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Unraveling the Green Growth Matrix: Exploring the Impact of Green Technology, Climate Change Adaptation, and Macroeconomic Factors on Sustainable Development

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Abstract: This study aims to investigate the influence of various economic, environmental, and social factors on sustainable development, with a specific focus on the impact of green technology and climate change adaptation. A panel dataset comprising 38 OECD member countries from 1990 to 2020 is employed, and a series of dynamic panel data models are estimated using the system generalized method of moments (GMM) approach. Numerous covariates, such as globalization, socio-economic conditions, economic and political values, climate and technological progress, and environmental determinants, are examined. The empirical findings highlight the significant role played by macroeconomic, institutional, social, and government policy-related factors in sustainable development. More importantly, our results provide novel and robust evidence that the diffusion of green technology and climate change adaptation positively affect green growth. The study's empirical outcomes are demonstrated to be robust to misspecification errors and statistically significant at traditional significance levels. These findings carry substantial policy implications for the development and implementation of strategies that promote climate change adaptation and green innovation. Consequently, policymakers should prioritize the integration of green technology and adaptive measures in their sustainable development agendas to foster a greener, more resilient future.

Keywords: green growth; green technology; technology diffusion; climate change adaptation; sustainable development; panel data

JEL Classification: O11; O31; O33; Q01; Q54; Q56

1. Introduction

Over the past decade, the challenges associated with technology diffusion have increasingly intensified discussions on environmental economics and policy. Numerous environmental issues, including climate change and air pollution, have been addressed through the development and dissemination of green (eco-friendly) technologies. Moreover, these technologies can be influenced by a variety of factors, such as economic, social, and political considerations [1–3]. Although investment in green technologies can mitigate the potential risks of environmental degradation and climate change, it is crucial to examine novel economic models and a diverse set of factors in order to effectively tackle these challenges. Consequently, a more recent objective on the global agenda is the establishment of a "green economy" that encapsulates the notion of sustainable development.

In recent years, the advancement of green technology diffusion has emerged as a critical aspect in the formation of green growth models and strategies [1]. As these green technologies gain prevalence, they facilitate the shift towards a more sustainable and environmentally conscious economy. The propagation of green technology is driven by an array of factors, encompassing technological innovation, economic incentives, policy structures, environmental concerns, and socio-economic elements [1,4–6]. Conversely, the progression of green technology diffusion is also shaped by the emergence of novel economic models and frameworks that strive to incorporate

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environmental considerations into economic growth. The perspective presented by Brock and Taylor [7] elaborates on the Green Solow model, which focuses on CO2 emission patterns and their underlying mechanisms, as a structural extension of the traditional Solow model. Indeed, Brock and Taylor [7] proposed the Green Solow model to demonstrate the relationship between environmental damage and economic growth. Consequently, they employed the neoclassical Solow growth model as a foundation for their investigation of the impact of economic activity on carbon emissions. Subsequently, Stefanski [8] incorporated pollution accounting into the green growth theoretical framework, focusing on the interplay between economic growth and carbon emissions.

From a theoretical perspective, earlier studies have proposed models to examine the dynamic implications of green growth on economic development and sustainability. Huang and Quibria [9] suggest that a theoretical framework for green growth elucidates the manner in which environmental, social, political, and economic factors influence the green growth process. In contrast, Popp [10] highlights the impact of technology transfer on advancing green growth by reducing the cost of environmental protection and promoting the diffusion of green technologies. Consequently, they emphasize the crucial role of economic and policy incentives, financial constraints, technological advancements, and research and development (R&D) activities in fostering green growth. Dinda [11] introduces a theoretical model for green growth to explore the enhancement of natural resources in order to facilitate sustainable development. This model posits that reducing waste, pollution, and greenhouse emissions, safeguarding biodiversity and ecosystems, and conserving natural resources can bolster sustainable development and economic growth.

In recent years, the primary effects of globalization on the environment, particularly in relation to green growth, have been extensively discussed by numerous studies. There are several ways in which globalization and green growth intersect. On the one hand, globalization has the potential to promote the dissemination of green technologies and practices, aiding countries in transitioning toward more sustainable forms of economic growth. Xia et al. [12] investigate the influence of globalization on environmental performance and discover a significant positive relationship between globalization and CO2 emissions. Furthermore, Bilal et al. [13] analyze the association between green technology innovation, CO2 emissions, and globalization, revealing that globalization exhibits a positive and significant interaction with CO2 emissions. Conversely, their findings also demonstrate that the combined impact of technology innovation and globalization as a moderating effect yields a significant and negative influence on CO2 emissions. Although its responsibility may be indirect, globalization has played a role in exacerbating the substantial environmental degradation we currently face. Consequently, if properly managed, globalization has the potential to serve as a catalyst for green growth.

Against this backdrop, the present study examines the impact of various macroeconomic factors at the national level, which may potentially influence the green growth. While certain determinants, such as the general trend in green technology diffusion and climate change adaptation, have been previously assessed in distinct models, there are theoretical grounds to consider their significance in relation to the green growth. In this study, we explore the following aspects as potential causative factors for the green growth: economic performance, globalization, green technology diffusion, climate change adaptation, and institutional and environmental values. A number of these factors, including foreign direct investment, economic growth, institutional quality, CO2 emissions, population, energy consumption, and green technology diffusion, have been investigated within the contexts of environmental sustainability and the determinants of green growth. However, few studies have specifically incorporated globalization, climate change, and climatic variables as determinants of the green growth (refer to, for instance, [14-18]). To the best of the authors' knowledge, no other research has evaluated the impact of these factors on the green growth. Furthermore, this study encompasses the most comprehensive collection of determinants for green growth. The investigation also employs dynamic panel data models, utilizing the system GMM approach to demonstrate the significant role of these determinants in green growth. The results are consistent with the model specifications. Additionally, this study enhances the existing body of empirical literature. Consequently, a green growth model has been developed, incorporating factors such as per capita income, government stability, the effects of globalization, climate change

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adaptation, foreign direct investment, carbon emissions, environmental performance, environment-related tax revenue, technology diffusion, and climatic variables.

The aims of this paper can be delineated into three primary objectives: (i) to investigate the economic, social, political, technological, and environmental factors influencing the green growth in 38 OECD countries; (ii) to address a significant knowledge gap by exploring whether the impacts of globalization, green technology diffusion trends, and climate change adaptation also contribute to the processes underlying green growth; and (iii) to employ various dynamic panel data models, utilizing the system GMM approach, in order to demonstrate that these factors indeed play a substantial role in the diffusion process of the green growth.

This study makes several contributions to the existing literature by introducing new dimensions to green growth. First, in contrast to previous research, we incorporate the factors of globalization, climate change adaptation, and green technology diffusion as the primary determinants of the green growth. Secondly, we enhance prior studies by presenting a comprehensive set of criteria that may influence the process of green growth. While the majority of countries have exhibited only limited progress in climate change and green technology, the adaptation and diffusion of these aspects have been experienced in virtually every nation. Such advancements should not be examined independently from a country's technological, environmental, and economic performance. Third, we expand upon earlier research by including an extensive array of factors that may impact the green growth, encompassing per capita income, government stability, the effects of globalization, climate change adaptation, foreign direct investment, carbon emissions, environmental performance, environment-related taxes, technology diffusion, and climatic variables. Last, in contrast to prior research, we employ dynamic panel data models over an extended time period, enabling us to account for slow adjustments and lagged effects.

Our empirical findings reveal that variables relating economic, social, environmental, and technological, political, and institutional dimensions are considered as determinants of green growth in the OECD counties. Particularly, the study investigates potential determinants of green growth, estimating six separate models to assess their effects. The results reveal positive relationships between green growth and factors such as green technology diffusion, economic growth, climate change adaptation, foreign direct investment, and government stability. Additionally, the findings highlight the importance of environmental sustainability alongside economic growth, with carbon emissions being a major contributor to climate change. Technology transfer and environmental policies also play significant roles in achieving green growth. Our results indicate a favorable association between green technology diffusion, economic growth, and climate change adaptation with green growth, which is vital for achieving environmental sustainability. Thus, our results emphasize that green technologies play a role in lowering greenhouse gas emissions and mitigating other environmental consequences while concurrently providing economic benefits such as enhanced efficiency and productivity. Overall, the study emphasizes the need for a comprehensive approach to green growth, incorporating economic, technological, institutional, and environmental variables. The results of this study bear significant policy implications, as they indicate that unfavorable macro-level circumstances at the country level may hinder the implementation of green policy and green growth initiatives aimed at promoting climate change adaptation and the diffusion of green technology.

The remainder of this paper is structured as follows: Section 2 provides a review of the existing literature. Section 3 elaborates on the empirical methodology and data employed in the study. Section 4 presents the empirical findings, and finally, Section 5 offers concluding remarks.

2. Literature review

In the process of green growth, the development of income and employment is driven by public and private investments that aim to reduce carbon emissions and pollution, enhance energy and resource efficiency, and prevent the loss of biodiversity and ecosystem services. According to the Porter hypothesis, there is a direct relationship between green technology, green growth, and the implementation of environmental protection regulations by the government. The transition towards more environmentally friendly economies is already underway, fueled by economic considerations

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and government policies. Consequently, green growth strategies have started to supersede sustainable development debates at both national and international levels.

Theoretically, Popp [10] addresses the impact of technology transfer on the advancement of green growth through the reduction of environmental protection costs and the improvement of green technologies. Additionally, he underscores the pivotal role of policy incentives, financial constraints, technology transition, and R&D activities in fostering green growth. Conversely, Hoffmann [19] investigates the influences of population growth, technological innovation, economic development, and policy constraints on green growth. His research indicates that the equitable distribution of income and wealth, reduction of greenhouse gas (GHG) emissions, mitigation of climate change, promotion of innovation, and implementation of structural adaptations are fundamental to the green growth process.

The first strand of empirical literature is primarily concerned with the relationship between CO2 emissions and GDP growth, given the increasing focus on environmental issues. Antal and Van Den Bergh [20] explore the association between CO2 emissions and GDP growth, with their findings highlighting the necessity of mitigating climate and environmental degradation and reducing dependence on development to achieve both environmental and economic objectives. Similarly, Aye and Edoja [21] employ a dynamic panel model to investigate the relationship between economic growth and CO2 emissions across 31 emerging economies. Their results reveal that economic growth exerts a negative influence on CO2 emissions in the low-growth regime and a positive influence in the high-growth regime, suggesting that the findings do not support the Environmental Kuznets Curve (EKC) hypothesis. Furthermore, the study concludes that causal relationships exist between economic growth, energy expenditure, financial development, and CO2 emissions. Subsequently, Chin et al. [22] utilize autoregressive distributed lag (ARDL) modeling to assess the impacts of CO2 emissions on green growth and sustainable development in Malaysia between 1997 and 2014. According to their findings, a positive correlation exists between economic growth and carbon emissions.

Furthermore, Chang and Hao [23] employ a panel GMM model with data from 2002 to 2012 to investigate the relationships between economic development, the environmental performance index, and the International Country Risk Guide's corruption index. Their findings reveal a positive correlation between economic growth, enhanced environmental performance, and reduced corruption, leading to economic expansion. Additionally, Zmami and Salha [24] assess the impacts of economic growth, urbanization, trade, investment, and energy consumption on CO2 emissions in Gulf Cooperation Council (GCC) countries over the period from 1980 to 2017, utilizing the panel ARDL approach. They discover that economic growth, energy consumption, urbanization, and foreign direct investment (FDI) exert positive effects on CO2 emissions in the long term.

In the second strand, numerous studies have concentrated on the determinants of green growth, encompassing economic, social, political, and environmental factors. Fernandes et al. [17] primarily analyze the effects of green growth on economic growth using dynamic panel techniques and a cross-country OECD dataset spanning 1990 to 2013. Their findings suggest that the transfer of sustainable technology promotes green growth, which is positively correlated with economic growth. You and Huang [25] investigate the determinants of green growth in China from 1998 to 2011 by employing the dynamic panel data estimation approach. They propose that China's green growth can be enhanced through innovation, reforms, quality, and productivity. However, only political changes may hinder the progress of China's green growth.

Similarly, Feng et al. [26] construct a green development performance index (GDPI) to analyze the factors of green growth in 165 countries between 2000 and 2014 using the data envelopment analysis (DEA). They suggest that an increase in GDPI is associated with a rise in energy structure, living altitude, and a decline in ecological carrying capacity. However, financial crises exert a detrimental influence on GDPI. Lastly, Tawiah et al. [14] employ fixed effect estimates to examine the factors of green growth in both developed and developing nations from using annual panel data from 2000 to 2017. According to their empirical results, economic development exhibits a favorable and robust association with green growth in both groups of nations. They observe mixed results among developed and developing countries. The relationships between internationalization drivers of green growth, trade openness, and FDI with green growth are negative and insignificant for developed countries, while trade openness and FDI have a negative and significant impact on developing countries. Furthermore, the influence of institutional quality on accelerating green growth is insignificant in both industrialized and developing countries and are not crucial drivers of green growth. Additionally, they find that increasing energy usage correlates with a decline in green growth. This finding aligns with the results of Frankel et al. [27], who concluded that FDI had a negative influence on green growth. This conclusion, however, contradicts the findings of Dean et al. [28], which demonstrate that FDI has a favorable relationship with green growth in China.

Among recent studies, Capasso et al. [29] conduct a survey analysis of 113 contemporary papers to investigate the connections between green growth, innovation, environmental issues, and economic growth. The findings emphasize the necessity for novel technology, new formal institutions, a theory-based approach, well-designed information systems, and government structures to independently predict environmental trends and minimize obstacles to green growth. Conversely, Yuan and Xiang [30] utilize panel data from Chinese industrial sectors between 2003 and 2014 to examine the influence of environmental legislation on technological innovation and green growth. Their findings reveal that environmental regulation, according to their research, exerts a detrimental effect on R&D expenditures and patents. Meng et al. [31] analyze the relationships between green technology innovation, environmental legislation, green dynamism, and smart manufacturing upgrading in China from 2015 to 2018. Their findings indicate a favorable impact of environmental regulations on green technology innovation.

Another strand in the literature explores the relationship between various measures of green growth and globalization. Zafar et al. [32] investigate the effects of globalization, using indicators such as research and development (R&D), open trade, and FDI, on green growth in OECD economies by applying the Pedroni cointegration test using data from 1991 to 2015. According to their estimations, both open trade and FDI have significant positive impacts on green growth in the short and long run; however, R&D expenditures exhibit a significant negative impact on green growth. In recent research, Xia et al. [12] examine the influence of globalization on environmental performance in wealthy and developing nations using GMM estimates and data spanning from the years from 1971 to 2018. Their estimates reveal a considerable positive correlation between globalization and CO_2 emissions, with GDP growth contributing to an increase in CO_2 emissions.

The theoretical and empirical literature encompasses green investment indicators and economic outputs resulting from green growth. In this context, green growth refers to an economy characterized by minimal carbon emissions, environmental quality and efficiency, natural capital, resource efficiency, and social inclusion [33]. Brock and Taylor [34] conduct a theoretical and empirical analysis of the relationship between the EKC and the Solow model, using data on CO_2 emissions, population, and investment share of GDP from 1960 to 1998. They construct a modified Solow model that integrates green technology to enhance environmental quality and develop their empirical model, known as the green Solow model, which provides new insights into the relationship between economic growth and environmental quality. Huang and Quibria [9] investigate the impact of innovation and finance on the green development process both theoretically, by establishing the Green Solow growth model, and empirically, by calculating the green growth index for 42 countries from 1990 to 2009. Their theoretical and empirical findings demonstrate a convergence of green growth among the sample nations and underscore the significance of government policies, financial performance, and external shocks in managing green growth. Furthermore, Jadoon et al. [35] assess the influence of green growth on the stability of the financial sector in 90 economies between 2010 and 2015 using the two-step system GMM approach. According to their findings, green growth exhibits a positive association with a country's financial stability.

Nonetheless, environmental degradation and extreme weather events resulting from climate change exacerbate the challenges associated with transitioning to green growth. To achieve sustainable environmental and developmental goals, it is crucial to establish policies that encourage the development of eco-friendly technologies. In order to enhance green technology, researchers have also explored the impact of CO_2 emissions, environmental legislation, green goods, green patents, environmental performance, climatic conditions, and environmental and resource productivity on green growth. The results are consistent with prior research (see, for example, [16,18,21,23,30,36]). In conclusion, these studies underscore the importance of reducing environmental costs and hazards,

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fostering environmental awareness, ensuring energy security, and mitigating environmental pollution.

From this literature review, it is evident that addressing the diffusion of green technologies and climate change adaptation from the perspective of globalization is essential for promoting green growth and a low-carbon environment. In this study, we build upon previous research by introducing new dimensions of the green growth. Furthermore, we expand upon past studies by incorporating a wide array of determinants that may influence the green growth.

3. Methodology and data

3.1. Dynamic panel data model

This study employs an annual panel dataset spanning from 1990 to 2020, encompassing 38 OECD member countries. The primary objective of the study is to scrutinize the dynamic and causal interrelationships among various factors, including globalization, economic, technological, political, and environmental variables, as well as the progress in green growth. Due to the nature of the data and estimated models, it is essential to consider factors such as model specification issues, autocorrelation, nonstationarity, heteroscedasticity, heterogeneity, and cross-section dependency in the analysis. Given that the unit root tests demonstrate the stationarity of the variables under consideration, this study examines the associations between the green growth index and its determinants by employing dynamic panel data estimation methods.

In prior literature, dynamic panel models have been employed to investigate various empirical determinants related to achieving environmental sustainability (refer to [4,13,22,37–42], for instance). The present study broadens the scope of analysis to encompass the effects of globalization, climate conditions, technological advancements, income levels, environmental policies and performance, economic aspects, political factors, and socioeconomic elements on green growth in select economies. Consequently, this research introduces novel inquiries regarding the impacts of technological, political, social, environmental, and economic components on the dissemination of green technology. Furthermore, the investigation is conducted using a dynamic system GMM model, rather than employing static models such as the fixed effects model. Thus, this study offers a fresh perspective on the influence of globalization, climatic conditions, technological diffusion, and various economic, political, social, and environmental factors on the expansion of green growth.

The most general representation of the model employed in this study is as follows:

$$\begin{aligned} ggi_{i,t} = f(&gdp_{i,t}, glo_{i,t}, fdi_{i,t}, gov_{i,t}, co_{2\,i,t}, gtd_{i,t}, \\ &cct_{i,t}, epi_{i,t}, tax_{i,t}, tai_{i,t}, pop_{i,t}, temp_{i,t}) + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where represents the green growth index, which is specified as a function twelve distinct variables. These variables include per capita gross domestic product (gdp), purchasing power parity (ppp), globalization index (glo), foreign direct investment (fdi), green technology diffusion (gtd), climate change adaptation (cct), carbon emissions measured in metric tons per capita (CO_2), environmental performance index (epi), environmentally-related taxes (tax), technology achievement index (tai), population growth (pop), and temperature levels (temp). All variables are expressed in terms of their natural logarithms. In this equation, time is denoted by $t = 1, 2, \dots, T$, representing years, while $i = 1, 2, \dots, N$ signifies the countries under consideration.

The relationship between the dependent variable and the independent variables is presumed to be log-linear. As a result, the particular formulation of the dynamic panel model can be articulated as follows:

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$$\begin{aligned}\ln(ggi_{i,t}) = \alpha_0 + \sum_{j=1}^{p} \rho_j \ln(ggi_{i,t-j}) + \alpha_1 \ln(gdp_{i,t}) + \alpha_2 \ln(glo_{i,t}) + \alpha_3 \ln(fdi_{i,t}) \\ + \alpha_4 \ln(gov_{i,t}) + \alpha_5 \ln(co_{2_{i,t}}) + \alpha_6 \ln(gtd_{i,t}) + \alpha_7 \ln(cct_{i,t}) \\ + \alpha_8 \ln\left(epi_{i,t}\right) + \alpha_9 \ln\left(tax_{i,t}\right) + \alpha_{10} \ln(tai_{i,t}) + \alpha_{11} \ln(pop_{i,t}) \\ + \alpha_{12} \ln(temp_{i,t}) + \varepsilon_{i,t}\end{aligned} \tag{2}$$

where p is the autocorrelation order, ln denotes natural logarithm, and the error term $\varepsilon_{i,t}$ has two orthogonal components: $\varepsilon_{i,t} = \eta_i + v_{i,t}$ with η_i denoting the time-invariant country specific effect and $v_{i,t}$ denoting idiosyncratic shocks, that is $E(\eta_i) = 0$, $\mathrm{E}(v_{i,t}) = 0$, and $E(\eta_i v_{i,t}) = 0$. Furthermore, the errors $v_{i,t}$ are not autocorrelated, that is $E(v_{i,t} v_{i,s}) = 0$ for $t \neq s$. Under these assumptions, and with the supplementary premise that no further sources of endogeneity are present, a regressor can be utilized as an instrument for itself within the GMM estimation. This approach obviates the need for variable transformation or model modification.

The application of the GMM approach for estimation is faced with two critical challenges: the proliferation of instruments and serial autocorrelation of error components. These issues become more pronounced in panel datasets consisting of samples with an extended time period and a limited number of individuals. The expansion of instruments refers to the presence of increasingly sophisticated tools in the model. This results in overidentification due to the incorporation of additional instrumental variables at various levels and differences. To ascertain the adequacy of the sample size and the potential for overidentification stemming from the number of instruments employed, the Sargan test [43] helps to ascertain whether the excess instruments are indeed valid and contribute to the overall explanatory power of the model.

Due to the presence of a considerable and statistically significant correlation among the variables glo, gtd, gdp, tai, and epi, it is not feasible to estimate the entire model as presented in Equation (2). As a result, we impose several restrictions on Equation (2) and estimate five alternative specifications of the general model. Table 1 outlines these models and their corresponding constraints imposed on Equation (2). In the process of excluding a variable or a set of variables, we take into account three main considerations. First, we assess whether any of the remaining index variables within the model incorporate the excluded variable as a component. Second, we evaluate whether the excluded variable potentially measures the same underlying concept that another variable in the model already captures. Lastly, we examine the presence of a high correlation between certain variables, which may give rise to severe multicollinearity issues.

Table 1. Model specifications.

Model name	**Exclusion restriction**	**Excluded variables**	**Implied relationship**
Model 1	$\alpha_3 = \alpha_4 = \alpha_5 = \alpha_8$	fdi, gov, co_2, epi, tax, tai	ggi = f(gdp, glo, gtd, cct, pop,
Model 2	$\alpha_4 = \alpha_5 = \alpha_8$	gov, co_2, epi, tax, tai	ggi = f(gdp, glo, gtd, fdi, cct, pop,
Model 3	$\alpha_2 = \alpha_5 = \alpha_8$	glo, co_2, epi, tax, tai	ggi = f(gdp, gtd, cct, fdi, gov, pop,
Model 4	$\alpha_2 = \alpha_7$	glo, cct, epi, tax, tai	ggi = f(gdp, gtd, fdi, gov, co_2, pop,
Model 5	$\alpha_2 = \alpha_5 = 0$	glo, co_2	ggi = f(gdp, gtd, cct, fdi, gov, epi,
Model 6	$\alpha_2 = 0$	glo	ggi = f(gdp, gtd, cct, fdi, gov, co_2,

Upon estimating each model utilizing the two-step system GMM technique, we perform three crucial diagnostic tests. The first diagnostic is the Sargan-Hansen *J*-test of overidentifying constraints, employed to ascertain the validity of the instruments used in the model. Subsequently, we conduct

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the first-order [AR(1)] and second-order [AR(2)] autocorrelation tests, which serve to determine whether an adequate number of lags have been incorporated to account for the presence of autocorrelation.

3.2. Data

The dataset required for this study has been obtained from diverse sources. The green growth indicators database encompasses innovations pertaining to environmental protection and climate change adaptation technologies. This dataset can be further divided into three sub-components: environmental management, water-related adaptations, and technologies aimed at mitigating the impacts of climate change. We use the green growth index, which is derived from OECD statistics based on patent application data, as a measure of green growth. The OECD green growth indicators are structured around five primary objectives, with each indicator being selected based on well-defined criteria and incorporated into a conceptual framework. This framework is organized into five groups in order to capture the essential aspects of green growth. These include environmental and resource productivity, the natural asset base, the environmental dimension of quality of life, economic opportunities and policy responses, and the socio-economic context, which encompasses population and growth characteristics. Figure 1 illustrates a time series plot of the average green growth index levels for the 38 OECD countries between 1990 and 2020.

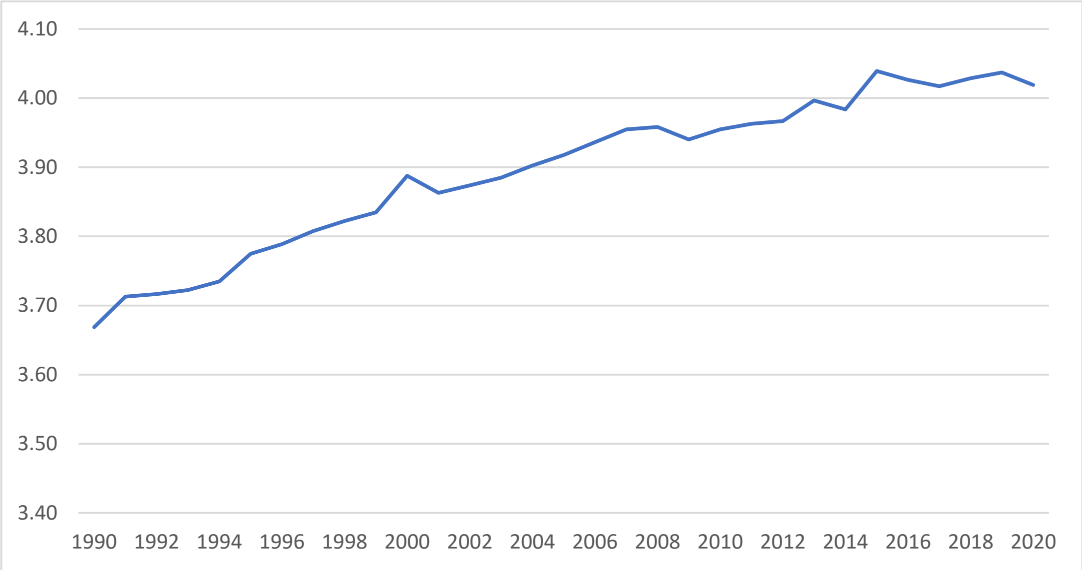

Figure 1. Time series plot of the average green growth index, 1990-2020. **Source:** Author's own calculations.

The globalization index employed in this study is sourced from the KOF Globalization Index database, which provides an average measure of the economic, social, and political dimensions of globalization. Another variable utilized for assessing the innovation performance of countries and companies, as well as for guiding the development of environmental and innovation policies for governments, is the climate change adaptation dataset. This dataset is derived from OECD statistics and is based on patent applications. Economic growth is measured using gross domestic product (GDP) per capita, with purchasing power parity (PPP) values obtained from the World Development Indicators (WDI) database, developed by the World Bank. Additionally, the WDI database is used to compute CO_2 emissions in tons per capita, as well as to obtain data on foreign direct investment (FDI) and population growth. Environmentally related tax revenues are sourced from the OECD statistics database.

The variable concerning government stability is extracted from the Political Risk Services (PRS) Group database, with index values ranging from 1 to 10—a higher index value indicates more favorable outcomes. Furthermore, country-level climate data, including temperature, are acquired

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from the World Bank Group's Climate Change Knowledge Portal. The environmental performance index comprises a data cluster consisting of 25 indicators and 10 policy categories. These policies pertain to environmental burden of disease, water (effects on human health), air pollution (effects on human health), water resources, biodiversity and habitat, forestry, fisheries, agriculture, and climate change. All data we employ are in natural logarithms.

Table 2 presents the descriptive statistics for all variables, encompassing the total number of observations (Obs), as well as their mean, standard deviation, minimum, and maximum values. The first column of Table 1 provides the variable names corresponding to the logarithmic levels.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
lggi	1,178	3.895	0.582	1.904	5.509
lgdp	1,178	4.356	0.300	3.239	5.083
lglo	1,178	1.875	0.067	1.616	1.959
lfdi	1,178	2.259	0.097	1.841	2.474
lgov	1,178	0.876	0.090	0.477	1.045
lco	1,178	0.842	0.253	0.080	1.438
lgtd	1,178	3.461	1.031	0.301	5.713
lcct	1,178	1.578	1.045	0.001	3.952
lepi	1,178	1.796	0.072	1.502	1.958
ltax	1,178	0.361	0.180	0.000	1.819
ltai	1,178	0.334	0.113	0.093	0.820
lpop	1,178	7.087	0.656	5.406	8.518
ltemp	1,178	1.135	0.226	0.000	1.485

Note: Obs. is the number of observations, Min is the minimum, Max is the maximum, while Std. Dev. denotes the standard deviation.

To assess the correlation coefficient estimates between the independent and control variables, Table 3 displays the results of the Pearson pairwise correlation matrix for these variables. The correlation estimates help determine the degree of linear association among variables in the model, which may aid in identifying potential multicollinearity.

The correlation coefficients for lgov and ltax exhibit a negative relationship with the green growth index. Conversely, other independent variables demonstrate a positive correlation with the green growth index. Moreover, several pairs of variables exhibit a high and positive correlation coefficient. Some of these pairs include lggi and lgtd, lggi and ltai, lggi and lpop, lgdp and lepi, lgdp and lglo, lgdp and lgtd, lgdp and lco, lglo and lgtd, lglo and lepi, lglo and ltai, lco and lgtd, lco and ltai, lgtd and ltai, and lcct and lepi.

Table 3. Pearson correlation coefficient estimates.

	lggi	lgdp	lglo	lfdi	lgov	lco	lgtd	lcct	lepi	ltax	ltai	lpop	ltemp
lggi	1.00												
lgdp	**0.30**	1.00											
lglo	**0.27**	**0.76**	1.00										
lfdi	**0.11**	**0.33**	**0.38**	1.00									
lgov	-0.06	0.05	0.09	0.03	1.00								
lco	**0.12**	**0.51**	**0.42**	-0.05	**0.15**	1.00							
lgtd	**0.73**	**0.54**	**0.60**	**0.18**	0.04	**0.44**	1.00						
lcct	**0.37**	**-0.19**	**-0.16**	**-0.17**	**0.14**	**0.15**	**0.25**	1.00					

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lepi	0.01	**0.64**	**0.54**	**0.17**	-0.08	**0.22**	**0.32**	**-0.41**	1.00				
ltax	**-0.32**	0.03	0.05	-0.07	0.03	0.02	**-0.20**	-0.07	**0.10**	1.00			
ltai	**0.40**	**0.58**	**0.54**	0.07	**0.14**	**0.45**	**0.64**	**0.14**	**0.36**	**-0.16**	1.00		
lpop	**0.88**	-0.06	0.00	0.02	**-0.13**	**-0.11**	**0.53**	**0.41**	**-0.20**	**-0.30**	**0.17**	1.00	
ltemp	**0.16**	**-0.26**	**-0.26**	**0.20**	**-0.13**	**-0.33**	**-0.10**	**0.11**	**-0.27**	-0.02	**-0.33**	**0.30**	1.00

Note: Boldface indicates significance at 1% level.

Table 4 presents the average values of the logarithmic levels of variables for each country over the 1990-2020 period. The US, Japan, and Germany exhibit the highest mean values for the green growth index, while Japan, the US, and Germany display the highest mean values for green technology diffusion. Similarly, Belgium, Switzerland, and the Netherlands possess the highest mean values for the globalization index. Furthermore, the US, Japan, and Korea hold the highest mean scores for climate change adaptation.

Table 4. Mean of variables by country over the period of 1990-2020.

country	lggi	lgdp	lglo	lfdi	lcct	lepi	lgtd	lco	lgov	ltax	ltai	lpop	ltemp
Australia	4.09	4.50	1.89	10.29	2.63	1.79	3.93	1.22	0.89	0.33	0.33	7.32	1.46
Austria	3.85	4.15	1.93	9.77	2.26	1.85	3.86	0.89	0.88	0.37	0.33	6.92	1.05
Belgium	3.90	4.51	1.94	9.62	1.07	1.79	3.84	1.00	0.87	0.38	0.34	7.03	1.17
Canada	4.39	4.54	1.90	8.60	1.80	1.78	4.19	1.21	0.89	0.11	0.43	7.51	0.38
Chile	3.76	3.72	1.84	10.51	0.80	1.66	3.61	0.64	0.88	0.10	0.26	7.21	1.15
Colombia	3.98	3.94	1.74	10.34	1.40	1.78	2.07	0.22	0.85	0.17	0.18	7.62	1.47
Costa Rica	3.27	3.74	1.79	8.92	1.33	1.72	2.30	0.31	0.84	0.32	0.25	6.62	1.48
Czechia	3.72	4.34	1.89	10.36	1.21	1.81	3.03	1.05	0.84	0.41	0.32	7.02	1.12
Denmark	3.69	4.53	1.93	10.88	1.80	1.82	3.81	0.93	0.87	0.63	0.37	6.74	1.08
Estonia	2.93	4.18	1.85	9.65	0.49	1.78	2.02	1.11	0.89	0.33	0.33	6.14	1.00
Finland	3.60	4.49	1.92	8.89	1.33	1.82	3.98	1.01	0.90	0.46	0.41	6.72	0.84
France	4.60	4.48	1.92	9.37	1.96	1.84	4.71	0.73	0.87	0.37	0.38	7.80	1.21
Germany	4.75	4.52	1.92	9.62	2.16	1.84	5.11	0.99	0.88	0.34	0.40	7.91	1.14
Greece	3.74	4.35	1.87	9.57	1.26	1.79	2.81	0.87	0.84	0.45	0.25	7.03	1.29
Hungary	3.61	4.21	1.89	9.35	1.67	1.76	3.14	0.72	0.86	0.45	0.26	7.00	1.21
Iceland	3.06	4.56	1.84	8.86	0.75	1.83	2.21	0.84	0.90	0.42	0.40	5.48	0.72
Ireland	3.62	4.56	1.92	9.70	0.86	1.78	3.39	0.96	0.88	0.38	0.32	6.62	1.12
Israel	3.66	4.43	1.85	10.53	2.16	1.76	3.79	0.94	0.85	0.44	0.33	6.83	1.42
Italy	4.57	4.48	1.89	10.55	1.50	1.84	4.29	0.82	0.82	0.51	0.29	7.77	1.23
Japan	4.90	4.48	1.84	8.97	2.94	1.81	5.64	0.97	0.87	0.19	0.47	8.10	1.19
Korea	4.33	4.11	1.83	9.98	2.69	1.70	2.14	0.34	0.84	0.37	0.24	7.68	1.22
Latvia	2.99	4.10	1.81	8.34	0.53	1.83	2.12	0.56	0.89	0.65	0.28	6.35	1.03
Lithuania	2.99	4.15	1.82	9.86	0.86	1.81	2.00	0.64	0.88	0.33	0.30	6.51	1.05
Luxembourg	3.39	4.82	1.91	10.19	0.63	1.86	3.16	1.31	0.97	0.39	0.23	5.68	1.16
Mexico	4.51	4.11	1.78	9.58	2.27	1.69	2.87	0.61	0.86	0.25	0.21	8.02	1.46
Netherlands	4.11	4.56	1.93	10.03	1.60	1.83	4.35	1.03	0.88	0.54	0.38	7.21	1.16
New Zealand	3.47	4.41	1.87	9.68	1.78	1.82	3.16	0.89	0.86	0.16	0.31	6.61	1.17
Norway	3.72	4.62	1.92	9.48	1.84	1.85	3.57	0.94	0.87	0.44	0.42	6.67	0.75
Poland	4.09	4.16	1.85	8.63	1.80	1.81	3.51	0.92	0.84	0.36	0.31	7.58	1.12
Portugal	3.73	4.34	1.89	9.98	1.49	1.77	2.62	0.71	0.87	0.45	0.25	7.01	1.32
Slovakia	3.37	4.21	1.86	8.63	0.89	1.81	2.40	0.84	0.86	0.35	0.30	6.73	1.12
Slovenia	3.17	4.35	1.83	9.08	1.33	1.80	2.60	0.85	0.94	0.56	0.35	6.31	1.15
Spain	4.37	4.40	1.90	8.06	1.96	1.79	3.77	0.79	0.86	0.28	0.32	7.64	1.29

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Sweden	3.84	4.54	1.93	10.26	1.44	1.85	4.25	0.73	0.86	0.40	0.43	6.96	0.86
Switzerland	3.93	4.65	1.94	10.79	1.25	1.90	4.41	0.72	0.95	0.21	0.39	6.88	0.98
Turkey	4.35	4.16	1.81	9.75	1.20	1.65	2.81	0.56	0.88	0.38	0.19	7.83	1.24
UK	4.59	4.48	1.93	9.30	2.05	1.83	4.57	0.91	0.88	0.39	0.41	7.79	1.10
US	5.38	4.62	1.89	9.38	2.96	1.77	5.49	1.26	0.90	0.07	0.72	8.47	1.20
Total	3.89	4.36	1.87	9.61	1.58	1.80	3.46	0.84	0.88	0.36	0.33	7.09	1.13

4. Empirical results and discussion

4.1. Empirical results

To investigate potential cross-sectional dependence, heterogeneity, and nonstationarity issues in the data, we conducted several statistical tests addressing each of these concerns. Results for the tests of cross-sectional dependence (CSD) are presented in Table 5. Cross-sectional dependence in panel data sets arises when observations or units exhibit correlation or interdependence across the cross-sectional dimension, potentially compromising the validity of statistical tests and yielding incorrect inferences. To assess the presence of cross-sectional dependence, we employed three tests: the Lagrange multiplier (LM) test proposed by Breusch and Pagan [44], the cross-sectional dependence (CD) test developed by Pesaran [45], and Pesaran's [46] LM cross-sectional dependence (CDLM) test.

Our findings indicate that the null hypothesis of no cross-sectional dependence can be rejected, revealing significant cross-sectional dependence in the data based on the *p*-values. This result supports the alternative hypothesis that cross-sectional dependence exists among OECD countries.

Upon establishing the presence of cross-sectional dependence for the variables and models, we proceeded to test for slope homogeneity. We employed two alternative tests for this purpose: Pesaran and Yamagata's [47] heteroskedasticity and autocorrelation consistent covariance (HAC) adjusted truncated slope homogeneity test ($\widetilde{\Delta}_{\mathrm{HAC}}$), calculated using Blomquist and Westerlund's [48] HAC adjustment, and its small-sample adjusted counterpart ($\widetilde{\Delta}_{\mathrm{adj,\,HAC}}$). Both tests were conducted using pooled ordinary least squares regressions with five distinct model specifications, each featuring lggi as the dependent variable. While models 1 through 5 consistently included the variables lglo, lgdp, lpop, and ltemp, they differed in terms of the additional independent variable incorporated, with lcct, lco, lgov, lgtd, ltai, lfdi, ltax, and lepi being introduced separately across the different specifications.In order to check for the possible cross-sectional dependence, heterogeneity, and nonstationarity issues, we report relevant statistical tests for each of these. The statistical tests for cross-sectional dependence (CSD) are reported in Table 5. Cross-sectional dependence in a panel data set refers to the presence of correlation or interdependence between the observations or units across the cross-sectional dimension of the data. This can occur when the observations are not independent of each other, which can affect the validity of statistical tests and lead to incorrect conclusions. To find the estimated results of the tests for cross-sectional dependence have been used three tests; the Lagrange multiplier (LM) test made by Breusch and Pagan [44], the cross-sectional dependence (CD) test proposed by Pesaran [45] and the LM cross-sectional dependence (CDLM) test proposed by Pesaran [46]. The findings of the tests reveal that the null hypothesis of no cross-sectional dependence can be rejected and that a cross-sectional dependence exists with rejections at the traditional significance levels based on the *p*-values reported in Table 5. The acceptance of the alternative hypotheses provided evidence for the existence of cross-sectional support among OECD nations. The detection of cross-sectional dependence in the panel data suggests that shocks originating in one of the 38 countries may have propagated to the others due to their interconnectedness.

After the application of a cross-sectional dependency exists of the variables and models, the findings of testing whether a slope homogeneity exists or not are given. Thus, there are two alternative tests to determine slope homogeneity. The first test is by Pesaran and Yamagata's [47] truncated slope homogeneity ($\widetilde{\Delta}_{\mathrm{HAC}}$) test with Blomquist and Westerlund's [48] heteroskedasticity and autocorrelation consistent covariance (HAC) adjustment. The second test is an adjusted version of the $\widetilde{\Delta}_{\mathrm{HAC}}$ test for small samples, designated by ($\widetilde{\Delta}_{\mathrm{adj,\,HAC}}$). Each test is constructed using a pooled ordinary least squares regression with five different model specifications. In each model, lggi is the

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dependent variable. Moreover, each of the models 1 to 5 includes the variables lcct, lfdi, lglo, lgov, lpop, ltax, and ltemp, but each also includes one of the variables lco, lgdp, lglo, lgtd, and ltai as independent variable, respectively.

Table 5 also presents the results from the slope homogeneity test. This test examines whether the relationship between variables remains consistent across all courtiers or if there are variations that warrant consideration in the analysis. The null hypothesis of slope homogeneity across countries is not rejected at all traditional significance levels by both regular and adjusted homogeneity tests, implying that the slopes do not vary across countries. Consequently, the impact of independent variables on economic growth appears to exhibit homogenous effects across the 38 countries under investigation. These findings suggest that the dynamic GMM estimation can be conducted without apprehension regarding slope heterogeneity, a crucial consideration as the GMM estimator becomes inconsistent for dynamic panel models in the presence of slope heterogeneity.

Table 5. Cross-sectional dependence and slope homogeneity tests.

Test	Statistic	*p*-value	Statistic	*p*-value
	Test in Model 1		**Test in Model 4**	
LM	393.895†	0.000	299.657†	0.000
CD	128.57†	0.000	103.36†	0.000
CD_{LM}	19.011†	0.000	13.889†	0.000
$\tilde{\Delta}_{HAC}$	0.832	0.406	0.588	0.556
$\tilde{\Delta}_{adj,\ HAC}$	1.126	0.260	0.796	0.426
	Test in Model 2		**Test in Model 5**	
LM	366.489†	0.000	429.607†	0.000
CD	140.75†	0.000	93.16†	0.000
CD_{LM}	15.329†	0.000	9.623†	0.000
$\tilde{\Delta}_{HAC}$	1.103	0.270	0.251	0.802
$\tilde{\Delta}_{adj,\ HAC}$	1.493	0.135	0.340	0.734
		Test in Model 3		
LM	290.148†	0.000		
CD	67.66†	0.000		
CD_{LM}	10.072†	0.000		
$\tilde{\Delta}_{HAC}$	-0.639	0.523		
$\tilde{\Delta}_{adj,\ HAC}$	-0.865	0.387		

Note: Table reports cross-sectional dependence and slope homogeneity tests. Tests are based on a pooled ordinary least squares regression. Dependent variable in each model is lggi. † denotes significance at the 1% level.

In light of the presence of cross-sectional dependence, this study employs second-generation panel unit root tests, which offer more reliable, consistent, and robust inferences in this case . The analysis aims to determine the stationarity of our variables using multiple panel unit root tests. Second-generation unit root tests typically enhance the conventional unit root test by incorporating cross-sectional dependence and additional variables or lags into the model, thereby improving the test's power and reducing the likelihood of false positive or false negative results. The tests employed in this study include the cross-sectionally augmented Im-Pesaran-Shin test developed by Pesaran [49], the modified cross-sectionally augmented Im-Pesaran-Shin tests proposed by Westerlund and Hosseinkouchack [50], and the augmented Dickey-Fuller test also by Pesaran [51]. These tests are denoted as CIPS, M-CIPS, and CADF, respectively.

The outcomes of the second-generation panel unit root tests, presented in Table 6, predominantly reject the unit root null hypothesis with both constant and constant-trend specifications at the 1% and 5% significance levels. These findings indicate that all series are stationary at the level, with the exception of ltax, for which the CIPS and CADF tests do not firmly reject the unit root null at a constant level. However, the M-CIPS test concurs that the ltax variable is stationary at both constant and trend levels. Similarly, the lpop variable exhibits comparable behavior.

Table 6. Panel unit root tests.

	Tests with a constant			Tests with a constant and trend		
Variable	CIPS	M-CIPS	CADF	CIPS	M-CIPS	CADF
lggi	-3.352 ***	-12.248 **	-2.395 ***	-3.719 ***	-12.925 **	-2.871 **
lgdp	-2.270 ***	-11.551 **	-2.433 ***	-2.383 *	-16.114 **	-2.366 ***
lglo	-2.816 ***	-13.954 **	-2.101 **	-3.388 ***	-21.116 **	-2.608 ***
lfdi	-3.662 ***	-19.074 **	-2.853 ***	-3.941 ***	-20.252 **	-4.257 **
lgov	-3.125 ***	-10.881 **	-2.848 ***	-3.526 ***	-11.771 **	-3.038 ***
lco	-2.077 *	-11.144 **	-1.770 *	-2.490 *	-13.662 **	-2.060 *
lgtd	-2.398 ***	-11.518 **	-2.562 ***	-2.543 *	-15.726 **	-2.333 *
lepi	-2.097 **	-19.129 **	-2.307 ***	-3.947 **	-18.983 **	-2.322 *
lcct	-2.322 ***	-12.127 **	-1.517 *	-3.414 **	-13.117 **	-2.483 *
ltax	-1.439	-13.554 **	-1.431	-1.824 *	-15.120 **	-2.523 *
ltai	-2.926 **	-13.772 **	-2.039 **	-2.666 **	-14.482 **	-2.478 *
lpop	-1.517	-14.184 **	-2.535 ***	-1.563 *	-12.410 **	-2.555 *
ltemp	-4.963 ***	-19.404 **	-3.244 ***	-5.380 **	-15.136 **	-3.632 ***

Note: CIPS is the cross-sectionally augmented Im-Peseran-Shin test of Peseran [49], M-CIPS is the modified CIPS tests of Westerlund and Hosseinkouchack [50], and CADF is the augmented Dickey-Fuller test of Pesaran [51]. **, and * denote the significance at the 1% and 5% levels, respectively. The null hypothesis for all tests is existence of a unit root.

In alignment with model predictions, both country-time and fixed effects are observed, enabling the model to address the issue of unobserved country-specific heterogeneity. We examine the endogeneity of independent variables using the Durbin-Wu-Hausman technique, which applies two-stage least squares (2SLS) to panel data, and find that some variables exhibit endogeneity. To account for this, we follow Arellano and Bond's [52] recommendation of transforming the specified equations into first-difference estimators. Subsequently, we employ dynamic panel GMM estimators, which effectively mitigate concerns related to serial correlation, endogeneity and heterogeneity in the estimation process.

The two-step system GMM is a statistical method employed in commonly empirical estimation of econometric models that entails estimating the model in two stages. First, a GMM estimator is used, followed by the construction of a consistent estimator of the structural parameters. This approach enhances the accuracy and reliability of the estimates. Prior to conducting empirical estimation, two critical issues—proliferation of instruments and serial autocorrelation of error components—are examined. Baltagi [53] contends that, in the presence of endogenous regressors, the system GMM estimator possesses the most desirable attributes for stationary dynamic panels with high cross-sectional (N) and short, fixed time (T) dimensions. This closely aligns with our context, which features $N = 38$ and $T = 30$.

Table 7 presents the outcomes of the empirical analysis examining the relationship between green growth and the explanatory variables under consideration. Standard errors for the parameter estimates are displayed in parentheses beneath the corresponding estimates. For all estimated models, the null hypothesis of valid over-identification restrictions is not rejected at any conventional significance levels, thereby affirming the reliability of the instruments. Instrument proliferation does not appear to pose a concern, as the total number of cross-sectional units across all models exceeds the total number of instruments.

Considering the characteristics of the panel data framework, the dynamic system GMM estimation with one lag should not reject the existence first-order serial correlation according to the Lagrange multiplier Arellano-Bond test [52]—LM-AR(1)—while rejecting the existence of second-order serial correlation AR(2) as per the LM-AR(2) test. The results of the LM-AR(1) tests in Table 6 are all significant at the 1% level, corroborating the AR(1) specification. Conversely, several LM-AR(2) tests are not significant at the 5% and 1% levels across all models, rendering the AR(2) specification invalid. Consequently, all models are estimated with one lag of the dependent variable, signifying that an AR(1) dynamic specification is adequate for capturing autocorrelation. In addition to these observations, the Sargan test results do not reject the null hypothesis of valid over-identification restrictions at any significance levels for all estimated models, thereby confirming the validity of the instruments.

This study investigates the potential determinants of green growth, and six distinct models are estimated to evaluate their effects. Table 7 summarizes the dynamic panel estimations for various model specifications of the green growth index. The first model illustrates the influence of economic performance, globalization, climate change adaptation, and green technology diffusion determinants on the green growth process, incorporating control variables for population and temperature. The coefficients of all determinants are positive and significant at all conventional significance levels, signifying a positive association with the green growth index. Green growth emphasizes enhancing economic productivity and efficiency while concurrently reducing the consumption of natural resources and minimizing waste and pollution. The positive relationship between green technology diffusion, economic growth, and climate change adaptation with green growth is crucial for realizing environmental sustainability. Green technologies contribute to the reduction of greenhouse gas emissions and other environmental impacts while simultaneously yielding economic advantages, such as increased efficiency and productivity.

Furthermore, adopting green growth policies can facilitate adaptation to the consequences of climate change, including rising temperatures and extreme weather events. For instance, investments in infrastructure resilient to flooding and other extreme weather occurrences can shield communities and businesses from the ramifications of climate change while concurrently yielding economic advantages. The results reveal a positive association between temperature and green growth.

Model 2 evaluates the influence of foreign direct investment on the advancement of green growth. The findings indicate a positive and significant relationship between foreign direct investment and green growth across all significance levels. In fact, foreign direct investment can foster green growth in several ways. First, it can grant access to capital, technology, and expertise essential for devising and executing green growth strategies. Second, foreign direct investment generates employment opportunities and stimulates economic growth, which can assist in amassing the resources required for investing in green growth. Third, foreign direct investment promotes international collaboration and partnerships, which can be instrumental in supporting green growth initiatives.

In Model 3, the impact of institutional factors on the progress of green growth is examined. The results reveal a positive relationship between government stability and green growth that is statistically significant at all conventional significance levels. Consequently, a stable and effective government can implement policies and regulations that encourage renewable energy, preserve natural habitats, and curtail greenhouse gas emissions. Moreover, a stable and effective government can facilitate the provision of essential infrastructure and services for sustainable development, including education, healthcare, and access to clean water and sanitation.

Model 4 presents the estimations of the impact of carbon emissions on green growth. The carbon emission coefficient is found to be positive and statistically significant at all conventional significance levels. In fact, green growth denotes environmentally sustainable economic growth, while carbon emissions are a primary contributor to climate change. A positive relationship between carbon emissions and green growth suggests that economic growth and environmental sustainability might be mutually exclusive. One rationale is that elevated levels of economic growth often result in increased carbon emissions. Another reason is that carbon emissions are a significant driver of climate change, which poses considerable risks to both economic growth and human well-being. Indeed, Model 4 illustrates a trade-off relationship. As a country prioritizes achieving high levels of economic growth and enhancing its green growth index score, it may have fewer resources to allocate to climate change adaptation measures. Additionally, escalating carbon emissions have a disastrous and substantial influence on climate change adaptation. Consequently, mitigating carbon emissions is of paramount importance in adjusting to the evolving climate.

Table 7. Dynamic panel estimations (system-GMM) for various model specifications of green growth.

Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
L.lggi	0.3581 ***	0.3619 ***	0.3734 ***	0.3683 ***	0.3681 ***	0.3655 ***
	(0.004)	(0.012)	(0.0073)	(0.009)	(0.0128)	(0.012)
lgdp	0.2288 ***	0.2293 ***	0.2581 ***	0.2630 ***	0.2447 ***	0.24864 ***
	(0.008)	(0.005)	(0.0075)	(0.009)	(0.0082)	(0.0097)
lglo	0.2207 ***	0.1797 ***				
	(0.004)	(0.046)				
lfdi		0.0027 ***	0.0011 ***	0.0057 ***	0.0026 ***	0.0055 ***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
lgov			0.0866 ***	0.0826 ***	0.0761 ***	0.0717 ***
			(0.004)	(0.004)	(0.0041)	(0.0058)
lco				0.1679 ***		0.1343 ***
				(0.0126)		(0.0124)
lgtd	0.0404 ***	0.0412 ***	0.0452 ***	0.0375 ***	0.0402 ***	0.03434 ***
	(0.001)	(0.002)	(0.0028)	(0.0026)	(0.0015)	(0.0025)
lepi					0.05053 ***	0.04212 ***
					(0.0088)	(0.0093)
lcct	0.0051 ***	0.0050 ***	0.0034 ***	-0.00137 ***	0.0034 ***	-0.0006
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ltax					0.0778 ***	0.0517 ***
					(0.0091)	(0.0113)
ltai					0.0664 ***	0.0712 ***
					(0.0061)	(0.0111)
lpop	0.4574 ***	0.4519 ***	0.4456 ***	0.4577 ***	0.4710 ***	0.47578 **
	(0.013)	(0.0132)	(0.0105)	(0.0129)	(0.0114)	(0.1990)
ltemp	0.0932 **	0.0925 ***	0.1042 ***	0.1188 ***	0.1038 ***	0.1173 **
	(0.002)	(0.003)	(0.004)	(0.0082)	(0.0042)	(0.0107)
Constant	-2.401 ***	-2.3303 ***	-2.8978 ***	-2.45663 ***	-2.4345 ***	-2.5802 ***
	(0.1063)	(0.1081)	(0.006)	(0.0787)	(0.09461)	(0.1173)
N	1140	1140	1140	1140	1140	1140
χ^2	673323.67 ***	436125.62 ***	154449.73 ***	417670.28 ***	56818.80 ***	61834.47 ***
LM-AR(1)	-1.7725 **	-1.7781 **	-1.7887 **	-1.7936 **	--1.7972 **	-1.7937 **
LM-AR(2)	0.4035	0.4020	0.3368	0.31768	0.25976	0.2669
Sargan *J* stat.	36.6705	36.6039	37.24119	36.66929	36.54309	36.60727

Note: Table reports system GMM estimates with Windmeijer-corrected standard errors in parentheses. *N* denotes number of observations, $\hat{\sigma}^2$ denotes residual variance, χ^2 denotes Chi-square statistic for joint significance of all slope parameters, LM-AR(1) and LM-AR(2) denote Arellano-Bond test for first and second order serial correlation in the first-differenced residuals, respectively. Sargan *J* stat is the Sargan test of the overidentifying restrictions. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

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Model 5 incorporates the environmental performance index, technology innovation, and environmental taxes into the green growth model. Notably, the CO2 variable cannot be included in this model due to the high correlation among these variables, stemming from the nature of the economy or the inclusion of a variable in an index variable. For instance, carbon emissions (CO2) constitute a sub-component of the EPI variable. The technology achievement index exerts a positive, significant impact, and a substantial contribution to the green growth index. This highlights the role of technology transfer in amplifying the effects of green growth among countries, as the development and adoption of new technologies are instrumental in promoting sustainable economic growth. Conversely, the environmental performance index and environmental taxes exhibit a positive and significant correlation with the green growth index. These observations underscore the significance of environmental concerns and policies in realizing green growth. Consequently, all variables in this model contribute to the progress of green growth.

Lastly, Model 6 presents the most comprehensive model by incorporating all determinants into a single equation, with the exception of globalization due to its high correlation with other variables. The model combines economic, technological, institutional, and environmental variables. The results are largely consistent with those obtained from individual equations. While carbon emissions have a detrimental impact on climate change adaptation, as observed in Model 4, they exhibit a negative and insignificant effect in Model 6. All other determinants contribute positively to the progress of green growth. In terms of marginal effects, the combined equation in Model 6 reveals that the variables exert greater marginal impacts compared to individual ones. We conclude that economic growth, population, carbon emissions, and temperature are the primary contributors to the green growth process.

4.2. Discussion

In this study, the determinants of green growth were analyzed empirically, considering various factors such as globalization, diffusion of green technologies, climate change adaptation, economic performance, environmental and political values, climatic conditions, and technological achievements of nations. The investigation was conducted using a comprehensive panel data set encompassing 38 OECD economies.

The empirical findings of our study reveal statistically significant and positive associations between green growth and an array of factors considered, such as green technology diffusion, income level, globalization, climate change adaptation, government stability, foreign direct investment, carbon emissions, environmental performance and taxes, technological achievements, population, and temperature level. These relationships are observed in the context of sustainable development within the selected countries. However, an intriguing observation was made regarding the impact of climate change adaptation, which exhibited a negative and insignificant effect on green growth when accounting for carbon emissions in models 4 and 6. This outcome suggests that carbon emissions pose a detrimental and significant influence on the progress of climate change adaptation efforts.

Firstly, in a complimentary context to our findings, Georgeson et al. [54] propose a policy framework for fostering green growth in both developing and developed economies, emphasizing the significance of economic, political, social, technological, and environmental approaches for transforming the green growth process. Consequently, enhancements in these aspects may facilitate the advancement of green growth. Primarily, a country's income level serves as a crucial factor in promoting green products and sustainable development. Anser et al. [41] identify a causal relationship between GDP growth and carbon emissions, as well as a bidirectional causality between economic growth and energy usage. In a similar vein, Chin et al. [22] report a positive association between economic growth and CO2 emissions. Concurrently, several studies [16,18, 21-23,30,36] have concluded that the influence of income level, CO2 emissions, environmental performance, climate conditions, and innovations enhance the green growth process.

Secondly, the foreign direct investment profiles of countries play an essential role in the adaption of the green growth process. Ayamba et al. [55] conclude that there is an insignificant effect of investments on environmental quality in the long run, but that pollution variables have a significant

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negative effect on investments in the short run. Zafar et al. [32] indicate that open trade and FDI have significant positive impacts on green growth both in the short and long run. Likewise, Ochoa-Moreno et al. [56] conclude that investments enhance CO2 emissions in the long run in Latin American economies. Lastly, Khan et al. [15] show significant causal relationships between policies of exports and imports, income level, and green innovation that has resulted in changes to consumption-based CO2 emission levels in G7 countries. In contrast, Tawiah et al. [14] find mixed results among developed and developing countries the links between trade openness and FDI with green growth are negative and insignificant for developed nations, whereas the influence of trade openness and FDI on developing countries is negative and significant. These findings are comparable to the conclusion of Shahzad et al. [57] on selected developed and developing countries. In this respect, our results are complementary to the empirical evidence presented in these studies, but in a more extensive coverage of countries, which includes both developing and developed countries.

Thirdly, globalization have also a significant role in green growth. Ahmad and Wu [58], find that globalization displays mixed effects. It induces ecological deterioration impact in the absence of its interaction with eco-innovation. On the other hand, Xia et al. [12] imply a significant positive relationship between globalization and CO2 emissions, moreover, GDP growth has increased CO2 emissions. Our results are complementary to existing evidence on the effect of globalization on green growth, but they encompass more nations, including emerging and developed ones.

Fourthly, green technology diffusion, climate change adaptation, government stability, economic development, technological achievement, and environmental performance are particularly prominent factors shaping the green growth. According to Samad and Manzoor [39], R&D expenditures, green technology, market size, and environmental taxation all have a substantial influence on green growth. Furthermore, Antal and Van Den Bergh [20] find that to achieve both environmental and economic goals, it is necessary to minimize climate change effects and environmental risks in long-term sustainability. The result is in line with the findings of several studies, see, for instance, [26,30–31,60–62]. In contrast, He et al. [59] conclude that environmental performance has an adverse effect on green growth in developing economies.

In summary, our empirical analysis underscores the positive contribution of green growth determinants in achieving a sustainable environment and development, as corroborated by the extant literature. However, our results extend beyond previous studies by incorporating a more comprehensive set of factors influencing green growth progress. Our investigation provides complementary evidence to prior research across an expanded range of time periods and OECD countries, encompassing both developing and developed economies. Most notably, our study is the first to establish that green growth does not independently emerge and diffuse from a country's green technology diffusion and climate change adaptation efforts. Instead, factors such as green technology diffusion, climate change adaptation, economic growth, and technological achievement within a country serve as significant drivers in promoting green growth.

5. Concluding remarks and policy implications

Green growth represents an approach to economic growth that acknowledges the imperative to protect the environment and foster sustainable development. The primary objective of this study is to identify an extensive array of macroeconomic factors that may influence the green growth index. To this end, we assess the potential causal factors contributing to green growth progress, such as economic performance, globalization, green technology diffusion, climate change adaptation, technological achievement, and institutional and environmental values. We employ the two-step system GMM estimation method, as proposed by Arellano and Bover [52] and Blundell and Bond [63], to estimate various dynamic panel data models. The association between green growth and a number of variables affecting it is examined using an annual frequency panel dataset spanning from 1990 to 2020.

Our empirical findings reveal that all examined factors exhibit a positive and statistically significant relationship with the green growth index, with the exception of carbon dioxide emissions in two of the alternative models estimated, which display a negative and insignificant effect. This

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result indicates a trade-off relationship between investments in climate change adaptation measures and those in sustainable development. Conversely, another finding concludes that there is a positive relationship between carbon emissions and the green growth index. In fact, high levels of economic growth often result in increased carbon emissions. It is plausible for a country to enhance its green growth index score while maintaining high carbon emissions if it can implement policies and technologies that bolster energy efficiency and encourage the utilization of renewable energy sources. Moreover, escalating carbon emissions may exert a catastrophic and significant influence on climate change adaptation in the same model. Consequently, a country might achieve a high green growth rate but remain more susceptible to the impacts of climate change, such as sea-level rise, drought, or high temperatures.

Taking into account the concurrent shifts in globalization and green growth, it can be inferred that both phenomena are responses to the growing interdependence of the world's economies and the necessity to advocate for sustainable development. Globalization has facilitated increased trade and investment between countries, subsequently stimulating economic growth and development. Simultaneously, the heightened awareness surrounding the imperative to preserve the environment has resulted in an emphasis on green growth, which aims to foster economic development while concurrently safeguarding the environment. Consequently, a positive relationship between globalization and green growth is observed, as both are centered on the promotion of sustainable development.

In light of our findings, it appears that certain determinants at the country level warrant careful consideration in promoting green growth. Our results suggest that the favorable impact of carbon emissions on the green growth index is also pertinent to sustainable development. A positive relationship between carbon emissions and the green growth index implies that countries capable of sustaining economic growth while reducing their carbon emissions are more likely to achieve sustainable development. This is because sustainable economic growth necessitates a balance between economic, social, and environmental factors, focusing on carbon emission reduction and clean energy source promotion.

Conversely, it seems that macro conditions at the country level may hinder the promotion of green technology development and diffusion. One such condition is that failure to reduce carbon emissions can have negative economic impacts. Another is that, as the effects of climate change intensify due to higher temperatures and rising carbon emissions, countries may incur increased costs associated with natural disasters, infrastructure damage, and public health. These costs can undermine economic growth and development.

Our findings hold implications for policymakers as they endeavor to foster economic growth and development while simultaneously addressing environmental concerns. We discover that green technology diffusion among countries and environmental precautions are drivers of green growth progress. If green technologies are not widely adopted and climate change adaptation does not advance, the environmental benefits of sustainable development will not be fully realized. Therefore, by implementing policies such as renewable energy incentives, public R&D investments, carbon pricing, environmental tax initiatives, preferential tariffs, energy efficiency standards, international cooperation and partnerships, sustainable transportation, education and awareness-raising, and natural resource management that promote sustainable development, policymakers can create sustainability for both the economy and the environment.

In fact, our conclusions suggest that a key feature of green growth is its emphasis on the triple bottom line of sustainability, encompassing environmental, technological, social, and economic factors. This implies that a country’s progress towards sustainable development is evaluated not only based on its environmental performance but also on its ability to achieve technological and economic growth that is both sustainable and equitable. Policymakers should carefully consider the potential effects of green growth on these factors and implement policies and strategies that can promote sustainable development and low-carbon emissions. This also holds true for a nation's diffusion of green technology and adaptation to climate change.

In summary, policymakers need to prioritize green growth by incorporating environmental considerations into their economic policies, promoting low-carbon and resource-efficient growth, encouraging private sector investment, collaborating and coordinating across various sectors and levels of government, and engaging the public and educating them about the benefits of sustainable development. This study may be beneficial in exploring the green growth index from multiple perspectives, applying the necessary variables at different levels of analysis and examining their interactions. Indeed, dynamic specifications applied to larger time series can aid in this effort by investigating the rate of dispersion and the influence of time on the green growth process. We believe that our findings lay the foundation for a more sophisticated understanding of the green growth determinants impacting country-level trends in sustainable environment and development.

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