



# Where is the gray side of green growth? Theoretical insights, policy directions, and evidence from a multidimensional approach

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## Abstract

Addressing the geographical relocation of the pollution-intensive gray side of low-carbon green production, our study analyzes potential determinants of green and gray growth performance of industrialized/developed countries (IDCs) and industrializing/emerging economies (IEEs) over the 1996–2015 period. We define green growth by low-carbon output, while we link gray growth to comparative advantages of pollution havens. Green and gray growth models include such predictors as domestic income and foreign direct investment (FDI) together with composite indices for globalization, environmental policy stringency (EPS), industrialization, and control of corruption. Considering non-stationarity, cross-section dependency, endogeneity, and heterogeneity concerns, we employ bootstrap and residual-based cointegration analyses followed by long-run estimations using the Common Correlated Effects Mean Group (CCEMG) and Dynamic Ordinary Least Squares (DOLS) estimators and causality examination through Dumitrescu-Hurlin and Emirmahmutoglu-Kose tests. The key findings of the study are as follows: (i) income is positively associated with green growth for both IEEs and IDCs, whereas the income-gray growth nexus is negative for IEEs. (ii) Although inward FDI stocks are positively related to green and gray growth of IEEs and outward FDI stocks are negatively associated with green and gray growth of IDCs, these relationships are mediated by EPS. (iii) Globalization encourages both green and gray growth for IDCs. (iv) Even though EPS inhibits green growth and encourage gray growth in IEEs, these direct effects widely depend on the indirect effects of control of corruption. (v) IEEs' higher gray growth performance is substantially explained by their increased industrial competitiveness, whereas the link is negative for IDCs. (vi) Control of corruption fosters both green and gray growth in IEEs. Overall, “growing gray” does not necessarily mean “not growing green” and vice versa. Globally, the low-carbon benefits of greening countries may be counterbalanced by the environmental costs of graying economies. From a policy perspective, IEEs need to reinforce environmental policies by green efficiency, green industrialization, and anti-corruption plans to decouple economic growth from carbon dioxide emissions.

**Keywords** Green growth, · Gray growth, · Environmental Kuznets curve, · Pollution haven hypothesis, · Environmental policy stringency, · Industrialization, · Control of corruption

**JEL classification** C33 · F21 · H23 · O25 · Q5

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The original online version of this article was revised: The correct image of Figures 1 and 2 is presented in this paper.

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## Introduction

There has been a widespread rise in the societal and individual awareness of direct and indirect costs of environmental pollution driven by greenhouse gas emissions. Carbon dioxide (CO<sub>2</sub>) pollutant dominates global greenhouse gases. According to the National Aeronautics and Space Administration (NASA) estimates, human activities have raised atmospheric concentrations of CO<sub>2</sub> by 47% since 1850, and this increase is more than what had happened naturally in 20,000 years (NASA 2020). More than half of these cumulative anthropogenic CO<sub>2</sub> emissions have been released

after 1970 because of the growth in population and economic activities. This human-induced CO<sub>2</sub> pollution is also the most important cause of climate change (Olivier and Peters 2019; IEA 2020; NASA 2020). The land-ocean temperature indices of NASA (2020) show that the 2000–2020 period covers all the warmest years (except for 1998) recorded since 1880. In 2018, CO<sub>2</sub> emissions constituted about 75% of total greenhouse gas emissions. The direct drivers of these global CO<sub>2</sub> emissions are the combustion of coal (39%), oil (31%), and natural gas (18%), representing a share of about 88% (Olivier and Peters 2019). Power industry (38%) and other industrial combustion (22%) together with transportation (19%) and buildings (10%) are responsible for about 89% of these CO<sub>2</sub> emissions (Crippa et al. 2019). China (30%), as the world's biggest manufacturer, and the USA (14%) and European Union countries (9%), as the huge energy users, are the top three CO<sub>2</sub> emitters with a share of about 53% followed by India (7%), Russia (5%), and Japan (3%) (Olivier and Peters 2019; IEA 2020). Furthermore, CO<sub>2</sub> emissions have been yet showing no signs of peaking despite the increased mitigation actions undertaken at both the national and international levels. However, during global crises with huge declines in output, CO<sub>2</sub> emissions tend to decrease as well. The latest example of these emission-reducing crises is the coronavirus (COVID-19) pandemic, which was first identified in late December 2019 in Wuhan, China. With the worldwide spread of the COVID-19 outbreak during the first quarter of 2020, many international borders were closed, a significant part of the world population was ordered to stay at home, and many people lost their jobs. Consequently, commuting and transport reduced, consumption patterns changed toward basic needs, and unemployment increased in many countries leading to a sharp slowdown in economic activities. These confinements and its economic effects reduced daily global CO<sub>2</sub> emissions by 17% in early April 2020 compared to the mean of 2019 (Le Quéré et al. 2020). The International Energy Agency (IEA) expects a temporary decline in global CO<sub>2</sub> by about 8% from 2019 to 2020. This expected reduction is six times larger than the previous one recorded in 2009 due to the global financial crisis (IEA 2020).

A vast interdisciplinary and multidimensional research has studied the close relationships between economic activities and CO<sub>2</sub> emissions from both theoretical and empirical perspectives (Grossman and Krueger 1991, 1995; Sharma 2011; Cherniwchan 2012; Udara Wilhelm Abeydeera et al. 2019). While investigating the environmental impacts of economic growth, traditional wisdom builds on the well-known Environmental Kuznets Curve (EKC) hypothesis which originally postulates an inverted U-shaped relationship between various indicators of environmental degradation and gross domestic product (GDP) per capita. Since it was unveiled by Grossman and Krueger (1991) and named by Panayotou (1993) together with further explanations of Grossman and

Krueger (1995) and Stern et al. (1996), researchers have been increasingly examining the EKC hypothesis for country groups and individual countries. In these studies, environmental pollution has been commonly measured and proxied by emissions and concentrations of greenhouse gases (mostly CO<sub>2</sub>) or by the ecological footprint from a broader viewpoint. The variations in environmental pollution have been widely explained empirically by changes in GDP along with some economic (e.g., industrialization, global investments, financial development, international trade, energy consumption, energy intensity, renewable energy, production structure, etc.) and non-economic (e.g., governance, political and social globalization, urbanization, population, etc.) factors (Cavlovic et al. 2000; Stern 2004; Tamazian et al. 2009; Apergis and Ozturk 2015; Shahbaz et al. 2016; Stern 2017; Allard et al. 2018; Shahbaz et al. 2018; Dogan et al. 2019; Sinha et al. 2019; Ng et al. 2020). The EKC pattern is quite attractive as it implicitly suggests no additional environmental policies since economic growth is also good for the environment in the long run. However, the results of ample research have remained ambiguous even controversial with varied turning points and different shapes (e.g., U, N, inverted N, etc.) of the EKC pattern (Cavlovic et al. 2000; Stern 2004; Allard et al. 2018; Sinha et al. 2019). The differences in samples, periods, country-specific factors, environmental indicators, pollutant types, measures of pollution, and econometric techniques are not able to explain all blurriness of the findings.

On the mixed evidence in the EKC literature, the impacts of environmental policies have gained increasing popularity among policy-makers and researchers (Albrecht 1998; Zhang and Yao 2018; Shahzad 2020; Yang et al. 2020). In a cross-country context, the link between environmental degradation and environmental policies has been reflected by combining the EKC pattern with the migration of pollution-intensive industries from developed to developing regions within the pollution haven hypothesis (PHH) framework (Mani and Wheeler 1998; Cole 2004; Daudin et al. 2011; Singhania and Saini 2021). The PHH argues that firms in developed countries with stringent environmental regulations will carry their pollutive activities to developing countries where environmental regulations are relatively lenient (Neumayer 2001; Millimet and Roy 2016; Garsous and Kozluk 2017; Balsalobre-Lorente et al. 2019). Thus, the inward and outward directions of foreign direct investment (FDI) operations motivated by the policy differences are regarded as a reason for the geographical shift of pollution-intensive industries (Cole 2004; Garsous and Kozluk 2017; Cai et al. 2018; Shapiro and Walker 2018). This consideration is supported by the global trade and investment patterns in which the participation of developing countries with no or lax environmental norms has considerably increased since the early 1980s particularly in the resource-driven and pollution-intensive industries. Because of their relatively

higher involvement in manufacturing sectors and increased competitive performance in industrial production compared to their counterparts, some developing countries experiencing rapid industrialization are grouped under the label of emerging industrial economies (UNIDO 2019). In line with the fast industrialization of emerging industrial economies, the global share of many developed countries implementing stringent environmental regulations have fallen gradually in pollution-intensive industrial activities. This trend is referred to as the de-industrialization and/or tertiarization of developed countries (Kollmeyer 2009; Montresor and Marzetti 2011) and fits well the relocation pattern predicted by the PHH in a globalized world economy, albeit empirical support remains limited.

The predicted polarization (clean-growing developed countries and dirty-growing emerging economies) has directed the interests of researchers to production activities of firms and thus growth performances of countries as a source of their CO<sub>2</sub> emissions. Recently, the increasing environmental concerns have forced and motivated many countries, albeit not all countries, to adopt stringent environmental regulations to limit pollution-intensive production activities or encourage resource productivity and energy efficiency (Grossman and Krueger 1995; Botta and Kozluk 2014; Galeotti et al. 2020). Although environmental regulations and taxes are considered as fundamental driving forces of easing environmental pollution (Zhang and Yao 2018; Shahzad 2020), the current literature demands more empirical investigation to provide sound evidence about the validity of the PHH since there exist studies supporting the pollution halo hypothesis (Balsalobre-Lorente et al. 2019) and the Porter hypothesis (Salehnia et al. 2020) as well. The pollution halo hypothesis argues that FDI inflows may reduce environmental pollution in the host (developing) country (Balsalobre-Lorente et al. 2019), while the Porter hypothesis asserts that stringent environmental policies encourage green productivity among local polluting firms (Porter and van der Linde 1995; van Leeuwen and Mohnen 2017). Therefore, the consideration of “stringency” of environmental policies, which also indirectly matters for pushing and pulling pollution-intensive FDI activities within the PHH, becomes a useful empirical strategy in modeling the environmental outcomes of globalization and pro-environmental policies (Ahmed 2020; Wolde-Rufael and Weldemeskel 2020; Yang et al. 2020). On the other hand, the success of environmental policies is somehow affected by prevailing public sector corruption which may obstruct both the setting of new environmental standards and the implementation of existing programs (Zhang et al. 2016; Candau and Dienesch 2017). Even though the pollution haven-corruption paradises nexus has attracted the interest of researchers (Welsch 2004; Pellegrini and Gerlagh 2006; Candau and Dienesch 2017; Danish and Wang 2019; Lapatinas et al. 2019), the current literature has paid a little attention to the indirect impacts of corruption which may

intervene in the relationship between environmental policies and decarbonization performance of countries.

Besides the holistic approach which considers both the production and consumption sides of CO<sub>2</sub> emissions, a new research strand adopts the green growth concept as international organizations like UNESCAP (2013) and OECD (2017, 2020) provide internationally comparable and measurable indicators of green growth. This relatively new perspective revisits two approaches to debate about the relationship between the environment and economic growth. For the first view, environmental degradation is an unavoidable outcome of economic growth, and thus low-carbon environmental quality can only be improved by slowing down the economic growth, i.e., degrowth, which is seldom considered in policy options (Sandberg et al. 2019). The second view claims that economic growth can be decoupled from CO<sub>2</sub> emissions through more efficient use of resources which implies green growth. The evolution of environmental degradation phenomenon to green and gray growth concepts has enabled researchers to trace the environmental impacts of economic growth directly (Capasso et al. 2019; Merino-Saum et al. 2020) through the distinction of GDP between the productivity-driven (WB 2012; OECD 2017; GGGI 2020) and pollution-intensive outputs (McCulligh 2018; Capasso et al. 2019). Both concepts include new insights into the globalization process which has economic, social, and political channels through which it affects the greening (Mostafa 2012; Balsalobre-Lorente et al. 2019) and graying (Boyce 2004; Shahbaz et al. 2018) directions of countries. Therefore, the globalization forces of CO<sub>2</sub> emissions should be reflected in EKC and PHH research from the green and gray growth perspectives.

Given the above-mentioned trends in global CO<sub>2</sub> emissions and directions in the literature, there is a need to determine the barriers and drivers of green and gray growth and explore the indirect impacts of environmental policy stringency (EPS) and control of corruption. Furthermore, to capture the potential geographical relocation of the pollution-intensive gray side of low-carbon green production, it is also important to compare high-income developed countries, which have more stringent environmental policies and relatively higher green growth performance, with middle-income emerging economies, which have relatively lenient environmental policies and higher gray growth performance. Therefore, the present study comprehensively analyzes potential determinants of green and gray growth performance of seven industrialized and developed countries (hereinafter IDCs) and seven industrializing and emerging economies (hereinafter IEEs) over the 1996–2015 period. The study grounds its theoretical framework on the global perspectives of the EKC hypothesis and the PHH (and the pollution halo and Porter hypotheses to some extent) to analyze how domestic income, inward (for IEEs) and outward (for IDCs) FDI stocks, globalization,

EPS, industrialization, and control of corruption affect green and gray growth experiences of countries. The sampled IDCs are Canada, France, Germany, Italy, Japan, the UK, and the USA, while IEEs include Brazil, China, India, Indonesia, Russia<sup>1</sup>, South Africa, and Turkey. These 14 countries are among the main CO<sub>2</sub> emitters (individually contributing more than 1% to the global total) with a share of about 70% of the world's total emissions released in 2018 (Olivier and Peters 2019; IEA 2020). The study contributes to the literature by integrating green and gray growth concepts, adopting the production-side CO<sub>2</sub> emissions and gray competitiveness approaches to environmental pollution, and combining the policy and research perspectives at a global scale. It differs from the previous research by also considering the indirect effects of EPS (through the interaction with FDI stocks) and control of corruption (through the interaction with EPS). In the remainder of the study, the next section conceptualizes green and gray growth phenomena followed by a presentation of the theoretical origins and indicators of the concepts. Then, the study explains the potential determinants of green and gray growth on a driver-barrier basis. Before the analysis, model specifications, variables, and data are described. The econometric analysis starts with a sequent control of variables and models for stationarity, cross-section dependency, endogeneity, and heterogeneity properties. Accordingly, the analysis proceeds with cointegration tests followed by long-run estimations and ends with a causality inspection. The study concludes with a discussion of the findings and limitations to provide some insights on the practical implications and future research.

## Conceptualization of green and gray growth

A country's economic growth is the increase in its GDP during a certain period. GDP is the value added created through the production of goods and services. Economic growth is a key measure of a country's ability to generate outputs from a given set of inputs including labor, physical capital, and natural resources. Therefore, economic growth can be achieved through either using more inputs, using these inputs productively, or both. Because of the scarcity of inputs, particularly of natural resources, there has been a longstanding concern related to the abilities of countries to sustain past growth rates in the future. Despite the overall increased awareness of communities regarding sustainability, the sustainable growth

<sup>1</sup> Despite the United Nations Industrial Development Organization (UNIDO 2019) currently defines Russia as an industrialized country, we included Russia in the IEEs group since the variance analysis based on comparisons of mean differences of examined variables revealed that Russia was similar to IEEs rather than IDCs for the 1996–2015 period. These sampled IEEs are sometimes grouped as BRIICST countries (e.g., Wolde-Rufael and Weldemeskel 2020) in the literature.

indicators substantially vary across countries. Some countries heavily rely on the extraction of subsoil assets, while other countries grow through productivity improvements (Rodríguez et al. 2018).

Beyond the sustainability concern stemmed from the limited availability of natural resources, the literature on the comparison of benefits and costs of economic growth related to human well-being and quality of life has flourished especially in the past two decades. This strand in the literature has linked a pure economic growth perspective to a sustainable growth aspect via the green growth concept. Green growth has its wide-ranging considerations varying from green consumer and green business to green economy and green world. The green growth concept has gained popularity in all academia, policy-making, and societal arenas leading to numerous definitions and a conceptual blurriness. Controversiality over defining the term “green growth” is because of several factors, among which are (i) interchangeable use of green growth and green economy, (ii) interdisciplinary and multidimensional comprehension, (iii) interest and involvement of many policy-making institutions, and (iv) implementation in different areas and adoption in varied sectors (Merino-Saum et al. 2020).

The United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP) indicates that the conventional “grow first, clean up later” approaches to economic growth have been increasingly posing a threat to the futures of economies and societies. As per UNESCAP (2013), a green growth is an approach to economic development that fosters environmentally sustainable, low-carbon, and socially inclusive development. Addressing the necessity, efficiency, and affordability of green transformation, the World Bank (WB 2012) describes green growth as “the efficient use of natural resources and minimization of pollution and environmental impacts for preventing physical disasters that cause undesired economic, political, and social consequences.” The Organisation for Economic Co-operation and Development (OECD) underlines environmental policies and defines green growth as “fostering economic growth and development while ensuring that natural assets continue to provide the resources and environmental services on which human well-being relies” (OECD 2017; OECD 2020). The Global Green Growth Institute (GGGI) considers green growth as one of the key pillars for sustainable and inclusive economic development and defines green growth as “a development approach that seeks to deliver economic growth that is both environmentally sustainable and socially inclusive.” These green growth definitions encompass four fundamental underlying dimensions: (i) efficient and sustainable use of natural resources; (ii) protection of natural capital and recognition of the limits of natural resources; (iii) green economic opportunities for investment, trade, employment, and innovation; and (iv) inclusive growth, which ensures access to basic services and resources,

health and safety, social equality, and social protection (GGGI 2020). On the basis of above-mentioned definitions, we adopt a production-based environmental pollution approach and define green growth as the production of goods and services with lesser CO<sub>2</sub> emissions. Hence, our green growth concept covers both the development of new environmental sector and an increase in the green productivity in traditional sectors. This approach allows to better compare countries' green growth performance.

The concept of gray growth is a relatively new aspect that we use to define environmentally unfriendly components of economic growth added by the production processes in pollution-intensive industries. In the sense of dirty industry aspect and pollution haven effect, "gray" is an ascription to the grayish color of most metals<sup>2</sup>. Indeed, almost every production activity of goods and services, regardless of how much they are green, has a gray side created in pollution-intensive (dirty) industries. Industries that have heavier impacts on the environment are involved in such economic activities, for example, the extraction of non-renewable natural resources including fossil fuels and minerals and the production of metals, electricity, wood/paper, and chemicals (Binder 2001). Gray growth can be intuitively recognized as growth contents that are not green, but it means more when considered in conjunction with the global reallocation of pollutive industries. This international dynamic pattern is mostly examined by the PHH (Neumayer 2001; Garsous and Kozluk 2017; Balsalobre-Lorente et al. 2019; Salehnia et al. 2020). The investigation of the cross-country predictions of the PHH and the EKC adjustment patterns has become more important with the consideration of the argument that the external costs of environmental problems can outweigh the internal benefits of economic growth. In this regard, the relevant literature needs more research on especially IEEs as the increasing comparative advantage and competitiveness in the pollution-intensive sectors are decisive in their growth performance.

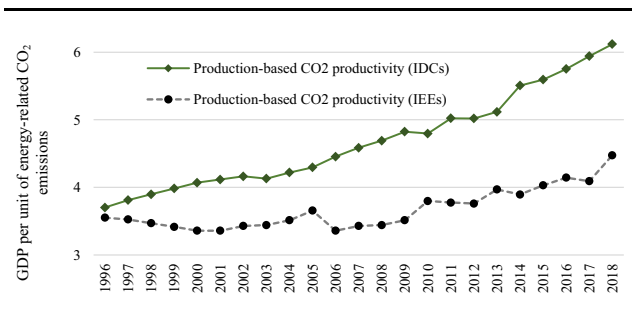
### Theoretical origins and indicators of green and gray growth

Despite its varied definitions, there are not many quantitative measurements of green growth. Since countries have different characteristics that affect their capabilities in adopting and implementing green growth initiatives, it is difficult to provide a common set of green growth indicators. Some indicators are measurable and equally relevant to all the countries, while some others are unmeasurable quantitatively

<sup>2</sup> But there are also studies defining pollution-intensive growth pathways with different colors. For example, Boyce (2004) and Capasso et al. (2019) use "brown" to explain environmentally unfriendly production technologies and economic activities.

and relevant to only a few countries. OECD (2017) provides a list of both main (measurable directly) and proxy (can be represented by other indicators when the main indicators are not available) indicators of green growth. In this list, as a useful concept, productivity (categorized into carbon and energy productivity, resource productivity, and multifactor productivity) is a key indicator of green growth. The OECD green growth database contains both production- and demand-based resource productivity where CO<sub>2</sub> productivity is assessed as the essential indicator of green growth. Figure 1 shows production-based CO<sub>2</sub> productivity measured as the constant (2015) US dollar GDP per unit of energy-related CO<sub>2</sub> emissions for the sampled country groups. Figure 1 shows that the mean values of the IDCs group are considerably higher than those of the IEEs group. Furthermore, the depiction of Fig. 1 reveals a divergence trend rather than a convergence process between the green growth performance of IDCs and IEEs.

Gray growth is widely regarded as the opposite of green growth, i.e., not to grow green, and thus usually not considered separately. This ignorance in the relevant literature has been apparently filled by the PHH literature. Relying on the observation that many firms in developed countries have been forced to adopt and obey higher environmental standards, studies examining the PHH take the roles of comparative advantages of pollution havens into account to find out whether the lenient environmental regulations in developing countries attract polluting industries from developed countries where the environmental regulations are relatively more stringent. Theoretically, it can be premised that countries with weak environmental regulation will, ceteris paribus, have a comparative advantage in polluting (dirty) industries. The PHH links the rapid growth of polluting industries driven by cross-border FDI activities in unregulated open economies to the lower cost advantage which these countries offer. The basic formulation of the PHH associates a positive relationship between FDI inflows and environmental pollution and concludes that production within polluting industries will shift to developing countries with lax environmental regulation. However, the empirical part of the



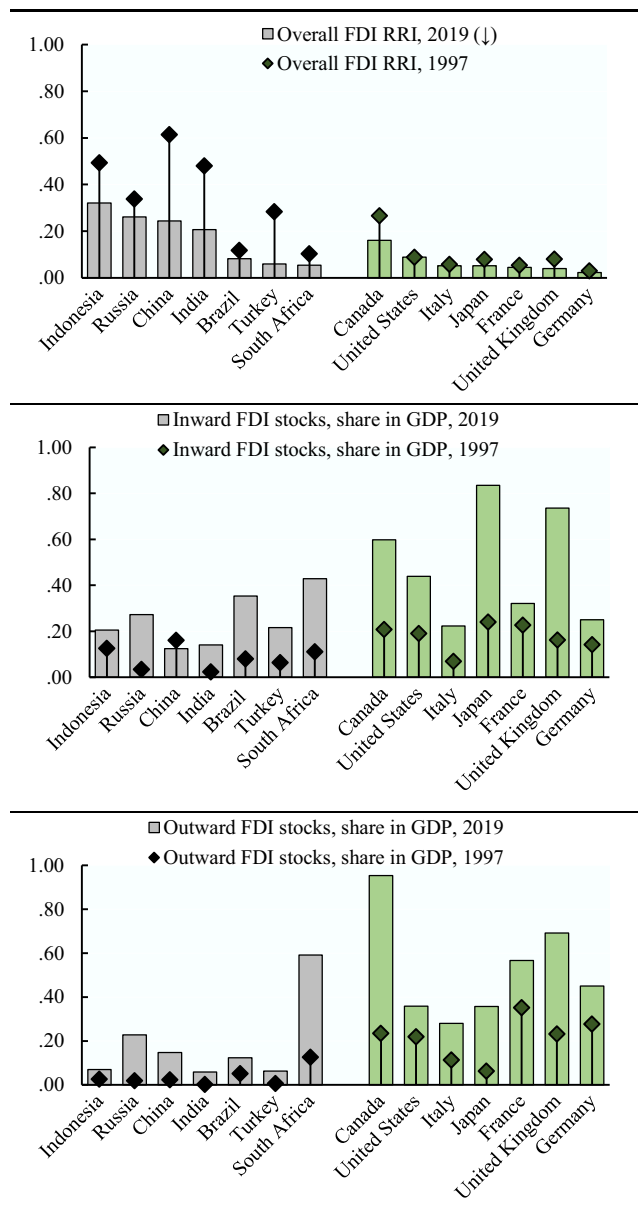
**Fig. 1** Production-based CO<sub>2</sub> productivity in the sampled country groups (Country averages, 1996–2018). Source: OECD (2020)

PHH literature is inconclusive<sup>3</sup> which revisits the Porter hypothesis which argues that stringent environmental regulations benefit firms (in developing countries) by fostering green innovation (Porter and van der Linde 1995; van Leeuwen and Mohnen 2017; Salehnia et al. 2020). The Porter hypothesis can be linked to the pollution halo hypothesis which argues that FDI inflows transfer their greener technologies to host countries where, consequently, pollution-mitigating spillover effects occur (Balsalobre-Lorente et al. 2019).

The main shortcoming of the PHH stems from the ignorance of economic structures and comparative advantages of home (developed) and host (developing) countries. Developing countries can be said to provide a “pollution haven” if their environmental standards are below their efficiency levels or if they refrain from enforcing their standards to attract more FDI (Neumayer 2001; Millimet and Roy 2016). Considering only FDI inflows to developing countries giving little or no attention to FDI outflows from developed countries and missing the agglomeration effects of FDI stocks are the weakness of the empirical PHH literature. An attempt has been made in the study to investigate the PHH differently by analyzing the impacts of inward and outward FDI stocks on countries’ green and gray growth performances. Adopting an open economy perspective and relying on the presumed mutual relationships between environmental policies, inward and outward FDI stocks, and economic structures of home and host countries, we use international competitiveness in pollution-intensive industries as a proxy for gray growth.

Essentially, aside from the environmental policies, FDI flows are presupposed to be sensitive to regulations on FDI flows. Figure 2 shows how restrictive FDI regulations and international FDI stocks (as a share of GDP) changed from 1997 to 2019 in the sampled countries. The OECD’s FDI Regulatory Restrictiveness Index (FDI RRI) in Fig. 2 measures the restrictiveness of statutory restrictions on FDI in countries by considering foreign equity limitations, discriminatory screening or approval mechanisms, restrictions on the employment of foreigners, and other operational restrictions such as restrictions on branching and capital repatriation or land ownership by foreign-owned enterprises. Restrictions are evaluated on a 0 (open) to 1 (closed) scale. This index can be a critical determinant of a country’s attractiveness to foreign investors (OECD 2020). At the top of Fig. 2, changes in overall FDI RRI (covering all types of restrictions on all economic sectors) indicate that the sampled countries became more open to the FDI from 1997 to 2019. Albeit substantial deregulations, IEEs have remained restrictive compared to IDCs. Considering their GDP growth, it can be inferred that IEEs generally attracted more FDI as they deregulated FDI flows. However, how much the deregulations affected FDI flows in IDCs seems unclear since their inward and outward FDI stocks increased considerably from 1997 to 2019.

<sup>3</sup> On the unclear evidence about the PHH, Mani and Wheeler (1998) argued that pollution havens were as transient as low-wage havens.



**Fig. 2** FDI regulatory restrictiveness indices and FDI stocks (1997, 2019). Source: OECD (2020) and UNCTAD (2020)

Within the PHH and gray growth aspects, differences between the stringencies of environmental policies of developed and developing countries matter for capturing the push and the pull effects on FDIs and pollution-intensive industries. Figure 3 comparatively shows that IDCs, on average, have more stringent environmental regulations than IEEs. Moreover, there is a divergence process rather than a convergence.

Consequently, according to the PHH, unregulated and open developing countries will grow gray through the growth of polluting industries, while developed countries grow green through the enhancement of clean industries. Defining a certain list for dirty industries (and clean industries) has been a longstanding attempt. Some studies (e.g., Albrecht 1998;

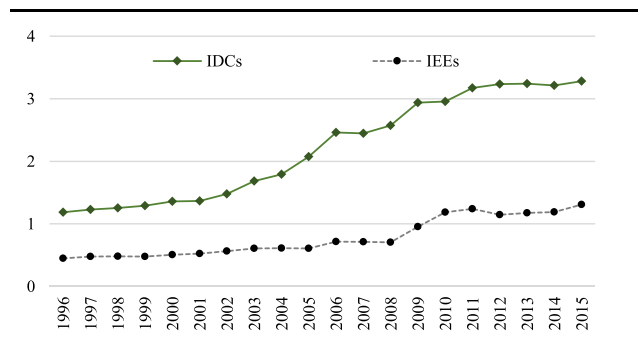


Fig. 3 EPS indices (country averages, 1996–2015). Source: OECD (2020)

Binder 2001; Shapiro and Walker 2018) disaggregate industries to determine more specific dirty sectors. Given the ever-increasing intersectoral linkages within the main industry, our study defines pollution-intensive industries broadly by considering all types of environmental pollution (noise-, air-, water-, light-, and metal-pollution) and categorizes them into five broad groups as presented in Table 1 based on the 3rd revision of the Standard International Trade Classification (SITC). This broad classification considers production activities that pollute the environment both directly and indirectly. It should be noticed that there are some clean components in these gray industries as green industries embody some dirty parts. Therefore, we cautiously define them as “pollution-intensive” sectors rather than purely “pollutive” or “dirty” industries.

Detailed explanations for products in the sub-sectors in 3rd and 4th revisions can be respectively found at UN (1986) and UN (2006)

Table 2 compares trade performances of IDCs and IEEs in the defined pollution-intensive industries and shows that IDCs’ performance decreased, whereas that of IEEs increased significantly from 1990 to 2018. This match reveals a geographical relocation of the pollution-intensive industries.

Because of its interconnections with FDI, environmental policy, and globalization, the gray side of green growth can be better captured by measuring countries’ comparative advantages in pollution-intensive industries. Under the assumption of free trade, revealed comparative advantage (RCA), as a metric, predicts that international trades are governed by relative productivity differences. Even the productivity differences cannot be measured directly, it can be indirectly captured by gauging RCA from the evidenced trade statistics. Adopting the methodology of the UNCTAD (2020), a country *i*’s RCA in a specific product group *d* can be calculated as an index through the formula shown in Eq. 1 where  $x_{i,d}$  and  $x_{w,d}$  are the values of country *i*’s and world’s total exports of product *d* which is produced in pollution-intensive sectors.  $X_{i,t}$  and  $X_{w,t}$  refer to the country’s total exports and world total exports, respectively.

$$RCA_{i,d} = \left( \frac{x_{i,d}}{X_{i,t}} \right) / \left( \frac{x_{w,d}}{X_{w,t}} \right) \tag{1}$$

Table 1 The study’s definition of pollution-intensive industries

Main category	SITC codes
Wood, wood products, and paper	244–248, 251, 633–635, 641–642
Chemicals	232, 266–267, 511–516, 522–525, 531–533, 541–542, 553–554, 562, 571–575, 579, 581–583, 591–593, 597–598, 621, 629
Metal and basic metal manufacturing	661–666, 670–679, 681–687, 689, 691–697, 699
Transport equipment	781–786, 791–793
Minerals	272–274, 277–278, 281–289, 321–322, 325, 333–335, 342–345, 351, 667

**Table 2** Trade performance of selected country groups in polluting industries (1990, 2018)

Share in national exports (country average)		Relative trade balance (country average)		Share in the world market (country total)	
1990	2018	1990	2018	1990	2018
IDCs					
.183	.075	-.049	-.155	.241	.152
IEEs					
.117	.196	-.139	-.072	.083	.147

Source: Authors' calculations from UN Comtrade (2020)

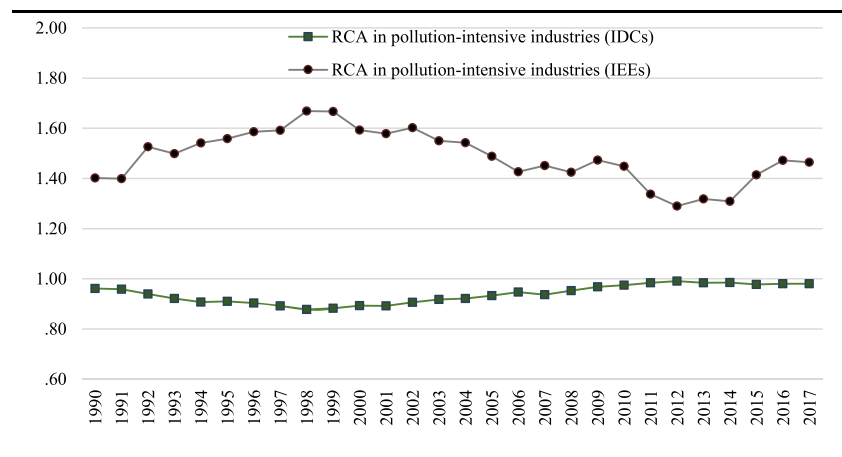
A RCA index between 0 and 1 indicates that the relevant country has a revealed comparative disadvantage in the product, while above 1, it indicates comparative advantage. The higher the value of a country's RCA index, the higher its export strength in the so-called dirty product of pollution-intensive sectors. RCA indices of countries in the pollution-intensive sectors are presented in Fig. 4, which shows that the sampled IEEs group, on average, has comparatively much higher RCA indices than those of IDCs which typically have disadvantages.

## Comparison of alternative green and gray growth indicators

Green and gray growth concepts can be represented by different indicators which have been also evolving accordingly as the definitions of green and gray growth change over time. To obtain consistent results comparable to those of the previous studies, there is a need to check whether the proxies cover different aspects. In this regard, the study has also compared the green and gray growth measurements with multidimensional alternative proxies to check the stability of the conceptualization. The study adopts a production-based CO<sub>2</sub> productivity approach and defines green growth as the GDP per kilogram of energy-related CO<sub>2</sub> emissions. As seen from

Table 3, the correlations (Pearson coefficients) between our green growth indicator and other headline indicators of OECD (2017, 2020) are rather high (except for green total factor productivity) revealing that our green growth measure is consistent with its varied aspects. Our green growth proxy strongly refers to lesser CO<sub>2</sub> (in terms of both production- and demand-based emissions) and reduced energy intensity. Even the green growth taken in this study is based on the production-side approach, it can be used interchangeably with demand-based CO<sub>2</sub> productivity as the correlations are higher than .97 for all three panels. Albeit at a lower magnitude, our green growth definition is also positively and significantly correlated with green total factor productivity measured as a pollution abatement component of GDP growth based on the methodology of Rodríguez et al. (2018). Total CO<sub>2</sub> emissions per capita, a widely used proxy of environmental degradation, is negatively and significantly (but weakly) correlated with our green growth indicator, whereas it is positively and moderately correlated with our gray growth measure. Our gray growth measure is the RCA in the pollution-intensive products. Consistently, it is negatively (but not strongly) correlated with the RCA indices in the so-called clean products that is calculated using UN Comtrade (2020) data based on the green product classification of Hamwey et al. (2013). This categorization considers waste management, energy efficiency, renewable energy, and environmental analysis.

**Fig. 4** RCA indices of country groups in pollution-intensive industries (country averages, 1990–2017). Source: Authors' calculations from UN Comtrade (2020)





**Table 3** Correlations between multidimensional measurements of green and gray growth (1996–2015)\*

	Mixed panel	IDCs sub-panel	IEEs sub-panel
Correlations of the study’s green growth proxy with its alternative measurements			
Production-based CO <sub>2</sub> intensity. Energy-related CO <sub>2</sub> per capita (metric tons)	-.920**	-.857**	-.987**
Demand-based CO <sub>2</sub> intensity. Energy-related CO <sub>2</sub> per capita (metric tons)	-.900**	-.830**	-.950**
Production-based CO <sub>2</sub> emissions (million metric tons)	-.795**	-.729**	-.990**
Energy intensity. Total primary energy supply per capita (metric tons of oil equivalent)	-.667**	-.595**	-.985**
Total primary energy supply (million metric tons of oil equivalent)	-.761**	-.694**	-.988**
Demand-based CO <sub>2</sub> productivity. GDP per unit of energy-related CO <sub>2</sub> emissions (2015 US dollars per kilogram)	.978**	.972**	.994**
Demand-based CO <sub>2</sub> productivity. Disposable income per unit of energy-related CO <sub>2</sub> emissions (2015 US dollars per kilogram)	.982**	.977**	.995**
Green (environmentally adjusted) total factor productivity. Pollution abatement component of GDP growth	.590**	.388**	.436**
Total CO <sub>2</sub> emissions per capita (metric tons)	-.386**	-.471**	-.269**
Correlations of the study’s gray growth measurement with its alternative proxies			
RCA indices in green/clean products (SITC 4th rev., 4-digit codes: 5121, 6973, 6975, 7148, 7162, 7414, 7763, 7782, 8744, 8841, 8997)	-.530**	-.606**	-.491**
Total CO <sub>2</sub> emissions per capita (metric tons).	.644**	.583**	.711**

\*Periods are not equal for all countries. Detailed explanations about the measurements can be found at OECD (2017) and OECD (2020)

\*\*Shows the statistical significance of correlation coefficients at the level of 1%

Source: Authors’ computation based on OECD (2020), UN Comtrade (2020), and IEA (2020) data

### Potential determinants of green and gray growth

The green growth literature is expanding with firm-level, country-specific, and cross-country studies. The existing literature on the predictors of green growth measures is twofold. One research strand has been dealing with the potential drivers, whereas the other stream has been trying to explore the barriers to green growth (Capasso et al. 2019; Hu et al. 2020). The relevant studies have major shortcomings since they tend to ignore countries’ transition to the green economy from the gray economy. Given the structural, social, political, and economic dimensions of green and gray growth paths of countries, together with the widely examined income and international investment predictors, our study grounds its underpinning framework in four pillars that are (i) globalization, (ii) environmental policy, (iii) economic structure, and (iv) institutional quality. We use composite index proxies for these dimensions to explore the impacts of a wide range of variables.

Globalization could either lead to a worldwide low-carbon green economy by encouraging higher environmental quality or to an environmental polarization in which the greening of the developed world is accompanied by the graying of the developing world (Boyce 2004). The latter case is closely related to the globalization-driven carbon emission hypothesis (Shahbaz et al. 2018), the validity of which tends to change over country classification by development and income levels (Shahbaz et al. 2016; Shahbaz et al. 2018). For capturing multifaceted environmental impacts of globalization, we use the KOF globalization index which measures the levels of economic, social, and

political dimensions of globalization on a scale of 1 (least globalized) to 100 (most globalized) (Gygli et al. 2019).

It is commonly believed that tackling environmental issues is the responsibility of the governments. Regarding environmental policies, the democratic countries may exhibit stronger commitments to environmental policies as compared to non-democratic regimes. However, as Povitkina (2018) underlines, more democracy may be associated with lower pollution in a low-corruption context. Prevalent corruption can impede the efficiency of environmental policies by distorting the allocation of incitements and limiting the overall fairness of the stringency of policies (Candau and Dienesch 2017). Besides, from a psychological aspect, it can be inferred that communities with approval of individual corruption activities tend to ignore the overall impact of environmental pollution and societal benefits of green growth. Additionally, environmental policies may fail in corrupt countries where policy instruments are used to support rent-seeking activities instead of protecting the environment (Lapatinas et al. 2019). Corruption can attract rent-seeking multinationals from countries where corruption is strictly controlled. Thus, environmental policies should be clear and transparent (Zhang et al. 2016) as the lack of transparency can encourage corruption. All these insights also affect the societal embracement of international green economy initiatives and standards such as those of the Kyoto protocol and the Paris agreement. On the other hand, the relevant literature does not provide concrete evidence for anti-corruption-environmental quality nexus as corruption can both “grease” and “sand” the wheels of green and gray growth through different channels. For capturing the effects of anti-corruption,

we take control of corruption variable which is one of the six dimensions of the Worldwide Governance Indicators Project (WGI 2020) which scores countries' governance indicators in units ranging from about -2.5 to 2.5, with higher values corresponding to better (stronger) control of corruption.

Recently some studies (e.g., de Angelis et al. 2019; Ahmed 2020; Wolde-Rufael and Weldemeskel 2020) have examined the nexus between EPS and different aspects of environmental performance. In the context of our study, stringent environmental policies may affect the green and gray growth performances of countries both by forcing firms to mitigate pollution (direct effect) and by motivating FDIs to seek for pollution havens with a lower cost of pollution (indirect effect). The first case, direct effect, is about the contribution of environmental regulation to environmental productivity within the Porter hypothesis, while the latter situation, indirect effect, is a research domain on the PHH. The existing PHH literature, however, essentially links the increased involvement of developing countries in pollution-intensive industries to their FDI attraction from developed countries by presuming the effects of environmental policies as self-evident. This empirical setting relies on a significant difference between the stringency of environmental policies in developed and developing countries and tends to miss the impacts of stringent environmental policies and disregard other motives of FDI flows. We design green and gray growth models to reflect the direct impacts of environmental policies and estimate models by also controlling the interaction between FDI stocks and EPS<sup>4</sup> to explore the presence of an indirect effect. We use the EPS index provided in the environment database of the OECD (2020). This index measures the degree of stringency of environmental policy instruments like emission taxes, incentive schemes, certification, feed-in tariffs, pollution standards, emission limits, and research-development subsidies on climate and air pollutive activities. The index ranges between 0 (not stringent) and 6 (highest stringency) (Botta and Kozluk 2014; OECD 2020).

Industrialization measured as the compositional shift from agricultural to industrial production (Cherniwchan 2012) and/or as manufacturing agglomeration (Yuan et al. 2020) is among the central determinants of environmental quality and green economic efficiency both within and between countries. From an economic structure perspective, our study proposes that industrialization patterns of countries matter for their pathways to green and gray growth. Much of the previous research uses the industry share in GDP as a core indicator of industrialization. Besides this one-data proxy, the United Nations Industrial Development Organization (UNIDO 2020) provides a composite index which is widely known as the Competitive Industrial Performance (CIP) index and constructed multidimensionally by using eight indicators of countries' industrial performance:

<sup>4</sup> A practical way to capture the indirect impacts of EPS and control of corruption was including interaction terms in the model. However, this practical advantage would produce a serious multicollinearity problem.

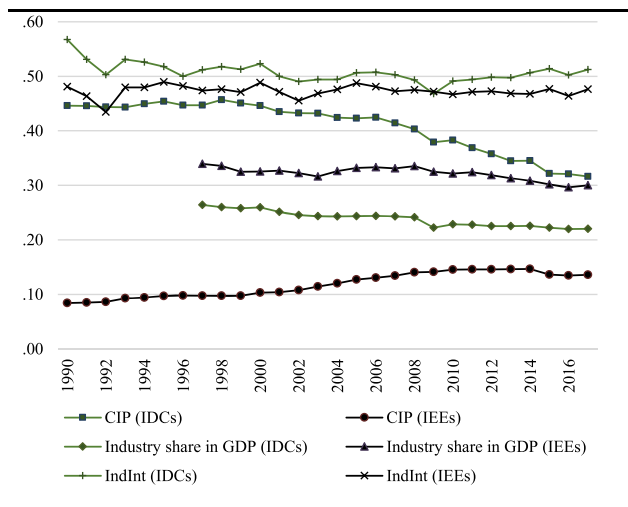


Fig. 5 Industrialization indicators of country groups (country averages, 1990-2017). Source: WDI (2020) and UNIDO (2020)

(i) impact on world manufactures trade, (ii) impact on world manufacturing value added, (iii) medium- and high-tech manufacturing value-added share in total manufacturing value added, (iv) medium- and high-tech manufactured exports share in total manufactured exports, (v) manufacturing value added per capita, (vi) manufacturing value-added share in total GDP, (vii) manufactured exports per capita, and (viii) manufactured exports share in total exports. The CIP index can range between 0 (the worst performance) and 1 (the best performance). Another useful indicator regarding the industrialization pattern of countries is the Industrialization Intensity Index (IndInt). The UNIDO (2020) measures IndInt by the simple average of the share of manufacturing value added in GDP which is relatively higher in developing countries and the share of medium and high-technology activities in manufacturing value-added which is relatively higher in developed countries. Figure 5 shows these industrialization indicators which exhibit that IDCs typically

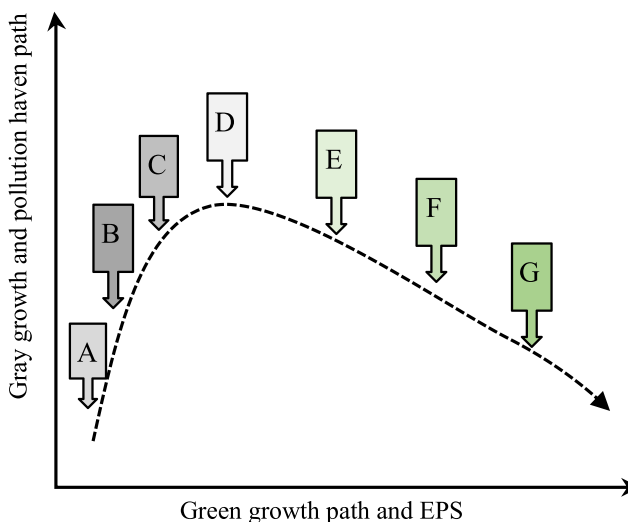


Fig. 6 Green/gray growth, (de)industrialization, and EPS directions proposed by the study. Source: Authors' adaptations from the EKC

have a relatively lower industry share in their GDP compared to that of IEEs. When the CIP is considered, the picture changes that IDCs’ industrial performance is much higher than that of IEEs. However, on average, the relatively higher CIP of IDCs is gradually diminishing, whereas IEEs are typically enhancing their CIP since the early 2000s. According to the 2018 CIP report of UNIDO (2020), China became the third best-performing country after Germany and Japan by overtaking the USA. IndInt does not vary significantly for the sampled country groups over time with slightly higher mean values of IDCs.

Combining these theoretical explanations and observed global trends, the green and gray growth paths of countries can be illustrated as in Fig. 6. We adapted this depiction from the EKC which originally postulates an inverted U-shaped relationship between environmental deterioration and GDP per capita. In the pattern of Fig. 6, the least developed countries with inconsiderable industrial activities belong to group A, while developing countries with resource-based and slow industrial development belong to group B. Fast-industrializing emerging economies are in group C, and countries with the structural transition toward green growth belong to group D. The PHH can be evidenced for countries in groups from A to D where environmental policies are not rigorous. Groups from E to G denote green growing countries with stringent environmental policies. Countries in groups E and F are among the de-industrializing economies. In this illustration, the last stage (group G) is the de-industrialization with little or no industrial

activities of leading green growing countries. When the examined countries are clustered based on CIP, green/gray growth trajectory, and EPS, IDCs are mostly in the groups F and G even they have some characteristics of group E, while IEEs are generally in the groups C and D with some similar characteristics of group B. This country heterogeneity can also explain why cross-country studies are unable to provide a common set of predictors for green and gray growth. Thus, additional empirical studies considering country heterogeneity are required to support the literature of aggregated cross-country research. Notably, trends in industrialization intensity and CIP data infer that classifying all developed countries as de-industrialized by only the low industry share in GDP may produce misunderstanding of these countries’ industrialization structures given the competitiveness and high-tech contents in their industrial activities.

### Econometric analysis of green and gray growth determinants

#### Model specification, variables, and data

In the empirical part, we estimate panel regression models of green growth and gray growth constructed as in Eq. 2 and Eq. 3, respectively, where all variables are described in Table 4.

$$greengr_{c,t} = \alpha_0 + \alpha_1 income_{c,t} + \alpha_2 infdist_{IEE,t} + \alpha_3 outfdist_{IDC,t} + \alpha_4 glob_{c,t} + \alpha_5 epsi_{c,t} + \alpha_6 indust_{c,t} + \alpha_7 contcorr_{c,t} + \varepsilon_c f_t + e_{c,t} \tag{2}$$

( $c = 1, 2, \dots, 14 = C$ ;  $c = 1, 2, \dots, 7 = IDC$ ;  $c = 1, 2, \dots, 7 = IEE$ ;  $t = 1996, 1997, \dots, 2015 = T = 20$ )

$$graygr_{c,t} = \beta_0 + \beta_1 income_{c,t} + \beta_2 infdist_{IEE,t} + \beta_3 outfdist_{IDC,t} + \beta_4 glob_{c,t} + \beta_5 epsi_{c,t} + \beta_6 indust_{c,t} + \beta_7 contcorr_{c,t} + \omega_c f_t + u_{c,t} \tag{3}$$

( $c = 1, 2, \dots, 14 = C$ ;  $c = 1, 2, \dots, 7 = IDC$ ;  $c = 1, 2, \dots, 7 = IEE$ ;  $t = 1996, 1997, \dots, 2015 = T = 20$ )

In these equations,  $c$  and  $t$  stand for the cross-section (countries) and time units (years),  $\alpha_0$  and  $\beta_0$  are country-specific intercepts, and  $\varepsilon$  and  $\omega$  denote heterogeneous factor loadings of the unobserved common factors ( $f$ ), while  $e$  and  $u$  are the composite error terms. Finally,  $\alpha_k$  and  $\beta_k$  ( $k=1,2,\dots,7$ ) parameters are the coefficients to be estimated. We respectively estimate each model for all sampled countries (hereinafter mixed panel) and IDCs and IEEs sub-panels using an annual balanced dataset of the period 1996–2015.

Besides the overall lack of longer time series, there is a missing data limitation in the control of corruption variable which is only available on a 2-year basis for the 1996–2002 sub-period. Therefore, we estimated the points of the years

1997, 1999, and 2001 linearly based on the average of the previous value and the next value relying on stable change without a shock in the missing years.

In our empirical setting, each of the following results is attributed to the support for the validity of the global EKC pattern: (i)  $\alpha_I > 0$  and  $\beta_I < 0$  for IDCs and  $\alpha_I < 0$  and  $\beta_I > 0$  for IEEs (strong support), (ii)  $\alpha_I > 0$  for both IDCs and IEEs but relatively greater in magnitude for IDCs and  $\beta_I < 0$  for both IDCs and IEEs but relatively lesser magnitude for IEEs (weak support), and (iii)  $\alpha_I < 0$  for both IDCs and IEEs but relatively lesser in magnitude for IDCs and  $\beta_I > 0$  for both groups but relatively greater magnitude for IEEs (weak support). The following results are to support the validity of the PHH: (i)  $\alpha_2 < 0$ ,  $\beta_2 > 0$  for IEEs and  $\alpha_3 > 0$ ,  $\beta_3 < 0$  for IDCs;  $\alpha_4 > 0$ ,  $\beta_4 < 0$

**Table 4** Variables, descriptions, and sources

Variables	Descriptions	Sources
Dependent variables		
<i>greengr</i>	Green growth. Production-based CO <sub>2</sub> productivity. GDP per unit of energy-related CO <sub>2</sub> emissions. Constant (2015) US dollars per kg	OECD (2020)
<i>graygr</i>	Gray growth. RCA indices in pollution-intensive industries	Authors' calculations from UN Comtrade (2020)
Explanatory variables		
<i>income</i>	Real GDP per capita. Thousand US dollars at constant (2015) prices	UNCTAD (2020)
<i>infdist</i>	Inward FDI stocks. Percentage share of total world. For IEEs only	
<i>outfdist</i>	Outward FDI stocks. Percentage share of total world. For IDCs only	
<i>glob</i>	Globalization. The KOF globalization index	Gygli et al. (2019)
<i>epsi</i>	EPS index	OECD (2020)
<i>indust</i>	Industrial competitiveness. CIP index	UNIDO (2020)
<i>contcorr</i>	Anti-corruption. Control of corruption index	WGI (2020)

for IDCs and  $\alpha_4 < 0$ ,  $\beta_4 > 0$  for IEEs;  $\alpha_5 > 0$ ,  $\beta_5 < 0$  for both IDCs and IEEs (strong support); (ii)  $\alpha_2 < 0$ ,  $\beta_2 > 0$  for IEEs and  $\alpha_3 > 0$ ,  $\beta_3 < 0$  for IDCs;  $\alpha_5 > 0$ ,  $\beta_5 < 0$  for both IDCs and IEEs (moderate support); and (iii)  $\alpha_2 < 0$ ,  $\beta_2 > 0$  for IEEs and  $\alpha_3 > 0$ ,  $\beta_3 < 0$  for IDCs (weak support). Additionally, based on the effects of FDI stocks and EPS, we cross-check the results on the PHH with a consideration of the pollution halo effect and Porter hypothesis to provide comprehensive evidence. For stronger support for the validity of the PHH, globalization will have a contribution to the green growth of IDCs and to the gray growth of IEEs. Industrial competitiveness is presupposed to discourage green growth ( $\alpha_6 < 0$ ) and promote gray growth ( $\beta_6 > 0$ ) for especially IEEs. Even one can expect control of corruption to encourage green growth ( $\alpha_7 > 0$ ) for all countries, the literature remains inconclusive on whether corruption greases or sands the wheels of green growth as both have been evidenced in some cases. Our study also considers the interaction between EPS and control of corruption to identify whether the direct impact of EPS is changed by the control of corruption. Similarly, we assess whether EPS alters the estimated relationship between green/gray growth and FDI stocks.

Descriptive statistics reported in Table 5 show that the IEEs sub-panel has a higher mean value than that of IDCs in only gray growth variable. The significance of mean differences confirms the compatibility of the study's country grouping.

Global trends in FDI data show that emerging economies mostly host FDIs coming from mainly high-income developed countries. Thus, we set IDCs as home countries and IEEs as host countries. Moreover, as Wagner and Timmins (2009) argue, when the externalities associated with FDI agglomeration are omitted from the analysis, the pollution haven effect may not be captured. Therefore, we included the stocks of inward and outward FDI flows. These considerations of home/host country characteristics and FDI agglomeration provide a better testing of the validity of the PHH when these

considerations are combined with the differences in EPS between country groups. International investment is also one of the contents of globalization measures. However, the KOF globalization index measure considers other capital flows besides FDI flows (not stocks). Therefore, in our case, globalization and FDI stocks are not correlated implying no multicollinearity problem<sup>5</sup>. Correlation coefficients presented in Table 6 illustrate that neither green growth nor gray growth is strongly correlated with the examined predictors.

### Cross-section dependence and stationarity

Cross-section dependence (hereinafter CD) and stationarity are important diagnostics that should be investigated before performing a panel data analysis. The efficiency of estimators depends on the stationarity of variables in panel data. Stationarity, which means that properties of series do not depend on the time points of the observations, can be detected through a variety of panel unit root tests distinguished between the first generation and second generation. The first group tests assume cross-sectional independence, while the second-generation tests take possible CD into account while controlling series for stationarity. The CD phenomenon means the possible impacts of some unobserved common factors on the variables and error term. CD can arise due to spatial or spillover effects or due to unobserved (or unobservable) common factors (Baltagi and Pesaran 2007; Chudik et al. 2011). CD tests need to be applied to both the individual series of variables and the model based on the residuals produced by the panel estimation. Therefore, in order to determine an appropriate unit root test, we first check the series for CD through Pesaran (2020) scaled LM, Pesaran (2020) CD, and

<sup>5</sup> Additionally, we control the models of all three panels for multicollinearity problem using the variance inflation factor values and found them less than 3, far below the commonly used rule of 10 (O'Brien 2007). Thus, multicollinearity is not a serious concern in our case.

**Table 5** Descriptive statistics

	Mean	Max.	Min.	Std. dev.
Mixed panel (14 countries; N=280)				
<i>greengr</i>	4.068	9.038	1.130	1.921
<i>graygr</i>	1.211	2.684	.361	.580
<i>income</i>	21.558	56.505	.666	17.287
<i>infdist</i>	4.028	39.484	.097	6.590
<i>outfdist</i>	4.796	39.726	.007	7.545
<i>glob</i>	71.083	89.220	41.314	12.072
<i>epsi</i>	1.497	3.854	.333	1.022
<i>indust</i>	.250	.584	.045	.163
<i>contcorr</i>	.562	2.139	-1.176	1.039
IDCs (7 countries; N=140)				
<i>greengr</i>	4.499*	9.038	2.196	1.589
<i>graygr</i>	.938*	1.705	.561	.282
<i>income</i>	38.038*	56.505	29.509	6.685
<i>infdist</i>	6.860*	39.484	.441	8.369
<i>outfdist</i>	9.061*	39.726	1.784	8.786
<i>glob</i>	81.324*	89.220	63.150	5.573
<i>epsi</i>	2.212*	3.854	.458	.918
<i>indust</i>	.385*	.584	.195	.105
<i>contcorr</i>	1.470*	2.139	-.030	.545
IEEs (7 countries; N=140)				
<i>greengr</i>	3.637*	8.140	1.130	2.122
<i>graygr</i>	1.485*	2.684	.361	.667
<i>income</i>	5.077*	10.949	.666	2.831
<i>infdist</i>	1.197*	4.640	.097	.995
<i>outfdist</i>	.530*	4.181	.007	.647
<i>glob</i>	60.843*	72.333	41.314	7.087
<i>epsi</i>	.782*	2.208	.333	.473
<i>indust</i>	.116*	.391	.045	.075
<i>contcorr</i>	-.346*	.733	-1.176	.458

\*Denotes that the difference between mean values of IDCs and IEEs is statistically significant at the level of 10%

Bias-adjusted CD (Pesaran et al. 2008) methods. All these tests are based on a null hypothesis of no cross-section dependency (correlation). Test results are reported in Table 7.

Results of the applied tests commonly reject the null hypothesis of no cross-section dependence for all variables in each panel. Thus, the second-generation unit root tests that are characterized by the rejection of the cross-sectional independence hypothesis are more appropriate in our case.

There are several unit root tests widely used in the literature considering cross-section dependency. However, some tests cannot provide correct inferences about stationarity in heterogeneous mixed panels. In this regard, Hadri and Kurozumi’s (2012) second-generation panel unit root test, which developed on CADF (the cross-sectionally augmented alternative of the standard augmented Dickey-Fuller regressions) test of Pesaran (2007), makes up the shortcoming by checking the

stationarity for mixed panels. The Hadri-Kurozumi test estimates the long-term variance both by using seemingly unrelated regression based on the bootstrap method ( $Z_A^{SPC}$ ) and by considering  $t$ -statistics and  $p$ -values ( $Z_A^{LA}$ ). The first statistic is more appropriate when series are cross-sectionally dependent as in our case. Reversing the null and alternative hypotheses, the Hadri-Kurozumi test builds on the null hypothesis of stationarity in heterogeneous panel data and allows for serial correlation. This test can produce reliable results regardless if the number of countries is less or more than that of years. On the other hand, the issue of heterogeneity matters for cross-country growth regressions (Maddala and Wu 2000) and thus needs to be considered in the panel unit root tests (Maddala and Wu 1999). Since panel unit root tests, as well as CD tests, may produce inconsistent results and considering the circumstances of short panel properties, heterogeneous modeling, and CD, we applied Hadri and Kurozumi’s (2012) second-generation together with Maddala and Wu’s (1999) first-generation panel unit root tests. The overall results of panel stationarity tests reported in Table 8 indicate that all variables are the first-difference stationary implying that they are integrated of order one, i.e.,  $I(1)$ , which enables us to proceed with cointegration analysis.

CD in a panel model somehow affects panel units directly or indirectly (through spillover) (Chudik et al. 2011) where heterogeneity of models also matters for unbiased estimation of cointegration equations. In order to determine an appropriate method for the cointegration analysis, we control the constructed models for the homogeneity/heterogeneity by the delta test proposed by Pesaran and Yamagata (2008) followed by the cross-sectional dependence examination through the Pesaran-scaled LM, Pesaran CD, and bias-adjusted CD tests. Additionally, we utilize an adjusted version of the Hausman’s (1978) augmented regression test for endogeneity, which is also widely known as the Durbin-Wu-Hausman test, to control each model for endogeneity which can arise from omitted variable bias, measurement error, and simultaneity in regression analysis.

The results of model specification control tests in Table 9 show that our estimation models in all three panel groups embody heterogeneity. CD test statistics indicate a CD for the models of the mixed panel and IDCs sub-panel. However, in the IEEs sub-panel case, results do not provide any support for the existence of CD for the green growth model together with weak and inconclusive inference for the gray growth model. Again, there exists an endogeneity problem in the gray growth model of IEEs sub-panel. Therefore, cointegration analysis and the estimation of the long-run coefficients proceeded with the consideration of heterogeneous panel and both cross-section dependence and independence (for the IEEs sub-panel) as well as endogeneity (for the IEEs sub-panel).

**Table 6** Pearson correlations between green growth, gray growth, and their potential determinants

Variables	Mixed panel (N=280)	IDCs sub-panel (N=140)	IEEs sub-panel (N=140)
Correlations between green growth and other variables			
<i>graygr</i>	.066	-.361***	.387***
<i>income</i>	.177**	-.405***	.301***
<i>infdist</i>	-.144**	-.444***	-.096
<i>outfdist</i>	-.090	-.431***	-.218***
<i>glob</i>	.221***	.346***	-.110
<i>epsi</i>	.308***	.431***	-.036
<i>indust</i>	.046	-.330***	-.206**
<i>contcorr</i>	.126**	-.464***	.120
Correlations between gray growth and other variables			
<i>greengr</i>	.066	-.361***	.387***
<i>income</i>	-.402***	.272***	.255***
<i>infdist</i>	-.242***	-.047	-.273***
<i>outfdist</i>	-.303***	-.103	-.124
<i>glob</i>	-.383***	.404***	-.079
<i>epsi</i>	-.442***	.103	-.503***
<i>indust</i>	-.605***	-.451***	-.541***
<i>contcorr</i>	-.304***	.570***	.151*

\*\*\*, \*\*, and \* show the statistical significance at the level of 1%, 5%, and 10%, respectively. Unreported coefficients revealed strong correlations between *infdist* and *outfdist* for all panel groups (.967 for the mixed panel, .975 for IDCs, and .764 for IEEs) confirming the appropriateness of the host-home country setting of the study

## Panel cointegration analysis

A cointegration analysis is conducted to explore whether there is a long-run equilibrium relationship between non-stationary variables. Panel cointegration tests are also divided into first- and second-generation depending on the presence of CD. In our case, we applied the panel bootstrap cointegration test proposed by Westerlund and Edgerton (2007). This method relies on the Lagrange multiplier test of McCoskey and Kao (1998) and proposes a bootstrap test for the null hypothesis of cointegration in panel data. The test allows for dependence both within and between countries and works well even in small samples. The Westerlund-Edgerton test produces a bootstrap *p*-value computed on the assumption of cross-sectional dependence. Considering the inconclusive inference about CD in the IEEs sub-panel, we also computed the non-parametric group Phillips-Perron (PP) and parametric Augmented Dickey-Fuller (ADF) statistics of Pedroni's (1999, 2004) residual cointegration tests which allow the cointegrating vectors and error processes to be heterogeneous across countries. Overall results in Table 10 strongly support the presence of a cointegration relationship between variables included in the green and gray growth model specifications of all panels.

## Estimation of long-run relationships

Given the evidence that green growth and gray growth move together over the long-run with their potential determinants in all panel groups, the long-run relationships can be further estimated. Considering CD and heterogeneous slopes, we use the Common Correlated Effects Mean Group (CCEMG) estimator proposed by Pesaran (2006). This technique is based on a simple average of the individual Common Correlated Effects (CCE) estimation. In relation to our study's case, the CCEMG approach is robust to the coexistence of strong and weak CD (Chudik et al. 2011) and to the unobservable common factors that follow nonstationary processes (Kapetanios et al. 2011). Because of the cross-sectional independence, we also employed standard Dynamic Ordinary Least Squares (DOLS) estimator for the IEEs sub-panel. According to the results of Kao and Chiang (2001), even though both have small sample bias, the DOLS estimator outperforms that of the Fully Modified Ordinary Least Squares (FMOLS) approach, another widely used method, by reducing bias better. Pedroni (2001) also showed that between-dimension DOLS estimator was more efficient than within-dimension. Since we have heterogeneous panel data of a relatively small sample of countries, we use the between-group DOLS estimator.

**Table 7** Results of cross-sectional dependency tests for variables

Variables	Pesaran-scaled LM	Pesaran CD	Bias-adjusted CD
Mixed panel (N: 280)			
<i>greengr</i>	(2.980)* [5.875]*	(−1.740)* [−1.687]*	(8.417)* [7.631]*
<i>graygr</i>	(5.378)* [8.202]*	(−.819) [−.448]	(13.916)* [12.668]*
<i>income</i>	(4.500)* [4.287]*	(−2.130)* [−2.188]*	(4.228)* [4.069]*
<i>glob</i>	(4.979)* [3.602]*	(−1.421)* [−1.666]*	(5.721)* [5.286]*
<i>epsi</i>	(3.415)* [4.309]*	(−2.551)* [−2.205]*	(10.095)* [9.436]*
<i>indust</i>	(7.897)* [9.463]*	(−1.521)* [−1.829]*	(11.964)* [10.431]*
<i>contcorr</i>	(2.069)* [2.187]*	(−2.129)* [−1.763]*	(7.710)* [6.946]*
IDCs sub-panel (N:140)			
<i>greengr</i>	(2.281)* [1.752]*	(−1.923)* [−2.869]*	(1.072) [.958]
<i>graygr</i>	(2.319)* [3.559]*	(−1.687)* [−1.555]*	(1.038) [.765]
<i>income</i>	(4.345)* [4.932]*	(−2.608)* [−2.794]*	(2.414)* [1.473]*
<i>outfdist</i>	(11.815)* [8.342]*	(−1.226) [−1.550]*	(−.935) [−1.154]
<i>glob</i>	(3.294)* [2.976]*	(−2.392)* [−2.603]*	(1.002) [.684]
<i>epsi</i>	(3.802)* [3.874]*	(−2.809)* [−2.715]*	(4.534)* [3.992]*
<i>indust</i>	(6.815)* [10.936]*	(−2.320)* [−2.558]*	(3.712)* [4.233]*
<i>contcorr</i>	(5.533)* [6.524]*	(−2.262)* [−2.202]*	(.363) [−.045]
IEEs sub-panel (N:140)			
<i>greengr</i>	(2.955)* [2.361]*	(−1.145) [−1.499]*	(6.866)* [5.976]*
<i>graygr</i>	(2.103)* [1.863]*	(−2.244)* [−1.916]*	(1.254)* [1.988]*
<i>income</i>	(2.520)* [2.294]*	(−1.589)* [−1.776]*	(.874) [.208]
<i>infdist</i>	(2.432)* [5.107]*	(−1.964)* [−2.115]*	(2.829)* [2.394]*
<i>glob</i>	(1.816)* [.964]	(−2.464)* [−1.967]*	(5.607)* [6.594]*
<i>epsi</i>	(3.910)* [5.860]*	(−1.973)* [−1.908]*	(.165) [−.202]
<i>indust</i>	(5.788)* [8.073]*	(−2.192)* [−2.081]*	(−1.315) [−1.683]
<i>contcorr</i>	(−.177) [.859]	(−2.937)* [−2.632]*	(1.452)* [1.882]*

\*Denotes the presence of CD at 10% significance level. Test statistics without and with the trend are shown in parentheses and brackets, respectively

The estimated long-run coefficients in Table 11 show that GDP per capita and green growth are positively associated for all three panels. Green growth is not monotonically increasing in income since the magnitude is higher for middle-income IEEs. The positive and higher magnitude in the case of IEEs seems to be inconsistent with the cross-country generalized EKC pattern in which the positive impact of income on green growth would be higher in high-income IDCs. However, this is not surprising as the IEEs group differs in economic structure from both developed and other developing countries. Moreover, our study adopted the production side of CO<sub>2</sub> emissions which enabled us to capture the green production capabilities, for that, IEEs has significant improvements since the early 2000s. These countries also have significant development in renewable energy sources like hydroelectric, wind, and solar power. For example, as Ng et al. (2020) argued, China and India are currently among the leading investors in renewable energy in the world. The structural impact has been underlined by several meta-analysis studies as well. The results of Cavlovic et al. (2000) revealed that both

methodological choices and pollutant types tended to affect income turning points and change the evidence of the validity of the EKC. Again, the EKC results of Ng et al. (2020) varied by different estimators across countries. Therefore, as Stern (2004, 2017) argued, new approaches are needed to disentangle the true relations between income and environment from a cross-country perspective.

The impact of inward FDI stocks in IEEs is significantly (when EPS is included) positive, while outward FDI stocks and green growth are negatively associated in IDCs. These results contradict the core prediction of the PHH and support the pollution halo hypothesis indicating a possible FDI pattern in which enterprises in IDCs are also carrying the green components of their production. This finding is in line with that of Tamazian et al. (2009) who found that increases in FDI inflows were associated with lower levels of per capita CO<sub>2</sub> emissions for BRIC countries that are all included in our IEEs sample. Even our results are inconsistent with the argument that developing countries become pollution haven for developed countries, our emerging

**Table 8** Results of panel stationarity tests

↓Panel	Test→ Variable↓	Hadri-Kurozumi		Maddala-Wu	
		Level	First difference	Level	First difference
Mixed	<i>greengr</i>	(−2.676) [−1.776]	(−.848)* [.898]*	(10.327) [33.989]	(135.168)* [131.053]*
IDCs		(−1.744) [−1.883]	(−.762)* [.276]*	(1.609) [13.899]	(65.670)* [58.384]*
IEEs		(−1.869) [−.902]*	(.305)* [−]	(5.776) [11.885]	(36.985)* [28.381]*
Mixed	<i>graygr</i>	(−2.079) [−2.366]	(.192)* [−.063]*	(29.319) [32.913]	(113.433)* [82.551]*
IDCs		(−2.301) [−1.762]	(−1.221)* [−.413]*	(8.889) [16.903]	(56.591)* [38.506]*
IEEs		(−2.088) [.275]*	(1.266)* [−]	(20.429) [16.009]	(56.825)* [44.044]*
Mixed	<i>income</i>	(14.793) [−1.525]	(.626) [−1.131]*	(16.819) [26.648]	(117.197)* [73.268]*
IDCs		(.771)* [−2.903]	(−) [−.216]*	(14.973) [19.144]	(40.239)* [34.969]*
IEEs		(2.020) [5.233]	(.811)* [−.106]*	(1.847) [9.306]	(58.214)* [40.418]*
IEEs	<i>infdist</i>	(−1.755) [3.128]	(.561)* [−.077]*	(9.015) [9.919]	(30.428)* [27.734]*
IDCs	<i>outfdist</i>	(−2.247) [−1.610]	(−.213)* [.067]*	(20.326) [18.705]	(47.857)* [36.727]*
Mixed	<i>glob</i>	(−2.831) [−2.762]	(−.257)* [3.249]	(37.105) [36.318]	(79.128)* [63.724]*
IDCs		(−1.773) [3.895]	(.251)* [1.745]	(14.203) [5.443]	(40.396)* [33.162]*
IEEs		(−1.884) [−2.207]	(−.423)* [2.001]	(17.889) [15.881]	(29.370)* [27.845]*
Mixed	<i>epsi</i>	(−2.938) [−1.546]	(−.734)* [−.306]*	(12.013) [19.941]	(88.891)* [58.741]*
IDCs		(−2.116) [−1.611]	(−1.182)* [−.788]*	(3.396) [11.369]	(51.507)* [34.386]*
IEEs		(−1.812) [5.357]	(2.364) [2.222]	(8.617) [8.572]	(37.384)* [24.355]*
Mixed	<i>indust</i>	(9.235) [−2.147]	(−1.539) [.875]*	(7.907) [15.730]	(71.068)* [59.198]*
IDCs		(−1.669) [−1.600]	(−.958)* [.327]*	(.569) [13.958]	(47.540)* [39.676]*
IEEs		(−2.194) [−1.497]	(−1.064)* [.812]*	(7.338) [2.269]	(44.099)* [32.071]*
Mixed	<i>contcorr</i>	(−3.251) [−2.509]	(−1.268)* [1.177]*	(21.952) [32.075]	(91.734)* [66.753]*
IDCs		(−2.179) [−1.998]	(−1.163)* [.739]*	(11.747) [13.933]	(44.288)* [30.767]*
IEEs		(5.772) [−1.847]	(−.654)* [.075]*	(18.142) [10.205]	(47.446)* [35.985]*

\*Shows stationarity at 10% significance level. Test statistics without and with the trend are shown in parentheses and brackets, respectively. Lag length varies from 1 to 5

countries group seems to have their own pollution havens from other developing countries. This premise is supported by Cai et al. (2018) who showed that China had become a pollution haven for 22 developed countries, and 19 developing countries had become China's pollution havens. Globalization is closely related to FDI activities and thus the PHH. However, the globalization-green growth nexus is inconclusive concerning the PHH as we found a positive and insignificant green growth effect of globalization for IEEs, whereas globalization encourages green growth for IDCs. The green effect of globalization in IEEs supports the findings of Shahbaz et al. (2016) who found globalization reducing CO<sub>2</sub> emissions in the case of African countries including South Africa. Even though the overall greening impact of globalization contradicts the globalization-driven carbon emission hypothesis confirmed by Shahbaz et al. (2018) and Wang et al. (2020) for developed countries, globalization may also change producers' as well as consumers' preferences toward green products through increasing the societal awareness and knowledge of environmental pollution as asserted by Mostafa (2012).

We found EPS inhibiting green growth for IEEs based on the DOLS estimation. This finding contradicts the policy-enforced green growth prediction of the Porter hypothesis. This evidence questions the emission-mitigating contribution of stringent environmental policies and contradicts the finding of Ahmed and Ahmed (2018) who found stringent environmental policies reducing CO<sub>2</sub> emissions for China, a widely examined emerging economy. The insignificant coefficient for IDCs supports the idea that enterprises in developed countries become green themselves, not made greener by policies. Again, this inference differs from the results of Ahmed (2020) suggesting that environmental regulations encourage green innovation in the panel of 20 OECD countries. Our results imply that the costs put on the pollutive activities of firms may be far below their efficiency levels which may be motivating firms to stay pollutive. Considering this inference together with the evidence of Wolde-Rufael and Weldemeskel (2020) who found an inverted U-shaped relationship between EPS and CO<sub>2</sub> emissions in BRIICTS countries (IEEs in our sample), we assert that more stringent policies may motivate (or force) producers in IEEs to emit less CO<sub>2</sub>. Although the



**Table 9** Results of model specification control tests

Control↓	Tests↓ Green growth model	Mixed panel	IDCs sub-panel	IEEs sub-panel
Homogeneity	<i>Delta-tilde</i>	11.563*** (.000)	7.595*** (.000)	5.137*** (.000)
	<i>Delta-tilde-adj</i>	14.162*** (.000)	9.653*** (.000)	6.529*** (.000)
Cross-section dependency	<i>Pesaran-scaled LM</i>	2.225** (.013)	3.422*** (.000)	1.009 (.157)
	<i>Pesaran CD</i>	1.265* (.100)	3.331*** (.000)	−.598 (.275)
	<i>Bias-adjusted CD</i>	3.886*** (.000)	3.203*** (.001)	1.204 (.114)
Endogeneity	<i>Durbin-Wu-Hausman</i>	2.335 (.801)	1.177 (.947)	1.303 (.935)
Gray growth model				
Homogeneity	<i>Delta-tilde</i>	7.363*** (.000)	5.386*** (.000)	5.702*** (.000)
	<i>Delta-tilde-adj</i>	9.018*** (.000)	6.846*** (.000)	7.247*** (.000)
Cross-section dependency	<i>Pesaran-scaled LM</i>	4.597*** (.000)	3.822*** (.000)	2.427*** (.008)
	<i>Pesaran CD</i>	−.133 (.447)	2.284** (.011)	2.054** (.020)
	<i>Bias-adjusted CD</i>	3.859*** (.000)	5.546*** (.000)	−.305 (.620)
Endogeneity	<i>Durbin-Wu-Hausman</i>	10.838* (.055)	3.600 (.608)	112.803*** (.000)

\*\*\*, \*\*, and \* show the statistical significance at the level of 1%, 5%, and 10%, respectively. Probabilities are in parentheses

green growth capabilities of countries are expected to depend on the industrial development level, we found industrialization with statistically insignificant influences for all panels. However, in the literature, it has been widely evidenced that industrial development is decisive in environmental degradation (e.g., Cherniwchan 2012; Zafar et al. 2020).

Some previous research such as that of Welsch (2004), Danish and Wang (2019), and Sinha et al. (2019) showed that good governance and anti-corruption practices might lower CO<sub>2</sub> emissions and improve the environmental quality in developing countries. Consistently, we found control corruption stimulating green growth significantly for IEEs. Our results unfold that EPS and control of corruption also have indirect impacts on green growth. Even though the negative impact of outward FDI stocks remains relatively stable in IDCs, the

impact of inward FDI stocks becomes positive and significant for IEEs when the indirect influence of EPS is reflected in the models. Again, the negative impact of EPS is lowered by the indirect (positive) effect of anti-corruption in the case of IEEs. Scholars are increasingly getting interested in the interaction between environmental policies and corruption since anti-corruption matters for the efficiency of environmental regulatory policies through public trust, conflict of interest, and bribery channels (Pellegrini and Gerlagh 2006; Povitkina 2018).

The gray growth estimates in Table 12 show that domestic income’s coefficient is negative and statistically significant in only DOLS estimation for IEEs. This result is in line with the estimated green contribution of the increased income but inconsistent with the global EKC pattern. The findings of the income effects on green and gray growth measures imply a

**Table 10** Results of cointegration tests

Model↓	Test statistics↓	Mixed panel	IDCs sub-panel	IEEs sub-panel
Panel bootstrap cointegration test				
Green growth	<i>LM stat.</i>	(17.766)* [38.527]*	(11.661)* [30.742]*	(13.359)* [26.286]*
	<i>Bootstrap prob.</i>	(.990) [.907]	(.986) [.718]	(.953) [.891]
Gray growth	<i>LM stat.</i>	(19.837)* [37.632]*	(15.280)* [31.902]*	(13.076)* [26.629]*
	<i>Bootstrap prob.</i>	(.956) [.807]	(.819) [.484]	(.931) [.763]
Pedroni residual cointegration test				
Green growth	<i>Group PP-stat.</i>	(−9.799)* [−16.490]*	(−14.389)* [−13.638]*	(−5.624)* [−17.070]*
	<i>Group ADF-stat.</i>	(−4.565)* [−6.047]*	(−4.442)* [−4.270]*	(−3.578)* [−3.725]*
Gray growth	<i>Group PP-stat.</i>	(−5.977)* [−8.228]*	(−3.114)* [−2.544]*	(−5.213)* [−8.640]*
	<i>Group ADF-stat.</i>	(−5.674)* [−6.613]*	(−4.008)* [−3.597]*	(−3.923)* [−4.517]*

Bootstrap values are obtained from 1000 replications. Assumed indirect effects of *contcorr* variable were excluded in the bootstrap test. Lag length varies from 1 to 2. Statistics without and with the trend are shown in parentheses and brackets, respectively

\*Shows the presence of a cointegration at 10% significance level

**Table 11** Long-run estimation of the determinants of green growth (*greengr*)

Sample→		Mixed panel	IDCs sub-panel	IEEs sub-panel	
	Estimator→	CCEMG	CCEMG	CCEMG	DOLS
Determinants↓					
	<i>income</i>	.127** [.055] (.022)	.056*** [.019] (.004)	.199* [.110] (.071)	.180*** [.056] (.003)
	<i>infdist</i> ( <i>epsi</i> excluded)	--	--	-.225 [.186] (.228)	.022 [.105] (.839)
	<i>infdist</i> ( <i>epsi</i> included)	--	--	.209 [.262] (.424)	.263** [.054] (.040)
	<i>outfdist</i> ( <i>epsi</i> excluded)	--	-.015* [.008] (.064)	--	--
	<i>outfdist</i> ( <i>epsi</i> included)	--	-.014*** [.005] (.008)	--	--
	<i>glob</i>	.013 [.011] (.188)	.073** [.030] (.014)	.007 [.006] (.309)	.010 [.007] (.152)
	<i>epsi</i> ( <i>contcorr</i> excluded)	-.003 [.061] (.964)	-.033 [.068] (.627)	.232** [.107] (.030)	-.835*** [.068] (.007)
	<i>epsi</i> ( <i>contcorr</i> included)	-.004 [.085] (.971)	-.065 [.075] (.390)	.094 [.390] (.809)	-.139*** [.024] (.000)
	<i>indust</i>	.101 [1.372] (.942)	.264 [.551] (.632)	-1.887 [5.662] (.739)	-2.624 [1.967] (.194)
	<i>contcorr</i>	.212* [.116] (.070)	.324 [.274] (.238)	.203 (.435) [.641]	.490*** (.043) [.000]
Wald $\chi^2$	<i>k</i> =6	--	23.88 (.000)***	5.32 (.504)	--
	<i>k</i> =5	10.31 (.067)*	38.04 (.000)***	8.33 (.139)	--
	<i>k</i> =4	2.41 (.660)	43.84 (.000)***	1.79 (.774)	--
$R^2$ ; Adjusted $R^2$		--	--	--	.998; .992

\*\*\*, \*\*, and \* indicate statistical significance at 1%, 5%, and 10% levels, respectively. Robust standard errors are in brackets, and probabilities are in parentheses. The Wald test statistics are computed when all variables are included (*k*=6), *contcorr* is excluded (*k*=5), and *epsi* and *contcorr* are excluded (*k*=4) in the estimated models. The  $R^2$  statistics are those produced when indirect impacts of *contcorr* and *epsi* are excluded

dynamic relationship with varied turning points and different shapes. Thus, the income-environment nexus tends to be sensitive to the variations in the country sample, theoretical

approach, methods, pollutant types, and measurements as stated by some studies in the EKC literature (Cavlovic et al. 2000; Stern 2004; Allard et al. 2018; Sinha et al. 2019).

**Table 12** Long-run estimation of the determinants of gray growth (*graygr*)

Sample→		Mixed panel	IDCs sub-panel	IEEs sub-panel	
	Estimator→	CCEMG	CCEMG	CCEMG	DOLS
Determinants↓					
	<i>income</i>	.018 [.014] (.227)	.014 [.010] (.160)	-.175 [.118] (.140)	-.081* [.020] (.057)
	<i>infdist</i> ( <i>epsi</i> excluded)	--	--	.026 [.112] (.820)	.145* [.077] (.073)
	<i>infdist</i> ( <i>epsi</i> included)	--	--	.060 [.053] (.251)	-.247** [.049] (.037)
	<i>outfdist</i> ( <i>epsi</i> excluded)	--	-.001 [.002] (.544)	--	--
	<i>outfdist</i> ( <i>epsi</i> included)	--	-.003* [.002] (.104)	--	--
	<i>glob</i>	-.001 [.007] (.992)	.001* [.001] (.090)	-.013 [.010] (.196)	-.006 [.003] (.186)
	<i>epsi</i> ( <i>contcorr</i> excluded)	.088 (.072) [.218]	-.001 [.011] (.940)	-.153 [.238] (.520)	.213** [.035] (.026)
	<i>epsi</i> ( <i>contcorr</i> included)	.018** [.008] (.027)	.002 [.010] (.843)	-.183 [.297] (.538)	-.261** [.055] (.041)
	<i>indust</i>	-.349* [.184] (.057)	-.720*** [.010] (.000)	-.494 [3.015] (.870)	3.897* [.928] (.052)
	<i>contcorr</i>	-.014 [.071] (.848)	-.050 [.037] (.169)	.010 [.046] (.833)	.891* (.249) [.070]
Wald $\chi^2$	<i>k</i> =6	--	5449.87*** (.000)	5.62 (.467)	--
	<i>k</i> =5	10.02* (.075)	31.56*** (.000)	6.14 (.293)	--
	<i>k</i> =4	35.02*** (.000)	18.45*** (.001)	3.42 (.491)	--
$R^2$ ; Adjusted $R^2$		--	--	--	.994; .971

\*\*\*, \*\*, and \* indicate statistical significance at 1%, 5%, and 10% levels, respectively. Robust standard errors are in [brackets] and probabilities are in parentheses. The Wald test statistics are computed when all variables are included (*k*=6), *contcorr* is excluded (*k*=5), and *epsi* and *contcorr* are excluded (*k*=4) in the estimated models. The  $R^2$  statistics are those produced when indirect impacts of *contcorr* and *epsi* are excluded

Increases in inward FDI stocks (without the indirect impact of EPS) encourage gray growth for IEEs, whereas outward FDI stocks' negative impact is small in magnitude and statistically insignificant for IDCs. These estimates are in favor of the simple prediction of the PHH and in line with that of Singhanian and Saini (2021) who found evidence supporting the validity of the PHH in the case of 21 developed and developing countries with high CO<sub>2</sub> emissions. However, we found a graying impact of globalization for IDCs which weakens the PHH pattern but supports the findings of Shahbaz et al. (2018) who confirmed a positive link between globalization and CO<sub>2</sub> emissions for developed economies. It can be inferred that globalization is spreading both the pro-environmental and environmentally harmful practices simultaneously for IDCs. The impacts of globalization on green and gray growth vary across countries' economic structures and development stages as evidenced by Shahbaz et al. (2016, 2018) and Wang et al. (2020). Our findings, like that of Cai et al. (2018), demonstrate that globalization brings about a dynamic relocation process rather than a static polarization (greening developed countries vs. graying developing countries) pattern of the PHH. Our results also show that industrial competitiveness is important in this dynamic shift of pollution havens. We found industrialization represented by industrial competitiveness as the strongest driving force to gray growth for IEEs, which is in line with the previous large-sample cross-country (e.g., Cherniwchan 2012; Apergis and Ozturk 2015; Zafar et al. 2020) and country-specific (e.g., the Turkey case of Pata 2018 and the China case of Yuan et al. 2020) studies which mostly measured industrialization by industry shares in GDP. Cherniwchan's (2012) results showed that cross-country pollution levels would converge during industrialization and industrialization was a significant determinant of this convergence. The negative relationship between industrialization and gray growth in IDCs unfolds that the industry can also be a progressive part of a greener economy and provides some lessons for their followers, i.e., IEEs.

The positive association (without the intervention by control of corruption) between EPS and gray growth in IEEs violates the predictions of both the PHH and Porter hypothesis. However, when the interaction between EPS and anti-corruption was considered, the relationship changed to negative which is consistent with the findings of de Angelis et al. (2019) who found that EPS was effective in reducing per capita CO<sub>2</sub> in the case of 32 countries (including all countries in our sample). These results highlight that the green contribution and gray effect of environmental policies need to be considered together with the anti-corruption. This suggestion is also supported by the conclusions of Welsch (2004), Candau and Dienesch (2017), Danish and Wang (2019), and Sinha et al. (2019). The results show that anti-corruption does not have a significant influence on pollution-intensive gray

growth in IDCs. The direct positive link between gray growth and control of corruption (which rejects the premise of pollution havens are corruption paradises) in IEEs may be better explained by these countries' lower level of control of corruption. The overall green growth experience of IDCs shows that their followers, IEEs, may change their gray advantage toward green efficiency through implementing stringent policies supplemented by anti-corruption. This potential green benefit of governance-enforced stringent policies is also asserted by some studies (e.g., Welsch 2004; Zhang et al. 2016).

Overall, the findings reveal that the gray effects of the examined determinants considerably differ from their green contribution. Thus, "growing green" does not necessarily mean "not growing gray" and vice versa in our case as countries may have both greening and graying sectors. Additionally, the varied results of CCEMG and DOLS estimations in the IEEs sub-panel highlight the importance of the inspection of CD and heterogeneity before performing a panel data analysis as suggested by Maddala and Wu (2000), Baltagi and Pesaran (2007), Chudik et al. (2011), and Ng et al. (2020).

### Panel causality test

In the final step, we investigate the short-run and the long-run causalities running from the examined explanatory variables to green and gray growth variables based on the Granger causality procedure. For the short-run causalities, we apply Dumitrescu and Hurlin's (2012) tests for heterogeneous panels to test for the existence of homogeneous non-causality among variables. Dumitrescu and Hurlin (2012) showed that their standardized panel statistics had good small sample properties, even in the presence of CD. This test is based on the null hypothesis of one variable that does not homogeneously cause another variable. Since this test can only be applied to stationary series, we converted the series into the first-order difference. For the long-run Granger causalities, we employ Emirmahmutoglu and Kose's (2011) test which considers CD and heterogeneity across countries. This test builds on the extension of the lag augmented vector autoregression approach of Toda and Yamamoto (1995) and produces Fisher statistics based on the meta-analysis. The simulation results of Emirmahmutoglu and Kose (2011) from a mixed panel involving level-stationary, first-difference stationary, cointegrated, and non-cointegrated series show that this test remains powerful even if the numbers of countries and years are small under both the CD and cross-section independency. Yet, as Shahbaz et al. (2018) suggest, the Emirmahmutoglu-Kose panel causality test is more applicable when the number of years is greater than that of countries. Therefore, this causality procedure fits well the properties of our panel data.

Results of both tests are displayed in Table 13. We only could establish a short-run causal relationship between *epsi*

**Table 13** Results of unidirectional panel causality tests

Null: (variable) does not Granger cause (↔) (variable)	Dumitrescu-Hurlin test (Zbar-stat.)			Emirmahmutoglu-Kose test (Fisher-stat.)		
	Mixed panel	IDCs sub-panel	IEEs sub-panel	Mixed panel	IDCs sub-panel	IEEs sub-panel
(income)↔(greengr)	−.044 (.965)	.774 (.439)	−.173 (.863)	39.516* (.073)	14.729 (.397)	24.787** (.037)
(infdist)↔(greengr)	--	--	−.622 (.534)	--	--	12.443 (.571)
(outfdist)↔(greengr)	--	−.276 (.783)	--	--	10.064 (.757)	--
(glob)↔(greengr)	.699 (.485)	1.409 (.159)	−.421 (.674)	38.185* (.095)	21.403* (.092)	16.781 (.268)
(epsi)↔(greengr)	.688 (.492)	3.562*** (.000)	−.429 (.668)	29.605 (.382)	19.781 (.137)	9.824 (.775)
(indust)↔(greengr)	−1.172 (.241)	−.706 (.480)	−.952 (.341)	35.424 (.158)	17.929 (.210)	17.495 (.231)
(contcorr)↔(greengr)	−.729 (.466)	−1.190 (.234)	.279 (.781)	20.439 (.848)	4.907 (.987)	15.533 (.343)
(income)↔(graygr)	4.275*** (.000)	−1.328 (.184)	7.070*** (.000)	50.568*** (.006)	10.387 (.733)	40.181*** (.000)
(infdist)↔(graygr)	--	--	1.585 (.113)	--	--	39.897* (.000)
(outfdist)↔(graygr)	--	−.384 (.701)	--	--	8.620 (.855)	--
(glob)↔(graygr)	−.164 (.870)	−1.103 (.270)	.872 (.384)	28.075 (.460)	9.986 (.763)	18.090 (.203)
(epsi)↔(graygr)	−.947 (.344)	−.304 (.761)	−.868 (.386)	35.824 (.147)	23.323** (.055)	12.501 (.566)
(indust)↔(graygr)	−1.124 (.261)	.186 (.853)	−.508 (.612)	39.742* (.070)	9.900 (.769)	29.842*** (.008)
(contcorr)↔(graygr)	−.803 (.422)	−.499 (.618)	−.233 (.816)	35.999 (.143)	24.263** (.043)	11.736 (.625)

\*\*\*, \*\*, and \* show the statistical significance at the levels of 1%, 5%, and 10%, respectively. Probabilities are shown in parentheses. Lag length varies from 1 to 2

and *greengr* for the IDCs sub-panel and between *income* and *graygr* for the mixed panel and IEEs sub-panel. In the long run, we found causalities from *income* to *greengr* in the mixed panel and IEEs sub-panel, from *glob* to *greengr* for the mixed panel and IDCs sub-panel, from *income* to *graygr* in the mixed panel and IEEs sub-panel, from *infdist* to *graygr* in the IEEs sub-panel, from *epsi* to *graygr* in the IDCs sub-panel, from *indust* to *graygr* for the mixed panel and IEEs sub-panel, and from *contcorr* to *graygr* in the case of IDCs.

## Conclusion

Given the fact that global CO<sub>2</sub> emissions induced by human's production activities keep increasing while some countries grow green by emitting less CO<sub>2</sub>, one can intuitively infer the relocation of gray production. Our study essentially purposed to explore where and why the gray side of green growth migrates. To this end, we modeled green and gray growth with such explanatory variables as domestic income, inward and outward FDI stocks, globalization, EPS, industrialization, and control of corruption. Moreover, we constructed our model so as to reflect both direct and indirect (through interactions) effects of EPS and control of corruption. We used a yearly balanced panel dataset covering the 1996–2015 period of 14

large CO<sub>2</sub> emitter countries which we also clustered into IDCs and IEEs sub-panels.

In the analysis procedure, we respectively inspected CD of the variables and models, stationarity of series, as well as heterogeneity and endogeneity of the models implementing a mix of both the first- and second-generation tests. After ascertaining the presence of cointegration between the variables, we then estimated the long-run relationships using the CCEMG estimators together with DOLS (for the cross-section independent models of IEEs) estimators. Finally, we estimated the short-run and the long-run causalities between the series of the green/gray growth variables and their examined determinants.

## Discussion of findings and implications

In the following, we comparatively discuss the empirical findings from the cases of IDCs and IEEs and highlight theoretical and practical implications to provide new insights to policymakers on the setting of environmental policies and to scholars on the modeling of green and gray growth.

Regarding the impacts of the traditional measure of economic growth, our results revealed that countries' green growth trajectories were not independent of their domestic income levels. A positive relationship is explored between

domestic income and green growth for all three panels with greater magnitude for IEEs. The estimated negative relationship between income and gray growth in IEEs refers that emerging economies lose comparative advantage in the export of pollution-intensive products as they become richer. We also confirmed causalities running from income to green growth and gray growth for the IEEs sub-panel. These effects are quite different from the global interpretation of the EKC pattern which predicts that high-income countries would grow green, while low- and middle-income countries (and emerging economies to some extent) grow gray. Country-specific characteristics and the evolving relocation process of pollution-intensive industries may explain these results. The sampled IEEs, which are in a transition from resource-driven to efficiency-driven economic structure with some green innovation activities as developed countries, have many resource-dependent competitors opening to the world market. Thus, IEEs are in a green competition with developed countries and gray competition with open developing countries. Consequently, in this dynamic catch-up process, technological progress should be directed toward greener technologies in emerging economies. Their cumulative efficiency experience reveals that IEEs are capable to embrace green innovation. Further studies may provide new evidence for these countries by exploring the long-term dynamic gains from green growth besides the short-term static returns of gray growth.

Our findings showed that the impacts of FDI stocks were also important for the green and gray growth pathways of countries but widely dependent on the indirect impacts of EPS. Along with a confirmed long-run causality, when we held constant the indirect impacts of EPS, we determined inward FDI stocks encouraging gray growth for IEEs. These findings are consistent with the PHH. Meanwhile, outward FDI stocks were found as a drag on the green growth of IDCs, and inward FDI stocks led to increased green growth for IEEs. Despite these findings indicate the pollution halo effect and question the validity of the PHH from the green growth side, it reveals that multinational enterprises in developed countries tend to carry not only gray parts of their greener production but also they transfer greener technologies to those emerging economies which get benefits from both increasing gray competitiveness and improving green productivity. However, when we include the EPS in the model, these effects considerably changed in magnitude, even in direction for IEEs' gray growth. Thus, future studies are suggested to consider the direct and indirect impacts of environmental policies when analyzing the PHH based on the nexus between inward FDIs and pollution-intensive gray growth.

Another finding weakening the validity of the PHH is the concurrence of both greening and graying effects of globalization in IDCs for which we also ascertained a long-run causality running from globalization to green growth. Given the insignificant effects of globalization on both green and gray

growth in IEEs, we can conclude that the gray (developing world) and green (developed world) polarization predicted by the global inference of PHH was not supported in our case. Trends in global data show that international trade and investment are still managed by the cross-country differences in productivity and returns regardless of any concern about environmental issues. With regard to long-term options, our findings of globalization underline that international green economy coalitions need to favor the best green practices for environmental quality.

An indirect link (through pushing or pulling FDIs) to the PHH is the environmental policy which also interacts with anti-corruption. When indirect impacts of control of corruption were excluded, we found stringent environmental policies failing to foster green growth for both IDCs and IEEs, albeit insignificant coefficients for IDCs. Gray growth and EPS are positively associated in the case of IEEs. We also found EPS causing both green and gray growth in the case of the IDCs sub-panel. Overall evidence about the PHH suggests future researchers to consider the Porter hypothesis as well as the pollution halo effect while examining the PHH.

In the case of IEEs, control of corruption significantly and directly stimulates both green and gray growth. This is consistent with the dual structure of these countries which have both green growth and gray competitiveness dynamics. Therefore, IEEs can get benefits from both increased green growth and gray competitiveness by controlling corruption. Anti-corruption may also help these countries in decoupling economic growth from pollution in their transition process from gray growth to green growth. Anti-corruption also matters for the efficacy of environmental policies as we determined that control of corruption might considerably intervene the estimated influences of EPS on green and gray growth, especially in the gray growth case of IEEs, for which the direction of the association significantly changed to negative when we allowed the indirect impacts of anti-corruption to mediate in the model. Why control of corruption promotes the greening of emerging economies can be explained by the premise that anti-corruption helps in formulating and implementing effective environmental policies including emission limit, process inspection, control monitoring, and punitive sanctions.

On the other hand, the positive association between gray growth and anti-corruption along with the substantial indirect impacts of anti-corruption, which mediate the influences of EPS, provide some answers for two widely asked questions: Do enterprises themselves become green or policies make them green? Does corruption grease or sand the wheels of green growth? In an emerging economy case, when environmental policies are that stringent only the most efficient enterprises with large-budget green investment can meet the high standards. Other companies may choose to stay gray as long as their gains exceed the incurred environmental cost. In this

process, however, some companies have to compete with the cheaper products coming from other developing countries where environmental policies are more lenient, and thus cost is relatively lower. These companies may need to ease the cost of greening through “greasing the wheel.” When corruption is strictly controlled, these companies may be forced to stay gray. Therefore, in IEEs, potential companies need to be supported until they can compete in greening with their counterparts in the world market. Besides temporary incentives, governments can also ease or customize the standards for companies that are endeavoring to be greener. For especially IEEs, policy-makers and local policy implementers need to support environmental policies by also controlling corruption. Again, scholars who further model green and gray growth should include the availability and stringency of environmental policies together with their interactions with anti-corruption and FDI motives to provide sound evidence.

Our findings revealed that countries’ industrial competitiveness was an important predictor of their gray growth pathways. However, its impact changes over country groups. Increasing industrial competitiveness diminishes gray growth for IDCs while stimulating for IEEs. There are also long-run causalities running from industrialization to gray growth in IEEs. Therefore, we can infer that developed countries do not necessarily de-industrialize to leave the gray side of production. This implicitly reveals a green industrial competition through which developed countries can even re-industrialize. Thus, investing more in green technologies in developed countries may increase environmental and resource productivity by also strengthening industrial competitiveness. For IEEs, however, one of these desired effects disappears that these countries are fostering their industrial competitiveness at a cost of receding green growth even the estimated effect is insignificant.

The findings of the gray growth-industrialization nexus suggest that green growth policies embodying both incitements and enforcement instruments should focus on environmental and resource productivity in emerging economies. However, when emerging economies keep enforcing their industrial firms to become green in industrial activities through stringent policies and the cost of industrial greening exceeds firms’ efficiency level, they can either leave industrial production or carry their industrial activities to other developing countries providing much lower environmental cost. Both trends can result in the so-called premature de-industrialization of emerging economies. This suggestion again is subject to more studies that conceptualize fast-industrialization, de-industrialization, re-industrialization, and premature de-industrialization aspects and provide evidence from the industrialization experiences of countries. Policy-makers in emerging economies need to consider finding new environmental policy instruments based on certification, awarding, and green subsidies to motivate their companies not to

become gray in their industrial activities rather than enforcing them to be green through punishment mechanism which in turn may enforce them to leave industrial activities.

One of the important contributions of the study is its findings of the significant indirect effects of control of corruption and EPS. The study opens avenues for future studies to consider these mutual and indirect linkages. Overall, green growth and gray growth are evolving concepts with global and country-specific origins. Thus, to define green growth as not to grow gray, and vice versa, may lead to a misunderstanding of the concepts. To develop an actionable green policy framework toward the promotion of new green sources of low-carbon global economy, our study highlights the importance and necessity of international green initiatives which define a clear list of measurable and internationally comparable green growth indicators categorized by emissions standards. These attempts will assist individual countries in decoupling their gray production from CO<sub>2</sub> emissions by enabling them to assess their own green growth performance and potentials. From a policy perspective, emerging economies need to reinforce the efficacy of the instruments of their stringent environmental policies by other strategies including green efficiency, green industrialization, and anti-corruption plans tailored to their structural capabilities. Policy-makers in developed countries should invest more in research and development on green technologies, green innovations, and renewable energy use under the changing global circumstances. At the international level, the treaty-based global green initiatives need to increase the inter-governmental and local collaborations to transform the gray-green polarization effect of globalization into an overall greening spread in light of the empirical evidence provided by the scientific literature.

### Study limitations and future research

The study had several limitations. The OECD’s EPS indices were only available until 2015 and for a limited number of countries. The study took the overall EPS index which encompasses both restrictions and incentives. Future studies may distinguish between punitive and motivational policy instruments to compare their low-carbon efficiency. The study also suffered from the lack of a clear and separate conceptualization of the green growth aspect which is widely used interchangeably with the green economy, green productivity, green efficiency, clean production, and sustainable development concepts which have a varied set of indicators without a consensus. Even though our green growth consideration is consistent with most of these aspects, the gray growth definition is specific to the RCA in pollution-intensive products. The RCA metric provides general information about countries’ overall competitiveness, but it does not capture the impacts of national policy implications such as tariffs, non-tariff measures, and

subsidies which may also affect comparative advantages. The possibility of policy-driven gray competitiveness calls for new studies. Although we considered the heterogeneity of the sample, the generalization of the results to individual countries with different idiosyncrasies needs some caution. In this regard, new studies with a country-specific empirical setting may reinforce the evidence provided by our study. Finally, our study considered the indirect impacts of anti-corruption and EPS but did not specify a mediation model. Future studies may model mediation effects to provide sound evidence on the intervention roles of corruption and environmental policies.

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**Availability of data and materials** The datasets generated and/or analyzed during the current study are available in the [Google-Drive] repository [[https://drive.google.com/file/d/1fr2\\_STNAC4-RFpdBh23k-64p9rJexLk0/view?usp=sharing](https://drive.google.com/file/d/1fr2_STNAC4-RFpdBh23k-64p9rJexLk0/view?usp=sharing)], and they are available from the corresponding author on reasonable request.

**Author contribution** MD designed the research method, collected data, and conducted analyses of the manuscript. OD reviewed the literature and specified the research gap and study motivation. Both authors equally contributed to the discussion of the findings and wrote the whole manuscript.

## Declarations

**Ethics approval and consent to participate** Not applicable (The manuscript does not report on or involve the use of any animal or human data or tissue. It used open access data which is not involving human participants, human data, or human tissue).

**Consent for publication** Not applicable (Our manuscript does not contain data from any individual person).

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