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ORIGINAL ARTICLE

A critical review of green growth indicators in G7 economies from 1990 to 2019

Kyle S. Herman[1] · Yeong Jae Kim[2] · Soheil Shayegh[3] · Jun Xiang[4]

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Abstract

Green growth policies aim to address both climate change and economic growth and are now prevalent throughout many economies. While green growth is sufficiently assessed in qualitative, case-study-based literature, quantitative and cross-country analyses are still limited. In response to this research deficit, our aim is twofold: (1) to develop a classification framework to quantitatively analyse green growth and (2) to identify key policy *inputs* and techno-economic or environmental *outputs* for green growth through a novel taxonomy. We focus on the G7 countries, since they have, historically, tended to align their economic policies. We employ a machine-automated K-means clustering algorithm, as well as correlation analyses, to assess where green growth "win–wins," or co-benefits to the economy and environment, might exist. Our findings suggest that enthusiasm should be tempered for public policy commitments for green growth; despite unified green growth policy in G7 countries—significant differences are observed for both policy inputs and environmental/economic outputs. As a result, we caution policymakers and researchers against drawing generalised conclusions about the effectiveness of green growth policies, even among highly developed economies. Finally, our research draws attention to data deficiencies which, evidently, reduce more robust assessment across countries and over time.

Keywords Green growth · Economic growth · Environmental taxes · Environmental win–wins · Build back better · Machine learning

Introduction

Green growth is based on the policy imperative to achieve climate neutrality and to reverse environmental destruction while, concurrently, to drive domestic competitiveness (Mardani et al. 2019; Denison et al. 2019; Pauw et al. 2018; Fankhauser et al. 2013). Policymakers are attracted to green growth policies because the latter can, ostensibly, confront multiple challenges at once: climate change, global competitiveness, industrial upgrading, and domestic innovation (Meckling 2019; Carvalho 2019; Green and Gambhir 2020). Ideally, well-implemented green growth policies stimulate the creation of new jobs and environmental technology innovations, the reduction of greenhouse gas (GHG) emissions, and an overall improvement in the economy, the environment, and the society at large (Khan et al. 2020; Mazzucato 2015; Scott et al. 2013; Bowen 2012a). Should green growth benefit both the environment and the economy, "win–wins" can be realised (Tobin 2020; Ambec and Lanoie 2008; Machiba 2011).

Handled by So-Young Lee, Institute for Global Environment Strategies, Japan.

✉ Kyle S. Herman
k.herman@sussex.ac.uk

[1] Science Policy Research Unit (SPRU), University of Sussex Business School, Brighton, Sussex, UK

[2] KDI School of Public Policy and Management, 263 Namsejong-ro, Sejong-si 30149, Republic of Korea

[3] RFF-CMCC European Institute on Economics and the Environment (EIEE), Centro Euro-Mediterraneo sui Cambiamenti Climatici, Milan, Italy

[4] Department of Economics and Division of Global Affairs, Rutgers University, Newark, NJ, USA

Even though a growing and substantially diverse group of countries have rolled out green growth policies in recent years (Georgeson et al. 2017; Barbier 2011, 2016),[1] surprisingly scant quantitative research exists at the country level or across countries concurrently (Barbier 2016; Bowen 2014). Instead, much of the current literature is based on qualitative research and single-country case studies (e.g., Barbier 2010; Bowen 2012a). This restricts deeper, policy-relevant comparison of green growth performance across countries (Capasso et al. 2019). If multiple countries are assessed at the same time, researchers often focus on only one or several green growth variables.

This article responds to this research deficit. First, we develop a novel green growth input–output framework, which is followed by a taxonomy for deeper, cross-country quantitative analysis. We use this framework and taxonomy to assess the universe of available data for G7 countries [Canada, France, Germany, Italy, Japan, the United Kingdom (UK), and the United States (US)]. We combine two methods—K-means and correlation analyses—to effectively reduce the dimensionality of the data, and to gain a deeper understanding of the relationships between variables.

In what follows, we ground our study in green growth concepts, and then introduce the data and framework. Using our novel framework, we explore the relationship between green growth inputs and economic/environmental outputs. We close with a discussion of how our framework, analysis and results can provide useful foundations for future empirical research on green growth.

What is green growth and how to assess it?

As climate change and environmental concerns have become more prominent in public debates over the last few decades, green growth policies have evolved accordingly (Bowen 2012b). Whereas in the past, much of the focus of climate change policies favoured neoclassical economic approaches (e.g., carbon trading), today's policymakers appear much more receptive to the idea that, to combat climate change, policies should be enacted to stimulate innovation, development, and new industrial sectors (Aghion et al. 2009; Acemoglu et al. 2016; Meckling and Allan 2020). This is the key difference between green growth policies and, for instance, carbon trading climate policies; the former are largely based on the idea that policies can encourage innovation and drive economies towards green and climate-neutral trajectories (Borel-Saladin and Turok 2013).

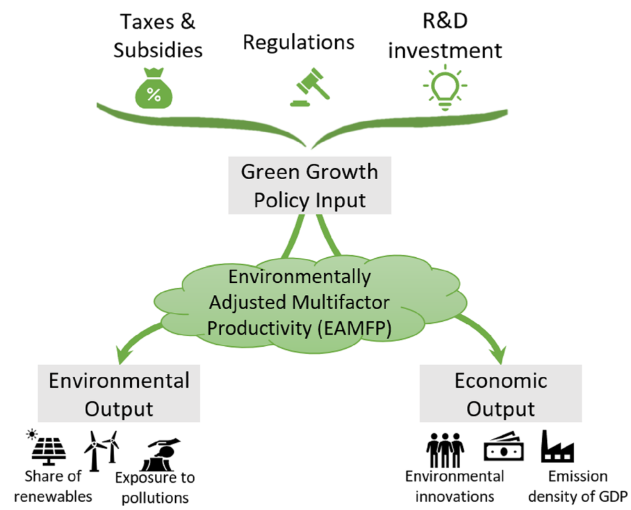


Fig. 1 Mapping of green growth policies, inputs, and outputs. Source: Authors rendition of green growth, based on OECD (2017)

Indeed, earlier versions of green growth are based on concepts such as "induced-innovation" (Ruttan and Hayami 1984), which led empirical researchers to focus on environmental policy-induced clean technology innovations (Johnstone et al. 2010; Herman and Xiang 2022a, b). Consequently, a major tenet of green growth rests on the expectation that policies can induce green innovations which, in turn, lead to sustained economic growth, and result in improvement upon key clean technologies (Popp 2002; Jaffe et al. 2005). Despite some debate in the literature (Barbier 2011; Rodrik 2014; Cárdenas Rodríguez et al. 2018), green growth policies are generally seen as helping to "foster economic growth and development while ensuring that natural assets continue to provide the resources and environmental services on which our well-being relies" (OECD 2011, p. 9).

If green growth policy inputs are difficult to measure, detecting the policy-inducement effects can be all the more onerous. The potential environmental and economic outputs are, indeed, even more complex than policy inputs. To bring some clarity to these interacting elements and variables, Fig. 1 presents an overview of green growth input policies [including taxes/subsidies, regulations, and research and development (R&D) investment] and their relationship to environmental and economic output, including "environmentally adjusted multifactor productivity" (EAMFP).

While interest in green growth policies initially arose during the 2008–2009 global financial crisis (Bowen and Hepburn 2014; Bowen et al. 2009), such policies have

[1] Beyond the G7 countries, a significant share of the COVID-19 recovery packages, in addition to emissions pledges in line with the Paris Agreement, has integrated elements of green growth within them. For example, 30% of the Next Generation European Union (EU) funds are allocated to fighting climate change. Separately, in line with the Paris Agreement, China, Japan, South Korea, and all EU countries have individually committed to 'net-zero' carbon emissions by a specified future year (mostly by 2050). Such commitments are almost entirely based on green growth initiatives to support green infrastructure development and the transition to low carbon economies (Tolliver et al. 2020).

gathered renewed momentum during and after the COVID-19 pandemic (Barbier 2020; Agrawala et al. 2020). The G7 group of wealthy industrialised countries have, in unison, expressed strong support for such policies to kickstart their economies. Indeed, in June 2021, they collectively committed to increasing global climate finance and endorsed the "build back better for the world" initiative—a mutually agreed-upon plan firmly rooted in green growth policies and concepts (Stern 2021; Bhattacharya et al. 2021; Bhattacharya and Stern 2021).[2] In June 2022, they announced the 'climate club' and the "first mover's coalition", both programs aiming at scaling up massive investments to drive a green economy revolution, which motivates the analysis of G7 countries in this study.[3]

Prior empirical literature

A recent study finds that, across 30 Organisation for Economic Co-operation and Development (OECD) member countries, green productivity rose faster than the traditional Total Factor Productivity (TFP) (Peng 2020). This suggests that, at least for OECD countries, economic growth has been decoupled from the climate and environment destruction. Others show that, in BRICS countries (Brazil, Russia, India, China, and South Africa), environmental-related technologies contribute positively to green growth (Ulucak 2020). Industrial upgrading and green growth are also quantitatively assessed for China, with evidence to suggest more targeted environmental regulations are paramount for environmental and economic win–wins (Yu and Wang 2021). However, the effect of green energy innovation on energy intensity is not uniform across countries (Chakraborty and Mazzanti 2020).

Beyond domestic innovation outputs, prior studies highlight the role of energy savings, GHG abatement, and green industrial upgrading as important output indicators of green growth outputs (Wang et al. 2020; Wang and Zhu 2020). Particular emphasis has been placed on the benefits to the environment—specifically for local air quality—from the deployment of renewable energy technologies (Ike et al. 2020; Ibrahim and Alola 2020). In this case, the green growth environmental output is better air quality, driven by two policy inputs: renewable energy R&D and subsidies (or feed-in-tariffs). Researchers also suggest that environmental factors and resource productivity of the economy are more suitable indicators for measuring green growth than other indicators (Alrasheedi et al. 2021).

Several recent studies focus on specific policy inputs such as environmental taxes and examined their effect on carbon emissions in G7 countries (Doğan et al. 2022; Hao et al. 2021; Liu et al. 2020). In this vein, Hao et al. (2021) demonstrate an important relationship between environmental taxes, carbon emissions, and other indicators including EAMFP growth.[4]

In general, EAMFP measures a country's ability to embark on economic growth while, concurrently, lowering undesirable outputs such as GHG emissions. Therefore, EAMFP is commonly used as a proxy for green growth performance (Albrizio et al. 2017, 2014; Kozluk and Zipperer 2015). Indeed, Hao et al. consider EAMFP a main green growth performance indicator and show that, after controlling for environmental taxes, it negatively impacts CO_2 emissions. In other words, they suggest that countries with higher EAMFP correspond to better carbon performance.

As discussed further below, however, it is unclear whether EAMFP is a policy input or an economic and environmental output—consequently, it does not easily fit within our novel green growth taxonomy. Moreover, the existence of such direct links between green growth policies, economic outputs, environmental outcomes, and productivity growth—as captured by EAMFP—are yet to be systematically analysed and validated across a wider set of countries and a longer time-series. This is one main impetus for our framework and taxonomy. Our findings do, indeed, warrant caution for using EAMFP as a main proxy for green growth without conducting further transformation of this instrumental variable. In other words, as shown in the results section, EAMFP is best understood as an indicator highlighting the link between policy inputs and environmental/economic outputs (see Fig. 1).

Systematic green growth analyses

The quantitative links between green growth policy initiatives and environmental and economic indicators can be further established through exploratory and statistical data analysis.

[2] https://www.imf.org/external/pubs/ft/fandd/2021/09/bhattacharya-stern-COP26-climate-issue.htm.

[3] https://www.whitehouse.gov/briefing-room/statements-releases/2021/06/13/carbis-bay-g7-summit-communique/.

[4] The OECD statistics platform defines EAMFP as follows: "EAMFP growth measures the residual growth in the joint production of both the desirable and the undesirable outputs that cannot be explained by changes in the consumption of factor inputs (including labour, produced capital and natural capital). Therefore, for a given growth of input use, EAMFP increases when GDP increases or when pollution decreases. As part of the growth accounting framework underlying the EAMFP indicator, the growth contribution of natural capital and growth adjustment for pollution abatement indicators are derived: Growth contribution of natural capital—measures to what extent a country's growth in output is attributable to natural resource use; Growth adjustment for pollution abatement—measures to what extent a country's GDP growth should be corrected for pollution abatement efforts—adding what has been undervalued due to resources being diverted to pollution abatement, or deducing the 'excess' growth which is generated at the expense of environmental quality" (https://stats.oecd.org/Index.aspx?DataSetCode=EAMFP).

However, a systematic approach is required given the extent, diversity, and coverage of these data. Accordingly, we propose a novel empirical framework to objectively assess green growth policy performance. As outlined above, while others have used green growth variables to quantitatively test different hypotheses, our approach is exploratory in nature; we begin by drawing on the entire universe of available green growth data, and then refine the analyses based on the quality of data, data coverage, and potential input–output relationships. In this manner, we convene a systematic framework to explore, map, and assess the available green growth data.

Our quantitative green growth framework is based on the bifurcation of inputs and outputs through their close association with EAMFP (see Fig. 1). Policy inputs are green growth measures such as environmental-related taxes, while outputs include both environmental outputs [e.g., exposure to ambient ozone or particulate matter (PM)] and economic outcomes [e.g., gains in CO_2 productivity as measured by emissions per unit of Gross Domestic Product (GDP)]. Therefore, the first phase of our empirical strategy involves curating, classifying, and creating a taxonomy for green growth data. Second, we employ a two-stage machine-aided empirical analysis to find underlying patterns of association in the data. For our quantitative case study, we focus on the G7 countries for two reasons: first, these countries have explicitly expressed collective and significant commitment to implementing green growth policies (Stern 2021); and, second, G7 countries are among the most highly developed countries in the world. This implies that the success signal in achieving green growth is expected to be the strongest and clearest among this set of countries. Nevertheless, we extend the proposed analysis to the whole sample of OECD countries. A brief discussion of the OECD results is provided in the appendix.

Data processing

We obtain green growth-related data from the OECD's Green Growth Indicators Handbook (2017) and the OECD-stat website[5] (OECD 2017, *Green Growth Indicators;* OECD 2011, *Towards Green Growth: Monitoring Progress*).[6,7]

While the OECD's green growth indicators are fairly comprehensive (including 162 variables covering 221 countries since 1990), we observed that many variables do not directly relate to green growth (e.g., "Life expectancy at birth" and "Net migration"). Moreover, many are duplicative (e.g., "Production-based CO_2 emissions" and "Production-based CO_2 emissions, index 2000 = 100"). Curating the data, therefore, mandates the important pre-screening of redundant or out of context green growth variables. Specifically, this involves eliminating variables based on three conditions: (1) variables with over 75% missing values; (2) variables not directly germane to green growth; (3) duplicative variables.

Our revised green growth dataset consists of 28 variables from 1990 to 2019 (see Tables 1 and 2). We then develop our input–output taxonomy by classifying each of the 28 variables into four categories:

1. *green growth policy inputs*: these indicators deal with climate or environmental policy, environmental tax, environmental investment, or other regulatory measures.
2. *environmental outputs*: these indicators consist of a direct measurement corresponding to the environment or the climate.
3. *economic outputs*: these indicators show environmentally related economic benefits (i.e., emissions and material productivity, patenting, and innovation).
4. *productivity growth*: EAMFP measures the change in productivity with respect to the environment and natural resources.[8] It includes only one variable.

Descriptive statistics for the green growth variables we select are provided in Table 2.

Upon completing our green growth taxonomy of 28 variables (Tables 1 and 2), we examine the quality and consistency of these data. Overall, we find that the OECD's green growth data have, for the most part, improved in the past decade (2010–2019) compared to the previous decades (1990–2009). Such improvements are attributed to the development of more robust environmental regulations and respective impact evaluations (Wang et al. 2019). However, as shown in Panel (A) of Fig. 2, data availability is unevenly distributed across different indicators and categories. For example, while some indicators such as "Mean population exposure to PM2.5" (coded as "ENV_1: environmental output 1") exhibit over 50% missing values, others such as "Energy intensity" (coded as "ECN_1: economic output 1") have zero missing values.

Panel (B) shows the distributions of missing data for the four categories within each G7 country. Canada exhibits the highest level of missing data for policy input indicators (around 25%), while Germany has the highest percentage of missing values for economic output indicators, which is

[5] https://stats.oecd.org/, accessed in March 2023.

[6] https://www.oecd.org/greengrowth/greengrowthknowledgeplatform.htm.

[7] "The OECD and GGGI are key members of the Green Growth Knowledge Partnership (GGKP), a global community of policy, business, and finance professionals and organisations committed to collaboratively generating, managing, and sharing knowledge on the transition to an inclusive green economy" (https://www.oecd-forum.org/posts/oecd-and-korea-champions-of-green-growth).

[8] EAMFP is a unique indicator. Since it is already widely used as a proxy for green growth performance, we elected not to classify it according to our three classifications. A more complete discussion of EAMFP is provided in the method section.

Table 1 List of main green growth variables and their classifications

Category	Variable name	Full name	ID
Policy input	ENVTAX GDP	Environmentally related taxes, % GDP	INP_1
	ENVTAX TR	Environmentally related taxes, % total tax revenue	INP_2
	ENVRD GBAORD	Environmentally related government R&D budget, % total government R&D	INP_3
	ERD GDP	Energy public research, development, and demonstration (RD&D) budget, % GDP	INP_4
	FIT SOLAR	Mean feed-in tariff for solar photovoltaics (PV) electricity generation	INP_5
	FIT WIND	Mean feed-in tariff for wind electricity generation	INP_6
	RERD ERD	Renewable energy public RD&D budget, % total energy public RD&D	INP_7
	PET FFS	Petroleum support, % total fossil fuel support	INP_8
Environmental output	PM PWM	Mean population exposure to PM2.5	ENV_1
	DMC BIO	Biomass, % of domestic material consumption (DMC)	ENV_2
	O3 MOR	Mortality from exposure to ambient ozone	ENV_3
	ODA ENV	Environmentally related official development assistance (ODA), % total allocable ODA	ENV_4
	PA MARINE	Marine protected area, % total exclusive economic zone	ENV_5
	PA TERRESTRIAL	Terrestrial protected area, % land area	ENV_6
	PM MOR	Mortality from exposure to ambient PM2.5	ENV_7
	RE NRG	Renewable electricity, % total electricity generation	ENV_8
	RE TPES EBIOM	Renewable energy supply (excluding solid biofuels), % total energy supply (TES)	ENV_9
	RE TPES	Renewable energy supply, % TES	ENV_10
Economic output	NRG INT	Energy intensity, TES per capita	ECN_1
	CO2 DBPROD	Demand-based CO_2 productivity, GDP per unit of energy-related CO_2 emissions	ECN_2
	CO2 PBPROD	Production-based CO_2 productivity, GDP per unit of energy-related CO_2 emissions	ECN_3
	DMC PROD	Non-energy material productivity, GDP per unit of DMC	ECN_4
	GPAT DE AI	Development of environment-related technologies, % inventions worldwide	ECN_5
	GPAT DE AT	Development of environment-related technologies, % all technologies	ECN_6
	GPAT DE CAP	Development of environment-related technologies, inventions per capita	ECN_7
	GPAT DE RTA	Relative advantage in environment-related technology	ECN_8
	NRG PROD	Energy productivity, GDP per unit of TES	ECN_9
Productivity growth	EAMFP EAMFPG	Environmentally adjusted multifactor productivity growth	PRD_1

Adopted from the OECD Green Growth database. Our classification (categories) divides the green growth variables into policy inputs, environmental and economic outputs, and productivity growth. The variable names and full names mirror those downloaded from the OECD. The IDs represent our coding scheme. For a full list and data of all green growth indicators, please visit https://stats.oecd.org

somewhat perplexing given both its economic prowess and leadership on the environment. The status of missing values for the other two indicators is more consistent across each respective G7 country.

Temporal distributions of missing data for each category across the time-series are provided in Panel (C) in Fig. 2. Unsurprisingly, the rate of missing data from the earliest period, 1990–1999, is the highest. From 2000 to 2009, the data are more complete. The 2010–2014 period contains the most complete data, but from 2015 to 2019, no productivity growth data exist.[9] As discussed further in our conclusion, future studies are needed to ameliorate missing data—for instance to impute missing data, to draw on data from novel sources such as satellite imagery—if indeed such databases do not improve drastically (Turner et al. 2015).

[9] The observed incompleteness in data for this last period is somewhat alarming, since the Paris Climate Agreement was signed and entered into force in late 2015. As a consequence of missing data following the landmark Paris Agreement, green industrial upgrading and country-level climate transitioning is difficult to assess. This limits the potential viability of Nationally Determined Contributions (NDCs) as a key Paris Climate policy lever. In other words, due to incomplete data, it is difficult to determine which countries effectively began to align with the landmark Paris Climate Agreement.

Table 2 Descriptive statistics of the green growth variables

ID	Variable name	Observation	Mean	Min	Max
INP_1	ENVTAX GDP	177	2	0.72	3.6
INP_2	ENVTAX TR	177	5.753	2.72	9.3
INP_3	ENVRD GBAORD	204	2.22	0.35	4.88
INP_4	ERD GDP	208	0.038	0	0.1
INP_5	FIT SOLAR	139	0.175	0	0.72
INP_6	FIT WIND	139	0.065	0	0.28
INP_7	RERD ERD	208	14.493	0.57	51.47
INP_8	PET FFS	70	57.033	12.46	97.36
ENV_1	PM PWM	98	12.918	6.21	25.91
ENV_2	DMC BIO	189	27.972	13.95	44.44
ENV_3	O3 MOR	210	24.47	6.22	57.65
ENV_4	ODA ENV	210	32.04	0.1	94.83
ENV_5	PA MARINE	154	14.634	0.34	45.57
ENV_6	PA TERRESTRIAL	154	19.139	5.73	37.78
ENV_7	PM MOR	210	346.984	96.96	800.1
ENV_8	RE NRG	210	20.791	1.63	66.56
ENV_9	RE TPES EBIOM	210	4.932	0.33	13.87
ENV_10	RE TPES	210	7.587	0.48	18.13
ECN_1	NRG INT	210	4.779	2.43	8.49
ECN_2	CO2 DBPROD	168	3.672	2.07	6.45
ECN_3	CO2 PBPROD	210	4.539	2.04	9.93
ECN_4	DMC PROD	189	3.678	0.93	7.24
ECN_5	GPAT DE AI	210	10.84	1.38	34.08
ECN_6	GPAT DE AT	210	9.559	5.09	15.7
ECN_7	GPAT DE CAP	210	22.891	2.53	82.37
ECN_8	GPAT DE RTA	210	1.012	0.69	1.43
ECN_9	NRG PROD	210	9562.5	4093.82	17,893.029
PRD_1	EAMFP EAMFPG	160	1.41	− 3.03	4.93

The 8 input, 10 environmental output, 9 economic output, and 1 productivity growth variables range from 1990 to 2019. The total number of observations with no missing value is 210 (30 years × 7 countries). The variables are not normalised

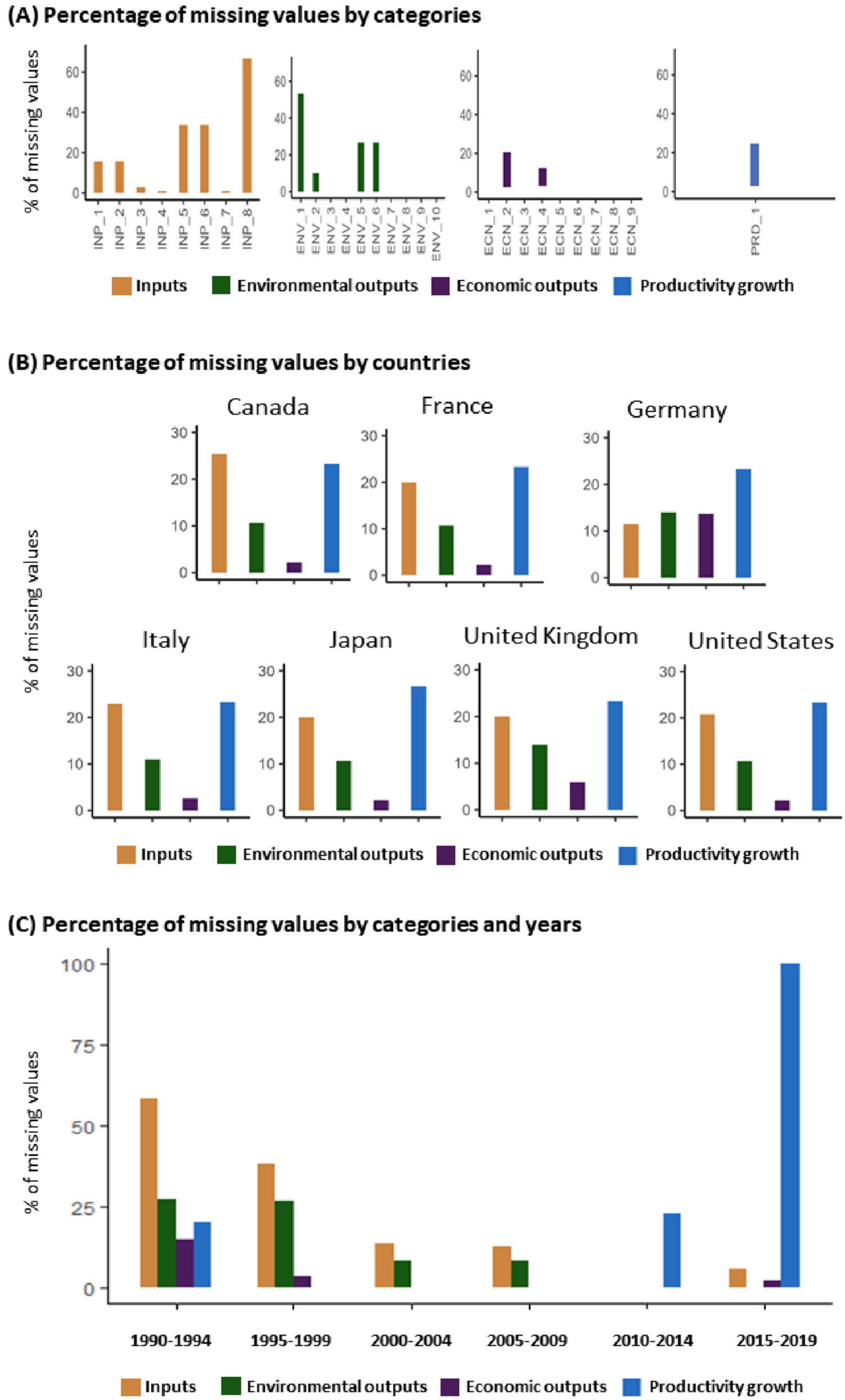
Pattern discovery and correlational analyses

Green growth is, overall, a complex process involving multiple scales, policy dimensions, and economic focal points (Patchell and Hayter 2013; Brunel and Levinson 2016). As briefly outlined in the section "What is green growth and how to assess it?", selecting which variables to use for quantitative analyses remains a key challenge.[10] For example, some researchers have focused on clean production and green supply chains (Wiebe and Yamano 2016), while others focus on green growth and low-carbon technologies (Sandberg et al. 2019). Yet, another group of researchers has sought to examine green growth with respect to green environmental technology innovations (del Río González 2009; Yin et al. 2015; Herman and Xiang 2019, 2020). The empirical approaches are splintered in this regard, because there exist no pre-specified units of analyses for green growth, although some composite indicators have recently been developed (Herman and Shenk 2021).

Due to the nature of the data—i.e., it is uneven across countries and contains many missing values (as shown in the previous section)—we employ machine-learning tools recognised as important to overcome selection bias, missing data, and high-dimensional aspects of complex data (Guo et al. 2017; Fokianos & Pitsillou 2018; Herman and Shenk 2022). In stage I of our quantitative analysis, we employ the K-means clustering algorithm to identify the optimal

[10] While regressions enable some post-analysis to test interconnection in the dataset, cluster analysis provides a more neutral approach for exploring possible interconnections and does not impose or assume any a priori relationship among the data points (Jain 2010; Khan and Ahmad 2004; Kulis and Jordan 2011).

Fig. 2 Schematic representation of missing values. **A** missing values by categories of variables (inputs, environmental, economic outputs, and productivity growth), **B** missing values by G7 countries, and **C** missing values by categories and years



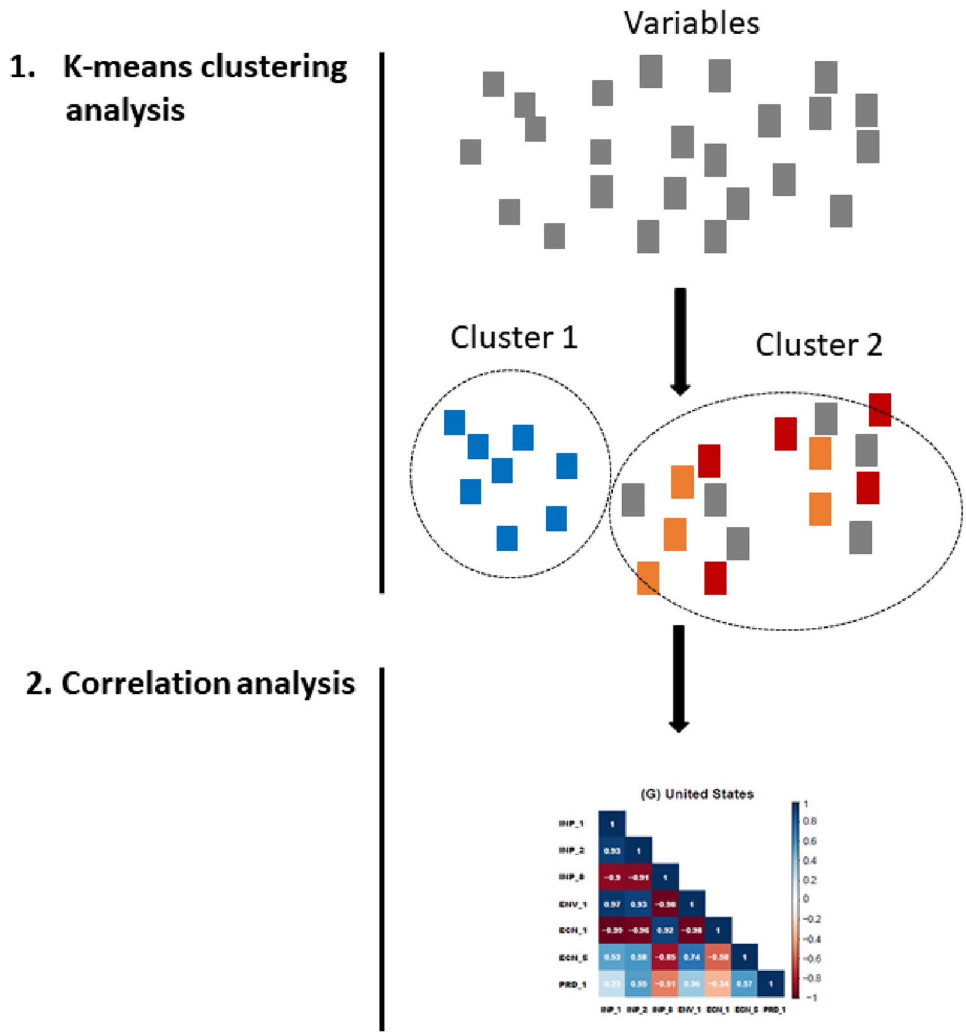


Fig. 3 A visual representation of two-stage data analysis input–output assessment framework

number of clusters. In stage II, we perform correlation analyses among the selected variables. A visual schematic of the two-stage data analysis is provided in Fig. 3.

Stage I: K-means clustering

In general, unsupervised K-means techniques effectively extract underlying structures within the data and, consequently, they are "exploratory in nature" (Jain 2010, p. 651). Most importantly, they can provide a relatively unbiased overview of the data (Jain 2010; Everitt 1993; Everitt et al. 2011), and also help to illuminate important factors within time-series data across a sample of countries (Jain 2010). The K-means method has a long history in social science and economics studies (Jain 2010; Drineas et al. 1999; Ferrari and de Castro 2015).

In technical parlance, partitional algorithms are usually used for K-means. These algorithms are an important component of pattern recognition for environmental policies (Herman and Shenk 2021, 2022). The mathematical objective of this approach is to reduce the number of features, where each feature is a dimension that represents the group (Jain and Dubes 1988; Everitt 1993; Everitt et al. 2011). We employ the K-means clustering method that clusters data *vis-a-vis* the separation of samples in *n* groups of equal variances, minimising the inertia or within-cluster sum-of-squares (Likas et al. 2003).[11] Finally, from a methodological standpoint, we closely mirror the steps outlined by Jain and

[11] While others have leveraged a diverse range of statistical methods to analyse the relationship between different indicators in the green growth literature (Hao et al. 2021; Cheng et al. 2020; Fankhauser et al. 2013), we develop this method, because our intention is not to look at acute relationships among selected green growth indicators, but rather to provide fertile ground for future empirical research investigations into green growth data, specifically with respect to policy inputs as they relate to environmental and economic outputs. Even though the use of regression models is a common approach, it requires careful treatment of interdependencies between independent and dependent variables as well as their expected relationship. Indeed, endogeneity concerns for these data are identified in prior literature (Galeotti et al. 2020; Rubashkina et al. 2015).

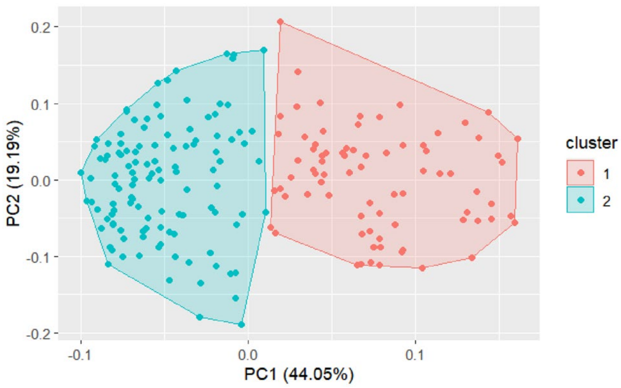


Fig. 4 The optimal number of clusters for K-means clustering results

Dubes (1988) during the deployment of our K-means clustering algorithms, enumerated in the replicable steps below.

To implement this analysis with our data, and to ensure replication by future researchers, we detail our methodological procedure:

1. We collect observations from the G7 countries for the 28 most salient green growth indicators in the OECD's green growth database (the section "Data processing"). We then normalise the data between 0 and 1 due to the over-dispersion of some variables, and to account for the fact that not all variables are supplied in the same format or referred to the same underlying metric.
2. We deploy the K-means clustering which results in two main clusters. Figure 4 provides the visual assessment of where delineation among the indicators occurs. It shows that the optimal number of groupings is two. As determining the optimal number of clusters is somehow subjective and depends on the methods, we employ a consensus-based algorithm. We choose the most optimal number of clusters as a result of using the consensus-based algorithm. The choice of 2 clusters is supported by 14 (46.67%) methods out of 30 methods [Elbow, Silhouette, Gap_Maechler2012, Ch, CCC, Cindex, Duda, Pseudot2, Beale, Ratkowsky, Mcclain, Mixture (VVE), Mixture (VEE), and Mixture (VVV)].
3. Since we aim for generalisable insights across G7 countries, we restrict our attention to indicators that (a) fall entirely within one cluster (i.e., they do not, in any of the cases, fall into more than one cluster) and (b) include EAMFP as a key green growth indicator. From the 28 green growth indicators in our initial analysis, seven variables (including the variable EAMFP) fall entirely within the first group. This suggests that, in the second stage of the process, we can establish a correlation matrix with these seven indicators to embark on deeper investigation. We do not proceed with further analysis for the remaining 21 indicators.

Stage II: correlation analysis

As mentioned, the K-means method identified seven variables that were clustered together. These are as follows: (1) three green growth policy inputs: *environmental tax as a percentage of GDP* (INP_1), *environmental tax as a percentage of total tax revenue* (INP_2), and *petroleum support as a percentage of total fossil fuel support* (INP_8); (2) one environmental output: *mean exposure of population to particulate matters* (ENV_1); (3) two economic outputs: *energy intensity as TES per head of population* (ECN_1) and *development of environmental technologies as a percentage of inventions worldwide* (ECN_5); (4) productivity growth: *EAMFP growth* (PRD_1).[12]

The fact that two green growth policy inputs are environmental tax measures indicates a strong underlying relationship between the environmental tax policy inputs and consequent environmental and economic outputs. This finding is generally consistent with prior literature (Ekins and Speck 2011; Khurshid and Deng 2021). Indeed, environmental taxes have often been used to explain reductions in carbon emissions (e.g., Di Cosmo and Hyland 2013; Li and Lin 2015)—what we would consider to be an important green growth output indicator. Environmental taxes are also seen as inducing innovators, firms, and investors to create less emissions-intensive products, or to otherwise drive attention towards cleaner production processes and related innovations (Andersson 2019; Criqui et al. 2019). In the second stage of our data strategy, provided in the section "Results", we perform a correlation analysis on the G7 countries' green growth data based on the seven prominent variables obtained in the prior K-means clustering stage.

Results

Panels A to G in Fig. 5 display the results of the correlation analysis at the country level.

Since exposure to PM causes millions of premature deaths every year, throughout nearly every country in the world (Silva et al. 2013, 2017), it is an important environmental output indicator for green growth. A green growth

[12] As mentioned above, the EAMFP output indicator is not easily classified as either an environmental or economic output. However, for sake of simplicity, we classify it as a productivity growth output here. In general, EAMFP is the indicator of a country's ability to embark on economic growth while, concurrently, lowering undesirable outputs such as GHG emissions. Therefore, we expect this indicator to provide a general snapshot of a country's green growth success, consistent with prior literature (Albrizio et al. 2017; Albrizio et al. 2014; Kozluk and Zipperer 2015).

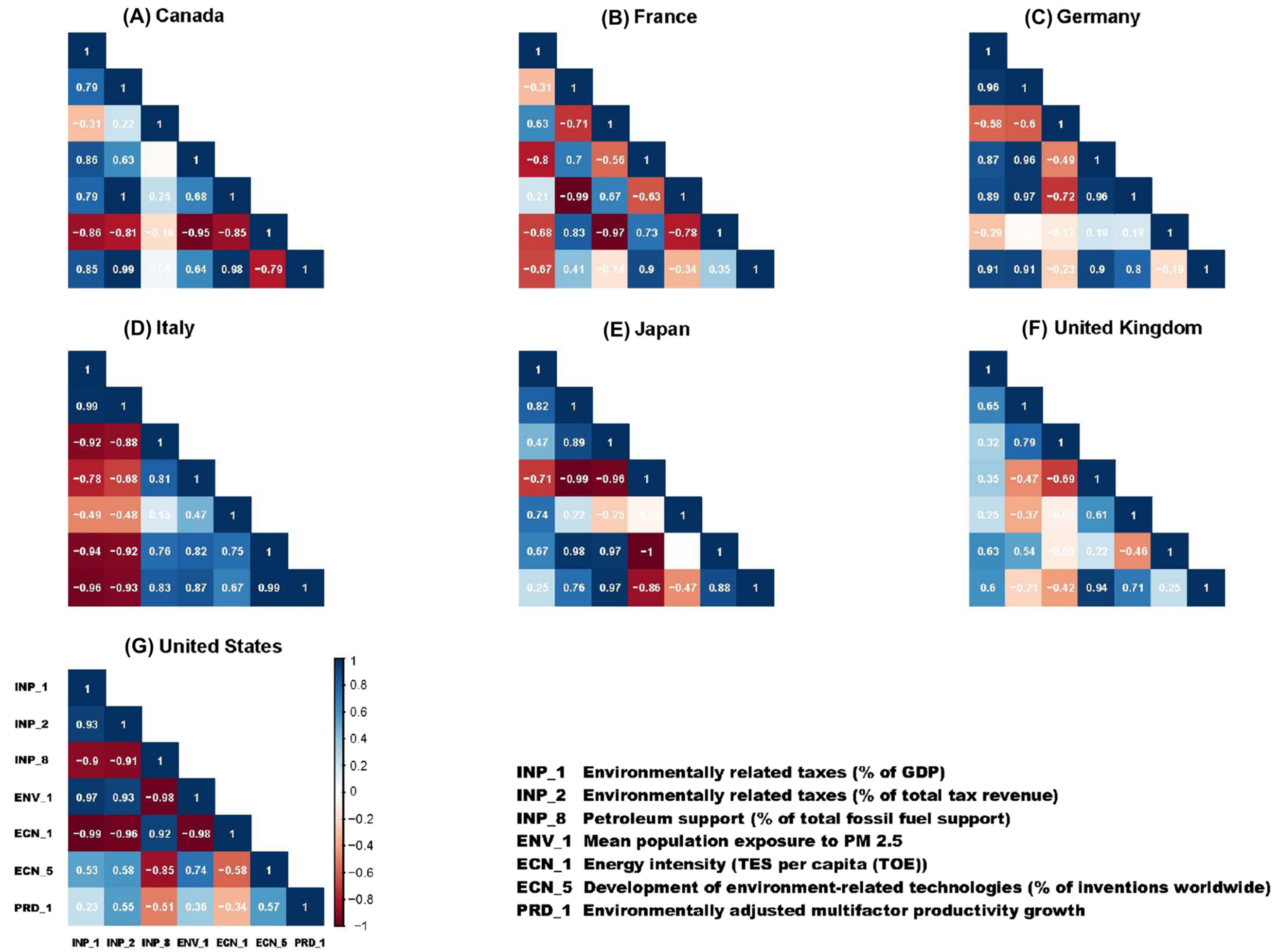


Fig. 5 Correlation analysis on the seven indicators from the first-stage clustering for each G7 country. Numbers inside the squares indicate the correlation coefficients. The colour indicates a positive (blue) or negative (red) correlation (note: TES stands for total energy supply and TOE stands for Tonnes of oil equivalent.)

win–win can be identified if there exists a negative correlation between *environmental taxes* (INP_1, INP_2) and *mean population exposure to PM* (ENV_1). However, in this case, we find a positive relationship between environmental tax and pollution across several countries, including Canada, Germany, and the US. There are two possible interpretations of this finding: (1) as environmental taxes increase, exposure to PM also goes up (i.e., not a green growth win–win); (2) or it is a null effect; environmental taxes and PM exposure both decrease over time due to a third confounding factor. The data trends provided in Fig. 6 in the Appendix suggest that, indeed, both policy inputs and the environmental output exhibit a downward trend in Canada, Germany, and the US over time.

For other countries like France and the UK, environmental taxes do not follow a clear trend, and these countries exhibit a mixed positive and negative correlation between the two inputs and the output. On the other hand, in Italy and Japan, a negative correlation between taxes and exposure to PM can be observed. This signifies a green growth win–win; as their environmental taxes increased, PM exposure fell.

Turning to the correlation between the environmental tax policy inputs and the first economic output [*energy intensity as TES per head of population* (ECN_1)], we again observe mixed correlation signs. Similar to our previous conjecture, we suspect that the positive results are driven by concurrent reduction in environmental taxes coupled with energy market trends favouring moderately cleaner fossil fuels such as natural gas over coal (Gencsu et al. 2019). The implications of this finding are important for policymakers; while G7 countries publicly agreed to the "build back better" G7 initiative, it is less clear how they will meet these commitments owing to such underlying heterogeneity in policy inputs, as well as environmental and economic outputs.

The analysis of the correlations between the environmental tax inputs and *development of environment-related technologies as a percentage of inventions worldwide* (ECN_5) divides the G7 countries into two groups. One group, including Canada, France, Germany, and Italy, show at least one negative correlation sign, indicating a seemingly harmful side effect of tax policies on the development of green technologies. On the other hand, the positive correlation signs for Japan, the UK, and the US indicate that the environmental tax policies in this group of countries have indeed been a driver for green innovation and "win–win" outcomes.

Another notable finding, shown in Fig. 5, is the relationship between the green growth policy inputs and *EAMFP* (PRD_1), a variable we were unable to strictly classify as an output or an input. As mentioned before, we consider this variable as a link between the policy input variables and the main outputs. In addition, as Fig. 6 in the Appendix shows, EAMFP does not follow a clear trend in all of the G7 countries. Since EAMFP consists of both input and output variables, it is not indicative of a green growth output, strictly speaking—i.e., as both an input and output variable, its explanatory power to assess the outcome of green growth policy inputs is much weaker. This calls for efforts to create a more robust green growth output indicator, going beyond EAMFP (Borel-Saladin and Turok 2013). Hence, caution is warranted here; researchers are advised that EAMFP is not uniformly applicable.

Indeed, as discussed above, this finding is also perplexing because several G7 countries experienced downward trends in environmental taxes in the last decade. Therefore, this indicates that EAMFP trends downward as environmental taxes are reduced, another important observation for policymakers. The final section goes into further detail and discusses the implications of our systematic framework and machine-automated analyses.

Discussion

What do our findings convey about green growth inputs and outputs in general? First of all, policymakers, companies, and investors require much better tools to understand how, and to what extent, green growth policies impact the economy and the environment. Reliable data, being a critical tool for anticipatory environmental and climate governance (Muiderman et al. 2020; Herman and Shenk 2021), are a prerequisite to effective green growth policy rollout, since it is the only way to assess how policy inputs lead to positive green growth outputs. Yet, based on our systematic framework and approach, which partially ameliorate underlying data deficiencies, we assert that much more investment and attention should be given to development, availability, and maintenance of green growth data—ideally in an open and freely accessible database.

The observed effects of implementing environmental policies with respect to their environmental and economic outputs also provide evidence in this regard. Indeed, this heterogeneous finding comports with a recent intervention which empirically demonstrates much variance among green growth outcomes (Mealy and Teytelboym 2020). As such, it is quite possible that measuring green growth requires an entirely new set of metrics which have yet to be formally introduced (Vazquez-Brust et al. 2014; Capasso et al. 2019).

Moreover, we caution that selective analysis of only several green growth variables is also problematic; without analysing the full dataset of available green growth variables, the broader socio-technical impacts of green growth policies, including economic and environmental win–wins (Tobin 2020), will remain poorly understood (Luderer et al. 2019).

Conclusion

The systematic framework, classification, clustering, and correlation analyses conducted here provide foundations for deeper empirical and quantitative analyses on green growth. These tools can help policymakers isolate instances of green growth win–wins or, alternatively, provide scope for anticipatory climate and green growth governance (Maffei et al. 2020). Bearing in mind the techniques and approaches we developed in this paper, future researchers could build upon these methods to gain more clarity on the economic and environmental outputs of green growth policy inputs. Based on our analyses, we provide several important conclusions and policy implications.

First, we highlight the significant limitations with the OECD's database and publicly accessible green growth data (which we attribute to individual countries rather than the OECD). The existence of missing data is problematic from the standpoint of green growth policy; without reliable data and indicators, it will be very difficult to understand the output effects of green growth policies, which in turn will make it exceedingly difficult for policymakers to accurately calibrate policies over time (Herman and Shenk 2022). As it stands, at least for the OECD's green growth data, comparative quantitative studies across this sample of countries remain limited, due in large part to incomplete and inconsistent data, even within what is considered the most complete cross-country, time-series, green growth data platform provided by the OECD.

Consequently, even though G7 countries have recently proclaimed much ambition to work together towards green growth in the post-COVID era, as of now, synergy of policies seems all but impossible given both the heterogeneity across countries compounded by the lack of adequate data for time-series analyses. The extent to which these impediments will slow down the G7's drive towards a twenty-first century green revolution remains an important and open question to explore in future research. Greater collaboration, especially on data, is called for. For richer causal analyses of green growth policies, a wider set of quantitative indicators are needed to capture the nuanced features of the green growth input–output assessment (Borel-Saladin and Turok 2013).

Despite the drawbacks with the data, our broader findings have important implications for policymakers and other green growth advocates. First, from the relational analyses, we have shown that environmental taxes continue to be an important tool to drive green growth outputs, at least in some countries. Second, we have shown that caution is warranted in drawing concrete conclusions based on EAMFP, an indicator widely used to assess progress on green growth. Instead, we show that EAMFP can act as an indicator highlighting the link between policy inputs (e.g., environmental taxes) and economic outputs (e.g., green innovation) and environmental outputs (e.g., pollution exposure).

In sum, our most important contribution is twofold. First, we have developed a taxonomy to enable more robust quantitative assessment of green growth policy inputs in relation to environmental and economic outputs. Second, we have exemplified how machine-learning methods, such as K-means clustering analysis and correlational techniques, might be applied for deeper investigation in the future. Hence, through our quantitative comparisons, we have made a first attempt at providing a taxonomy to increase the efficacy of green growth policies and provide scope for better climate governance.

Appendix A: Data trends for the key indicators of G7

See Fig. 6.

Appendix B: The analysis of OECD sample

In addition to the full analysis of G7 countries as shown in the main text, we conducted a similar analysis using the complete list of 38 OECD countries.[13] That is, based on the same 28 green growth variables (see Table 1) covering the years from 1990 to 2019, we conducted the two-stage analysis as outlined in the main text for the whole sample of OECD countries.

As explained earlier, our approach is not restricted to only analysing the case of G7 countries. That being said, it is a well-thought-out decision for us to focus on the sample of G7 countries in the main text, since this group of countries have explicitly committed to green growth, and they are also much more homogeneous. Compared to the G7 countries, the OECD countries are significantly more heterogeneous.

As a result, the first-stage analysis of the K-means clustering generated strikingly different findings. While the optimal number of clusters remained two, the variables in these clusters have changed a great deal. Once again, all the observations of the variable EAMFP (PRD_1) fell entirely within the first cluster. However, instead of six other green growth indicators in the case of G7 countries, only one indicator fell entirely within the first cluster together with EAMFP for the sample of all OECD countries. This is a policy input variable concerning the support for fossil fuel production [petroleum support as a percentage of total fossil fuel support (INP_8)], which happens to be one of the three input variables from the G7 analysis.

For the same reasons, we restrict our attention to the indicators that fall entirely within the same cluster (i.e., they do not, in any of the cases, fall into more than one cluster), and focus only on the cluster including EAMFP. Therefore, in the second-stage analysis of correlation, we show a correlation matrix with only these two indicators (INP_8 and PRD_1) for the sample of 38 OECD countries. We do not proceed with further analysis for the rest 26 indicators. The correlation results are displayed in Table 3.

Not surprisingly, we observe both positive and negative correlation coefficients between the two variables for the sample of OECD countries. It is important to point out that the data for INP_8 begin in the year of 2010, and the data for PRD_1 end in 2013. In other words, there are only four overlapping years between these two variables, and as a result, only four observations are used in the calculation of correlation for each OECD country. This suggests a strong limitation of the correlation results based on these two variables. For those few countries without correlation results, it is either because the data are missing for INP_8 or the values

[13] For the list of OECD countries, see https://www.oecd.org/about/members-and-partners/

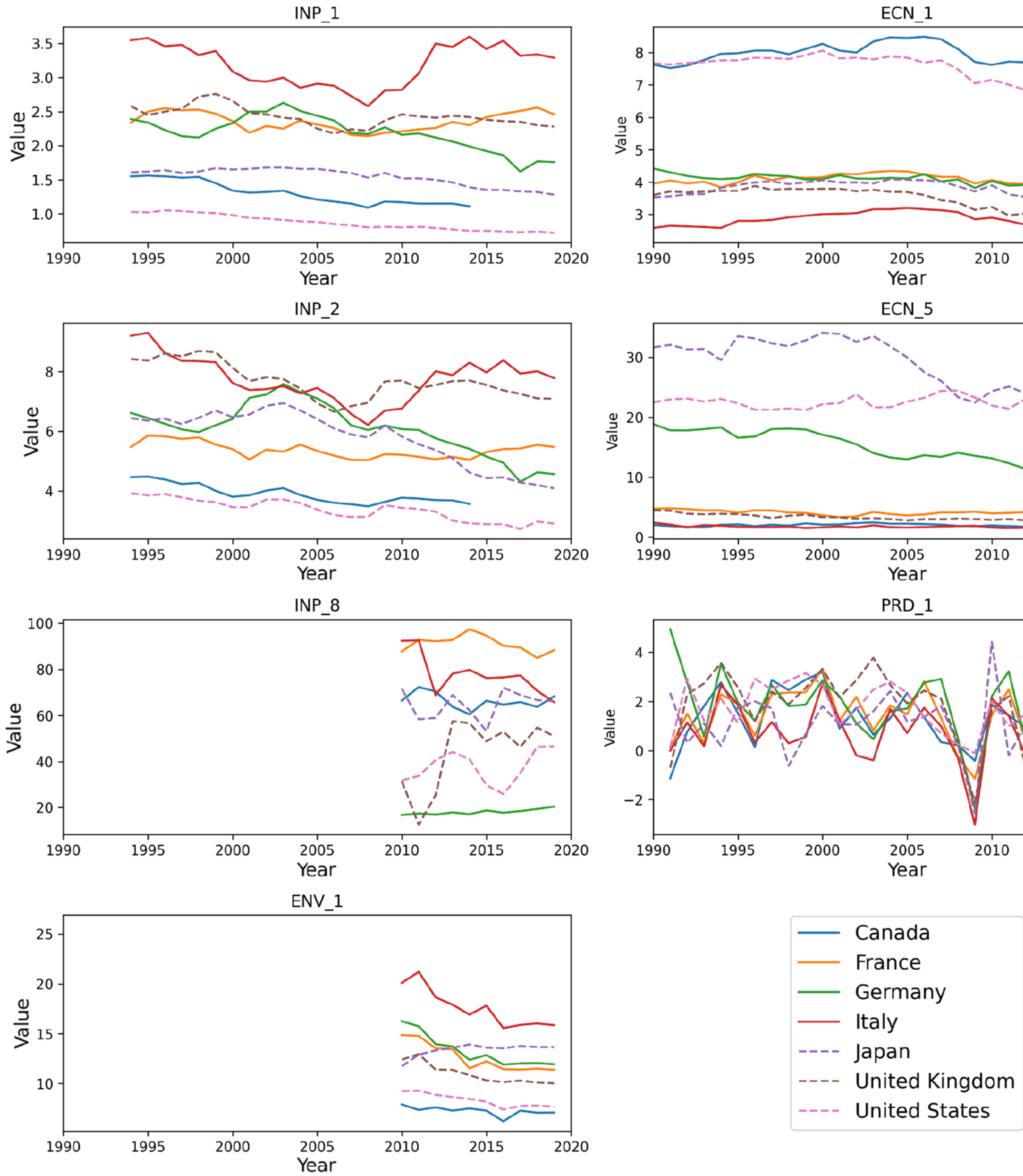


Fig. 6 Trends of policy inputs (INP_1, INP_2, and INP_8), economic outputs (ECN_1 and ECN_5), environmental output (ENV_1), and EAMFP (PRD_1) for each country in the G7 group. Notes: Dots in 1990, 1995, 2000, and 2005 of ENV_1 are not represented in figure

of INP_8 are identical for those four overlapping years (correlation is undefined if the variance of one variable is zero). Overall, the correlation analysis for the sample of OECD countries is quite limited. This analysis demonstrates that when missing data are severe and the samples of countries are more heterogeneous, the proposed methods could produce some weak results.

Table 3 Correlation between INP_8 and PRD_1 for OECD countries

Country	Correlation between INP_8 & PRD_1	Country	Correlation between INP_8 & PRD_1
Australia	− 0.5955	Japan	0.972
Austria	− 0.2489	Korea	0.0625
Belgium	− 0.6772	Latvia	− 0.1573
Canada	0.0611	Lithuania	− 0.5697
Chile	− 0.866	Luxembourg	–
Colombia	0.9407	Mexico	–
Costa Rica	− 0.4579	The Netherlands	0.0698
Czech Republic	0.2674	New Zealand	–
Denmark	− 0.9379	Norway	− 0.8696
Estonia	0.6155	Poland	− 0.8793
Finland	0.5442	Portugal	1
France	− 0.1424	Slovak Republic	0.9939
Germany	− 0.2318	Slovenia	− 0.0783
Greece	− 0.7195	Spain	0.5118
Hungary	− 0.1373	Sweden	− 0.9304
Iceland	–	Switzerland	0.232
Ireland	− 0.0008	Turkey	0.632
Israel	0.819	United Kingdom	− 0.4158
Italy	0.8346	United States	− 0.506

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Data availability The data used in this study are available upon request from the corresponding author.

Declarations

Conflict of interest The authors declare no conflict of interest.

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