pollut. Res.* **29**, 49309–49321.

Zhang, C., Liu, H., Bressers H, T. A. & Buchanan, K. S. 2011 Productivity growth and environmental regulations – accounting for undesirable outputs: analysis of Chinas thirty provincial regions using the Malmquist–Luenberger index. *Ecol. Econ.* **70** (12), 2369–2379.

Zhang, J., Zeng, W., Wang, J., Yang, F. & Jiang, H. 2017 Regional low-carbon economy efficiency in China: analysis based on the Super-SBM model with CO_2 emissions. *J. Cleaner Prod.* **163**, 202–211.

Zhang, Q., Yan, F., Li, K. & Ai, H. 2019 Impact of market misallocations on green TFP: evidence from countries along the Belt and Road. *Environ. Sci. Pollut. Res.* **26** (34), 35034–35048.

Zhang, J., Lu, G. & Skitmore, M. & Ballesteros-Pérez, P. 2021 A critical review of the current research mainstreams and the influencing factors of green total factor productivity. *Environ. Sci. Pollut. Res.* **28** (27), 35392–35405.

Zhou, P., Ang, B. W. & Poh, K. L. 2006 Slacks-based efficiency measures for modeling environmental performance. *Ecol. Econ.* **60** (1), 111–118.

Zhou, P., Ang, B. W. & Zhou, D. Q. 2012 Measuring economy-wide energy efficiency performance: a parametric frontier approach. *Appl. Energy* **90** (1), 196–200.

Zhu, X., Chen, Y. & Feng, C. 2018 Green total factor productivity of China's mining and quarrying industry: a global data envelopment analysis. *Resour. Policy* **57**, 1–9.

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