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Determinants of global green growth efficiency and productivity: a comprehensive three stages data envelopment analysis

Thanh Ngo[1,2] · Tu Le[3,4] · Hai Hong Trinh[5] · Aviral Kumar Tiwari[6]

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Abstract

This is the first study on green growth (GG) efficiency from a global perspective (115 countries from 1996 to 2018) that considers natural depletions, alongside CO_2 emissions, as undesirable outputs of the GG efficiency estimation in the first stage. More importantly, by examining different ways to treat those undesirable outputs and in combination with the double bootstrap slack-based measure data envelopment analysis approach in the second stage, we found that the models that use the reciprocal values of the undesirable outputs have higher explanatory power than the others. Consequently, in the third stage, we examine the GG efficiency and productivity change over time of the sampled countries using the model with reciprocal values. The study finds that countries with better governance quality, among other factors, can positively improve their green growth efficiency.

Keywords Green growth · Efficiency · Data envelopment analysis · Undesirable outputs · Cross-country · Determinant

JEL Classification O11 · O44 · O57 · Q01

Thanh Ngo
T.Ngo@massey.ac.nz

[1] School of Aviation, Massey University, Palmerston North, New Zealand

[2] VNU University of Economics & Business, Hanoi, Vietnam

[3] Faculty of Finance & Banking, University of Economics and Law, Ho Chi Minh City, Vietnam

[4] Vietnam National University, Ho Chi Minh City, Vietnam

[5] College of Business and Management, VinUniversity, Hanoi, Vietnam

[6] Indian Institute of Management Bodh Gaya (IIM Bodh Gaya), Gaya, Bihar, India

1 Introduction

The issues of green economy and green growth (GG) can be traced back to the 1980 s; however, they have received much consideration and policy attention after the global financial crisis of 2008 (e.g. Loiseau et al., 2016; Merino-Saum et al., 2020; OECD, 2011a, 2011b; OECD, 2012; UNEP, 2011a, 2011b; Zoboli et al., 2014). Since a green economy can be defined as one that can improve "well-being and social equity, while significantly reducing environmental risks and ecological scarcities" (UNEP, 2011b, p. 2), GG can be accordingly defined as the process of "fostering economic growth and development while ensuring that natural assets continue to provide the resources and environmental services on which our well-being relies" (OECD, 2011b, p. 9). Consequently, there is a rich body of literature on different aspects of GG, including its indicators (Barbier, 2011; Casadio Tarabusi & Guarini, 2018; Kim et al., 2014; Puppim de Oliveira et al., 2013), its determinants (Capasso et al., 2019; Ngo et al., 2022; Samad & Manzoor, 2015; Yao et al., 2025), as well as policy recommendations and implementation paths (Gu et al., 2018; Guo et al., 2018; Wei et al., 2025).

From an economic point of view, while it is important to examine the factors that can influence the GG of a country, e.g., higher economic growth tends to be associated with higher GG (Tawiah et al., 2021), it would also be important to assess if that country is efficient in terms of using its resources to achieve a certain level of GG, i.e., GG efficiency. It is argued that the improvement of (green) innovation capabilities, with an emphasis on improving efficiency, is important for GG. In this sense, GG efficiency focuses on the efficient use of resources in achieving coordinated development of the social economy (Ma et al., 2019). It is noted that efficiency is well-examined in topics such as agriculture, banking, and aviation (Hammami et al., 2022; Ngo & Tripe, 2017; Ngo & Tsui, 2021; Seiford & Zhu, 2002) using the two most popular tools of data envelopment analysis (DEA) and stochastic frontier analysis (SFA), the former is a non-parametric and the latter is a parametric approach. Both approaches have their pros and cons; however, DEA tends to be more flexible with small samples and with complex settings where multiple outputs are involved (Boubaker et al., 2025; Nguyen et al., 2019). However, studies on GG efficiency appear to be more recent and mostly focused on Chinese cities and regions (Guo et al., 2018; Ma et al., 2019; Pan et al., 2019; Wang, Li, et al., 2021; Wang, Wang, et al., 2021; Wu et al., 2020; Yang & Hu, 2010; Zhao et al., 2020). Exceptions include a study on 26 OECD countries (Zhou et al., 2007), a study on the Japanese industrial sector (Sueyoshi & Goto, 2014), and another study on 116 Italian provincial capital cities (Lo Storto, 2016). While the latter two are country-specific studies, the former is an examination at a cross-country level of the OECD. Given that OECD members are advanced economies and many of them would be similarly evaluated as efficient, the study of Zhou et al. (2007) faced difficulty to further compare those efficient countries and thus, the discrimination as well as explanation power of this study was limited.[1] Therefore, there is a lack of comprehensive GG efficiency study at cross-country or even global perspectives.

It is noted that GG efficiency represents how efficient an economic production system is in achieving more economic outputs and less environmental costs, in a condition of

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[1] Zhou et al. (2007) also use a non-radial DEA model in their analysis. Although it helps improve the discriminatory power of their analysis, the obvious differences between the efficiency scores of the two models (e.g. the radial and non-radial efficiency of Australia in 1995 are 1.000 and 0.075, respectively) raise another question about the reliability and accuracy of their study.

stable input of productive factors or even with less inputs, which synthetically considers the restrain imposed by limited resources and pollution to environment (Baranova et al., 2025; Yang & Hu, 2010). Accordingly, studies on GG efficiency often use labour, capital, energy, and technology as inputs whilst economic development (e.g. GDP or GDP growth), green innovations/patents, and environmental pollutions are considered as outputs (Pan et al., 2019; Wu et al., 2020). Since it involves multiple outputs, DEA is the common tool for most of those studies (Wang, Li, et al., 2021; Zhao et al., 2020). It is also noted that while economic development and green innovations are desirable outputs (i.e., the higher they are the better for the economy), pollutions such as CO_2 and greenhouse gas emissions are undesirable ones (i.e., the fewer the better). As such, the study's objectives are (i) to measure the global GG efficiency and productivity considering natural depletions and CO_2 emissions, and (ii) to identify the best way to account for those depletions and emissions. Accordingly, we ask the following research questions. What is the level of global GG efficiency and productivity, given the economic-environment trade-off situation? How, and what would be the best way to account for such trade-offs? To answer these questions, we examine the efficiency and productivity of 115 countries in using their inputs to produce (more) desirable GG outputs and (less) undesirable GG outputs, including pollution and natural depletions, for the period of 1996–2018. By considering different approaches to treat the undesirable outputs in the estimation of GG efficiency/productivity, and by examining their explanatory power using a double-bootstrap technique, it is the first study to identify the best GG efficiency measurement for the empirical analysis.

In recent years, there are several ways to deal with those undesirable outputs (Halkos & Petrou, 2019), with the two most popular are to treat them as inputs or to use their reciprocal as desirable outputs (Liu et al., 2010; Seiford & Zhu, 2002). You and Yan (2011) proposed a ratio model to treat the desirable and undesirable outputs simultaneously. In this paper, we therefore employ all those three approaches to see which one provide a better explanatory power for the empirical analysis. Since the directional distance function is argued to be more efficient in dealing with undesirable variables (Chung et al., 1997; Färe & Grosskopf, 2004) because it allows for simultaneous increase in desirable and decrease in undesirable outputs (Andersson et al., 2014; Halkos & Petrou, 2019), we also employ the slack-based measure (SBM) of (Tone, 2001) in our DEA estimations.

Most of the studies above, therefore, implicitly argued that GG could be measured by capturing the desirable economic development (e.g., GDP growth) and the undesirable environmental pollutions (e.g., CO_2). One may notice that it is a simplified definition of GG, as it does not consider the role that natural resources play in this setting. Sohag et al. (2019) and Ahmed et al. (2021), among others, proposed that the depletion of natural resources should also be accounted for in GG. Following Ngo et al. (2022), therefore, we also consider minerals (including crude oil, coal, and natural gas) depletion and forest depletion as additional undesirable outputs of GG (efficiency). This is the fourth approach to estimate GG efficiency – more details on those approaches are presented in the next section.

Such approaches lead to an important question of how to choose the best GG efficiency measurement. We argue that the chosen measurement should be the one having the best, or at least higher, explanatory power in the analysis. We, therefore, investigate the key determinants (e.g., financial development, population, and government effectiveness) of those GG efficiency in the second stage, employing the double-bootstrap truncated regression technique (Algorithm 2, Simar & Wilson, 2007). This technique has been popularly applied in the DEA literature (e.g., Le et al., 2022; Lee et al., 2021; Ngo & Le, 2022; Wu et al., 2025; Yu et al., 2021) because it helps incorporate those explanatory variables directly into the re-sampling and re-estimation of the GG efficiency. Consequently, it can correct the bias arising from the potential correlations between those determinants and the input/output variables used in the GG efficiency estimation. Once this best measurement of GG efficiency is identified, we continue to examine the GG productivity changes over time using the DEA-Malmquist index approach (Cao et al., 2020; Chen et al., 2025; Kerstens & Woestyne, 2014; Wang, Wang, & Wu, 2024) to have a more detailed understanding of the matter.

In this sense, the contribution of the paper is threefold. Firstly, it is the first study on GG efficiency and productivity from a global perspective using national-level data; previous studies focused more on regions/cities within a country or using firm-level data (Ma et al., 2019; Mohy-ud-Din et al., 2025; Pan et al., 2019; Wang, Wang, et al., 2021; Ye et al., 2025). Secondly, it explores different approaches to treat the undesirable outputs in the DEA literature and uses a double-bootstrap technique in identifying the best approach to empirically measure GG efficiency and productivity. Although there are a few attempts to review the pros and cons of those treatments (Halkos & Petrou, 2019; Liu et al., 2010), it is the first time a comprehensive empirical examination was conducted. And thirdly, the study also provides new evidence on the development of GG efficiency and productivity changes over time.

The rest of the paper is constructed as follows. The next section describes the method used in this study (e.g., double bootstrap DEA), the choices of its inputs and outputs, the choices of the explanatory variables, as well as the description of our data. Section 3 presents the empirical results as well as the relevant discussions. Section 4 then concludes the study.

2 Methodologies

2.1 The first stage: Estimation of GG efficiency and productivity using DEA

The literature suggests that the efficiency of a firm can be measured by using either a non-parametric (e.g., DEA) or parametric approach (e.g., SFA). As discussed previously, DEA is more suitable for this study since it can handle the multiple inputs/outputs setting and the undesirable outputs problem (Wang, Wang, & Wu, 2024; Yu et al., 2021; Zhao et al., 2020). Consider a sample of countries or economies in which the j^{th} country uses inputs X_{ij} to produce outputs Y_{rj}, its GG efficiency (GGE) can be defined by solving the below problem (Charnes et al., 1978).

$$\text{Max}\hat{\delta_j} = \frac{\sum_{r=1}^{s} U_{rj} Y_{rj}}{\sum_{i=1}^{m} V_{ij} X_{ij}} \tag{1}$$

$$\text{subject to :}$$

$$\frac{\sum_{r=1}^{s} U_{rk} Y_{rk}}{\sum_{i=1}^{m} V_{ik} X_{ik}} \leq 1; k = 1, 2, \ldots, n$$

$$U_r, V_i \geq 0; r = 1, 2, \ldots, s; i = 1, 2, \ldots, m$$

where U_r and V_i are the optimal weights assigned to Y_{rj} and X_{ij}, respectively. Note that the true efficiency score δ_j cannot be observed directly but it will be empirically estimated as $\hat{\delta}_j$. If $\hat{\delta}_j = 1$, we say that the j^{th} country is efficient; otherwise, if $\hat{\delta}_j < 1$ then that country is inefficient in terms of using its inputs to produce its (GG) outputs. Note again that Y_{rj} are categorized into desirable and undesirable outputs (see the previous section). To address the imbalance in data magnitudes, all variables were normalized before DEA calculation (Zhu & Cook, 2007).

As discussed in Andersson et al. (2014) and Chen et al. (2023), among others, it would be best to account for both the maximization of desirable outputs and the minimization of undesirable ones at once using the directional distance function approach proposed by Chung et al. (1997). We, therefore, follow Tone (2001), Liu et al. (2010), and Boubaker et al. (2025) to employ a slack-based measure (SBM) in our DEA estimations. Under SBM DEA, Eq. (1) can be re-written as:

$$EF_j = \min \frac{1 - \frac{1}{k}\sum_{i=1}^{k} s_i^- / x_{ij}}{1 + \frac{1}{m}\sum_{r=1}^{m} s_r^+ / y_{rj}} \tag{2}$$

$$\text{subject to}$$

$$\sum_{i=1}^{m} \lambda_k x_{ik} + s_{ij}^- = x_{ij}$$

$$\sum_{r=1}^{s} \lambda_k y_{rk} - s_{rj}^+ = y_{rj}$$

$$k = 1, 2, .., n$$

λ_k, s_i^-, $s_r^+ \geq 0$.

We follow the GG literature and select the annual GDP growth rate as the desirable output (Chen et al., 2023; Hao et al., 2021; Tawiah et al., 2021; Wu et al., 2020). More importantly, we employ four different approaches dealing with the undesirable outputs to further examine their explanatory power. According to the reviews of Zhu et al. (2020) and Halkos and Petrou (2019), undesirable outputs can be treated in three common ways: (1) by considering them as inputs, (2) using data transformation, and (3) using a ratio model. The first option is to treat undesirable outputs as normal inputs in the production function because both inputs and undesirable outputs are the values that need minimizing so they can be treated in the same way. This approach is used by many studies in different fields (Liu et al., 2010; Reinhard et al., 2000; Seiford & Zhu, 2002). The second option is to transform the undesirable outputs into desirable ones such as their reciprocals (Lovell et al., 1995; Zhu et al., 2020). In this sense, the fewer the undesirables, the more the reciprocals and they justify the requirement of desirable outputs. The third option aggregates the undesirable outputs in a ratio form with the desirable ones, in which the ratio form gives both desirable and undesirable outputs a more distinct way to describe the effect of the presence of the two on the efficiency scores (You & Yan, 2011). Accordingly, for our first measurement GG1, we use the reciprocal values of undesirable outputs as desirable outputs, while GG2 treats the undesirables as inputs and GG3 uses the ratios between desirable and undesirable ones as outputs. In addition, the measurement of GG4 utilizes net green growth as the sole desirable output – net green growth is defined as GDP growth excluding pollution and natural depletions (Ahmed et al., 2021; Ngo et al., 2022; Sohag et al., 2019; Tawiah et al., 2021). By compare and contrast the results of all those methods for handling undesirable outputs in GG (i.e., GG1-GG4), in addition to a base model of ignoring such outputs (i.e., GG0), we expect to identify the best data-driven measure of GG that should be used in further GG efficiency analysis. Our DEA models are presented in Table 1 below.

2.2 The second stage: Double-bootstrap truncate regression and the explanatory power of GG measurements

The explanatory power of the GG measurements can be evaluated in a second-stage regression where those measurements are examined against a set of key determinants or explanatory variables. We argue that a good measurement should be associated with the popular explanatory variables that have been found in the literature such as financial development (Adams et al., 2018; Ahmed et al., 2021; Ngo et al., 2022) and environmental policies (Barbier, 2011; Marconi, 2009; Zhao et al., 2020). For instance, financial development can create opportunities for industries to access advanced or environment-friendly machinery and technologies and thus, improve GG and its efficiency (Adams et al., 2018; Ahmed et al., 2021; Ozturk & Acaravci, 2013). Similarly, environmental policies of governments can

Table 1 Five DEA models of Green Growth Efficiency (GGE)

Variables	Model 0 (GG0)	Model 1 (GG1)	Model 2 (GG2)	Model 3 (GG3)	Model 4 (GG4)
GG					O
GDP	O	O	O		
NRP			I		
NFD			I		
CO_2			I		
1/NRP		O			
1/NFD		O			
1/CO_2		O			
GDP/NRP				O	
GDP/NFD				O	
GDP/CO_2				O	
Labour	I	I	I	I	I
Capital	I	I	I	I	I

GDP gross domestic product; *NRP* minerals (including crude oil, coal, and natural gas) depletion; *NFD* forest depletion; *CO_2* level of carbon-dioxide emissions from electricity and heat production; *GG* green growth (defined as GDP excluding NRP, NFD, and CO_2). The traditional Model 0 ignores the role of the undesirable outputs; Model 1 treats the reciprocal values of undesirable outputs as desirable outputs; Model 2 treats the undesirables as inputs; Model 3 uses the ratios between desirable and undesirable ones as outputs; and Model 4 treats GG as the sole output. 'O' denotes that the variable is used as an output while 'I' denotes that it is an input of the DEA models accelerate the development of technical production which helps reduce the environmental damage (Marconi, 2009). There is also evidence that productivity and efficiency are the results of human capital and research and development (R&D), and the increase in knowledge and education can promote economic development while reducing the use of natural resources and minimizing negative externalities such as emissions and wastes (Capasso et al., 2019; Hao et al., 2021; Tawiah et al., 2021). Ma et al. (2021) further suggested that the effectiveness of government policies can affect the external operating environment and decisions of economic entities, which in turn will affect the quality and efficiency of GG.

As a cross-country analysis, we also consider the interactions between countries. In this sense, foreign direct investment (FDI) and trade balance (TRADE) are important external factors. For instance, Stevens (1993), Neumayer (2002) and Zhao et al. (2020) argued that foreign trade enables domestic enterprises to contact and assimilate environment-friendly technologies and thus improve their productivity and efficiency. Meanwhile, FDI can either bring greener technologies and knowledge for enterprises in the host country, i.e., the 'pollution halo' hypothesis (Chen et al., 2021; Hatzipanayotou et al., 2002; Zhao et al., 2020), or it can sometimes transfer polluting industries to the host country to avoid stricter regulations in home country, i.e., the 'pollution haven' hypothesis (Pradhan et al., 2021; Yang et al., 2021). We, therefore, use FDI as an influential factor to test its effect on GG efficiency. We also use a dummy variable, GROUP, to account for the income level of the countries being examined.

Specifically, the relationship between GG efficiency (GGE) and its determinants is expressed as:

$$GGE = \alpha_0 + \alpha_1 FD + \alpha_2 RD + \alpha_3 POP + \alpha_4 EDU + \alpha_5 FDI + \alpha_6 TRADE + \alpha_7 GOV + \alpha_8 GROUP + \varepsilon \tag{3}$$

where *GGE* is the country's green growth efficiency scores derived from Eq. (1), namely GGE1, GGE2, GGE3, and GGE4 – see Table 1; *FD* is the financial development of the country; *RD* stands for the country's expenditures on research and development; *POP* represents population growth; *EDU* stands for the country's expenditures on education; *FDI* is the foreign direct investment; *TRADE* represents the trade balance; *GOV* represents the governance indicator[2]; and *GROUP* is the dummy variable representing the income level of the examined country. Note that the time and country subscripts are omitted for ease of expression. Note again that the more variables that can be explained, aligning with the previous literature, the higher the explanatory power that a GGE measurement holds. We summarize the expected signs and effects of those variables in Table 2 as follows.

Simar and Wilson (2007) argued that for the second-stage DEA regression as in Eq. (3), bias may arise due to the potential correlation between the explanatory variables and the inputs and outputs of GGE (as in Eq. (1)). To correct for this bias, they suggested to use a double-bootstrap truncated regression technique (Algorithm 2, Simar & Wilson, 2007) to simultaneously estimate the GGE under the influences of such explanatories. Specifically, instead of estimating Eq. (3) independently from Eq. (2), one can use a re-sampling method

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[2] We applied the principal component analysis (Jolliffe, 2002) to combine the six governance indicators of Voice and accountability, Political stability and absence of violence/terrorism, Government effectiveness, Regulatory quality, Rule of law, and Control of corruption (World Bank, 2021b) into a single component, i.e., GOV. For our dataset, this component retains 86.22% of all information and thus, is a good proxy for the country's overall governance capabilities and institutions (see Appendix 3).

Table 2 Expected roles of the determinants for GGE

Variables	Expected impact	Explanation	Supporting literature
FD	±	Financial development (FD) promotes technological advancements and thus, reduces emissions and pollution. Contradictory, FD could also increase the consumption of energy and natural resources and hence, detrimental to GGE.	Sadorsky (2010), Chang (2015), Tamazian and Bhaskara Rao (2010), Sehrawat et al. (2015), Al-Mulali et al. (2015)
RD	+	Research and development (R&D) promotes technological advancements.	Samad and Manzoor (2015), Capasso et al. (2019), Hao et al. (2021), Ngo et al. (2022)
POP	–	Population (POP) represents the demand for energy and resources consumption.	Sherbinin et al. (2007), Lehmijoki and Palokangas (2010), Marsiglio (2011),
EDU	±	A higher level of knowledge and education (EDU) represents higher awareness regarding green growth. However, it is normally associated with higher consumption, infrastructure development, and industrialization.	Samad and Manzoor (2015),, Nguyen et al. (2019), Hao et al. (2021), Tawiah et al. (2021)
FDI	±	While foreign direct investment (FDI) can bring in investments and technologies, it can sometimes transfer polluting industries to host countries.	Suliman and Elian (2014), Hille et al. (2019), Siddikee and Rahman (2020), Zhao et al. (2020), Chen et al. (2021)
TRADE	±	Foreign trade (TRADE) enables domestic enterprises to contact and assimilate environment-friendly technologies; however, it can also bring in pollution-intensive technologies from one country to another.	Lehmijoki and Palokangas (2010), Herwartz and Walle (2014), Tawiah et al. (2021), Ngo et al. (2022)
GOV	+	The effectiveness of government policies (GOV) can affect the operating environment for businesses, thus affecting their activities toward green growth.	Chang et al. (2018), Capasso et al. (2019), Farooq et al. (2021), Kulin and Johansson Sevä (2021), Ma et al. (2021), Butt et al. (2023)
GROUP	±	There are differences between advanced and developing countries regarding green growth efficiency.	Tawiah et al. (2021), Kulin and Johansson Sevä (2021), Hwang et al. (2023), Chatti and Majeed (2023)

to create a new (pseudo) dataset from the original dataset and then re-estimate both equations simultaneously. By repeating this process for B times (normally $B = 1000$ is enough), a distribution of these bias-corrected bootstrapped efficiency scores can be obtained. It is noted that the bootstrap technique only deals with pooled cross-sectional data but not panel regression; however, it is sufficient for our testing purposes. The details of this double bootstrap technique are provided in Appendix 2, but readers are encouraged to check for Simar and Wilson (2007) for a thorough discussion and explanation.

2.3 The third stage: Green growth productivity changes over time

After the second stage, an optimal GG measurement and model could be identified based on its explanatory power, i.e., if it can explain the most variables in Table 2. Consequently, such a measurement and model are important for further research. We, therefore, continue to examine the productivity changes over time of GGE using that optimal model/measurement. As discussed in Matsumoto et al. (2020) and Chen et al. (2023), among others, while GGE is an important measurement reflecting the efficiency of green growth in a certain year being examined (e.g., in 2020 and 2021, independently), it lacks the dynamic perspective that helps understand the changes in green growth over time (e.g., between 2020 and 2021). In contrast, the Malmquist-type index (Balk et al., 2020; Cao et al., 2020; Makridou et al., 2016; Ngo & Nguyen, 2012) can capture the GGE productivity change (TFPCH) in terms of technical efficiency change (EFCH), scale efficiency change (SECH), and technological change (TECH). Regarding the two points $A^t(x^t,y^t)$ and $A^{t+1}(x^{t+1},y^{t+1})$ of the same unit A at time t and $t+1$, respectively (see Fig. 1), the seminal work of Färe et al. (1994) defined that

$$m_0\left(x^{t+1},y^{t+1},x^t,y^t\right)=\left[\frac{d_c^t\left(x^{t+1},y^{t+1}\right)}{d_c^t\left(x^t,y^t\right)}\times\frac{d_c^{t+1}\left(x^{t+1},y^{t+1}\right)}{d_c^{t+1}\left(x^t,y^t\right)}\right]^{\frac{1}{2}}\tag{4}$$

With some extensions:

$$m_0 = \frac{d_v^{t+1}\left(x^{t+1},y^{t+1}\right)}{d_v^t\left(x^t,y^t\right)}\times\frac{s^{t+1}\left(x^{t+1},y^{t+1}\right)}{s^t\left(x^t,y^t\right)}\times\left[\frac{d_c^t\left(x^{t+1},y^{t+1}\right)}{d_c^{t+1}\left(x^{t+1},y^{t+1}\right)}\times\frac{d_c^t\left(x^t,y^t\right)}{d_c^{t+1}\left(x^t,y^t\right)}\right]^{\frac{1}{2}}\tag{5}$$

$$\text{Or}, TFPCH=EFCH\times SECH\times TECH\tag{6}$$

where the notation $d_c^t\left(x^t,y^t\right)$ represents the vertical distance of the point (x^t,y^t) to the CRS frontier S_c^t, the notation $d_v^t\left(x^t,y^t\right)$ represents the vertical distance of the point (x^t,y^t) to the VRS frontier S_v^t, and the notation $s^t(x^t,y^t)$ represents the vertical distance of the two frontiers S_c^t and S_v^t at time t.

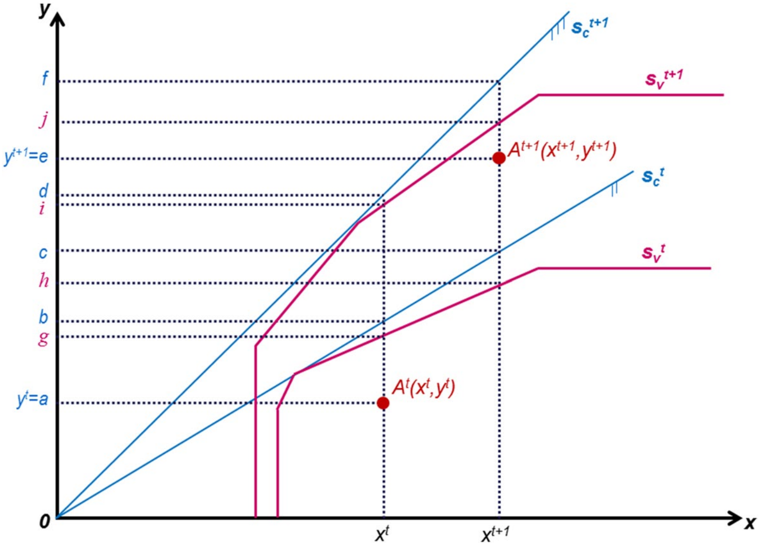

Fig. 1 Malmquist output-based index of productivity changes. Source: Adapted from Färe et al. (1994)

2.4 Data

The data for the calculation of GG in the first stage (i.e., *GDP*, *NRP*, *NFD*, and CO_2), and other macroeconomic variables in the second stage (i.e., *FDI*, *TRADE*, *EDU*, and *POP*), are collected from the World Development Indicators (World Bank, 2021a). Data for the governance indicators are extracted from the Worldwide Governance Indicators (World Bank, 2021b) while *FD* was extracted from the International Monetary Fund (Sahay et al., 2015). After matching 13,671 (country-year) observations in the World Development Indicators, 14,818 observations in the Worldwide Governance Indicators, and 7059 observations for *FD*, we ended up with an unbalanced panel dataset totalling 1264 country-year observations covering 115 countries during the 1996–2018 periods (please see Appendix 1 for a list of countries involved in this study). We limit ourselves to the year 2018 because the data for *NRP* and CO_2 after this year are largely missing (World Bank, 2021a).

The statistics of the variables in this study are presented in Table 3. It shows the development over time of the global GDP, labour and capital; however, the natural depletion has also increased with the CO2 emissions, albeit slightly reduced in recent years, staying at a moderate level (i.e., the value of CO2 alone accounts for more than 37% of GDP across the 1996–2018 period). The average country of our sample had a moderate level of financial development with *FD*=0.47 but spent around 1.11% and 4.71% of its GDP on R&D and EDU, respectively. It is an open economy with the *FDI* inflows of around 7% of GDP and its trade balance accounts for more than 95% of its GDP.

Table 3 Descriptive statistics of the variables of interest

Variable	1996–2001		2002–2007		2008–2013		2014–2018		1996–2018	
	Obs	*Mean*	*Obs*	*Mean*	*Obs*	*Mean*	*Obs*	*Mean*	*Obs*	*Mean*
GDP	112	640.38	361	710.43	419	720.75	372	784.64	1264	729.49
Labour	112	20.78	361	19.82	419	21.80	372	22.93	1264	21.48
Capital	112	140.04	361	153.65	419	152.32	372	176.83	1264	158.82
NRP	102	6.23	317	14.81	392	14.25	341	8.10	1152	11.88
NFD	109	0.72	347	0.71	411	0.82	367	0.99	1234	0.83
CO2	112	248.99	349	282.88	407	271.56	362	276.03	1230	274.03
FD	112	0.44	361	0.47	419	0.48	372	0.47	1264	0.47
RD	112	1.08	361	1.08	419	1.11	372	1.14	1264	1.11
POP	112	49.21	361	45.37	419	49.70	372	49.79	1264	48.45
EDU	112	4.53	361	4.66	419	4.86	372	4.64	1264	4.71
FDI	112	4.49	361	9.60	419	8.16	372	5.03	1264	7.33
TRADE	112	77.11	361	96.24	419	97.22	372	98.81	1264	95.62
GOV	112	0.51	361	0.17	419	−0.10	372	−0.20	1264	−0.00
GROUP	112	1.48	361	1.53	419	1.61	372	1.65	1264	1.59

Obs stands for observations, *GDP* represents the gross domestic product (in billion constant 2015 US dollar), *Labour* represents the total labour force (in million people), *Capital* represents the gross fixed capital formation (in billion constant 2015 US dollar), *NRP* represents the value of mineral depletion (in billion constant 2015 US dollar), *NFD* represents the value of forest depletion (in billion constant 2015 US dollar), *CO2* represents the value of carbon emissions (in billion constant 2015 US dollar), *FD* stands for the financial development index, *RD* stands for the expenditures on research and development (% of GDP), *POP* stands for total population growth (in million people), *EDU* stands for the expenditure on education (% of GDP), *FDI* is the net inflows of foreign direct investment (% of GDP), *TRADE* is the trade balance (% of GDP), *GOV* represents the governmental index (computed as the first principal component of the six worldwide governance indicators), and *GROUP* is a categorical variable that takes the value of 1 if the country is classified as low-income, a value of 2 for an emerging country, and 3 for an advanced market

3 Results and discussions

3.1 Green growth efficiency of countries around the world

In the first stage, the VRS assumption (Banker et al., 1984) was used in the SBM DEA of Eq. (2) to evaluate the yearly GGE of the 115 countries, accounting for the scale differences among those countries. Figure 2 illustrates the yearly average GGE results from the five models in Table 1, where they share similar patterns but differences in values. Overall, the GGE were stable over time; however, some degradations were found around 2007–2010 (which may be due to the global financial crisis), but it has been recovered and improved for the last eight years of the examined period. Except for Model 3 which seems to be an outlier, the average GEE of our sampled countries ranged from 0.602 (in Model 4) to 0.758 (Model 2), indicating an inefficiency of about 25–40%. This suggests that GG has received increasing but moderate attention in promoting sustainable growth in many countries, especially in the post-2008 period.

However, there is a difference in GG efficiency between country groups. Figure 3 indicates that advanced markets such as the OECD countries are the most green-growth efficient across all five models. Three models (i.e., Models 0, 1 and 4) identified the emerging markets (such as China, India, and Vietnam) as more efficient than low-income countries, while Models 2 and 3 found a contradictory result. Because it is previously noted that Model 3 should be treated as an outlier, and since the difference between the efficiency scores of the two groups is small in Model 3 (see Fig. 3), we argue that the LIC is the worst-performing group in terms of GGE. Nevertheless, such differences in GGE scores across countries/groups, and the inconsistency across the models require further examination of the key vari-

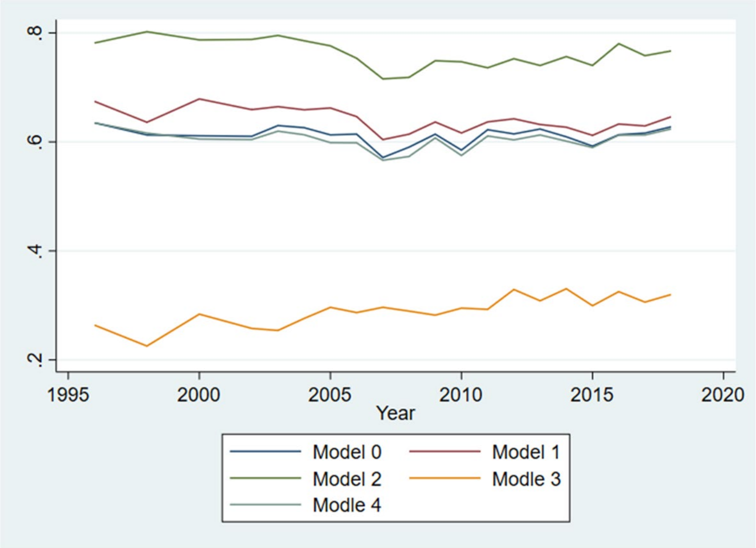

Fig. 2 Average GG efficiency scores of countries, 1996–2018. Notes: Model 0 ignores the role of the undesirable outputs; Model 1 treats the reciprocal values of undesirable outputs as desirable outputs; Model 2 treats the undesirables as inputs; Model 3 uses the ratios between desirable and undesirable ones as outputs; and Model 4 treats the GG indicator as the sole output

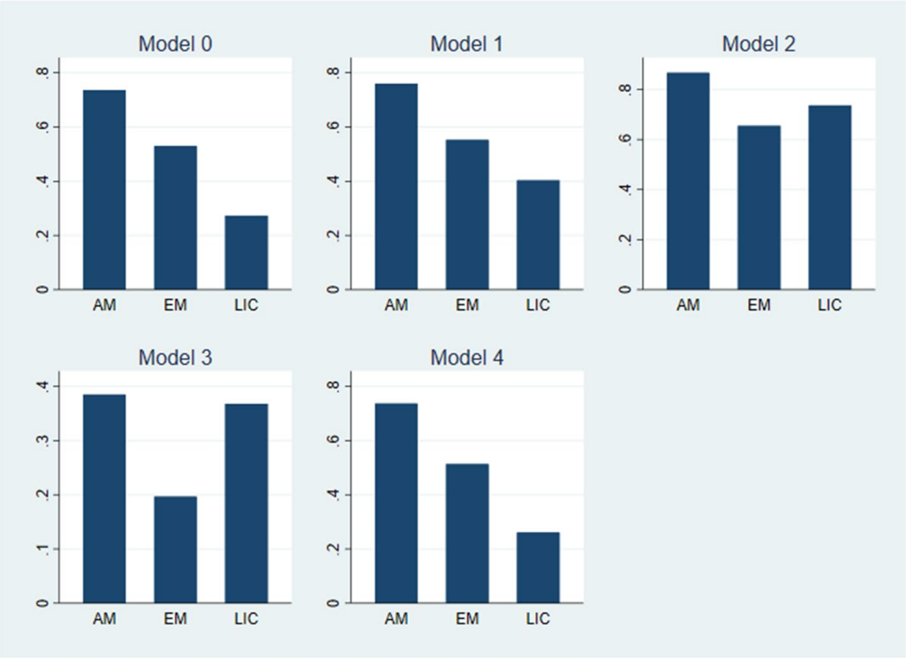

Fig. 3 The comparison of the average GGE among country groups and across the five models. Notes: Model 0 ignores the role of the undesirable outputs; Model 1 treats the reciprocal values of undesirable outputs as desirable outputs; Model 2 treats the undesirables as inputs; Model 3 uses the ratios between desirable and undesirable ones as outputs; and Model 4 treats the GG indicator as the sole output. There are 616, 550, and 98 observations for advanced (AM), emerging (EM), and low-income (LIC) countries, respectively

ables that can influence GGE, which GGE measurement is more appropriate, and how we can correct the GGE biases using the bootstrap method, among others, in the second-stage analysis.

3.2 The determinants of GGE: bias-correction via bootstrapping

The double bootstrap DEA results of all five models are presented in Table 4. The first thing to note is about the explanatory power of those models. Excluding the intercept, Models 2 and 3 can explain seven variables, followed by Models 1 and 4 (five variables each), and then Model 0 (only four variables). It, therefore, strengthens our argument in the Introduction section that Model 0, when ignoring the role of natural depletion and emissions (i.e., the undesirable outputs), fails to account for the 'true' GG and GGE, which should be influenced by such control variables (e.g., *POP* or *GOV*). In addition to our previous findings in Section 3.1 above that Model 3 is an outlier, Table 5 further reports the cumulative correlation among the five models, of which Model 1 has the highest value of 3.1376. Consequently, we argue that Model 1 is the best and our further analyses, therefore, are based on this model.

Secondly, our empirical findings strengthen the arguments on the impacts of control variables such as financial development, research, and institutions on green growth efficiency (see also Table 2). In particular, we found that *FD* and *RD* both have negative impacts

Table 4 Results of the bootstrap truncated regressions

	Model 0		Model 1		Model 2		Model 3		Model 4	
FD	−7.526	***	−3.171	***	−1.402	***	38.404	***	−7.934	***
	(0.672)		(0.252)		(0.201)		(10.397)		(0.802)	
RD	0.311	**	0.090		−0.445	***	−0.594		0.097	
	(0.146)		(0.064)		(0.066)		(2.334)		(0.185)	
POP	0.000		0.000		0.000	***	0.000	***	0.000	*
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
EDU	−0.213	***	−0.082	***	0.076	***	1.946	***	−0.211	***
	(0.045)		(0.022)		(0.019)		(1.058)		(0.053)	
FDI	0.005		0.002		−0.001		−0.346	**	0.006	
	(0.003)		(0.002)		(0.002)		(0.169)		(0.004)	
TRADE	0.008	***	0.005	***	0.007	***	0.141	***	0.009	***
	(0.001)		(0.001)		(0.001)		(0.033)		(0.002)	
GOV	−0.092		−0.054	**	−0.171	***	−17.930	***	−0.257	***
	(0.057)		(0.026)		(0.025)		(2.844)		(0.070)	
GROUP	1.859	***	0.931	***	−0.126	**	−9.872	***	2.016	***
	(0.149)		(0.073)		(0.063)		(3.818)		(0.189)	
CONSTANT	0.371		1.177	***	1.433	***	−37.148	***	−0.005	
	(0.409)		(0.195)		(0.166)		(12.459)		(0.520)	
Wald chi2(8)	402.6***		647.66***		239.16***		44.8***		311.68***	

Model 0 ignores the role of the undesirable outputs; Model 1 treats the reciprocal values of undesirable outputs as desirable outputs; Model 2 treats the undesirables as inputs; Model 3 uses the ratios between desirable and undesirable ones as outputs; and Model 4 treats the GG indicator as the sole output. *FD* is the financial development of the country, *RD* stands for the country's expenditures on research and development, *POP* represents population growth, *EDU* stands for the expenditure on education, *FDI* is the foreign direct investment, *TRADE* represents the trade balance, *GOV* represents the governance indicator, and *GROUP* is a categorical variable that takes the value of 1 if the country is classified as low-income, a value of 2 for an emerging country, and 3 for an advanced market. Bootstrap standard errors are in parentheses. *, **, *** denote the significance at 10, 5, and 1% levels, respectively. The dependent variable of all models is the bias-corrected GGE inefficiency scores estimated from bootstrap DEA

Table 5 Spearman's ranking correlation among biased-corrected GGE measurements

Model 0				
0.9673	**Model 1**			
0.8043	0.8247	**Model 2**		
0.2897	0.3911	0.5602	**Model 3**	
0.9850	0.9545	0.8078	0.3234	**Model 4**
Cumulative coefficient				
3.0463	***3.1376***	***2.9970***	***1.5644***	***3.0707***

Model 0 ignores the role of the undesirable outputs; Model 1 treats the reciprocal values of undesirable outputs as desirable outputs; Model 2 treats the undesirables as inputs; Model 3 uses the ratios between desirable and undesirable ones as outputs; and Model 4 treats the GG indicator as the sole output. All numbers are significant at the 1% level

on GGE inefficiency and thus, positive impacts on GGE, suggesting that countries need to be more open to exchanging financial services and technologies to help improve their green economy. Besides, improving institutions (*GOV*) such as government effectiveness, (environmental) regulations and laws could also enhance the practices of sustainable development and green growth; such progress has been found in advanced markets (*GROUP*). Contradictory, *POP*, *EDU*, and *TRADE* are found to have negative impacts on GGE. For *POP*, it is argued that a larger population will increase the consumption of natural resources, thus increase the emission of waste and pollutants (Mendonça et al., 2020) and ultimately contribute to GGE inefficiency (Tawiah et al., 2021). For *EDU*, a study of Costantini and Monni (2008) on a sample of 179 countries during the 1970–2003 period further argued that the impact of human capital (proxied via education) on CO2 emission follows an inversed U-shape relationship, i.e., the Environmental Kuznets Curve (Ozturk & Acaravci, 2013; Tamazian & Bhaskara Rao, 2010). In this sense, improving *EDU* would increase CO2 until a certain threshold but when *EDU* surpasses that level, it can start reducing CO2 emission and thus, later positively contribute to GG. In a similar vein but using Chinese data, Li et al. (2022) and Liu et al. (2023) also reported that education has no statistical impact on green growth in the short run, but it does in the long run. Accordingly, we suggest that countries should continue to invest in education to reach the long-run effect of *EDU* on GGE. Regarding *TRADE*, our finding is consistent with the pollution haven hypothesis (Bashir, 2022; Chen et al., 2021) where underdeveloped countries may be exposed to pollution-intensive technologies from the host countries (Tawiah et al., 2021) - note that out of 115 countries in our sample, 79 are EM and LIC (see also Appendix 1).

3.3 GGE productivity changes over time, 1996–2018

Figure 4 illustrates the average GGE productivity changes over time (TFPCH) for 115 countries during the 1996–2018 period. Accordingly, one can argue that the TFPCH showed a sharp decline around the global financial crisis of 2006–2008, but it has been under a recovery trend after that. Such patterns of development are also found in the TECH and SECH components of TFP, suggesting that the two are the main drivers of TFPCH. Since the mean values of EFCH, TECH, and SECH are close to unity at 1.000, 1.014, and 0.997, respectively, there is evidence that the three components play similar roles in the GGE productivity changes over time (which has a mean of 1.007, also closes to unity). This finding is interesting as it indicates that there has been not much improvement in global GGE, particularly regarding how countries utilized their labour and capital to both produce more GDP and less pollution and natural depletion. Although trivial, the slightly higher mean of TECH over the other two components indicates the important contribution of (green) technology to green growth, which has been well documented (Chatti & Majeed, 2023; Wang, Padhan, et al., 2024; Yikun et al., 2023), especially for developing economies (Chatti & Majeed, 2023; Naimoglu & Akal, 2023; Wang, Padhan, et al., 2024; Wenlong et al., 2023; Yikun et al., 2023; Yu et al., 2023). We also note that technology is indeed promoted via FD and RD, as discussed in the previous section.

We further examine the GGE productivity changes (TFPCH) across countries and report the top-10 and bottom-10 performers in Fig. 5. Particularly, we ranked the countries depending on their number of (yearly) observations because countries which are committed to green growth (thus reporting more data on their natural depletions and emissions) are aware of the situation and tend to perform better. As observed in the second, third and fourth panels of Fig. 5, even the bottom 10 such as Belgium (BEL) and Singapore (SGP) still achieved a high TFPCH of more than 0.9.

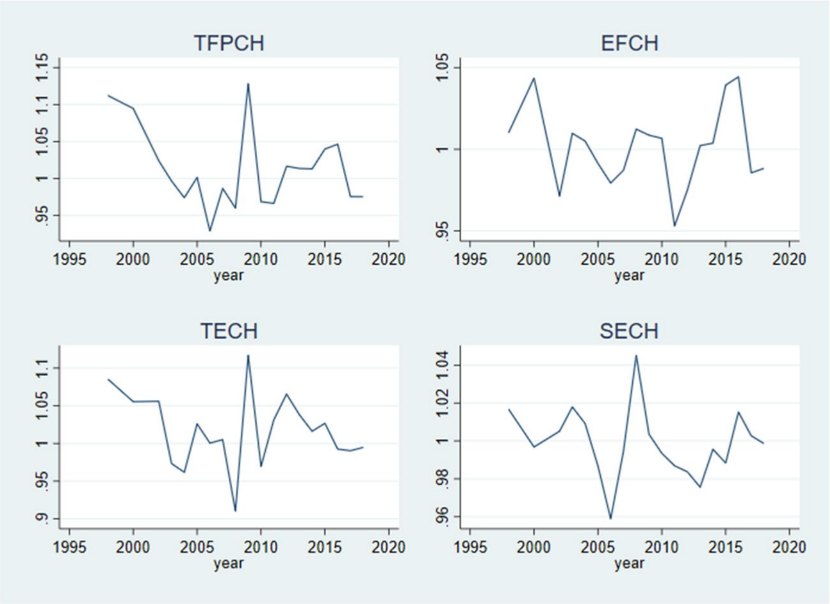

Fig. 4 Average GGE productivity changes over time, 1996–2018. Notes: TFPCH, GGE productivity change (Malmquist index); EFCH, technical efficiency change; TECH, technological change; and SECH, scale efficiency change

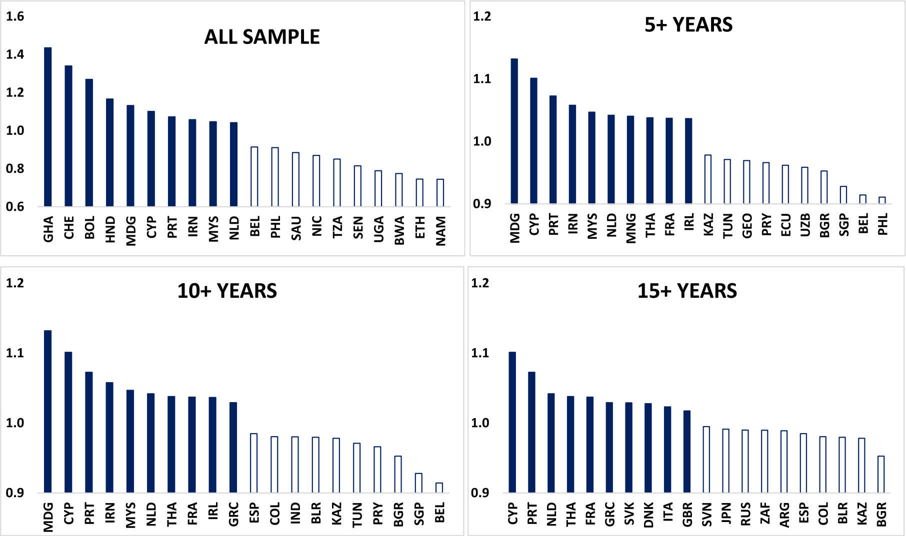

Fig. 5 Average GGE productivity changes over time of the top-10 (solid bars) and bottom-10 (hollow bars) countries

It is not a surprise to see countries like Switzerland (CHE), Cyprus (CYP), Thailand (THA), the Netherlands (NLD), France (FRA) or Italy (ITA) stand as the top performers across the four panels of Fig. 5. Those countries are well-examined as leaders in developing their service sector, especially tourism, which requires fewer resources but provides large outputs and less environmental damage, rather than relying on the industry sector (Kim et al., 2014; Lee, 2019; Schenau, 2017). For instance, it is argued that Korea had embarked on a GG strategy cooperating with the COP 15 commitments since the early 2010 s (Mathews, 2012). Or, in Cyprus, there is evidence that green tourism plays an important role in its economic development (Ibnou-Laaroussi et al., 2020; Marsiglio, 2015). For the Netherlands, the promotion and practices of cycling are found to be a root cause of (local) tourism, which not only contributes to green growth but also supports social and physical well-being (den Hoed, 2020). Similar arguments apply to the case of Switzerland (Herrera Anchustegui & Glapiak, 2023; Raza et al., 2024) and Italy (Farinelli, 2004; Javed et al., 2023; Lucchese et al., 2016). Since those top countries have TFPCH scores greater than unity and indicate that they are continuing to improve their GGE; our finding reveals that the world is presenting its continuous effort to transition into a more sustainable society by increasing its green growth efficiency.

Regarding the ‘ALL SAMPLE’ panel, we notice that the bottom 10 includes Namibia (NAM), Ethiopia (ETH), Botswana (BWA), and other LICs. It suggests that there is an imbalanced picture regarding green growth and sustainable development across countries. Such additional evidence of the pollution haven hypothesis, as discussed earlier in previous sections, encouraged us to look deeper into different country groups in the next section.

3.4 GGE productivity around the world: An imbalanced picture

Figure 6 illustrates the average GGE productivity measures between the three country groups, whereas the solid lines represent the developed countries (AM), the hollow lines represent the developing ones (EM), and the dashed lines represent the low-income group (LIC) - see also Appendix 1 for the list of countries involved.

Similar to Fig. 4, we also observed that the patterns of TFPCH for the three groups are influenced by the patterns of TECH, strengthening the role of technologies in the green growth context. For EFCH, we note that the efficiency changes for AM countries are more stable (around unity) but more volatile for the other two groups, suggesting the efforts of those countries in trying to improve their GG efficiency, i.e., combine labour and capital to produce more GDP and less natural depletions/emissions. Interestingly, we also found the pattern of EFCH for LIC countries was about two years behind EM countries, especially for the post-2010 period. Hence, we argue that the LICs are learning from their closer peers, which are the EM countries, rather than from the top performers of AM countries. Regarding SECH, a high volatility pattern for the LICs suggests that those countries need to improve their scale (efficiency) of development, i.e., more labour and, especially, capital are needed to produce more GDP. For instance, Table 6 shows that while the LIC group has a labour force of about half of AM countries, its capital is only about 5% of the AM group. Meanwhile, EM countries have a much higher labour force and capital, compared to the LIC one. By improving their scale of production via capital investment, which could be achieved through institutions (GOV), financial development (FD), and foreign direct investment (FDI), LIC countries could, therefore, improve their scale efficiency and GGE produc-

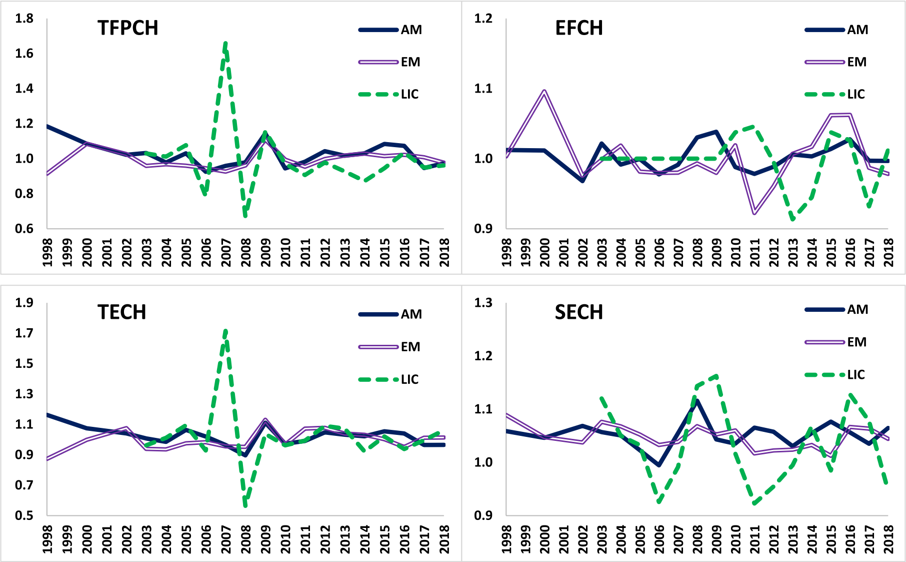

Fig. 6 The imbalance picture of GGE productivity across country groups

Table 6 Scale of production across country groups

Group	Unit	GDP	Labour	Capital
Advanced markets (AM)	billion 2015 USD	1192.63	14.56	254.05
Emerging markets (EM)	million people	336.91	31.72	78.39
Low-income markets (LIC)	billion 2015 USD	21.53	7.49	11.64

tivity. Nevertheless, such an imbalanced development of GGE between the developed and developing world indicates that the latter countries will need more help and support from the former to overcome the green growth challenges.

4 Conclusions and policy implications

Although the issues of green growth (GG) and green growth efficiency (GGE) have received much attention in recent years (Chen et al., 2023; Ngo et al., 2022; Wang, Li, et al., 2021), studies from cross-country or even global perspectives are scanty. Our paper, therefore, aimed to bridge this gap via the examination of the GEE of 115 countries during the 1996–2018 period. We followed a three-stage analysis approach, where GGE is measured under five DEA models treating the undesirable factors of emission and resource depletion differently (Tawiah et al., 2021; You & Yan, 2011; Zhou et al., 2007) in the first stage and then regressed against a set of common determinants using the double bootstrap technique (Boubaker et al., 2025; Simar & Wilson, 2007) in the second stage. Based on the explanatory power of those models, Model 1 (which treats the reciprocal values of the undesirable outputs as desirable ones) is chosen for the third stage analysis of the GGE productivity changes over time following a Malmquist index approach (Balk et al., 2020; Cao et al., 2020; Färe et al., 1994). This is another (methodological) contribution of the paper.

Our empirical results reveal that the common factors of financial development, research and development, and institutions all have positive impacts on GGE, suggesting that to improve their green economy, countries need to be more open to exchanging financial services, technologies, and knowledge alongside improving their own institutional environment. On the other hand, it also shows that the world is in a situation of overpopulated, overdemanding (in terms of natural resources), and imbalanced development between countries, especially for the low-income markets, strengthening the pollution haven hypothesis. Our examination of the GGE productivity changes over time also reveals that its improvements are thanks to the changes in technology instead of the changes in scale or technical efficiency. Therefore, (green) technology is still important to improve GGE productivity, especially in underdeveloped markets. Overall, our study showed that the world is making continuous efforts for a more sustainable transformation through increasing its green growth efficiency.

Consequently, our study proposes several policy implications regarding the global development of GG as follows. Firstly, our findings strengthen the argument that technology is the main driver of GG (Fig. 4 and the relevant discussions) and thus, policymakers across the globe should emphasize the promotion and adoption of innovative technologies to facilitate sustainable development and reduce environmental impacts (Wei et al., 2025). Secondly, the study also underscores the importance of technology transfer, especially from advanced to emerging and low-income economies (see Fig. 6 and the relevant discussions). Policymakers, therefore, should prioritize efforts to facilitate technology transfer, collaboration, and knowledge sharing between countries. This can be achieved through initiatives such as foreign direct investment (FDI), research and development (RD) collaborations, and international trade in green technologies (Fernandes et al., 2021; Song et al., 2024), as have been highlighted in Section 3.2. Thirdly, underdeveloped countries should improve their institutions to create a GG-friendly environment to attract more investments and technological transfers to improve their scale efficiency and thus, GGE productivity (discussed in Section 3.4). Fourthly, our study also highlights the importance of managing the potential trade-offs between economic development and environmental sustainability, whereas environmental degradation can be seen as an undesirable product of economic growth. Policymakers, therefore, should adopt comprehensive strategies to ensure technological advancements align with sustainable practices, resource conservation, and emissions reduction targets.

The study faced some limitations that could be improved in future research. Firstly, it is important to extend the dataset to more countries and longer periods; here, we limited ourselves to the 1996–2018 period due to data limitation. Secondly, advanced and novel DEA methods such as meta-frontier, common set of weights, and even the combination with machine learning and artificial intelligence (Alharbi et al., 2025; Valero-Carreras et al., 2024; Yang et al., 2024) could also help explore for information regarding GGE. And lastly, methodological improvements regarding uncertainty in data (Boubaker et al., 2020) and other macro-level settings including climate changes, wars and conflicts (Park & Park, 2025; Tran et al., 2025) should also be considered in GGE assessments.

Appendix 1. Sampled countries

No.	Country	Code	Group	No.	Country	Code	Group	No.	Country	Code	Group
1	Angola	AGO	EM	40	Gambia	GMB	LIC	79	Norway	NOR	AM
2	Albania	ALB	EM	41	Greece	GRC	AM	80	Nepal	NPL	LIC
3	Argentina	ARG	EM	42	Guatemala	GTM	EM	81	New Zealand	NZL	AM
4	Armenia	ARM	EM	43	Hong Kong	HKG	AM	82	Oman	OMN	EM
5	Australia	AUS	AM	44	Honduras	HND	LIC	83	Pakistan	PAK	EM
6	Austria	AUT	AM	45	Croatia	HRV	EM	84	Panama	PAN	EM
7	Azerbaijan	AZE	EM	46	Hungary	HUN	EM	85	Peru	PER	EM
8	Burundi	BDI	LIC	47	Indonesia	IDN	EM	86	Philippines	PHL	EM
9	Belgium	BEL	AM	48	India	IND	EM	87	Poland	POL	EM
10	Burkina Faso	BFA	LIC	49	Ireland	IRL	AM	88	Portugal	PRT	AM
11	Bulgaria	BGR	EM	50	Iran	IRN	EM	89	Paraguay	PRY	EM
12	Bahrain	BHR	EM	51	Iceland	ISL	AM	90	Romania	ROU	EM
13	Belarus	BLR	EM	52	Israel	ISR	AM	91	Russia	RUS	EM
14	Bolivia	BOL	EM	53	Italy	ITA	AM	92	Rwanda	RWA	LIC
15	Brazil	BRA	EM	54	Japan	JPN	AM	93	Saudi Arabia	SAU	EM
16	Botswana	BWA	EM	55	Kazakhstan	KAZ	EM	94	Sudan	SDN	LIC
17	Canada	CAN	AM	56	Kenya	KEN	LIC	95	Senegal	SEN	LIC
18	Switzerland	CHE	AM	57	Kyrgyz	KGZ	LIC	96	Singapore	SGP	AM
19	Chile	CHL	EM	58	Cambodia	KHM	LIC	97	El Salvador	SLV	EM
20	China	CHN	EM	59	South Korea	KOR	AM	98	Serbia	SRB	EM
21	Cote d'Ivoire	CIV	LIC	60	Lao PDR	LAO	LIC	99	Slovak	SVK	AM
22	Congo	COD	LIC	61	Sri Lanka	LKA	EM	100	Slovenia	SVN	AM
23	Colombia	COL	EM	62	Lesotho	LSO	LIC	101	Sweden	SWE	AM
24	Costa Rica	CRI	EM	63	Lithuania	LTU	AM	102	Chad	TCD	LIC
25	Cyprus	CYP	AM	64	Luxembourg	LUX	AM	103	Togo	TGO	LIC
26	Czech	CZE	AM	65	Latvia	LVA	AM	104	Thailand	THA	EM
27	Germany	DEU	AM	66	Macao	MAC	AM	105	Tajikistan	TJK	LIC
28	Denmark	DNK	AM	67	Morocco	MAR	EM	106	Tunisia	TUN	EM
29	Algeria	DZA	EM	68	Moldova	MDA	LIC	107	Turkey	TUR	EM
30	Ecuador	ECU	EM	69	Madagascar	MDG	LIC	108	Tanzania	TZA	LIC
31	Egypt	EGY	EM	70	Mexico	MEX	EM	109	Uganda	UGA	LIC
32	Spain	ESP	AM	71	Mali	MLI	LIC	110	Ukraine	UKR	EM
33	Estonia	EST	AM	72	Malta	MLT	AM	111	Uruguay	URY	EM
34	Ethiopia	ETH	LIC	73	Mongolia	MNG	EM	112	United States	USA	AM
35	Finland	FIN	AM	74	Mauritius	MUS	EM	113	Uzbekistan	UZB	LIC
36	France	FRA	AM	75	Malaysia	MYS	EM	114	Vietnam	VNM	EM
37	UK	GBR	AM	76	Namibia	NAM	EM	115	South Africa	ZAF	EM
38	Georgia	GEO	EM	77	Nicaragua	NIC	LIC				
39	Ghana	GHA	LIC	78	Netherlands	NLD	AM				

Appendix 2. Algorithm 2 in double bootstrap DEA (Simar & Wilson, 2007)

Step 1: The original data of outputs, $Y_{r,j}$ and inputs, $X_{i,j}$ is used to calculate DEA efficiency scores $\hat{\delta}_i$.

Step 2: The maximum likelihood method is used to calculate $\hat{\beta}$ of β and $\hat{\sigma_\varepsilon}$ of σ_ε in the truncated regression of $\hat{\delta}_i$ on z_i using $m<n$ observations where $\hat{\delta}_i > 1$.

Step 3: Loop over steps (3.1–3.4) for 100 times to derive a set of bootstrap estimates $A = \left[\left(\hat{\beta^*}, \hat{\sigma_\varepsilon^*}\right)_b\right]_{b=1}^{100}$:

Step 3.1: For each $i=1, 2, \ldots m$, draw ε_i from the $N\left(0, \hat{\sigma}_\varepsilon^2\right)$ distribution with left truncation at $\left(1 - z_i\hat{\beta}\right)$

Step 3.2: Again, for each $i=1, 2, \ldots n$, calculate $\delta_i^* = z_i\hat{\beta} + \varepsilon_i$

Step 3.3: Set $x_i^* = x_i, y_i^* = y_i\left(\frac{\hat{\delta}_i}{\delta_i^*}\right)$ for all $i=1, 2, \ldots n$.

Step 3.4: Calculate the new technical efficiency $\hat{\delta}_i^*$ by replacing $Y^* = [Y_1^*, \ldots, Y_n^*], X^* = [X_i^*, \ldots, X_n^*]$

Step 4: For each $i=1, 2, \ldots n$, estimate the bias corrected estimator $\hat{\hat{\delta}}_i$ on z_i, providing estimates $\hat{\hat{\beta}}$, $\hat{\hat{\sigma}}$

Step 6: Loop over steps (6.1–6.3) for 1000 times to acquire a set of bootstrap estimates$K = \left[\left(\hat{\beta^*}, \hat{\sigma^*}\right)_b\right]_{b=1}^{2000}$:

Step 6.1: For each $i=1, 2, \ldots n$, draw ε_i from the $N\left(0, \hat{\hat{\sigma}}\right)$ distribution with left truncation at $\left(1 - z_i\hat{\hat{\beta}}\right)$

Step 6.2: Again, for each $i=1, 2, \ldots m$, calculate $\delta_i^{**} = z_i\hat{\hat{\beta}} + \varepsilon_i$

Step 6.3: The maximum likelihood method is used to calculate the truncated regression of δ_i^{**} on z_i, providing estimates $\hat{\hat{\beta}}^*$, $\hat{\hat{\sigma}}^*$

Step 7: Use bootstrap values in K and the original estimates $\hat{\hat{\beta}}$, $\hat{\hat{\sigma}}$ to generate $(1-\alpha)$ computed confidence intervals for each element of β and for σ_ε

Appendix 3. Principal Component Analysis for the GOV variable

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	5.1731	4.7908	0.8622	0.8622
Comp2	0.3823	0.1166	0.0637	0.9259
Comp3	0.2657	0.1634	0.0443	0.9702
Comp4	0.1022	0.0572	0.0170	0.9872
Comp5	0.0450	0.0133	0.0075	0.9947
Comp6	0.0317	.	0.0053	1.0000

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Data availability Data are publicly available from the World Bank.

Declarations

Competing interests The authors declare no conflict of interest.

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