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# The causal relationship between green technologies, green innovation and GDP growth

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**ABSTRACT**

This study investigates the relationship between green technologies, green innovation, and GDP growth across 85 countries over the periods 1990–2019 and 2009–2019. We employ a novel Granger non-causality test that accounts for cross-sectional dependence and heteroskedasticity. Our findings indicate that green technologies significantly contribute to GDP growth, particularly in emerging economies. However, regional heterogeneity exists, with developed economies showing more complex interactions between green innovation and GDP. These results suggest that tailored green growth policies are essential to maximise the economic benefits of green technologies. This study provides policymakers with insights into the role of green innovation in fostering sustainable economic growth.

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**Article highlights**

- The study finds strong evidence of a bidirectional Granger causality between green technologies and GDP growth. This means that not only do green technologies promote economic growth, but economic growth also fuels further investments in green technologies, creating a self-reinforcing cycle of innovation and growth.
- While green technologies drive GDP growth, green innovation (measured by green patents per capita) does not have the same immediate effect. Instead, GDP growth leads to more green innovation, particularly in advanced economies, suggesting that economic prosperity facilitates research and development in green technologies.
- The impact of green technologies on GDP growth varies by region. In emerging and developing economies, green technologies contribute significantly to economic growth. However, in advanced economies, the initial costs of transitioning to green technologies may slow growth in the short term, indicating the need for different policy approaches.
- The study shows that energy intensity and urbanisation are significant drivers of GDP growth. Reducing energy intensity through green technologies improves economic efficiency, while urbanisation creates new economic opportunities, especially in developing regions.
- The findings highlight the importance of tailored policy interventions. Emerging economies can benefit from aggressive green technology adoption to spur immediate growth, while advanced economies need policies that mitigate the short-term costs of transitioning to green innovation, ensuring long-term sustainability without sacrificing economic output.

## 1. Introduction

Green policy is a strategy for economic growth and development that places a premium on preserving the quality and quantity of natural resources (Ekins, 2002; Hackett & Dissanayake, 2014; OECD, 2011a). By doing so, we can ensure that the environment will continue to provide essential environmental services for our future well-being (OECD, 2011a, 2011b). In addition, green growth refers to the economic opportunities presented by the transition to a green economy, such as encouraging investment, competition, and innovation in support of sustainable and green economic growth (see OECD, 2011b, Tufail et al., 2024). The Green Economy Initiative was first introduced in 2008 by the United Nations Environment Programme (UNEP, 2011). Subsequently, the Paris Agreement 2015 represented a consensus among roughly 200 countries and regions to advance the development of clean, low-carbon energy that could essentially propagate green growth (Kaminker & Stewart, 2012; Mohammed et al., 2022; Sharif et al., 2023). Nevertheless, numerous countries have increased their use of scientific and technological methods to combat environmental degradation, such as land use, air pollution, water pollution, etc.; see Stern et al. (1996), Zhang and Wen (2008) among many others.

According to Grossman and Krueger (1991), the rate of technological advancement determines how much of an impact economic growth has on environmental quality. Furthermore, technological advancements spur the creation of environmentally friendly production methods, which increase clean productivity; see also Schmalensee (2012) and Hao et al. (2023). Given that natural capital, which includes the environment, is an input in the production function, environmental conservation could result in a greater use of natural capital and, consequently, an increase in income; see Hinterberger et al. (1997), Wackernagel and Rees (1997) and Hallegatte et al. (2012). Market failures, such as external costs and poorly defined property rights, are prevalent in the utilisation of environmental resources; addressing these failures can increase the effective supply of natural capital and thus output; it can also increase the welfare of people directly through improvements in air and water quality, which may not be captured by standard GDP statistics but is nonetheless the primary goal of economic policy (Hallegatte et al., 2012; Jaffe et al., 2005). Without necessarily slowing the processes down, green growth involves making growth processes more resource-efficient, cleaner, and more resilient, see Hallegatte et al. (2012), Hickel and Kallis (2020), Schmalensee (2012) and Hao et al. (2023).

Green growth is an economic theory that promotes the conservation of natural capital by creating new employment, international trade, and capital investment opportunities (see OECD, 2011b, 2017). Not only does it highlight those who benefit from development but also those who contribute to the responsible management of natural resources. Social inclusion is therefore a crucial mechanism for achieving green growth and distributing its benefits (Liu et al., 2024; Vinuesa et al., 2020; Zwarteveen, 1997). The implementation of green growth policies through innovation promotion and changes in consumer behaviour is accelerating, but comparable data on the scope of this change and the jobs as well as socio-economic opportunities it generates remain difficult to quantify statistically (see, for example, Hammer et al., 2011; Shao et al., 2020). Innovation has made mixed strides forward–but government

spending on research and development (R&D) is rising (OECD, 2017). However, the portion allocated to environmental and energy-related objectives has remained unchanged. Energy-focused research, development, and demonstration (RD&D) initiatives are also shifting towards renewable energy sources. The rate of innovation in environmental technologies has slowed globally. Long-term incentives are required to effectively channel innovation towards environmental goals (OECD, 2017). Therefore, it is imperative to ascertain whether and how green growth indicators support the expansion of the green economy. Our study's research question is whether green growth indicators (such as green patents and green innovation per capita) contribute to GDP growth. In light of this, we intend to determine whether green technologies and green innovations are associated with greater economic growth or vice versa.

This paper's primary and relatively practical contribution is reflected in two facets: first, empirically, we motive our empirical model by the theoretical proponents of Romer (1992) and Nordhaus (1974, 2018) to assess the causal relationship between green technologies, green innovation, and GDP growth. Romer's research highlights the link between technological change and the economy, with positive externalities influencing it, while Nordhaus discusses climate change challenges and government policies' potential for long-term economic growth. Different from these authors, to capture the investment spillover effects against the backdrop of the infamous Pollution Haven and Pollution Halo hypotheses, we extend the model to include foreign direct investment. In addition, we replace our core green growth indicators, namely green patents, and green innovation per capita, with a novel composite measure of green growth referred to as the green growth index. This approach differs from the existing studies. The index is comprised of approximately 150 environmental and growth-induced variables. Secondly, in our empirical application, we employed the Granger non-causality test, which allows for cross-sectional dependence and cross-sectional heteroskedasticity in the errors (see Juodis et al., 2021; Xiao et al., 2023) and computational efficiency for cross-sectional heterogeneity in samples that are significantly smaller in $T$ than $N$, i.e., $T \ll N$ (see Juodis et al., 2021), which reflects our case. Our sample spans 1990–2019 and 2009–2019 for 85 countries, respectively. One way to improve the accuracy and dependability of findings about the relationship between GDP growth and green technologies is by using a Granger non-causality bias-corrected estimator. An accurate assessment of the causal relationship between GDP growth and green technologies is crucial for policymakers because it can help them determine the level of government investments and subsidies needed to support green technology. Furthermore, bias-corrected estimators could enhance forecasting accuracy, address issues related to endogeneity, and provide strategies for promoting sustainable economic growth. In general, this approach has significant implications for making strategic decisions and shaping economic policies. It also contributes to the reliability and strength of the methodology used.

Green technologies and innovations are increasingly seen as pivotal drivers of sustainable economic growth (see Huang et al., 2024; Jianing et al., 2024; Magazzino et al., 2024; Solangi et al., 2024; Zeng et al., 2024; Zhao et al., 2023). In light of the Paris Agreement and growing global awareness of environmental degradation, understanding the economic impacts of these innovations has become critical. This study contributes to the literature by utilising a novel Granger non-causality test that accounts for cross-sectional dependence, a methodological advancement over traditional approaches. By analysing data from 85 countries between 1990–2019 and 2009–2019, this paper provides new insights into the bidirectional relationship between green technologies and GDP growth. Furthermore, it offers region-specific policy recommendations, emphasising the importance of tailored green growth strategies.

The study is categorised into four sections: section one introduces the context of green technologies, green innovations, and GDP growth; section two briefly discusses the materials and methods used; section three highlights the empirical results and discussions; and section four concludes the study, while in the appendix, we briefly discuss some existing literature and findings.

## 2. Materials and methods

### 2.1. Empirical model

In the existing literature, Romer (1992) research emphasised the inherent connection between technological change and the economy. The study pointed out that the limitations and potentials of future events,

known as positive externalities, can greatly impact the economy. In addition, Nordhaus (1974, 2018) highlighted the fundamental challenges of climate change, emphasising the negative effects of economic activities, also known as negative externalities. Romer and Nordhaus both emphasise that while the market economy is a powerful driver of development, it also has significant shortcomings. Their work has expanded our understanding of how government policies can potentially enhance long-term economic growth. Based on these proponents, we assume that:

$$GDP\ growth = f\ (green\ technologies, green\ innovations, X) \tag{1}$$

Where X represents potential factors or determinants of GDP growth and green technologies, as well as green innovations. Following My Thi Thi and Tran Phu Do (2024), we assess the endogenous relationship between green technologies, green innovation and GDP growth against the backdrop that technology innovation drives economic growth, with the endogenous growth theory underpinning this relationship. We derive the following empirical model for our investigation:

$$\begin{aligned} \text{GDP growth}_{it} &= \beta_0 + \beta_1 \text{Green Technologies/Innovations}_{it} + \beta_2 \text{Urbanisation}_{it} \\ &+ \beta_3 \text{Energy Intensity}_{it} + \beta_4 \text{Foreign Direct Investment} + \epsilon_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} \text{Green Technologies/Innovations}_{it} &= \beta_0 + \beta_1 \text{GDP growth}_{it} + \beta_2 \text{Urbanisation}_{it} \\ &+ \beta_3 \text{Energy Intensity}_{it} + \beta_4 \text{Foreign Direct Investment} + \epsilon_{it} \end{aligned} \tag{3}$$

Where $\beta_0$, $\beta_1$ to $\beta_4$, $\epsilon$ denote the constant terms, the parameter coefficients, and error terms, respectively. $i$ and $t$ are the cross-section of countries and period of the study, correspondingly.

We assume that the relationship between urbanisation and economic growth is proportional; see Elliott et al. (2017), Liu (2009) and Hanif et al. (2019). Urbanisation is also referred to as the transformation of rural populations into urban people or the urbanisation of rural areas (Li et al., 2019; Sit & Yang, 1997). The industrialisation that results from urbanisation influences energy consumption (Fang et al., 2022; Sadorsky, 2013; Shahbaz et al., 2017). Urbanisation influences energy demand by increasing the demand for housing, transport, and other publicly provided utilities; see Zhang et al. (2018). Urbanisation increases traffic due to industrial activity (Güneralp & Seto, 2008), puts pressure on the agricultural sector to produce more food for both rural and urban populations (Epstein & Jezeph, 2001; WHO, 2016), boosts commercialisation (McMichael, 2000; Song & Knaap, 2004), modifies the urban structure (Blonigen & Cristea, 2015; Güneralp & Seto, 2008), stimulates financial development, which encourages investment activities and industrialisation (Douglas et al., 2002; Güneralp & Seto, 2008), increases the demand for production materials, and stimulates the movement of labour from the countryside to the city (Douglas et al., 2002; Kamal-Chaoui & Robert, 2009; Rephann & Isserman, 1994) as it earnestly influences energy demand (Shahbaz et al., 2017). Fossil fuel energy consumption considerably increases carbon emissions in the atmosphere, causing numerous environmental hazards (Crist et al., 2017).

The Pollution Halo Hypothesis supports the transfer of greener and more sustainable technologies, such as pollution abatement, renewable energy, and energy conservation methods, to host countries. Duan and Jiang (2021) discovered that FDI often results in lower emissions in the receiving countries. Foreign direct investment (FDI) has a positive halo effect on the environment, as demonstrated by numerous studies (see, for instance, Chen et al., 2022; Cheng et al., 2020; Elliott & Zhou, 2013; Mahadevan & Sun, 2020; Zugravu-Soilita, 2017, among others). However, the so-called Pollution Haven Hypothesis posits that there is a positive relationship between FDI inflow and emissions because polluting industries tend to relocate productions from countries with more stringent environmental policies to countries with less stringent ones (see, for example, Bakhsh et al., 2017; Haug & Ucal, 2019; He, 2006; Lee & Brahmasrene, 2013, among others). Globally, the halo effect and the haven effect are frequently discovered simultaneously (Duan & Jiang, 2021).

### 2.2. Data sources and descriptive statistics

We use panel data spanning the years 1990 to 2019 and 2009 to 2019. Based on the availability of data on the studied series, these time periods were chosen for the study. Table A1 clarifies the series and their

measurement units, while Table 1 provides summary statistics for the variables. Table 1 indicates that Green Technologies had the highest mean value, followed by the quadratic term of Green Technologies, GDP growth, energy intensity, Green Innovation, urbanisation, the quadratic term of Green innovation, and foreign direct investment. Missing data were handled using multiple imputation techniques to avoid biases in the analysis. All transformations (logarithms) are described, and the data sources are included for reproducibility. Estimations were performed using Stata 18. Countries used in the study are grouped into developed and developing countries. The developed countries are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, and United States. Developing countries are Chile, Columbia, Costa Rica, Israel, Mexico, Albania, Algeria, Argentina, Azerbaijan, Bahamas, Bangladesh, Barbados, Brazil, Bulgaria, China, Croatia, Cuba, Ecuador, Egypt, Georgia, Ghana, India, Indonesia, Iran, Jordan, Kazakhstan, Kenya, Liechtenstein, Malaysia, Malta, Moldova, Monaco, Morocco, Nigeria, Pakistan, Panama, Peru, Philippines, Romania, Russia, Saudi Arabia, Singapore, South Africa, Sri Lanka, Thailand, Trinidad and Tobago, Tunisia, Ukraine, United Arab Emirates, Uruguay, Uzbekistan and Vietnam.

To shed light on our important variables, we observed that GDP growth has experienced an average rate of 1.48% per annum with a standard deviation of 1.41%. Both Green Technologies and Green Innovation have experienced average growth rates of 2.64% and 1.27% per annum with standard deviations of 1.14% and 1.60%, respectively. However, the Green Growth Index has shown a stronger increase over the period 2009 to 2019 with an average rate of 4.03% and a standard deviation of 0.19%. This finding suggests that a great deal of focus has been placed on green growth during the sample period and that there may have been substantial protection of natural capital, efficient and sustainable use of resources, social inclusion, and an increase in green technologies and innovations. The scatter plot in Figure 1 illustrates the relationship between green growth indicators and GDP growth rate from 1990 to 2019 as well as 2009 to 2019. During these periods, we observed that green growth indicators have strongly and positively influenced the GDP growth of our sample countries. This suggests that more green technologies and innovation, protection of natural capital, efficient and sustainable use of resources, and social inclusion have substantially explained positive variations in GDP growth over time.

### 2.3. Panel cross-sectional dependence tests

In any event when cross-sectional unit interdependence is ignored, the error term in a regression will exhibit cross-sectional dependence. The correlation between units violates the fundamental OLS assumption that the error term is independent and identically distributed (see Chudik & Pesaran, 2013, 2015). Cross-sectional dependence in the error term can lead to omitted variable bias or endogeneity, resulting in estimation inconsistencies; see also Pesaran (2015). Cross-sectional dependence can be calculated using the correlation between units. For example, unit $i$ and unit $j$ errors can be correlated. If the correlation is high,

**Table 1.** Descriptive statistics.

| 1990–2019 sample | Mean | Std. dev. | Min. | Max. | Obs. |
|---|---|---|---|---|---|
| GDP growth | 1.48 | 1.41 | −4.49 | 4.23 | 2550 |
| Green Technologies | 2.64 | 1.14 | 0.00 | 5.30 | 2550 |
| Green Innovation | 1.27 | 1.60 | 0.00 | 6.09 | 2550 |
| Urbanisation | 0.94 | 0.86 | −2.14 | 3.62 | 2550 |
| Energy intensity | 1.41 | 1.10 | 0.00 | 4.03 | 2550 |
| Foreign Direct Investment | 0.76 | 1.20 | −5.16 | 6.08 | 2550 |
| Green innovation[1] | 0.79 | 0.79 | 0.00 | 2.47 | 2550 |
| Green Technologies[2] | 1.51 | 0.59 | 0.00 | 2.30 | 2550 |
| 2009–2019 sample | Mean | Std. dev. | Min. | Max. | Obs. |
| GDP growth | 1.33 | 1.35 | −3.41 | 3.89 | 935 |
| Green growth Index | 4.03 | 0.19 | 3.48 | 4.35 | 935 |
| Urbanisation | 0.92 | 0.75 | −1.56 | 3.32 | 935 |
| Energy intensity | 2.04 | 0.55 | 0.00 | 3.77 | 935 |
| Foreign Direct Investment | 0.79 | 1.38 | −5.16 | 4.96 | 935 |

Note: Green innovation[1] and Green Technologies[2] denote the quadratic terms of green innovation per capita and green patents, respectively.

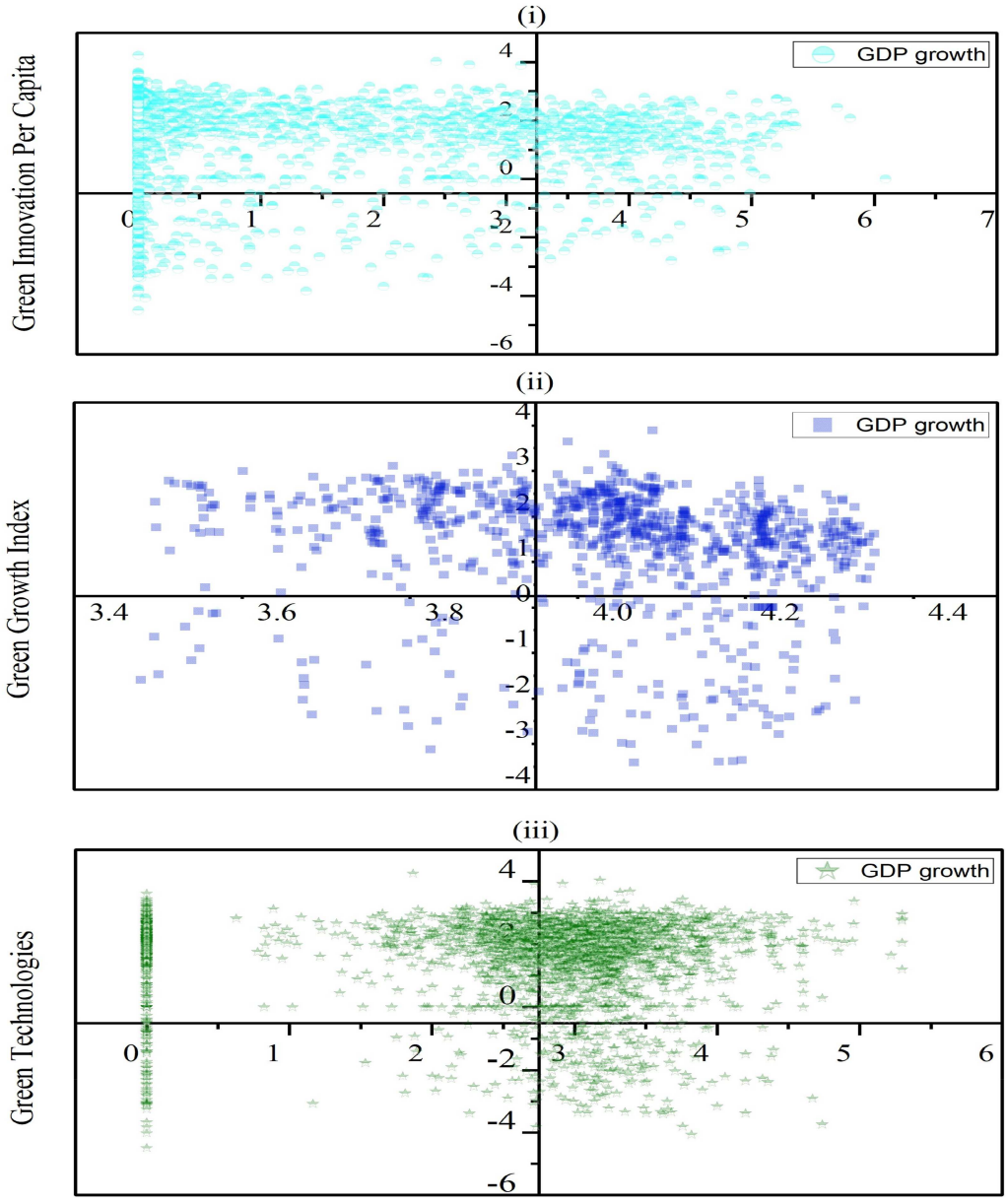


**Figure 1.** Scatter plot of green growth indicators and GDP growth. Note: In this figure, we present the scatter plots depicting the relationship between green growth indicators and GDP growth. Figure (i) illustrates the relationship between Green Innovation per capita and GDP growth for the period 1990 to 2019. Figure (ii) illustrates the relationship between Green Growth Index and GDP growth for the period 2009 to 2019. Figure (iii) illustrates the relationship between Green Technologies and GDP growth rate for the period 1990 to 2019. All variables are in their natural logarithm.

cross-sectional dependence is evident. The test for cross-sectional dependence identifies panel variables or residuals with weak cross-sectional dependence. We conducted this important test using the Cross-sectional Dependence (CD) from Pesaran (2015, 2021), the power-enhanced Cross-sectional Dependence (CDw+) from Fan et al. (2015), the CD* from Pesaran and Xie (2021), and the weighted Cross-sectional Dependence test (CDw) from Juodis and Reese (2022).

### *2.4. Panel slope heterogeneity*

Pesaran and Yamagata (2008) proposed the test for slope heterogeneity, which standardises Swamey's test for slope homogeneity under the assumption that all slope coefficients across cross-sectional units are

identical. However, if the homogeneous assumption is present in the proposed model, the test for slope heterogeneity appears to be reliable but may produce inefficient estimates. In contrast, if the proposed model contains slope heterogeneity, the homogeneous assumption may also result in biased and inconsistent estimates. In this context, the test for slope heterogeneity performs plausible and implicit estimates for the two hypotheses and compares them to determine the best option. Given that the unrestricted model relies on a cross-sectional unit-specific OLS regression model, i.e., the model under the alternative assumption, the restricted model relies on a weighted fixed-effects method, which supports the homogeneous slopes.

### 2.5. Panel unit root tests

To capture the stationarity of the series, we use Cross-sectional Augmented Dickey-Fuller (CADF) and Cross-sectional Im, Pesaran and Shin (CIPS) unit root tests that implement the t-test for unit roots in cross-sectionally dependent heterogeneous panels as demonstrated by Pesaran (2007). Comparable to the test proposed by Im et al. (2003), it relies on the average of the Dickey Fuller (DF) or Augmented Dickey Fuller (ADF) t-statistics for each unit in the panel. The null hypothesis assumes non-stationary series. To eliminate series dependence, Cross-sectional Augmented Dickey-Fuller (CADF) averages of lagged levels and first differences are used instead of DF or ADF regressions. A simplified CADF statistic with finite first and second order moments is also considered. Avoiding size distortions helps linear trend and residual serial correlation models; see Pesaran (2007). Contrary to the CADF, the CIPS has three deterministic specifications, and perhaps individual dynamic specifications are permitted. Under the three specifications, the CIPS unit root test allows models: (i) (i) without trends or intercepts; (ii) with incidental linear trends; and (iii) with individual-specific intercepts.

### 2.6. Panel Granger non-causality bias-corrected estimator

To estimate the causal relationship between GDP growth and green indicators, we employ the linear dynamic panel model below, which simplifies the Granger non-causality model, in accordance with Juodis et al. (2021):

$$y_{it} = \varnothing_{0,i} + \sum_{p=1}^{P} \varnothing_{p,i} y_{i,t-p} + \sum_{p=1}^{P} \beta_{p,i} x_{i,t-p} + \epsilon_{it}, \tag{4}$$

for all values of $i = 1,...,N$ and $t = 1,...,T$. It is assumed that $x_{i,\,t}$ is a scalar to avoid narrowing the scope of the discussion and to facilitate explanation. Individual-specific effects are denoted by $\phi_{0,i}$, error terms by $\epsilon_{i,\,t}$, heterogeneous autoregressive coefficients by $\phi_{p,\,i}$ where $p = 1,...,P$, and heterogeneous feedback coefficients by $\beta_{p,\,i}$ also known as Granger causality parameters. The constraint that $y_{it}$ has the same number of lags as $x_{i,\,t}$ has the advantage of requiring less computation when choosing a lag length. It is possible to formulate the null hypothesis that $x_{i,\,t}$ does not Granger-cause $y_{i,\,t}$ using linear bounds on the parameters in Equation (3):

$$H_0: \ \beta_{p,i} = 0, \ \text{for all } i \text{ and } p. \tag{5}$$

The alternate hypothesis could also be formulated as:

$$H_1: \beta_{p,i} \neq 0, \quad \text{for some } i \text{ and } p. \tag{6}$$

If the null hypothesis is not rejected, then it follows that $x_{i,\,t}$ does not Granger-cause $y_{i,\,t}$. The same holds true when $x_{i,\,t}$ is a $k \times 1$ vector of regressors consisting of a battery of relevant variables. In our empirical model, we denote $y_{i,\,t}$ as GDP growth and $x_{i,\,t}$ as green growth indicators, that is, green growth index, green innovation per capita, green technologies and other covariates such as urbanisation, foreign direct investment and energy intensity.

This new method for testing the null hypothesis of no Granger causality developed by Juodis et al. (2021) is applicable to models with heterogeneous or homogeneous coefficients. Their method is novel

because it assumes the Granger-causality parameters are homogeneous and equal to zero under the null hypothesis. A pooled fixed effects-type estimator can then be used for just these parameters, with the assurance of a convergence rate of $\sqrt{NT}$, where $N$ is the number of cross-sectional units in the panel and $T$ is the number of time-series observations. Dhaene and Jochmans (2015) Half Panel Jackknife (HPJ) method is used in their testing procedure to control for the so-called *Nickell bias* of the pooled estimator. The resulting method performs admirably under conditions that are important in the real world: a large number of cross-section units, a moderate time dimension, a wide variety of nuisance parameters, and a long persistence.

When compared to other methods, the Granger non-causality test has several benefits. Particularly when $T$ is even moderately large, the GMM approach of Holtz-Eakin et al. (1988) is not appealing. This is because the standard GMM-based inference is notoriously inaccurate when too many instruments are used; for examples, see Bun and Sarafidis (2015) and Juodis and Sarafidis (2022)'s remark 8. Furthermore, inferences may not be valid even asymptotically when feedback based on past own values is heterogeneous, i.e., the autoregressive parameters vary across individuals. Dumitrescu and Hurlin (2012) method, on the other hand, allows for a variety of slopes under both the null and alternative hypotheses, but their test statistic is only supported theoretically for sequences with $N/T^2 \to 0$. This means that this technique may experience severe size distortions when $T$ is significantly less than $N$, i.e., $T \ll N$. Juodis et al. (2021) conduct a lengthy Monte Carlo experiment to demonstrate that their method is more effective than that of Dumitrescu and Hurlin (2012). Xiao et al. (2023) acknowledged the test's multivariate applicability, robustness relative to homogeneous and heterogeneous alternatives, and support for cross-section dependence and cross-section heteroskedasticity, among other desirable characteristics. The Granger non-causality test is particularly suited for our study due to its robustness in handling cross-sectional dependence, as it rules out any form of cross-sectional correlations among the error terms and heteroskedasticity; its focus on uncovering causal relationships; and its efficiency in dealing with large N, small-to-moderate T datasets. These advantages make it a superior choice over GMM and traditional panel regression methods for achieving the objectives of our study.

In empirical application, several studies have utilised this method to investigate a wide range of topics, such as product services agglomeration and green economic development (see Du & Zhang, 2023), environmental policy stringency and financial development (see Hassan et al., 2025), among many others. To address potential endogeneity, we follow the control function approach (CFA) where we use common factors (residuals) as exogenous variables. This approach is in support of Breitung et al. (2024), Laage (2024), and Hoshino (2024). This paper identifies structural parameters in models with endogenous regressors by applying the CFA. In order to account for the dependence between the regressors and residual, conditional mean independence is the underlying assumption. However, because of the panel nature of the data, the precise assumption is different from standard CFA assumptions.

## 3. Empirical results

### 3.1. Panel cross-sectional dependence and slope heterogeneity

First, using the cross-sectional dependence tests listed in Table 2, dependencies in the residual terms were investigated. We find strong dependencies in the error terms. This discovery prompts the use of econometric techniques that could produce accurate results even in the presence of cross-sectional dependencies. Second, the slope heterogeneity test also shown in Table 2 was used to test the heterogeneity assumption. The slope coefficients were heterogeneous in nature, as revealed by the tests. The results of this test require the use of econometric techniques that could address the heterogeneity problem. Additionally, we endeavour to capture the heterogeneous nature of the sample by splitting into sub-samples for the estimations.

### 3.2. Panel unit root tests

Thirdly, in Table 3 we performed unit root tests to confirm the integration characteristics of the variables. Since we observe strong cross-sectional dependence in the error terms, it is essential to employ unit root

**Table 2.** Cross-sectional dependence and slope heterogeneity tests.

| Cross-sectional dependence | CD | CDw | CDw+ | CD* |
|---|---|---|---|---|
| GDP growth | 30.69*** | 0.08 | 830.43*** | 1.82 |
| Green Technologies | 27.92*** | −3.22*** | 689.05*** | 1.97** |
| Green Innovation | 173.08*** | −5.29*** | 3604.51*** | −2.11** |
| Urbanisation | 160.95*** | −4.93*** | 3351.90*** | 4.24*** |
| Energy intensity | 80.71*** | −3.54*** | 1679.74*** | −2.56** |
| Foreign Direct Investment | 77.27*** | −2.49** | 1662.49*** | 4.59*** |
| Green innovation$^2$ | 168.75*** | −5.08*** | 3514*** | 1.23 |
| Green Technologies$^2$ | 35.71*** | −3.20*** | 815.73*** | −0.59 |
| Slope Heterogeneity | Delta - M1 | *P*-value | Delta - M2 | *P*-value |
| | 12.28*** | 0.00 | 3.90*** | 0.00 |
| ~ | 12.82*** | 0.00 | 4.05*** | 0.00 |
| Δ adj. | | | | |

Note: Green innovation$^2$ and Green Technologies$^2$ denote the quadratic terms of green innovation per capita and green patents, respectively. Asterisk *** and *** represent 1% and 5% significance levels. M1 = Model without the quadratic terms. M2 = Model with the quadratic terms. Critical values: ± 1.645 = 10%, ± 1.96 = 5%, and ± 2.576 = 1% for slope heterogeneity.

**Table 3.** Panel unit root tests.

| Unit root tests | CIPS Levels | CIPS First difference | CADF Levels | CADF First difference |
|---|---|---|---|---|
| **Variables - M1** | | | | |
| GDP growth | −6.19*** | −6.19*** | −5.77*** | −6.19*** |
| Green Technologies | −6.19*** | −6.19*** | −5.91*** | −6.19*** |
| Green Innovation | −6.19*** | −6.19*** | −5.51*** | −6.19*** |
| Urbanisation | −6.19*** | −6.19*** | −5.89*** | −6.19*** |
| Energy intensity | −3.26*** | −3.26*** | −3.22*** | −3.26*** |
| Foreign Direct Investment | −6.19*** | −6.19*** | −5.94*** | −6.19*** |
| Green innovation$^2$ | −6.19*** | −6.19*** | −5.68*** | −6.19*** |
| Green Technologies$^2$ | −6.19*** | −6.19*** | −5.91*** | −6.19*** |
| **Variables – M2** | | | | |
| GDP growth | −6.19*** | −6.19*** | −5.73*** | −6.19*** |
| Green Growth Index | −6.19*** | −6.190*** | −6.18*** | −6.19*** |
| Urbanisation | −6.190*** | −6.190*** | −6.19*** | −6.19*** |
| Energy intensity | −6.19*** | −6.190*** | −6.00*** | −6.19*** |
| Foreign Direct Investment | −6.190*** | −6.190*** | −5.95*** | −6.19*** |

Note: Green innovation$^2$ and Green Technologies$^2$ denote the quadratic terms of green innovation per capita and green patents, respectively. Asterisk *** represent 1% significance levels. M1 = Model for 1990 to 2019 sample. M2 = Model for 2009 to 2019 sample. ***Critical values: −2.36 = 1%, −2.20 = 5%, and −2.11 = 10% for CIPS and CADF.***

approaches that can capture the interdependence of the units and demonstrate the actual stationarity of the panel data. Therefore, we used the CIPS and CADF unit root methods proposed by Pesaran (2007). All series gained stationarity at both levels and first difference, indicating that they could be cointegrated over the long term, as revealed by the tests. At 1% significance levels, we rejected the null hypothesis that states that all variables are not stationary. Our evidence suggests a strong order of integration of all the variables. Also, both our full and the later samples all exhibited a substantial level of integration and stationarity.

### 3.3. Correlations and multicollinearity tests

In Table 4, we illustrate correlations between the series. Urbanisation, energy intensity, and foreign direct investment all had significant positive correlations with the emergence of GDP growth, except for green technologies, which showed no significant correlation, whereas green innovation showed a negative and significant correlation with GDP growth. This suggests that as the series increased or decreased, so too did the effusions of GDP growth, and vice versa. In contrast to the scatterplot in Figure 1, it is evident that the relationship between green technologies, green innovations and GDP growth is heterogeneous, and perhaps the impact of green technologies and green innovations on GDP could vary among countries. This is notable and more prima facie evidence to assess the relationship between green technologies, green innovations and GDP growth, considering the heterogeneous nature of the countries in our sample. In conclusion, based on the correlation coefficients between the input variables, none of the covariates were affected by multicollinearity. This is subsequently substantiated by our variance inflation factor analyses displayed in the bottom part of Table 4 for both the full and later samples. According to the results, all the

**Table 4.** Correlations and multicollinearity tests.

| Correlations | GDP growth | Green Technologies | Green innovations | Urbanisation | Energy intensity | FDI |
|---|---|---|---|---|---|---|
| *Green Technologies* | 0.02 | 1 | | | | |
| *Green innovations* | –0.10*** | 0.17*** | 1 | | | |
| *Urbanisation* | 0.21*** | –0.05** | –0.22** | 1 | | |
| *Energy intensity* | 0.16*** | 0.24*** | 0.14*** | –0.02 | 1 | |
| *Foreign direct investment* | 0.05** | 0.10*** | 0.35*** | –0.05 | 0.18*** | 1 |
| ***Multicollinearity Test—M1*** | VIF | Tolerance | M2 | VIF | Tolerance | |
| *Green Technologies* | 1.22 | 0.82 | GGI | 1.38 | 0.72 | |
| *Green innovations* | 1.16 | 0.86 | --- | --- | --- | |
| *Urbanisation* | 1.09 | 0.92 | Urbanisation | 1.23 | 0.81 | |
| *Energy intensity* | 1.08 | 0.92 | Energy intensity | 1.09 | 0.92 | |
| *Foreign direct investment* | 1.05 | 0.95 | Foreign direct investment | 1.06 | 0.95 | |

Note: Asterisk *** and *** represent 1% and 5% significance levels. M1 = Model for 1990 to 2019 sample. M2 = Model for 2009 to 2019 sample. FDI = Foreign Direct Investment, Urban = Urbanisation. GGI = Green Growth Index.

**Table 5.** Granger non-causality univariate and common factor causalities - full sample.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Technologies | 0.16** | 0.06 | 2.47 | Accepted |
| **Optimal lag length = 4** | | | | |
| Dep. Var. = Green Technologies | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.27** | 0.10 | 6.64 | Accepted |
| **Optimal lag length = 15** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Technologies | 0.13** | 0.06 | 2.13 | Accepted |
| Common Factor | –0.15 | 0.11 | –1.37 | Rejected |
| **Optimal lag length = 4** | | | | |
| Dep. Var. = Green Technologies | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | –0.65 | 0.62 | –1.05 | Rejected |
| Common Factor | 1.60*** | 0.26 | 6.10 | Accepted |
| **Optimal lag length = 20** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Innovation | –0.19 | 0.10 | –1.88 | Rejected |
| **Optimal lag length = 27** | | | | |
| Dep. Var. = Green Innovation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.60** | 0.30 | 1.96 | Accepted |
| **Optimal lag length = 27** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Innovation | 0.04 | 0.07 | 0.06 | Rejected |
| Common Factor | –2.77*** | 0.30 | –9.23 | Accepted |
| **Optimal lag length = 20** | | | | |
| Dep. Var. = Green Innovation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 5.56*** | 1.17 | 4.74 | Accepted |
| Common Factor | –5.82*** | 0.16 | –36.60 | Accepted |
| **Optimal lag length = 20** | | | | |

Note: Asterisk ***, and *** represent 1%, and 5% significance levels. Univariate and bivariate causality models for 1990 to 2019 full sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

variables had tolerance levels greater than 0.20 and VIF values less than 5, indicating no evidence of multicollinearity.

### 3.4. Baseline results: Granger non-causality

After satisfying all the pre-tests to ensure the statistical reliability of our model and series, we begin our empirical analyses by first looking at the univariate Granger non-causal relationship between GDP growth and green technologies, as well as GDP growth and green innovation for our sample of 85 countries from 1990 to 2019. In each scenario, we evaluate the feedback relationship. Subsequently, we introduced the residuals (common factors) from a first-stage regression using the dynamic common correlated effect mean group estimator and included them in the respective models to critically assess their influences. This follows the control function approach to address potential endogeneity issues. When the coefficients of the residuals (common factors) exhibit significance, it indicates endogeneity and indicates that the estimated coefficients of the regressors are corrected for endogeneity. We present the findings in Table 5 for the full sample and Table A2 for advanced economies and Table A3 for emerging/developing economies, respectively. Our evidence suggests that green technologies and GDP growth have a bidirectional

Granger causal relationship, implying that there is a feedback effect of both at 5% significance levels with optimal lag lengths of 4 and 15, correspondingly. However, green technologies are directly and substantially linked with GDP growth and vice versa. By contrast, we observed that green innovation per capita has no substantial influence on GDP growth since we could not find any significant Granger causal relationship between them with an optimal lag length of 27.

On the other hand, we find that GDP growth unidirectionally Granger causes green innovation per capita at a 5% significance level. As it is assumed that unobserved common factors are likely to influence the relationship between GDP growth and the other variables, which could statistically and potentially cause omitted variable bias and produce unreliable estimates, we, however, employed Ditzen et al. (2022)'s method for identifying the unobserved common factors. In these episodes, we observed that there seem to be common factors that could influence GDP growth to not Granger-cause green technologies whilst the common factors do not influence green technologies to Granger-cause GDP growth with optimal lag lengths of 4 and 20, respectively. This implies that even with the existence of unobserved common factors, green technologies proportionally and significantly Granger cause GDP growth. Contrary to this, we observed that green innovation per capita's relationship with GDP growth is likely to be influenced by unobserved common factors with an optimal lag length of 27. Our evidence suggests that the common factors adversely influence green innovation per capita not to significantly Granger-cause GDP growth.

Furthermore, we applied similar assumptions to our samples of advanced and emerging/developing economies. Green technologies and green innovation per capita have bidirectional or feedback relationships with GDP growth in advanced economies. Our evidence suggests that GDP growth has a positive, direct, and substantial Granger causal relationship with green technologies. Green technologies, on the other hand, adversely Granger-cause GDP growth at a 5% significance level with an optimal lag length of 10. Meanwhile, we observed that both green innovation and GDP growth adversely and substantially Granger cause each other at 5% significance levels with an optimal lag length of 10. It is important to highlight that unobserved common factors are substantially influential, as they are likely to cause green technologies to Granger-cause GDP growth, whereas they influence green innovation per capita to not Granger-cause GDP growth with an optimal lag length of 7. We present the outcome in Table A2. Meanwhile, in emerging/developing economies, both green technologies and green innovation per capita do not have a direct and substantial Granger causal relationship with GDP growth, but GDP growth unidirectionally Granger causes both at 5% significance levels; see Table A3.

More importantly, it is crucial to emphasise that common factors are probably substantial in assessing the relationship between green growth indicators and GDP growth and cannot be ignored. Therefore, it is pertinent to comprehend some covariates that are likely to influence these relationships. This is evident in our preceding analyses which illuminated the importance of common factors.

Assessing whether GDP growth and other covariates have bidirectional or unidirectional causal relationships is the next step of the Granger non-causality estimations. Chudik and Pesaran (2015) show that when dealing with panel data with cross-sectional dependence, there seems to be a high rate of consistency and an asymptotic distribution. So, it is important to use covariates to account for the effects of multiple unobserved common factors and to consider jackknife as well as recursive de-meaning bias correction processes to mitigate the small-sample time series bias. The other covariates that we consider in this context are energy intensity, urbanisation, and foreign direct investment combined with green growth indicators such as environmental-related technologies' patents proxied by green technologies and green innovations per capita proxied by green innovation. We assessed the two-way causal effects of all the variables, treating each variable as a dependent variable. First, we examined the Granger non-causality relationship between GDP growth and green technologies/innovation indicators, considering the mechanisms of energy intensity, urbanisation, and foreign direct investment. Throughout our analyses for the full sample, we allow for a maximum of 20 lags between the dependent variables and the covariates. We chose 12 lags based on Bayesian Information Criteria values, which suggested the optimal lag length.

We present the outcome of the Granger non-causality estimations for our full sample in Table 6. We modelled GDP growth against green technologies, green innovations, energy intensity, urbanisation, and foreign direct investment. Our evidence suggests that the null hypothesis that the variables do not Granger cause GDP growth is rejected at 5% significance levels for green technologies, urbanisation, and energy intensity. However, we find that both green innovation and foreign direct investment do not Granger

**Table 6.** Granger non-causality - full sample multivariate causalities.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Technologies | 0.310** | 0.127 | 2.44 | Accepted |
| Green Innovation | −0.062 | 0.101 | −0.61 | Rejected |
| Urbanisation | −0.327** | 0.132 | −2.46 | Accepted |
| Energy intensity | 0.849*** | 0.162 | 5.23 | Accepted |
| Foreign Direct Investment | 0.203 | 0.138 | 1.47 | Rejected |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green Technologies | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.341*** | 0.079 | 4.28 | Accepted |
| Green Innovation | 0.055 | 0.084 | 0.66 | Rejected |
| Urbanisation | −1.130*** | 0.139 | −8.11 | Accepted |
| Energy intensity | −0.506*** | 0.122 | −4.13 | Accepted |
| Foreign Direct Investment | −0.110 | 0.135 | −0.82 | Rejected |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green Innovation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.293*** | 0.060 | 4.92 | Accepted |
| Green Technologies | 0.137 | 0.082 | 1.66 | Rejected |
| Urbanisation | −0.327*** | 0.063 | −5.18 | Accepted |
| Energy intensity | −2.922*** | 0.147 | −19.89 | Accepted |
| Foreign Direct Investment | 0.452*** | 0.112 | 4.02 | Accepted |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Urbanisation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.013 | 0.052 | 0.26 | Rejected |
| Green Technologies | 0.031 | 0.034 | 0.90 | Rejected |
| Green Innovation | −0.890*** | 0.026 | −34.80 | Accepted |
| Energy intensity | 3.345*** | 0.059 | 56.40 | Accepted |
| Foreign Direct Investment | 0.104 | 0.099 | 1.05 | Rejected |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Foreign Direct Invest | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.058 | 0.123 | −0.48 | Rejected |
| Green Technologies | −0.039 | 0.119 | −0.33 | Rejected |
| Green Innovation | 0.776*** | 0.221 | 3.50 | Accepted |
| Urbanisation | −0.350 | 0.185 | −1.89 | Rejected |
| Energy intensity | −3.309*** | 0.170 | −19.50 | Accepted |
| **Optimal lag length = 12** | | | | |

Note: Asterisk *** and ** represent 1%, and 5% significance levels. Multivariate causality models for 1990 to 2019 full sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

cause GDP growth. In this regard, the null hypothesis is therefore accepted. The test results also validate the variables' regression outcomes by the Half-panel Jackknife (HPJ) bias-corrected pooled estimator, allowing us to comprehend the variables' determinants.

According to the results, green technologies, urbanisation, and energy intensity significantly drive GDP growth. In contrast, we find that the relationship between GDP growth and green technologies is bidirectional, as evidenced by two-way Granger causality between them, indicating a feedback effect. Meanwhile, we find that a unidirectional Granger causality of GDP growth on green technologies and green innovation in a substantial manner. This suggests that only GDP growth can explain variations in green technologies and green innovation, but not the other way around. Based on the results, we argue that the historical values of green technologies, energy intensity, and urbanisation contain information that could be used to predict GDP growth in addition to the information contained in the historical values of GDP growth. Moreover, according to our green growth indicators, only green technologies drive GDP growth, whereas green innovation has no effect for our full sample. To account for the drivers of green technologies and green innovation, we observed that energy intensity and urbanisation, apart from GDP growth, drive green technologies, whereas foreign direct investment, energy intensity and urbanisation drive green innovation.

Further, we divide our sample into advanced and emerging/developing economies due to the sample's slope heterogeneity. Based on the IMF's classification of advanced, emerging, and developing economies, the clustering is performed. We present our findings in Table A4 for advanced economies and Table A5 for emerging and developing economies, respectively. We find that in advanced economies, green technologies, green innovations, urbanisation, and energy intensity Granger-cause GDP growth at 5% significance levels except foreign direct investment, which does not Granger-cause GDP growth. More importantly, all causal relationships are bidirectional. This indicates that GDP growth and green growth indicators have

feedback effects, as their historical data can significantly aid in predicting the future values of each indicator. Throughout our analyses for the advanced economies' sample, we allow for a maximum of 12 lags between the dependent variables and the covariates. We chose 4 lags based on Bayesian Information Criteria values, which suggested the optimal lag length. To account for the drivers of green technologies and green innovation in advanced economies, we observed that aside from GDP growth, energy intensity, green innovation and urbanisation drive green technologies, whereas only urbanisation and energy intensity drive green innovation; see Table A4 for more details.

Similarly, we assessed the scenarios in emerging and developing economies as depicted in Table A5. Our evidence suggests that green innovation and energy intensity Granger-cause GDP growth at 5% significance levels. By contrast, GDP growth, green innovation, urbanisation, energy intensity and foreign direct investment significantly drive and perhaps Granger-cause green technologies. We observed that urbanisation, energy intensity and foreign direct investment substantially Granger-cause green innovation. Moreover, we only find a bidirectional causal relationship among green technologies, green innovation, and urbanisation. However, GDP growth unidirectionally Granger-causes urbanisation, green technologies, and foreign direct investment. Throughout our analyses for the emerging and developing economies' sample, we allow for a maximum of 12 lags between the dependent variables and the covariates. We chose 7 lags based on Bayesian Information Criteria values, which suggested the optimal lag length.

### 3.5. Discussion

Our results provide important insights into the relationship between green technologies, green innovation, and GDP growth, revealing both significant findings and regional heterogeneity that align with theoretical expectations and previous empirical work. One of the most significant findings is the bidirectional Granger causality between green technologies and GDP growth. This suggests that not only do green technologies contribute to economic growth, but economic growth also drives further investment in green technologies. This finding highlights a virtuous cycle where investments in green technologies—such as renewable energy and energy-efficient innovations—not only generate direct economic benefits but also create the conditions for further technological advancements as economies grow. This aligns with Romer's endogenous growth theory, where technological innovation is both a cause and consequence of growth. As countries expand economically, they have more resources to allocate to research and development in green technologies, further enhancing productivity and economic output.

The core question seeks to determine whether green technologies drive GDP growth or if economic growth incentivises green investments. This bidirectional result suggests that both dynamics are at play, implying that policies aimed at fostering green technology can be self-reinforcing. This has important policy implications, as governments should not only focus on encouraging green innovation but also create the macroeconomic conditions (e.g., stable growth and investment incentives) that further spur technological progress. While green technologies exhibit a bidirectional relationship with GDP growth, our results show a unidirectional Granger causality from GDP growth to green innovation per capita. This suggests that, unlike green technologies, green innovation in terms of patents and new environmental technologies is predominantly driven by economic growth rather than being a direct cause of growth itself. This result indicates that green innovation, particularly in developed economies, may be seen as a byproduct of economic prosperity. Countries with higher GDP growth tend to invest more in research and development, which leads to an increase in green patents and innovations. However, the reverse does not hold—innovations themselves do not directly stimulate growth in the short term, potentially due to the long lead times required for these innovations to translate into widespread economic gains.

This finding nuances our understanding of the relationship between green innovation and GDP. While innovation is crucial for long-term growth, its immediate impact on GDP may be limited, especially in advanced economies where innovations often require significant time and capital investment to scale. This highlights the need for policies that bridge the gap between innovation and economic implementation, ensuring that the innovations created through research are quickly translated into growth-enhancing technologies. The analysis reveals significant regional heterogeneity in the relationship between green technologies and GDP growth. In emerging and developing economies, green technologies strongly

contribute to GDP growth. However, in advanced economies, this relationship is more complex and sometimes negative due to the high costs of transitioning to green technologies.

This result underscores the different stages of economic and technological development across countries. In emerging economies, green technologies provide immediate growth opportunities by improving energy efficiency, reducing costs, and opening new markets. However, in advanced economies, the transition costs—such as compliance with stricter environmental regulations and the replacement of established energy systems—may initially outweigh the economic benefits, leading to slower growth or even temporary declines.

The research question asks whether green technologies contribute to growth, and this finding suggests that the answer depends on a country's stage of development. For emerging economies, green technologies represent an untapped resource for rapid economic expansion. For developed economies, the benefits are more long-term, with short-term costs potentially slowing immediate growth. This reinforces the importance of region-specific policies that recognise the different economic realities of green technology adoption.

Our results show that energy intensity and urbanisation are significant drivers of GDP growth, particularly in emerging and developing economies. Energy intensity, which measures the amount of energy consumed per unit of GDP, is crucial for understanding how efficiently economies use energy to produce output. A decrease in energy intensity, driven by the adoption of green technologies, directly contributes to economic growth by lowering energy costs and improving resource efficiency. Urbanisation, which tends to increase demand for infrastructure, housing, and services, also drives growth by creating new economic opportunities, especially in rapidly developing regions. The inclusion of energy intensity and urbanisation in the analysis helps contextualise the role of green technologies within broader economic trends. In countries where urbanisation is accelerating and energy intensity is high, green technologies play a crucial role in reducing energy consumption and enhancing economic efficiency. This suggests that green growth policies should be closely integrated with urbanisation strategies, ensuring that cities are built with sustainability and energy efficiency in mind.

In advanced economies, the impact of green innovation on GDP growth is less pronounced, with some results suggesting that the short-term costs of transitioning to green technologies—such as compliance with environmental regulations and the need for infrastructure upgrades—can dampen economic growth. This finding highlights the transitional nature of green innovation in advanced economies. While long-term gains from green technologies are likely, the short-term costs of adopting new technologies, particularly in heavily industrialised countries, may reduce immediate economic output. This result supports Nordhaus (2018) framework, which emphasises the need for government intervention to manage the short-term costs of environmental policies while ensuring long-term economic benefits.

This finding refines the answer to the research question by suggesting that while green technologies contribute to GDP growth, the timing of their impact varies between advanced and emerging economies. Policymakers in advanced economies need to consider the short-term economic trade-offs of green transitions and design policies that mitigate these initial costs, such as subsidies for green investments or incentives for businesses to adopt new technologies more rapidly.

Overall, our results provide strong evidence that green technologies and innovation play a critical role in driving GDP growth, but their impact is not uniform across regions or economic contexts. The findings underscore the importance of region-specific policies that account for both the benefits and costs of green growth. In emerging economies, green technologies offer immediate growth opportunities, while in advanced economies, the short-term costs must be managed to unlock long-term economic benefits. These results are significant in informing policymakers on how to design effective green growth strategies tailored to the specific economic and technological conditions of their countries.

We find compelling evidence that indicators of green growth, such as efficient and sustainable use of resources, green technologies, green innovation per capita, protection of natural capital, green economic opportunities, and social inclusion, are major contributors to GDP growth, in support of Ekins (2002), Hackett and Dissanayake (2014), OECD (2011a), and Song et al. (2019). However, the association between green growth indicators and GDP growth appears to be region-specific. Some factors appear to be common between developing and emerging economies, with green technologies having a significant impact on GDP growth. These factors are energy intensity and green innovation per capita. Consistent

with our findings, Du and Zhang (2023) conclude that in emerging and developing economies such as China, green technologies promote green economic development, which is aided by stringent product-service agglomeration-based environmental policy. In advanced economies, green innovation per capita, urbanisation, and energy intensity negatively impact GDP growth; urbanisation significantly and positively influences the negative impact of green technologies on GDP growth, whereas in emerging and developing economies, energy intensity positively drives green technologies to impact GDP growth.

Frequently, industries in advanced economies employ obsolete practices that contribute to environmental degradation; see Hart and Milstein (2003), Mol and Sonnenfeld (2000), Porter and Kramer (2018) and My Thi Thi and Tran Phu Do (2024). To transition to green innovation, substantial funds must be invested in the research, development, and implementation of modern technologies and procedures (see also Duque-Grisales et al. (2020) and Irfan et al. (2022)). During this period of transition, companies in these industries may experience higher costs, lower profits, and decreased competitiveness relative to their counterparts in nations with less stringent environmental regulations (Hallegatte et al., 2012; Jaffe et al., 2005). Exports, employment, and investment, all of which contribute to GDP growth, may be affected. Examples of common green innovations include renewable energy sources and energy-efficient technologies. These may have higher initial costs than conventional energy options, but they pay for themselves in the long run (Hallegatte et al., 2012). Developed nations are typically subject to stricter environmental regulations and compliance requirements. Although these measures are necessary for addressing environmental issues, they can place a disproportionate financial and administrative burden on businesses, particularly small and medium-sized enterprises; see, for example, Duque-Grisales et al. (2020), Hart and Milstein (2003), Irfan et al. (2022), and Jaffe et al. (2005), among many others. Compliance expenses may have a short-term negative impact on GDP if they inhibit business expansion and investment.

## 4. Conclusion

This research extensively explores the relationship between green technologies and innovation indicators. green growth indicators and GDP growth by applying a novel Granger non-causality estimator that has the statistical strength of dealing with cross-sectional dependence, cross-sectional heterogeneity, and cross-sectional heteroskedasticity. The sample for the study spans the years 1990 to 2019 and 2009 to 2019 for 85 countries.

Overall, we find compelling evidence that green indicators, such as efficient and sustainable resource use, green technologies, green innovation per capita, natural capital protection, green economic opportunities, and social inclusion, are significant GDP growth drivers. However, regional heterogeneity appears to exist in the relationship between green growth indicators and GDP growth. Green technologies appear to have a substantial impact on the GDP growth of emerging and developing economies as a result of some factors in common, most likely energy intensity and green innovation per capita. In advanced economies, green innovation per capita, urbanisation, and energy intensity negatively impact GDP growth; urbanisation significantly and positively influences the negative impact of green technologies on GDP growth, whereas in emerging and developing economies, energy intensity positively drives green technologies to impact GDP growth.

To account for the drivers of green technologies and green innovation, we observed that energy intensity and urbanisation, apart from GDP growth, drive green technologies, whereas foreign direct investment, energy intensity and urbanisation drive green innovation. In addition, we find that the green growth index and GDP growth are bidirectionally related in both advanced and emerging/developing economies, but the signs of the relationship differ: positive in advanced economies, which is not significantly caused by covariates, and negative in emerging/developing economies, which is significantly caused by energy intensity.

### *4.1. Theoretical implication*

Romer's endogenous growth theory emphasises that technological innovation is a key driver of sustained economic growth. According to Romer (1992), investments in knowledge, research, and development generate positive externalities that fuel long-term economic expansion. This is particularly relevant in the

context of green technologies, where innovations aimed at improving energy efficiency, reducing emissions, and promoting sustainable practices can lead to broader economic benefits by enhancing productivity and creating new markets. Romer's model suggests that the more a country invests in innovation—particularly in green technologies—the more it will experience growth due to the spillover effects of these innovations.

Our findings largely align with Romer's theory, particularly in the case of emerging economies, where green technologies were shown to have a significant and positive impact on GDP growth. This supports the idea that technological advancements in green innovation drive economic growth, as they help reduce the negative externalities associated with environmental degradation while also enhancing production efficiency. The feedback loop observed between GDP growth and green technologies in our analysis suggests that as countries grow, they are more likely to invest in green innovation, which in turn stimulates further economic growth. This bidirectional relationship reinforces Romer's claim that innovation is both a cause and a consequence of growth.

However, our results diverge from Romer's theory when examining the impact of green innovation in advanced economies. In these countries, we observed a more complex relationship, where green innovation did not consistently lead to GDP growth. This could be attributed to the high initial costs associated with transitioning to green technologies, particularly in industries that are deeply embedded in traditional energy-intensive practices. These costs, which include compliance with stricter environmental regulations, can temporarily dampen economic growth—a scenario not fully accounted for in Romer's model, which assumes that innovation always results in positive externalities without considering the transitional costs.

Nordhaus (1974, 2018) work on the economics of climate change, particularly his focus on the trade-offs between economic growth and environmental protection, provides a useful framework for interpreting these findings. Nordhaus emphasises that while technological progress is essential for mitigating the effects of climate change, it also requires substantial government intervention, such as carbon pricing and subsidies for green technologies, to correct market failures. His model highlights the tension between short-term economic costs and long-term environmental and economic benefits.

Our findings align with Nordhaus's theory in that they show how government policies—particularly those promoting green innovation—can lead to long-term sustainable growth, but not without short-term challenges. For instance, the negative or weaker correlation between green innovation and GDP growth in advanced economies may reflect the high compliance costs associated with stringent environmental regulations. These costs, consistent with Nordhaus's view, could temporarily slow down growth, particularly in the early stages of transitioning to green technologies. This suggests that while innovation is crucial for addressing environmental externalities, the economic benefits may not be immediate, particularly in highly regulated environments.

In summary, our findings support Romer's assertion that innovation drives growth, especially in emerging economies where green technologies provide immediate economic benefits. However, our results also highlight the nuances of Nordhaus's work, showing that in advanced economies, the short-term costs of adopting green technologies—such as compliance with regulations—can temper the immediate growth effects, even though the long-term outlook remains positive. This underscores the importance of well-designed government interventions that support green innovation while mitigating the transitional economic costs.

### 4.2. Future research direction

The study also identifies key areas for future research, particularly the need for long-term policy frameworks that foster innovation in developing economies. Future research could investigate how different sectors, such as energy, manufacturing, and transportation, specifically benefit from green technologies and innovations. This would provide more granular insights into the industries that drive the overall impact of green growth on GDP. Given that the study finds a delayed or less immediate effect of green innovation on GDP, future research could explore the long-term impact of green innovations, especially in advanced economies. This could involve examining a longer time horizon to capture the full benefits of green innovation adoption. We also urge future researchers to conduct a comparative study on policy interventions, such as investigating the effectiveness of different green growth policies (e.g., subsidies,

carbon taxes, and R&D incentives) across various regions. Comparative studies could analyse how policy frameworks affect the adoption of green technologies and their impact on economic growth. With the rise of green finance instruments, future research could explore how financial tools like green bonds, carbon credits, and sustainable investments influence the development and diffusion of green technologies and their economic impacts. Future research could focus on how green technology spillovers between countries influence GDP growth, particularly in the context of international trade and foreign direct investment (FDI). This would provide insights into the global diffusion of green technologies and their role in shaping economic growth patterns across borders.

### 4.3. Limitations of the study

1. The study relies on data from 1990–2019 and 2009–2019, covering 85 countries. While this provides a broad perspective, certain countries or regions with limited data availability may not be adequately represented. This could limit the generalisability of the findings to countries with more robust data systems.
2. The use of green patents per capita as a proxy for green innovation may not capture the full spectrum of green technological advancements, particularly in countries where innovation occurs but is not formally patented. Alternative measures of innovation might yield different results.
3. The study primarily focuses on the short- to medium-term impact of green technologies and innovation on GDP growth. It may not fully capture the long-term benefits of green innovation, particularly for advanced economies, where the adoption of green technologies may involve upfront costs but yield significant future economic gains.
4. While the study accounts for regional differences, the results may still mask substantial heterogeneity within regions or countries. Factors such as local policy environments, economic structures, and stages of technological development could influence how green technologies affect GDP growth, making it difficult to generalise the findings across all countries.

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The authors declare no competing interest.

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## Appendix

### *Brief literature review*

The relationship between development and the environment became more intense as the global population approached 8 billion; see Chamie (2023). Air and marine pollution, global warming, resource depletion, and biodiversity destruction have risen to the surface and irreparably hampered human society's development, impeding the advancement of sustainable development; see also Crist et al. (2017). Environmental protection is a critical component of sustainable development, which emphasises the coexistence of human society and nature (Ruggerio, 2021). How can we achieve the Sustainable Development Goals (SDGs) while maintaining a rapid rate of development that is environmentally friendly? This is a contentious issue among academics. According to Jaffe et al. (2005), the adoption of green technology is critical for the long-term development of society as a whole. With reference to Faucheux and Nicolaï (2011), green innovation is an innovative means of lessening the environmental burden and contributing to the advancement of a given sustainable goal. In order to ensure that natural resources continue to provide the resources and environmental services that are essential to our well-being, green growth aims to promote economic growth and development. To achieve this, it must stimulate investment and innovation, which is likely to support long-term growth and create fresh economic opportunities, see OECD (2011b, 2017).

Prior study identified green innovation as one of the most important strategies for the development of harmony between humans and the natural world, summing it up as six pursuits. The authors emphasised that: (i) products, processes, and methods are examples of innovation objects; (ii) market orientation, which emphasises satisfying consumer needs and maintaining a competitive edge; (iii) ecological considerations, which emphasise minimising any negative impact for which there is no theoretical guidance; (iv) considering the big picture reduce material flow; (v) motivating factor: the objective of reducing emissions for economic or environmental reasons; and (vi) green

technologies and innovation standards for businesses are enhanced.[1] Green innovation will be a key factor in future economic growth (Song et al., 2019).

Green innovation utilises green-related technologies to conserve energy, prevent and control pollution, recycle waste, and create environmentally friendly products (Chen et al., 2006; Luo et al., 2022).

Hickel and Kallis (2020) argue that (i) complete decoupling from carbon emissions is extremely unlikely to be achieved at a rate fast enough to keep global warming from exceeding 1.5 °C or 2 °C, even under positive policy conditions, and (ii) there is no direct evidence that unconditional decoupling from resource use can be achieved on a global scale against the backdrop of continued economic growth. In addition, they contend that the objective of green growth is likely misguided and that policymakers should consider other options as well. Jaffe et al. (2005) stressed that in the event of inadequate or ineffective environmental policies, it is highly probable that investments in the creation and adoption of new environmentally friendly technologies will be significantly less than what would be deemed socially acceptable. Information issues and beneficial knowledge as well as adoption spillovers have the potential to further erode innovation's incentives. Meanwhile, Du et al. (2021) emphasised that environmental regulation will substantially encourage the development of green technologies and the improvement of industrial structures when economic development levels are typically high. Consequently, environmental regulation can contribute to the greening of the economy in two ways: the development of new environmentally friendly technologies and the improvement of industrial structure.

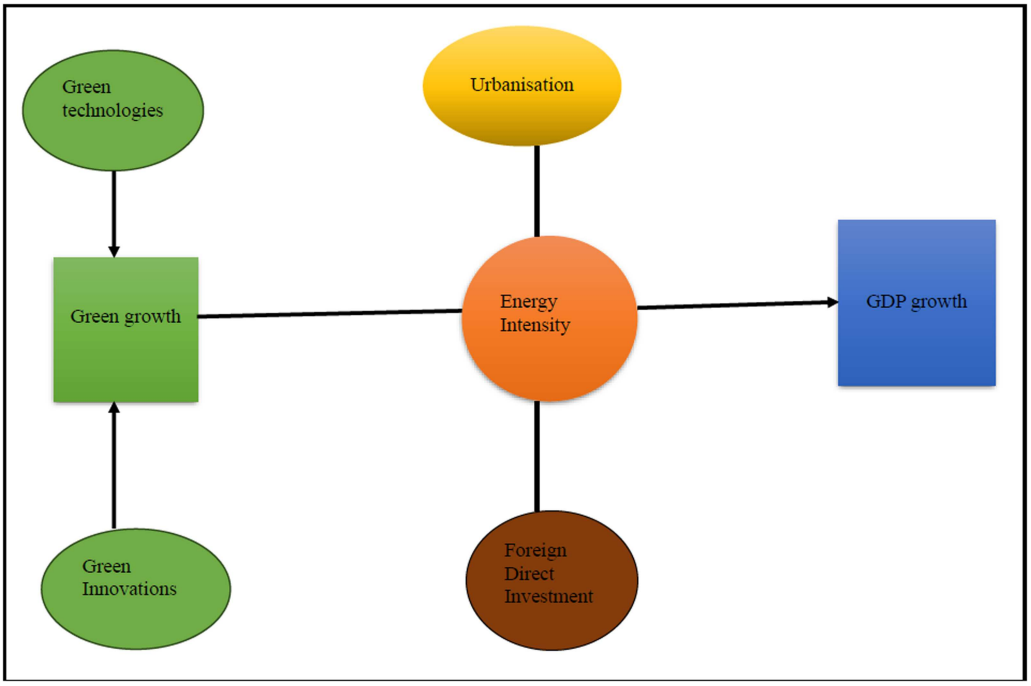


**Figure A1.** The causal relationship between green technologies, green innovations, foreign direct investment, energy intensity, urbanisation, and GDP growth.

[1] Schiederig et al. (2012) explored the literature on green innovation and innovation management. The authors understand that the terms environmental, eco/ecological, and green innovation are all being used interchangeably.

## Appendix A: Supplementary Results

**Table A1.** Variables and data sources.

| Variables | Units of Measurement/code | Sources |
|---|---|---|
| Green Technologies | Number of environmental-related patent registrations DSD_PAT_IND@DF_PAT_IND | OECD statistics Database |
| Green Innovation | Number of environmental-related patent registration, share of population DSD_PAT_IND@DF_PAT_IND | OECD statistics Database |
| Urbanisation | Urban population growth rate, % share of total population SP.URB.TOTL.IN.ZS | World Development Indicators, World Bank |
| Energy Intensity | Energy intensity level of primary energy (MJ/$2017 PPP GDP) EG.EGY.PRIM.PP.KD | World Development Indicators, World Bank |
| Foreign Direct Investment | Foreign Direct Investment inflows, % share of GDP BX.KLT.DINV.WD.GD.ZS | World Development Indicators, World Bank |
| Green Innovation$^2$ | Quadratic term of Number of environmental-related patent registration, share of population | Authors' calculation |
| Green Technologies$^2$ | Quadratic term of Number of environmental-related patent registration, % share of population | Authors' calculation |
| Green Growth Index (GGI) | Scores for the Green Growth Index range from 1 to 100. It is a composite measure of green economic opportunities, natural capital protection, efficient and sustainable resource use, and social inclusion. Includes 37 environmental and growth-induced variables. | Green Growth Institute. Available at: https://gggi-simtool-demo.herokuapp.com/ |

**Table A2.** Granger non-causality univariate and common factor causalities - advanced.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Technologies | −0.97** | 0.41 | −2.36 | Accepted |
| **Optimal lag length = 10** | | | | |
| Dep. Var. = Green Technologies | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.60** | 0.22 | 2.73 | Accepted |
| **Optimal lag length = 10** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Technologies | −1.85*** | 0.30 | −6.32 | Accepted |
| Common Factor | −3.63*** | 0.43 | −8.44 | Accepted |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Green Technologies | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −4.72*** | 0.30 | −15.74 | Accepted |
| Common Factor | 5.37*** | 0.26 | 20.68 | Accepted |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Innovation | −1.38*** | 0.40 | −3.52 | Accepted |
| **Optimal lag length = 10** | | | | |
| Dep. Var. = Green Innovation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −2.35*** | 0.41 | −5.71 | Accepted |
| **Optimal lag length = 10** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Innovation | 0.09 | 0.22 | 0.42 | Rejected |
| Common Factor | −4.81*** | 0.31 | −15.74 | Accepted |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Green Innovation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −2.99*** | 0.52 | −5.74 | Accepted |
| Common Factor | 4.30*** | 0.41 | 10.52 | Accepted |
| **Optimal lag length = 7** | | | | |

Note: Asterisk *** and ** represent 1% and 5% significance levels. Univariate and bivariate causality models for 1990 to 2019 advanced economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A3.** Granger non-causality univariate and common factor causalities - emerging/developing.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Technologies | −0.33 | 0.52 | −0.64 | Rejected |
| **Optimal lag length = 17** | | | | |
| Dep. Var. = Green Technologies | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.93** | 0.32 | 2.89 | Accepted |
| **Optimal lag length = 17** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Technologies | 0.21 | 0.23 | 0.91 | Rejected |
| Common Factor | 37.88*** | 0.51 | 73.61 | Accepted |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green Technologies | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 27.09*** | 0.64 | 42.37 | Accepted |
| Common Factor | −22.56*** | 0.27 | −83.97 | Accepted |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Innovation | 0.74 | 0.43 | 1.72 | Rejected |
| **Optimal lag length = 17** | | | | |
| Dep. Var. = Green Innovation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.55*** | 0.10 | 5.56 | Accepted |
| **Optimal lag length = 17** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Innovation | 4.58*** | 0.20 | 22.65 | Accepted |
| Common Factor | 20.37*** | 0.42 | 48.66 | Accepted |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green Innovation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −2.13*** | 0.28 | −7.56 | Accepted |
| Common Factor | 3.62*** | 0.12 | 29.09 | Accepted |
| **Optimal lag length = 12** | | | | |

Note: Asterisk *** and ** represent 1% and 5% significance levels. Univariate and bivariate causality models for 1990 to 2019 emerging/developing economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A4.** Granger non-causality - advanced.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Technologies | −0.505*** | 0.097 | −5.20 | Accepted |
| Green Innovation | −0.221** | 0.074 | −2.97 | Accepted |
| Urbanisation | 0.456*** | 0.122 | 3.75 | Accepted |
| Energy intensity | −3.042*** | 0.176 | −17.33 | Accepted |
| Foreign Direct Investment | 0.045 | 0.172 | 0.26 | Rejected |
| **Optimal lag length = 4** | | | | |
| Dep. Var. = Green Technologies | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.058** | 0.029 | −1.97 | Accepted |
| Green Innovation | 0.045** | 0.017 | 2.61 | Accepted |
| Urbanisation | −0.129** | 0.041 | −3.13 | Accepted |
| Energy intensity | −0.137** | 0.052 | −2.62 | Accepted |
| Foreign Direct Investment | 0.007 | 0.009 | 0.75 | Rejected |
| **Optimal lag length = 4** | | | | |
| Dep. Var. = Green Innovation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.379*** | 0.084 | −4.52 | Accepted |
| Green Technologies | 0.016 | 0.119 | 0.13 | Rejected |
| Urbanisation | −0.665*** | 0.140 | −4.75 | Accepted |
| Energy intensity | 7.858*** | 0.142 | 55.17 | Accepted |
| Foreign Direct Investment | 0.091 | 0.130 | 0.70 | Rejected |
| **Optimal lag length = 4** | | | | |
| Dep. Var. = Urbanisation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.151** | 0.061 | −2.46 | Accepted |
| Green Technologies | 0.246 *** | 0.045 | 5.88 | Accepted |
| Green Innovation | −0.508*** | 0.053 | −9.60 | Accepted |
| Energy intensity | −0.722*** | 0.089 | −8.15 | Accepted |
| Foreign Direct Investment | 0.270** | 0.099 | 2.73 | Accepted |
| **Optimal lag length = 4** | | | | |
| Dep. Var. = Foreign Direct In- | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.045 | 0.207 | 0.22 | Rejected |
| Green Technologies | 0.132 | 0.203 | 0.65 | Rejected |
| Green Innovation | −0.689** | 0.264 | −2.61 | Accepted |
| Urbanisation | −0.218 | 0.451 | −0.48 | Rejected |
| Energy Intensity | 0.652 | 0.808 | 0.81 | Rejected |
| **Optimal lag length = 4** | | | | |

Note: Asterisk *** and ** represent 1% and 5% significance levels. Multivariate causality models for 1990 to 2019 advanced economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A5.** Granger non-causality - emerging/developing.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Technologies | 0.021 | 0.105 | 0.20 | Rejected |
| Green Innovation | −0.606*** | 0.153 | −3.96 | Accepted |
| Urbanisation | −0.092 | 0.120 | −0.76 | Rejected |
| Energy intensity | 1.126*** | 0.192 | 5.86 | Accepted |
| Foreign Direct Investment | −0.154 | 0.190 | −0.81 | Rejected |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Green Technologies | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.304** | 0.098 | 3.11 | Accepted |
| Green Innovation | −0.325*** | 0.100 | −3.25 | Accepted |
| Urbanisation | 0.588*** | 0.136 | 4.32 | Accepted |
| Energy intensity | 0.437** | 0.190 | 2.31 | Accepted |
| Foreign Direct Investment | −0.520*** | 0.130 | −4.00 | Accepted |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Green Innovation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.029 | 0.061 | −0.47 | Rejected |
| Green Technologies | 0.012 | 0.070 | 0.17 | Rejected |
| Urbanisation | 0.700*** | 0.073 | 9.63 | Accepted |
| Energy intensity | 0.421*** | 0.782 | 5.38 | Accepted |
| Foreign Direct Investment | 1.433*** | 0.099 | 14.43 | Accepted |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Urbanisation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.256*** | 0.061 | 4.19 | Accepted |
| Green Technologies | −0.187*** | 0.046 | −4.07 | Accepted |
| Green Innovation | −0.535*** | 0.073 | −7.29 | Accepted |
| Energy intensity | 2.145*** | 0.085 | 25.34 | Accepted |
| Foreign Direct Investment | −0.482*** | 0.059 | −8.11 | Accepted |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Foreign Direct In- | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.122** | 0.049 | −2.47 | Accepted |
| Green Technologies | 0.152 | 0.088 | 1.72 | Rejected |
| Green Innovation | 0.139 | 0.072 | 1.91 | Rejected |
| Urbanisation | −0.070 | 0.120 | −0.59 | Rejected |
| Energy intensity | 0.764*** | 0.093 | 8.24 | Accepted |
| **Optimal lag length = 7** | | | | |

Note: Asterisk *** and ** represent 1% and 5% significance levels. Multivariate causality models for 1990 to 2019 emerging/developing economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

## *Robustness/Extension*

Here, we aim to find the relationship between another alternative measure of green growth indicators and GDP growth. In this case, we used the global green growth index developed by the Green Growth Institute which is a composite measure of efficient and sustainable resource use, natural capital protection, green economic opportunities, and social inclusion variables. However, we substitute green technologies and green innovation with green growth index in our baseline models to assess its causal relationship with GDP growth combined with the other covariates.

We extended the scenarios we used in previous analyses, in which we included unobserved common factors and covariates in two-way analyses in this context. Table A6, Tables A7 and A8 present the findings of univariate and common factors of green growth index and GDP growth Granger non-causal relationship for our full sample, advanced and emerging/developing economies, respectively. We find evidence that, on typical, green growth indicators Granger cause GDP growth in a proportional and significant manner at a 5% significance level and a lag length of 20. GDP growth, on the other hand, does not Granger cause green growth indicators as measured by the green growth index. This implies that even when unobserved common factors are modelled together, there is a one-way effect from green growth indicators to GDP growth but not vice versa.

When GDP growth and unobserved common factors are modelled together to assess their Granger causal relationship with GDP growth, the situation is inherently different. We discover that the common factor has a negative and significant impact on GDP growth to disproportionately Granger causes green growth indicators at a 5% significance level and an optimal lag length of 1. Green growth indicators, on the other hand, Granger causes GDP growth in a proportional and significant manner with an optimal lag length of 12. Even though we find a two-way or feedback relationship between green growth indicators and GDP growth when we consider the influence of unobserved common factors, the signs of the relationship are dissimilar.

To allow for heterogeneity, we split our sample into advanced and emerging/developing economies. We present the outcome in Table A7 for advanced economies and Table A8 for emerging/developing economies. We find that green growth indicators Granger cause GDP growth in advanced economies in a proportional and significant manner. When we include the covariates, urbanisation, energy intensity, and foreign direct investment in the model, this revelation becomes apparent, and the relationship is bidirectional. These covariates appear to be insignificant, but

their influence significantly causes green growth indicators to have a positive impact on GDP growth, which differs from what we observed when we assessed the direct effect and included the unobserved common factors.

This supports the argument that some factors can influence the relationship between green growth indicators and GDP growth at the same time, which cannot be overlooked. Similarly, in emerging and developing economies, covariates have a disproportional influence on the relationship between green growth indicators and GDP growth, which differs from the results obtained using the univariate and common factor models. Our evidence suggests that green growth indicators are likely to be negatively influenced by energy intensity, thereby exacerbating GDP growth. This could imply that emerging and developing economies rely heavily on non-renewable energies to power the production of goods and services, which would jeopardise natural capital protection, green economic opportunities, and social inclusion, as well as potentially stifle GDP growth. In contrast, we find that, in both advanced and emerging/developing economies, the green growth index and GDP growth are bidirectionally related, but the signs of the relationship differ; positive in advanced economies but negative in emerging/developing economies.

In a separate analysis, we substitute green technologies and green innovation per capita with their quadratic terms, i.e., the square root of green technologies and green innovation per capita. Throughout the analyses, we refer to green technologies and green innovation per capita as green technologies$^2$ and green innovation$^2$, respectively. In the baseline models, we use the same approach. As a result, we have Granger non-causality test results for the entire sample (Table A12), advanced economies, and emerging/developing economies (Table A13 and Table A14, respectively). The assumption behind these approaches is to determine whether scaling up green technologies, which is likely to reflect in green innovation per capita, would have a significant impact on GDP growth or vice versa. This goal is motivated by previous findings that show that green technologies and green innovation per capita have a negative impact on GDP growth in advanced economies. We find that an excessive increase in green technologies would have a negative impact on economic growth. This indicates that the quadratic term of green technologies will reduce GDP growth with optimal lag length of 28 and a significance level of 5%. This relationship is only unidirectional, that is, a Granger causality from green technologies to GDP growth.

Even after incorporating the effect of the other covariates, we find that only green technologies Granger cause GDP growth, and energy intensity has a positive effect on this relationship. However, the quadratic term of green innovation is likely to negatively Granger cause GDP growth with optimal lag length of 28 and a significance level of 5%. In contrast to the quadratic term of the impact of green technologies on GDP growth, we find that the quadratic term of green innovation per capita and GDP growth is bidirectionally related, albeit with dissimilar signs. Green innovation per capita has a negative and significant Granger effect on GDP growth, whereas GDP growth has a positive and significant Granger effect on green innovation per capita. The relationships are unaffected by the inclusion of the other covariates. We found that the quadratic terms of green technologies and green innovation per capita are negatively and bidirectionally related to GDP growth in our sub-sample analyses of advanced economies. Even when the other covariates are included, the signs remain unchanged. Green technologies and green innovation per capita tend to exhibit positive Granger causality with GDP growth.

The Grange causality between green technologies' quadratic term and GDP growth is unidirectional, whereas the Granger causality between green innovation per capita and GDP growth is bidirectional. When the other covariates are included in the respective models, however, there appear to be significant differences. When the other covariates are included, the Granger causal relationship between quadratic term of the green technologies and GDP growth tends to be negative due to the positive and significant influence of energy intensity. Given the positive influences of urbanisation, energy intensity, and foreign direct investment, the Granger causal relationship between GDP growth and the quadratic term of green technologies tends to lose significance when the other covariates are included.

**Table A6.** Granger non-causality - green growth index univariate and common factor causalities - full sample.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Growth Index | 151.071*** | 0.826 | 182.80 | Accepted |
| **Optimal lag length = 20** | | | | |
| Dep. Var. = Green Growth Index | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.010 | 0.008 | −1.29 | Rejected |
| **Optimal lag length = 1** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Growth Index | 1.160** | 0.579 | 2.00 | Accepted |
| Common Factor | 0.590 | 0.654 | 0.90 | Rejected |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green Growth Index | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.018** | 0.006 | −2.89 | Accepted |
| Common Factor | 0.013*** | 0.004 | 3.02 | Accepted |
| **Optimal lag length = 1** | | | | |

Note: In this table, we report the results for the model in which we replace green technologies and green innovation with the Green Growth Index. Asterisk *** and ** represent 1% and 5% significance levels. Univariate and Bivariate causality models for 2009 to 2019 full sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A7.** Granger non-causality - green growth index univariate and common factor causalities - advanced.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Growth Index | −2.810** | 1.327 | −2.12 | Accepted |
| **Optimal lag length = 10** | | | | |
| Dep. Var. = Green Growth Index | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.017 | 0.023 | 0.75 | Rejected |
| **Optimal lag length = 1** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Growth Index | −3.263** | 1.598 | −2.04 | Accepted |
| Common Factor | 0.091 | 0.951 | 0.10 | Rejected |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Green Growth Index | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.023** | 0.007 | 3.06 | Accepted |
| Common Factor | 0.000 | 0.004 | 0.06 | Rejected |
| **Optimal lag length = 1** | | | | |

Note: In this table, we report the results for the model in which we replace green technologies and green innovation with the Green Growth Index. Asterisk *** and ** represent 1% and 5% significance levels. Univariate and Bivariate causality models for 2009 to 2019 advanced economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A8.** Granger non-causality - green growth index univariate and common factor causalities - emerging/developing.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Growth Index | 13.39*** | 2.03 | 6.59 | Accepted |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green Growth Index | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.01 | 0.01 | 0.91 | Rejected |
| **Optimal lag length = 1** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Growth Index | −16.79*** | 2.30 | −7.29 | Accepted |
| Common Factor | 2.34 | 1.77 | 1.32 | Rejected |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green Growth Index | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.02*** | 0.00 | 3.90 | Accepted |
| Common Factor | −0.01 | 0.01 | −1.23 | Rejected |
| **Optimal lag length = 1** | | | | |

Note: In this table, we report the results for the model in which we replace green technologies and green innovation with the Green Growth Index. Asterisk *** and ** represent 1% and 5% significance levels. Univariate and Bivariate causality models for 2009 to 2019 emerging/developing economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A9.** Granger non-causality - green growth index multivariate causalities - full sample.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Growth Index | 8.594*** | 0.791 | 10.87 | Accepted |
| Urbanisation | −1.378 | 1.164 | −1.18 | Rejected |
| Energy intensity | −1.812 | 1.087 | −1.67 | Rejected |
| Foreign Direct Investment | 0.145 | 0.718 | 0.20 | Rejected |
| **Optimal lag length = 13** | | | | |
| Dep. Var. = Green Growth Index | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.021 | 0.018 | 1.12 | Rejected |
| Urbanisation | −0.399*** | 0.018 | −21.80 | Accepted |
| Energy intensity | −0.587*** | 0.048 | −12.23 | Accepted |
| Foreign Direct Investment | −0.021 | 0.027 | −0.80 | Rejected |
| **Optimal lag length = 13** | | | | |
| Dep. Var. = Energy Intensity | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.119 | 0.332 | 0.36 | Rejected |
| Green Growth Index | −16.027*** | 0.221 | −72.59 | Accepted |
| Urbanisation | −1.310*** | 0.256 | −5.11 | Accepted |
| Foreign Direct Investment | 0.071 | 0.255 | 0.28 | Rejected |
| **Optimal lag length = 14** | | | | |
| Dep. Var. = Urbanisation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.197 | 0.459 | 0.43 | Rejected |
| Green Growth Index | −11.728*** | 0.666 | −17.60 | Accepted |
| Energy intensity | 2.203*** | 0.132 | 16.66 | Accepted |
| Foreign Direct Investment | −0.164 | 0.193 | −0.85 | Rejected |
| **Optimal lag length = 13** | | | | |
| Dep. Var. = Foreign Direct In- | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.571 | 0.817 | −0.70 | Rejected |
| Green Growth Index | 21.517*** | 0.631 | 34.08 | Accepted |
| Urbanisation | −3.058*** | 0.532 | −5.75 | Accepted |
| Energy intensity | −16.582*** | 0.522 | −31.77 | Accepted |
| **Optimal lag length = 14** | | | | |

Note: In this table, we report the results for the model in which we replace green technologies and green innovation with the Green Growth Index. Asterisk *** and ** represent 1% and 5% significance levels. Multivariate causality models for 2009 to 2019 full sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A10.** Multivariate causalities—advanced economies.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Growth Index | 6.11** | 1.11 | 5.48 | Accepted |
| Urbanisation | 1.12 | 1.22 | 0.92 | Rejected |
| Energy intensity | −2.07 | 1.13 | −1.82 | Rejected |
| Foreign Direct Investment | 0.08 | 0.77 | 0.01 | Rejected |
| **Optimal lag length = 5** | | | | |
| Dep. Var. = Green Growth Index | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.05*** | 0.02 | 3.34 | Accepted |
| Urbanisation | 0.17*** | 0.02 | 7.13 | Accepted |
| Energy intensity | 0.65*** | 0.02 | 27.66 | Accepted |
| Foreign Direct Investment | −0.02 | 0.02 | −1.11 | Rejected |
| **Optimal lag length = 5** | | | | |
| Dep. Var. = Energy Intensity | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.22 | 0.20 | −1.13 | Rejected |
| Green Growth Index | 1.99*** | 0.25 | 7.81 | Accepted |
| Urbanisation | −0.43** | 0.16 | −2.77 | Accepted |
| Foreign Direct Investment | 0.03 | 0.12 | 0.28 | Rejected |
| **Optimal lag length = 5** | | | | |
| Dep. Var. = Urbanisation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.60 | 0.69 | 0.87 | Rejected |
| Green Growth Index | 11.66*** | 0.45 | 0.87 | Accepted |
| Energy intensity | −3.11*** | 0.16 | −19.51 | Accepted |
| Foreign Direct Investment | −0.02 | 0.09 | −0.23 | Rejected |
| **Optimal lag length = 5** | | | | |
| Dep. Var. = Foreign Direct In- | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.28 | 2.05 | −0.14 | Rejected |
| Green Growth Index | 11.46*** | 1.92 | 5.97 | Accepted |
| Urbanisation | 3.09*** | 0.59 | 5.20 | Accepted |
| Energy intensity | 0.50 | 1.11 | 0.45 | Rejected |
| **Optimal lag length = 5** | | | | |

Note: In this table, we report the results for the model in which we replace green technologies and green innovation with the Green Growth Index. Asterisk *** and ** represent 1% and 5% significance levels. Multivariate causality models for 2009 to 2019 advanced economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A11.** Multivariate causalities - emerging/developing.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Growth Index | −1.09*** | 1.62 | −12.99 | Accepted |
| Urbanisation | −2.08 | 1.17 | −1.77 | Rejected |
| Energy intensity | −4.25*** | 0.70 | −6.02 | Accepted |
| Foreign Direct Investment | −1.23 | 1.17 | −1.05 | Rejected |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Green Growth Index | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.51** | 0.02 | −3.14 | Accepted |
| Urbanisation | 0.03*** | 0.01 | 3.31 | Accepted |
| Energy intensity | 0.38*** | 0.02 | 19.82 | Accepted |
| Foreign Direct Investment | 0.14*** | 0.02 | 7.67 | Accepted |
| **Optimal lag length = 8** | | | | |
| Dep. Var. = Energy Intensity | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.31 | 0.27 | 1.14 | Rejected |
| Green Growth Index | −3.89*** | 0.63 | −6.20 | Accepted |
| Urbanisation | −1.60*** | 0.30 | −5.40 | Accepted |
| Foreign Direct Investment | 0.01 | 0.27 | 0.04 | Rejected |
| **Optimal lag length = 8** | | | | |
| Dep. Var. = Urbanisation | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.48 | 0.53 | 0.90 | Rejected |
| Green Growth Index | −0.65 | 0.36 | −1.78 | Rejected |
| Energy intensity | 1.42*** | 0.15 | 9.73 | Accepted |
| Foreign Direct Investment | −0.79*** | 0.20 | −3.87 | Accepted |
| **Optimal lag length = 8** | | | | |
| Dep. Var. = Foreign Direct In- | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.01 | 0.79 | 0.02 | Rejected |
| Green Growth Index | 0.93** | 0.42 | 2.22 | Accepted |
| Urbanisation | −2.72*** | 0.24 | −11.28 | Accepted |
| Energy intensity | −4.80*** | 0.24 | −19.70 | Accepted |
| **Optimal lag length = 8** | | | | |

Note: In this table, we report the results for the model in which we replace green technologies and green innovation with the Green Growth Index. Asterisk *** and ** represent 1% and 5% significance levels. Multivariate causality models for 2009 to 2019 emerging/developing economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A12.** Granger non-causality - quadratic effect full sample.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Technologies$^2$ | −2.38*** | 0.65 | −3.64 | Accepted |
| **Optimal lag length = 28** | | | | |
| Dep. Var. = Green Technologies$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.00 | 0.01 | −0.44 | Rejected |
| **Optimal lag length = 1** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Technologies$^2$ | 0.70** | 0.23 | 3.00 | Accepted |
| Green innovation$^2$ | −0.20 | 0.15 | −0.71 | Rejected |
| Urbanisation | −0.28 | 0.30 | −0.93 | Rejected |
| Energy intensity | 0.99*** | 0.25 | 3.87 | Accepted |
| Foreign Direct Investment | −0.20 | 0.21 | 0.94 | Rejected |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green Technologies$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.16 | 0.01 | 1.69 | Rejected |
| Green innovation$^2$ | 0.06*** | 0.01 | 7.54 | Accepted |
| Urbanisation | −0.04** | 0.01 | −2.62 | Accepted |
| Energy intensity | −0.03** | 0.01 | −2.16 | Accepted |
| Foreign Direct Investment | −0.01 | 0.01 | −1.55 | Rejected |
| **Optimal lag length = 1** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green innovation$^2$ | −0.47** | 0.21 | −2.22 | Accepted |
| **Optimal lag length = 28** | | | | |
| Dep. Var. = Green innovation$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.63*** | 0.03 | 5.39 | Accepted |
| **Optimal lag length = 8** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green innovation$^2$ | −0.51*** | 0.14 | −3.74 | Accepted |
| Green Technologies$^2$ | 0.54** | 0.19 | 2.86 | Accepted |
| Urbanisation | −0.25 | 0.18 | −1.41 | Rejected |
| Energy intensity | 1.02*** | 0.18 | 5.60 | Accepted |
| Foreign Direct Investment | 0.10 | 0.19 | 0.55 | Rejected |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green innovation$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.14*** | 0.04 | 3.31 | Accepted |
| Green Technologies$^2$ | 0.03 | 0.06 | 0.53 | Rejected |
| Urbanisation | 0.03 | 0.05 | 0.54 | Rejected |
| Energy intensity | −0.64*** | 0.07 | −8.51 | Accepted |
| Foreign Direct Investment | 0.31*** | 0.06 | 5.34 | Accepted |
| **Optimal lag length = 12** | | | | |

Note: In this table, we report the results for the model in which we replace green technologies and green innovation with their quadratic terms. Asterisk *** and ** represent 1% and 5% significance levels, respectively. Univariate and multivariate causality models for the 1990–2019 full sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A13.** Granger non-causality - quadratic effect full sample.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Technologies$^2$ | −1.72** | 0.74 | −2.31 | Accepted |
| **Optimal lag length = 10** | | | | |
| Dep. Var. = Green Technologies$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.05*** | 0.01 | −3.74 | Accepted |
| **Optimal lag length = 1** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Technologies$^2$ | −1.38*** | 0.37 | −3.75 | Accepted |
| Green innovation$^2$ | −0.46** | 0.18 | −2.55 | Accepted |
| Urbanisation | 0.39 | 0.22 | 1.79 | Rejected |
| Energy intensity | −3.01*** | 0.21 | −14.03 | Accepted |
| Foreign Direct Investment | 0.07 | 0.20 | 0.37 | Rejected |
| **Optimal lag length = 4** | | | | |
| Dep. Var. = Green Technologies$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.04** | 0.01 | −2.83 | Accepted |
| Green innovation$^2$ | 0.02 | 0.02 | 1.01 | Rejected |
| Urbanisation | −0.04** | 0.02 | −2.27 | Accepted |
| Energy intensity | −0.07*** | 0.02 | −3.20 | Accepted |
| Foreign Direct Investment | 0.01 | 0.00 | 1.78 | Rejected |
| **Optimal lag length = 1** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green innovation$^2$ | −3.11*** | 0.85 | −3.66 | Accepted |
| **Optimal lag length = 10** | | | | |
| Dep. Var. = Green innovation$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.49** | 0.18 | −2.69 | Accepted |
| **Optimal lag length = 10** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green innovation$^2$ | −0.46** | 0.20 | −2.32 | Accepted |
| Green Technologies$^2$ | −1.38*** | 0.18 | −7.71 | Accepted |
| Urbanisation | 0.39** | 0.15 | 2.58 | Accepted |
| Energy intensity | −3.01*** | 0.21 | −14.03 | Accepted |
| Foreign Direct Investment | 0.07 | 0.21 | 0.35 | Rejected |
| **Optimal lag length = 4** | | | | |
| Dep. Var. = Green innovation$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | −0.16*** | 0.04 | −3.59 | Accepted |
| Green Technologies$^2$ | 0.41*** | 0.06 | 6.95 | Accepted |
| Urbanisation | −0.26*** | 0.05 | −4.88 | Accepted |
| Energy intensity | 3.33*** | 0.09 | 36.75 | Accepted |
| Foreign Direct Investment | 0.02 | 0.09 | 0.26 | Rejected |
| **Optimal lag length = 4** | | | | |

Note: In this table, we report the results for the model in which we replace green technologies and green innovation with their quadratic terms. Asterisk *** and ** represent 1% and 5% significance levels. Univariate and Multivariate causality models for 1990 to 2019 advanced economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

**Table A14.** Granger non-causality - quadratic effect emerging/developing economies.

| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
|---|---|---|---|---|
| Green Technologies$^2$ | 6.10*** | 0.51 | 11.85 | Accepted |
| **Optimal lag length = 12** | | | | |
| Dep. Var. = Green Technologies$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | -0.00 | 0.01 | -0.03 | Rejected |
| **Optimal lag length = 1** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green Technologies$^2$ | 0.10 | 0.22 | 0.45 | Rejected |
| Green innovation$^2$ | −1.66*** | 0.23 | −7.31 | Accepted |
| Urbanisation | −0.15 | 0.24 | −0.65 | Rejected |
| Energy intensity | 1.09*** | 0.23 | 4.66 | Accepted |
| Foreign Direct Investment | −0.19 | 0.18 | −1.02 | Rejected |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Green Technologies$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.12** | 0.05 | 2.58 | Accepted |
| Green innovation$^2$ | −0.17** | 0.09 | −2.02 | Accepted |
| Urbanisation | 0.39*** | 0.10 | 4.08 | Accepted |
| Energy intensity | −0.10 | 0.10 | −0.98 | Rejected |
| Foreign Direct Investment | −0.33*** | 0.06 | −5.34 | Accepted |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green innovation$^2$ | 1.97** | 0.72 | 2.73 | Accepted |
| **Optimal lag length = 17** | | | | |
| Dep. Var. = Green innovation$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.14*** | 0.04 | 3.96 | Accepted |
| **Optimal lag length = 17** | | | | |
| Dep. Var. = GDP growth | Coefficients | Std. Err. | Z-stat. | Decision |
| Green innovation$^2$ | −1.66*** | 0.27 | −6.24 | Accepted |
| Green Technologies$^2$ | 0.10 | 0.19 | 0.52 | Rejected |
| Urbanisation | −0.15 | 0.19 | 0.52 | Rejected |
| Energy intensity | 1.09*** | 0.20 | 5.48 | Accepted |
| Foreign Direct Investment | −0.19 | 0.22 | −0.85 | Rejected |
| **Optimal lag length = 7** | | | | |
| Dep. Var. = Green innovation$^2$ | Coefficients | Std. Err. | Z-stat. | Decision |
| GDP growth | 0.01 | 0.04 | 0.22 | Rejected |
| Green Technologies$^2$ | −0.01 | 0.06 | −0.20 | Rejected |
| Urbanisation | 0.14** | 0.05 | 2.84 | Accepted |
| Energy intensity | 0.43*** | 0.05 | 8.79 | Accepted |
| Foreign Direct Investment | 0.74*** | 0.05 | 13.91 | Accepted |
| **Optimal lag length = 7** | | | | |

Note: In this table, we report the results for the model in which we replace green technologies and green innovation with their quadratic terms. Asterisk *** and ** represent 1% and 5% significance levels. Univariate and Multivariate causality models for 1990 to 2019 emerging/developing economies' sample. Accepted denotes the rejection of the null hypothesis that no evidence of Granger causality exists. Rejected denotes the acceptance of the null hypothesis.

| SN | Country | SN | Country | SN | Country | SN | Country |
|---|---|---|---|---|---|---|---|
| 1 | Australia | 26 | Netherlands | 51 | Ecuador | 76 | South Africa |
| 2 | Austria | 27 | New Zealand | 52 | Egypt | 77 | Sri Lanka |
| 3 | Belgium | 28 | Norway | 53 | Georgia | 78 | Thailand |
| 4 | Canada | 29 | Poland | 54 | Ghana | 79 | Trinidad and Tobago |
| 5 | Chile | 30 | Portugal | 55 | India | 80 | Tunisia |
| 6 | Colombia | 31 | Slovak Republic | 56 | Indonesia | 81 | Ukraine |
| 7 | Costa Rica | 32 | Slovenia | 57 | Iran | 82 | United Arab Emirates |
| 8 | Czech Republic | 33 | Spain | 58 | Jordan | 83 | Uruguay |
| 9 | Denmark | 34 | Sweden | 59 | Kazakhstan | 84 | Uzbekistan |
| 10 | Estonia | 35 | Switzerland | 60 | Kenya | 85 | Viet Nam |
| 11 | Finland | 36 | Türkiye | 61 | Liechtenstein | | |
| 12 | France | 37 | United Kingdom | 62 | Malaysia | | |
| 13 | Germany | 38 | United States | 63 | Malta | | |
| 14 | Greece | 39 | Albania | 64 | Moldova | | |
| 15 | Hungary | 40 | Algeria | 65 | Monaco | | |
| 16 | Iceland | 41 | Argentina | 66 | Morocco | | |
| 17 | Ireland | 42 | Azerbaijan | 67 | Nigeria | | |
| 18 | Israel | 43 | Bahamas | 68 | Pakistan | | |
| 19 | Italy | 44 | Bangladesh | 69 | Panama | | |
| 20 | Japan | 45 | Barbados | 70 | Peru | | |
| 21 | Korea | 46 | Brazil | 71 | Philippines | | |
| 22 | Latvia | 47 | Bulgaria | 72 | Romania | | |
| 23 | Lithuania | 48 | China (People's Republic of) | 73 | Russia | | |
| 24 | Luxembourg | 49 | Croatia | 74 | Saudi Arabia | | |
| 25 | Mexico | 50 | Cuba | 75 | Singapore | | |

**Figure A2.** List of countries in our sample.