What Drives Green Growth? ESG Risks, Green Innovation, and Productive Capacity in the OECD Countries

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Abstract

This paper studies what drives green growth in 18 OECD countries from 2003 to 2022 using green GDP as the main measure. We focus on productive capacities, economic complexity, green technology, economic policy uncertainty, ESG uncertainty, and energy use. To capture nonlinear and state-dependent effects, we apply quantile-based and wavelet methods. We find that stronger productive capacities and higher economic complexity support green growth, especially once countries reach higher development states. A larger share of green technology patents also boosts green GDP after it passes a certain threshold. By contrast, higher economic policy and ESG uncertainty reduce green growth, in particular when green performance is already weak. Changes in energy use are positively linked to green GDP, but the long-run gains depend on cleaner and more efficient energy supply. The results suggest that stable policies, green innovation, and structural upgrading are central for sustained green growth.

Keywords: Green growth; Green technology; Economic policy uncertainty; Energy use; OECD countries

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1. Introduction

Green growth is a favorable solution to tackle current challenges by matching economic progression with the protection of the environment. Green growth has the ability to protect the planet. Moreover, it fosters inclusive and equitable development (Fay, 2012). Green growth is aligned with fostering renewable energy use, expanding sustainable agricultural practices and leads to conservation. Green growth associates with the objectives of SDGs. It is focused on tacking climate change, protection of marine life and preservation of terrestrial biodiversity (SDG13,14,15) (Kallqvist, 2021; Qin *et al*., 2023). Green growth is also associated with poverty eradication, reduction in inequalities and decent work (SDG 1, 8, 10) (OECD, 2018). Green growth is associated with sustainable technologies, opportunities for green jobs that ameliorates poverty and leads to the development of vibrant economies (Zhang, *et al*., 2023; Yikun *et al*, 2023; Yasmeen *et al*, 2023).

Further, green growth has the capacity to recuperate the health and well- being of the population across the world. Green growth builds more resilient societies by addressing issues on air and water pollution (Adams, 2008). Green growth ensures long term stability and enhances competitiveness. It further addresses SDG 9 (Xing *et al*., 2024; Wahab *et al*., 2024; Simeon *et al*., 2024). Green growth represents the trajectory where economic prosperity and environmental sustainability is achieved. It enables to achieve the SDG goals in an impactful way.

There is an urgent need to strengthen productive capacities for laying the groundwork for green growth. Building productive capacities enables more efficient use of resources and cleaner technologies. When a country improves productive capacity in particular for areas like energy efficiency, natural capital management and institutional quality, it creates opportunities to separate economic expansion and environmental degradation. The Productive Capacity Index is a multidimensional tool. It was developed by UNCTAD to assess the ability of the economy to produce goods and services. The policy makers should use productive capacity index to identify the strengths and weaknesses in national production system and create pathways for inclusive and sustainable growth.

Further green growth can be improved through green technology. Using eco-friendly technologies in the energy sector fosters green growth (Su *et al*., 2020; Ullah *et al*., 2021). Technology innovation will provide efficiency in energy production and its utilization. Further, it will enable conservation of natural resources and minimize carbon emissions. It allows the simultaneous achievement of economic and ecological goals and fosters economic expansion. Technology advancement is crucial to industrial transformation and addressing environmental challenges will be costly without it. The OECD countries have integrated growth in their national and bilateral policies. The OECD countries includes green growth in ecological performance evaluations and technology and capital market reviews.

Green technology stimulates sustainable development. It identifies environmentally friendly sources of growth, develops environmental friendly industries and creates jobs and technologies (Ghisetti *et al*., 2017). To attain green growth it is essential to foster investments and innovations that signify the foundation of sustainable development and enhance economic opportunities (Przychodzen *et al*, 2020). The advancement of studies on green growth require intense research on the conditions of its formation and its impact on sustainable development. The stakeholders who are interested in green economic development include business, the planners and the public who set environmental goals for sustainable development (Ramdhani *et al*., 2017).

Investments in Environmental Social Governance is essential for driving towards green growth. According to Feng and Yuan (2024), the investments integrates sustainability factors into decision making. It motivates businesses to implement environmentally responsible practices, uphold social standards and establish strong governance. The inclusion of ESG criterion in investment strategies enhances capital flows to companies that highlight environmental stewardship, social responsibility and ethical governance. Such practices aligns investment portfolio with sustainable values and also impacts corporate behavior positively (Feng and Yuan, 2024). The studies by Qian and Yu (2024) and Tan *et al*. (2024) deliberate that ESG investments fosters green growth by directing financial resources to enterprises dedicated to sustainable practices. Such processes promote a faster transition to an environmentally conscious economy.

The inspiration for the present study is taken from the serious juncture at which the present global economy stands today: climate change and environmental deterioration are posing up challenges that have not been observed earlier. As the nations take up the challenges, the transformation to green growth arise not as a policy option but crucial for sustainable development. Often the OECD countries set an example at the frontier of technology and economic development with green technology, productive capacities and ESG. It has therefore become necessary to undertake a study driven by the need to understand the synergistic effects of these factors in driving the green growth program. It is against this background that this study seeks to decipher that with productive capacity, green technology initiatives and ESG may foster inclusive economic growth that is sustainable.

Against the above background, this research aims to establish how the OECD nations could transform into green economy that might point out the best practices that other countries may follow. The study might signal the key challenges and opportunities for the OECD countries towards the pathway to sustainability. What makes this study important is its contribution to the expanding field of sustainable development. The study adds insights to the understanding of environment and sustainability and its interplay with green technology, productive capacities and ESG framework. This study helps to highlight the process by which the OECD countries are able to use their resources, technological capabilities and ESG structures to lead green growth. The study suggests that green technology, productive capacities and ESG have critical roles and enable green growth.

This study presents a perspective by combining the assessment of productive capacities, green technology and ESG in the presence of economic complexity, economic policy uncertainty and energy consumption in the framework of green GDP analysis, in the context of the OECD countries. Diverse from the earlier research that usually studies these aspects separately, the present analysis delves into their interdependence and impact on promoting green growth. By concentrating on the OECD countries that lead in the implementation of sustainable policies, this research correlates essential parameters that impact economic growth along with considering the preservation of ecology. The research is conducted on empirical data using reliable statistical methods to understand the nonlinear impacts of these factors on green growth. The study also provides important policy prescriptions to align economic and environmental goals efficiently.

The rest of the paper is designed as follows. Section 2 reviews the related earlier studies. Section 3 explains the data, models, and methods. Section 4 discusses the major empirical results. Section 5 concludes with policy recommendations.

2. Review of Literature

The literature argues that green growth is imperative for sustainable development. However, there are various factors that impact green growth. Based on the current scope of research, the explorations in the literature along the following dimensions is made: i) prodcutive capacities and green growth; ii) green technology and green growth; and iii) uncertainty and green growth.

2.1 Prodcutive capacities and green growth

The UNCTAD (2006, 2020) discusses that the concept of productive capacities has three major aspects. It includes productive resources, entrepreneurial abilities and production linkages which determine the country's ability to produce goods and services and assists in the growth of the economy. Against the backdrop of this definition the UNCTAD has recognized eight broad categories defined over several indicators that explain the main conduits through which a country could develop its productive capacities. The major categories include transport and infrastructure; energy; information and communication technology; human capital; private sector; natural resources and structural change in production. Thus deliberations about the effects of productive capacities on green growth involves exploration how these dimensions relating to productive capacities affect green growth.

Ahmed *et al*. (2020) argues that natural resource abundance leads to degradation of the environment. While human capital reduces environmental degradation. In another study Liu *et al*., (2023) explored the effect of human capital on green growth for China for the period 1991 to 2019. The results based on ARDL model indicate positive levels of education on green growth in China in the long run. In a similar vein, Rahim *et al*. (2021) for the next elven countries explored the importance of human capital in facilitating the growth process. In a similar vein, Wang *et al*., (2023) for Chinese provinces obtained positive effects of human capital on green growth. Their study highlights the importance of government decision making to promote human capital formation in the context of the Chinese provinces.

The literature has discussed how institutional quality impact a country's ecological preservations and socioeconomic expansion (see e.g., Ahmed *et al*., 2022; Salman *et al*., 2019; Sarkodie and Adams, 2018). The study by Ahmed *et al*., (2022) established in the context of South Asian economies how institutional quality and financial development improves long term green growth. In a similar vein, the study by Osabohien *et al*. (2022) demonstrated that green environment crucially impacts the overall welfare of the economy.

The study by Lau *et al*., (2014) in the context of Malaysia found that good institutions are imperative to reduce carbon emissions and secure green growth. In a similar vein, the study by Abid (2017) found in the context of 41 European countries and 58 Middle East African countries that good institutions are crucial to foster economic growth and also assist in the mitigation of carbon emissions. Again Bhattacharya *et al*. (2017) for 85 developing and advanced countries found that institutions play a major role for mitigating carbon emissions and fostering economic growth. Further the study by Sarkodie and Adams (2018) for South Africa obtained that disaggregated and aggregated energy and political institutions play a key position in environmental quality.

A handful of studies have explored the importance of industrial structure for fostering green growth. The study by Zhu *et al.* (2019) for Chinese provinces for the period 1999 to 2016 found industrial structural transformation promotes green growth. Li *et al.* (2017) in the context of 30 Chinese provinces found that changes in manufacturing process have negative implications on total factor productivity.

In the light of the above discussion we may conclude that the major components of productive capacities contribute towards green growth. Thus the first testable hypothesis of the study is framed:

H1:It is likely that enhanced productive capacities would spur green growth in the OECD countries.

2.2 Green technology and green growth

Green technology is an operative method for fostering green economic growth (Sohag *et al.*, 2019b) and implementation of cleaner technologies significantly leads to a decline in carbon emanations (Yin *et al.*, 2015). For steady and effective reduction in carbon emissions improvement in technological competence is required (Kwon *et al.*, 2017). There are numerous studies in the literature that have established the positive effect of green technology on green growth (Ganda, 2019; Chen and Lei, 2018; Gu *et al.*, 2019; Mensah *et al.*, 2018; Jordaan *et al.*, 2017; Sohag *et al.*, 2019a; Nikzad and Sedigh, 2017; Wangetal, 2019; Zhang *et al.*, 2017). Some works have demonstrated how green technology and renewable energy lead to pollution reduction (Lin and Zhu, 2019a, 2019b; Gu *et al.*, 2019; Sarkodie and Strezov, 2018). The studies by (Alam and Murad, 2020; Sarkodie and Adom, 2018) have documented that use of clean energy reduces environmental pollution and thus negative externalities. In sum, green technology and innovations is an important factor that reduces energy consumption and fosters green growth. Suki *et al.* (2022) using a sample set of ASEAN economies for the period 1992 to 2018 explored the effect of green technology innovation on green growth. The findings based on CS-ARDL method revealed that green technology has negative effects on carbon dioxide emissions. The study argues that there is an urgent need for research and development to improve the number of technological patents.

The study by Guo *et al.* (2020) documents that sustainable technology transfer referred in the literature as "environmentally sound technology," plays an important role in fostering sustainable development goals at the global and local context. The efforts to pursue such goals will reduce the negative impacts of non green economic development and improve the standards of living (Ishak, Jamaludin and Abu, 2017; UNCTAD, 2018). The importance of sustainable technology transfer has made nations aware of the importance of pollution control and resource conservation (Hansen, Li and Svarverud, 2018). Focusing on green technology had directed nations towards integrated sustainable solutions that take into consideration environment, society and economy (UNCTAD, 2018). Many countries have invested in infrastructure supporting and technology development for example Clean Energy Finance Corporation (Austria), National Bank for Economic and Social Development (Brazil), Green Investment Bank (United Kingdom), and Green Technology Bank (China) (Geddes, Schmidt and Steffen, 2018; Mazzucato and

Penna, 2016; Guo *et al.*, 2020). In addition the OECD announced 12 green investment banks (OECD, 2017a, 2017b). Nonetheless the development and introduction of sustainable technology face political constraints (Yoshino *et al.*, 2019), lack of market awareness (Agyemang *et al.*, 2018); knowledge and awareness (Liao and Shi, 2018) and financial barriers (Bhandari *et al.*, 2019).

Based on the above discussions, we predict that green technology transfer will raise investments and use of sustainable technology, leading towards an increase in green growth. Such processes will lead to more efficient use of natural resources and negative externalities will recede. Thus, the second testable hypothesis is framed as follows:

H2: Green technology has a positive impact on green growth.

2.3 Uncertainty and green growth

Uncertainty has been a crucial part of green GDP growth. The study by Liu *et al.*, (2023) explored the impact of EPU on green growth by using a sample of BRICS countries for the period 1990 to 2020. The study obtained that EPU impedes green growth in the BRICS countries. The study by Hallegatte *et al.* (2012) claim that Economic Policy Uncertainty is a major driving factor for green growth. The study argues that economic policies can set right efficiency losses of economic operations owing to knowledge externalities, information asymmetries and other externalities. A series of policy tools such as price regulations and subsidies are required to boost green GDP. However the study concludes that polices alone cannot influence green growth.

At the backdrop of uncertainty there should be adequate policies to foster green growth. According to the study by Sonnenschein and Mundaca (2016) market policies enables in adjusting the changes in the price system of production factors related to green oriented industries. To counter economic policy uncertainty there should be adequate technological policies and tax credits that may assist green technologies to attain innovation turnover (Cecere and Corrocher, 2016; Wang and Shao, 2019). Policy uncertainty will spillover into the macro process of green development. The study by Gu *et al.* (2021) in the context of China argues that the impact of EPU on green growth is multidimensional. The same findings are obtained in the study by MA *et al.*, (2022).

The preceding discussion highlighted the importance of uncertainty in impacting green growth. Most of the earlier studies focused on EPU as a major factor to impact green growth. The current research proposes that along with EPU based, uncertainty from ESG risks can impede green growth. Accordingly the third testable hypothesis of the study is proposed as follows :

H3: Economic Policy Uncertainty and ESG uncertainty are crucial determinants of green growth.

2.4 Scope of the scholarship

Green economy has attracted the attention of governments, economists and environmentalists due to the acute threat on environmental problems which includes climate change, global food insecurity and ecological degradation among others. Policy initiatives and governance such as initiatives by the United Nations and Paris agreement are few examples that are aiming to drive towards green growth. Yet studies are limited on the factors affecting green growth. Moreover research in this area is still at its initial stages with a large number of studies investigating heterogeneous issues that are lumped as green growth. There has been considerable efforts to define the concept of green economy however there is an urgent need to provide a detailed examination of the factors that drive economies to implement green economy.

This research has significant implications for both theory and practice in the field of sustainable economics. By elucidating the nonlinear impacts of EPU, ESG, green technology and productive capacities on green growth and identifying the key factors affecting the relationship we contribute our advancement in sustainable economics. Moreover our results offer valuable insights to corporate managers trying to develop effective ESG strategies that are responsible for regional and industrial contexts. Such processes enhance the capacity to navigate the challenges posed by ESG.

3. Data and Empirical Strategy

3.1. Data and variables mapping

This study examines the structural and institutional factors influencing green growth in 18 OECD countries from 2003 to 2022. To support this analysis, we compiled a panel dataset comprising environmental, innovation and policy-driven indicators extracted from internationally recognised sources.

The OECD context is particularly relevant. These countries represent a relatively homogeneous group of advanced economies, enabling more precise comparisons to be made in terms of productive capacity, regulatory maturity and policy engagement in sustainability-driven transitions. They were also among the first to adopt the ESG framework and proactive green innovation strategies, which underpinned their structural change.

The timeframe, which covers the period from 2003 to 2022, captures the critical period during which climate policy moved to the forefront of global economic discussions. This period includes pivotal policy events such as the adoption of the Kyoto Protocol in the early 2000s, the aftermath of the 2008 financial crisis, the Paris Agreement in 2015, and green recovery ambitions following the 2019–2020 pandemic. These events provide a rich context for assessing how structural and innovation-related factors have shaped environmentally sustainable economic outcomes.

To operationalise this analysis, we adopt Green GDP as the focal variable. Unlike traditional GDP, which only captures the market-based value of goods and services, Green GDP adjusts for environmental costs such as air pollution, waste generation, and natural resource depletion. Developed by Skare *et al.* (2021), this measure integrates quantitative factors (e.g. energy use and pollution) and qualitative dimensions (e.g. opportunity costs), offering a more accurate measure of long-term economic sustainability (Stjepanović *et al.*, 2022).

The core explanatory variables were selected to reflect key domains relevant to green transformation. Specifically, i) *Economic Complexity Index (ECI SITC)*: obtained from the Atlas of Economic Complexity by the Harvard Growth Lab, this variable captures the knowledge intensity and structural diversity of a country's exports. It reflects not only the number of products that a country exports, but also the ubiquity or rarity of those products in other economies. Higher ECI values indicate that a country exports a wide range of sophisticated products that are not widely available elsewhere and require in-depth knowledge and organisational capabilities. From a sustainability perspective, a complex export structure is often associated with higher added value, lower material intensity and cleaner production processes, making it a relevant indicator for green growth analysis; and ii) *Green Technology Share (GT%)*: sourced from the OECD Data Explorer, this variable measures the proportion of green/environmentally related patents in total patent activity. It reflects a country's commitment to and capacity for developing technological solutions to environmental challenges, such as climate change mitigation, resource efficiency, pollution control and clean energy generation. High GT% values suggest that a significant proportion of national R&D efforts are directed towards sustainability goals, indicating strategic alignment between innovation policy and environmental objectives. This variable is particularly relevant in the context of green growth, as the generation and diffusion of clean technologies are key enablers of decoupling economic performance from environmental degradation (Dechezleprêtre *et al*., 2008; Cho *et al*., 2018; Shahbaz *et al*., 2024). Furthermore, patent data offer a forward-looking perspective on technological potential as patents precede market adoption and indicate sectors of potential future industrial transformation (Bergek *et al*., 2014; Verhoeven *et al*., 2016).

In addition to these core variables, we incorporate a broader set of institutional and contextual indicators. In particular, i) **Productive Capacities Index (PCI)** developed by the UN Trade and Development (UNCTAD), is a multidimensional measure that captures countries' capabilities to produce goods and services in a sustainable and competitive manner. The PCI aggregates performance across eight core dimensions: human capital, natural capital, energy, transport, information and communication technology (ICT), institutions, private sector development and structural change. These components are derived from over 40 standardised indicators and are designed to reflect the quantity, quality, and depth of a country's development capacity. By incorporating this variable into our analysis, we can gain a comprehensive understanding of the structural readiness of OECD countries to implement and benefit from the green transformation of their economies; and ii) **Economic Policy Uncertainty Index (EPU)** and **ESG Uncertainty Index (ESGUI)** both of which were developed by PolicyUncertainty.com, serve as measures of institutional volatility and regulatory ambiguity in economic and sustainability domains. The EPU captures fluctuations in uncertainty relating to macroeconomic and fiscal policy by analysing the frequency of policy-related terms in major newspapers, alongside data on tax code expiries and disagreements among economic forecasters. In contrast, the ESGUI focuses specifically on uncertainties in environmental, social and governance (ESG) policies. It quantifies the frequency and intensity of public discourse involving terms related to ESG regulations, green finance, climate commitments and corporate sustainability reporting. ESG frameworks are becoming increasingly influential in shaping investment and corporate strategies, especially within the OECD. The presence of volatile or unclear ESG signals may delay the deployment of green technologies, deter long-term investment and create uncertainty around compliance costs or future regulation (Ilhan *et al*., 2021; Berg *et al*., 2022). In the context of our study, both indicators are particularly relevant. High levels of economic policy uncertainty can reduce firms' willingness to invest in long-term, capital-intensive green innovations. Likewise, uncertainty surrounding ESG can impede the transition to more sustainable business models by undermining the clarity and credibility of environmental commitments.

This extended variable framework enables us to explore not only the technological and productive drivers of sustainable growth but also the institutional and global dynamics that shape long-term green economic performance. Table 1 presents list of variables, abbreviations and the data sources for each of these variables discussed in this study, ensuring transparency and facilitating the reproducibility of our analytical framework.

Table 1: Data overview

Data Description	Abbreviation	Source / Institution
Green GDP	GG	Mendeley Data Skare, M., Tomic, D., & Stjepanovic, S. (2021)*
Productive Capacities Index	PCI	UNCTAD
Economic Complexity Index (SITC)	ECI	Harvard Growth Lab (Atlas of Economic Complexity)
Economic Policy Uncertainty Index	EPU	PolicyUncertainty.com
ESG Uncertainty Index	ESG	PolicyUncertainty.com
Green Technology Share (%)	GT	OECD
Energy consumption	EnC	Our world in data

3.2 Quantile-on-Quantile regression (QQR) by Sim and Zhou (2015)

To capture the heterogeneous and state-dependent dynamics between green growth and its structural, technological, and uncertainty-related determinants, we employ the Quantile-on-Quantile Regression (QQR) approach proposed by Sim and Zhou (2015). Unlike traditional quantile regression, which estimates the conditional quantiles of the dependent variable as a function of the mean of explanatory variables, the QQR method examines how specific quantiles of an independent variable influence corresponding quantiles of the dependent variable. This dual quantile structure allows a more nuanced assessment of non-linear and asymmetric dependence across the entire conditional distribution. In our context, the QQR framework reveals whether, for instance, high levels of economic complexity or green technology exert a different impact on green growth when economies are in strong versus weak performance states.

Formally, let G_t denote the growth-adjusted green output (ΔGG) and $\mathrm{X_t}$ represents the respective explanatory variable (PCI, ECI, EPU, ESG, GT, or ΔENC). Following Sim and Zhou (2015), the relationship between the τ-th quantile of G_t and the θ-th quantile of $\mathrm{X_t}$ can be expressed as:

$$G_t = \alpha(\theta,\tau) + \beta(\theta,\tau)(\mathrm{X_t} - \mathrm{X}_\theta) + \varepsilon_t(\theta,\tau) \tag{1}$$

where α is the quantile-specific intercept, $\beta(\theta,\tau)$ captures the elasticity of the τ-th quantile of G_t with respect to the θ-th quantile of $\mathrm{X_t}$, X_θ is the θ-th quantile of the independent variable estimated via the Gaussian kernel, and ε_t is the quantile-specific residual. By estimating $\beta(\theta,\tau)$ over the grid of quantiles $\theta,\tau \in (0.1, 0.9)$, the QQR model generates a three-dimensional surface describing how the impact of each determinant varies across both the distribution of green growth and its drivers.

3.3 Cross-Quantilogram by Han et al. (2016)

To further examine the dynamic dependence structure between green growth and its determinants across the conditional distribution, we employ the cross-quantilogram (CQ) approach proposed by Han et al. (2016). Unlike standard correlation or Granger causality tests that focus on mean relationships, the CQ framework evaluates quantile-based dependence between two time series at different quantile combinations and time lags. This technique captures tail dependence and directional predictability, allowing us to identify whether extreme events (e.g., high uncertainty, low productivity) in one variable systematically precede or follow specific outcomes in green growth.

Formally, the cross-quantilogram between G_t and an explanatory variable X_t is defined as:

$$\rho_{\tau,\theta}(k) = \frac{E[\psi_\tau(G_t - q_G(\tau))\psi_\theta(X_{t-k} - q_X(\theta))]}{\sqrt{E[\psi_\tau^2(G_t - q_G(\tau))]}\sqrt{E[\psi_\theta^2(X_{t-k} - q_X(\theta))]}} \quad (2)$$

where $q_G(\tau)$ and $q_X(\theta)$ denote the τ-th and θ-th conditional quantiles of G_t and X_t, respectively; $\psi_\tau(u) = 1[u < 0] - \tau$ is the quantile hit process that measures whether the observation lies below the corresponding quantile; and k represents the lag order. The statistic $\rho_{\tau,\theta}(k)$ thus measures the directional dependence between the θ-th quantile of X_{t-k} and τ-th quantile of G_t at lag k.

This method offers several advantages in our context of green growth analysis. First, it captures nonlinear and asymmetric interactions that cannot be detected through conventional linear models. Second, it accounts for the persistence and lead–lag structure of dependence, revealing whether fluctuations in uncertainty, technology, or productive capacity precede or lag changes in green growth across different states of the distribution. Finally, the CQ framework provides a quantile-specific dependence map, enabling visualization of how lower- or upper-tail shocks in each determinant affect the dynamics of green growth over time.

3.4 Cross-in-quantile by Balcilar, Gupta and Pierdzioch (2016)

To complement the quantile-on-quantile and cross-quantilogram analyses, we adopt the causality-in-quantile (CiQ) framework developed by Balcilar, Gupta, and Pierdzioch (2016). This method evaluates whether an explanatory variable X_t Granger-causes growth-adjusted green output G_t at different points of their conditional distributions, rather than only at the mean. Traditional Granger causality tests assume linearity and distributional homogeneity, which may overlook causal relationships that occur only during extreme episodes—such as periods of severe uncertainty, technological surges, or energy-related shocks. The CiQ approach relaxes these assumptions and allows for nonlinear, tail-specific, and regime-dependent causal effects.

Formally, the CiQ test examines whether the conditional quantile function of G_{t+1} differs when conditioning on the history of X_t. Let $Q_{G_{t+1}}(\tau|\mathcal{F}_t)$ denote the τ-th conditional quantile of green growth given information set $\mathcal{F}_t$. The null hypothesis of no quantile-specific causality is:

$$\mathrm{H}_0: Q_{G_{t+1}}(\tau|G_t, X_t) = Q_{G_{t+1}}(\tau|G_t) \qquad \text{for all } \tau \in (0,1)$$

Under the alternative, past values of X_t shift the τ-th quantile of G_{t+1}, implying causality. Balcilar *et al.* (2016) propose a test statistic built from the empirical quantile regression process, allowing inference without imposing parametric restrictions on the relationship between X_t and G_t. This provides a flexible tool capable of detecting causal effects that are nonlinear in magnitude and asymmetric across quantiles.

Applying this method to the six determinants—PCI, ECI, EPU, ESG, GT, and ΔENC—enables assessment of whether each variable exerts predictive power on green growth during low-growth states (τ =0.1-0.3), normal conditions (τ =0.4-0.6), and high-growth states (τ =0.7-0.9). Importantly, the CiQ approach does not assume that causal effects are homogeneous: an explanatory variable may lack predictive power during tranquil periods but exercise strong influence during boom or stress regimes.

To operationalize the test, quantile regression residuals are used to construct the CiQ statistic across quantiles 0.1-0.9. These are then compared with stimulated 5% and 10% critical values, allowing identification of regime-specific rejection regions for the null hypothesis of no causality.

3.5 Wavelet-quantile regression by Adebayo and Özkan (2024)

Following Adebayo and Özkan (2024), a traditional quantile regression (QR) model for two time series can be written as,

$$Q_\tau(Y \mid X) = \beta_0(\tau) + \beta_1(\tau)X$$

where $Q_\tau(Y \mid X)$is the conditional quantile of the response variable Yat quantile level τ, given the factor variable X. The parameters $\beta_0(\tau)$and $\beta_1(\tau)$represent the intercept and slope at that specific quantile.

Quantile regression, introduced by Koenker and Bassett (1978), expands the scope of classical linear regression by focusing on conditional quantiles rather than the conditional mean. Unlike ordinary least squares, which only describes how the average of the dependent variable responds to changes in an explanatory variable, QR allows researchers to study how different points of the distribution behave. This feature is especially useful when the relationship between variables is not uniform across the distribution. QR is also less sensitive to outliers and can accommodate heteroskedasticity, making it a practical tool in many empirical settings. Through this approach, researchers gain a clearer view of heterogeneous effects that may be hidden when relying solely on mean-based methods (Chernozhukov *et al*., 2013; Koenker, 2005; Machado and Silva, 2005).

However, the traditional QR framework does not distinguish between different time horizons. It implicitly treats short-term and long-term variations as identical, even though prior studies highlight that this assumption may not hold (Irfan *et al*., 2022; Liu *et al*., 2023; Olanipekun *et al*., 2023; Umar *et al*., 2020).

To address this gap, we employ the Wavelet Quantile Regression developed by Adebayo and Özkan (2024) which evaluates how the effect of a factor variable X on the conditional quantiles of Y evolves across different time scales. The method proceeds in two stages.

First, we decompose the time series Y_t and X_t using the maximal overlap discrete wavelet transform (MODWT) of Percival and Walden (2000), following the steps outlined in Kumar and Padakandla (2022). Let $X[i]$ be a signal of length $T = 2^J$. Using the low-pass and high-pass filters $h_1[i]$and $g_1[i]$, we obtain the first-level approximation and detail coefficients through convolution,

$$\alpha_1[i] = \sum_k h_1[i-k]X[k],$$
$$d_1[i] = \sum_k g_1[i-k]X[k].$$

We then apply the same filtering procedure to the approximation coefficients. We have the followings,

$$\alpha_{j+1}[i] = \sum_k h_{j+1}[i-k]X[i],$$
$$d_{j+1}[i]= \sum_k g_{j+1}[n-k]X[j].$$

Repeating this process for J levels produces a set of detail coefficients for both variables, each representing fluctuations at a specific time scale.

In the second stage, we run quantile regressions using the wavelet detail coefficients of Y and X at each scale. The WQR model for quantile level τ and decomposition level j is:

$$Q_\tau(d_j[Y] \mid d_j[X]) = \beta_0(\tau) + \beta_1(\tau)d_j[X].$$

3.6 Wavelet-quantile correlation by Kumar and Padakondlas (2022)

Following Kumar and Padakondlas (2022), we decompose the return series and Y_t using the maximal overlapping discrete wavelet transform (MODWT) of Percival and Walden (2000). Consider a signal $X[i]$ of length $T = 2^J$. Let $h_1[i]$ and $g_1[i]$ be the low-pass and high-pass filters associated with an orthogonal wavelet. Convolution of $X[i]$ with these filters yields the approximation coefficients $a_1[i]$ and the detail coefficients $d_1[i]$,

$$a_1[i] = \sum_k h_1[i-k]s[k]$$

$$d_1[i] = \sum_k g_1[i-k]s[k]$$

The approximation coefficients $a_1[i]$ are then passed through upsampled versions of the original filters, denoted $h_2[i]$ and $g_2[i]$, where the up-sampling operator $U(\cdot)$ inserts a zero between each adjacent element of the filter. Repeating this procedure produces the multi-level decomposition. For $j = 1,2, \dots, J_0 - 1$, with $J_0 \leq J$,

$$a_{j+1}[i] = \sum_k h_{j+1}[i-k]a_j[k]$$

$$d_1[i] = \sum_k h_{j+1}[n-k]a_j[j]$$

where $h_{j+1}[i] = U(h_j[i])$ and $g_{j+1}[i] = U(g_j[i])$. After completing the J-level decomposition for both X_t and Y_t, we apply quantile correlation to each pair of detail coefficients $(d_j[X], d_j[Y])$. This produces a scale-specific dependence measure, the Wavelet Quantile Correlation, defined for quantile τ at scale j as,

$$WQC_\tau(d_j[X], d_j[Y]) = \frac{qcov_\tau(d_j[Y], d_j[X])}{\sqrt{var\left(\phi_\tau\left(d_j[Y] - Q_{\tau,d_j[Y]}\right)\right) var(d_j[X])}}$$

$$qcov_\tau(d_j[Y], d_j[X]) = cov\left\{I\left(d_j[Y] - Q_{\tau,d_j[Y]} > 0\right), x\right\}$$

4. Main Results

The summary statistics are presented in Table 2. The table indicates substantial dispersion in growth-adjusted green output (ΔGG). Specifically, the median is positive, but the interquartile range is negative and the overall range is wide, suggesting volatility with occasional extremes. The structural variables: productive capacity (PCI) and economic complexity (ECI) exhibit moderate spread, reflecting relatively stable structural fundamentals across economies. In contrast, the green-technology share (GT) varies meaningfully across country-years, indicating cross-country differences in the adoption of clean innovation. The two policy-uncertainty measures (EPU and ESG uncertainty) are right-skewed and heavy-tailed, consistent with episodic spikes during periods of geopolitical or financial stress. Finally, Energy consumption changes (ΔENC) show the largest variability, underscoring the critical role of energy dynamics in shaping the green growth trajectory.

Table 2: Summary statistics

	ΔGG (in billions)	PCI	ECI	EPU	ESG	GT	ΔENC
Mean	53.1	60.99	2.15	132.82	29.46	29.79	-3.90
Std. Dev	265	6.63	0.88	80.33	8.43	10.83	199.09
Min	-2700	39.5	0.33	27	7.41886	10.37	-1955.85
25%	-17	57.2	1.47	80.77	23.94	22.41	-32.18
50%	33.1	62.3	2.36	111.63	29.31	27.73	5.53
75%	106	66.5	2.78	155.60	33.96	34.96	34.38
Max	1090	71.1	3.87	669.01	59.28	79.55	1334.18
Jarque-Bera	264.74*	39.78*	19.19*	1429.36*	23.57*	194.46*	255.42*
Obs.	341	359	359	359	359	359	341

Note: *, **, *** denote 10%, 5%, 1% levels.

The correlation heatmap in Figure 1 illustrates the pairwise associations among the main variables. In particular, ΔGG comoves positively with PCI, ECI, and GT which is consistent with greener growth in economies with stronger productive structures, more complex export baskets, and greener innovation portfolios. Conversely, ΔGG is negatively associated with EPU and ESG uncertainty, reflecting the drag from uncertainty on long-horizon green investment. Changes in energy consumption (ΔENC) also exhibit a weak but discernible link to ΔGG, reflecting the energy intensity of growth adjustments. Overall, the correlations are moderate in magnitude, supporting the need for more advanced econometric methods to capture heterogeneous effects beyond linear associations.

Table 3 reports results from the panel quantile unit root tests across the conditional distribution (0.1-0.9 quantiles). The test statistics consistently reject the unit root null for all variables at conventional significant levels, confirming their stationarity throughout the distribution. This robustness across quantiles strengthens confidence in our empirical framework, as it indicates that the variables' statistical properties are stable not only on average but also at different points of the conditional distribution. More specifically, the rejection of unit roots for ΔGG, PCI, ECI, GT, EPU, ESG, and ΔENC ensures the validity of subsequent panel estimations without the risk of spurious regressions.

Figure 1: Correlation matrix heatmap

Figure 2 presents Sim and Zhou (2015) results. The PCI panel shows a clear state-dependent pattern. Specifically, at low PCI quantiles, coefficients are negative across most of the ΔGG distribution, indicating that weak productive structures constrain green growth. As PCI rises, the coefficients turn positive, particularly at higher ΔGG quantiles, suggesting that strong productive capacity amplifies gains when economies are already on a greener trajectory. This asymmetry highlights a threshold effect, where only sufficiently high levels of productive capacity generate sustained improvements in green output, underscoring the importance of structural capacity building for long-term green growth.

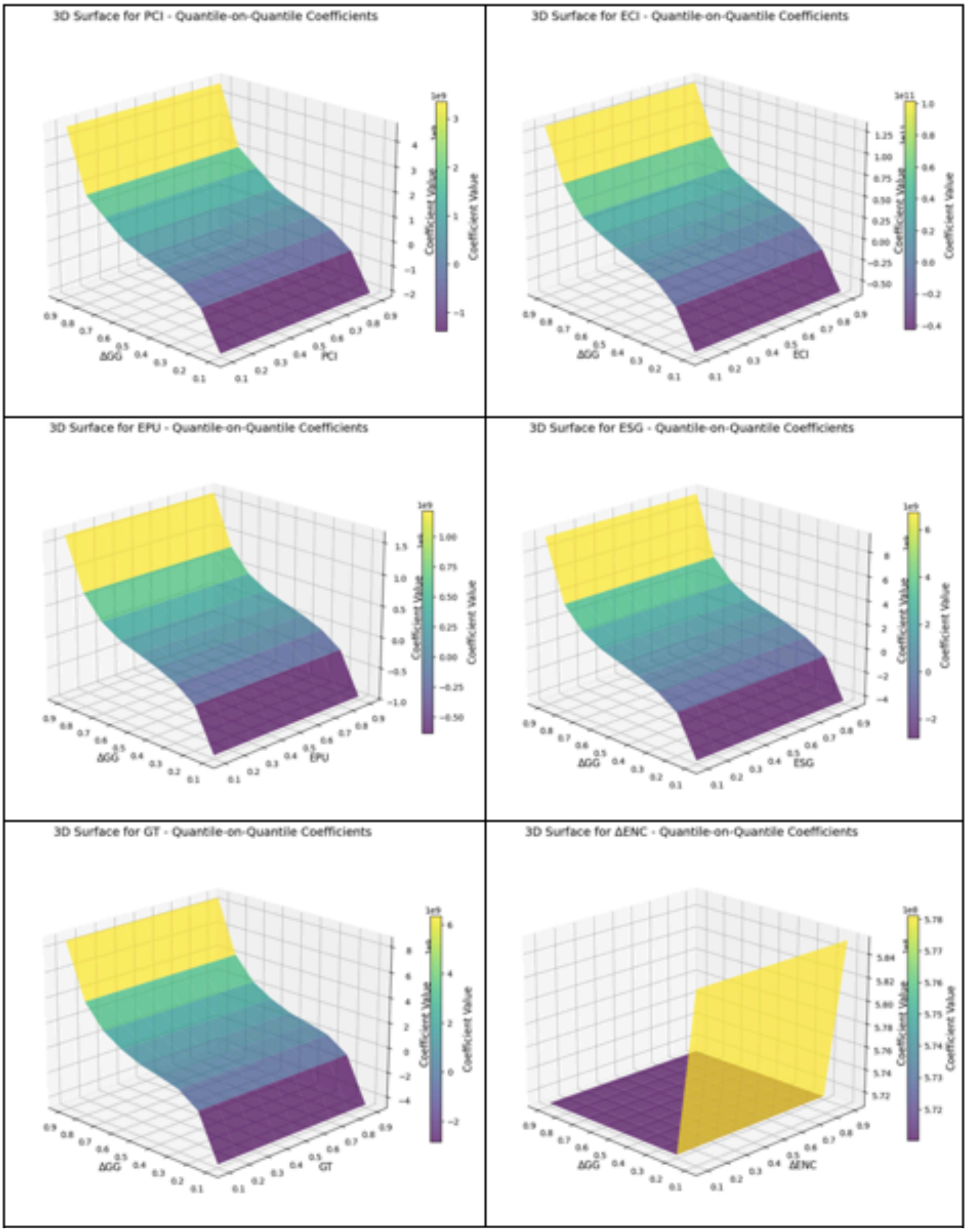
The ECI panel indicates that low levels of ECI have little or even negative impact on growth-adjusted green output (ΔGG), reflecting limited green benefits in less sophisticated economies. As ECI rises, the coefficients turn positive and strengthen, particularly at higher ΔGG quantiles, suggesting that complex production and export structures amplify green growth when economies are already on a stronger trajectory. This asymmetric pattern highlights that advancing economic complexity is a key driver of sustained green growth, especially in high-performing states.

Table 3: Panel quantile unit root test (ADF test)

Quantile	Variable	t-statistic	p-value	Quantile	Variable	t-statistic	p-value
Quantile 0.1	ΔGG	-12.6128	0.0000	Quantile 0.1	ECI	-3.193	0.0204
Quantile 0.2	ΔGG	-12.6128	0.0000	Quantile 0.2	ECI	-3.193	0.0204
Quantile 0.3	ΔGG	-12.6128	0.0000	Quantile 0.3	ECI	-3.193	0.0204
Quantile 0.4	ΔGG	-12.6128	0.0000	Quantile 0.4	ECI	-3.193	0.0204
Quantile 0.5	ΔGG	-12.6128	0.0000	Quantile 0.5	ECI	-3.193	0.0204
Quantile 0.6	ΔGG	-12.6128	0.0000	Quantile 0.6	ECI	-3.193	0.0204
Quantile 0.7	ΔGG	-12.6128	0.0000	Quantile 0.7	ECI	-3.193	0.0204
Quantile 0.8	ΔGG	-12.6128	0.0000	Quantile 0.8	ECI	-3.193	0.0204
Quantile 0.9	ΔGG	-12.6128	0.0000	Quantile 0.9	ECI	-3.193	0.0204
Quantile 0.1	EPU	-6.5855	0.0000	Quantile 0.1	ESG	-9.0551	0.0000
Quantile 0.2	EPU	-6.5855	0.0000	Quantile 0.2	ESG	-9.0551	0.0000
Quantile 0.3	EPU	-6.5855	0.0000	Quantile 0.3	ESG	-9.0551	0.0000
Quantile 0.4	EPU	-6.5855	0.0000	Quantile 0.4	ESG	-9.0551	0.0000
Quantile 0.5	EPU	-6.5855	0.0000	Quantile 0.5	ESG	-9.0551	0.0000
Quantile 0.6	EPU	-6.5855	0.0000	Quantile 0.6	ESG	-9.0551	0.0000
Quantile 0.7	EPU	-6.5855	0.0000	Quantile 0.7	ESG	-9.0551	0.0000
Quantile 0.8	EPU	-6.5855	0.0000	Quantile 0.8	ESG	-9.0551	0.0000
Quantile 0.9	EPU	-6.5855	0.0000	Quantile 0.9	ESG	-9.0551	0.0000
Quantile 0.1	GT	-5.9717	0.0000	Quantile 0.1	PCI	-3.2912	0.0153
Quantile 0.2	GT	-5.9717	0.0000	Quantile 0.2	PCI	-3.2912	0.0153
Quantile 0.3	GT	-5.9717	0.0000	Quantile 0.3	PCI	-3.2912	0.0153
Quantile 0.4	GT	-5.9717	0.0000	Quantile 0.4	PCI	-3.2912	0.0153
Quantile 0.5	GT	-5.9717	0.0000	Quantile 0.5	PCI	-3.2912	0.0153
Quantile 0.6	GT	-5.9717	0.0000	Quantile 0.6	PCI	-3.2912	0.0153
Quantile 0.7	GT	-5.9717	0.0000	Quantile 0.7	PCI	-3.2912	0.0153
Quantile 0.8	GT	-5.9717	0.0000	Quantile 0.8	PCI	-3.2912	0.0153
Quantile 0.9	GT	-5.9717	0.0000	Quantile 0.9	PCI	-3.2912	0.0153
Quantile 0.1	ΔENC	-22.8499	0.0000				
Quantile 0.2	ΔENC	-22.8499	0.0000				
Quantile 0.3	ΔENC	-22.8499	0.0000				
Quantile 0.4	ΔENC	-22.8499	0.0000				
Quantile 0.5	ΔENC	-22.8499	0.0000				
Quantile 0.6	ΔENC	-22.8499	0.0000				
Quantile 0.7	ΔENC	-22.8499	0.0000				
Quantile 0.8	ΔENC	-22.8499	0.0000				
Quantile 0.9	ΔENC	-22.8499	0.0000				

The surface of EPU panel exhibits a clear downward slope along the EPU dimension, indicating that higher levels of uncertainty consistently depress green growth outcomes. At low EPU quantiles, the coefficients are positive across most ΔGG quantiles, suggesting that policy stability supports green expansion. However, as EPU rises, the relationship turns negative throughout the distribution, with the strongest adverse effects observed in both the lower and upper tails of ΔGG. These results highlight the state-dependent nature of uncertainty shocks, with both constrain recovery in weak green-growth states and erode momentum in stronger ones, underscoring the importance of a stable policy environment for sustaining long-horizon green investment.

Figure 2: Sim and Zhou (2015) quantile-on-quantile results



The surface of ESG panel reveals a clear negative slope along the ESG dimension, showing that higher levels of uncertainty systematically weaken growth-adjusted green output (ΔGG). At low quantiles of ESG uncertainty, coefficients remain positive across most ΔGG quantiles, indicating that stability in sustainability frameworks supports green growth. However, as uncertainty increases, the relationship turns markedly negative across the distribution, with particularly strong adverse effects in both the lower and upper tails of Δ GG. These results highlight that ESG-related uncertainty not only constrains recovery in weak green-growth states but also erodes momentum in stronger ones, emphasizing the importance of credible and stable ESG framework for sustaining long-term green investment.

The results of the green technology share (GT) show that low levels of GT provide limited benefits for growth-adjusted green output (ΔGG), but as GT rises the coefficients turn strongly positive across the distribution. The strongest effects occur when both GT and ΔGG are high, indicating that deeper penetration of green technologies amplifies existing green growth momentum through spillovers and scale effects. This highlights the pivotal role of sustained green innovation in driving and reinforcing long-term sustainable growth.

The results of changes in energy consumption panel (ΔENC) reveal a nonlinear pattern. Specifically, at low ΔENC quantiles, coefficients are flat and negligible, indicating that modest shifts in energy use do not meaningfully affect growth-adjusted green output (ΔGG). By contrast, at higher ΔENC quantiles the coefficients rise sharply, particularly for economies in stronger green-growth states, suggesting that large increases in energy demand are associated with amplified growth outcomes. This threshold-driven effect underscores the critical importance of directing energy expansions toward clean sources to ensure that rising demand supports rather than undermines long-term green growth.

Figure 3 reports Han *et al.* (2016) cross-quantilogram results. For PCI and ECI across different lags, the patterns show that PCI exhibits weak or negative short-run dependence with growth-adjusted green output (ΔGG), with positive effects emerging only at longer horizons and in higher quantiles, indicating a delayed and state-dependent role. By contrast, ECI displays strong and persistent positive dependence across mid-to-upper quantiles at all lags, suggesting that greater economic complexity reinforces green growth more immediately and consistently. These results highlight that while productive capacity contributes gradually, economic complexity provides a more robust and timely driver of sustained growth.

In terms of the cross-quantilogram estimates for EPU and ESG uncertainty, the results show that EPU exerts strong negative dependence on growth-adjusted green output (ΔGG) in the short run, particularly at lower quantiles, but its effects dissipate quickly over longer lags. In contrast, ESG-related displays more persistent and widespread negative dependence across quantiles and horizons, constraining recovery in weak states and curbing momentum in strong ones. This asymmetry highlights that while policy uncertainty delivers sharp but short-lived shocks, ESG uncertainty has a more durable dampening effect, underscoring the importance of stable sustainability frameworks for long-term green growth.

Regarding to the cross-quantilogram estimates for GT and ΔENC, our results show that GT exhibits persistent positive dependence with ΔGG, particularly at mid-to-upper quantiles and across short-to-medium lags, indicating that green technology adoption quickly reinforces and sustains green growth. By contrast, ΔENC displays a more heterogeneous pattern. In particular, short-run increases in energy use are positively associated with ΔGG, especially in stronger states, but these effects weaken and even turn negative at longer horizons. This contrasts highlights that while green innovation provides a durable engine for sustainable growth, energy-driven expansions are more conditional and transient.

Figure 3: Cross-quantilogram heatmap results for lags 1, 2, 4

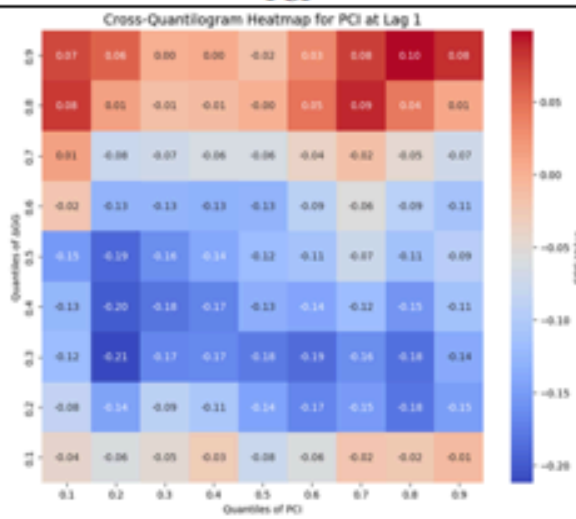
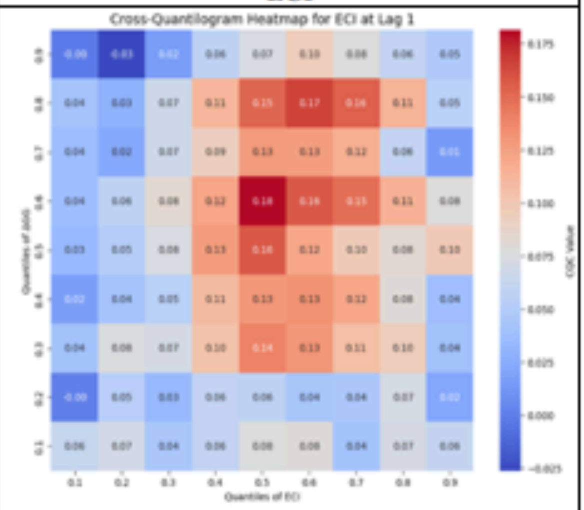
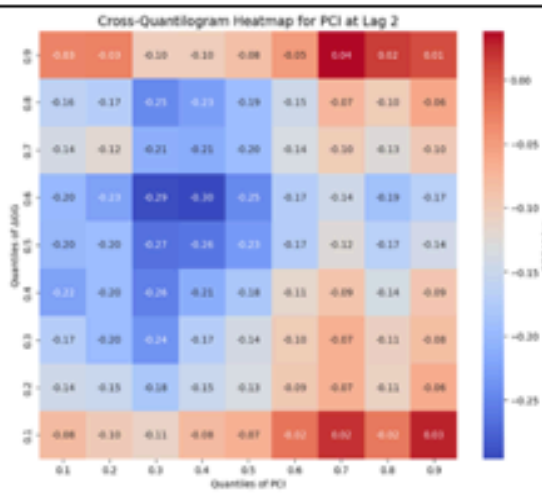
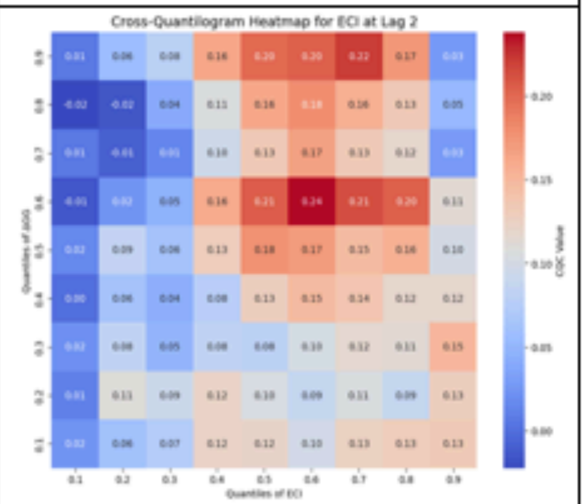
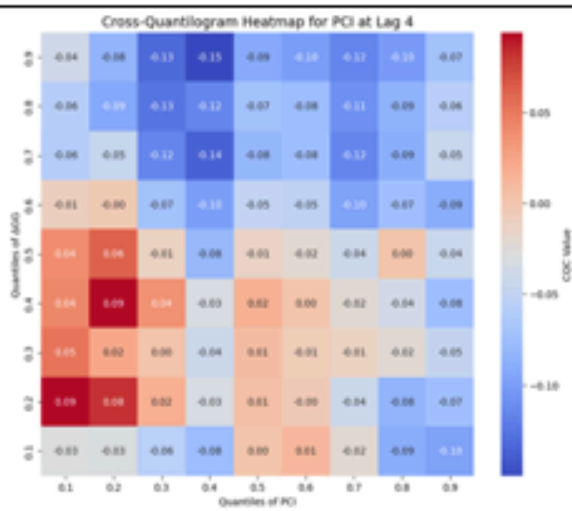
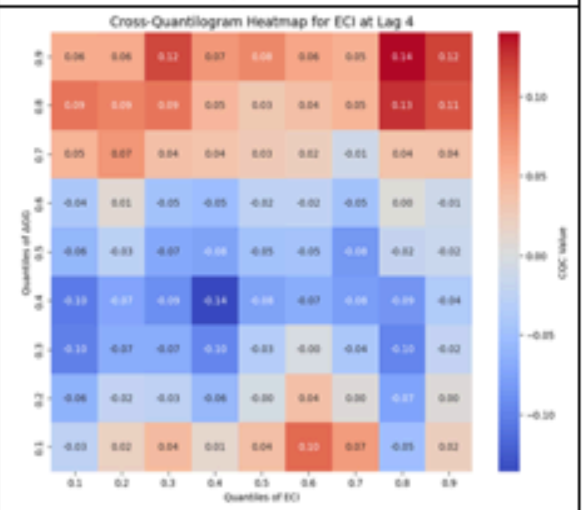
	PCI	ECI
Lag1		
Lag2		
Lag4		

Figure 3: Continued

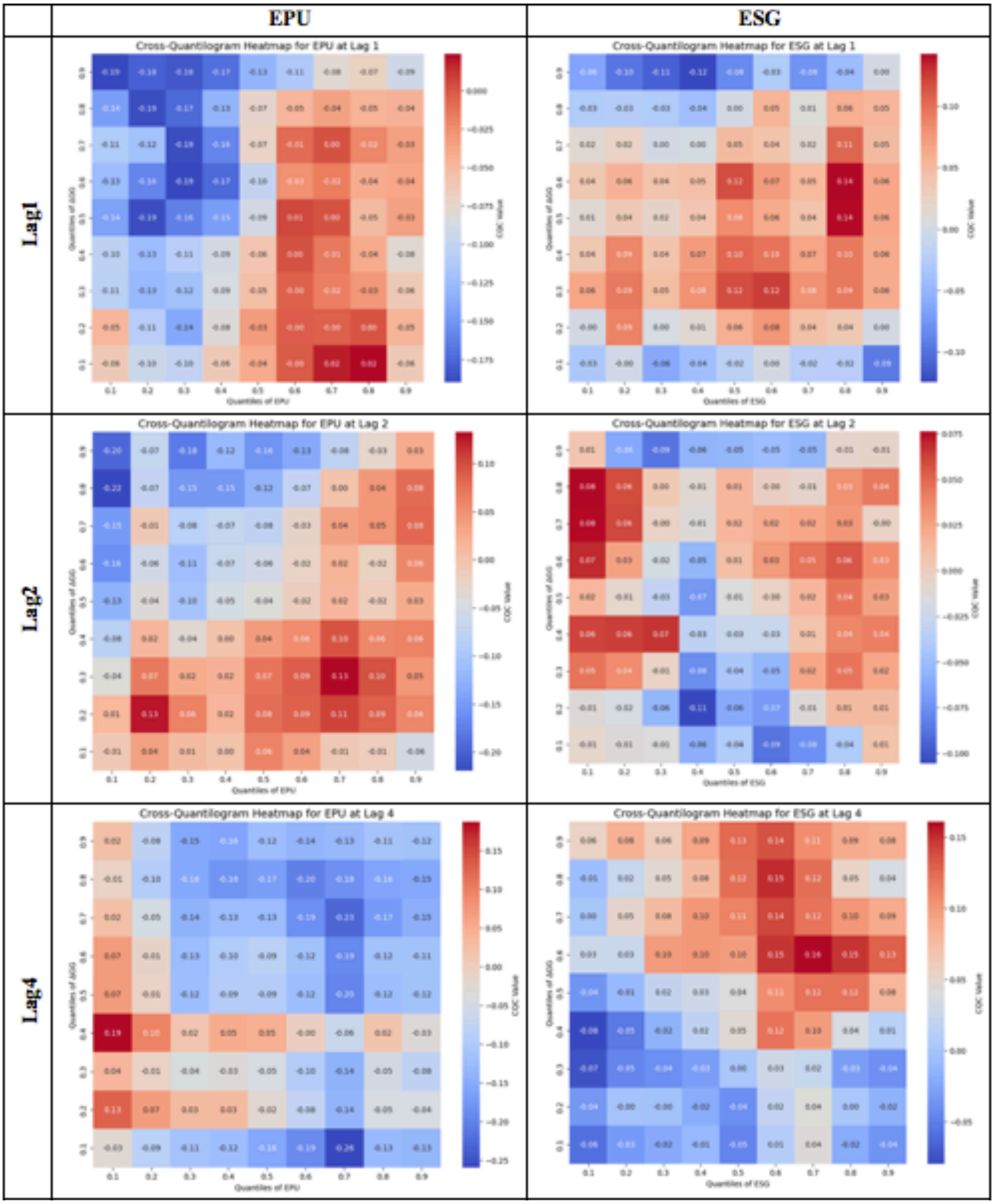
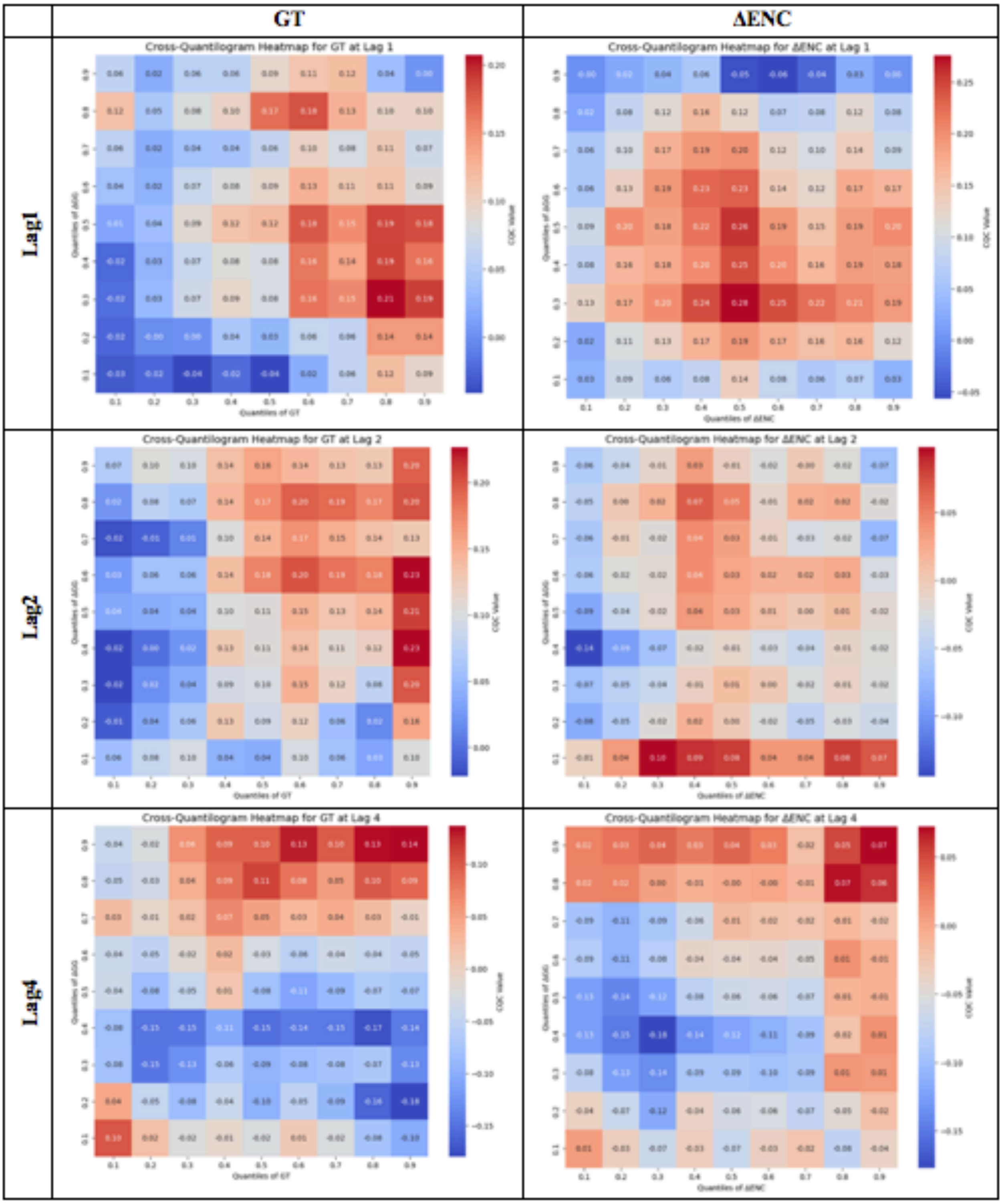


Figure 3: Continued



Overall, our cross-quantilogram evidence underscores that structural drivers such as complexity and green innovation exert durable positive effects, whereas uncertainty acts as a significant drag, and energy consumption dynamics yield conditional, short-lived gains.

Table 4: Balcilar *et al.* (2016) causality-in-quantile results

Quantile	PCI	ECI	EPU	ESG	GT	ΔENC
0.1	-2100***	-63000***	-960***	-4400***	-4600***	585***
0.2	-640***	-21000***	-310***	-1200***	-1100***	571***
0.3	-53	-560	-82*	-120	15.69	571***
0.4	281***	9890***	53.69	523***	450**	571***
0.5	551***	18700 ***	159***	1090***	816 ***	571***
0.6	889***	29000***	270***	1620***	1460***	571***
0.7	1500***	41500***	451***	2530***	2400***	571***
0.8	2130***	71900 ***	808***	4230***	4190***	571***
0.9	4570***	131000***	1620***	9240***	8490***	571***

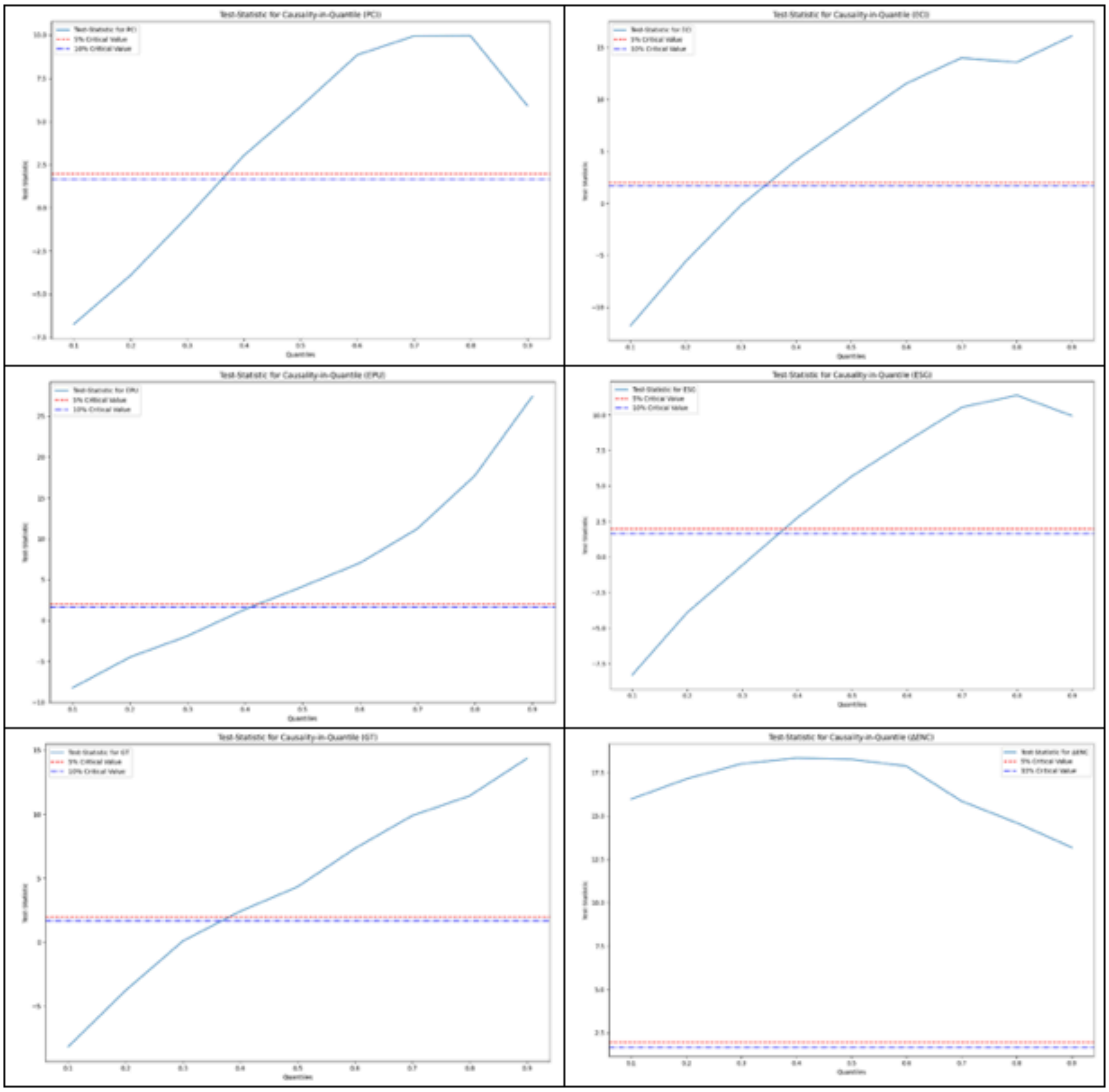
Note: All values are reported in units of millions. Asterisks denote statistical significance at conventional levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 4 reports the causality-in-quantile test results of Balcilar *et al.* (2016), showing how the determinants of ΔGG vary across the conditional distribution. The findings reveal substantial heterogeneity and asymmetry. Productive capacity (PCI) exerts negative effects at lower quantiles, indicating that weak productive structures constrain green growth in fragile states, but becomes strongly positive at higher quantiles, suggesting a threshold effect where capacity building reinforces greener trajectories. Economic complexity (ECI) with coefficients rising sharply toward the upper quantiles, underscoring the robust role of structural sophistication in supporting sustainable growth. By contrast, economic policy uncertainty (EPU) and ESG-related uncertainty (ESG) are predominantly negative at the lower quantiles, highlighting their destabilizing role in weak states. Green technology (GT) also displays threshold dynamics. In particular, initially negative at lower quantiles, but turning strongly positive from the median upwards, with the largest effects in the upper tail, reflecting the amplifying role of clean innovation once adoption passes a critical mass. Finally, changes in energy consumption (ΔENC) are positive and significant across all quantiles with relatively stable coefficients, pointing to a uniform association that may capture scale effects rather than clean transition per se. Overall, our causality-in-quantile results highlight that structural drivers (ECI, GT, PCI) act as engines of green growth primarily in stronger performing states, while uncertainty dampens outcomes most in weaker states, and energy dynamics exert a stable but less discriminating influence across the distribution.

Figure 4 plots the causality-in-quantile test results. For the PCI panel, the result show no significant causal effect on ΔGG in the lower quantiles, but the test statistic rises above the 5% and 10% critical values from the 0.4 quantile onwards, remaining significant through the mid-to-upper tails. This indicates that productive capacity exerts a strong predictive influence on green growth when economies are already on moderate to high growth trajectories, underscoring its state-dependent role in reinforcing sustainable performance.

For the ECI panel, the test statistic is below the critical values at lower quantiles, but from the 0.4 quantile onwards it rises above the 5% threshold and increases sharply, remaining highly significant through the upper tail. This indicates that economic complexity exerts a strong and persistent causal influence on ΔGG in moderate and high growth regimes, underscoring its central role in sustaining green performance.

Figure 4: Balcilar *et al.* (2016) causality-in-quantile results



Note: The y-axis presents test statistics, and the x-axis is quantiles of independent variables.

The test statistic for the EPU panel is below the critical values at lower quantiles but crosses the 5% threshold from the 0.4 quantiles onwards, rising sharply toward the upper tail. This indicates that economic policy uncertainty has a significant causal effect on ΔGG in moderate and high growth regimes, with the influences strongest at the upper quantiles.

For the ESG-related uncertainty panel, the test statistic lies below the critical values at lower quantiles, indicating no significant causality in weak green growth states. From the 0.4 quantile onwards, the statistic surpasses the 5% threshold and remains above it through the upper quantiles, demonstrating strong and persistent causality in moderate and high growth regimes. This suggests that ESG-related uncertainty exerts a significant and sustained influence on ΔGG, particularly when economies are already performing strongly.

The test statistic for the GT panel remains below the critical values at lower quantiles but crosses the 5% threshold around the 0.3 quantile and continues to rise steadily, remaining well above the critical region across higher quantiles. This pattern indicates a significant causal relationship between green technology and ΔGG in moderate and high growth regimes. The results highlight the strengthening role of green innovation as economies transition toward higher levels of sustainable growth.

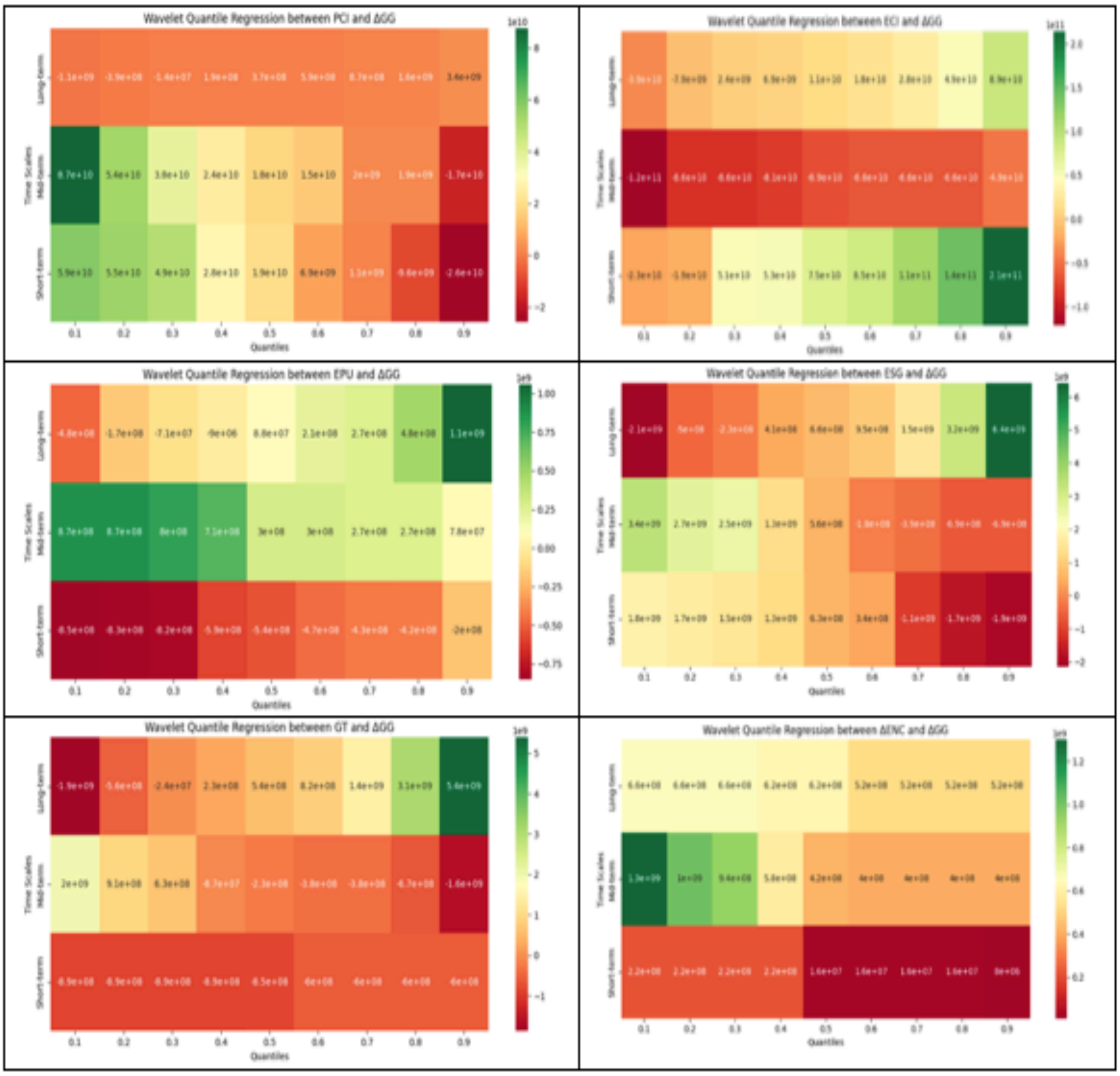
Regarding to the ΔENC panel, the test statistic remains well above the 5% and 10% critical values across all quantiles, indicating a strong and statistically significant causal relationship between changes in energy consumption and ΔGG throughout the distribution. The relatively flat pattern across quantiles suggests a consistent influence on energy dynamics on green growth, with the effect most pronounced in the mid-range quantiles. This implies that variations in energy use exert a stable and pervasive impact on green growth, regardless of the economy's performance state.

The wavelet-quantile regression heatmap (Figure 5) illustrates how the relationship between each variable of interests and ΔGG varies across both quantiles (horizontal axis) and time-frequency scales (vertical axis). For the PCI panel, at short-term scales, the coefficients are relatively small and mostly neutral to mildly positive at lower quantiles, implying that short-run variations in productive capacity have limited or short-lived effects on green growth, particularly in weaker performance states. However, the relationship strengthens markedly at medium-term scales, where positive coefficients dominate the middle quantiles (0.4-0.6), indicating that structural capacity improvements begin to exert a stabilizing and supportive influence on sustainable growth over intermediate horizons. At the long-term scale, the coefficients are consistently large and positive—especially in the higher quantiles (0.7-0.9)—demonstrating that productive capacity has a strong and persistent contribution to green growth in the long run.

For the economic complexity panel, at short-term scales, the coefficients are mostly small and positive toward the higher quantiles (07-0.9), suggesting that increases in complexity produce immediate but modest benefits for high-performing economies. At medium-term scales, the coefficients become more stable and largely positive, particularly in mid-to-upper quantiles, indicating that structural sophistication enhances green growth cumulative diversification and innovation effects. In contrast, long-term scales show stronger and more uniformly positive coefficients across nearly all quantiles, confirming that complexity plays a sustained role in supporting green growth over longer horizons.

Regarding to the economic policy uncertainty panel, at shot-term scales, the coefficients are predominantly negative, especially in the lower and middle quantiles, suggesting that shoer-run spikes in policy uncertainty hinger green growth, particularly in weak and moderate performance states. At the medium-term scale, the coefficients shift toward neutral or slightly positive levels at higher quantiles, implying that moderate uncertainty may encourage adaptive policy and investment adjustments in stronger economies. Over the long term, the coefficients become consistently positive across nearly all quantiles, with the strongest effects observed in upper quantiles (0.7-0.9). This pattern indicates that in the long run, economies with established green frameworks are better able to absorb or even capitalize on policy uncertainty, transforming it into innovation-driven adaptation.

Figure 5: Adebayo and Özkan (2024) wavelet-quantile regression results



For the ESG-related uncertainty panel, at short-term scales, the coefficients are largely negative across the distribution, indicating that spikes in ESG uncertainty immediately suppress growth-adjust green output, particularly in lower and mid quantiles. Moving to medium-term scales, the coefficients become less negative and occasionally positive in the higher quantiles, suggesting that as uncertainty stabilizes, well-performing economies can partially offset its adverse impact through policy adaptation and stronger institutional frameworks. At long-term scales, the coefficients shift to consistently positive, especially in the upper quantiles, implying that sustained improvements in ESG governance and disclosure ultimately support long-run green growth performance.

For the green technology panel, at short-term scales, the coefficients are mostly negative across all quantiles, indicating that short-run increases in green technology investment may initially impose adjustment costs or exhibit delayed benefits for green growth. In the medium-term scales, the coefficients become neutral to moderately positive, particularly in mid-to-upper quantiles, suggesting that as technological diffusion progresses, innovation begins to stimulate greener outcomes. At long-term scales, the coefficients turn strongly positive, with the highest values appearing in the upper quantiles, implying that mature green technology adoption drives sustained improvements in green growth, especially in already high-performing economies.

Regarding to the changes in energy consumption panel, at short-term scales, the coefficients are predominantly negative across all quantiles, suggesting that rapid or short-lived fluctuations in energy consumption hinder green growth, particularly in lower-performing states. At the medium-term scale, the coefficients become positive, especially in the middle and upper quantiles, indicating that stable and moderate increases in energy use contribute to ΔGG as economies transition toward cleaner production and efficiency gains. At long-term scales, the coefficients remain positive and stable across nearly all quantiles, implying a persistent and broad-based contribution of energy consumption to green growth over time, likely reflecting structural shifts toward renewable and efficient energy systems.

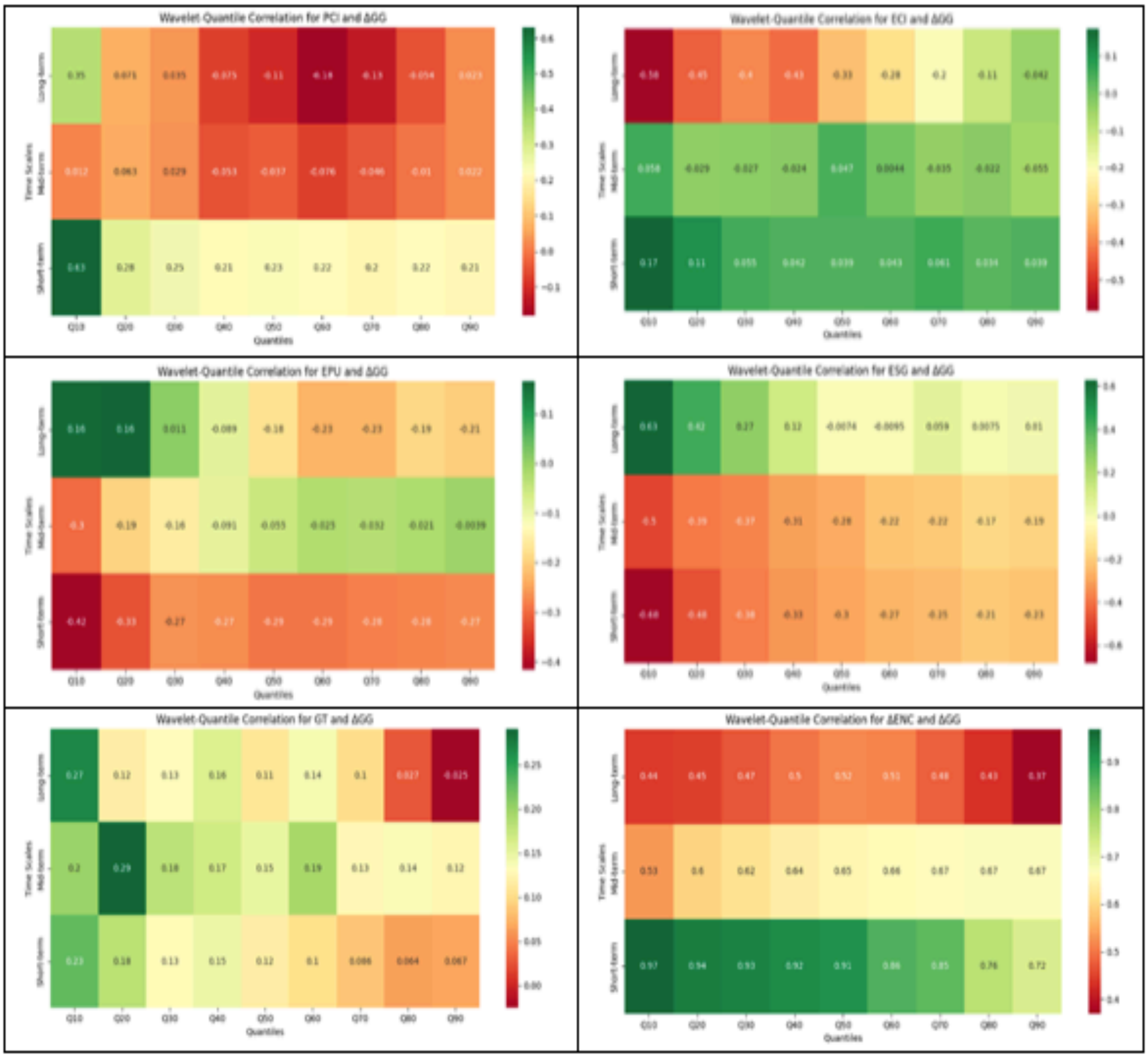
Figure 6 illustrates the strength and direction of the wavelet quantile correlation between each variable of interest and ΔGG across time-frequency scales and quantiles. At short-term scales, the correlations are weak to moderately positive (ranging from 0.18 to 0.29), indicating that fluctuations in productive capacity exert only limited immediate influence on green growth. In the medium-term scale, correlations remain mostly weak or near zero across quantiles, implying that short- and medium-horizon co-movements between PCI and ΔGG are not particularly strong or persistent. However, at long-term scales, the correlations strengthen considerably, especially in the lower quantiles (up to 0.75), revealing a stable and positive long-run association between productive capacity and green growth. The middle quantiles (0.4-0.6) show mild attenuation, suggesting that the relationship is most pronounced at the extremes of the growth distribution.

For the ECI panel, at short-term scales, correlations are consistently positive and moderately strong (0.07-0.15) across all quantiles, suggesting that short-run fluctuations in economic complexity are closely aligned with movements in green growth. In the medium-term, coefficients remain positive and relatively stable (around 0.02-0.03), implying a sustained but moderate co-movements over intermediate horizons. At the long-term scale, the pattern strengthens further, with positive correlations dominating mid-to-upper quantiles and reaching up to 0.61 in the highest quantile. This indicates that the link between economic complexity and green growth is persistent and intensifies over longer horizons, particularly for economics in higher growth rates.

For the EPU panel, at short-term scales, the correlations are predominantly negative (around -0.44 t0 -0.17), especially in the lower quantiles, indicating that short-run spikes in policy uncertainty hinder green growth, particularly for economies with weaker green performance. In the medium-term, the correlations weaken in magnitude and become slightly positive at higher quantiles, suggesting that economies with stronger green growth may partially absorb short-lived uncertainty shocks. At long-term scales, the correlations turn mildly positive (up to 0.14) across most quantiles, implying that the negative short-run impact of policy uncertainty dissipates over time and that stable institutional frameworks may mitigate its adverse effects.

For the ESG panel, at short-term scales, correlations are strongly negative across all quantiles (around -0.48 to -0.27), indicating that immediate fluctuations in ESG uncertainty significantly hinder green growth, particularly in low-performing economies. Over the medium-term, the correlations weaken in magnitude and turn mildly positive in upper quantiles, suggesting that the adverse effects of ESG uncertainty gradually diminish as economies adapt through improved disclosure and governance. At long-term scales, the correlations become distinctly positive (up to 0.42), especially at lower quantiles, signifying that sustained stability and clearer ESG frameworks contribute positively to long-run green growth outcomes.

Figure 6: Kumar and Padakondla (2022) wavelet-quantile correlation



For the green technology panel, at short-term scales, the correlations are mildly positive (around 0.11-0.13), suggesting that short-run green technology developments have an immediate but modest association with green growth. Over the medium-term, the correlations strengthen substantially, particularly in the lower and middle quantiles (up to 0.29), indicating that as technological diffusion takes hold, the positive relationship between green innovation and green growth becomes more pronounced. At long-term scales, the correlations remain positive in most quantiles but weaken slightly toward the upper tail, implying that while the green technology-growth nexus persists over time, its marginal contribution stabilizes in highly developed green economies.

Regarding to the energy consumption panel, at short-term scales, correlations are strongly positive across all quantiles, indicating that short-run changes in energy use are closely aligned with green growth dynamics, possibly reflecting energy-driven production responses or transitional energy demand effects. At the medium-term scales, the correlations remain positive but slightly moderate (0.33-0.47), suggesting a more balanced relationship as economies adjust toward cleaner and more efficient energy structures. Over the long-term scale, correlations weaken further and turn mildly negative (-0.44 to -0.37), implying that persistent increases in energy consumption may eventually exert downward pressure on sustainable growth, potentially due to resource constraints or the environmental costs of prolonged energy dependence.

5. Conclusion

This paper examined how productive capacities, economic complexity, green technology, and different forms of uncertainty shape green growth in 18 OECD countries between 2003 and 2022, using green GDP as the main indicator of performance. The results show that green growth is not driven by single factors in isolation but by the interaction between structural strength, innovation capacity and a stable policy environment. The effects are also clearly nonlinear and state-dependent: what matters for countries at the lower end of the green growth distribution is not always the same as what matters for those already performing well.

First, we find that productive capacity and economic complexity support green growth, but their contribution is strongest once a country has already reached a certain level of structural development. At low quantiles of productive capacity, green growth is often constrained, while at higher levels, productive capacity amplifies gains and helps to sustain a greener trajectory. Economic complexity shows an even more robust and persistent positive effect, especially in the upper part of the green growth distribution. This suggests that moving towards more knowledge-intensive and diversified productive structures is central for long-run green growth.

Second, green technology plays a pivotal but threshold-driven role. Low levels of green technology and isolated innovations provide only limited benefits and may even entail short-run adjustment costs. When the share of green technologies becomes sizeable, however, their impact on green GDP turns strongly positive and reinforces existing green growth momentum. This pattern is consistent with diffusion and scale effects: once clean technologies are embedded in production systems, they support both higher output and lower environmental damage.

Third, uncertainty is a clear drag on green growth, especially in weaker states. Economic policy uncertainty and ESG-related uncertainty both tend to depress green GDP when green growth is already fragile. Policy uncertainty shocks have sharp but relatively short-lived impacts, whereas ESG uncertainty is more persistent and affects a wider range of quantiles and horizons. These results underline that unclear or unstable policy signals, including around ESG rules and climate commitments, can delay long-term green investment and weaken the credibility of the transition.

Fourth, changes in energy consumption are positively associated with green GDP across quantiles, but this relationship is conditional. In the short term, rising energy use tends to coincide with higher growth, reflecting scale effects. Over the longer term, the benefits depend on whether additional energy demand is met from cleaner and more efficient sources. Without continued improvements in energy mix and efficiency, higher energy use can lead to environmental stress that may undermine future green growth.

Taken together, the evidence suggests several policy implications for OECD countries. In particular, firstly, build and rebalance productive capacities. Policymakers should treat productive capacities as a foundation for green growth. This means sustained investment in human capital, transport and digital infrastructure, reliable energy systems and effective institutions. Since the positive effects of productive capacity are strongest at higher levels of green growth, there is a risk that existing leaders pull further ahead. Targeted support for lagging regions and sectors is needed so they can cross the threshold at which productive capacity begins to reinforce green outcomes rather than simply raising conventional output.

Second, use industrial policy to push economic complexity in a green direction. The strong link between economic complexity and green GDP implies that industrial and innovation policy should focus on developing more complex, low-carbon export baskets rather than simply expanding any high-tech activity. Support for sectors that combine high value added with low material and carbon intensity, such as advanced manufacturing, digital services and clean technology supply chains, can raise both complexity and environmental performance. Trade and competition policy should also aim to keep markets open enough for firms to learn, upgrade and participate in green global value chains.

Third, scale and diffuse green innovation, not only invent it. The results on green technology indicate that small pockets of green patents are not enough; benefits arise when green technologies reach sufficient scale and diffusion. Policy thus needs to support the full innovation cycle: basic R&D, demonstration projects, standards, deployment and diffusion. Instruments may include targeted R&D grants, tax credits for clean investment, green public procurement and risk-sharing through green investment banks and development finance institutions. Policies should pay attention to diffusion to SMEs and lagging regions, not only to technological frontiers in a few large firms or cities.

Fourth, reduce policy and ESG uncertainty through clear, credible frameworks. Because both economic policy uncertainty and ESG uncertainty depress green growth, especially in weaker states, a central policy task is to provide stable and predictable rules. This includes: i) setting clear and time-consistent climate targets and transition pathways; ii) avoiding frequent reversals in carbon pricing, subsidies and regulations; iii) harmonising ESG disclosure standards and supervisory expectations across agencies; and iv) communicating changes with enough lead time for firms and investors to adjust. A credible, predictable policy and ESG framework lowers risk premia, lengthens planning horizons and encourages firms to commit capital to long-term green projects.

Fifth, align energy demand with a clean and efficient supply. The positive but conditional role of energy consumption suggests that energy policy should not aim to reduce energy use mechanically, but to change how energy is produced and used. Investments in renewable generation, grid upgrades, storage, demand-side management and energy efficiency standards can ensure that higher energy demand, where it occurs, is met in ways consistent with green growth. At the same time, phasing out fossil-fuel subsidies and tightening performance standards for carbon-intensive assets can reduce the risk that energy-driven growth leads to environmental lock-in. Support for households and workers most exposed to the transition will be important for maintaining social and political support.

Last, use OECD experience to guide and support broader transition. Because OECD economies are often early adopters of green policies and ESG frameworks, their experiences in managing productive capacities, complexity, green innovation and uncertainty can provide useful lessons for other countries. Sharing data, tools (such as green GDP metrics and productive capacity indices), and policy designs can reduce learning costs elsewhere and help to avoid repeated policy mistakes. At the same time, OECD countries should recognise that their own green growth is interconnected with the rest of the world through trade, technology transfer and finance, and design policies that support, rather than hinder, a wider global transition.

Overall, the findings indicate that green growth in advanced economies is not automatic. It depends on the long-run development of structural and technological capacities, combined with credible and stable policy signals that lower uncertainty around the transition. The challenge for policymakers is to manage these elements together, rather than treating productive capacity, innovation, ESG and energy use as separate agendas.

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