sustainability

MDPI

Article

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

Busra Agan [1] and Mehmet Balcilar [1,2,3,*]

[1] Department of Economics, OSTIM Technical University, Ankara 06374, Turkey; busra.agan@ostimteknik.edu.tr
[2] Department of Economics and Business Analytics, University of New Haven, 300 Boston Post Road, West Haven, CT 06516, USA
[3] Department of Economics, Eastern Mediterranean University, Northern Cyprus, via Mersin 10, Famagusta 99628, Turkey
* Correspondence: mehmet@mbalcilar.net

Abstract: The primary objective of this paper is to investigate the extent to which climate change adaptation and green technology diffusion serve as key drivers for green growth. Additionally, the study examines the influence of various economic, environmental, and social factors on green growth. Utilizing an annual panel dataset comprising 38 OECD member countries from 1990 to 2020, a series of dynamic panel data models are estimated using the system generalized method of moments (GMM) approach. The empirical results provide novel and robust evidence that the diffusion of green technology and climate change adaptation exert a significant positive influence on green growth. Furthermore, the findings highlight the significant role played by macroeconomic, institutional, social, and government policy-related factors in promoting green growth. These insights have substantial policy implications for the development and implementation of strategies that encourage climate change adaptation and green innovation. As a result, policymakers should prioritize the integration of green technology and climate change adaptation 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

Citation: Agan, B.; Balcilar, M. Unraveling the Green Growth Matrix: Exploring the Impact of Green Technology, Climate Change Adaptation, and Macroeconomic Factors on Sustainable Development. *Sustainability* **2023**, *15*, 8530. https://doi.org/10.3390/su15118530

Academic Editor: Luigi Aldieri

Received: 29 April 2023
Revised: 19 May 2023
Accepted: 22 May 2023
Published: 24 May 2023

1. Introduction

Green technologies and climate change adaptation play a crucial role in promoting green growth by reducing environmental impacts and fostering sustainable development. Recent research findings reveal that the diffusion of green technologies significantly contributes to enhancing resource efficiency, reducing emissions, and creating new economic opportunities [1]. Simultaneously, climate change adaptation measures may help build resilience in various sectors, ensuring long-term sustainability. According to the well-known Porter [2] hypothesis, both green growth and green technology development directly relate to the implementation of environmental protection regulations. However, developments in green technologies and climate change adaptation are influenced by a variety of factors, such as economic, social, and political considerations [1,3], which leads to continuing debates surrounding the effectiveness of specific technologies and adaptation strategies, emphasizing the need for clear evidence on the specific conditions affecting their effectiveness. This study fills a knowledge gap on the effect of a comprehensive set of country-specific factors, particularly green technology diffusion and climate change regulations, through evidence based on well-defined, comprehensive data from the Organisation for Economic Co-operation and Development (OECD) countries.

The concept of green growth has arisen in international policy discussions as a way of promoting economic growth while simultaneously providing the highest possible level of environmental quality [4]. Therefore, growth is considered to be a fundamental approach to achieve sustainable development [5–7]. Although green technology diffusion is argued to have a favorable effect on green growth [8], its propagation is driven by an array of factors, encompassing technological innovation, economic incentives, policy structures, environmental concerns, and socio-economic elements [8–12].

The literature on green growth and its determinants is vast and focuses on different aspects, both on theoretical [13–15] and empirical [5,15–19] grounds. Recent empirical studies focus on several dimensions, including economic, political, technological, environmental, and other determinants of green growth. In this context, several studies point to three important observations. First, the development of green technologies promotes green growth, thus decreasing CO_2 emissions and being useful in achieving energy efficiency [6,16–20]. Second, climate change adaptation encourages green growth [21–25]. Third, economic growth and globalization could promote green growth [26–28].

Among the studies considering the nexus of green growth, green technology, and low-carbon transition, Herman [29] highlights the need for industrial policies and national innovation systems to transition to low-carbon economies. The literature includes green investment indicators and economic outputs from green growth, which refers to an economy with minimal carbon emissions, environmental quality, efficiency, natural capital, resource efficiency, and social inclusion [4]. Hoffmann [30] argues that the equitable distribution of income and wealth, reducing greenhouse gas emissions, promoting innovation, and implementing structural adaptations are essential for green growth. Brock and Taylor [31] conduct a theoretical and empirical analysis of the relationship between the environmental Kuznets curve (EKC) and the Solow model that integrates green technology, providing new insights into the relationship between economic growth and environmental quality.

More recent studies have shown a strong correlation between green growth and technological innovation [32], specifically, environmental-related technologies, research and development (R&D) investments, and renewable energy sources [20,33–35]. Additionally, research suggests that investing in human resources, R&D for green energy technologies, and implementing measures such as environmental taxes can significantly contribute to the establishment of a sustainable green economy [36–39]. Meng et al. [40] have analysed the relationships between green technology innovation, environmental legislation, green dynamism, and smart manufacturing, finding that environmental regulations have a favourable impact on green technology innovation. Related studies (see, e.g., [41]) have found that green innovation and institutional quality improve environmental sustainability. Dai et al. [42] show that the promotion of green innovation through outward foreign direct investment is significant when market incentive regulations exhibit high intensity. On the other hand, Zhang et al. [43] have found that regional green development is significantly promoted by higher education, and technological innovation plays a crucial role in this relationship.

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 [38,44–48]). In conclusion, these studies underscore the importance of reducing environmental costs and hazards, fostering environmental awareness, ensuring energy security, and mitigating environmental pollution.

Among the studies considering the factors affecting green growth, the first strand of empirical literature is primarily concerned with the relationship between CO_2 emissions and GDP growth. Antal and Van Den Bergh [49] explore the association between CO_2 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 [44] have found that economic growth exerts a negative influence on CO_2 emissions in the low-growth regime and a positive influence in the high-growth regime. Subsequently, Chin et al. [50] have utilized an autoregressive distributed lag (ARDL) model to assess the impacts of CO_2 emissions on green growth and sustainable development and have found a positive correlation between economic growth and carbon emissions.

In the second strand, numerous studies have concentrated on the determinants of green growth, encompassing economic, social, political, and environmental factors. Fernandes et al. [51] have analyzed the effects of green growth on economic growth using dynamic panel techniques and a cross-country OECD dataset that includes findings that suggest that the transfer of sustainable technology promotes green growth. You and Huang [52] investigate the determinants of green growth in China from 1998 to 2011 by employing the dynamic panel data estimation approach. They find 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. [53] 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. Tawiah et al. [54] employ fixed effect estimates to examine the factors of green growth in both developed and developing nations using annual panel data from 2000 to 2017, finding that economic development exhibits a favorable and robust association with green growth in both groups of nations. However, they find mixed results among developed and developing countries with respect to other factors, trade openness, and foreign direct investment (FDI). Additionally, they find that increasing energy usage correlates with a decline in green growth. This finding aligns with the results of Frankel et al. [55] who conclude that FDI had a negative influence on green growth. This conclusion, however, contradicts the findings of Dean et al. [56], which demonstrate that FDI has a favorable relationship with green growth in China. Similarly, Ali et al. [57] suggest that foreign direct investment, energy consumption, and economic growth have a substantial positive impact on the CO_2 emissions of economies of Brazil, Russia, India, China, and South Africa (BRICS).

A few studies consider the relationship between various measures of green growth and globalization. Xia et al. [58] investigate the influence of globalization on environmental performance and discover a significant positive relationship between globalization and CO_2 emissions. Zafar et al. [59] investigate the effects of various measures of globalization in OECD economies by using data from 1991 to 2015. According to their estimations, both trade openness 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 a recent study, Xia et al. [58] have examined the influence of globalization on environmental performance in developed and developing nations. Their estimates reveal a considerable positive correlation between globalization and CO_2 emissions.

The above review of former studies evidences 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 green growth. Thus, our study contributes to the literature by using an empirical approach that makes a combined assessment of many factors affecting green growth with a particular emphasis on green technology diffusion and climate change adaptation.

Against this backdrop, this study examines the impact of various macroeconomic factors at the national level, which may potentially influence green growth. While certain determinants, such as the general trend in green technology diffusion and climate change adaptation, have been previously assessed in different studies (see, for example [60–63]), there are theoretical grounds on which their significance in relation to green growth should be considered. Hence, we investigate various factors that could potentially relate to green growth, including economic performance, globalization, the diffusion of green technology, adaptation to climate change, and institutional and environmental values. A few studies have also incorporated globalization, climate change, and climatic variables as determinants of green growth (refer to, for instance, [47,48,54,64]). Thus, we also consider these variables in our empirical analysis. To the best of the authors' knowledge, no other study has evaluated the multiple effects of these factors on 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 [65,66] to demonstrate the significant role of these determinants in green growth. The results are consistent with the model specifications. Thus, this study enhances the existing body of empirical literature.

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

The study makes several contributions to the existing literature. First, in contrast to previous studies, we incorporate the factors of globalization, climate change adaptation, and green technology diffusion as the primary determinants of 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 adaptation and green technology development, the adaptation and diffusion of these aspects have been experienced in virtually every nation. Such advancements should not be examined independent of a country's technological, environmental, and economic performance. Third, we expand upon earlier studies by including an extensive array of factors that may impact green growth, encompassing per capita income, government stability, globalization, climate change adaptation, foreign direct investment, carbon emissions, environmental performance, environment-related taxes, technology diffusion, and climatic variables. Lastly, 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 to economic, social, environmental, technological, political, and institutional dimensions should be considered significant determinants of green growth in the OECD countries. 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 growth, green technology diffusion, and climate change adaptation, 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 conditions 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 elaborates on the empirical methodology. Section 3 presents data, descriptive statistics, and the empirical findings and discussion. Finally, Section 4 offers concluding remarks.

2. Econometric Methodology

This study employs an annual panel dataset spanning from 1990 to 2020, encompassing 38 OECD member countries. 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. The nature of the data and the specified green growth model can be best estimated using the dynamic panel GMM approach [61].

In the literature, dynamic panel models have been employed to investigate various empirical determinants related to achieving environmental sustainability (refer to [9,54,67–71], for instance). Consequently, this study introduces novel inquiries regarding the impacts of technological, political, social, environmental, and economic components on the diffusion of green technology and green growth.

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

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

where *ggi* expresses the green growth index as a dependent variable. The independent variables are gross domestic product per capita (*gdp*), globalization index (*glo*), foreign direct investment (*fdi*), green technology diffusion (*gtd*), climate change adaptation (*cct*), carbon emission per capita (*co*), government stability (*gov*), environmental performance index (*epi*), environment-related tax (*tax*), technology achievement index (*tai*), population growth (*pop*), and temperature level (*temp*). All variables are expressed in terms of their natural logarithms. In this equation, time is denoted by $t = 1, 2, \ldots, T$, representing years, while $i = 1, 2, \ldots, N$ 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:

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

where p is the autocorrelation order, ln denotes a 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. The error components satisfy $E(\eta_i) = 0$, $\mathrm{E}(v_{i,t}) = 0$, 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 avoids the need for variable transformation or model modification.

The green growth model in Equation (2) is estimated in a first-differenced form in order to eliminate individual effects η_i. The green growth model presented in Equation (2) causes a correlation between errors and the lagged first-differenced endogenous variables. To address this correlation, instrumental variables (IVs) are employed. The GMM framework proposes these IVs due to their potentially low correlation with the first-differenced dependent variable. Alternatively, Arellano and Bond [65] recommended using lags of the endogenous variable's own levels to instrument its first differences, a technique referred to as the Arellano–Bond GMM. Nevertheless, Blundell and Bond [66] observed that lagged levels frequently serve as weak instruments for first differences and suggested incorporating all obtainable information on both endogenous and exogenous variables. This technique, called the Arellano–Bond system GMM method, yields more efficient and unbiased estimates in situations with small samples. System GMM enhances first-differenced GMM by concurrently estimating both differences and levels, with distinct instrumentation for each of the two equations. In applying the Arellano–Bond system GMM model, we employ the first and second lags of all variables in the regression as GMM-style instruments. To guarantee the use of all pertinent variables as instruments and prevent bias in the parameter estimates, we incorporate one instrument for each variable and lag distance, rather than one instrument for each variable, time period, and lag distance. This approach is based on the understanding that when the number of instruments grows in relation to the number of observations, the parameter estimates tend to be biased towards feasible generalized least squares [66].

The two-step system GMM approach we employ 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. Baltagi [72] 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 $T = 30$. The endogeneity of independent variables is assessed using the Durbin–Wu–Hausman test, which employs two-stage least squares (2SLS). The results indicate that some variables exhibit endogeneity. To address this issue, we follow Arellano and Bond's [65] suggestion of transforming the specified equations into first-difference estimators. Consequently, dynamic panel GMM estimators are used, effectively alleviating concerns related to serial correlation, endogeneity, and heterogeneity in the estimation procedure.

The implementation of the GMM approach for estimation encounters two critical challenges: the proliferation of instruments and the serial autocorrelation of error components. These issues are particularly prominent in panel datasets that comprise samples with an extended time period and a limited number of individuals. The proliferation of instruments refers to the presence of increasingly complex instruments in the model, which can result in overidentification due to the inclusion of additional instrumental variables at various levels and differences. To evaluate the appropriateness of the sample size and the potential for overidentification arising from the number of instruments utilized, the Sargan test [73] helps to determine whether the supplementary instruments are 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 the 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.

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 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.

Table 1. Model specifications.

Model Name	Exclusion Restriction	Excluded Variables	Implied Relationship
Model 1	$\alpha_3 = \alpha_4 = \alpha_5 = \alpha_8 = \alpha_9 = \alpha_{10} = 0$	fdi, gov, co_2, epi, tax, tai	ggi = f(gdp, glo, gtd, cct, pop, temp) + ε
Model 2	$\alpha_4 = \alpha_5 = \alpha_8 = \alpha_9 = \alpha_{10} = 0$	gov, co_2, epi, tax, tai	ggi = f(gdp, glo, gtd, fdi, cct, pop, temp) + ε
Model 3	$\alpha_2 = \alpha_5 = \alpha_8 = \alpha_9 = \alpha_{10} = 0$	glo, co_2, epi, tax, tai	ggi = f(gdp, gtd, cct, fdi, gov, pop, temp) + ε
Model 4	$\alpha_2 = \alpha_7 = \alpha_8 = \alpha_9 = \alpha_{10} = 0$	glo, cct, epi, tax, tai	ggi = f(gdp, gtd, fdi, gov, co_2, pop, temp) + ε
Model 5	$\alpha_2 = \alpha_5 = 0$	glo, co_2	ggi = f(gdp, gtd, cct, fdi, gov, epi, tai, tax, pop, temp) + ε
Model 6	$\alpha_2 = 0$	glo	ggi epi, tai, tax, pop, temp) + ε

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. Furthermore, the investigation is conducted using a dynamic system GMM model [74] rather than static models such as the fixed effects model.

3. Empirical Results and Discussion

3.1. Data and Descriptive Statistics

The dataset used in this study was obtained from diverse sources. The green growth index is taken from the OECD statistics database (available at https://www.oecd.org/greengrowth/green-growth-indicators/, accessed on 14 October 2022) based on patent application data. It encompasses innovations pertaining to environmental protection and climate change adaptation technologies. This dataset can be subdivided into three smaller components, namely environmental management, adaptations related to water, and measures taken to lessen the impact of climate change. The three components include environmental and resource productivity, the natural asset base, the environmental dimension of quality of life, economic opportunities, policy responses, and the socio-economic context, which encompasses population and growth characteristics.

To evaluate environmental innovations, we utilize patent statistics from the World Intellectual Property Organization's (WIPO) patent dataset (available at https://www3.wipo.int/ipstats/, accessed on 2 October 2022) to create both green technology diffusion and general technology diffusion measures. This dataset allows for the assessment of innovation performance at the country and firm levels, as well as the formulation of environmental and innovation policies by governments. The climate change adaptation is based on patent applications and derived from OECD statistics (available at https://stats.oecd.org/, accessed on 2 October 2022). Additionally, the globalization index is provided from the KOF Globalization Index database (available at https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html/, accessed on 2 October 2022), which provides an average measure of the economic, social, and political dimensions of globalization.

The World Bank's World Development Indicators (WDI) database (available at https://databank.worldbank.org/source/world-development-indicators/, accessed on 6 October 2022) provides purchasing power parity (PPP) adjusted GDP per capita figures in US dollars, as well as per capita CO_2 emissions in metric tons. Additionally, we collect foreign direct investment from the WDI, which we express as percentage of GDP. Additionally, population growth is taken from WDI. Environmentally related tax revenues are sourced from the OECD statistics database (available at https://stats.oecd.org/, accessed on 10 October 2022).

The environmental performance index is provided by the Socioeconomic Data and Applications Center (SEDAC) (available at https://sedac.ciesin.columbia.edu/data/set/epi-environmental-performance-index-2022/, accessed on 10 October 2022). According to Emerson et al. (2010) [75], this index is derived from a set of 25 indicators and 10 policy categories. These classifications include policies related to the environmental impact on human health, such as the burden of disease, water, and air pollution, as well as policies related to natural resources, such as water, biodiversity, habitat, forestry, fisheries, agriculture, and climate change. Lastly, the authors compute the technology achievement index (TAI) to assess the technological performance of nations. The TAI, derived from data obtained from the WDI, OECD statistics, and WIPO statistics, aims to enhance sustainability by considering environmental and technological outputs. This comprehensive index evaluates multiple dimensions, including human skill development, the invention of new technologies, the prevalence of old technologies, and the diffusion of emerging technologies.

Figure 1 illustrates a time series plot of the average green growth index, which is the dependent variable in all models, for the 38 OECD countries between 1990 and 2020. Although green growth has been steady throughout the period of 1990 to 2020, the growth has been weaker since 2015.

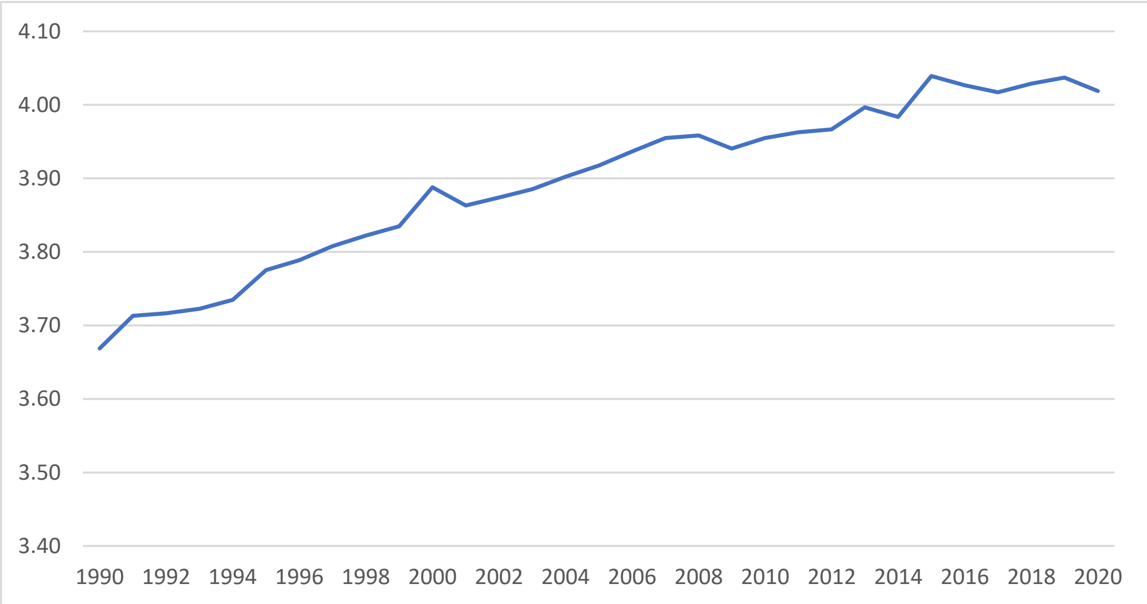

Figure 1. Time series plot of the average green growth index, 1990–2020. Source: authors' calculation based on the OECD statistics database (available at https://www.oecd.org/greengrowth/green-growth-indicators/, accessed on 14 October 2022).

Table 2 provides descriptive statistics for all variables, including the total number of observations (Obs), as well as the mean, standard deviation, minimum, maximum, and SQ-Shapiro–Wilk *W* test (SW-W) for normal distribution values. Means for each country over the sample period are also provided. Among the countries in the sample, the United States, Japan, and Germany demonstrate the highest mean values for the green growth index. In terms of green technology diffusion, Japan, US, and Germany emerge as the leading nations. Furthermore, Belgium, Switzerland, and the Netherlands exhibit the highest mean values for the globalization index. Additionally, US, Japan, and Korea display the highest mean scores for climate change adaptation efforts. An examination of the overall statistics reveals considerable variation across the variables, with green growth, green technology diffusion, CO_2 emissions, and population growth exhibiting greater variation compared to the other metrics. The Shapiro–Wilk *W* test indicates that none of the variables are normally distributed.

Table 2. Descriptive statistics.

Country	lggi	lgdp	lglo	lfdi	lcct	lepi	lgtd	lco	lgov	ltax	ltai	lpop	ltemp
Mean of variables by country over the period of 1990–2020													
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
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
Overall statistics													
Obs.	1178	1178	1178	1178	1178	1178	1178	1178	1178	1178	1178	1178	1178
Mean	3.90	4.36	1.88	2.26	0.88	0.84	3.46	1.58	1.80	0.36	0.33	7.09	1.14
Std. Dev.	0.58	0.30	0.07	0.10	0.09	0.25	1.03	1.05	0.07	0.18	0.11	0.66	0.23
Min.	1.90	3.24	1.62	1.84	0.48	0.08	0.30	0.00	1.50	0.00	0.09	5.41	0.00
Max.	5.51	5.08	1.96	2.47	1.05	1.44	5.71	3.95	1.96	1.82	0.82	8.52	1.49
SW-W	0.99 †	0.97 †	0.88 †	0.98 †	0.98 †	0.97 †	0.99 †	0.94 †	0.98 †	0.85 †	0.94 †	0.97 †	0.58 †

Notes: Obs. is the number of observations, Min. is the minimum, Max. is the maximum, while Std. Dev. denotes the standard deviation. SQ-W stands for the Shapiro–Wilk *W* test for normal data. † indicates significance at the 1% level.

Table 3 displays the Pearson pairwise correlation coefficient estimates, which assist in determining the degree of linear association among variables in the model. Despite the non-normal distribution of the variables, using coefficients as indicators of linear association remains viable, as non-normality only undermines the validity of statistical tests that rely on these estimates. The correlation estimates also help identify potential multicollinearity among the variables. The correlation coefficients for lgov and ltax show a negative relationship with the green growth index; however, for lgov, the value is a mere −0.06 and it is not statistically significant, rendering the inference of a negative relationship unconvincing. In contrast, other independent variables reveal a positive correlation with the green growth index. Furthermore, several pairs of variables demonstrate a high and positive correlation coefficient. Some notable instances 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 pairwise correlation matrix.

	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					
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.

3.2. Cross-Sectional Dependence, Slope Homogeneity, and Nonstationarity Tests

To investigate potential cross-sectional dependence, heterogeneity, and nonstationarity issues in the data, we use statistical tests addressing each of these concerns. The results of the tests of cross-sectional dependence (CSD) are presented in Table 4. To assess the presence of cross-sectional dependence, we employed three tests: the Lagrange multiplier (LM) test proposed by Breusch and Pagan [76], the cross-sectional dependence (CD) test developed by Pesaran [77], and Pesaran's [78] LM cross-sectional dependence (CDLM) test. Test results 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.

Upon establishing the presence of cross-sectional dependence for the variables, we proceeded to test for slope homogeneity. We employed two alternative tests for this purpose: Pesaran and Yamagata's [79] heteroskedasticity and autocorrelation consistent covariance (HAC) adjusted truncated slope homogeneity test ($\widetilde{\Delta}_{\text{HAC}}$), calculated using Blomquist and Westerlund's [80] HAC adjustment, and its small-sample adjusted counterpart ($\widetilde{\Delta}_{\text{adj, HAC}}$). Each test is constructed using a pooled ordinary least squares regression with five different model specifications. In each model, lggi is the dependent variable. Moreover, each model, 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 variables, respectively.

Table 4 additionally reports the results of the slope homogeneity tests. These tests show whether the relationship between variables remains constant across all countries, or if there are variations that require consideration in the analysis. Based on both regular and adjusted homogeneity tests, the null hypothesis of slope homogeneity across countries is not rejected at all traditional significance levels, indicating that the slopes do not differ among countries. As a result, the impact of independent variables on economic growth appears to manifest homogenous effects across the 38 countries being scrutinized. These findings imply that the GMM estimation can be used without concerns regarding slope heterogeneity—an essential requirement since GMM estimators become inconsistent for dynamic panel models with the presence of slope heterogeneity.

Table 4. 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
$\widetilde{\Delta}_{HAC}$	0.832	0.406	0.588	0.556
$\widetilde{\Delta}_{adj,\ HAC}$	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
$\widetilde{\Delta}_{HAC}$	1.103	0.270	0.251	0.802
$\widetilde{\Delta}_{adj,\ HAC}$	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		
$\widetilde{\Delta}_{HAC}$	−0.639	0.523		
$\widetilde{\Delta}_{adj,\ HAC}$	−0.865	0.387		

Notes: table reports cross-sectional dependence and slope homogeneity tests. † 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 tests we employ include the cross-sectionally augmented Im–Pesaran–Shin test, developed by Pesaran [81], the modified cross-sectionally augmented Im–Pesaran–Shin tests, proposed by Westerlund and Hosseinkouchack [82], and the augmented Dickey–Fuller test, also developed by Pesaran [83]. These tests are denoted as CIPS, M-CIPS, and CADF, respectively. The results of the unit root tests, presented in Table 5, 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 in levels, with the exception of ltax, for which the CIPS and CADF tests do not firmly reject the unit root null in the model with constant. However, the M-CIPS test concurs that the ltax variable is stationary in the same model. Similarly, the lpop variable exhibits comparable behavior.

Table 5. 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 ***

Notes: CIPS is the cross-sectionally augmented Im–Pesaran–Shin test of Pesaran [81], M-CIPS is the modified CIPS tests of Westerlund and Hosseinkouchack [82], and CADF is the augmented Dickey–Fuller test of Pesaran [83]. ***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively. The null hypothesis for all tests is the existence of a unit root.

3.3. Model Estimation Results

Given the findings in the previous section, we estimate the model specified in Equation (2) using the two-step system GMM estimator. We estimate six different specifications of the model based on the restrictions in Table 2. Table 6 presents the estimation results. 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 by the Sargan test at any conventional significance level, 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 [65]—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

Table 6. Dynamic panel model estimates.

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	673,323.67 ***	436,125.62 ***	154,449.73 ***	417,670.28 ***	56,818.80 ***	61,834.47 ***
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

Notes: Table reports system GMM estimates with Windmeijer-corrected standard errors in parentheses. N denotes number of observations, 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 5% and 1% levels, respectively.

Table 6 presents the estimates of the dynamic panel model specified in Equation (2) across various specifications outlined in Table 1. The first model examines the impact of economic performance, globalization, climate change adaptation, and the diffusion of green technology on green growth, while also incorporating control variables such as population and temperature. The coefficients of all determinants are positive and statistically significant at conventional significance levels, indicating a positive association with the green growth index. Green growth is characterized by the enhancement of economic productivity and efficiency, alongside the reduction in natural resource consumption and waste and pollution minimization. The positive correlation between the diffusion of green technology, economic growth, and climate change adaptation through green growth is essential for achieving environmental sustainability. Furthermore, the results reveal a positive association between temperature and green growth. The implementation of green growth policies can facilitate adaptation to the consequences of climate change, including rising temperatures and extreme weather events. For example, investments in infrastructure resilient to flooding and other extreme weather phenomena can protect communities and businesses from the adverse effects of climate change while simultaneously generating economic benefits.

Model 2 integrates the impact of FDI on green growth. The results demonstrate a positive and statistically significant association between FDI and green growth across all significance levels. Indeed, FDI can contribute to green growth through various channels. First, it can provide access to capital, technology, and expertise, which are crucial for the development and implementation of green growth strategies. Second, FDI generates employment opportunities and stimulates economic growth, which can help accumulate the necessary resources for investment in green growth. Third, FDI fosters international cooperation and partnerships, which can play a significant role in supporting green growth initiatives.

In Model 3, the influence of institutional factors on green growth is considered. The findings indicate a positive association between government stability and green growth, which is statistically significant at all conventional significance levels. As a result, a stable and effective government can enact policies and regulations that promote renewable energy, conserve natural habitats, and reduce greenhouse gas emissions. Furthermore, a stable and effective government can enable the delivery of vital infrastructure and services for sustainable development, encompassing education, healthcare, and access to clean water and sanitation.

Model 4 provides estimates of the impact of carbon emissions on green growth. The carbon emission coefficient is observed to be positive and statistically significant at all conventional significance levels. In fact, green growth represents environmentally sustainable economic growth, while carbon emissions are a primary contributor to climate change. A positive association between carbon emissions and green growth implies that economic growth and environmental sustainability may be mutually exclusive. One explanation is that elevated levels of economic growth frequently result in increased carbon emissions. Another rationale 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 demonstrates a trade-off relationship. As a country endeavors to achieve high levels of economic growth and improve its green growth index score, it may have limited resources to allocate to climate change adaptation measures. Additionally, escalating carbon emissions exerts a detrimental and substantial impact on climate change adaptation. Consequently, mitigating carbon emissions is of paramount importance in adapting to the changing climate.

Model 5 integrates the environmental performance index, technology innovation, and environmental taxes into the green growth model. Notably, the CO_2 variable cannot be included in this model due to its high correlation with the other variables in the model. For instance, CO_2 constitutes a sub-component of the environmental performance index. The technology achievement index exerts a positive, statistically significant impact, and a substantial contribution to green growth. This highlights the role of technology transfer in augmenting the effects of green growth among countries, as the development and adoption of new technologies are crucial for promoting sustainable economic growth. In contrast, the environmental performance index and environmental taxes display a positive and significant association with the green growth index. These observations underscore the importance of environmental concerns and policies in achieving green growth. Consequently, all variables in this model enhance green growth.

Finally, Model 6 presents the most comprehensive model by incorporating all explanatory variables into a single equation, with the exception of globalization due to its high correlation with other variables. The findings are largely consistent with those obtained from sub-specifications (Models 1 through 5). 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 variables contribute positively to green growth. In terms of marginal effects, the comprehensive equation in Model 6 reveals that the variables exert greater marginal impacts compared to those obtained from sub-specifications.

3.4. Discussion

In this study, the determinants of green growth were empirically analyzed, taking into account 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 dataset encompassing 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, taxes, technological achievements, population, and temperature level. 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 exert a detrimental and significant influence on the progress of climate change adaptation efforts.

In a context complementary to our findings, Georgeson et al. [84] proposed a policy framework that fosters green growth in both developing and developed economies. They emphasized the significance of employing economic, political, social, technological, and environmental approaches in the transformation of the green growth process. As a result, improvements in these aspects will potentially facilitate the progression of green growth. Fundamentally, a country's income level serves as a critical factor in promoting green growth and sustainable development. Anser et al. [70] identified a causal relationship between GDP growth and carbon emissions, along with a bidirectional causality between economic growth and energy usage. Similarly, Chin et al. [50] found a positive association between economic growth and CO_2 emissions. Moreover, several studies have concluded that the impact of income level, CO_2 emissions, environmental performance, climate conditions, and innovations augment the green growth process [6,17–20].

FDI plays a vital role in the adoption of the green growth process. Ayamba et al. [85] established that FDI has an insignificant effect on environmental quality in the long term, but pollution variables exert a significant negative impact on FDI in the short term. Zafar et al. [59] demonstrated that trade openness and FDI exert significant positive effects on green growth in both the short term and the long term. Similarly, Ochoa-Moreno et al. [86] concluded that FDI contributes to increased CO_2 emissions in the long term in Latin American economies. Furthermore, Khan et al. [64] identified significant causal relationships between export and import policies, income level, and green innovation, resulting in changes to consumption-based CO_2 emission levels in G7 countries. These findings align with Shahzad et al.'s [87] conclusions for selected developed and developing countries. In this regard, our results corroborate the empirical evidence presented in these studies while extending the analysis to a more comprehensive scope that encompasses both developing and developed countries.

Considering the role of globalization in green growth, Ahmad and Wu [88] find that globalization displays mixed effects; specifically, it has a negative impact on the environment without its interaction with eco-innovation. On the other hand, Bilal et al. [68] examine the relationship between green technology innovation, CO_2 emissions, and globalization and indicate that globalization has a positive and significant interaction with CO_2 emissions.

Green technology diffusion, climate change adaptation, government stability, economic development, technological achievement, and environmental performance are particularly prominent factors shaping green growth. According to Samad and Manzoor [89], R&D expenditures, green technology, market size, and environmental taxation all have a substantial influence on green growth. Furthermore, Antal and Van Den Bergh [49] find that to achieve both environmental and economic goals, it is necessary to minimize climate change effects and environmental risks in long-term sustainability. In this respect, our results are in line with the findings of several studies (see, for instance, [90–92]). In contrast, He et al. [93] conclude that environmental performance has an adverse effect on green growth in developing economies.

In summary, our empirical analysis highlights the positive contribution of economic, environmental, technological, and social factors in achieving sustainable development, as supported by the extant literature. However, our findings go beyond previous studies by incorporating a more comprehensive set of factors influencing the progress of green growth. Our investigation offers complementary evidence to preceding research across a broader range of time periods and OECD countries, encompassing both developing and developed economies. Notably, our study is the first to establish that green growth does not emerge independently and diffuses 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 act as significant drivers in fostering green growth.

4. Concluding Remarks and Policy Implications

Green growth represents an approach to economic growth that acknowledges the imperative of environmental protection and the promotion of sustainable development. The primary objective of this study is to identify an extensive array of macroeconomic factors that potentially influence green growth. To achieve this, 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 method to estimate various dynamic panel data models. The relationship between green growth and a range of variables affecting it is examined using an annual frequency panel dataset spanning the period 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 climate change adaptation, which displays a negative effect. This outcome suggests a trade-off relationship between investments in climate change adaptation measures and those in sustainable development. Contrarily, another finding indicates a positive relationship between carbon emissions and green growth. Indeed, high levels of economic growth often result in increased carbon emissions. Consequently, a country could enhance its green growth score while maintaining high carbon emissions if it implements policies and technologies that bolster energy efficiency and encourage the utilization of renewable energy sources. 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. Furthermore, escalating carbon emissions might exert a catastrophic and significant influence on climate change adaptation. As a result, a country might attain a high green growth rate but remain more susceptible to the impacts of climate change, such as sea-level rise, drought, or high temperatures. Our results shows that GDP per capita demonstrates a positive and significant impact on green growth. Moreover, green technology diffusion exhibits a positive relationship with green growth. Similarly, population growth and temperature levels have a positive association with the green growth index.

Our findings indicate that globalization has a positive and significant effect on green growth. Considering the simultaneous shifts in globalization and green growth, it can be deduced that both phenomena are responses to the increasing interconnectivity of global economies and the need to prioritize sustainable development. Globalization has facilitated expanded trade and investment across nations, leading to economic growth and progress. Simultaneously, the growing recognition of the importance of environmental preservation has placed a focus on green growth, which seeks to promote economic development while ensuring environmental protection. Consequently, a positive relationship between globalization and green growth is observed, as both are centered on the promotion of sustainable 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, which encompasses 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 impacts of green growth on these factors and adopt policies and strategies that foster sustainable development and low-carbon emissions. This holds true for both the dissemination of green technology and the adaptation to climate change within a nation. Otherwise, it appears that macro-level conditions within a country could impede the advancement of the green growth process. These conditions include the adverse economic consequences resulting from a failure to reduce carbon emissions, as well as the escalating costs associated with natural disasters, infrastructure damage, and public health issues due to the intensifying effects of climate change, such as higher temperatures and increased carbon emissions. These costs have the potential to undermine economic growth and development.

To summarize, this study provides valuable insights into the green growth process by adopting a multi-perspective approach, incorporating relevant variables across various levels of analysis, and examining their interrelationships. 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 determinants of green growth impacting country-level trends in sustainable environment and development. Future studies could consider replicating the present study using longer-term datasets and conducting comparative analyses across continents or regions. Furthermore, exploring the impact of regional-level effects on green growth would contribute to the existing body of knowledge in this field.

Author Contributions: Methodology, M.B.; Software, B.A. and M.B.; Validation, M.B.; Formal analysis, B.A.; Data curation, B.A.; Writing—original draft, B.A.; Writing—review & editing, M.B.; Project administration, M.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is available from the authors upon request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Du, K.; Li, P.; Yan, Z. Do Green Technology Innovations Contribute to Carbon Dioxide Emission Reduction? Empirical Evidence from Patent Data. *Technol. Forecast. Soc. Chang.* **2019**, *146*, 297–303. [CrossRef]
2. Porter, M.E. America's Green Strategy. *Sci. Am.* **1991**, *264*, 168. [CrossRef]
3. Fatima, T.; Shahzad, U.; Cui, L. Renewable and Nonrenewable Energy Consumption, Trade and CO_2 Emissions in High Emitter Countries: Does the Income Level Matter? *J. Environ. Plan. Manag.* **2021**, *64*, 1227–1251. [CrossRef]
4. OECD. *Environment at a Glance 2020*; OECD Publishing: Paris, France, 2020; ISBN 9789264498556.
5. Candra, O.; Chammam, A.; Alvarez, J.R.N.; Muda, I.; Aybar, H. The Impact of Renewable Energy Sources on the Sustainable Development of the Economy and Greenhouse Gas Emissions. *Sustainability* **2023**, *15*, 2104. [CrossRef]
6. Guo, M.; Nowakowska-Grunt, J.; Gorbanyov, V.; Egorova, M. Green Technology and Sustainable Development: Assessment and Green Growth Frameworks. *Sustainability* **2020**, *12*, 6571. [CrossRef]
7. Mpofu, F.Y. Green Taxes in Africa: Opportunities and Challenges for Environmental Protection, Sustainability, and the Attainment of Sustainable Development Goals. *Sutainability* **2022**, *14*, 10239. [CrossRef]
8. Popp, D.; Newell, R.G.; Jaffe, A.B. Chapter 21—Energy, the Environment, and Technological Change. In *Handbook of the Economics of Innovation, Volume 2*; Hall, B.H., Rosenberg, N., Eds.; North-Holland: Amsterdam, The Netherlands, 2010; pp. 873–937. [CrossRef]
9. Vona, F.; Patriarca, F. Income Inequality and the Development of Environmental Technologies. *Ecol. Econ.* **2011**, *70*, 2201–2213. [CrossRef]
10. Zeng, Y.; Dong, P.; Shi, Y.; Wang, L.; Li, Y. Analyzing the co-evolution of green technology diffusion and consumers' pro-environmental attitudes: An agent-based model. *J. Clean. Prod.* **2020**, *256*, 120384. [CrossRef]
11. Rodrik, D. Green Industrial Policy. *Oxf. Rev. Econ. Pol.* **2015**, *30*, 469–491. [CrossRef]
12. Stefanski, R. On the Mechanics of the Green Solow Model. OxCarre Working Papers, No. 47. 2013, pp. 1–36. Available online: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=f63dfcdab93dca9688378f09a3bc49acf0b705aa (accessed on 14 October 2022).
13. Huang, Y.; Quibria, M.G. Green Growth: Theory and Evidence. *WIDER Working Paper*. No. 2013/056. 2013, pp. 1–24. Available online: http://hdl.handle.net/10419/81020 (accessed on 14 October 2022).
14. Popp, D. The Role of Technological Change in Green Growth. *World Bank Policy Res. Work. Pap.* No. 6239. 2012, pp. 1–59. Available online: https://elibrary.worldbank.org/doi/abs/10.1596/1813-9450-6239 (accessed on 14 October 2022).
15. Dinda, S. A Theoretical Basis for Green Growth. *Int. J. Green Econ.* **2013**, *8*, 177–189. [CrossRef]
16. Maiti, M. Does Improvement in Green Growth Influence the Development of Environmental Related Technology? *Innov. Green Dev.* **2022**, *1*, 100008. [CrossRef]
17. Batrancea, L.M.; Pop, M.C.; Rathnaswamy, M.M.; Batrancea, I.; Rus, M.I. An Empirical Investigation on the Transition Process toward a Green Economy. *Sustainability* **2021**, *13*, 13151. [CrossRef]
18. Lenaerts, K.; Tagliapietra, S.; Wolff, G.B. The Global Quest for Green Growth: An Economic Policy Perspective. *Sustainability* **2022**, *14*, 5555. [CrossRef]
19. Hussain, J.; Lee, C.C.; Chen, Y. Optimal Green Technology Investment and Emission Reduction in Emissions Generating Companies under the Support of Green Bond and Subsidy. *Technol. Forecast. Soc. Chang.* **2022**, *183*, 121952. [CrossRef]
20. Danish; Ulucak, R. How Do Environmental Technologies Affect Green Growth? Evidence from BRICS Economies. *Sci. Total Environ.* **2020**, *712*, 136504. [CrossRef]
21. Mertz, O.; Halsnæs, K.; Olesen, J.E.; Rasmussen, K. Adaptation to Climate Change in Developing Countries. *Environ. Manag.* **2009**, *43*, 743–752. [CrossRef]
22. Karki, G.; Bhatta, B.; Devkota, N.R.; Acharya, R.P.; Kunwar, R.M. Climate Change Adaptation (CCA) Interventions and Indicators in Nepal: Implications for Sustainable Adaptation. *Sustainability* **2021**, *13*, 13195. [CrossRef]
23. Siao, H.J.; Gau, S.H.; Kuo, J.H.; Li, M.G.; Sun, C.J. Bibliometric Analysis of Environmental, Social, and Governance Management Research from 2002 to 2021. *Sustainability* **2022**, *14*, 16121. [CrossRef]
24. Oplani, M.; Cehi, A.; Cop, T.; Ban, S.G.; Njavro, M. Adaptation to Climate Change in Adriatic Croatia—The View of Policymakers. *Sustainability* **2023**, *15*, 7085.
25. Zhao, Y.; Liu, S. Effects of Climate Change on Economic Growth: A Perspective of the Heterogeneous Climate Regions in Africa. *Sustainability* **2023**, *15*, 7136. [CrossRef]
26. Luo, R.; Ullah, S.; Ali, K. Pathway towards Sustainability in Selected Asian Countries: Influence of Green Investment, Technology Innovations, and Economic Growth on CO_2 Emission. *Sustainability* **2021**, *13*, 12873. [CrossRef]

27. Tsimisaraka, R.S.M.; Xiang, L.; Andrianarivo, A.R.N.A.; Josoa, E.Z.; Khan, N.; Hanif, M.S.; Khurshid, A.; Limongi, R. Impact of Financial Inclusion, Globalization, Renewable Energy, ICT, and Economic Growth on CO_2 Emission in OBOR Countries. *Sustainability* **2023**, *15*, 6534. [CrossRef]
28. Wang, M.; Ding, X.; Choi, B. FDI or International-Trade-Driven Green Growth of 24 Korean Manufacturing Industries? Evidence from Heterogeneous Panel Based on Non-Causality Test. *Sustainability* **2023**, *15*, 5753. [CrossRef]
29. Herman, K.S. Green Growth and Innovation in the Global South: A Systematic Literature Review. *Innov. Dev.* **2023**, *13*, 43–69. [CrossRef]
30. Hoffmann, U. Can Green Growth Really Work? Can Green Growth Really Work and what are the True (Socio-)Economics of Climate Change? United Nations Conference on Trade and Development (UNCTAD) Discussion Papers, No. 222. 2015, pp. 1–25. Available online: http://unctad.org/en/PublicationsLibrary/osgdp2015d4_en.pdf (accessed on 14 October 2022).
31. Brock, W.A.; Taylor, M.S. The Green Solow Model. *J. Econ. Growth* **2010**, *15*, 127–153. [CrossRef]
32. Abid, N.; Ceci, F.; Ikram, M. Green Growth and Sustainable Development: Dynamic Linkage between Technological Innovation, ISO 14001, and Environmental Challenges. *Environ. Sci. Pollut. Res.* **2022**, *29*, 25428–25447. [CrossRef]
33. Wang, X.; Shao, Q. Non-Linear Effects of Heterogeneous Environmental Regulations on Green Growth in G20 Countries: Evidence from Panel Threshold Regression. *Sci. Total Environ.* **2019**, *660*, 1346–1354. [CrossRef]
34. Brunel, C. Green Innovation and Green Imports:Links between Environmental Policies, Innovation, and Production. *J. Environ. Manag.* **2019**, *248*, 109290. [CrossRef]
35. Zhao, M.; Liu, F.; Song, Y.; Geng, J. Impact of Air Pollution Regulation and Technological Investment on Sustainable Development of Green Economy in Eastern China: Empirical Analysis with Panel Data Approach. *Sustainability* **2020**, *12*, 3073. [CrossRef]
36. Hao, L.N.; Umar, M.; Khan, Z.; Ali, W. Green Growth and Low Carbon Emission in G7 Countries: How Critical the Network of Environmental Taxes, Renewable Energy and Human Capital Is? *Sci. Total Environ.* **2021**, *752*, 141853. [CrossRef]
37. Zhang, D.; Mohsin, M.; Rasheed, A.K.; Chang, Y.; Taghizadeh-Hesary, F. Public Spending and Green Economic Growth in BRI Region: Mediating Role of Green Finance. *Energy Policy* **2021**, *153*, 112256. [CrossRef]
38. Chang, C.P.; Hao, Y. Environmental Performance, Corruption and Economic Growth: Global Evidence Using a New Data Set. *Appl. Econ.* **2017**, *49*, 498–514. [CrossRef]
39. Zmami, M.; Ben-Salha, O. An Empirical Analysis of the Determinants of CO_2 Emissions in GCC Countries. *Int. J. Sustain. Dev. World Ecol.* **2020**, *27*, 469–480. [CrossRef]
40. Meng, F.; Xu, Y.; Zhao, G. Environmental Regulations, Green Innovation and Intelligent Upgrading of Manufacturing Enterprises: Evidence from China. *Sci. Rep.* **2020**, *10*, 14485. [CrossRef]
41. Udeagha, M.C.; Ngepah, N. Dynamic ARDL Simulations Effects of Fiscal Decentralization, Green Technological Innovation, Trade Openness, and Institutional Quality on Environmental Sustainability: Evidence from South Africa. *Sustainability* **2022**, *14*, 10268. [CrossRef]
42. Dai, L.; Mu, X.; Lee, C.C.; Liu, W. The Impact of Outward Foreign Direct Investment on Green Innovation: The Threshold Effect of Environmental Regulation. *Environ. Sci. Pollut. Res.* **2021**, *28*, 34868–34884. [CrossRef]
43. Zhang, T.; Ma, Z.; Shang, Y. Higher Education, Technological Innovation, and Green Development—Analysis Based on China's Provincial Panel Data. *Sustainability* **2023**, *15*, 4311. [CrossRef]
44. Aye, G.C.; Edoja, P.E. Effect of Economic Growth on CO_2 Emission in Developing Countries: Evidence from a Dynamic Panel Threshold Model. *Cogent Econ. Finance* **2017**, *5*, 1379239. [CrossRef]
45. Yuan, B.; Xiang, Q. Environmental Regulation, Industrial Innovation and Green Development of Chinese Manufacturing: Based on an Extended CDM Model. *J. Clean. Prod.* **2018**, *176*, 895–908. [CrossRef]
46. Li, D.; Zhao, Y. How Does Environmental Regulation Effect Green Growth? An Empirical Investigation from China. *Pol. J. Environ. Stud.* **2021**, *30*, 1247–1262. [CrossRef]
47. Xu, S.C.; Li, Y.F.; Zhang, J.N.; Wang, Y.; Ma, X.X.; Liu, H.Y.; Wang, H.N.; Tao, Y. Do Foreign Direct Investment and Environmental Regulation Improve Green Technology Innovation? An Empirical Analysis Based on Panel Data from the Chinese Manufacturing Industry. *Environ. Sci. Pollut. Res.* **2021**, *28*, 55302–55314. [CrossRef]
48. Hussain, Z.; Mehmood, B.; Khan, M.K.; Tsimisaraka, R.S.M. Green Growth, Green Technology, and Environmental Health: Evidence From High-GDP Countries. *Front. Public Health* **2022**, *9*, 816697. [CrossRef] [PubMed]
49. Antal, M.; Bergh, J.C.V.D. Green Growth and Climate Change: Conceptual and Empirical Considerations. *Clim. Policy* **2016**, *16*, 165–177. [CrossRef]
50. Chin, M.Y.; Puah, C.H.; Teo, C.L.; Joseph, J. The Determinants of Co_2 Emissions in Malaysia: A New Aspect. *Int. J. Energy Econ. Policy* **2018**, *8*, 190–194.
51. Fernandes, C.I.; Veiga, P.M.; Ferreira, J.J.M.; Hughes, M. Green Growth versus Economic Growth: Do Sustainable Technology Transfer and Innovations Lead to an Imperfect Choice? *Bus. Strat. Environ.* **2021**, *30*, 2021–2037. [CrossRef]
52. You, J.; Huang, Y. Green-to-Grey China: Determinants and Forecasts of Its Green Growth. *Munich Pers.* No. 58101. 2014, pp. 1–52. Available online: https://mpra.ub.uni-muenchen.de/58101/ (accessed on 14 October 2022).
53. Feng, C.; Wang, M.; Liu, G.C.; Huang, J.B. Green Development Performance and Its Influencing Factors: A Global Perspective. *J. Clean. Prod.* **2017**, *144*, 323–333. [CrossRef]
54. Tawiah, V.; Zakari, A.; Adedoyin, F.F. Determinants of Green Growth in Developed and Developing Countries. *Environ. Sci. Pollut. Res.* **2021**, *28*, 39227–39242. [CrossRef]

55. Frankel, J.A.; Rose, A.K.; Kopp, R.; Schmalensee, R.; Weitzman, M.; Grossman, G.M.; Krueger, A.B.; Tobey, J.A. Is Trade Good or Bad for The Environment? Sorting Out the Causality. *Econ. Int. Trade Environ.* **1991**, *87*, 85–91.
56. Dean, J.M.; Lovely, M.E.; Wang, H. Are Foreign Investors Attracted to Weak Environmental Regulations? Evaluating the Evidence from China. *Int. Econ. Integr. Domest. Perform.* **2017**, *58*, 155–168. [CrossRef]
57. Ali, N.; Phoungthong, K.; Techato, K.; Ali, W.; Abbas, S.; Dhanraj, J.A.; Khan, A. FDI, Green Innovation and Environmental Quality Nexus: New Insights from BRICS Economies. *Sustainability* **2022**, *14*, 2181. [CrossRef]
58. Xia, W.; Apergis, N.; Bashir, M.F.; Ghosh, S.; Doğan, B.; Shahzad, U. Investigating the Role of Globalization, and Energy Consumption for Environmental Externalities: Empirical Evidence from Developed and Developing Economies. *Renew. Energy* **2022**, *183*, 219–228. [CrossRef]
59. Zafar, M.; Kousar, S.; Sabir, S.A. Impact of Globalization on Green Growth: A Case of OECD Countries. *J. Indian Stud.* **2020**, *5*, 145–159.
60. Shang, Y.; Lian, Y.; Chen, H.; Qian, F. The Impacts of Energy Resource and Tourism on Green Growth: Evidence from Asian Economies. *Resour. Policy* **2023**, *81*, 103359. [CrossRef]
61. Agan, B.; Balcilar, M. On the Determinants of Green Technology Diffusion: An Empirical Analysis of Economic, Social, Political, and Environmental Factors. *Sustainability* **2022**, *14*, 2008. [CrossRef]
62. Sun, K.; Cao, X.; Xing, Z. Can the Diffusion Modes of Green Technology Affect the Enterprise's Technology Diffusion Network towards Sustainable Development of Hospitality and Tourism Industry in China? *Sustainability* **2021**, *13*, 9266. [CrossRef]
63. Ojo, T.O.; Adetoro, A.A.; Ogundeji, A.A.; Belle, J.A. Quantifying the Determinants of Climate Change Adaptation Strategies and Farmers' Access to Credit in South Africa. *Sci. Total Environ.* **2021**, *792*, 148499. [CrossRef]
64. Khan, S.A.R.; Yu, Z.; Sharif, A.; Golpîra, H. Determinants of Economic Growth and Environmental Sustainability in South Asian Association for Regional Cooperation: Evidence from Panel ARDL. *Environ. Sci. Pollut. Res.* **2020**, *27*, 45675–45687. [CrossRef] [PubMed]
65. Arellano, M.; Bond, S. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Rev. Econ. Stud.* **1991**, *58*, 277–297. [CrossRef]
66. Blundell, R.; Bond, S. Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *J. Econ.* **1998**, *87*, 115–143. [CrossRef]
67. Paramati, S.R.; Shahzad, U.; Doğan, B. The Role of Environmental Technology for Energy Demand and Energy Efficiency: Evidence from OECD Countries. *Renew. Sustain. Energy Rev.* **2022**, *153*, 111735. [CrossRef]
68. You, W.H.; Zhu, H.M.; Yu, K.; Peng, C. Democracy, Financial Openness, and Global Carbon Dioxide Emissions: Heterogeneity Across Existing Emission Levels. *World Dev.* **2015**, *66*, 189–207. [CrossRef]
69. Chen, C.; Lan, Q.; Gao, M.; Sun, Y. Green Total Factor Productivity Growth and Its Determinants in China's Industrial Economy. *Sustainability* **2018**, *10*, 1052. [CrossRef]
70. Anser, M.K.; Usman, M.; Godil, D.I.; Shabbir, M.S.; Sharif, A.; Tabash, M.I.; Lopez, L.B. Does Globalization Affect the Green Economy and Environment? The Relationship between Energy Consumption, Carbon Dioxide Emissions, and Economic Growth. *Environ. Sci. Pollut. Res.* **2021**, *28*, 51105–51118. [CrossRef]
71. Bilal, A.; Li, X.; Zhu, N.; Sharma, R.; Jahanger, A. Green Technology Innovation, Globalization, and CO_2 Emissions: Recent Insights from the OBOR Economies. *Suatainability* **2022**, *14*, 236. [CrossRef]
72. Baltagi, B.H.; Feng, Q.; Kao, C. A Lagrange Multiplier Test for Cross-Sectional Dependence in a Fixed Effects Panel Data Model. *J. Econ.* **2012**, *170*, 164–177. [CrossRef]
73. Sargan, J.D. The Estimation of Economic Relationships Using Instrumental Variables. *Econometrica* **1958**, *26*, 393–415. [CrossRef]
74. Blundell, R.; Bond, S.; Windmeijer, F.; Blundell, R.; Bond, S.; Windmeijer, F. *Estimation in Dynamic Panel Data Models: Improving on the Performance of the Standard*; Emerald Group Publishing Limited: Bradford, UK, 2001; Volume 15, ISBN 0762306882.
75. Emerson, J.; Esty, D.C.; Levy, M.A.; Kim, C.H.; de Sherbinin, A.; Srebotnjak, T.; Mara, V.; Jaiteh, M. *2010 Environmental Performance Index*; Yale Center for Environmental Law and Policy: New Haven, CT, USA, 2010; pp. 1–87.
76. Breusch, T.S.; Pagan, A.R. The Lagrange Multiplier Test and Its Applications to Model Specification in Econometrics. *Rev. Econ. Stud.* **1980**, *47*, 239–253. [CrossRef]
77. Pesaran, M.H. General Diagnostic Tests for Cross-Sectional Dependence in Panels. *Empir. Econ.* **2021**, *60*, 13–50. [CrossRef]
78. Pesaran, M.H. An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis. In *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*; Department of Applied Economics, University of Cambridge: Cambridge, UK, 2008; pp. 371–413. [CrossRef]
79. Pesaran, M.H.; Yamagata, T. Testing Slope Homogeneity in Large Panels. *J. Econ.* **2008**, *142*, 50–93. [CrossRef]
80. Blomquist, J.; Westerlund, J. Testing Slope Homogeneity in Large Panels with Serial Correlation. *Econ. Lett.* **2013**, *121*, 374–378. [CrossRef]
81. Pesaran, M.H. A Pair-Wise Approach to Testing for Output and Growth Convergence. *J. Econ.* **2007**, *138*, 312–355. [CrossRef]
82. Westerlund, J.; Hosseinkouchack, M. Modified CADF and CIPS Panel Unit Root Statistics with Standard Chi-Squared and Normal Limiting Distributions. *Oxf. Bull. Econ. Stat.* **2016**, *78*, 347–364. [CrossRef]
83. Pesaran, M.H. General Diagnostic Tests for Cross Section Dependence in Panels. Working Paper, No. 1240; Institute for the Study of Labor (IZA): Bonn, Germany, 2004; pp. 1–39. Available online: https://docs.iza.org/dp1240.pdf (accessed on 14 October 2022).

84. Georgeson, L.; Maslin, M.; Poessinouw, M. The Global Green Economy: A Review of Concepts, Definitions, Measurement Methodologies and Their Interactions. *Geo Geogr. Environ.* **2017**, *4*, e00036. [CrossRef]
85. Ayamba, E.C.; Haibo, C.; Abdul-Rahaman, A.R.; Serwaa, O.E.; Osei-Agyemang, A. The Impact of Foreign Direct Investment on Sustainable Development in China. *Environ. Sci. Pollut. Res.* **2020**, *27*, 25625–25637. [CrossRef]
86. Ochoa-Moreno, W.S.; Quito, B.A.; Moreno-Hurtado, C.A. Foreign Direct Investment and Environmental Quality: Revisiting the Ekc in Latin American Countries. *Sustainability* **2021**, *13*, 12651. [CrossRef]
87. Shahzad, U.; Ferraz, D.; Doğan, B.; Rebelatto, D.A.d.N. Export Product Diversification and CO_2 Emissions: Contextual Evidences from Developing and Developed Economies. *J. Clean. Prod.* **2020**, *276*, 124146. [CrossRef]
88. Ahmad, M.; Wu, Y. Combined Role of Green Productivity Growth, Economic Globalization, and Eco-Innovation in Achieving Ecological Sustainability for OECD Economies. *J. Environ. Manag.* **2022**, *302*, 113980. [CrossRef]
89. Samad, G.; Manzoor, R. Green Growth: Important Determinants. *Singap. Econ. Rev.* **2015**, *60*, 1550014. [CrossRef]
90. Dercon, S. Is Green Growth Good for the Poor? *World Bank Res. Obs.* **2014**, *29*, 163–185. [CrossRef]
91. Barbier, E.B. Is Green Growth Relevant for Poor Economies? *Fond. Pour Études Rech. Sur Dév. Int.* **2015**, *45*, 178–191. [CrossRef]
92. Bo, L.; Yunbao, X.; Chengbo, D.; Chao, T.; Guangde, Z.; Yameen, T. Green Growth and Carbon Neutrality Targets in BRICS: Do ICT-Trade and Bank Credit Matter ? *Res. Sq.* **2022**, 1–10. [CrossRef]
93. He, R.; Baležentis, T.; Štreimikienė, D.; Shen, Z. Sustainable Green Growth in Developing Economies: An Empirical Analysis on the Belt and Road Countries. *J. Glob. Inf. Manag.* **2022**, *30*, 1–15. [CrossRef]