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Climate-related financial regulation, renewable energy and the ecological footprint of production: evidence from developed and developing economies

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Abstract

Accelerating demand for goods and services intensifies the ecological footprint of production. This study examines how the regulatory intensity of climate-related financial policies affects the footprint, and whether renewable energy deployment conditions the effect. Annual data for 72 countries over 2000–2020 are used, classified into developed and developing economies. The model includes income and its quadratic and cubic terms, renewable energy consumption, regulatory intensity, and their interaction, estimated by location-scale Method of Moments Quantile Regression and checked against a two-stage instrumental-variables estimator with defactored regressors. Greater regulatory intensity reduces the footprint on average, globally and in each group, with a stronger effect in developed economies. The interaction is insignificant globally and in developed economies, but negative and significant across all nine deciles in developing ones. There, regulation's marginal effect is indistinguishable from zero when renewable penetration is low (9.5%) and clearly negative when it is high (45.9%), while the effectiveness threshold rises from 26% to 52% with environmental pressure. The results support the Environmental Kuznets Curve hypothesis in developed countries, whereas in developing countries growth continues to intensify degradation. Developed economies can therefore tighten prudential requirements and supervision, while developing ones need to pair regulatory reform with renewable deployment targets.

Keywords: *Green financial regulation; Ecological sustainability; Renewable energy; Sustainable capital allocation; Panel data heterogeneity.*

JEL code: *Q56; Q58; G28; G18; C21*

1. Introduction

Ecological pressure on planet Earth has reached levels rarely recorded in Earth's history, as the global population uses resources faster than the planet's regenerative capacity can replenish them. According to the Global Resources Outlook (2024), natural resource extraction increased sharply by approximately 250% over the last 30 years, reflecting growing demand for the inputs productive activities require. Likewise, global energy-related carbon emissions rose from 37.4 $GtCO_2$ in 2023 to 37.8 $GtCO_2$ in 2024, indicating that the world economy still depends heavily on conventional energy sources despite recent global efforts in the energy sector (International Energy Agency [IEA], 2025). According to the International Renewable Energy Agency (IRENA, 2024), countries worldwide added 473 GW of renewable capacity in 2023; however, this expansion may still fall short of the level required to mitigate environmental degradation and, more critically, to achieve the global target of tripling renewable capacity by 2030 (IEA, 2024).

In this regard, environmental sustainability appears to depend not only on the absorptive capacity of renewable energy but also on institutional and financial mechanisms that steer action to mitigate environmental damage from growing resource demand. Accordingly, the financial dimension assumes a central role, as energy transitions require substantial investment and regulatory mechanisms redirecting decision-making toward less resource- and carbon-intensive activities. However, with the 2030 horizon in view, the financial resources available to limit global warming remain three to six times below the required levels (Intergovernmental Panel on Climate Change [IPCC], 2022), widening the gap to that objective. Additionally, developing countries face an annual investment shortfall of approximately four trillion dollars to meet the Sustainable Development Goals (United Nations Conference on Trade and Development [UNCTAD], 2023).

In this context, climate-related financial policies emerge as economic and environmental instruments that incentivize capital allocation by incorporating climate risks and sustainability criteria. Therefore, examining their regulatory intensity is essential to understanding how appropriate capital allocation can serve as a mechanism to improve environmental performance. Accordingly, this analysis is grounded in the Institutional Theory of North (1990) and Scott (1995), who argue that institutions establish formal rules and that regulation is crucial to how public policies shape economic and environmental outcomes. In addition, the study draws on Porter's Hypothesis, proposed by Porter and van der Linde (1995), which posits that

environmental regulations can stimulate innovation and productive efficiency, thereby improving environmental performance.

This study examines the role of the Regulatory Intensity of Climate-Related Financial Policies (CRFPI-RI) in mitigating the ecological footprint. This indicator captures not only the existence of climate-related financial policies but also their regulatory intensity, binding nature, and prudential component (D'Orazio, 2023). The analysis therefore assesses whether financial system agents subject to stringent climate-related regulation can redirect capital toward sustainable activities and, consequently, reduce the ecological footprint of production.

Accordingly, this study aims to examine how CRFPI-RI affects the ecological footprint of production across 72 countries over the period 2000–2020, distinguishing between developed and developing economies. The analysis also incorporates control variables for economic growth and renewable energy consumption, using annual data obtained from official online sources. Subsequently, the data are analyzed using the Method of Moments Quantile Regression (MMQR) approach developed by Machado and Santos Silva (2019), which assesses the effect of CRFPI-RI on the ecological footprint of production at different points of its conditional distribution. The study addresses three questions. First, does the regulatory intensity of climate-related financial policies reduce the ecological footprint of production, and does the effect vary along its conditional distribution? Second, is that effect conditional on the degree of renewable energy penetration? Third, does it differ between developed and developing economies, and does the income–footprint relationship behave differently in each group? Also, linking the intensity of climate-related financial regulation (SDG 13) to renewable energy deployment (SDG 7) and to the resource appropriation embedded in production (SDG 12), the study speaks to three Sustainable Development Goals.

Recent literature has advanced considerably on green finance, climate-related financial policies, and environmental performance. Nevertheless, a relevant gap remains regarding the role of regulatory intensity and its association with the ecological footprint of production, particularly from a global perspective (Ha, 2025). This matters because such policies involve not only the allocation of green resources but also changes in the investment allocation rules within the financial system (D'Orazio & Thole, 2022). This distinction matters because financial development itself may increase environmental pressures in emerging economies (Degirmenci et al., 2025). Three studies come closest to this design. Luo et al. (2024) examine macroprudential rather than climate-specific regulation in eleven economies; Balsalobre-

Lorente et al. (2023) interact financial depth, not the rule itself, with policy stringency in APEC; and Fatima et al. (2024) interact the energy transition with stringency in the OECD, taking greenhouse gases as the outcome. None estimates the effect of climate-related financial regulatory intensity on the ecological footprint conditional on renewable capacity, along the distribution and across levels of development.

This study contributes in four ways. First, it measures the financial dimension as a rule rather than a volume; the CRFPI-RI index records how binding that regulation is, while the green bonds, green credit, and financial depth used elsewhere confuse the supply of regulation with the demand for financing. Second, it takes the production-based ecological footprint as the dependent variable, which covers six components of biocapacity use, rather than carbon emissions, which are only one of them. Third, it estimates the effect of regulation conditional on renewable penetration in 72 countries between 2000 and 2020, and finds something the literature has not reported. The interaction is insignificant globally and in developed economies, yet negative and significant across all nine deciles in developing ones, where the marginal effect of regulation is indistinguishable from zero when renewable penetration is low (9.5%) and clearly negative when it is high (45.9%). Climate regulation, in other words, lowers the footprint of a developing economy only once there is renewable capacity to absorb the capital it redirects. Fourth, the estimates do not rest on a conditional mean; MMQR with location-scale effects is estimated across nine deciles, and a two-stage instrumental-variables estimator with defactored regressors treats renewable consumption, regulation, and their interaction as endogenous, addressing the reverse causality that most of the literature leaves open.

The paper proceeds as follows. Section 2 presents the theoretical framework and empirical evidence. Section 3 describes the methodological procedure. Section 4 discusses empirical results. Finally, Section 5 presents the conclusions and policy implications.

2. Literature review

2.1. Theoretical background

The relationship between the ecological footprint and climate-related financial policies can be framed through Institutional Theory (North, 1990), which argues that institutions define the formal and informal rules that shape the behavior of economic agents; Scott (1995) emphasizes the regulative pillar as central to examining the role of public and financial policies. Climate-related financial policies therefore operate as formal institutions that shape incentives within the financial system, redirect capital toward sectors with lower natural resource intensity, and

strengthen monitoring of financing allocated to activities associated with environmental degradation. Greater regulatory intensity may thus help reduce the ecological footprint of production. There is an important difference here. Conventional environmental regulation acts on the polluter; financial regulation acts on whoever lends to the polluter. Its environmental effects are therefore indirect; they pass through the lending and investment decisions of banks and institutional investors, and they depend on how far those decisions respond to regulatory pressure.

The Porter Hypothesis provides a formal basis for explaining how policy-based regulation may improve environmental performance. Porter (1991) and Porter and van der Linde (1995) argue that well-designed environmental regulations do not constrain economic activity; rather, they stimulate innovation and promote technological transformation, encouraging firms to increase efficiency, upgrade production processes, and reduce the environmental burden of their activities. Within this study, climate-related financial policies constitute regulatory instruments that reshape capital allocation. By incorporating climate and prudential criteria into the financial system, these criteria guide banks and investors toward activities that exert lower environmental pressure. Moving Porter's argument into the financial domain, however, takes one further step. Financial regulation does not tell firms how to produce; it prices the risk of lending to them. Firms adjust because their financing terms have changed, not because a production standard was imposed on them. For the innovation offset to appear, the regulatory signal must be credible and expected to last.

Complementing both, this study argues that climate-oriented financial policies can serve as a mechanism to mitigate the ecological footprint generated by economic activity; they function as formal rules that transform incentives within the financial system and guide financial agents toward more sustainable choices. Stronger regulatory intervention may therefore reduce the ecological footprint of production, suggesting an expected negative relationship between the two variables examined. This study additionally incorporates the Environmental Kuznets Curve Hypothesis to assess the potential non-linear relationship between economic activity and environmental degradation.

The Environmental Kuznets Curve is the framework in which the two preceding arguments come together. Grossman and Krueger (1991) and Stern (2004) separate environmental impact into scale, composition, and technique effects. Climate-related financial regulation leaves scale untouched, since it neither limits output nor changes income; what it changes is the relative cost

of capital across sectors, and, with it, both the composition and the incentive to adopt cleaner techniques. The implication is stronger than a negative coefficient; the income level at which composition and technique outweigh scale should arrive sooner. The three theories then work as one chain, since institutional theory explains why formal rules move financial agents, the Porter Hypothesis explains how firms respond, and the decomposition explains how that response reaches the footprint. Regulation travels this route through the cost of capital, disclosure, and the credibility of a commitment expected to last, so its effect depends on the availability of low-carbon projects to absorb the capital it redirects; renewable energy is where that capital becomes lower-pressure. Figure 1 sets out this structure.

2.2. Review of empirical evidence

The empirical evidence is organized around five themes that follow the causal sequence set out in Section 2.1. Each theme closes with a specific limitation, and the five limitations converge on a single research gap, stated at the end of the section.

2.2.1. The Environmental Kuznets Curve and economic growth

The relationship between economic growth and the ecological footprint is a critical issue in recent literature, as it depends on countries' energy, technological, and institutional structures. Within the Environmental Kuznets Curve (EKC) framework, economic activity may initially increase environmental degradation as resource use intensifies. However, at higher growth levels, technological innovation, productive transformation, and environmental policies may reduce it, as indicated by PMG-ARDL and MMQR, respectively (Khalid et al., 2025; Satrovic et al., 2024). In the Arctic region, where economies depend heavily on natural resources, production activity and resource rents drive environmental degradation. However, green innovation mitigates this effect (Li et al., 2022), estimated with FMOLS, DOLS, FE-OLS, and MMQR. In several industrialized countries, financial globalization and renewable energy consumption reduce environmental degradation across all quantiles, particularly where economic growth and resource dependence increase environmental pressure (Miao et al., 2022), as indicated by MMQR and panel causality tests. In Latin America, fossil-energy-based productivity tends to intensify environmental degradation, whereas renewable-energy-based productivity alleviates it (Soto et al., 2025), as shown using quantile-on-quantile regression. Using second-generation estimators with Driscoll-Kraay standard errors, Rasheed, Yuhuan, Haseeb, et al. (2025) find that industrial structure and financial development increase the carbon footprint in high-income economies, while Kilinc-Ata et al. (2025), through wavelet quantile

regression, show these effects vary across quantiles and time horizons. Across this body of work, however, the turning point is estimated in terms of income and technology. At the same time, the institutional environment enters as a control rather than a moderator, as if its position were independent of the rules governing capital allocation.

2.2.2. The ecological footprint as an environmental indicator

The studies reviewed do not measure environmental pressure in the same way. Some rely on the ecological footprint (Awad et al., 2025; Cai et al., 2024; Jarijari et al., 2025; Luo et al., 2024; Nathaniel et al., 2025; Sun et al., 2025), others on carbon emissions (Anwar & Abbas, 2026; Miyan et al., 2025; Shahbaz et al., 2025; Yu, Long, et al., 2026, Yu, Quan, et al., 2026), and a third group on the load capacity factor (Ahmed et al., 2025b; Erdem et al., 2026) or on composite sustainability indices (Degirmenci & Ünsal, 2026). The distinction is not merely one of scale. The ecological footprint aggregates six components measured in global hectares, of which carbon is only one, so emission-based evidence captures a single dimension of the pressure the footprint measures. Erdem et al. (2026) detect no causal link between green finance and the load capacity factor. The predominance of emission-based evidence, therefore, leaves open the question of whether the financial channel's results hold when environmental pressure is measured comprehensively.

2.2.3. Green finance

Climate-related financial policies play a central role in directing capital flows toward sustainable projects that mitigate environmental damage. Using panel quantile regression, Anwar and Abbas (2026) report that green finance reduces carbon emissions in G-7 countries, whereas green production increases them, though the effectiveness depends on geopolitical factors. In BRICS economies, green finance policies improve environmental performance by reducing emissions and supporting sustainable growth (Yu, Long, et al., 2026), as shown by MMQR and Westerlund cointegration tests. In ASEAN-4 countries, green finance, together with green innovation, reduces carbon emissions while supporting the EKC, particularly at lower quantiles (Miyan et al., 2025), as estimated using MMQR and bootstrap quantile regression. Nuta et al. (2025), applying quantile regression with wavelet analysis, argue that green bonds and the clean energy transition foster sustainable development. However, global uncertainty may hinder climate cooperation and divert capital from environmental objectives. Shahbaz et al. (2025), through MMQR with Driscoll-Kraay validation, find that inclusive finance lowers emissions throughout the distribution in African economies, and Ayaydın et al.

(2025), using FMOLS and DOLS with Driscoll-Kraay standard errors, report that financial technology moderates the green energy transition's effect on the ecological footprint in BRICS-T economies. The evidence is nonetheless not uniform; as Erdem et al. (2026) note, applying Dumitrescu-Hurlin causality tests, they detect no causal link between green finance and the load capacity factor in the OECD. In all these cases, the financial dimension is captured by the volume of green financing, access to financial services, or technological penetration- market outcomes that confound the supply of regulation with the demand for financing, rather than the institutional rule that governs it.

2.2.4. Climate-related financial regulation

A smaller group of studies examines regulatory intensity itself. Yu, Quan, et al. (2026), through MMQR with bootstrap quantile regression, find that green finance reduces carbon emissions and that government effectiveness exerts a stronger effect than climate-related financial policies, indicating that the institutional environment enhances policy efficiency in OECD countries. Luo et al. (2024), combining fixed-effects models with quantile regression, find that macroprudential policies reduce the ecological footprint in the eleven largest economies mainly at the lower quantiles, an effect amplified by environmental policy stringency. Balsalobre-Lorente et al. (2023), using FMOLS, report that the interaction between financial development and environmental policy stringency lowers the ecological footprint in APEC economies. Fatima et al. (2024), combining DOLS, FMOLS, and CCR with MMQR and bootstrap quantile regression, find that the same stringency strengthens the energy transition's emission-reducing effect across all quantiles in OECD countries. Degirmenci and Ünsal (2026), with RCCE and AMG estimators, extend the discussion to the fiscal dimension of green budgeting in the European Union. The transition toward renewable energy, eco-innovation, and more stringent environmental policies reduces environmental degradation in OECD and G-7 countries when it incorporates effective regulatory reforms and applies MMQR and FE-OLS (Afshan et al., 2022; Usman et al., 2021). The regulatory variable in this literature is therefore either general prudential policy or the stringency of environmental policy. The intensity with which financial regulation incorporates climate criteria has not been used as a treatment variable. Where a moderator is introduced, it is another policy indicator rather than the productive capacity that must absorb the reallocated capital.

2.2.5. Renewable energy consumption

Renewable energy consumption is a key factor in decoupling economic growth from environmental degradation, contributing to sustainability when integrated with innovation, green finance, and appropriate regulatory policies (Awad et al., 2025; Nathaniel et al., 2025; Özcan, 2024). In Sub-Saharan African countries, renewable energy consumption mitigates the degradation caused by export diversification. However, the magnitude depends on the distribution of ecological footprints (Awad et al., 2025), shown using FMOLS, DOLS, and quantile regression. Nathaniel et al. (2025), applying second-generation techniques together with AMG and MMQR, reach a similar conclusion and emphasize that education shapes consumption behavior. Ahmed et al. (2025a), using MMQR, FGLS, and CuP-FM, find that wind energy reduces the ecological footprint across all quantiles in the fifteen largest economies, while Ahmed et al. (2025b), also using MMQR, report heterogeneous effects of energy sustainability and institutional productivity on the load capacity factor. The evidence is not uniform, however. For G-20 economies, Cai et al. (2024) find that renewable energy consumption reduces the ecological footprint, while Sun et al. (2025), using MMQR with Driscoll-Kraay validation, find that it increases it, attributing this to environmental performance depending on infrastructure quality, institutional efficiency, and appropriate technological and financial conditions. Jarijari et al. (2025), using MMQR with PCSE and FGLS, likewise report that the mitigating effects of green finance and renewable energy may reverse without adequate governance support and institutional transparency. This conditional effect is thus acknowledged only after the fact, invoked to explain unexpected signs rather than specified ex ante as an interaction, so the environmental return to renewable deployment remains unmeasured as a function of the institutional conditions that sustain it.

2.2.6. Research gap

These five strands point to the same gap. The financial side has been measured mostly by volume, mixing the supply of regulation with the demand for financing, and mostly against carbon emissions, only one part of the ecological footprint. Where regulatory intensity does appear, it is general prudential policy (Luo et al., 2024) or environmental policy stringency (Balsalobre-Lorente et al., 2023; Fatima et al., 2024), not climate-specific financial regulation, and it is moderated by other policy indicators rather than the low-carbon capacity that must absorb the redirected capital. What no study has estimated, then, is the effect of climate-related financial regulatory intensity on the ecological footprint conditional on renewable penetration, along the distribution and across levels of development. The question is not only academic; prudential authorities are already using climate instruments without knowing whether they

reduce environmental pressure or move it elsewhere, and if the answer depends on renewable capacity and financial depth, the same standard would work differently from one country to the next. Building on this framework, six hypotheses are tested:

H1. The relationship between income per capita and the ecological footprint of production is non-linear; a cubic specification tests whether environmental pressure declines beyond a certain income threshold.

H2. Greater regulatory intensity in climate-related financial policy reduces the ecological footprint.

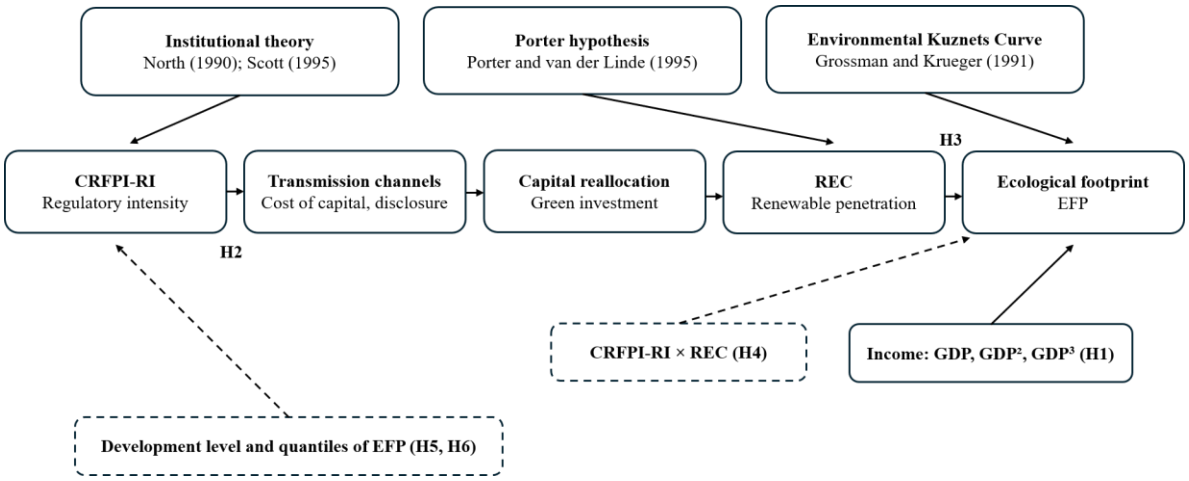
H3. Renewable energy consumption reduces the ecological footprint.

H4. Regulatory intensity and renewable penetration are complementary, so that the effect of regulation on the ecological footprint becomes more negative as renewable capacity grows.

H5. These effects vary across the conditional distribution of the ecological footprint.

H6**.** The response to regulatory intensity is stronger in developed than in developing economies.

Figure 1. Conceptual framework.



3. Methodological framework

3.1. Data

This study uses annual data from official sources for 72 countries over the period 2000–2020, selected based on data availability, resulting in a balanced panel of 1,512 observations. Countries were grouped by level of development using the World Bank (2025) classification, based on the Atlas method (Table A1). Developed countries correspond to high-income economies, whereas developing countries include upper-middle-income, lower-middle-income, and low-income economies. The dependent variable is the natural logarithm of the Ecological Footprint per capita of production. The period ends in 2020 because the regulatory intensity index, the study's treatment variable, does not run beyond that year. It still covers the formative phase of climate-related financial regulation, from near-absence to its expansion after the Paris Agreement, which most developing economies stand in today. Since regulatory intensity has continued to rise since 2020, the estimates are best read as a lower bound.

The production-based ecological footprint is used rather than the load capacity factor. The latter captures both sides of environmental sustainability. However, its denominator, biocapacity, depends on how much land a country has and how productive its ecosystems are, things climate-related financial regulation cannot change over two decades. Including it would introduce variation the mechanism cannot explain and would muddy the comparison between developed and developing economies, where per capita biocapacity differs mostly because natural endowments differ. The independent variables included in the model are the natural logarithm of per capita economic growth and its squared term, which allows the study to test the Environmental Kuznets Curve hypothesis, as well as renewable energy consumption and the CRFPI-RI variable. Table 1 describes the variables used in the econometric modeling.

Table 1. Description of variables.

Variable	Description	Abbreviation	Measurement	Source
Ecological footprint of production	Ecological footprint of production per capita, measured in global hectares.	*EFP*	Natural logarithm	(NFA, 2024)
Economic growth	Gross domestic product per capita at constant 2015 US dollars.	*GDP*	Natural logarithm	WDI (2025)
Squared economic growth	Squared term of gross domestic product per capita at constant 2015 US dollars.	GDP^2	Natural logarithm	WDI (2025)
Cubed economic growth	Cubed term of gross domestic product per capita at constant 2015 US dollars.	GDP^3	Natural logarithm	WDI (2025)
Renewable energy consumption	Renewable energy consumption is measured as the percentage of total final energy consumption.	*REC*	Share of total final energy	WDI (2025)

			consumption (%)	
Regulatory Intensity of Climate-Related Financial Policies	This variable captures the regulatory intensity of climate-related financial policies, reflecting the extent to which financial systems incorporate climate risks and promote capital allocation toward environmentally sustainable activities.	*CRFPI-RI*	Index	D'Orazio (2023)

The inclusion of the CRFPI-RI variable represents a relevant contribution to the empirical analysis of the ecological footprint. Unlike conventional studies that primarily rely on traditional macroeconomic and trade-related factors (Quan et al., 2024; Pinzon et al., 2026), this study extends the analysis to the financial regulatory dimension, which remains insufficiently explored in environmental economics. Specifically, CRFPI-RI enables the study to assess whether greater regulatory intensity in climate-related financial policies can serve as an institutional mechanism to reduce environmental impact, encourage capital reallocation toward sustainable activities, and mitigate climate-related risks through the financial system. The CRFPI-RI variable is an index constructed by aggregating climate-related financial policies across regulatory areas, applying weights that reflect the binding nature of each instrument, and including a disaggregated indicator of the prudential component. This structure captures not only the presence of climate-related financial policies but also the depth and intensity of the regulatory framework (D'Orazio, 2023), so higher index values indicate greater regulatory intensity in climate-related financial policies.

Table 2 reports the main descriptive statistics for the variables used in the study, revealing substantial heterogeneity across the territorial units examined, particularly in renewable energy consumption and the regulatory intensity of climate-related financial policies. The minimum and maximum values show a high degree of dispersion that may reflect structural differences among the countries analyzed, and the skewness, kurtosis, and Jarque–Bera statistics indicate that all variables deviate from normality at the 1% significance level. The correlation matrix shows that GDP and GDP^2 correlate positively with EFP, while REC exhibits a moderate negative correlation and CRFPI-RI a weak negative association. This behavior and distribution therefore support an econometric approach that remains robust to non-normality and distributional heterogeneity, and MMQR is suitable for this type of data, as it captures heterogeneous effects across the conditional distribution of the ecological footprint without relying strictly on the normality assumption.

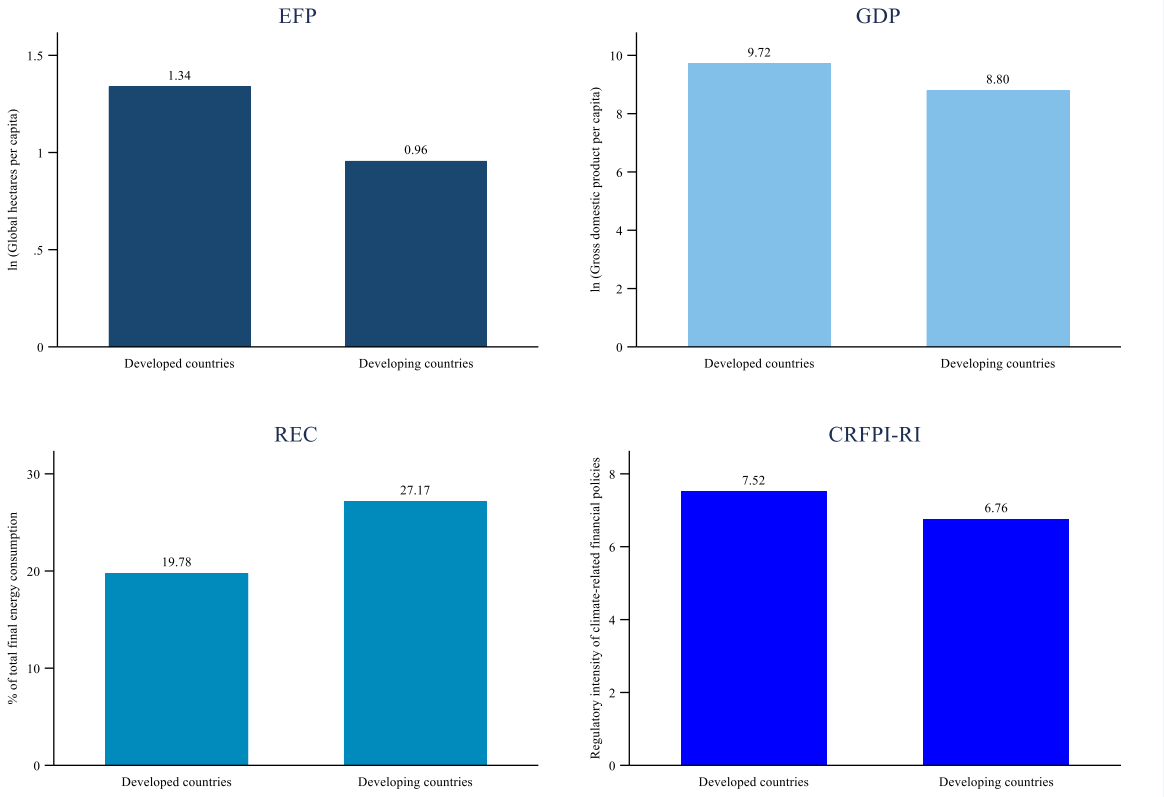
Table 2. Descriptive statistics of the variables included in the econometric specification.

Variable	Mean	St Dev.	Min	Max	Kurtosis	Skewness	Jarque-Bera	Correlation
EFP	1.1585	0.7841	-1.0788	2.7568	2.6956	-0.4493	56.71***	-
GDP	9.2844	1.2813	6.3048	11.6299	2.0496	-0.2689	75.13***	0.7802*
GDP^2	87.8411	23.4071	39.75117	135.2564	1.9193	-0.0672	74.72***	0.7651*
GDP^3	845.4535	326.3309	250.6253	1573.029	1.8984	0.1184	79.98***	0.7474*
REC	23.2727	21.2034	0	91.3	3.7731	1.1598	376.7***	-0.5099*
CRFPI-RI	7.1589	12.7706	0	73.26	9.2209	2.4326	3929***	-0.0353

Note. *** denotes statistical significance at the 1% level.

Subsequently, Figure 2 reports the average values of the variables examined by country group. Developed countries exhibit higher levels of EFP and GDP, suggesting that higher economic growth tends to coincide with greater environmental degradation. Similarly, CRFPI-RI records higher values in developed countries, which may reflect stronger institutional and financial capacity to implement climate-related regulatory frameworks. By contrast, REC values are higher in developing countries, which generally have lower levels of industrialization and lower total energy demand, thereby increasing the relative share of energy derived from renewable sources.

Figure 2. Mean values of the study variables by country income group.



Note: The GDP^2 and GDP^3 variables are not reported separately, as these represent quadratic and cubic transformations of GDP.

3.2. Econometric methodology

3.2.1. Estimation strategy

The empirical strategy proceeds in four stages, each conditioning the next. First, preliminary diagnostics establish which estimators are admissible and whether a long-run relationship holds, variance inflation factors, the Pesaran (2015, 2021) CD test, the cross-sectionally augmented IPS (CIPS) test of Pesaran (2007), the slope homogeneity tests of Pesaran and Yamagata (2008) and Blomquist and Westerlund (2013), and the residual-based cointegration framework of Banerjee and Carrion-i-Silvestre (2017). Since these diagnostics reject slope homogeneity and the framework anticipates effects that vary across the distribution of environmental pressure, the second stage estimates the baseline model using the MMQR estimator with location-scale effects, as in Machado and Santos Silva (2019). The third stage adds an interaction term between regulatory intensity and renewable energy consumption, both centered on their sample means. It evaluates marginal effects at selected percentiles of the moderator following Brambor et al. (2006). The fourth stage addresses simultaneity and reverse causality through the two-stage instrumental variable estimator with defactored regressors of Norkutė et al. (2021) and Cui et al. (2022). Sections 4.1, 4.3 and 4.4 report the corresponding results.

3.2.2. Model specification

Based on the theoretical framework outlined above, this study specifies an econometric model to examine the relationship between the per capita ecological footprint of production and its explanatory variables. Equation (1) expresses this relationship as follows:

$$EFP_{it} = \alpha_0 + \gamma_1 GDP_{it} + \gamma_2 GDP_{it}^2 + \gamma_3 GDP_{it}^3 + \gamma_4 REC_{it} + \gamma_5 CRFPI - RI_{it} + \gamma_6 CRFPI - RI * REC_{it} + \varepsilon_{it} \quad (1)$$

where EFP denotes the natural logarithm of the per capita ecological footprint of production; GDP represents the natural logarithm of gross domestic product per capita; and GDP^2 and GDP^3 denote the squared and cubed terms of GDP, which the model includes to test the Environmental Kuznets Curve hypothesis. $CRFPI - RI$ captures the regulatory intensity of climate-related financial policies. According to the Porter Hypothesis, this study expects $\gamma_4 < 0$, indicating that greater regulatory intensity in climate-related financial policies is associated

with a lower production ecological footprint. $CRFPI - RI * REC$ captures the impact of the intensity of renewable energy adoption.

The subscript it denotes country i in period t.

3.2.3. Panel data structure

The econometric model follows a panel data structure, which Equation (2) defines as follows:

$$D = \{Y_{it}, X_{it} : i = 1, \dots, N; t = 1, \dots, T\} \quad (2)$$

where $i = 1,2,3, \dots ,72$ represents each country examined, and $t = 2000, 2001, 2002, \dots ,2020$ denotes the year of observation. Y_{it} represents the dependent variable, while X_{it} denotes a vector of explanatory variables specified in Equation (1). One of the main advantages of the panel data structure lies in its ability to combine cross-sectional and temporal variation across countries and over time. This structure allows the study to exploit more information, improve estimator robustness, and control for unobserved characteristics across units of analysis that may remain constant over time, such as institutional, geographical, or structural factors (Hsiao, 2014; Baltagi, 2021). Consequently, the panel data design also enables a comparative analysis between developed and developing countries.

3.2.4. Quantile specification

To examine heterogeneity across the conditional distribution of the ecological footprint of production, this study employs the MMQR approach developed by Machado and Santos Silva (2019), which incorporates location-scale fixed effects. Compared with methods that focus on the conditional mean, MMQR enables analysis of how explanatory variables affect the ecological footprint at different conditional quantiles of its distribution. The quantile-based estimation can be expressed as follows:

$$QY_{it}(\tau|X_{it}) = \emptyset_i + X'_{it}\beta(\tau) \quad (3)$$

where $QY_{it}(\tau|X_{it})$ defines the conditional quantile τassociated with the distribution of the dependent variable Y_{it}, while X_{it} contains a vector of explanatory variables. $\phi_i$captures the unobserved individual effects for each cross-sectional unit, and $\beta(\tau)$denotes the vector of coefficients estimated for each conditional quantile. Based on the model specified in Equation (1), the empirical quantile equation takes the following form:

$$QEFP_{it}(\tau|X_{it}) = \alpha_0 + \gamma_1(\tau)GDP_{it} + \gamma_2(\tau)GDP_{it}^2 + \gamma_3(\tau)GDP_{it}^3 + \gamma_4(\tau)REC_{it} + \gamma_5(\tau)CRFPI - RI_{it} + \gamma_6(\tau)CRFPI - RI * REC_{it} + \varepsilon_{it} \quad (4)$$

The regressions are estimated at the quantiles $\tau \in \{0.10, 0.20, 0.30, \ldots, 0.90\}$. The lower quantiles of the distribution capture observations with relatively low EFP levels. Conversely, the upper quantiles correspond to observations with higher EFP levels. The panel is short in the time dimension relative to the cross-section (T = 21, N = 72). This does not compromise the estimator. Unlike check-function approaches, which fit one individual effect per unit and per quantile, MMQR lets individual heterogeneity enter as location and scale shifts that do not vary with τ and are estimated from moment conditions. The quantile function is then recovered from the standardized residuals of the whole panel. Precision at each quantile therefore rests on the 1,512 observations available rather than on the length of each country's series, and the bias associated with finite T is of order 1/T. The two-stage instrumental variable estimates reported in Section 4.4 confirm the main results and additionally account for the factor structure of the error term.

4. Results and discussion

4.1. Preliminary Results

The MMQR estimation for the panel of 72 countries over the 2000–2020 period requires a series of preliminary diagnostic tests to ensure the consistency of the estimated coefficients. First, the analysis assesses multicollinearity among the independent variables. Second, it examines cross-sectional dependence among panel units to determine the appropriate panel unit root test. Third, it evaluates slope heterogeneity to verify whether estimators that impose homogeneous slope coefficients across cross-sectional units are appropriate. Finally, it determines the order of integration of the variables and tests for cointegration, thereby ensuring that the estimated relationships among non-stationary series are statistically valid and consistent. Accordingly, this section presents these diagnostic analyses sequentially, following the methodological framework adopted in the study.

Table 3 reports the variance inflation factor (VIF) values, indicating that multicollinearity is not a concern in the model specification, as all VIF values remain below the conventional threshold of 10 and, under the more conservative criterion, below 5. These results indicate that the explanatory variables do not exhibit substantial linear dependence.

Table 3. Variance inflation factor statistics.

Variable	VIF	1/VIF
GDP	1.38	0.7236
REC	1.46	0.7297
CRFPI-RI	1.01	0.9903
CRFPI-RI * REC	1.08	0.9260

Subsequently, Table 4 reports the results of the Pesaran (2015, 2021) cross-sectional dependence (CD) test, which rejects the null hypothesis of cross-sectional independence for all model variables at the 1% significance level. These findings confirm that the countries included in the sample are cross-sectionally dependent, likely reflecting economic, financial, institutional, and diplomatic linkages, as well as other forms of international interconnectedness. Consequently, these results justify the use of second-generation panel econometric tests, which are specifically designed to remain robust to cross-sectional dependence.

Table 4. CD test and second-generation unit root test.

Variables	CD test	p-value
EFP	14.93***	0.000
GDP	164.24***	0.000
REC	8.57***	0.000
CRFPI-RI	154.15***	0.000
CRFPI-RI * REC	2.58**	0.010

Notes: *** and ** represent significance at the 1% and 5% levels, respectively. The null hypothesis assumes weak cross-sectional dependence, whereas the alternative hypothesis assumes strong cross-sectional dependence.

Given the marked economic, energy, and regulatory heterogeneity across the 72 countries, the next step is to test whether the slope coefficients are common to all units. Slope homogeneity is assessed with the Pesaran and Yamagata (2008) test and then re-examined using the cross-sectionally robust version of Blomquist and Westerlund (2013), which accommodates the cross-sectional dependence detected earlier. As Table 5 shows, both the Δ and Δ_adj statistics reject homogeneity at the 1% level in the baseline and extended specifications. Estimators that impose a common slope across countries are therefore unsuitable here, which motivates the use of heterogeneous approaches such as the MMQR, in which the effect of each regressor is allowed to vary with the conditional distribution of EFP. Since the original delta test assumes cross-sectional independence, the model is also augmented with the cross-sectional averages of all

variables, following the common correlated effects framework of Pesaran (2006) and keeping the treatment consistent with the cointegration analysis in the next subsection.

Table 5. Results of the slope homogeneity test.

Statistic	Value
Δ	6.358***
Δ_adj	8.705***

Notes: *** denotes statistical significance at the 1% level. The null hypothesis assumes slope homogeneity.

Likewise, Table 6 reports the results of the cross-sectional augmentation of the IPS panel unit root test. The findings reject the null hypothesis of a unit root in first differences at the 1% significance level for all variables, indicating that all series are integrated of order one (I(1).

Table 6. CD test and second-generation unit root test.

Variables	CIPS (Pesaran, 2007)	
	Level	1st difference
EFP	2.956	-22.633***
GDP	0.853	-6.071***
REC	7.992	-18.037***
CRFPI-RI	3.172	-15.021***
CRFPI-RI * REC	13.016	−2.791***

Notes: *** represents significance at the 1% level. CIPS allows for cross-sectional dependence through a single unobserved common factor.

Since all variables are integrated of order one, establishing a cointegrating relationship is necessary to guarantee the consistency of the MMQR estimates and rule out spurious regression. The analysis adopts the residual-based framework of Banerjee and Carrion-i-Silvestre (2017), which accommodates cross-sectional dependence and has been used in ecological footprint studies by Liu et al. (2022) and Musah et al. (2024). It is implemented using Pesaran's (2006) CCE estimator, so that cointegration is supported when the CCE residuals are stationary and free of latent-factor dependence. As Panel A of Table 7 shows, neither the CD nor the bias-adjusted CD* statistic rejects weak cross-sectional dependence in the pooled sample, indicating that the common factors have been effectively absorbed.

Table 7. CCE panel cointegration test.

	CCE-MG	**CCE-P**
Panel A. Cross-sectional dependence tests for the residuals		
CD	−1.00	−2.63***
	(0.317)	(0.009)
CD*	−1.50	−2.34**
	(0.133)	(0.019)

Panel B. Stationarity tests for the residuals		
CIPS	−22.625***	−7.463***
	(0.000)	(0.000)

Notes: *** and ** represent the 1% and 5% significance levels, respectively. Panel A: The null hypothesis of the CD test assumes weak cross-sectional dependence. The null hypothesis of the CD* test assumes cross-sectional independence in the presence of common factors. Panel B: The null hypothesis assumes a unit root in the residual series. CCE-MG denotes the Mean Group variant, and CCE-P denotes the Pooled variant. The specification includes the interaction term CRFPI-RI × REC. The results are qualitatively identical when the interaction term is omitted.

Next, the Mean Group specification reports CD (-2.63) and CD* (-2.34) statistics, which may reflect the mechanical orthogonality induced by the inclusion of cross-sectional averages rather than substantive dependence among latent factors. Second, Panel B reports CIPS statistics that reject the null hypothesis at the 1% significance level for both the CCE-MG (-22.625) and CCE-P (-7.463) estimators. Therefore, the stationarity of the residuals provides evidence of cointegration, indicating that the variables share a long-run equilibrium relationship. This finding supports the validity of the subsequent MMQR estimation.

4.2. MMQR Estimation Results.

This section examines the drivers of the ecological footprint using a Method of Moments Quantile Regression (MMQR) approach for panel data, drawing on a sample of 72 countries, 37 developed and 35 developing economies, observed over 21 years. The analysis includes linear, quadratic, and cubic terms of GDP, as well as renewable energy consumption and the regulatory intensity of climate-related financial policies. The MMQR approach captures heterogeneous relationships across the conditional distribution of EFP, and results are presented comparatively across developed and developing countries. Figures 3 to 5 illustrate the estimated coefficients across conditional quantiles and country groups.

Table 8 reports the global estimation. GDP is negative and significant at the 1% level across all nine quantiles, while GDP^2 is positive and GDP^3 is negative, both significant at the 1% level throughout the distribution. This pattern traces an inverted N-shaped relationship between economic growth and EFP, with turning points at GDP ≈ 7.06 and 10.44. EFP declines at the lowest income levels, rises between the two thresholds, and falls again beyond GDP ≈ 10.44 (US$34,045) at the 50th quantile, lending support to the EKC at the global level. REC is negative and significant at the 1% level in the location and quantile coefficients, with a larger magnitude at the lower quantiles, a 1.18% to 1.34% reduction in EFP. CRFPI-RI is also negative and significant across all quantiles, indicating that greater regulatory intensity in climate-related financial policies lowers the ecological footprint. However, the effect is stronger where environmental degradation is already lower.

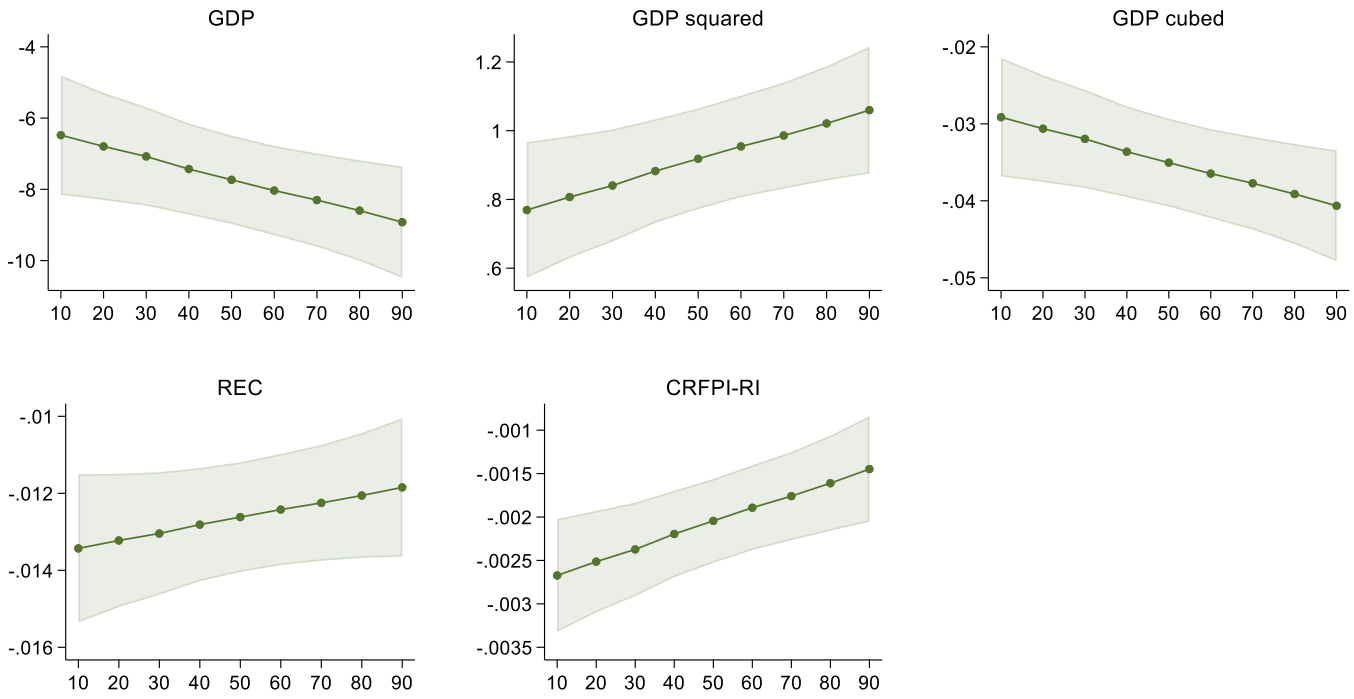
Table 8. MMQR estimates for the determinants of the ecological footprint: Global sample.

Variables	Location	Scale	Lower Quantile			Cuantiles medios			Higher Quantile		
			Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
GDP	-7.7038***	-0.8140**	-6.4780***	-6.7954***	-7.0761***	-7.4307***	-7.7314***	-8.0340***	-8.3003***	-8.5970***	-8.9221***
	(0.6325)	(0.3536)	(0.8539)	(0.7674)	(0.7061)	(0.6527)	(0.6329)	(0.6398)	(0.6675)	(0.7193)	(0.7968)
GDP²	0.9151***	0.0968**	0.7693***	0.8071***	0.8404***	0.8826***	0.9183***	0.9543***	0.9860***	1.0212***	1.0599***
	(0.0745)	(0.0417)	(0.1006)	(0.0904)	(0.0832)	(0.0769)	(0.0746)	(0.0754)	(0.0787)	(0.0848)	(0.0939)
GDP³	-0.0349***	-0.0038**	-0.0291***	-0.0306***	-0.0320***	-0.0336***	-0.0350***	-0.0365***	-0.0377***	-0.0391***	-0.0406***
	(0.0029)	(0.0016)	(0.0039)	(0.0035)	(0.0033)	(0.0030)	(0.0029)	(0.0029)	(0.0031)	(0.0033)	(0.0037)
REC	-0.0126***	0.0005	-0.0134***	-0.0132***	-0.0130***	-0.0128***	-0.0126***	-0.0124***	-0.0122***	-0.0121***	-0.0118***
	(0.0007)	(0.0004)	(0.0010)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0009)
CRFPI-RI	-0.0021***	0.0004***	-0.0027***	-0.0025***	-0.0024***	-0.0022***	-0.0020***	-0.0019***	-0.0018***	-0.0016***	-0.0014***
	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Constant	22.1261***	2.3471**	18.5916***	19.5068***	20.3161***	21.3386***	22.2058***	23.0781***	23.8462***	24.7018***	25.6391***
	(1.7891)	(1.0002)	(2.4153)	(2.1706)	(1.9973)	(1.8462)	(1.7902)	(1.8099)	(1.8882)	(2.0346)	(2.2538)
Observations	1512	1512	1512	1512	1512	1512	1512	1512	1512	1512	1512
R^2 (location equation)		0.4515									

Note. Standard errors in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. R^2 corresponds to the within R^2 of the location equation, whose coefficients coincide with those of the fixed-effects estimator.

Table 9 reports results for developed countries. GDP is negative and significant in the location coefficient and in the 10th to 80th quantiles. At the same time, GDP^2 is positive, and GDP^3 is negative and significant across the distribution, except for GDP^2 at the 90th quantile, with magnitudes decreasing towards the upper quantiles. These signs trace an inverted N-shaped relationship, with turning points at GDP ≈ 8.57 and 10.67. Since the lower root lies below the observed income range, the relevant segment runs from the increasing to the decreasing phase: EFP rises until GDP ≈ 10.67 (US$43,169 at the 50th quantile) and then declines. The threshold falls from US$48,632 at the 10th quantile to US$35,507 at the 90th quantile, indicating that countries with higher conditional EFP reach the turning point at lower income levels.

Figure 3. MMQR coefficients across quantiles, global sample.



Note: Shaded areas denote 95% confidence intervals. Estimates from Table 8.

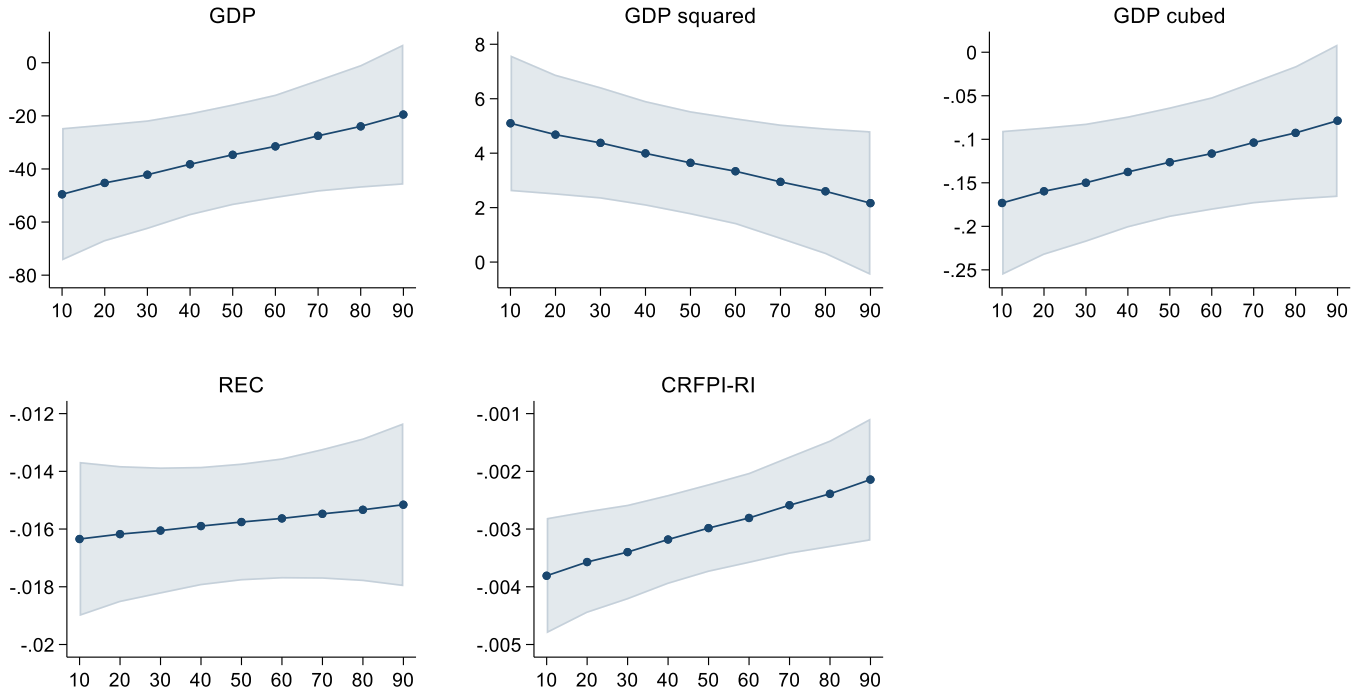
REC is negative and significant at the 1% level across all quantiles in developed countries, declining slightly from 1.63% at the 10th quantile to 1.52% at the 90th.

Table 9. MMQR estimates for the determinants of the ecological footprint: Developed countries.

Variables	Location	Scale	Lower Quantile			Cuantiles medios			Higher Quantile		
			Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
GDP	-34.7620***	9.6773*	-49.5555***	-45.2652***	-42.1687***	-38.2267***	-34.6596***	-31.5013***	-27.5100**	-23.9573**	-19.4987
	(9.6872)	(5.7127)	(12.7513)	(11.2735)	(10.4704)	(9.8376)	(9.7042)	(9.9728)	(10.7632)	(11.8160)	(13.4962)
GDP^2	3.6557***	-0.9446*	5.0997***	4.6810***	4.3787***	3.9939***	3.6457***	3.3374***	2.9478***	2.6010**	2.1658
	(0.9689)	(0.5714)	(1.2755)	(1.1276)	(1.0472)	(0.9839)	(0.9706)	(0.9974)	(1.0765)	(1.1819)	(1.3500)
GDP^3	-0.1266***	0.0304	-0.1732***	-0.1597***	-0.1499***	-0.1375***	-0.1263***	-0.1164***	-0.1038***	-0.0926**	-0.0786*
	(0.0321)	(0.0190)	(0.0423)	(0.0374)	(0.0347)	(0.0326)	(0.0322)	(0.0331)	(0.0357)	(0.0392)	(0.0448)
REC	-0.0158***	0.0004	-0.0163***	-0.0162***	-0.0161***	-0.0159***	-0.0158***	-0.0156***	-0.0155***	-0.0153***	-0.0152***
	(0.0010)	(0.0006)	(0.0014)	(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0013)	(0.0014)
CRFPI-RI	-0.0030***	0.0005**	-0.0038***	-0.0036***	-0.0034***	-0.0032***	-0.0030***	-0.0028***	-0.0026***	-0.0024***	-0.0021***
	(0.0004)	(0.0002)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Constant	110.5833***	-32.6656*	160.5188***	146.0370***	135.5845***	122.2786***	110.2378***	99.5770***	86.1045**	74.1122*	59.0624
	(32.1001)	(18.9301)	(42.2518)	(37.3562)	(34.6971)	(32.6015)	(32.1582)	(33.0488)	(35.6666)	(39.1536)	(44.7206)
Observations	777	777	777	777	777	777	777	777	777	777	777
R^2 (location equation)		0.4687									

Note. Standard errors in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. R^2 corresponds to the within R^2 of the location equation, whose coefficients coincide with those of the fixed-effects estimator.

Figure 4. MMQR coefficients across quantiles in developed countries.



Note: Shaded areas denote 95% confidence intervals. Estimates from Table 9.

CRFPI-RI is negative and significant at the 1% level across all quantiles in developed countries. The scale coefficient is positive and significant at the 5% level (0.0005), confirming that the effect diminishes as EFP rises, from -0.0038 at the 10th quantile to -0.0021 at the 90th, indicating that these policies work more effectively where environmental degradation is already lower.

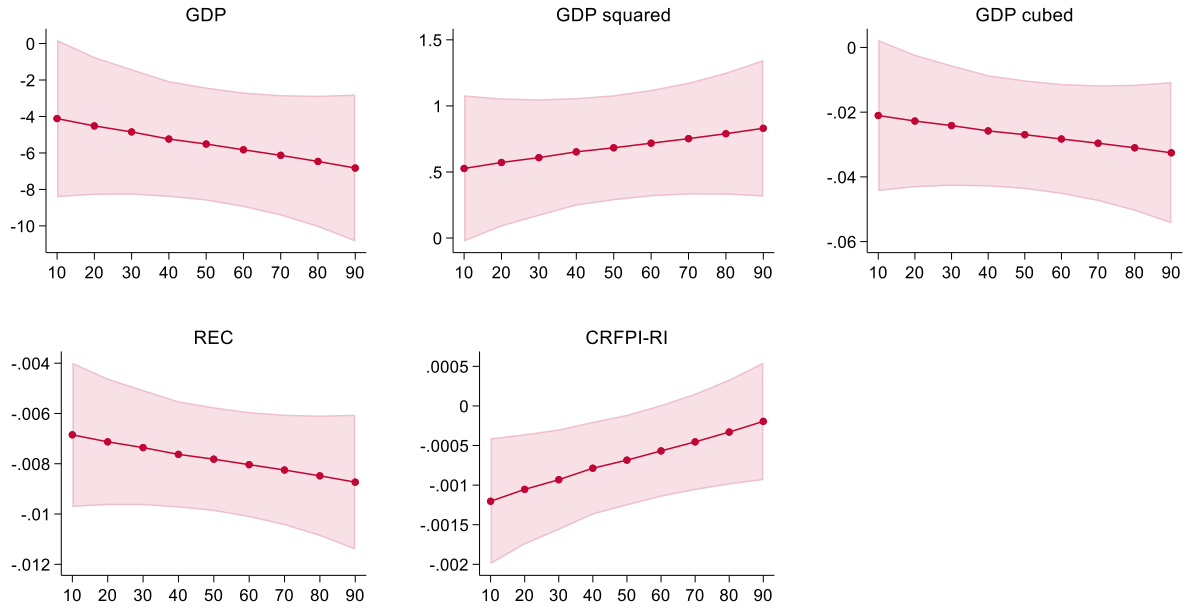
Table 10. MMQR estimates for the determinants of the ecological footprint: Developing countries.

Variables	Location	Scale	Lower Quantile			Cuantiles medios			Higher Quantile		
			Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
GDP	-5.4853***	-0.8685	-4.1141*	-4.5171**	-4.8458***	-5.2360***	-5.5100***	-5.8235***	-6.1299***	-6.4639***	-6.8265***
	(1.5849)	(0.9118)	(2.2026)	(1.9321)	(1.7574)	(1.6219)	(1.5841)	(1.6043)	(1.6870)	(1.8381)	(2.0580)
GDP^2	0.6804***	0.0973	0.5268*	0.5720**	0.6088***	0.6525***	0.6832***	0.7183***	0.7526***	0.7900***	0.8306***
	(0.2031)	(0.1169)	(0.2823)	(0.2477)	(0.2252)	(0.2079)	(0.2030)	(0.2056)	(0.2162)	(0.2356)	(0.2638)
GDP^3	-0.0269***	-0.0037	-0.0210*	-0.0227**	-0.0241**	-0.0258***	-0.0270***	-0.0283***	-0.0296***	-0.0310***	-0.0325***
	(0.0086)	(0.0049)	(0.0119)	(0.0105)	(0.0095)	(0.0088)	(0.0086)	(0.0087)	(0.0091)	(0.0100)	(0.0111)
REC	-0.0078***	-0.0006	-0.0068***	-0.0071***	-0.0074***	-0.0076***	-0.0078***	-0.0080***	-0.0082***	-0.0085***	-0.0087***
	(0.0011)	(0.0006)	(0.0015)	(0.0013)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0014)
CRFPI-RI	-0.0007**	0.0003*	-0.0012***	-0.0011***	-0.0009***	-0.0008***	-0.0007**	-0.0006*	-0.0005	-0.0003	-0.0002
	(0.0003)	(0.0002)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Constant	14.9156***	2.6829	10.6801*	11.9251**	12.9403***	14.1456***	14.9921***	15.9604***	16.9067***	17.9386***	19.0586***
	(4.0807)	(2.3478)	(5.6717)	(4.9747)	(4.5257)	(4.1771)	(4.0794)	(4.1316)	(4.3444)	(4.7330)	(5.2988)
Observations	735	735	735	735	735	735	735	735	735	735	735
R^2 (location equation)		0.4687									

Note: Standard errors in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. R^2 corresponds to the within R^2 of the location equation, whose coefficients coincide with those of the fixed-effects estimator.

Table 10 reports findings for developing countries. GDP is negative and significant in the location coefficient and across all quantiles, with significance rising from 10% at the 10th quantile to 1% from the 30th onwards. GDP^2 remains positive and GDP^3 negative, following the same strengthening pattern towards the upper quantiles, tracing an inverted N-shaped relationship with turning points at GDP ≈ 6.67 and 10.20 (roughly US$26,907 at the 50th quantile). The upper threshold lies above the maximum GDP observed in this group, so the reversal remains a projected, not yet realized outcome, pointing to more resource-intensive productive structures and weaker mitigation capacity.

Figure 5. MMQR coefficients across quantiles in developing countries.



Note: Shaded areas denote 95% confidence intervals. Estimates from Table 10.

REC remains negative and significant across the distribution, with magnitude increasing towards the upper quantiles but remaining weaker than in developed countries, reflecting constraints in technology and infrastructure, as well as continued reliance on fossil fuels. CRFPI-RI is negative and significant up to the 60th quantile, then loses significance beyond that point, indicating a more modest effect that may reflect weaker financial systems and limited regulatory capacity in developing economies. Table 11 summarises the GDP levels at which EFP begins to decline in each group.

Table 11. Income thresholds at which EFP begins to decline, by country group.

Quantile	Global	Developed countries	Developing countries
Q10	43,025	48,632	36,714 *
Q20	40,192	47,142	34,669 *

Q30	35,057	46,880	32,547 *
Q40	35,360	45,182	29,133 *
Q50	34,045	43,169	26,907 *
Q60	30,397	40,988	26,615 *
Q70	30,780	39,820	25,547 *
Q80	29,365	38,407	24,930 *
Q90	28,978	35,507	24,790 *

Note. Thresholds are expressed in constant 2015 US dollars. They are obtained by solving $\partial \ln EFP / \partial \ln GDP = 0$ over the cubic specification, taking the upper root, which corresponds to the income level beyond which the ecological footprint begins to decline. Thresholds are computed using the quantile-specific coefficients reported in Tables 8-10. * indicates that the threshold lies above the maximum income observed in the group.

Taken together, these findings reveal structural differences across the global panel and the two country groups, not in the functional form common to all three, but in the position of the threshold relative to the observed range of economic growth. Developed countries reach and partially exceed the turning point (GDP ≈ 10.67), while in developing countries the threshold (GDP ≈ 10.20) falls outside the observed income range. This is consistent with Abbasi et al. (2023), who identify an inverted N-shaped relationship in a global sample controlling for green and nuclear energy. The present study's reversal threshold at GDP ≈ 10.44 in the global panel contrasts with the steadily increasing relationship documented by Dong et al. (2016), whose uniform pattern more closely resembles developing countries here.

In developed countries, the inverted N-shape is consistent with the EKC framework and with Özokcu and Özdemir (2017), who document the same pattern across 26 high-income OECD economies using carbon emissions as a proxy, suggesting it does not depend on the pollutant chosen. As Yaduma et al. (2015) anticipate, the threshold's gradual decline across quantiles, from US$48,632 to US$35,507, indicates that the relationship is not homogeneous across countries facing different environmental pressures, a pattern that the MMQR approach captures with precision. The turning point at GDP ≈ 10.67 also places a subset of developed countries on the descending segment, consistent with the technique and composition effects documented by Churchill et al. (2018). However, the transition still appears underway for some economies in this group. In developing countries, by contrast, the turning point lies outside the observed range of economic growth, so at the income levels actually recorded, growth continues to intensify EFP. This aligns with Al Numan et al. (2025), who confirm an inverted-N shape across nine ASEAN countries, with these economies on the ascending segment and still short of the second threshold, a feature to be treated with caution in any EKC analysis (Stern, 2004). Harbaugh et al. (2002) note that turning points are sensitive to functional form, controls, and

sample composition, while Cole et al. (1997) document that EKC estimates frequently place thresholds at very high income levels.

This comparison is itself a relevant result, since the difference lies not in the threshold level but in its accessibility within the income range actually recorded. Huang et al. (2023) similarly argue that the reversal is deferred rather than unattainable, and show that climate-related financial regulation together with renewable energy can accelerate the threshold crossing for economies still on the ascending segment. REC reduces the ecological footprint across the global sample and both country groups, confirming clean energy as one of the most consistent mitigating factors, consistent with Appiah et al. (2023), Ahmed et al. (2022), and Akpanke et al. (2024) for OECD and G7 countries.

Its mitigating effect nevertheless remains heterogeneous. In developed countries, the coefficient is larger and more stable across quantiles, suggesting that renewable energy serves as a structural mitigation mechanism, supported by stronger technological, regulatory, and infrastructural conditions. In contrast, in developing countries, the magnitude remains lower, consistent with Azimi and Rahman (2024), who find that the environmental effectiveness of renewable energy depends on institutional and structural thresholds. CRFPI-RI is negative and significant across all country groups, confirming that greater regulatory intensity in climate-related financial policies lowers the ecological footprint, consistent with D'Orazio and Dirks (2022) for G20 countries, Ha (2025) for European countries, and Yen and Ha (2025) for the European Union. The coefficient magnitude nonetheless differs across groups, larger in developed countries and smaller in developing ones. In developed economies, greater financial-system depth, institutional strength, and capital-market sophistication support a more effective transmission to credit allocation, consistent with Jóźwik et al. (2025), who show that green finance reduces the ecological footprint in economies with advanced green financial development. In developing countries, the smaller CRFPI-RI effect reflects lower financial depth and weaker regulatory frameworks, consistent with D'Orazio and Pham (2025), who document that climate-related financial policies differ markedly by institutional quality between advanced and developing economies.

The effect of CRFPI-RI weakens towards the upper quantiles in all three samples, losing significance from the 70th quantile onwards in developing countries, so more stringent financial regulatory policies are required as environmental pressures intensify. Overall, the results suggest that EFP responds not to a single determinant but to the interaction among economic

growth, the clean energy transition, climate-related financial regulation, and structural differences in countries' levels of development. These results for CRFPI-RI allow this study to contrast its findings with the Porter and van der Linde Hypothesis (1995), under which environmental regulation does not constrain economic activity but operates as an incentive-based instrument that redirects it toward productive efficiency and improves environmental performance. The negative and significant relationship between CRFPI-RI and EFP across nearly all quantiles in both country groups supports this, indicating that climate-related financial regulation shapes incentives within the financial system and capital allocation decisions rather than merely serving as a normative instrument.

4.3. Interaction effects between climate-related financial regulation and renewable energy

To examine whether the effect of CRFPI-RI on EFP varies with renewable energy adoption, the specification is extended to include a CRFPI-RI × REC interaction term. Table 12 presents the MMQR estimates for the global sample and both country groups. The GDP, GDP^2, and GDP^3 terms retain their sign, significance, and magnitude relative to the baseline model in Section 4.2, confirming that the specification is robust to the inclusion of the interaction term. REC and CRFPI-RI retain the behavior described in Section 4.2. REC remains negative and significant at the 1% level across all quantiles, larger in developed countries (≈0.016) than in developing economies (≈0.008). CRFPI-RI retains its negative sign and significance in the global sample and developed countries but loses significance in developing countries once the interaction term is introduced, an early sign that its effectiveness there is conditional on renewable energy adoption.

The core finding is the CRFPI-RI × REC interaction term, not significant in the global sample or among developed countries, but negative and significant across the entire distribution in developing countries, a doubly asymmetric relationship. Table 13 and Figure 6 report the marginal effects of CRFPI-RI on EFP in developing countries at the 25th (REC ≈ 9.5%), 50th (REC ≈ 28%), and 75th (REC ≈ 45.9%) percentiles of REC, following the standard procedure for interaction models (Aiken & West, 1991; Brambor et al., 2006) and Hainmueller et al.'s (2019) recommendation to evaluate marginal effects within the common support of the moderator, with delta-method standard errors.

Table 12. MMQR estimates of the extended specification including the CRFPI-RI × REC interaction term

	Localización	Escala	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Panel A. Global sample											
GDP	-7.7225***	-0.8350**	-6.4613***	-6.7891***	-7.0781***	-7.4429***	-7.7487***	-8.0581***	-8.3355***	-8.6373***	-8.9704***
	(0.6330)	(0.3543)	(0.8551)	(0.7678)	(0.7064)	(0.6529)	(0.6335)	(0.6405)	(0.6689)	(0.7206)	(0.7982)
GDP²	0.9166***	0.0985**	0.7678***	0.8065***	0.8406***	0.8836***	0.9197***	0.9562***	0.9889***	1.0245***	1.0637***
	(0.0745)	(0.0417)	(0.1007)	(0.0904)	(0.0832)	(0.0769)	(0.0746)	(0.0754)	(0.0787)	(0.0848)	(0.0940)
GDP³	-0.0349***	-0.0039**	-0.0291***	-0.0306***	-0.0320***	-0.0336***	-0.0351***	-0.0365***	-0.0378***	-0.0392***	-0.0407***
	(0.0029)	(0.0016)	(0.0039)	(0.0035)	(0.0033)	(0.0030)	(0.0029)	(0.0029)	(0.0031)	(0.0033)	(0.0037)
REC	-0.0126***	0.0005	-0.0134***	-0.0132***	-0.0130***	-0.0128***	-0.0126***	-0.0124***	-0.0122***	-0.0120***	-0.0118***
	(0.0007)	(0.0004)	(0.0010)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0009)
CRFPI-RI	-0.0021***	0.0004***	-0.0027***	-0.0025***	-0.0024***	-0.0022***	-0.0020***	-0.0019***	-0.0018***	-0.0016***	-0.0014***
	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
CRFPI-RI × REC (÷100)	0.0005	0.0005	-0.0003	-0.0001	0.0001	0.0003	0.0005	0.0007	0.0009	0.0011	0.0013
	(0.0014)	(0.0008)	(0.0019)	(0.0017)	(0.0016)	(0.0015)	(0.0014)	(0.0015)	(0.0015)	(0.0016)	(0.0018)
Constant	21.8853***	2.4386**	18.2020***	19.1593***	20.0032***	21.0686***	21.9618***	22.8655***	23.6757***	24.5569***	25.5297***
	(1.7919)	(1.0028)	(2.4206)	(2.1735)	(1.9997)	(1.8485)	(1.7934)	(1.8132)	(1.8937)	(2.0400)	(2.2595)
Observations	1,512	1,512	1,512	1,512	1,512	1,512	1,512	1,512	1,512	1,512	1,512
R^2 (location equation)	0.4515										
Panel B. Developed countries											
GDP	-36.1000***	8.8130	-49.6515***	-45.6815***	-42.7926***	-39.3848***	-36.0079***	-33.2251***	-29.4820***	-26.2668**	-22.1427
	(9.8282)	(5.7598)	(13.0302)	(11.4933)	(10.6502)	(10.0166)	(9.8420)	(10.0741)	(10.8608)	(11.8937)	(13.5939)
GDP²	3.7888***	-0.8587	5.1092***	4.7224***	4.4409***	4.1088***	3.7798***	3.5087***	3.1439***	2.8307**	2.4288*
	(0.9826)	(0.5758)	(1.3027)	(1.1491)	(1.0647)	(1.0013)	(0.9839)	(1.0071)	(1.0858)	(1.1891)	(1.3591)
GDP³	-0.1310***	0.0276	-0.1735***	-0.1610***	-0.1520***	-0.1413***	-0.1307***	-0.1220***	-0.1103***	-0.1002**	-0.0873*
	(0.0326)	(0.0191)	(0.0432)	(0.0381)	(0.0353)	(0.0332)	(0.0326)	(0.0334)	(0.0360)	(0.0394)	(0.0451)
REC	-0.0160***	0.0003	-0.0165***	-0.0163***	-0.0162***	-0.0161***	-0.0160***	-0.0159***	-0.0157***	-0.0156***	-0.0155***
	(0.0011)	(0.0006)	(0.0014)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0013)	(0.0015)
CRFPI-RI	-0.0026***	0.0006**	-0.0035***	-0.0032***	-0.0030***	-0.0028***	-0.0026***	-0.0024***	-0.0022***	-0.0020***	-0.0017***
	(0.0005)	(0.0003)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
CRFPI-RI × REC (÷100)	0.0035	0.0003	0.0030	0.0032	0.0033	0.0034	0.0035	0.0036	0.0038	0.0039	0.0041
	(0.0024)	(0.0014)	(0.0031)	(0.0028)	(0.0026)	(0.0024)	(0.0024)	(0.0024)	(0.0026)	(0.0029)	(0.0033)
Constant	114.6402***	-29.7782	160.4293***	147.0148***	137.2536***	125.7392***	114.3289***	104.9261***	92.2785**	81.4146**	67.4799
	(32.5823)	(19.0948)	(43.1963)	(38.1013)	(35.3084)	(33.2090)	(32.6296)	(33.3994)	(36.0066)	(39.4290)	(45.0648)
Observations	777	777	777	777	777	777	777	777	777	777	777
R^2 (location equation)	0.4698										
Panel C. Developing countries											
GDP	-5.2880***	-0.9975	-3.7473*	-4.1495**	-4.5360***	-4.9901***	-5.3248***	-5.7014***	-6.0442***	-6.4033***	-6.8158***

	(1.5783)	(0.9049)	(2.1596)	(1.9282)	(1.7508)	(1.6154)	(1.5778)	(1.6049)	(1.6901)	(1.8325)	(2.0488)
GDP²	0.6635***	0.1145	0.4867*	0.5328**	0.5772***	0.6293***	0.6677***	0.7109***	0.7503***	0.7915***	0.8388***
	(0.2017)	(0.1156)	(0.2759)	(0.2464)	(0.2237)	(0.2064)	(0.2016)	(0.2051)	(0.2160)	(0.2342)	(0.2618)
GDP³	-0.0265***	-0.0044	-0.0196*	-0.0214**	-0.0231**	-0.0252***	-0.0267***	-0.0283***	-0.0299***	-0.0315***	-0.0333***
	(0.0085)	(0.0049)	(0.0116)	(0.0104)	(0.0094)	(0.0087)	(0.0085)	(0.0086)	(0.0091)	(0.0099)	(0.0110)
REC	-0.0079***	-0.0006	-0.0071***	-0.0073***	-0.0075***	-0.0078***	-0.0080***	-0.0082***	-0.0084***	-0.0086***	-0.0088***
	(0.0010)	(0.0006)	(0.0014)	(0.0013)	(0.0012)	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0012)	(0.0014)
CRFPI-RI	-0.0003	0.0003*	-0.0008*	-0.0006	-0.0005	-0.0004	-0.0002	-0.0001	-0.0000	0.0001	0.0003
	(0.0003)	(0.0002)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
CRFPI-RI × REC (÷100)	-0.0054***	-0.0002	-0.0051*	-0.0052**	-0.0052**	-0.0053**	-0.0054***	-0.0055***	-0.0056**	-0.0057**	-0.0058**
	(0.0021)	(0.0012)	(0.0028)	(0.0025)	(0.0023)	(0.0021)	(0.0021)	(0.0021)	(0.0022)	(0.0024)	(0.0027)
Constant	14.0582***	2.9893	9.4410*	10.6465**	11.8046***	13.1654***	14.1686***	15.2969***	16.3243***	17.4003***	18.6364***
	(4.0771)	(2.3376)	(5.5789)	(4.9808)	(4.5235)	(4.1739)	(4.0767)	(4.1465)	(4.3661)	(4.7340)	(5.2925)
Observations	735	735	735	735	735	735	735	735	735	735	735
R^2 (location equation)	0.4698										

Note. Standard errors in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. REC and CRFPI-RI are centered on their sample means, so their coefficients are interpreted as the effect of each variable evaluated at the mean level of the other. The interaction term is constructed as (centered CRFPI-RI × centered REC)/100. This rescaling multiplies the reported coefficient by 100. It is applied solely to aid readability, since the unscaled coefficient would be of the order of 10^{-5}, and it affects neither statistical significance nor model fit. The marginal effect of CRFPI-RI on EFP is therefore given by $\partial EFP/\partial CRFPI\text{-}RI = \beta(CRFPI\text{-}RI) + [\beta(interaction)/100] \cdot$ centered REC. R^2 corresponds to the within R^2 of the location equation, whose coefficients coincide with those of the fixed-effects estimator.

The marginal effect of CRFPI-RI is not significant at any quantile when REC is at its 25th percentile, becomes significant in the lower quantiles (Q10 to Q40) at the 50th percentile, and is negative and significant throughout the distribution at the 75th percentile (-0.0019 to -0.0010). Regulation therefore mitigates EFP only where renewable energy adoption is sufficiently developed (Rasheed et al., 2024; Rasheed, Yuhuan and Ahmed, 2025). The Johnson and Neyman (1936) threshold rises monotonically from 26% of REC at the 10th quantile to 52% at the 90th, indicating that countries with a larger ecological footprint need a substantially broader renewable base before CRFPI-RI has a tangible effect.

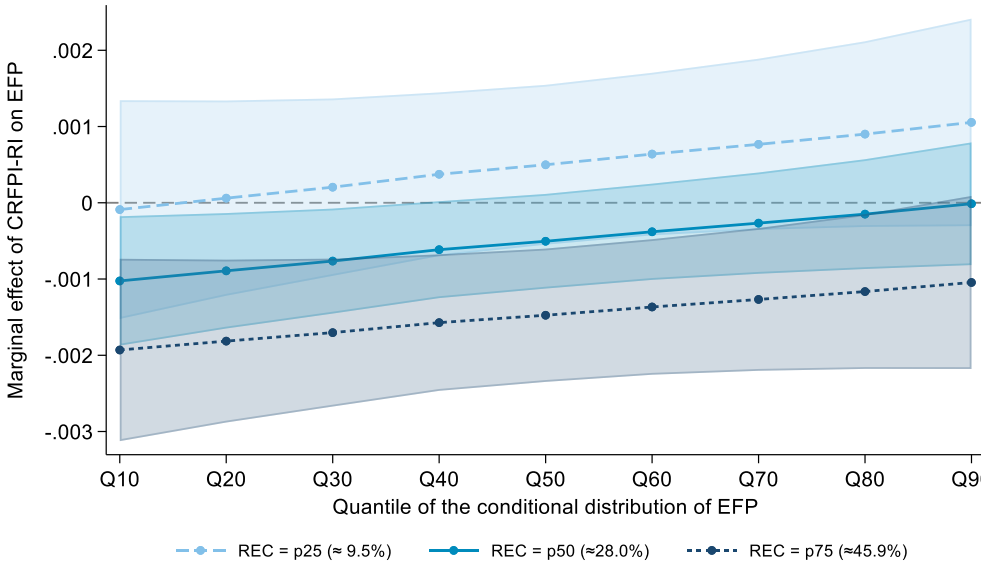
Table 13. Marginal effects of CRFPI-RI on EFP in developing countries by REC level.

Quantile	REC ≈ 9.5% (p25)	REC ≈ 28% (p50)	REC ≈ 45.9% (p75)
Q10	-0.0001	-0.0010**	-0.0019***
	(0.0007)	(0.0004)	(0.0006)
Q20	0.0001	-0.0009**	-0.0018***
	(0.0007)	(0.0004)	(0.0005)
Q30	0.0002	-0.0008**	-0.0017***
	(0.0006)	(0.0004)	(0.0005)
Q40	0.0004	-0.0006*	-0.0016***
	(0.0005)	(0.0003)	(0.0005)
Q50	0.0005	-0.0005	-0.0015***
	(0.0005)	(0.0003)	(0.0004)
Q60	0.0006	-0.0004	-0.0014***
	(0.0005)	(0.0003)	(0.0005)
Q70	0.0008	-0.0003	-0.0013***
	(0.0006)	(0.0003)	(0.0005)
Q80	0.0009	-0.0001	-0.0012**
	(0.0006)	(0.0004)	(0.0005)
Q90	0.0011	-0.0000	-0.0010*
	(0.0007)	(0.0004)	(0.0006)

Note. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Marginal effects $\partial EFP/\partial CRFPI\text{-}RI = \beta(CRFPI\text{-}RI) + [\beta(CRFPI\text{-}RI \times REC)(\div 100)] \cdot$ centered REC, computed from the Panel C estimates for developing countries in Table 12 and evaluated at the 25th percentile, the sample median, and the 75th percentile of the group distribution. Delta method standard errors in parentheses.

These results point to a key contrast. In developed countries, CRFPI-RI and REC operate independently; institutional quality and financial depth appear sufficient to transmit regulatory effects to capital allocation without a renewable energy complement. In developing countries, the two interact in a complementary manner, so regulation alone has no automatic effect; its effectiveness depends on the adoption of renewable energy exceeding a given threshold.

Figure 6. Marginal effect of CRFPI-RI on EFP across the conditional distribution, by level of REC in developing countries.



Note. Shaded areas are 95% confidence intervals obtained through the delta method. The horizontal dashed line at zero marks the null effect. At the 25th percentile of REC, the effect is not statistically distinguishable from zero.

These results are partly consistent with Luo et al. (2024), who find that, for the eleven largest economies, macroprudential policy effectiveness on the ecological footprint is amplified under more stringent environmental policy, with the mitigation benefit concentrated below the median and fading towards the upper quantiles. This pattern appears here among developing countries at intermediate REC levels. Complementarity between financial and environmental instruments, therefore, cannot be assumed globally, consistent with D'Orazio and Pham (2025), who report that developed economies achieve sustained EFP reductions through mature regulatory frameworks, whereas developing countries respond to targeted policies. In less-developed contexts, REC serves as an enabler of CRFPI-RI rather than a substitute.

4.4. Endogeneity and reverse causality

The estimates presented above could be affected by simultaneity, omitted variable bias, and reverse causality. A two-stage instrumental variables (TSIV) approach with defactored regressors is therefore applied (Norkutė et al., 2021; Cui et al., 2022). The approach starts with a model that includes a multifactor structure in the error term and allows the regressors to be correlated with unobserved common factors. REC, CRFPI-RI, and the interaction term are treated as endogenous. In the first stage, the common factors in the covariates are extracted by principal components, and their number is determined through the eigenvalue ratio test of Ahn and Horenstein (2013). The defactored covariates and their lags thus become valid instruments. The second stage is estimated using instrumental variables, with the defactored lags as

instruments for the three endogenous variables, while controlling for country and period fixed effects. The validity of the instrument set is assessed through the Hansen J test reported in Table 14.

Table 14. Two-Stage Instrumental Variables of the EFP.

EFP	**(1) Pooled**	**(2) Mean Group**	**(3) Mean Group**	**(4) Mean Group**
	Global	Global	Developed countries	Developing countries
GDP_c	−0.3527	0.5868**	0.1087	0.8482
	(1.0116)	(0.2960)	(0.3643)	(0.5963)
GDP_c²	−0.4403*	−0.1494*	−0.3082	0.3838
	(0.2348)	(0.0804)	(0.4601)	(0.3855)
GDP_c³	−0.0946	−0.0294	0.2664	0.1748
	(0.0738)	(0.0470)	(0.1851)	(0.1267)
REC_c	−0.0068	−0.0141***	−0.0097**	−0.0122***
	(0.0055)	(0.0027)	(0.0040)	(0.0043)
CRFPI-RI_c	0.0005	−0.0005	0.0002	−0.0029
	(0.0006)	(0.0019)	(0.0030)	(0.0026)
CRFPI-RI × REC (÷100)	0.0006	−0.0048	−0.0146	−0.0206
	(0.0041)	(0.0132)	(0.0249)	(0.0141)
Constante	1.8320***	0.7120**	1.4242***	0.9532***
	(0.4998)	(0.3014)	(0.3343)	(0.2637)
Observations/countries	1.368 / 72	1.368 / 72	703 / 37	665 / 35
Effective periods	19	19	19	19
rho (variance explained by factors)	0.684	—	—	—
Hansen J (p-value)	0.416	—	—	—

Note. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Standard errors in parentheses. Columns (2) to (4) allow for heterogeneous slopes. Hausman test of no correlation with the common factors, $\chi^2(6) = 4.76$, $p = 0.574$

This approach has been preferred to System GMM dynamic panel estimators, which assume cross-sectional independence and slope homogeneity, both of which were rejected in subsection 4.1. Those estimators also rely on differencing the variables, which eliminates the long-run relationship established earlier. For the same reason, the Arellano–Bond AR(1) and AR(2) serial correlation tests, which are designed specifically for that class of dynamic panel GMM estimators, do not apply to the present specification. Instrument validity is assessed instead using the Hansen J test of overidentifying restrictions and the Hausman test for correlation between the covariates and the common factors, both reported in Table 14. To more specifically isolate simultaneity and reverse causality, the main estimator is additionally applied to a specification in which the potentially endogenous regressors enter with a one-period lag. Since the lag of a product coincides with the product of the lags, the lagged interaction term carries no contemporaneous information, as the results in Table A4 of the appendix show.

The estimation results in Table 14 support the robustness of the main estimates documented in sections 4.2 and 4.3. The Hansen J test does not reject the validity of the instruments, and the

Hausman test does not reject the absence of correlation between the covariates and the unobserved common factors, which account for 68.4% of the error variance. Renewable energy consumption retains its negative and significant relationship in both groups of countries. The remaining coefficients lose precision due to the reduction to 19 effective periods resulting from instrumentation and factor extraction. However, all the location coefficients in the relevant regression fall within the 95% confidence intervals of the instrumental variables estimator (Table A2), so both procedures are statistically compatible. The specification with lagged regressors preserves the same moderating behavior obtained under the contemporaneous specification. Finally, the location and scale decomposition of the quantile estimation (Table A3) shows that in developing economies the direct effect of CRFPI-RI operates through the scale parameter. In contrast, the interaction term operates through the location parameter.

Table 15. Reverse causality test

Dependent variable CRFPI-RI	**(1) EFP in levels**	**(2) EFP in first differences**
EFP (t−1)	5.166	—
	(6.985)	
ΔEFP (t−1)	—	−4.267
		(3.988)
GDP (t−1)	−2.566	1.088
	(8.387)	(7.898)
REC (t−1)	−0.222	−0.246
	(0.193)	(0.194)
Country fixed effects	Yes	Yes
Period fixed effects	Yes	Yes
Observations/countries	1,440 / 72	1,368 / 72
Within R^2	0.445	0.444
F (EFP coefficient = 0)	0.55	1.14
p-value	0.462	0.288

Nota: All regressors enter with a one-period lag. The F statistic corresponds to the Wald test for the ecological footprint coefficient. None of the reported coefficients reaches statistical significance at conventional levels.

Finally, the possibility of reverse causality deserves consideration, since countries with a lower EFP might be the ones most inclined to adopt demanding climate-related financial regulation. This is examined using a reduced-form specification in which CRFPI-RI is the dependent variable and EFP, GDP, and REC are regressed on one-period lags. The model is estimated using within fixed effects, with country and period effects, and robust standard errors clustered at the country level. The significance of the reverse channel is assessed via a Wald test on EFP. The time effects isolate the channel specific to each country, separating it from the global adoption trend. Table 15 reports the results and shows that the coefficient on lagged EFP is not significant in either levels or differences, with p-values of 0.462 and 0.288. GDP and REC are not significant either. Almost all the temporal variation in the index is, moreover, shared, since the period effects grow without interruption, become significant from 2011 onwards, and the

mean rises from 0.41 in 2000 to 20.75 in 2020 (Table A5). Reverse causality would require countries with a lower EFP to move ahead of the rest in tightening CRFPI-RI, yet the results show they advance at the same time, regardless of their EFP level.

5. Concluding remarks and policy implications

This study provides evidence on the importance of regulatory intensity in climate-related financial policies for environmental performance. Reducing the ecological footprint depends not only on economic growth and the expansion of clean energy but also on the financial system's capacity to reallocate capital towards activities with lower environmental impact. That effect is stronger in developed economies, which may reflect the greater capacity of more advanced financial systems to allocate capital efficiently within productive structures that absorb regulatory pressures more effectively. Renewable energy consumption likewise acts as a productive resource that helps reduce the ecological footprint, and in developing economies it complements regulation, since the interaction term is negative and significant across the nine conditional quantiles. In contrast, in developed economies it does not differ statistically from zero. The validation of the EKC hypothesis in developed countries suggests that stronger climate-related financial regulation and broader adoption of renewable energy create favorable conditions for economic expansion that reduces the production ecological footprint. In developing economies, by contrast, economic growth continues to intensify it, particularly where regulatory capacity remains weaker and renewable uptake is lower.

From the perspective of Porter's Hypothesis, financial regulation mitigates the production ecological footprint by improving capital allocation, thereby creating incentives to strengthen productive capacity and resource-use efficiency. The contrast between groups, however, shows that this effect is neither automatic nor homogeneous. In developing economies, it depends on the installed renewable capacity. Without that capacity, regulation redirects capital to a productive destination that can absorb it. Therefore, these results allowed us to confirm the hypotheses (H1 – H6) that were put forward. The study yields policy implications that differ by group. In developed economies, where regulation reduces the ecological footprint irrespective of the level of renewables, the appropriate course is to strengthen the binding character of prudential requirements, supervisory mechanisms and the treatment of climate risk in credit allocation. In developing economies, the order of measures matters, since regulatory reform should be coordinated with renewable deployment targets rather than introduced independently, sequencing prudential demands as installed capacity advances. International standards should therefore allow for differentiated timetables, given that a uniform requirement would be

enforceable precisely where the conditions for its effectiveness are weakest. Access to international climate finance and institutional strengthening remain necessary conditions for reaching these thresholds.

The findings also show how the Sustainable Development Goals depend on one another. Tightening climate-related financial regulation counts as progress on climate action (SDG 13), yet in developing economies it does little to reduce resource use (SDG 12) until renewable energy penetration reaches a certain threshold (SDG 7), so regulatory reform works best alongside renewable deployment rather than ahead of it. Some limitations remain. The data are aggregated at the country level; the period ends in 2020 because the regulatory intensity index goes no further; and that index captures how a rule is designed rather than how it is enforced. The dependent variable is production-based and aggregate, so it cannot separate genuine abatement from the relocation of polluting production, nor identify which components of the footprint drive the result. Future work could disaggregate by productive sector or type of financial institution, re-estimate the model on a consumption-based footprint and by component, and extend the analysis once post-2020 data become available.

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Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of interests statement

The authors declare no conflict of interest.

Ethical approval

Not applicable.

Consent to participate

Not applicable.

Consent to publish

Not applicable.

References

Abbasi, K. R., Awan, A., Bandyopadhyay, A., Rej, S., & Banday, T. P. (2023). Investigating the inverted N-shape EKC in the presence of renewable and nuclear energy in a global sample. Clean Technologies and Environmental Policy, 25(4), 1179–1194.

Afshan, S., Ozturk, I., & Yaqoob, T. (2022). Facilitating renewable energy transition, ecological innovations and stringent environmental policies to improve ecological sustainability: Evidence from MM-QR method. Renewable Energy, 196, 151–160. https://doi.org/10.1016/j.renene.2022.06.125

Ahmed, Z., Ahmad, M., Rjoub, H., Kalugina, O. A., & Hussain, N. (2022). Economic growth, renewable energy consumption, and ecological footprint: Exploring the role of environmental regulations and democracy in sustainable development. Sustainable Development, 30(4), 595–605. https://doi.org/10.1002/sd.2251

Ahmed, Z., Rasheed, M. Q., & Pinzon, S. (2025a). Analyzing the effects of wind energy and transportation on the ecological footprint: A pathway to sustainable development in leading economies. Environment, Development and Sustainability. Advance online publication. https://doi.org/10.1007/s10668-025-06498-5

Ahmed, Z., Rasheed, M. Q., & Pinzon, S. (2025b). Sustainable pathways in leading emitters: Unveiling environmental repercussions of institutions, trade globalization, and energy sustainability, accessibility, and efficiency. International Journal of Sustainable Development & World Ecology, 32(5), 525–539. https://doi.org/10.1080/13504509.2025.2499275

Ahn, S. C., & Horenstein, A. R. (2013). Eigenvalue ratio test for the number of factors. Econometrica, 81(3), 1203–1227.

Aiken, L. S., & West, S. G. (1991). Multiple regression: Testing and interpreting interactions. Sage.

Akpanke, T. A., Deka, A., Ozdeser, H., & Seraj, M. (2024). Ecological footprint in the OECD countries: Do energy efficiency and renewable energy matter? Environmental Science and Pollution Research, 31, 15062–15078. https://doi.org/10.1007/s11356-024-32151-1

Al Numan, A., Tahrim, F., Esquivias, M. A., Biswas, M. K., & Primanthi, M. R. (2025). Testing the pollution haven and inverted N-shaped EKC hypotheses in the ASEAN region: The impact of FDI and energy mix on environmental quality. Environmental and Sustainability Indicators, 26, 100698.

Anwar, A., & Abbas, A. (2026). Analyzing the nexus between green finance, green production practices, and environmental quality in an era of geopolitical uncertainty. Green Finance, 8(1), 186–213. https://doi.org/10.3934/GF.2026007

Appiah, M., Li, M., Naeem, M. A., & Karim, S. (2023). Greening the globe: Uncovering the impact of environmental policy, renewable energy, and innovation on ecological footprint. Technological Forecasting and Social Change, 195, 122781. https://doi.org/10.1016/j.techfore.2023.122781

Awad, A., Albaity, M., Mallek, R. S., & Ozturk, I. (2025). Moderating the role of renewable energy use on the nexus between export diversification and ecological footprint in Sub-Saharan Africa. Sustainable Futures, 9, 100796. https://doi.org/10.1016/j.sftr.2025.100796

Ayaydın, H., Ergün, T., Barut, A., Erdem, A., & Pilatin, A. (2025). FinTech driven green energy transition foreign direct investment and ecological footprint in BRICST countries. Scientific Reports, 15, Article 34838. https://doi.org/10.1038/s41598-025-18898-8

Azimi, M. N., & Rahman, M. M. (2024). Renewable energy and ecological footprint nexus: Evidence from dynamic panel threshold technique. Heliyon, 10(13), e33442. https://doi.org/10.1016/j.heliyon.2024.e33442

Balli, H. O., & Sørensen, B. E. (2013). Interaction effects in econometrics. Empirical Economics, 45(1), 583–603.

Balsalobre-Lorente, D., Topaloglu, E. E., Nur, T., & Evcimen, C. (2023). Exploring the linkage between financial development and ecological footprint in APEC countries: A novel view under corruption perception and environmental policy stringency. Journal of Cleaner Production, 414, Article 137686. https://doi.org/10.1016/j.jclepro.2023.137686

Baltagi, B. H. (2021). Econometric analysis of panel data (6th ed.). Springer.

Banerjee, A., & Carrion-i-Silvestre, J. L. (2017). Testing for panel cointegration using common correlated effects estimators. Journal of Time Series Analysis, 38(4), 610–636.

Blomquist, J., & Westerlund, J. (2013). Testing slope homogeneity in large panels with serial correlation. Economics Letters, 121(3), 374–378. https://doi.org/10.1016/j.econlet.2013.09.012

Brambor, T., Clark, W. R., & Golder, M. (2006). Understanding interaction models: Improving empirical analyses. Political Analysis, 14(1), 63–82.

Cai, Z., Tang, Y., & Lin, J. (2024). Exploring the impact of circular economy practices on ecological footprint, inflation rate, and renewable energy consumption: Evidence from G20 economies. Environmental Science and Pollution Research. https://doi.org/10.1007/s11356-024-32688-1

Churchill, S. A., Inekwe, J., Ivanovski, K., & Smyth, R. (2018). The environmental Kuznets curve in the OECD: 1870–2014. Energy Economics, 75, 389–399.

Cole, M. A., Rayner, A. J., & Bates, J. M. (1997). The environmental Kuznets curve: An empirical analysis. Environment and Development Economics, 2(4), 401–416.

Cui, G., Norkutė, M., Sarafidis, V., & Yamagata, T. (2022). Two-stage instrumental variable estimation of linear panel data models with interactive effects. The Econometrics Journal, 25(2), 340–361.

D'Orazio, P. (2023). Dataset for the climate-related financial policy index (CRFPI). Data in Brief, 48, 109044. https://doi.org/10.1016/j.dib.2023.109044

D'Orazio, P., & Dirks, M. W. (2022). Exploring the effects of climate-related financial policies on carbon emissions in G20 countries: A panel quantile regression approach. Environmental Science and Pollution Research, 29, 7678–7702. https://doi.org/10.1007/s11356-021-15655-y

D'Orazio, P., & Pham, A.-D. (2025). Evaluating climate-related financial policies' impact on decarbonization with machine learning methods. Scientific Reports, 15, 1694. https://doi.org/10.1038/s41598-025-85127-7

D'Orazio, P., & Thole, S. (2022). Climate-related financial policy index: A composite index to compare the engagement in green financial policymaking at the global level. Ecological Indicators, 141, 109065. https://doi.org/10.1016/j.ecolind.2022.109065

Degirmenci, T., Erdem, A., & Aydin, M. (2025). The nexus of industrial employment, financial development, urbanization, and human capital in promoting environmental sustainability

in E7 economies. International Journal of Sustainable Development & World Ecology, 32(2), 242–258. https://doi.org/10.1080/13504509.2024.2426184

Degirmenci, T., & Ünsal, Y. (2026). Achieving sustainable development through the green budget in the European Union: The role of renewable energy, energy productivity, and environmental policy. Sustainable Development. Advance online publication. https://doi.org/10.1002/sd.70624

Dong, B., Wang, F., & Guo, Y. (2016). The global EKCs. International Review of Economics & Finance, 43, 210–221.

Erdem, A., Demirtas, N., Cirak, A. N., Barut, A., & Amoozegar, A. (2026). How green finance, digitalization, and transport technologies affect the load capacity factor in Organization for Economic Cooperation and Development countries. Asian Journal of Water, Environment and Pollution, 23(2), Article 025150110. https://doi.org/10.36922/AJWEP025150110

Fatima, N., Xuhua, H., Alnafisah, H., Zeast, S., & Akhtar, M. R. (2024). Enhancing climate action in OECD countries: The role of environmental policy stringency for energy transitioning to a sustainable environment. Environmental Sciences Europe, 36, Article 157. https://doi.org/10.1186/s12302-024-00978-7

Footprint Data Foundation, York University Ecological Footprint Initiative, & Global Footprint Network. (2025). National Footprint and Biocapacity Accounts, 2025 edition [Data set]. https://data.footprintnetwork.org

Grossman, G. M., & Krueger, A. B. (1991). Environmental impacts of a North American Free Trade Agreement (NBER Working Paper No. 3914). National Bureau of Economic Research. https://doi.org/10.3386/w3914

Ha, L. T. (2025). Do the climate-related financial policies promote ecological sustainability? Insights from European countries. Environment, Development and Sustainability, 27(10), 23869–23888. https://doi.org/10.1007/s10668-023-03957-9

Hainmueller, J., Mummolo, J., & Xu, Y. (2019). How much should we trust estimates from multiplicative interaction models? Simple tools to improve empirical practice. Political Analysis, 27(2), 163–192.

Harbaugh, W. T., Levinson, A., & Wilson, D. M. (2002). Reexamining the empirical evidence for an environmental Kuznets curve. The Review of Economics and Statistics, 84(3), 541–551.

Hsiao, C. (2014). Analysis of panel data (3rd ed.). Cambridge University Press.

Huang, J., Zhang, D., Zhang, Z., Kong, W., Yan, J., & Xia, F. (2023). Trapped in dilemma: Inverted N-shaped EKC evidence of economic growth and ecological land in a spatial spillover perspective. Applied Geography, 161, 103145.

Jarijari, T., Deka, A., & Cavusoglu, B. (2025). The synergistic role of natural resources, green finance and green technological innovations in promoting environmental sustainability in Sub-Saharan Africa. Resources Policy, 105, Article 105598. https://doi.org/10.1016/j.resourpol.2025.105598

Johnson, P. O., & Neyman, J. (1936). Tests of certain linear hypotheses and their application to some educational problems. Statistical Research Memoirs, 1, 57–93.

Jóźwik, B., Sarıgül, S. S., & Saçık, S. Y. (2025). Green finance and ecological footprint: Empirical analysis in countries with the highest green financial development. Sustainability, 17(23), 10509. https://doi.org/10.3390/su172310509

Khalid, M. W., Shah, A. H., Khan, A. U., & Nicita, L. (2025). Revisiting the EKC hypothesis in high-income EU countries: The role of technological innovation, green energy, and transport energy in shaping ecological footprints. Sustainable Futures, 10, 101174. https://doi.org/10.1016/j.sftr.2025.101174

Kilinc-Ata, N., Camkaya, S., & Topal, S. (2025). What role do foreign direct investment and technology play in shaping the impact on environmental sustainability in Newly Industrialized Countries (NIC)? New evidence from wavelet quantile regression. Sustainability, 17(11), Article 4966. https://doi.org/10.3390/su17114966

Kripfganz, S., & Sarafidis, V. (2021). Instrumental-variable estimation of large-T panel-data models with common factors. The Stata Journal, 21(3), 659–686.

Li, X., Zhu, S., Li, Y., & Chang, R. (2022). What is the asymmetric influence of natural resource rent and green innovation on the ecological sustainability of the ARCTIC region. Resources Policy, 79, 103051. https://doi.org/10.1016/j.resourpol.2022.103051

Liu, X., Razzaq, A., Shahzad, M., & Irfan, M. (2022). Technological changes, financial development and ecological consequences: A comparative study of developed and developing economies. Technological Forecasting and Social Change, 184, 122004.

Luo, H., Sun, Y., & Zhang, L. (2024). Effects of macroprudential policies on ecological footprint: The moderating role of environmental policy stringency in the top 11 largest countries. Scientific Reports, 14, Article 7423. https://doi.org/10.1038/s41598-024-58015-9

Machado, J. A. F., & Santos Silva, J. M. C. (2019). Quantiles via moments. Journal of Econometrics, 213(1), 145–173. https://doi.org/10.1016/j.jeconom.2019.04.009

Miao, Y., Razzaq, A., Adebayo, T. S., & Awosusi, A. A. (2022). Do renewable energy consumption and financial globalisation contribute to ecological sustainability in newly industrialized countries? Renewable Energy, 187, 688–697. https://doi.org/10.1016/j.renene.2022.01.073

Miyan, M. S., Cheong, C. W. H., Sharif, A., & Afshan, S. (2025). Green finance, innovation, and environment: Testing the EKC in ASEAN-4 with MMQR approach. Global Transitions. https://doi.org/10.1016/j.glt.2025.09.001

Musah, M., Boateng, F., Kumah, E. A., & Adebayo, T. S. (2024). Financial flows and environmental quality in ECOWAS member states: Accounting for residual cross-sectional dependence and slope heterogeneity. Environment, Development and Sustainability, 26(1), 1195–1228.

Nathaniel, S. P., Dauda, R. O., & Ajide, K. B. (2025). Linking energy consumption to ecological footprint in sub-Saharan Africa with education as a moderator. Energy Geoscience, 6, 100398. https://doi.org/10.1016/j.engeos.2025.100398

Norkutė, M., Sarafidis, V., Yamagata, T., & Cui, G. (2021). Instrumental variable estimation of dynamic linear panel data models with defactored regressors and a multifactor error structure. Journal of Econometrics, 220(2), 416–446.

North, D. C. (1990). Institutions, institutional change and economic performance. Cambridge University Press.

Nuta, F. M., Abban, O. J., & Nuta, A. C. (2025). Green finance's role for sustainable development in the context of COP targets. Sustainable Energy Technologies and Assessments, 82, Article 104501. https://doi.org/10.1016/j.seta.2025.104501

OECD. (2025). The effects of climate policies on emissions: Evidence from a comprehensive and systematic review of the ex-post empirical literature. OECD Publishing. https://doi.org/10.1787/ec1f7f0d-en

Özcan, K. A. (2024). Determinants of ecological footprint: A quantile regression approach. Systems, 12(2), 59. https://doi.org/10.3390/systems12020059

Özokcu, S., & Özdemir, Ö. (2017). Economic growth, energy, and environmental Kuznets curve. Renewable and Sustainable Energy Reviews, 72, 639–647.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica, 74(4), 967–1012.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Econometrics, 22(2), 265–312. https://doi.org/10.1002/jae.951

Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. Econometric Reviews, 34(6–10), 1089–1117. https://doi.org/10.1080/07474938.2014.956623

Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. Empirical Economics, 60(1), 13–50. https://doi.org/10.1007/s00181-020-01875-7

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. Journal of Econometrics, 142(1), 50–93.

Pinzon, S., Rodríguez-Crespo, E., Tillaguango, B., & Laguna-Molina, N. E. (2026). Ecological footprint under the lens: A bibliometric coupling analysis of institutional and socioeconomic factors. Energy Nexus, 100643.

Porter, M. E. (1991). America's green strategy. Scientific American, 264(4), 168.

Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. Journal of Economic Perspectives, 9(4), 97–118.

Quan, Z., Xu, X., Jiang, J., Wang, W., & Gao, S. (2024). Uncovering the drivers of ecological footprints: A STIRPAT analysis of urbanization, economic growth, and energy sustainability in OECD countries. Journal of Cleaner Production, 475, 143686.

Rasheed, M. Q., Yuhuan, Z., & Ahmed, Z. (2025). Can enhancing competitive industrial performance and adopting renewables stimulate progress toward carbon neutrality targets? Evidence from Asian developing countries. Energy & Environment. Advance online publication. https://doi.org/10.1177/0958305X251389830

Rasheed, M. Q., Yuhuan, Z., Haseeb, A., Ahmed, Z., & Saud, S. (2024). Asymmetric relationship between competitive industrial performance, renewable energy, industrialization, and carbon footprint: Does artificial intelligence matter for environmental sustainability? Applied Energy, 367, Article 123346. https://doi.org/10.1016/j.apenergy.2024.123346

Rasheed, M. Q., Yuhuan, Z., Haseeb, A., & Saud, S. (2025). Unpacking the stance of upgradation of industrial structure, technological trade, and sustainable development in top-ten high-income countries. Natural Resources Forum, 49(4), 3703–3727. https://doi.org/10.1111/1477-8947.12546

Satrovic, E., Cetindas, A., Akben, I., & Damrah, S. (2024). Do natural resource dependence, economic growth and transport energy consumption accelerate ecological footprint in the most innovative countries? The moderating role of technological innovation. Gondwana Research, 127, 116–130. https://doi.org/10.1016/j.gr.2023.04.008

Scott, W. R. (1995). Institutions and organizations. Sage.

Shahbaz, M., Barut, A., Alofaysan, H., & Çamkaya, S. (2025). The impact of inclusive finance and lifelong learning on carbon neutrality: Evidence from African countries. Research in International Business and Finance, 78, Article 102996. https://doi.org/10.1016/j.ribaf.2025.102996

Soto, G. H., Zambrano-Monserrate, M. A., Pilatin, A., & Martinez-Cobas, X. (2025). Energy resource productivity and environmental quality: A quantile-on-quantile study of Latin America from 1990 to 2022. Utilities Policy, 95, 101944. https://doi.org/10.1016/j.jup.2025.101944

Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. World Development, 32(8), 1419–1439.

Sun, Y., Li, T., & Mehmood, U. (2025). Balancing acts: Assessing the roles of renewable energy, economic complexity, Fintech, green finance, green growth, and economic performance

in G-20 countries amidst sustainability efforts. Applied Energy, 378, 124846. https://doi.org/10.1016/j.apenergy.2024.124846

Usman, O., Iorember, P. T., Jelilov, G., Isik, A., Ike, G. N., & Sarkodie, S. A. (2021). Towards mitigating ecological degradation in G-7 countries: Accounting for economic effect dynamics, renewable energy consumption, and innovation. Heliyon, 7(12), e08592. https://doi.org/10.1016/j.heliyon.2021.e08592

World Bank. (2025). World Bank country and lending groups. World Bank Data Help Desk.

World Bank. (2026). World development indicators [Data set]. https://databank.worldbank.org/source/world-development-indicators

Yaduma, N., Kortelainen, M., & Wossink, A. (2015). The environmental Kuznets curve at different levels of economic development: A counterfactual quantile regression analysis for CO2 emissions. Journal of Environmental Economics and Policy, 4(3), 278–303.

Yen, N. H., & Ha, L. T. (2025). Climate-related financial policies as an enabler of circularity: A new insight from selected countries of the European Union. International Journal of Climate Change Strategies and Management, 17(1), 612–632. https://doi.org/10.1108/IJCCSM-02-2024-0028

Yu, J., Long, H., Shahzad, I., & Wang, J. (2026a). Driving sustainable development in BRICS through green finance and economic growth: A quantile regression perspective. Journal of Innovation & Knowledge, 11(1), Article 100879. https://doi.org/10.1016/j.jik.2025.100879

Yu, L., Quan, L., Aoudi, L., & Shao, X. (2026b). Can green finance and effective governance accelerate the low-carbon transition? A quantile analysis of OECD countries. Journal of Innovation & Knowledge, 16. Advance online publication.

Zhang, S., & Chen, K. (2023). Green finance and ecological footprints: Natural resources perspective of China's growing economy. Resources Policy, 85, 103898. https://doi.org/10.1016/j.resourpol.2023.103898

Appendices

Table A1. List of countries included in the sample.

N.º	Country	Geographic region
Developed countries (n = 37)		
1	Australia	East Asia and Pacific

2	Austria	Europe and Central Asia
3	Bahrain	Middle East and North Africa
4	Belgium	Europe and Central Asia
5	Canada	North America
6	Chile	Latin America and the Caribbean
7	Croatia	Europe and Central Asia
8	Cyprus	Europe and Central Asia
9	Czech Republic	Europe and Central Asia
10	Denmark	Europe and Central Asia
11	Finland	Europe and Central Asia
12	France	Europe and Central Asia
13	Germany	Europe and Central Asia
14	Greece	Europe and Central Asia
15	Hungary	Europe and Central Asia
16	Ireland	Europe and Central Asia
17	Israel	Middle East and North Africa
18	Italy	Europe and Central Asia
19	Japan	East Asia and Pacific
20	Latvia	Europe and Central Asia
21	Lithuania	Europe and Central Asia
22	Luxembourg	Europe and Central Asia
23	Netherlands	Europe and Central Asia
24	New Zealand	East Asia and Pacific
25	Norway	Europe and Central Asia
26	Panama	Latin America and the Caribbean
27	Poland	Europe and Central Asia
28	Portugal	Europe and Central Asia
29	Saudi Arabia	Middle East and North Africa
30	Singapore	East Asia and Pacific
31	South Korea	East Asia and Pacific
32	Spain	Europe and Central Asia
33	Sweden	Europe and Central Asia
34	Switzerland	Europe and Central Asia
35	United Arab Emirates	Middle East and North Africa
36	United Kingdom	Europe and Central Asia
37	United States of America	North America
Developing countries (n = 35)		
38	Argentina	Latin America and the Caribbean
39	Bangladesh	South Asia
40	Brazil	Latin America and the Caribbean
41	Bulgaria	Europe and Central Asia
42	Cambodia	East Asia and Pacific
43	China	East Asia and Pacific
44	Colombia	Latin America and the Caribbean
45	Costa Rica	Latin America and the Caribbean
46	Ecuador	Latin America and the Caribbean
47	Egypt	Middle East and North Africa
48	Fiji	East Asia and Pacific
49	Georgia	Europe and Central Asia

50	Ghana	Sub-Saharan Africa
51	India	South Asia
52	Indonesia	East Asia and Pacific
53	Kazakhstan	Europe and Central Asia
54	Kenya	Sub-Saharan Africa
55	Lebanon	Middle East and North Africa
56	Malaysia	East Asia and Pacific
57	Mexico	Latin America and the Caribbean
58	Mongolia	East Asia and Pacific
59	Morocco	Middle East and North Africa
60	Nepal	South Asia
61	Nigeria	Sub-Saharan Africa
62	Pakistan	South Asia
63	Paraguay	Latin America and the Caribbean
64	Peru	Latin America and the Caribbean
65	Philippines	East Asia and Pacific
66	Russia	Europe and Central Asia
67	South Africa	Sub-Saharan Africa
68	Sri Lanka	South Asia
69	Thailand	East Asia and Pacific
70	Turkey	Europe and Central Asia
71	Ukraine	Europe and Central Asia
72	Viet Nam	East Asia and Pacific

Note: Classification based on the World Bank Atlas method (2025).

Table A2. Compatibility between the MMQR and TSIV estimates.

Variable	MMQR (location)	TSIV (Mean Group)	TSIV 95% CI	Compatible
		Global panel		
REC_c	−0.0126	−0.0141	[−0.0195; −0.0087]	Yes
CRFPI-RI_c	−0.0021	−0.0005	[−0.0043; 0.0033]	Yes
CRFPI-RI_c × REC_c (÷100)	0.0005	−0.0048	[−0.0307; 0.0210]	Yes
		Developed countries		
REC_c	−0.0160	−0.0097	[−0.0176; −0.0019]	Yes
CRFPI-RI_c	−0.0026	0.0002	[−0.0057; 0.0060]	Yes
CRFPI-RI_c × REC_c (÷100)	0.0035	−0.0146	[−0.0633; 0.0341]	Yes
		Developing countries		
REC_c	−0.0079	−0.0122	[−0.0206; −0.0038]	Yes
CRFPI-RI_c	−0.0003	−0.0029	[−0.0081; 0.0022]	Yes
CRFPI-RI_c × REC_c (÷100)	−0.0054	−0.0206	[−0.0481; 0.0070]	Yes

Note. The location coefficient of the method-of-moments model falls within the confidence interval of the instrumental-variables estimator in all nine comparisons. Intervals are computed as b ± 1.96·SE from the Mean Group estimates reported in Table 14. Their width reflects the loss of precision in instrumental-variables estimation, so compatibility should be read as the absence of contradiction rather than as independent confirmation.

Table A3. Location and scale decomposition of the MMQR estimates

Variable	Location	Scale	Dominant channel
Global panel			
REC_c	−0.0126***	0.0005	Location
CRFPI-RI_c	−0.0021***	0.0004***	Both
CRFPI-RI_c × REC_c (÷100)	0.0005	0.0005	Neither
Developed countries			
REC_c	−0.0160***	0.0003	Location
CRFPI-RI_c	−0.0026***	0.0006**	Both
CRFPI-RI_c × REC_c (÷100)	0.0035	0.0003	Neither
Developing countries			
REC_c	−0.0079***	−0.0006	Location
CRFPI-RI_c	−0.0003	0.0003*	Scale
CRFPI-RI_c × REC_c (÷100)	−0.0054***	−0.0002	Location

Note. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The dominant channel identifies the parameter through which each variable operates, based on the significance of the location and scale coefficients reported in Table 12.

Table A4. Marginal effect of CRFPI-RI with regressors lagged one period in developing countries.

REC (level)	Q10	Q50	Q 90
9.5% (p25)	−0.00043	0.00008	0.00059
	(0.587)	(0.885)	(0.436)
28.0 % (p50)	−0.00117***	−0.00063**	−0.00010
	(0.009)	(0.049)	(0.815)
45.9 % (p75)	−0.00187***	−0.00131***	−0.00076
	(0.004)	(0.005)	(0.213)

Note. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. P-values are in parentheses. All regressors enter with a one-period lag. The REC levels correspond to the 25th, 50th, and 75th percentiles of the group distribution.

Table A5. Evolution of CRFPI-RI and estimated time effects.

Year	Mean	Standard deviation	Time effect
2000	0.41	2.02	—
2005	1.69	4.39	0.834
2010	5.06	9.94	4.690*
2015	11.15	14.85	11.061***
2020	20.75	16.89	20.988***

Note. *** and * denote significance at the 1% and 10% levels, respectively. Time effects are taken from column (1) of Table 15 and are expressed relative to the 2001 base year. The share of the error variance attributable to between-country heterogeneity is 0.680.