Green Finance and Ecological Outcomes: A Quantile Approach to Biodiversity and Carbon Emissions in OECD Countries

Abstract

Purpose: This study examined the combined impact of green finance, innovation, taxes and environmental policy stringency (EPS) on environmental and ecological dynamics for the OECD countries using data from 1994 to 2020.

Methodology: The study employed advanced econometric techniques, including cross-sectionally augmented Dickey-Fuller (CADF), cross-sectionally augmented Im, Pesaran and Shin (CIPS), Westerlund (2007) cointegration, Methods of Moment Quantile Regression (MMQR) and Dumitrescu & Hurlin (2012) panel causality test.

Findings: The empirical evidence established a heterogeneous impact of green finance across quantiles with a negative impact on biodiversity loss and a positive impact on CCO_2 emissions and biocapacity. Moreover, green taxes and policy stringency decrease biodiversity loss and carbon emissions. A bidirectional causality is identified between CO_2 and biodiversity.

Practical implications: The results advocate targeted financial policies, driven by technological innovation, to improve the capability of OECD countries in mitigating emissions and preserving biodiversity.

Originality: This unique study contributes to existing literature by considering the impact of green finance, innovation and policy tools on both environmental and ecological dynamics (both biodiversity loss and bio-capacity) across different quantiles.

Keywords: *Green finance, Biodiversity, Biocapacity, Green taxes, OECD, MMQR*

1. Introduction

Environmental challenges have garnered significant attention worldwide, with their prevalence expected to intensify further (Qin et al., 2023). The significant role of carbon emissions in climate change cannot be ignored, resulting in rising global temperatures that have negatively impacted the environment and human health (Su et al., 2022). In addition, biodiversity underpins the necessary elements of human well-being (Li et al., 2024) and contributes to environmental sustainability (Di Vaio et al., 2021).

According to UNEP (2019), climate change is a significant concern, as it promotes unpredictable weather events, leading to damaged infrastructure and a reduction in food supply. Global warming, accompanied by flooding and sea level rise, leads to population migration (Agan, 2024; Qin et al., 2023). The rise in global temperature is mainly attributed to economic activities and is the focus of empirical and theoretical studies (Gyamfi et al., 2022). Consumption-based carbon emissions (CCO_2) increase with imports and overall economic growth and decrease with exports and the use of renewable energy (Hassan et al., 2022). An increase in imports by developed economies increases both consumer and production-based carbon emissions (Mahmood, 2022). Notably, since the 1990s, production has relocated from developed to emerging economies to benefit from the lower cost of production resulting from weak regulation and labor cost[1]. This caused increased environmental degradation in the source countries such as South Africa, India, Indonesia, Iran and China, but reduced production-based CO_2 in the destination countries. CO_2 produced in one country impacts the climate of the world as a whole rather than the CO_2 source country. Consequently, developed countries are not immune to flooding, temperature and sea level rise, posing infrastructure damage and giving rise to extreme climate events. In response, the Paris agreement (COP21) recognizes the challenge and acknowledges the link between CO_2 and resulting negative events (Su et al., 2022).

In this regard, a growing body of literature suggests the main causes of CO_2 emission are industrialization (Rehman et al., 2021), renewable energy consumption and rapidly increasing international trade over the last three to four decades (Amin et al., 2022). There is now an overwhelming consensus over the cause and consequences of CO_2 emissions for the global ecosystem. Thus, the focus has shifted towards developing technologies to implement the Paris

[1] https://www.ilo.org/publications/offshoring-and-internationalization-employment-challenge-fair-globalization

Agreement 2015 and Glasgow in 2021 to phase out CO_2 emissions. To achieve these objectives, the focus has remained on technologies, improving regulations and developing strategies for carbon mitigation. However, there is limited literature that has analyzed the impact of green finance and its ability to promote green innovation for OECD economies.

Carbon emission and climate change association have been the subject of past studies (such as Rahman et al., 2025); however, biodiversity loss, which is interlinked with carbon dynamics and ecosystem resilience, has received limited attention. A study by Sarkodie and Strezov (2019) identified that both carbon emissions and biodiversity loss are central issues in attaining environmental sustainability. Climate mitigation without considering biodiversity conservation reduces carbon emissions in the short-term but may contribute to ecological imbalance in the long run (Sarkodie and Strezov, 2019). Therefore, integrating biodiversity loss and biocapacity consideration with carbon mitigation is vital to ensure consistent and holistic environmental protection.

In this regard, the use of green finance and taxes is capturing policymakers' attention in advancing low-carbon innovation (green innovation) and biodiversity conservation (Umar et al., 2023; Rahman et al., 2025). Green finance channels the funds from private and public investment into sustainable activities such as reforestation, ecosystem restoration and renewable energy deployment. In contrast, environmental or green taxes internalize ecological costs and discourage biodiversity degradation (Gao et al., 2025). Literature (Umar et al., 2023; Rahman et al., 2025; Guan et al., 2025) suggests that green finance is an emerging source of funds to support economic development whilst adhering to an environmentally conservative agenda. Therefore, green finance has gained traction amongst pro-environmental conservationists and policymakers to reorient polluting economies, and hence to reduce CO_2 emissions and biodiversity loss. Despite its benefits, there is a lower level of takeoff and a general level of awareness due to information asymmetry between investors and borrowers. Therefore, this study examines the complex interplay of environmental taxes and green finance and the collective impact on carbon emissions and answers the following questions. (a) Does green finance, taxes and innovation affect both carbon emissions and biodiversity? (b) Does Environmental Policy Stringency (EPS) affect the role of green finance in carbon emissions, biodiversity and biocapacity?

This study contributes to existing literature by examining both carbon emissions and biodiversity to measure a wider spectrum of environmental outcomes and relationships with determinants. Moreover, the study also uses two different measures for biodiversity to consider both biodiversity loss and bio-productive capacity within the OECD countries. Further, the study tests the moderating role of environmental policy stringency (EPS) in the relationship between green finance and ecological outcomes. The reason for studying OECD countries is based on the fact that they account for about 46% of the global GDP and are net importers of greenhouse gas emissions (OECD, 2024)[2]. Moreover, OECD countries are the main users of renewable energy and have diverse economic structures, from high-value manufacturing to high consumer-driven economies, providing a comprehensive sample to examine the benefits of environmental measures.

The following section of this article examines the pertinent literature related to green finance, innovation, tax and policy stringency on carbon emissions. Section 3 explained the methodology applied, and Section 4 reports results and discussion emerging from the findings. Section 5 concludes the study and provides recommendations.

2. Literature Review

2.1. Green finance, innovation and taxes

Over recent years, several studies have examined the role of green finance, innovation, taxation and policy stringency. The emerging literature disintegrates the relationship between rapid industrialization and its environmental outcomes, such as carbon emissions and biodiversity loss, leading to extreme climate events and threatening the human environment (Wang et al., 2022; Sachs, 2015). The intense global transition toward sustainability has reshaped the role of the financial system, emphasizing the role of green finance. Literature (Sharif et al., 2023; Meo et al., 2022) demonstrates that green finance offers a lower interest rate to low-carbon emitting firms and promotes a clean environment and thus, a crucial enabler for decarbonization. Shi et al. (2024) highlight a positive relationship between green finance and innovation in enterprises, especially in the highly polluted firms, with a significant positive moderating role of investors' preferences. Bai and Lin (2023) suggest that green finance promotes green innovation, while zero-inflated factors significantly reduce the non-sustainable behavior of enterprises. Notwithstanding, Wang et al.

[2] https://www.oecd.org/en/data/insights/statistical-releases/2024/05/share-of-oecd-economies-in-global-gdp-broadly-stable-at-46-in-2021-compared-to-2017.html?

(2023) explore a bidirectional causal relationship between CO_2 and green finance, and highlight that their relationship depends on government policy, regulatory framework and market maturity. Recent evidence suggests that green finance and taxes improve the environmental quality and human capital index reduces it. Likewise, technology innovation, when integrated with green finance, reduces carbon emissions (Javed et al., 2024; Wang et al., 2025). Lu et al. (2025) study documented inconsistent results; the impact of green finance in mitigating carbon emission was found to be significant only in the urban region of China.

In addition to green finance, studies explore that environmental taxes promote green infrastructure, innovation, green productivity, and boost private investment in sustainable projects (Deng et al., 2024; Masoud et al., 2024). According to the OECD (2021), environmental taxes serve as an effective tool to moderate firms' polluting behavior and to promote sustainable economic policies. Similarly, Murad et al. (2025) established that carbon taxes increase the cost of fossil fuel consumption and push industries towards the use of renewable energy and green technologies to reduce the cost of doing business. However, studies also investigate that the effectiveness of environmental taxes depends on the economic growth stage of a country, price elasticity, enforcement mechanism and complementary policies. In the meantime, Guo et al. (2022) suggest that environmental taxes have the potential to reduce CO_2 emissions, thereby promoting a sustainable ecosystem. Sharif et al. (2023) propose replacing energy subsidies with the provision of heat pumps and biofuels to reduce carbon emissions in 5 Nordic countries. Dogan et al. (2022) supported the efficacy of environmental taxes in G7 countries if accompanied by effective litigation in support of the transformation to environmentally friendly approaches.

2.2. Environmental policy stringency and environmental degradation

In addition, green finance facilitates technological innovation, enabling businesses toward a green transition. Sun et al. (2022) demonstrate that financial and policy measures drive environmentally friendly innovation, depending on countries' infrastructure, regulatory framework and institutional quality. Umar and Safi (2023) show that EPS, green initiatives, and export significantly reduce carbon emissions and improve environmental quality. However, Sterner and Köhlin (2012) find that over-strict policies may stifle economic growth if they fail to account for industry-specific challenges and technological feasibility. Thus, finding a balance between stringent regulations and economic adaptability is critical to ensuring long-term sustainability.

Despite growing literature on environmental quality, limited research exists on the multivariate analysis of eco-friendly actions such as environmental taxes, green finance, technological innovation and EPS on CCO_2, biodiversity loss and biocapacity for the OECD countries. The existing research (Lu et al., 2025; Murad et al., 2025) mainly focused on carbon emissions but ignored biodiversity due to indecisiveness on biodiversity measures. For instance, Li et al. (2024) used the biodiversity export footprint (export of species, such as mammals, birds, plants, insects, reptiles, amphibians, fishes and molluscs), provided by the International Union for Conservation of Nature (IUCN). Habibullah et al. (2022) considered the Red List Index (RLI) for biodiversity loss, and recently Rahman et al. (2025) employed biocapacity for biodiversity production. This study used both biodiversity loss—measured by RLI—and biocapacity to cover the wider performance of the biodiversity determinants. Further, according to the best of the author's knowledge, the literature lacks empirical examinations on whether EPS affects the environmental outcomes of green finance. To fill these gaps in the literature, this study investigates the environmental outcomes of EPS, green technological innovation and green taxes in the OECD countries in the context of CCO_2, biodiversity and biocapacity.

3. Methodology

3.1. Theoretical framework and rationale of the study

This study integrates ecological economics, green finance, environmental policy and innovation theory to describe their potential impact on carbon emissions and biodiversity in the OECD countries. Ecological economics emphasizes that economic activities are usually limited to ecological limits, highlighting the importance of the green financial system in economic and environmental sustainability (Costanza et al., 1997). In this context, green finance is theorized to provide investment for promoting sustainable technologies and hence to reduce carbon emissions and promote biodiversity (Wang et al., 2022). However, the Porter hypothesis suggests that EPS and environmental regulations can promote technological innovation, which improves environmental and economic indicators (Porter and Linde, 1995). Moreover, Pigovian tax theory suggests that environmental taxes align economic and financial activities with environmental sustainability by internalizing the social costs of pollution, and hence promote sustainable practices (Pigou, 2017). Howevr, the multi-purpose nature of environmental taxes, green finance and environmental policy may result in trade-off where carbon emissions may not always be reduced and can even sometimes undermine biodiversity goals (Rockström et al., 2009).

3.2. Data and variables

The study undertakes yearly data for the period of 1994 to 2020, on 27 OECD countries. The time span and sample countries within the OECD panel are selected based on the availability of data. More specifically, data for green taxes is available from 1994, while the latest data for EPS is available till 2020. The focus of the study is on environmental taxes (as a percentage of total taxation), which can be used to promote green finance and innovation, based on environmental policies. The environmental performance is measured from two different dynamics: consumption-based CO_2 for environmental impact, and biodiversity and biocapacity for ecological outcomes.

For biodiversity loss, the study uses RLI, following earlier studies (Habibullah et al., 2022; Szabo et al., 2012) that provide information related to the average extinction risk of species, such as mammals, birds, cycads, amphibians and corals at the national level (World Bank, 2024)[3]. These estimations are provided by the IUCN: Red List Index (RLI) of threatened species. The RLI is a life barometer metric that ranges from 1 to 0, representing least concern (no extinction) to completely extinct (gone). In addition, to measure the productivity of the country's inhabitants, the study follows Rahman et al. (2025) and uses the biocapacity index, provided by Ecological Footprint Network, summing all the bio-productive areas within a country to support harvest (cropland, grazing land, forest and fishing grounds) and other carbon emissions absorber areas (Ecological Footprint Network, 2025)[4]. Countries that reduce carbon emissions, biodiversity loss, and improve biocapacity per person perform well in maintaining environmental quality (Dada et al., 2023; Habibullah et al., 2022).

Moreover, the green taxes are the environmentally related revenue, mainly collected from four bases: transport, resources, energy products (including vehicle fuels) and pollution taxes. These taxes are primarily comprised of tax revenue, base, rate and exemption. Further, due to data availability and following Umar and Safi (2023), this study is interested in the public green finance—the funds provided by the government for R&D related to sustainable energy projects. The green innovation is measured by the % of green patents (number of environment-related inventions) to all domestic technological patents, aiming to decrease carbon emissions. The EPS measures how strict government policies are for implementing air pollution and environmental

[3] https://ourworldindata.org/grapher/red-list-index
[4] https://www.footprintnetwork.org/resources/data/

risk mitigation policies. It can be assumed that an optimal level of environmental taxes promotes green finance and innovation by ensuring environmentally compliant policies which reduce carbon emissions and improve biodiversity. Further, the impact of economic growth, measured by GDP per capita (constant $2015), and total population on environmental quality are controlled in the model. The size of Population and GDP growth are employed as controlled variables to control for scale effects and innovation diffusion (Ahmad et al., 2018). GDP captures economic intensity and population accounts for demographic pressure and consumption patterns with implications for both biodiversity and emissions. Table 1 provides the variables' details.

Table 1: Variables detail

Variables	**Symbol**	**Description**	**Source**
Green Taxes	GT	Environmental taxes revenue (% of total taxation)	OECD
Green Innovation	GI	Patents on environmental technologies (% to all domestic innovation)	OECD
Green Finance	GF	Environment related government R&D budget (% to total R&D)	OECD
Environment Policy stringency	EPS	Index	OECD
Consumption-based carbon emissions	CCO_2	Annual consumption-based CO_2 emissions (Mt)	World Bank
Biodiversity	BIOD	Red List Index	World Bank
Population	POP	Number of total individuals	World Bank
Economic Growth	EG	GDP 2015 (constant)	World Bank
Biocapacity	BIOC	Biocap ghs per person	Ecological Footprint Network

To reduce heterogeneity, all variables are transformed into logarithms due to different measurement units. For empirical analysis, the following models are constructed, following Umar and Safi (2023) and Paramati et al. (2025), to investigate the impact of green finance, technological innovation, and taxes on environmental quality—biodiversity and CCO_2 emissions.

$$lnCCO_{2,it} = \beta_o + \beta_1 lnGF_{it} + \beta_2 lnGI_{it} + \beta_3 lnGT_{it} + \beta_4 lnEPS_{it} + \beta_5 lnPOP_{it} + \beta_6 lnGDP_{it} + \varepsilon_{it} \dots\dots\dots\dots\dots\dots (1)$$

$$lnBIOD_{it} = \beta_o + \beta_1 lnGF_{it} + \beta_2 lnGI_{it} + \beta_3 lnGT_{it} + \beta_4 lnEPS_{it} + \beta_5 lnPOP_{it} + \beta_6 lnGDP_{it} + \varepsilon_{it} \dots\dots\dots\dots\dots\dots (2)$$

$$lnBIOC_{it} = \beta_o + \beta_1 lnGF_{it} + \beta_2 lnGI_{it} + \beta_3 lnGT_{it} + \beta_4 lnEPS_{it} + \beta_5 lnPOP_{it} + \beta_6 lnGDP_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

In the above equations, CCO_2 is consumption-based carbon emissions, $BIOC$ and $BIOD$, are biocapacity and biodiversity; GF, GI and GT represent green finance, innovation and taxes; EPS environmental policy stringency, POP is population, GDP is gross domestic product, ε is error term for the sample i during the time period t and finally, β indicates parameters of change in dependent variables. Moreover, to investigate the moderating role of EPS, the study adds the interaction term of green finance and EPS ($lnGF^{*}EPS$) in the above three basic equations.

3.3. Methodological techniques

The study data drive analysis starts with the descriptive analysis to summarize data key characteristics, followed by slope heterogeneity and cross-sectional dependency (CSD) to examine robust panel estimation. Unit root and cointegration tests are conducted to test the variables' data for stationarity and long-run relationships. Panel quantile regression and the Generalized Methods of Moments (GMM) are used to capture heterogeneous effects across quantiles and long-run relationships. Finally, the Dumitrescu and Hurlin (2012) causality test is employed to determine the directionality of relationships among the variables. The data analysis was conducted on Stata 19 and EViews 13. Fig. 1 illustrates the flow of methodological tests applied in the study.

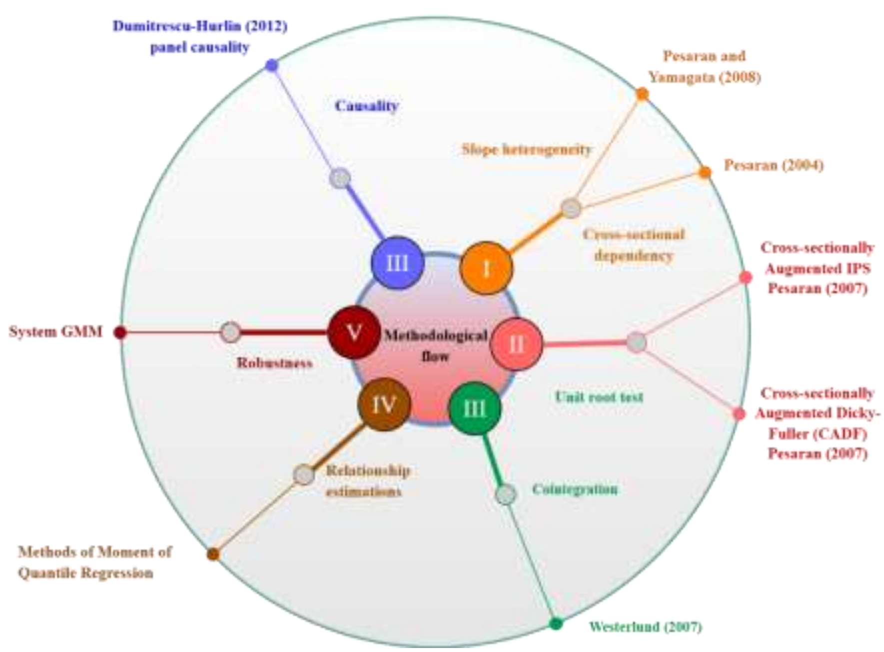

Figure 1: Methodological flowchart
Source: Author's own work

3.3.1. Cross-sectional dependency (CSD)

This study employed Pesaran’s (2004) CSD test to examine the inter-dependency among the variables. This test explores the correlation between the residuals derived from panel regression. Mathematically, it can be expressed as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i-1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \dots\dots\dots..(4)$$

Whereas $\hat{\rho}_{ij}$ indicates the pairwise residual’s correlation, *T* is time dimension, and *N* represents cross-sectional units.

3.3.2. Slope heterogeneity

Testing the panel data for slope heterogeneity is essential considering the varied nature of selected countries' economic composition and interdependencies of macroeconomic variables. In this regard, the study employed Pesaran and Yamagata (2008) slope heterogeneity test which covers both the Delta and Adjusted-Delta. The null hypothesis states that the coefficients are homogeneous against the alternative hypothesis of heterogeneity. Slope heterogeneity can be expressed as follows:

$$\Delta = (N)^{\frac{1}{2}}(2k)^{-\left(\frac{1}{2}\right)}\left(\frac{1}{N}S - k\right) \dots\dots\dots(5)$$

While the bias-adjusted equation for $\Delta^{\sim}$ can be expressed as follows:

$$\Delta_{\mathrm{Adj}} = (N)^{\frac{1}{2}}\left(\frac{2k(T-k-1)}{T+1}\right)^{-\left(\frac{1}{z}\right)}\left(\frac{1}{N}S - 2k\right) \dots\dots..(6)$$

3.3.3. Unit root test

To examine stationarity or integration order in the time series, the study employed cross-sectionally augmented Im, Pesaran and Shin (CIPS), proposed by Pesaran (2007) and cross-sectionally augmented Dickey-Fuller unit root tests. CIPS test extends standard IPS framework to account for CSD with averages of cross-sectional units and differences of individual series. Notably, it also accommodates slope heterogeneity, distinguishing it from traditional unit root tests. Empirically, the CIPS test can be expressed as follows:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \dots \dots \dots \dots (7)$$

3.3.4. Cointegration test

The Westerlund (2007) cointegration test is employed to examine the long-run relationship among the variables. This test offers stable and reliable estimates while explicitly accounting for cross-sectional dependence in the error terms (Kapetanios et al., 2011). According to Westerlund (2007) cointegration test, the null hypothesis must incorporate the absence of cointegration for at least one group (Gt) and (Pt) cross-sections. The empirical equations of Westerlund can be expressed as follows.

$$\eta_i(L)\Delta y_{it} = \delta_{1i} + \delta_{2i} + \eta_i(y_{it-1} - \beta' x_{it-1} + \lambda_i(L)' v_{it} + e_{it} \dots \dots \dots \dots \dots (8)$$

Where $\delta_{1i} = \eta_i(1)\varphi_{2i} - a_i\varphi_{1i} + \eta_i\varphi_{2i}$ and $\delta_{2i} = -\eta_i\varphi_{2i}$

In Eq. (7), η_i denotes the vector of cointegration between the variables x and y, and βi is the coefficient for error correction. The following are the test statistics.

$$G_t = \frac{1}{N}\sum_{i=1}^{N} \frac{a_i'}{\psi(a_i')} \dots \dots \dots \dots \dots (9)$$

$$G_a = \frac{1}{N}\sum_{i=1}^{N} \frac{Ta_i'}{a_i'(1)} \dots \dots \dots \dots \dots \dots .. (10)$$

Panel cointegration is estimated by the following equation;

$$P_s = \frac{a_i'}{\psi(a_i')} \dots \dots \dots \dots (11)$$

$$P_a = Ta'_i \dots \dots \dots \dots \dots (12)$$

The terms *Gt* and *Ga* represent the statistics for the group means, and the *Pt* and *Pa* represent the panel statistics. In the above equations, ψ is the dependent variable, $P_a = T\mathrm{a}_i'$, is the percentage of the error. The null hypothesis tests no cointegration $(\alpha_i = 0)$ against the alternative hypothesis $(\alpha_i < 0)$ demonstrating the existence of cointegration.

3.3.5. Panel Quantile Regression and System GMM

To estimate the relationship among the variables, the study applied the Methods of Moment Quantile Regression (MMQR) proposed by Machado and Santos Silva (2019). This model overcomes the limitations of the traditional quantile regression technique and provides more robust results, as it is less sensitive to the effect. Initially Koenker & Bassett (1978), introduced quantile regression, which is a generalized median regression model, followed by other quantiles (Jahanger et al. 2023). Empirically, the conditional quantile regression for two variables (y_i, and x_i) can be stated as follows.

$$Q_{di}\left(\tau \,\middle|\, c_i\right) = c_i^T \beta_\tau \dots\dots..(13)$$

Eq. (13) examines the relationship between two variables at the upper and lower levels and effectively supports the conditional distribution; yet it is unable to consider the unobserved heterogeneity in a cross-section, based on Eq. (13). According to the literature (Galvao and Kato 2016; Kato et al., 2012), unnoticed heterogeneity can be monitored by considering econometric theories in the quantile regression technique. Hence, Eq. (13) can be rewritten as Eq. (14) to fit for panel quantile regression.

$$Q_{di}\left(T_{\mathrm{k}} \,\middle|\, \alpha_{it} c_{it}\right) = \alpha_i + c_{it}\beta(T_k) \dots\dots..(14)$$

Further, for robustness, the study applies the system generalized method of moments (GMM) technique. This approach is comparatively more effective for robustness due to several reasons. For instance, it controls endogeneity, Nickell bias, measurement error, heteroskedasticity, unobserved individual heterogeneity and simultaneous reverse causality (Apergis and Ozturk, 2015; Ganda, 2019).

3.3.6. Causality test

To check the direction of the relationship among the variables, this study used Dumitrescu & Hurlin's (2012) causality test. This test extends the Granger causality approach to heterogeneous panels and considers CSD, and provides reliable results even when the data is not balanced (Dumitrescu & Hurlin, 2012). The equation for D-H causality can be written as follows.

$$Y_{i,t} = \alpha_{it} + \sum_{n=1}^{n} \gamma(n)\, y_{i,t-n} + \sum_{n=1}^{n} \beta_i(n)\, x_{i,t-n} + u_{it} \dots\dots\dots\dots\dots (15)$$

In Eq. (14), α_i represents the individual effect, $\gamma(n)$ is the lag parameter, n is the length of the lag, and $\beta_i(n)$ ($\beta_{1+}\beta_2$………$\beta_{n,}$) is the slope of the parameter.

The acceptance or rejection of the null hypothesis depends on the P values in D-H causality. The methodological techniques can be represented as follows.

$$W_{N,T}^{Hnc} = \frac{1}{N}\sum_{i=1}^{N} W_{i,t} \dots\dots\dots\dots..(16)$$

4. Findings and discussion

The descriptive analysis of the selected variables is documented in Appendix 1; Gross domestic product (GDP) used as a proxy for economic growth recorded the highest standard deviation of 1.439 amongst all variables. As can be seen in Table A1 in the online Appendix, the skewness ranges from 0 to -2 and kurtosis from 0 to 11 for all the variables. To test for robustness, the study employed the Jarque and Bera (1987) test, which shows that the data is not normally distributed, except for the GDP, leading to the rejection of the null hypothesis. Moreover, it implies that the data requires robust econometric analysis.

To test the data for potential correlations, it is required that the independent variables' slopes differ across the cross-sections in a panel dataset. As can be seen in Table A2 in the online Appendix, the delta and adjusted delta values reported are significant at 1% level, suggesting the presence of heterogeneity in the independent variables' slopes. Therefore, the data is tested for cross-sectional dependency (CSD) of the variables using Pesaran (2007). The findings reported in Table A3 prove the presence of CSD in the panel data. To test for the integration order of the variables, a number of econometric tests, Cross-sectionally Augmented Im, Pesaran and Shin (CIPS) and Cross-sectionally Augmented Dickey-Fuller (CADF) were employed as exhibited in Appendix 3.

Results documented in Appendix 3 reported Biodiversity (lnBIOC), consumption-based carbon emissions (lnCCO_2), green finance (lnGF) and environmental policy stringency (lnEPS) significant at both the level and first difference, whilst others are found stationary at first difference (integration at difference). Given the varied order stationary findings, it is essential to test the data for long-run relationships by employing Westerlund's (2007) cointegration second-generation test. Westerlund's (2007) cointegration test confirms the existence of long-run cointegration among the variables; the findings are reported in Table A4 (online Appendix).

4.1. MMQR estimations for carbon emissions

The study used the MMQR method to calculate the coefficient of the long-term relationship across quartiles. Results documented in Table 2 show that in the lower quartile (0.25), green finance has a negative association with carbon emission and confirms the former role in facilitating low-carbon investment, in line with the findings of Zhang et al. (2022). On the other hand, the coefficient for green finance is reported as positive for the mean and upper quartile. The varied outcomes of green finance at low and high quartile levels in curtailing carbon emission can be attributed to greenwashing, an immature market, lack of regulations and weak project implementation, as pointed by Wang et al. (2023). Based on findings, it is hypothesized that green finance impact can be improved across quantiles if aided by stringent regulatory control and project scrutiny in the regions with higher carbon emissions.

The results in Table 2 demonstrate the significant negative impact of EPS on the carbon emission at lower and mean quartiles and insignificant at the upper quartile. The results suggest that proactive implementation of robust environmental policies is effective in reducing carbon emissions in line with OECD (2019) findings. However, it is hypothesized that the EPS coefficient becomes insignificant due to possible relocation of high carbon emission activities to regions (Pollution havens) with a weaker regulatory framework.

The study yielded mixed results for environmental taxes (ET) on carbon emission; there is a positive impact in the lower quartile (0.25), insignificant in the mean quantile (0.5) and a significant negative impact in the upper quantile. The results suggest weak enforcement of environmental taxes and slow transformation to clean technologies in the lower quartile of sample countries, as previously established by Sterner and Kohlin (2012). The significant negative coefficient for the upper quantile validates the Pigouvian tax theory (Nordhaus, 2018) that environmental taxes (pollution prices) yield strong results when high emission sources experience significant costs (incentives) for rising (reducing) pollution.

Green innovation impact is significant and negative on carbon emission across quantiles, in particular, the magnitude is established strongly in the lower quantiles. The findings suggest that advancement in green technologies improves energy-efficient production, reduces overall carbon emission and assists in achieving environmental goals (Chang et al. 2023).

Table 2: Quantile regression ($lnCCO_2$)

Variables	Location	Scale	0.25	0.50	0.75	0.90
lnGF	0.004	0.036*	-0.035*	0.003*	0.032**	0.052*
	(0.016)	(0.009)	(0.02)	(0.016)	(0.017)	(0.019)
lnEPS	-0.063*	-0.048*	-0.111*	-0.059*	-0.02	0.007
	(0.021)	(0.011)	(0.026)	(0.021)	(0.022)	(0.024)
lnGT	-0.008	-0.145*	0.138*	0.019	-0.137*	-0.219*
	(0.046)	(0.025)	(0.056)	(0.047)	(0.048)	(0.052)
lnGI	-0.146*	0.03*	-0.176*	-0.144*	-0.12*	-0.103**
	(0.039)	(0.021)	(0.048)	(0.039)	(0.04)	(0.045)
lnPOP	0.595*	0.075*	0.52*	0.601*	0.662*	0.703*
	(0.031)	(0.017)	(0.038)	(0.031)	(0.032)	(0.035)
lnGDP	0.419*	-0.111*	0.53*	0.41*	0.32*	0.258*
	(0.03)	(0.016)	(0.037)	(0.031)	(0.032)	(0.034)
C	-1.845*	2.001*	-3.86*	-1.688*	-0.059	1.062**
	(0.422)	(0.229)	(0.519)	(0.445)	(0.445)	(0.473)

*Note: *, ** and *** represent significance level at 1%. Values in parentheses are Z-scores.*
Source: Author's own work

The graphical illustration in Figure 2 depicts the impact of the study variables on the CCO_2 emissions across quantiles, corroborating the heterogeneous findings of MMQR in Table 2. As can be seen in Figure 2, the strong negative impact of green finance and EPS on the carbon emissions in the lower quantiles is transformed into positive in the upper quantiles. In contrast, the transition of the positive impact of green taxes in the lower quantile turns into a significant negative impact in the upper quantile, as depicted in Figure 2. Also, Figure 2 illustrates that the negative impact of green innovation on carbon emissions weakens as the graph transitions from the lower to the upper quantile. To summarize, the graphical illustration in Figure 2 confirms the findings documented in Table 2.

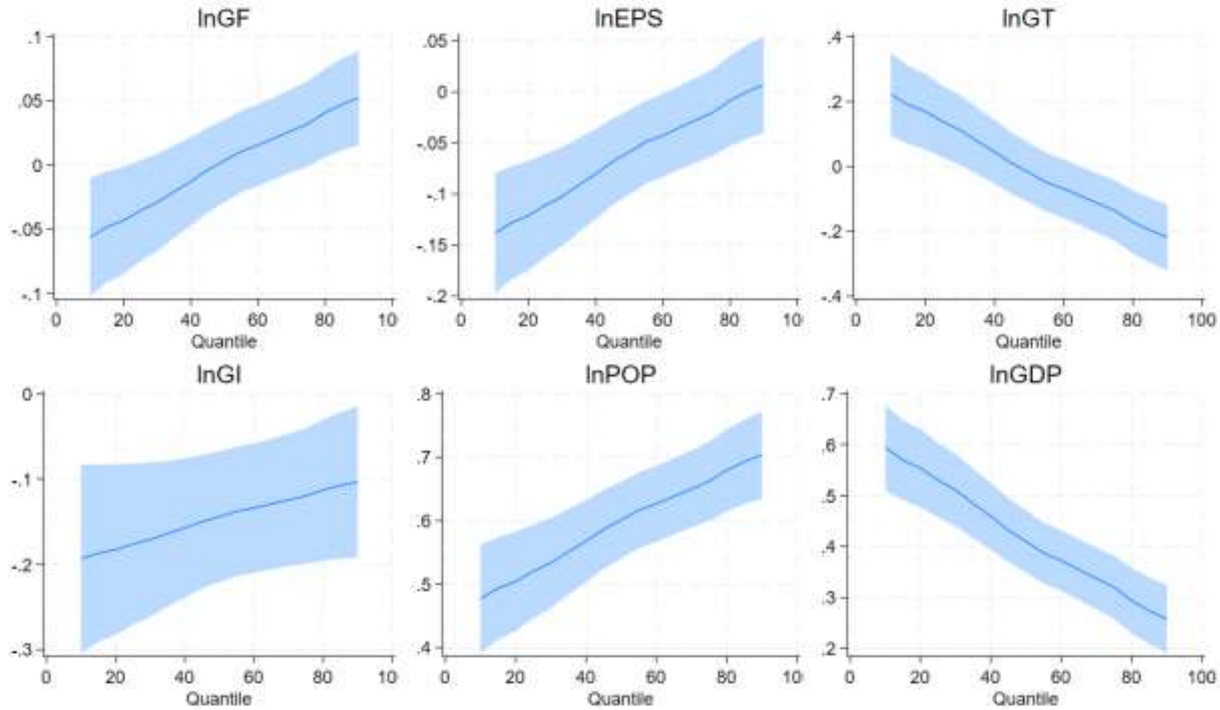

Figure 2: $\ln CCO_2$ (Model 1)

Source: Author's own work

4.2. MMQR estimations for biodiversity and biocapacity

This section presents MMQR results for the biodiversity and biocapacity, indicators of ecological performance. Biodiversity is measured through the Red List Index (RLI), where a high RLI value indicates low biodiversity loss and extinction risk. Results in Table 3 indicate that green finance reduces the biodiversity loss at upper quantiles; this suggests the strong positive impact of green finance in countries with a high biodiversity environment. As we can see in Table 3, the EPS has significantly reduced biodiversity loss across quantiles, notably stronger in the lower quantile. Based on findings, it can be assumed that robust environmental policies are more effective in countries with lower biodiversity and heightened species extinction risk. Our findings established the importance of governance in curtailing biodiversity and corroborate the previous findings of Habibullah et al. (2022).

Likewise, green taxes are also found in positive association with the biodiversity loss across quantiles, notably significant in the middle and upper quantiles. The results suggest the effectiveness of carbon taxes in curtailing biodiversity loss and species extinction risk, particularly in countries with strong governance and ecosystems, in line with the findings of Albert (2004). The coefficient for green innovation is found insignificant across quantiles, implying no impactful role in biodiversity preservation.

Table 3: Quantile regression (lnBIOD)

Variables	Location	Scale	0.25	0.5	0.75	0.9
lnGF	-0.003 (0.013)	0.014 (0.013)	-0.014 (0.022)	0.025 (0.01)	0.012** (0.005)	0.016** (0.008)
lnEPS	0.056* (0.02)	-0.032 (0.021)	0.081** (0.033)	0.049** (0.015)	0.022** (0.007)	0.012 (0.012)
lnGT	0.054** (0.025)	-0.01 (0.026)	0.061 (0.044)	0.051** (0.02)	0.043** (0.01)	0.04* (0.015)
lnGI	-0.016 (0.024)	0.016 (0.025)	-0.028 (0.041)	-0.013 (0.019)	0.001 (0.009)	0.006 (0.014)
lnPOP	-0.02 (0.02)	-0.003 (0.021)	-0.018 (0.036)	-0.021 (0.016)	-0.023** (0.008)	-0.024** (0.012)
lnGDP	0.001 (0.018)	0.008 (0.019)	-0.004 (0.032)	0.003 (0.014)	0.009* (0.007)	0.012 (0.011)
C	0.148 (0.216)	-0.101 (0.228)	0.224 (0.38)	0.126 (0.17)	0.042 (0.082)	0.008 (0.133)

*Note: *, ** and *** represent significance level at 1%. Values in parentheses are Z-scores.*
Source: Author's own work

Figure 3 depicts the graphical illustration of the estimated quantile regression of independent variables on biodiversity loss. As can be seen in Figure 3 that green finance, EPS stringency, and taxes improve biodiversity, but their impact is strong in countries with higher biodiversity loss and less pronounced in countries with better biodiversity conservation. The results implied that a holistic approach is required to improve on the biodiversity losses, notably in OECD countries on the lower and median quantiles. However, the marginal impact of green taxes, EPS and green finance diminishes in higher quantiles comprised of advanced OECD countries with dynamic governance.

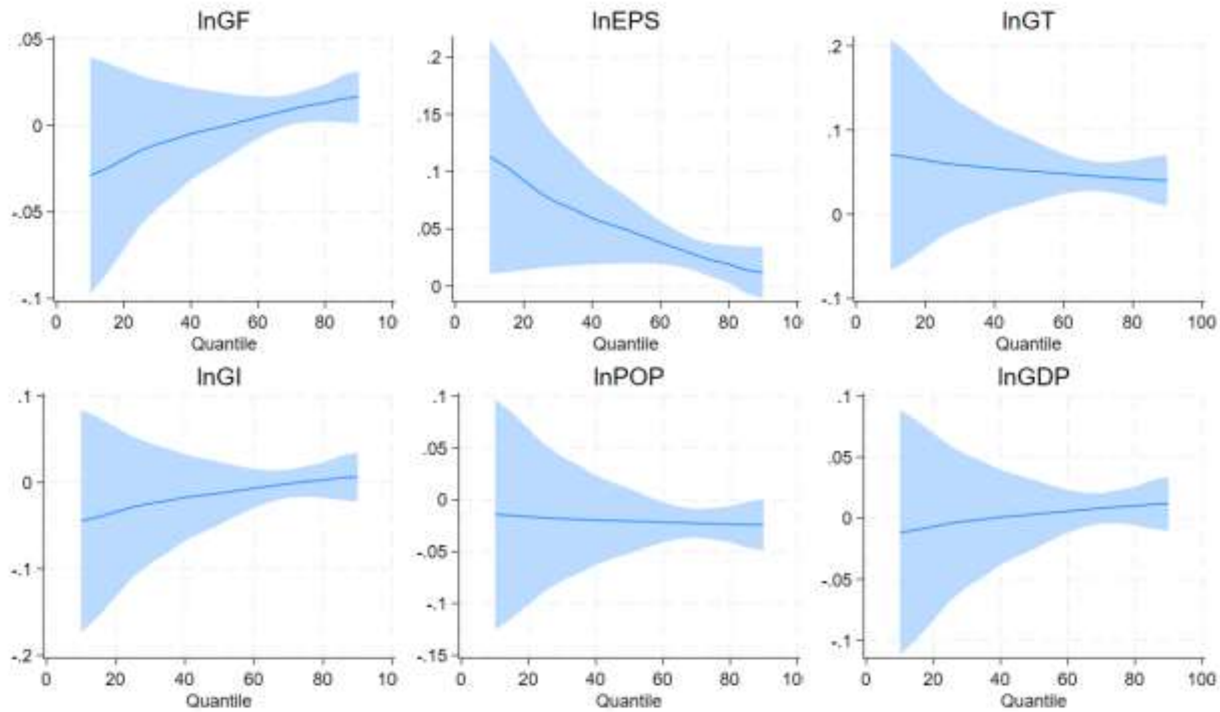

Figure 3: lnBIOD (Model 2)
Source: Author's own work

Table 4 below presents the MMQR results of biocapacity in relation to green finance, innovation, taxes, environmental policy and other controlling variables. The results reported a significant positive impact of green finance on the biocapacity across the quantiles. However, the magnitude of the coefficient reduces with the transition to the upper quantile. The results can be attributed to the prior investment gap in sustainable projects in land usage and the ecosystem. The study findings are in line with Flammer et al. (2025) and Wang et al. (2023) study who reported the significance of the capital allocation mechanism in improving ecological productivity and stability. As can be seen in Table 4, EPS recorded a significant negative impact on the biodiversity in upper quantiles and an insignificant impact in lower quantiles. The results suggest that enhanced environmental regulations improve biodiversity when enforced in countries with severely degraded ecosystems, in contrast to the findings of Rahman et al. (2025) of no impact of EPS.

Likewise, the green taxes recorded a significant negative impact on the biocapacity across quantiles with marked magnitude in the upper quantile, in line with the findings of Rahman et al. (2025). The findings reveal that instead of improving, environmental or green taxes degrade ecological sustainability due to association with low ecosystem productivity as evident in the sample countries of Finland, Sweden and Canada, which have abundant biocapacity (Global Footprint Network, 2023). The estimated results could be attributed to the inefficient enforcement of green taxes, shifting of cost to end consumers and inefficient reinvestment of fiscal resources into ecological improvements (Rehman et al., 2025). In contrast to green taxes, the green innovation recorded a significant positive impact on biocapacity in the lower and mean quantiles. The outcomes reveal that countries with lower and median biocapacity baseline productivity, such as Greece, Portugal, and the Czech Republic, are more susceptible to improvement because of green innovation. Therefore, there is a need to focus on the sustained adoption of eco-innovative technologies to enhance biocapacity production and the ecological system, as supported by Popp and Grégoire-Zawilski (2023).

As hypothesized, the population documented a significant negative impact on the biocapacity across the quantiles, thus confirming the population strain on the ecological resources and production capacity. By contrast, GDP is found in significant positive association with the biocapacity across quantiles, notably stronger in the upper quantiles. The results confirm an important proposition that high GDP can coexist with high biocapacity if coupled with substantial ecological investment and stringent regulatory enforcement. This is evident from OECD member countries of Norway, Sweden and Switzerland, which recorded high per capita income paired with better governance and significant investments in sustainable projects.

Table 4: MMQ regression (lnBIOC)

Variables	Location	Scale	0.25	0.5	0.75	0.9
lnGF	0.491* (0.048)	-0.084* (0.027)	0.565* (0.051)	0.499* (0.048)	0.413* (0.057)	0.352* (0.07)
lnEPS	0.092 (0.058)	-0.117* (0.033)	0.012 (0.062)	-0.079 (0.058)	-0.201* (0.069)	-0.285* (0.084)
lnGT	0.645* (0.088)	-0.193* (0.049)	-0.472* (0.094)	-0.625* (0.088)	-0.826* (0.105)	-0.965* (0.127)
lnGI	0.191** (0.083)	-0.084** (0.047)	0.266* (0.089)	0.2** (0.083)	0.112 (0.099)	0.051 (0.120
lnPOP	1.071* (0.068)	-0.177* (0.038)	-0.912* (0.073)	-1.052* (0.068)	-1.236* (0.081)	-1.364* (0.098)
lnGDP	0.755* (0.059)	0.171* (0.033)	0.602* (0.063)	0.737* (0.059)	0.915* (0.07)	1.038* (0.085)
C	1.85* (0.741)	-0.553 (0.416)	-1.356*** (0.789)	-1.791** (0.738)	-2.366* (0.877)	-2.766** (1.069)

*Note: *, ** and *** represent significance level at 1%. Values in parentheses are Z-scores.*
Source: Author's own work

Figure 4 exhibits the visual representation of independent variables influencing the biocapacity across different quantiles and confirms the findings presented in Table 4. As depicted in Figure 4, the positive impact of green finance and innovation on biocapacity reduces with transition to the upper quantile. In contrast, the EPS and environmental taxes graphs displayed a substantial negative impact on the biocapacity in the upper quantiles and a weak impact in the countries with baseline biocapacity deficit.

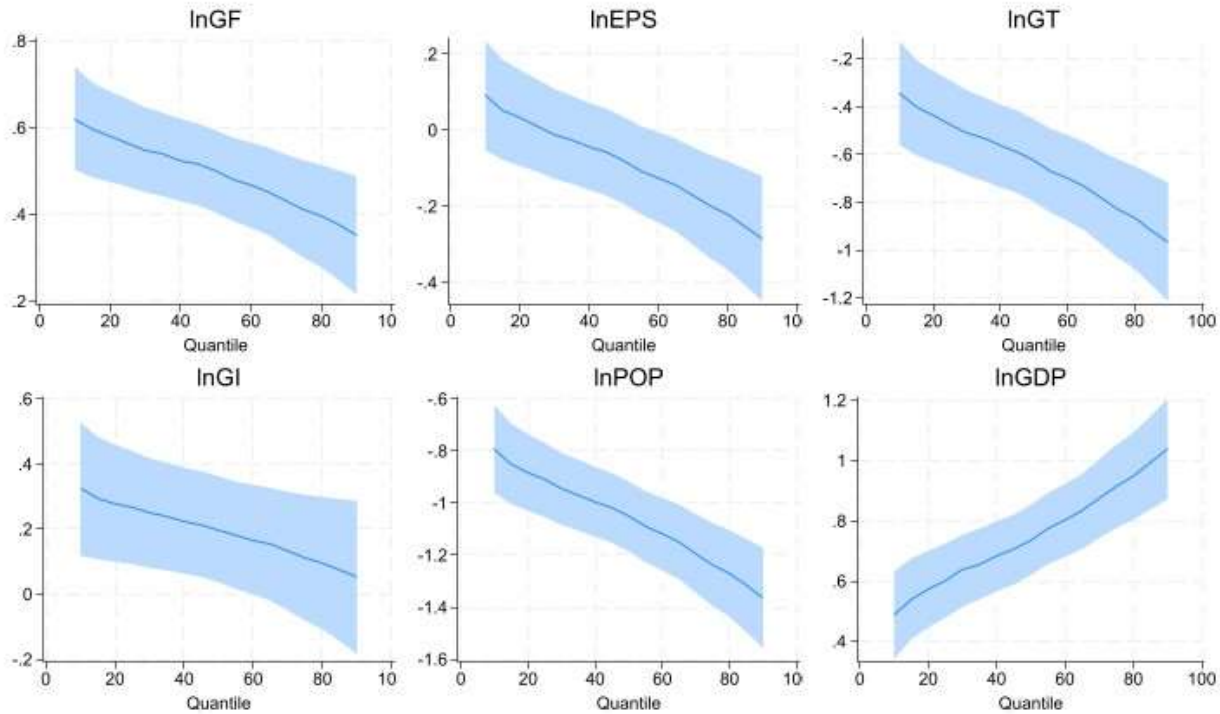

Figure 4: lnBIOC (Model 3)
Source: Author's own work

To further investigate the data dynamics, the study tests the moderating impact of EPS on the relationship between green finance and environmental and ecological measures. The results reveal a varied impact of EPS as a moderator. Results documented in Tables A5, A6 and A7 in the online Appendix (plotted in Figures 5, 6 and 7) show that EPS does not moderate the relationship between green finance and carbon emissions. Notably, in the case of biodiversity, the moderation term (lnEPS*GF) is reported as significantly negative, mainly for lower and mean quantiles; thus, pointing to the moderating role of EPS in diminishing the positive role of green finance in improving biodiversity conservation. In simple terms, the introduction of stringent environmental policies can diminish the efficacy of green finance in improving the productivity of farming land, species, and forestation in the OECD countries with initial low biocapacity. To ensure the robustness of MMQR estimates and address the potential endogeneity issue, the study uses GMM regression on the study variables. The regression results documented in Table A8 (online Appendix) mainly confirm the findings of MMQR on the determinants of CCO_2, biodiversity loss and biocapacity production in the OECD countries.

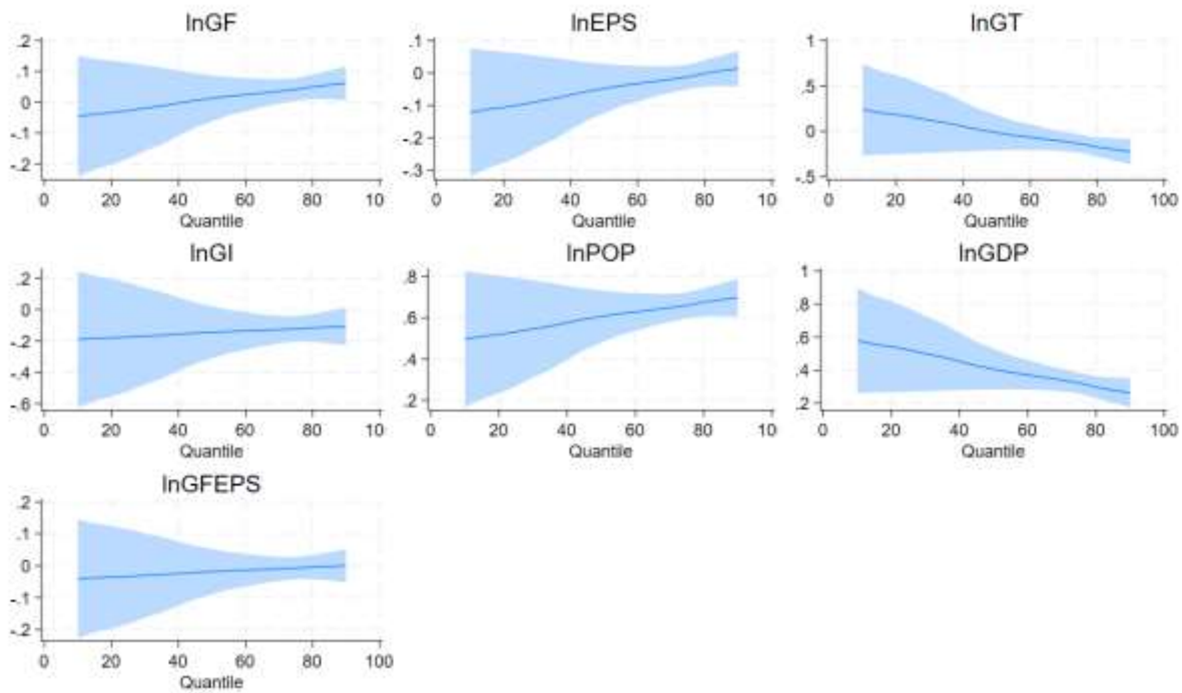

Figure 5: MMQR plots for lnCCO2 with lnGF*EPS
Source: Author's own work

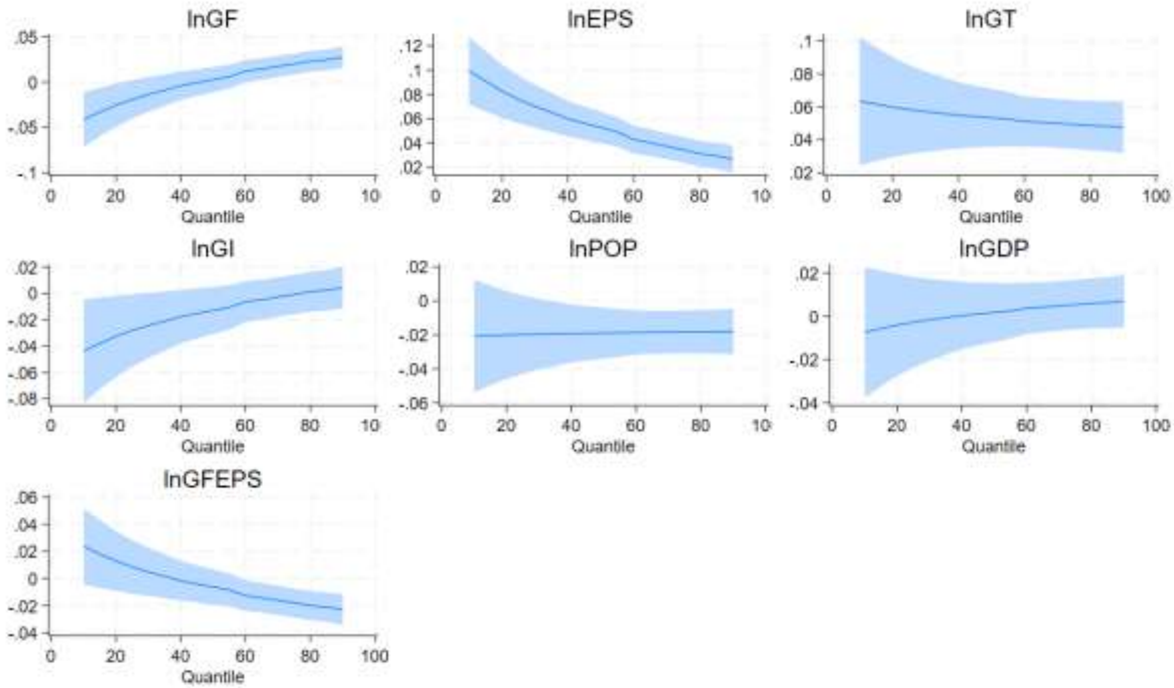

Figure 6: MMQR plots for lnBIOD with lnGF*EPS
Source: Author's own work

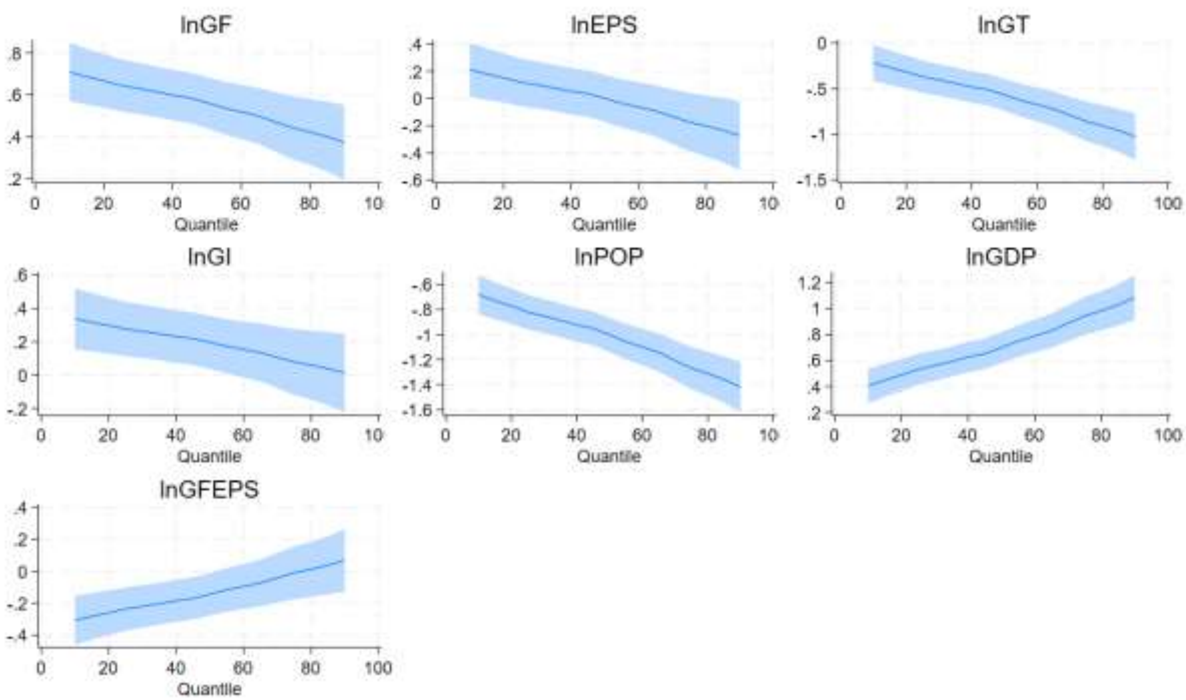

Figure 7: MMQR plots for lnBIOC with lnGF*EPS
Source: Author's own work

4.3. Pairwise Dumitrescu-Hurlin panel causality

Table 5 summarizes the findings of the D-H causality tests. The results reveal a bidirectional causality between CCO_2 and biodiversity, indicating a mutual causal relationship between the variables, suggesting that changes in CCO_2 affect biodiversity, and vice versa. Furthermore, the analysis identifies a bidirectional causal relationship between green taxes and both CO_2 and biodiversity, highlighting that green taxes affect both CCO_2 and biodiversity. Moreover, green finance and environmental technology exhibit a bidirectional causal relationship with both CO_2 and biodiversity, underscoring their interconnected roles in shaping environmental outcomes. However, unidirectional causality running from EPS to CCO_2 is explored.

Table 5: D-H causality test

Variable	lnBIOC	lnCCO₂	lnGT	lnEPS	lnGI	lnGF	lnGDP	lnPOP
lnBIOC	--	2.77*	3.294*	1.892*	3.122*	1.87**	0.799	5.296*
$\ln CCO_2$	2.002*	--	2.419*	1.315	4.743*	2.83*	1.737**	21.318*
lnGT	2.383*	3.456*	--	1.334	2.523*	1.7**	1.204	17.746*
lnEPS	5.124*	3.087*	2.835*	--	5.81*	2.337*	1.586	11.756*
lnGI	3.351*	3.1*	2.173*	1.263	--	1.902*	0.933	7.406*
lnGF	1.671**	2.498*	2.967*	1.573	1.775**	--	1.089	5.87*
lnGDP	7.271*	3.431*	3.418*	4.597*	5.075*	3.092*	--	13*
lnPOP	13.786*	4.247*	4.215*	1.762**	3.955*	3.263*	1.065	--

*Note: *, ** and *** indicates P<0.01, P<0.05, and P<0.1 (significance at 1%, 5% and 10%)*
Source: Author's own work

5. Conclusion

This study examines the impact of green finance, environmental technological innovation, EPS and environmental or green taxes on CCO_2, biodiversity loss and biocapacity in the OECD countries by employing the MMQR approach. The study identified a positive impact on green finance (except in the lower quantile) on CCO_2. However, a negative and positive impact of green finance on biodiversity loss and biocapacity is explored, respectively. Moreover, a negative impact of green technological innovation, green taxes and policy stringency on carbon emissions is observed, suggesting their effectiveness in reducing CCO_2 emissions. Regarding biodiversity loss, a positive impact of green finance, EPS and green technological innovation is identified, suggesting their vital positive role in biodiversity conservation. Further, the study identified that a positive and significant impact of green finance on biocapacity; however, EPS and green taxes negatively affect it. In addition, a bidirectional causality between CCO_2 and biocapacity is also identified by employing D-H causality, highlighting the interconnectedness between CCO_2 and ecological dynamics.

5.1. Policy implications

The study's empirical evidence provides substantial policy direction for the OECD countries to mitigate CCO_2 emissions, improve biodiversity conservation and sustain biocapacity. To ensure the practical relevance and robustness of these recommendations, the study critically addresses trade-offs, implementation barriers and proposes monitoring mechanisms. The study reveals that green finance and taxes are not uniformly positive across all sustainability objectives. Policymakers must explicitly consider these trade-offs in the policy design. Incorporating the consequences of green finance along with objectives will enable decision-makers to strike a pragmatic balance. Moreover, to ensure that policy measures provide intended outcomes and remain adaptable, institutionalizing monitoring and evaluation (M&E) is vital to adopt. This could include defined measures, time-bound targets for reducing CCO_2, biodiversity indices and biocapacity. Further, the effective implementation of environmental policies is often constrained by institutional inertia, fragmented governance and limited budgets. For instance, regulatory reforms and improving capacity building for regulatory bodies are essential in connecting finance with sustainability. Expanding research and development through public-private partnerships needs not only funding but also stable and long-term political commitments, cross-sectoral and industrial coordination.

More specifically, an improved environmental tax mechanism is essential, where companies or sectors harming biodiversity pay higher taxes, which can be used for protecting ecosystems under a clear and integrated policy. The coordination between government departments must be improved for setting up special teams and tasks to ensure climate, biodiversity and economic policies work with integration.

5.2. Limitations of the study

This study considers only public green finance, excluding private sector contributions that may also influence environmental outcomes. Future research should incorporate private green finance and explore how institutional quality factors affect the relationship between green finance and environmental performance. Moreover, future studies may examine the non-linear impact of the determinants on these environmental outcomes.

Data availability: The study used data available on public domains, for which the links are embedded in the mentioned data sources.

OECD = Organisation for Economic Co-operation and Development

CSD = Cross-sectional dependency

CIPS = cross-sectionally augmented Im, Pesaran and Shin

CADF = cross-sectionally augmented Dickey-Fuller

BIOC = Biocapacity

BIOD = Biodiversity

GF = Green Finance

EPS = Environmental Policy Stringency

CCO2 = Consumption-based carbon emissions

MMQR = Methods of Moment Quantile Regression

GMM = Generalized Methods of Moments

DH = Dumitrescu and Hurlin

GT = Green Taxes

GI = Green Innovation

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