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Green Economic Complexity, Biodiversity Finance, and the Load Capacity Factor: The Moderating Role of Climate-Related Financial Policy

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ABSTRACT

The load capacity factor (LCF) is a preferred sustainability indicator due to its ability to measure the ecological footprint and the biocapacity to support both. However, two drivers of ecological outcomes are gaining popularity, green economic complexity (GEC) and biodiversity finance (BF), but these are both explored in different literatures. The impacts on the climate of their financial policy framework have not been proven. This study estimates the interaction effects between GEC and BF on LCF and investigates if any moderation of these relationships exists between GEC and BF through the climate-related financial policy index (CRFPI). Based on the concepts of ecological modernization, finance–growth and legitimacy and institutional theories it examines a balanced panel of 101 countries for 23 years. Cross-sectional dependence, slope heterogeneity, stationarity and cointegration are established by second generation diagnostics followed by pooled OLS, random-effects, GMM and dynamic fixed-effects estimators. After controlling for country heterogeneity, both variables positively influence the LCF, with a 1-SD increase in BF and GEC resulting in an increase of LCF of approximately 0.35 and 0.11 respectively. It is lowered in contrast with digitalization, population growth and urbanization. The interaction terms are negative, contradicting the moderation hypotheses, indicating that the ecological returns to green capabilities and biodiversity capital are negative as the financial regulation becomes more carbon-based. The study provides the first country-level evidence of the connection between biodiversity finance and green complexity to the LCF in an institutional-moderation approach.

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1. Introduction

The economic-environmental debate has shifted from the sides to the middle of macro-financial policy. The empirical studies of this tension for decades are based on one-sided measures of environmental stress, most importantly carbon dioxide (CO2) emissions and ecological footprint. These indicators are a measure of pressure which human activity imposes on nature, but they do not indicate how much pressure nature can still withstand. The load capacity factor (LCF) proposed by Siche et al. (2010) can be used to correct this one-sidedness by dividing a country's biocapacity by its ecological footprint. Numbers greater than one will indicate an ecological reserve, while numbers less than one will indicate a deficit. The LCF has been adopted by an expanding body of literature as a favored outcome variable for its ability to integrate both the supply and demand sides of the ecological ledger in a ratio interpretable way (Pata & Isik, 2021; Guloglu et al., 2023; Dada et al., 2025; Guo et al., 2025).

Three separate pieces of literature bear on what drives the LCF. The first is about the complexity of the production process. Building on the economic complexity tradition (Hidalgo & Hausmann, 2009), researchers want to know both the value of an economy's productive base, and how much of that value is derived from knowledge-intensive activities and how much is derived from "green" activities. The more diversified exports the economies have, the lower their greenhouse-gas emission intensities (Romero & Gramkow, 2021). Mealy and Teytelboym (2022) further developed the idea for green products to create a measure of green economic complexity (GEC). There is recent evidence connecting GEC directly to the LCF in G20 economies (Zeraibi et al., 2026). But not all research agrees: Maneejuk and Yamaka (2025) find that while more green complexity can lower emissions, it can also cause a drop in emissions below certain thresholds; Gbolonyo et al. (2026) find that greater economic complexity in Sub-Saharan can lead to growth at the expense of environmental sustainability. The ecological dividend of complexity is a matter of choice rather than a given.

The second literature is about the financing of nature. The Kunming–Montreal Global Biodiversity Framework pledges to advance efforts to raise at least USD 200 billion annually to fund biodiversity by 2030. This target is reacting to an estimated financing gap of approximately USD 600-800 billion per year (Convention on Biological Diversity [CBD], 2022; Deutz et al., 2020). There has been academic interest since. Public–private partnerships are often needed for private biodiversity investments, as these investments depend on monetizing ecosystem services, and sovereign biodiversity loss poses systemic financial risk (Flammer et al., 2025; Mies, 2025), respectively. Studies across the country suggest that green finance helps to lessen biodiversity loss and boost biocapacity (Khan et al., 2025). But a cautionary narrative is emerging that reported growth in biodiversity finance is as much definitional growth and greenwashing as it is reallocation of real capital (Christiansen et al., 2025; Gan, 2025).

The third literature is related to the institutional structure of green finance. The climate-related financial policy index (CRFPI) was created by D'Orazio and Thole (2022). The index rates the national engagement in green prudential regulation, credit allocation, financial guidelines, disclosure requirements and green-bond taxonomies. Financial policies relating to climate change have been proven to lower the CO2 emission in the G20 (D'Orazio & Dirks, 2022), and to increase the environmental performance in Europe (Ha, 2025). Concurrently, central-bank guidelines and supervisory regimes continue to focus more on financial-stability issues than on ecosystem outcomes (Dikau & Volz, 2021; Kedward et al., 2023). So, it remains to be seen whether a more robust policy response to climate change yields better results, including biocapacity, which relies on land use and biodiversity.

These literatures have been parallel in the sense that there is a definite gap. No studies have measured both GEC and BF as contributors to the LCF. Nor has any study questioned whether the level of engagement of a country's financial policy has an impact on either the strength of the

relationship or the strength of the country's climate policy. This is significant for two reasons. Estimates of the ecological return to green capabilities and biodiversity capital rely on the institutional (financial policy) context, and the absence of this layer in such estimates could result in misstated ecological returns and policy relevance. On the other hand, financial regulation focused on climate may be overly relying on to meet other ecological goals if it is not aligned to biodiversity goals (Network for Greening the Financial System [NGFS], 2022; Pörtner et al., 2023).

The study has three contributions. First, it is one of the first to integrate GEC and BF into one model of ecological sustainability. This enables an evaluation of their relative explanatory power, rather than being drawn from individual strands of literature. Second, it brings the institutional-moderation logic, which has been applied primarily to the firm-level and financial-market outcomes (Song & Dong, 2024; Ge & Zhang, 2025), to the country-level, biocapacity-based LCF. Third, the analysis is based on the moderator of the CRFPI, not a generic proxy for policy uncertainty, thereby making the result more applicable to a specific policy instrument, the composition and stringency of a country's climate-related financial regulation. This empirical finding confirms the NGFS (2022) and Kedward et al. (2023) who called for embedding nature related goals into financial policy, as the findings suggest this policy would reduce the ecological benefit from green complexity and biodiversity finance.

The rest of the paper is structured as follows: The theoretical framework and hypotheses are developed in section 2. Section 3 presents the data and econometric approach. The results are presented and discussed in Section 4. Section 5 ends with implications, limitations and directions for future research.

2. Literature Review

2.1 Theoretical Foundation: Ecological Modernization Theory

The study is founded on ecological modernization theory (EMT), which suggests that ecological problems are not solved through a slowdown in economic growth but through changes in the institutional infrastructure of modern economies where ecological aspects are integrated in production, financial and regulatory processes (Mol & Spaargaren, 2000). EMT is the result of three interacting agents: science and technology, which internalize ecological rationality in their investment choices; market actors, who internalize an ecological rationality in their investment choices; and nation state, whose rules and incentives push them towards ecological objectives. These three agents are directly related to the three constructs of the model as illustrated in Figure1.

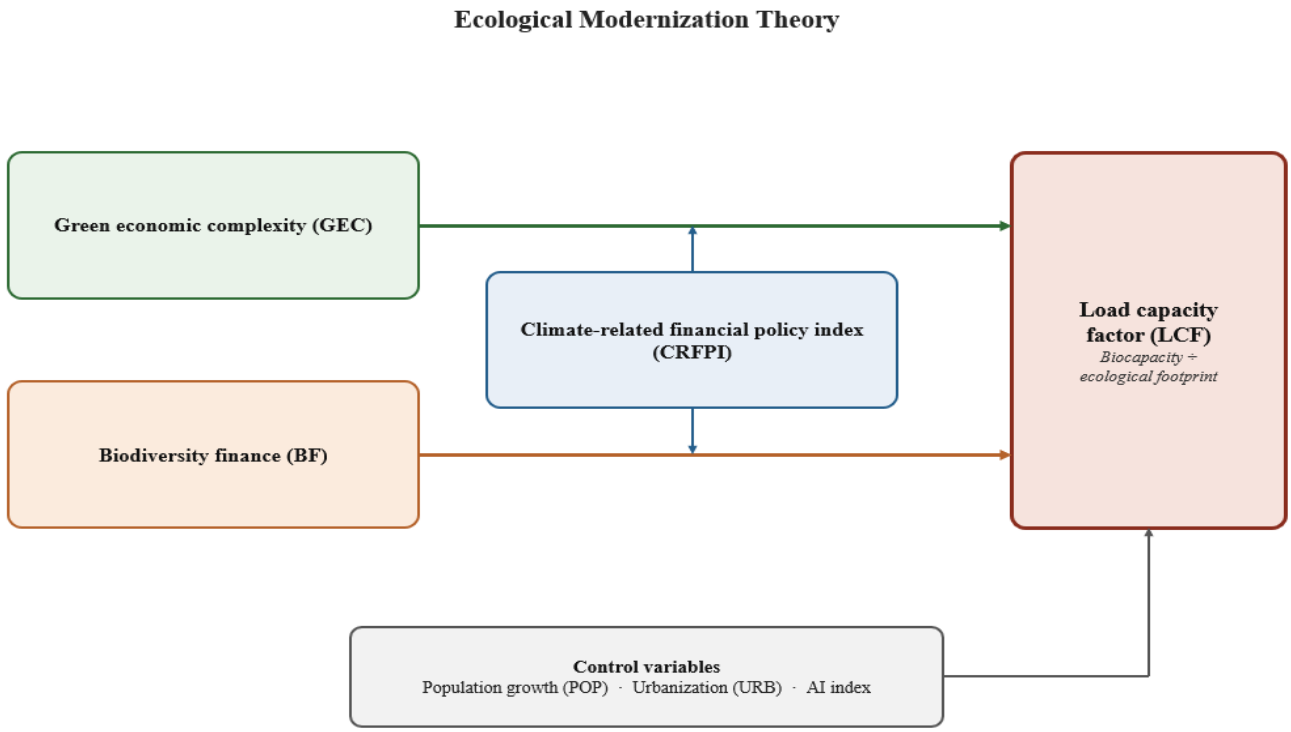
Technological pillar incorporates diversification in more complex, knowledge-based activities, which helps to incorporate cleaner process technology and increase value added per unit of resource throughput (Romero & Gramkow, 2021). Green economic complexity (GEC), defined as a country's technological sophistication levels in its productive structure with respect to green products (Mealy & Teytelboym, 2022), suggests that the higher the levels of technological modernization, the greater the load capacity factor (H1) should be, as is the case for G20 economies in accordance with the evidence provided by Zeraibi et al. (2026). This is possible, not necessarily the reality: when the necessary degree of sophistication is not reached, implementing a greening production structure might not result in ecological benefits (Maneejuk & Yamaka, 2025).

For the market pillar, EMT is urging financial actors to shift investments to conservation and restoration. The financial reflection of this change is called 'biodiversity finance' (BF) and can be expected to increase the 'biocapacity' in comparison to the ecological footprint (H2). It pays off when it is credible (that is, the label is expanded for reputational purposes, but there are no real conservation results; Christiansen & Islar, 2025; Gan, 2025).

In the state pillar, EMT takes up the task of guiding technology and markets toward ecological goals, with the role of regulation. This institutional reform in the financial system is captured by the

climate-related financial policy index (CRFPI) (D'Orazio & Thole, 2022) and is therefore modelled as a moderator that should increase the ecological return to green economic complexity (H3) and biodiversity finance (H4). A second implication of EMT is a "boundary condition": institutions influence outcomes in terms of what they encode. Given the focus of climate-related financial rules on carbon-transition risk and financial stability (Campiglio et al., 2018), their impact on land- and biodiversity-dependent outcomes may be less than assumed, making the sign of the moderation an empirical question that we address in Section 4. The variables controlling population growth, urbanization, and the AI index (Section 3.1) are included in the population growth model. The resulting model is summarized in figure 1.

Figure 1: *Conceptual Model Based on Ecological Modernization Theory*



2.2 The load capacity factor as a measure of environmental sustainability

An LCF greater than one indicates biocapacity is greater than the demand of the footprint, whereas an LCF less than one indicates that the demand of the footprint is greater than the biocapacity (Siche et al., 2010; Dada et al., 2025). The LCF has been used in more studies to replace the more limited proxies like the ecological footprint or CO2 emissions alone, because it integrates the two sides of the ecological ledger (Pata & Isik, 2021; Zeraibi et al., 2026).

The literature on determinants is widespread across the major regional groups, and the central theme of this literature is 'heterogeneity'. Guo et al. (2025) determines that there is a positive relationship between natural resources, technological innovation and income with the LCF, and that information and communication technology (ICT) infrastructure and institutional quality facilitate sustainability in the N-11 economies. Government debt weakens the LCF in the G20 even though environmental-policy stringency strengthens the LCF (Zeraibi et al., 2026). For Nigeria, the effects of income, institutional quality and urbanization on the LCF are stronger in the short run but weaker in the long run (Dada et al., 2025). Resource efficiency and use of fossil fuels lower the LCF in India while alternative energy increases it (Ozkan et al., 2025). An Indo-Pacific panel connects globalization,

tourism and renewable energy to LCF outcomes (Alam et al., 2025).

Increasingly, variables from the financial sector take up a greater proportion of this literature, since ecological outcomes are, in a meaningful sense, financial outcomes. In OECD economies, the LCF is influenced by financial institutions and markets (Özbay et al., 2024). Furthermore, digitalization and technological innovation have been associated with the LCF in G8 and N-11 panels (Mehmood et al., 2023; Guo et al., 2025). Whether the flow of credit and technology favors one activity or another, however, depends on which activities are associated with greater resource efficiency. The direction of these effects, however, will be determined by which of the activities is related to greater resource efficiency. The eco-impact of a driver is therefore not necessarily the same across countries, times or across the LCF distribution. This is the reason for a moderate model.

2.3 Green economic complexity and environmental outcomes

Economic complexity is a new indicator that reflects the variety and level of development of the productive knowledge contained in a country's export portfolio (Hidalgo & Hausmann, 2009). Then this logic is further condensed to environmentally beneficial products in green economic complexity. It reflects a country's actual demonstrated ability to competitively produce and export green products and its potential to expand its diversification in their production (Mealy & Teytelboym, 2022).

There is a large body of evidence that is mixed on the relationship between complexity and environmental outcomes. There is a positive link between economic complexity and environmental performance in a world sample (Boleti et al., 2021) as well as between economic complexity and the intensity of greenhouse-gas emissions (Romero & Gramkow, 2021) (see Appendix 3: Summary of relevant literature). According to country studies, CO2 emissions decrease over time as the complexity increases (Can & Gozgor, 2017). Neagu et al., (2022) indicate that the complexity in the economies of the CEE countries is moving towards green products. Zeraibi et al. (2026) report that green complexity is associated with a positive effect on the LCF in the conditional distribution for the G20 economies, which is shown to be bidirectional. According to Ageli (2025), economic complexity and financial technology facilitate cleaner production in the emerging markets.

Other findings go against this. The conventional economic complexity can have different impacts on the environment depending on the stage of development and the increase in the complexity of the economy due to scale effects can lead to degradation (Doğan et al., 2019). In Sub-Saharan Africa, it is observed that increasing economic complexity contributes to economic growth but at the cost of income equity and environmental sustainability (Gbolonyo et al., 2026). With a distinct green-complexity index, Maneejuk and Yamaka (2025) identify threshold effects: below a minimum level of green complexity, increasing complexity does not lead to a decreasing emissions level, but it may increase. This difference puts emphasis on the fact that complexity has an ecological function as such and that it is not necessarily a sign of sophistication. Instead, it relies on the direction of sophistication as it will be used, and this is what drives us to use a different construct, the green construct, in this study.

2.4 Biodiversity finance and environmental sustainability

Biodiversity finance is a new field of research and empirical study. The amount of public biodiversity investment worldwide is estimated to be far below what biodiversity conservation would require (Seidl et al., 2020; Deutz et al., 2020). This disconnect between aspiration and capital puts into question whether implementing biodiversity finance will improve ecological outcomes — and this is a first order empirical question.

So far it is good but not conclusive. Khan et al. (2025) employ an OECD panel and method-of-moments quantile regression, showing that with an OECD panel and method-of-moments quantile regression, green finance is not only linked to higher consumption-based CO2 emissions, but also to lower biodiversity loss and higher biocapacity. A

difference between the two means that the ecological footprint of biodiversity finance should be more visible in ecological indicators that are based on biocapacity (like the LCF) than in emission-based indicators. It has been shown that biodiversity losses are measurable at the global level when the conservation spending is measured (Waldron et al., 2017). So, at the sovereign level, market-based measures of systemic risk (Mies, 2025) are increased by land-use change and drought and freshwater depletion. This means that a healthy biodiversity ecosystem is beneficial to both the ecological and financial stability of the world. In addition, Poyser (2026) investigates if the funding of biodiversity science and innovation in Europe leads to lower biodiversity loss. These studies reveal the increasing focus on the results and not just the numbers of biodiversity finance.

However, a more cynical body of literature warns against interpreting rapid gains in biodiversity finance as a measure of proportional gains in ecological improvement. Christiansen et al. (2025) suggest that much of the recent rise is due to conceptual innovation with respect to the measure of "biodiversity-related" finance. For example, just a portion of green-bond proceeds are earmarked for biodiversity-related uses; and flows are dominated by low-risk districts, rather than the most biodiverse countries. At the firm level, there is evidence of a causal relationship between corporate greenwashing and the increase of biodiversity risk in China (Gan, 2025). This strand is directly relevant to the moderating role of climate-related financial policy because, after all, greenwashing is the very market failure that disclosure rules, taxonomies and verification standards aim to address.

Climate-related financial policy as an institutional moderator 2.5

The CRFPI is the most comprehensive cross-country indicator of the level of action taken by central banks, supervisors and governments to integrate climate factors into financial policies. It spans 74 countries for 2000 to 2020 and reviews five policy fields: green prudential regulation, green credit allocation, green financial guidelines, other green disclosure requirements and green-bond taxonomies and issuance. There are four aggregation variants, which vary in the way they weigh and in whether they consider the policy bindingness (D'Orazio & Thole, 2022; D'Orazio, 2023). With the use of this index, D'Orazio and Dirks (2022) demonstrate that climate related financial policies are associated with a lower level of CO2 emissions in G20 economies and have more pronounced effects on higher emission quantiles. Ha (2025) discovers that for 17 European countries there is a positive relation between climate related financial policy and environmental performance.

Related literature considers the policy context as a moderator explicitly. The relationship between corporate incentives and green investment is influenced by climate policy uncertainty, contingent on financing constraints (Song & Dong, 2024). It also can harm corporate ESG performance, which can be counterbalanced by financing access and ownership structure (Ge & Zhang, 2025). On the macro-level, the connection between foreign investment and the LCF in BRICS economies is dampened by environmental-policy stringency (Yıldırım et al., 2024). These studies demonstrate a policy regime by which the same economic driver can yield different ecological outcomes.

Climate financial policy, however, is not necessarily accompanied by an automatic effect of the enhancement of biodiversity-related benefits; there are theoretical reasons for this. Climate and biodiversity crises are coupled. However, if mitigation measures are not designed in conjunction with the goal of biodiversity, they can have adverse effects on biodiversity, for example in the form of large-scale bioenergy or monoculture afforestation (Pörtner et al., 2023). In recent years, financial regulators have just started to recognise nature-related risks as risks separate from climate risks (NGFS, 2022; Kedward et al., 2023). The direction of the moderating effect of the CRFPI on the LCF is thus an empirical issue. Starting with the institutional and Porter-hypothesis logic, we hypothesize a positive moderation, even though a negative moderation would be consistent with

misalignment between climate and biodiversity policies.

2.6 Research gap and hypotheses

Three lines of converging and mutually independent lines of evidence are established in the literature. There is a linkage of GEC with LCF in G20 contexts, but not with other financial variables related to biodiversity (Zeraibi et al., 2026). The OECD panels have connected BF with biocapacity and biodiversity loss but not with the composite LCF (Khan et al., 2025). The effectiveness it can achieve could also rely on the credibility of institutions (Christiansen et al., 2025; Gan, 2025). Financial policy has been proven to lower emissions and to soften the economic–environmental connection at the firm and market level when it accounts for climate change. However, its moderating role has not been tested at the country level with the LCF as the outcome (D'Orazio & Dirks, 2022; Song & Dong, 2024; Ge & Zhang, 2025). We therefore propose:

H1: *Green economic complexity has a significant positive effect on the load capacity factor.*

H2: *Biodiversity finance has significant positive effect on the load capacity factor.*

H3: *The climate-related financial policy index positively moderates the relationship between green economic complexity and the load capacity factor.*

H4: *The climate-related financial policy index positively moderates the relationship between biodiversity finance and the load capacity factor.*

In the empirical model (Figure 2), GEC and BF are direct predictors of the LCF. The CRFPI enters both directly and as a moderator of each of these paths.

3. Data and Methodology

3.1 Data and variables

The Dependent Variable (DV) is the Load Capacity Factor (LCF). LCF is defined as the relationship between Biocapacity (BC) and Ecological Footprint (EF) and is measured using data from the National Footprint and Biocapacity Accounts of the Global Footprint Network (GFN). Green Economic Complexity (GEC) and Biodiversity Finance (BF) will serve as independent variables of interest. Climate-Related Financial Policy Index (CRFPI) will act as a moderator. The digital-technology diffusion (AI), population growth (POP) and urbanisation (URB) are controlled for in the model following the STIRPAT logic. Sample is a balanced panel of 101 countries over 23 years.

GEC is based on the green-complexity framework of Mealy and Teytelboym (2022), which is a measure based on the ability of a country to produce and export environmentally beneficial products. BF is a composite indicator derived from biodiversity-related official development assistance received, research and development expenditure, protected areas and forest areas (as % of land area) and GDP per capita. The CRFPI is the fourth version of D'Orazio and Thole (2022) version of aggregation (CRFPI4). This variant includes equal weights, considers policy bindingness and features detailed prudential indicators (D'Orazio, 2023). The AI variable is a combination of digital-infrastructure and technology-trade indicators (Table 1). A summary of the variables, proxies and sources is given in Table 1. Descriptive statistics (Table 2) are reported in levels.

Table 1: *List of Variables*

Variable	Symbol	Proxy / components	Source
"Load capacity factor	LCF	Biocapacity / ecological footprint	Global Footprint Network
Green economic complexity	GEC	Green complexity of the export basket, following Mealy and Teytelboym (2022)	UN
Biodiversity finance	BF	Composite: biodiversity-related ODA received; R&D expenditure; protected areas (% of land); forest area (% of land); GDP per capita	OECD/UN; World Bank WDI
Climate-related financial policy index	CRFPI	CRFPI4 aggregation (equal weights, bindingness, detailed prudential indicators)	D'Orazio and Thole (2022); D'Orazio (2023)
Artificial intelligence / digitalization	AI	Composite: fixed broadband and fixed telephone subscriptions per 100 people; individuals using the Internet (%); secure Internet servers per 10,000 people; high-technology exports; ICT goods and ICT service exports (%)	World Bank WDI; ITU
Urbanization	URB	Urban population (% of total population)	World Bank WDI
Population growth	POP	Annual population growth (%)	World Bank WDI"

3.1.1. Construction of the biodiversity finance index

The biodiversity finance (BF) index is the weighted average of five indicators (Table 1): official development assistance (ODA) received for biodiversity; research and development expenditure; percentage of protected areas of land area; percentage of forest area of land area; GDP per capita. External financing for biodiversity is captured in ODA and R&D expenditure represents the internal capacity to finance and innovate conservation effort, while protected area and forest area represents the conservation effort financed by this money. Given the lack of a theoretical basis for assigning weights to these indicators, they are aggregated using the entropy weight method (Shannon, 1948; Zou et al., 2006) that does this by objective weighting based on the information content of each indicator: indicators that change more across observations have more information and thus are weighted higher. There are 5 steps in the procedure. where i represents each of the n = year and j represents the five indicators and xij is each indicator's raw value. Each indicator is rescaled to the unit interval [0, 1] using equation (1), then converted to proportions using equation (2), and entropy ej calculated for each indicator using equation (3) where pij ln pij = 0 when pij = 0; and the divergence 1 − ej is converted to weights that sum to one using equation (4); and the weighted average of the rescaled indicators is computed using equation (5) to get the level of biodiversity finance or conservation effort.

The pooled panel is normalized and weighted to compare BF between countries and years. Since entropy weights quantify the dispersion of each indicator and not its conceptual value, the usage of only biodiversity related ODA as another measurement of BF is discussed as a robustness extension in Section 5.3.

3.2 Econometric Model

3.2.1 Cross sectional dependence

Countries are exposed to common stocks such as commodities and financial cycles, technological diffusion and the international coordination of climate policy. If these cross-sectional dependence (CSD) biases are not addressed the inference is biased, making the first generation of panel tests invalid. Hence, we employ the CD test formulated by Pesaran (2004) which is suitable for use in large N Small T panels. Its statistic is.

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

where $\hat{\rho}_{ij}$ is the pairwise correlation of the residuals of countries *i* and *j*; under the null of independence, CD is asymptotically standard normal.

3.2.2 Slope homogeneity

The effect of the regressors may vary across countries, as they have different income levels, institutions and ecological endowments. We reject the null of homogeneous slopes using the delta ($\tilde{\Delta}$) and bias adjusted delta statistics found in Pesaran and Yamagata (2008). We also use the version of Blomquist and Westerlund (2013), which is robust to heteroskedasticity and serial correlation. No homogeneity means that the pooled estimate is an average effect.

3.2.3 Unit root test

In the presence of CSD, the first-generation unit root tests tend to reject the null hypothesis. We therefore use the cross-sectionally augmented IPS (CIPS) test of Pesaran (2007). The test complements the Dickey–Fuller regression for each country by using the cross-sectional means of the lagged level and first differences.

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{it}$$

The CIPS statistic is the cross-sectional average of the individual *t*-statistics on b_i.

3.2.4 Cointegration tests

To confirm a stable long-run relationship between the LCF and its determinants, we apply the residual-based tests of Pedroni (1999, 2004). These tests allow heterogeneous cointegrating vectors and dynamics across countries. We also apply the Kao (1999) tests, which impose homogeneity. Because both families assume cross-sectional independence, the error-correction tests of Westerlund (2007), which accommodate CSD through bootstrapped critical values, provide a natural robustness check.

3.2.5 Baseline and moderate models

The baseline specification is:

$$LCF_{it} = \alpha_i + \beta_1 GEC_{it} + \beta_2 BF_{it} + \beta_3 CRFPI_{it} + \gamma_1 AI_{it} + \gamma_2 POP_{it} + \gamma_3 URB_{it} + \varepsilon_{it} \quad (1)$$

where α_i captures country-specific effects. Equation (1) is estimated by pooled OLS, random effects (RE) and GMM. A dynamic specification adds $LCF_{i,t-1}$ to capture the persistence of ecological balances, from which long-run effects are recovered as $\beta_k/(1-\rho)$. The Hausman (1978) test discriminates between fixed and random effects. Following Arellano and Bond (1991) and Blundell and Bond (1998), the GMM estimator instruments potentially endogenous regressors with their own lags. Given T = 26, the bias in the dynamic fixed-effects estimator is limited (Nickell, 1981).

To test H3 and H4, the moderation model adds the interaction terms while retaining all constitutive terms, as recommended by Brambor et al. (2006):

$$LCF_{it} = \alpha_i + \beta_1 GEC_{it} + \beta_2 BF_{it} + \beta_3 CRFPI_{it} + \delta_1 (GEC_{it} \times CRFPI_{it}) + \delta_2 (BF_{it} \times CRFPI_{it}) + \boldsymbol{\gamma}' \mathbf{X}_{it} + \varepsilon_{it} \quad (2)$$

The conditional marginal effects are $\partial LCF/\partial GEC = \beta_1 + \delta_1 CRFPI$ and $\partial LCF/\partial BF = \beta_2 + \delta_2 CRFPI$. H3 (H4) is supported if $\delta_1 > 0$ ($\delta_2 > 0$). The interacted variables are mean centered to reduce non-essential collinearity.

4. Results and Discussion

This section first describes the data (Tables 2–3). It then reports the diagnostics for cross-sectional dependence and slope heterogeneity (Tables 4–5), which determine the choice of unit root and cointegration tests (Tables 6–7). Finally, it discusses the baseline estimates (Table 8) and the

moderation results (Table 9) in relation to prior studies.

4.1 Descriptive statistics and correlations

The mean LCF for the sample is 0.981, which is slightly below the threshold for sustainability and unity. (Table 2) It has a slightly lower biocapacity than its ecological footprint (Siche et al., 2010; Mehmood et al., 2023). The dispersion of the panel is high (standard deviation= 1.116; range= 0.071–10.854), which shows that there are both countries with high deficits and countries with high ecological reserves.

Table 2: *Descriptive statistics*

Variable	Obs	Mean	Std Dev.	Min	Max
LCF	2,626	0.981	1.116	0.071	10.854
BF	2,626	0.211	0.480	0.039	3.656
GEC	2,626	1.985	1.050	0.087	4.759
CRFPI	2,626	8.751	13.723	0.000	93.165
AI	2,626	1.171	3.283	0.000	100.000
POP	2,626	1.248	1.480	−10.927	21.700
URB	2,626	57.743	22.269	11.641	99.359

The average (mean = 0.211) and the distribution of BF are low and right-skewed, respectively, meaning that very few countries have large-scale funding for biodiversity related activities. This trend aligns with evidence that biodiversity finance is focused on a few districts (Christiansen et al., 2025). Compared to the normal, GEC is moderately dispersed by a mean of 1.985. The relative heterogeneity of the CRFPI is the largest and most variable of all, with a standard deviation (13.723) greater than the mean (8.751) and a range of 0 to 93.165. This is indicative of the presence of both country-years with no climate oriented financial regulation and those with advanced financial regulation. The distribution of AI is concentrated in a few observations (mean = 1.171; maximum = 100). POP averages 1.248% but includes sharp declines (−10.927%) and rapid expansion (21.700%). URB has an average of 57.743% and ranges from rural to fully urbanized economies.

Table 3: *Correlation matrix*

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) LCF	1.000						
(2) BF	−0.015	1.000					
(3) GEC	−0.392***	−0.071***	1.000				
(4) CRFPI	−0.045**	0.005	0.167***	1.000			
(5) AI	0.007	0.359***	−0.124***	0.040**	1.000		
(6) POP	0.186***	0.079***	−0.510***	−0.145***	0.027	1.000	
(7) URB	−0.068***	−0.072***	0.458***	0.153***	−0.149***	−0.255***	1.000

The LCF is negatively correlated with GEC (r = −0.392), CRFPI (r = −0.045) and URB (r = −0.068), and positively correlated with POP (r = 0.186). There are no significant correlations with BF or AI. These are bivariate associations, and will be re-examined in the multivariate models below, which control other factors. The size of the absolute correlation between the regressors is at least 0.510 (between GEC and POP) well below the threshold of 0.80, so multicollinearity does not upset the estimates.

4.2 Cross-sectional dependence and slope heterogeneity

The CD test rejects the null of cross-sectional independence at the 1% level for every variable.

Table 4: *Cross Sectional dependence test (Pesaran, 2004)*

Variable	CD statistic	p-value
LCF	31.032***	0.000
BF	157.760***	0.000
GEC	33.958***	0.000
CRFPI	268.580***	0.000
AI	29.313***	0.000
POP	38.745***	0.000
URB	197.687***	0.000

Dependence is strongest for CRFPI (CD = 268.580; mean ρ = 0.74), URB (197.687; 0.55) and BF (157.760; 0.44), indicating synchronized movements across countries. The effect of the strong dependence in CRFPI is in line with the regional "bandwagon" pattern observed in the adoption of climate-related financial policies (CRFPs) (D'Orazio & Thole, 2022). The mean absolute correlations are large for LCF, GEC, AI and POP (e.g., 0.60 for LCF), while the mean correlation is small (e.g., 0.08 for LCF). The size of the cross-country correlations is thus large but mixed. The findings support second generation approaches.

Table 5: *Slope heterogeneity tests*.

Test	Statistic	p-value
$\tilde{\Delta}$	31.208***	0.000
Adjusted $\tilde{\Delta}$	37.507***	0.000
Blomquist and Westerlund (2013)		
$\tilde{\Delta}$	53.846***	0.000
Adjusted $\tilde{\Delta}$	64.714***	0.000

The slopes are not considered homogeneous, with both the standard and adjusted statistics being rejected at the 1% level (Table 5). The rejection is not an artefact of heteroskedasticity or autocorrelation since the Blomquist–Westerlund version is robust to these effects. The effects of BF, GEC and the control on the LCF, therefore, vary from country to country, as reported in the LCF literature (Guloglu et al., 2023; Yang et al., 2024; Guo et al., 2025). Model estimates based on

common slopes should be regarded as mean effects.

4.3 Unit root and cointegration analysis

The reported results of the CIPS test of Pesaran (2007) are given in Table 6. For LCF, BF, GEC and CRFPI, the level statistics (−2.343, −3.144, −2.501 and −2.531) exceed the 1% critical value (−2.140) rejecting the null of a unit root. The first difference of the series is also stationery. Hence the variables are integrated of order zero, I (0), thus lowering the possibility of spurious regression.

Table 6: *Panel unit root test (CIPS)*

Variable	Level	First difference	Order
LCF	−2.343***	−4.873***	I (0)
BF	−3.144***	−5.433***	I (0)
GEC	−2.501***	−4.844***	I (0)
CRFPI	−2.531***	−4.970***	I (0)

Despite the stationarity in levels, there is evidence of cointegration tests showing long run co-movement (Table 7) The null hypothesis of no cointegration is rejected by all three Pedroni tests at 1% level. The Kao test results agree with the above: The Dickey–Fuller, augmented Dickey–Fuller and unadjusted Dickey–Fuller statistics are significant at the 1% level; the modified Dickey–Fuller statistics at the 5% level; and the unadjusted modified Dickey–Fuller statistics at the 10% level. The evidence indicates that the LCF is on a stable trend, given its determinants.

Table 7: *Panel cointegration tests*

"Test / statistic	Statistic	p-value
"Panel A: Pedroni (1999, 2004)"		
Modified Phillips–Perron t	5.565***	0.000
Phillips–Perron t	−5.045***	0.000
Augmented Dickey–Fuller t	−4.311***	0.000
Panel B: Kao (1999)		
Modified Dickey–Fuller t	2.025**	0.022
Dickey–Fuller t	−4.657***	0.000
Augmented Dickey–Fuller t	−4.722***	0.000
Unadjusted modified Dickey–Fuller t	1.499*	0.067
Unadjusted Dickey–Fuller t	−5.069***	0.000"

4.4 Baseline estimates

The baseline estimates are shown in Table 8. The models are all significant at the 1% level. The level of explanatory power is modest, 0.171 in pooled OLS and 0.070 in RE, as is found in macro panels in which there is significant cross-country heterogeneity. The Hausman test ($\chi^2 = 115.04$, $p < 0.01$) is rejected, suggesting that country effects are correlated with the regressors. Hence, the GMM and dynamic specifications, columns (3) and (4), are the most important ones discussed here, because they are aimed at unobserved

heterogeneity and endogeneity (Arellano & Bond, 1991; Blundell & Bond, 1998). The pooled and RE estimates are used as benchmarks.

4.4.1 Biodiversity finance and the load capacity factor

In the RE (0.445), the GMM (0.721) and dynamic (0.017) models, BF has a positive and significant relationship with the LCF at 1% level. It is not significant if unobserved country effects are ignored as in the pooled specification. For a given increase in the BFI of 1 SD (0.480), the LCF increases approximately 1 SD (0.346) or approximately one third of the sample mean in the GMM model. In the dynamic model, the implied long-run effect is 0.017/ (1 − 0.965) ≈ 0.49. H2 is thus supported.

The outcome is in line with the finance–growth principle applied to ecological productivity. Investment for conservation, restoration and sustainable land use seems to raise biocapacity and alleviate ecosystem pressures.

Table 8: *Baseline regression results (dependent variable: LCF)*

	Random effects	GMM	Dynamic FE
	(2)	(3)	(4)
LCF_{t-1}	–	–	0.965***
			(0.001)
BF	0.445***	0.721***	0.017***
	(0.127)	(0.158)	(0.001)
GEC	0.093***	0.105***	0.020***
	(0.018)	(0.018)	(0.001)
CRFPI	−0.002***	−0.002***	–
	(0.001)	(0.001)	
AI	−0.018***	−0.022***	–
	(0.003)	(0.004)	
POP	−0.021***	−0.023***	–
	(0.007)	(0.007)	
URB	−0.014***	−0.016***	–
	(0.002)	(0.002)	
Constant	1.568***	1.610***	–
	(0.141)	(0.110)	
Observations	2,626	2,626	2,424
R^2	–	0.071	–
R^2 (overall / within / between)	0.005 / 0.070 / 0.009	–	–
F-statistic / Wald χ^2	164.742***	32.023***	1,239,098.924***
AIC	–	1,230.145	–
BIC	–	1,271.258	–

	Random effects	GMM	Dynamic FE
Hausman χ^2 (FE vs. RE)	115.04***	–	–

This is in line with Khan et al., (2025), who conclude that green finance improves biocapacity and decreases biodiversity loss in OECD countries. It also echoes the global evidence that spending on conservation leads to a decrease in biodiversity loss (Waldron et al., 2017). In two ways our results corroborate these findings: Firstly, they demonstrate that this effect persists for the composite LCF and is observed across a much wider universe of 101 countries across income groups. Second, it is instructive that the study by Khan et al. (2025) found that green finance increases emissions from consumption. The effects of biodiversity capital are primarily on the supply side of the ecological ledger—biocapacity—and not on the demand side (fossil-energy). This is why an outcome that solely reflects emissions would be an understatement. Evidence of financial institutions and markets shaping load capacity (Özbay et al., 2024), of green finance initiatives supporting environmental transitions (Hossain et al., 2024), and arguments that dedicated capital flows are required to stop land conversion and habitat loss (Deutz et al., 2020) also support the result.

The discovery does not refute but only supports skeptical literature. Beware of reported increases in biodiversity finance that overestimate actual conservation spending, warn Christiansen et al. (2025). Physical results (protected and forest area) are also part of our BF composite, which could account for the strong ecological signal in our results. The inflation they described would reduce the estimated effect, if it exists.

4.4.2 Green economic complexity and the load capacity factor

GEC has negative and significant relationship in the pooled model (−0.497), but positive and significant relationship in the RE (0.093), GMM (0.105) and dynamic (0.020) models. The predicted change in LCF caused by a one standard deviation increase in the GEC (1.050) is approximately 0.110 (11% of the mean), in the GMM model. The long-run dynamic effect is about 0.57. The within-country variation is supported by H1.

The sign reversal is a note of information. The pooled regression is characterized by cross country differences. Economies with more complex productive structures are more industrial and urban (URB correlates at 0.458 with GEC and −0.510 with POP) and have bigger footprints compared to their biocapacity (POP correlates at −0.510 with GEC and 0.532 with URB). After adjusting to the other country's characteristics, the within-country effect is positive: for each improvement in the capabilities of a country in green products, the country's LCF also improves. This is in line with EMT and NRBV, where green capabilities are integrated into cleaner processes, and these capabilities are built up into a sustainable ecological asset. The within-country result is consistent with Zeraibi et al. (2026), as they determine that green complexity increases the LCF in the G20 countries. It also concurs with evidence that economic complexity can lead to better environmental performance (Boleti et al., 2021) and lower emissions intensity (Romero & Gramkow, 2021; Can & Gozgor, 2017).

However, the negative cross-sectional association is consistent with the less positive line of literature. Doğan et al. (2019) explain that complexity's environment effect is dependent on development stages. Gbolonyo et al. (2026) reveal that complexity in Sub-Saharan Africa is associated with a sacrifice of environmental sustainability. Maneejuk and Yamaka (2025) determine that additional sophistication doesn't necessarily lower emissions if the product is not green enough. These positions are squared in our results. At the country level, the more complex the country, the larger the footprint in terms of structure. At the country level, there are scale effects, with higher complexity being linked with structurally larger footprints. But when it comes to countries, the improvement

towards green products balances the ecological situation. The latter is the policy-relevant effect as it describes what occurs when a particular country develops green capabilities.

4.4.3 Climate-related financial policy

In the pooled model, the coefficient of CRFPI is of no consequence, while in the RE and GMM models, the coefficient for CRFPI is slight and negative but significant (−0.002). The economic magnitude is not large, as a one-standard-deviation increase (13.723) reduces the LCF by approximately 0.027 (3% of the mean). This result differs from the studies showing that financial policies in the G20 lead to less CO2 emissions (D'Orazio & Dirks, 2022) and that environmental performance in Europe improves (Ha, 2025). There are three possibilities. First, the result is different: the LCF measures biocapacity and land-based pressures which are not addressed by carbon regulation. Second, climate policy is formulated primarily as a financial-stability risk management measure and to redirect investment to low-carbon activities, instead of to achieve an ecosystem outcome (Campiglio et al., 2018; D'Orazio & Popoyan, 2019; Dikau & Volz, 2021). There is a risk of land-use pressure (P) from some low-carbon investments including bioenergy, hydropower and large-scale investments. Third, policies might be implemented because of deteriorating environmental conditions, giving rise to reverse causality which the estimators might not eliminate. This finding aligns with research by D'Orazio and Thole (2022) that found that engagement in climate-related financial policy does not always correspond to positive environmental outcomes, to be interpreted as a correlation and not a causal relationship.

AI has negative and significant influences in the RE and GMM models (−0.018, −0.022). A one standard deviation increase (3.283) decreases the LCF by approximately 0.072 (7% of the mean). This is in line with empirical evidence that, at the macro level, rebound effects of energy efficiency tend to outpace the energy-saving effects of digitalization in energy use and rebound effects of digitalization in energy use outweigh the rebound effects of energy efficiency in energy use (Lange et al., 2020). Data centers, data networks and the production of digital devices are driving up the global emissions footprint of ICT (Belkhir & Elmeligi, 2018). This finding contrasts with the findings by Guo et al. (2025) which found that ICT infrastructure positively contributes towards the environmental sustainability in N-11 economies. The gap indicates that ecological benefits of digitalization can only be achieved in combination with clean energy and resource-efficiency policies.

The population growth also rates LCFs as −0.021 and −0.023. Increased consumption causes increased footprint and decreased per-capita biocapacity with an increasing population. This is in line with the research that has found population growth as a source of environmental pressure (Hashmi & Alam, 2019; Khan et al., 2021; Jie et al., 2023). The pooled model shows positive urbanization (0.007), while the RE (−0.014) and GMM (−0.016) models have negative urbanization. It is important to realize that the structure of highly urbanized countries is different from the structure of less urbanized countries, but within a country, further increases in urbanisation increase energy consumption, urbanisation of land and natural land use conversion, which reduces the LCF. The largest control variable effect is for an increase in URB, which is associated with a decrease in LCF of approximately 0.356, or 36% of the mean, and is comparable in size to the effect of BF. This is consistent with the negative relationship between urbanization and LCF in Nigeria, as stated by Dada et al., (2025) and OECD data which agrees with the negative impact of urbanization on LCF, as stated by Guloglu et al., (2023).

4.5 Moderating role of climate-related financial policy

Table 9 looks at the interaction between GEC and BF on the CRFPI. The interaction of GEC with CRFPI, as well as BF with CRFPI, is negative and significant at the 5% level of significance, with values of −0.001 and −0.003, respectively. Strong climate-related financial policy has a negative impact on the positive effects of green complexity and biodiversity finance on the LCF, in contrast to

H3 and H4. Biodiversity finance is dampened more. The Letterhead and the Letterhead plus material are thus not supported.

Table 9: *Moderating role of CRFPI (dependent variable: LCF)*

	Green economic complexity	Biodiversity finance
	(1)	(2)
GEC × CRFPI	−0.001**	
	(0.000)	
BF × CRFPI		−0.003**
		(0.001)
Constant	0.992***	0.987***
	(0.008)	(0.007)
Observations	2,626	2,626
R^2	0.002	0.003
F-statistic	6.137***	6.371***
AIC	1,406.798	1,406.554
BIC	1,418.545	1,418.301

The negative moderation can be explained in several ways. The first and most significant is misalignment of policy. Financial policies focused on climate change could allocate funding to low carbon investments that have significant land-use impacts, or investment away from biodiversity and land-based goals. Climate and biodiversity targets are linked but may be conflicting, if not co-designed (Pörtner et al., 2023). In fact, financial supervisors have only just started to recognize that there are financial risks that are not climate risks but are related to nature (NGFS, 2022; Kedward et al., 2023). This is in line with the bigger dampening of the nature of biodiversity finance. The second is substitution: as the regulation sends capital to green activities, the marginal ecological value of extra green capabilities or biodiversity capital could be less. The third is that, if disclosure programmers are still in their infancy, the reputational benefits gained from green and biodiversity labelling can be greater than the actual results. This is like the legitimacy seeking actions of Suchman (1995) and the definitional inflation reported by Christiansen et al. (2025).

The finding contrasts with the positive moderation suggested by the Porter hypothesis and institutional theory, as well as findings that environmental policy increases the LCF in the G20 (Zeraibi et al., 2026). The moderating effect of policy is consistent, however, with evidence that the moderating role of policy varies by instrument type and outcome (Yıldırım et al., 2024). Moreover, it is in line with firm-level evidence that policy context can drive up or pull-down green investment (Song & Dong, 2024; Ge & Zhang, 2025). The idea behind this theoretical implication is that institutions shape outcomes according to the goals that they encode. As it stands, climate-relevant financial policy does not reflect biocapacity goals, it reflects carbon.

Two caveats apply. The fit of both models is very low (R^2 = 0.002 and 0.003). Note that the conditional marginal effects of GEC and BF at various levels of CRFPI cannot be computed from

these estimates (Brambor et al., 2006; Hainmueller et al., 2019). The moderation results must be interpreted, therefore, as indicative evidence of a dampening interaction, and not as accurate estimates.

5. Conclusion

5.1 Main findings

This research investigated whether there is a relationship between green economic complexity and biodiversity finance and how this relationship is mediated by climate-related financial policy conditions. It was based on a balanced sample of 101 countries for 23 years. The diagnostic tests confirmed that the data were cross-sectional dependent, had non-constant slopes, were stationary, and were long-run dependent. There are four salient observations. Biodiversity finance has the strongest positive impact on the LCF: for everyone standard deviation increases in biodiversity finance, the LCF increases by approximately 35% of the average of the LCF in the sample. Second, even though this LCF is lower for more complex economies cross-sectionally, it is higher for the green economic complexity within countries. Third, on the other side of the equation, a small negative relationship exists between climate-related financial policy and the LCF, as is the case with digitalization, population growth and urbanization (the latter has the most disturbing impact among the controls). Fourth, climate-related financial policy does not boost these positive effects of the two drivers, but instead diminishes them, particularly with respect to biodiversity finance, in contrast to H3 and H4.

5.2 Theoretical implications

The outcomes do with three theoretical contributions. First, they introduce a concept of finance–growth theory to ecological productivity. Capital spent on biodiversity has been linked to biodiversity's biocapacity, a measure of its capacity to provide ecosystem services, meaning there is a strong argument for seeing biodiversity finance as a part of climate finance. Second, they advance ecological modernization theory and the NRBV by demonstrating that the ecological benefit of green capabilities is an in-country effect which can be observed when compared across countries. This resolves an earlier apparent difference in the results of complexity studies. Thirdly, they validate the institutional theory and the Porter hypothesis. Formal institutions regulate economic–ecological relations, but only in the direction of the goals that they represent. The impacts of climate-related financial policy on biodiversity-and land-based benefits do not necessarily outweigh the financial stability and carbon-transition risks and can be mitigated. Therefore, in the case of environmental finance, the conditions of alignment of the policy goal and the ecological outcome being studied should be stated in the moderation theory.

5.3 Policy implications

Four implications follow. The scale-up and targeting of biodiversity finance to conserve and restore biodiversity are first and foremost priorities for governments and development partners. They should also move to an outcome-based accounting, where reported flows correspond to actual results of the ecological benefits (Christiansen et al., 2025). Second, over the long run, industrial and trade policies can boost the LCF through the development of green productive capacities by supporting green research and development and encouraging diversification towards green products (Mealy & Teytelboym, 2022; Zeraibi et al., 2026). Third, financial regulators should embed nature-related risks and biodiversity targets in climate-related financial plans and policies, such as climate-related financial taxonomies, disclosure mandates and prudential treatment. This would enable these frameworks to supplement rather than supplant biodiversity finance and green upgrading (NGFS, 2022; Kedward et al., 2023). Fourth, sustainable urban planning — that is, one that is compact, resource-saving — is required, along with digitalization tied to clean energy, to keep the ecological costs of urban and technological growth manageable.

5.4 Limitations and future research

The study has certain limitations that can be addressed in future research. The first being that the moderation models are estimated without

including the constitutive terms, so the conditional marginal effects are only indicative. Future research should include estimation of fully specified interaction models and report marginal-effect plots over the range of policy stringency. Second, GMM and dynamic estimators handle endogeneity but fail to capture as completely as they can the problems of cross-sectional dependence and slope heterogeneity found here. A more robust and distribution sensitive estimate would be achieved using common correlated effects, CS-ARDL or quantile approaches. Third, the biodiversity-finance composite brings together financial flows and land-based outcomes, and the original sample of the CRFPI is not as comprehensive as the sample used here (74 countries, 2000-2020). Biodiversity-finances disaggregated data and policy indices more up to date would focus identification. Fourth, the analysis is at the country level. Future research might focus on the individual CRFPI policy areas, different income groups or regions, and could explore specific nature-related financial policies as they appear to see which regulatory designs support the positive ecological returns on green capabilities and biodiversity capital.

Declaration of Conflicting Interest

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References

Ageli, M. M. (2025). Economic complexity, FinTech, green innovation, and environmental degradation in emerging markets. *Frontiers in Environmental Science, 13*, Article 1668815. https://doi.org/10.3389/fenvs.2025.1668815

Akadiri, S. S., Ozkan, O., & Alola, A. A. (2025). Investigating the determinants of load capacity factor in Nigeria: An asymmetric quantile approach on urbanization, economic growth, FDI, and resource dependency. *Resources Policy, 104*, Article 105586. https://doi.org/10.1016/j.resourpol.2025.105586

Alam, Q., Voumik, L. C., Rahman, M. H., & Khan, M. A. K. A. (2025). Impact of globalization, tourism, energy, and education on load capacity factors in selected 14 Indo-Pacific nations: An advanced econometric analysis. *All Earth, 37*(1), 1–16. https://doi.org/10.1080/27669645.2025.2477413

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies, 58*(2), 277–297. https://doi.org/10.2307/2297968

Belkhir, L., & Elmeligi, A. (2018). Assessing ICT global emissions footprint: Trends to 2040 & recommendations. *Journal of Cleaner Production, 177*, 448–463. https://doi.org/10.1016/j.jclepro.2017.12.239

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

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Boleti, E., Garas, A., Kyriakou, A., & Lapatinas, A. (2021). Economic complexity and environmental performance: Evidence from a world sample. *Environmental Modeling & Assessment, 26*(3), 251–270. https://doi.org/10.1007/s10666-021-09750-0

Brambor, T., Clark, W. R., & Golder, M. (2006). Understanding interaction models: Improving empirical analyses. *Political Analysis, 14*(1), 63–82. https://doi.org/10.1093/pan/mpi014

Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., & Tanaka, M. (2018). Climate change challenges central banks and financial regulators. *Nature Climate Change, 8*(6), 462–468. https://doi.org/10.1038/s41558-018-0175-0

Can, M., & Gozgor, G. (2017). The impact of economic complexity on carbon emissions: Evidence from France. *Environmental Science and Pollution Research, 24*(19), 16364–16370. https://doi.org/10.1007/s11356-017-9219-7

Christiansen, J., Irvine-Broque, A., Dempsey, J., Nelson, S., Shapiro-Garza, E., Bigger, P., & Islar, M. (2025). Off the charts? Reasons to be skeptical of the growth in biodiversity finance. *Current Opinion in Environmental Sustainability, 75*, Article 101544. https://doi.org/10.1016/j.cosust.2025.101544

Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics, 188*(2), 393–420. https://doi.org/10.1016/j.jeconom.2015.03.007

Convention on Biological Diversity. (2022). *Kunming-Montreal Global Biodiversity*

Framework (Decision CBD/COP/DEC/15/4). Secretariat of the Convention on Biological Diversity.

Dada, J. T., Tabash, M. I., Al-Faryan, M. A. S., & Akinbobola, T. O. (2025). Determinants of load capacity factor in Nigeria: Implications for sustainable development. *Economics and Culture, 22*(1), 17–33. https://doi.org/10.2478/jec-2025-0002

Deutz, A., Heal, G. M., Niu, R., Swanson, E., Townshend, T., Zhu, L., Delmar, A., Meghji, A., Sethi, S. A., & Tobin-de la Puente, J. (2020). *Financing nature: Closing the global biodiversity financing gap*. The Paulson Institute, The Nature Conservancy, and the Cornell Atkinson Center for Sustainability.

Dietz, T., & Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence, and technology. *Human Ecology Review, 1*(2), 277–300.

Dikau, S., & Volz, U. (2021). Central bank mandates sustainability objectives and the promotion of green finance. *Ecological Economics, 184*, Article 107022. https://doi.org/10.1016/j.ecolecon.2021.107022

Doğan, B., Saboori, B., & Can, M. (2019). Does economic complexity matter for environmental degradation? An empirical analysis for different stages of development. *Environmental Science and Pollution Research, 26*(31), 31900–31912. https://doi.org/10.1007/s11356-019-06333-1

D'Orazio, P. (2023). Dataset for the climate-related financial policy index (CRFPI). *Data in Brief, 48*, Article 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*(5), 7678–7702. https://doi.org/10.1007/s11356-021-15655-y

D'Orazio, P., & Popoyan, L. (2019). Fostering green investments and tackling climate-related financial risks: Which role for macroprudential policies? *Ecological Economics, 160*, 25–37. https://doi.org/10.1016/j.ecolecon.2019.01.029

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*, Article 109065. https://doi.org/10.1016/j.ecolind.2022.109065

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics, 80*(4), 549–560. https://doi.org/10.1162/003465398557825

Flammer, C., Giroux, T., & Heal, G. M. (2025). Biodiversity finance. *Journal of Financial Economics, 164*, Article 103987. https://doi.org/10.1016/j.jfineco.2024.103987

Gan, Y. (2025). When green claims turn brown: The impact of corporate greenwashing on biodiversity risk in China. *The Quarterly Review of Economics and Finance, 104*, Article 102067.

Gbolonyo, E. Y., Ofori, I. K., & Ojong, N. (2026). Does economic complexity promote inclusive green growth in developing economies? *Journal of International Development, 38*(5), 883–904. https://doi.org/10.1002/jid.70096

Ge, H., & Zhang, X. (2025). From uncertainty to sustainability: How climate policy uncertainty shapes corporate ESG? *International Review of Economics & Finance, 98*, Article 104011.

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

Guloglu, B., Caglar, A. E., & Pata, U. K. (2023). Analyzing the determinants of the load capacity factor in OECD countries: Evidence from advanced quantile panel data methods. *Gondwana Research, 118*, 92–104. https://doi.org/10.1016/j.gr.2023.02.013

Guo, Y., Alnafrah, I., Hou, X., Almenweer, R. A., & Mehmood, U. (2025). What natural resources and technological advancements affect environmental quality: Evidence from load capacity factors in N-11 nations. *Natural Resources Forum, 49*(2), 1769–1794. https://doi.org/10.1111/1477-8947.12442

Ha, L. T. (2025). Do 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. https://doi.org/10.1017/pan.2018.46

Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of Management Review, 20*(4), 986–1014. https://doi.org/10.2307/258963

Hashmi, R., & Alam, K. (2019). Dynamic relationship among environmental regulation, innovation, CO2 emissions, population, and economic growth in OECD countries: A panel investigation. *Journal of Cleaner Production, 231*, 1100–1109. https://doi.org/10.1016/j.jclepro.2019.05.325

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica, 46*(6), 1251–1271. https://doi.org/10.2307/1913827

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences, 106*(26), 10570–10575. https://doi.org/10.1073/pnas.0900943106

Hossain, M. R., Rao, A., Sharma, G. D., Dev, D., & Kharbanda, A. (2024). Empowering energy transition: green innovation, digital finance, and the path to sustainable prosperity through green finance initiatives. *Energy Economics, 136*, Article 107736. https://doi.org/10.1016/j.eneco.2024.107736

Jie, H., Khan, I., Alharthi, M., Zafar, M. W., & Saeed, A. (2023). Sustainable energy policy, socio-economic development, and ecological footprint: The economic significance of natural resources, population growth, and industrial development. *Utilities Policy, 81*, Article 101490. https://doi.org/10.1016/j.jup.2023.101490

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics, 90*(1), 1–44. https://doi.org/10.1016/S0304-4076(98)00023-2

Karolyi, G. A., & Tobin-de la Puente, J. (2023). Biodiversity finance: A call for research into financing nature. *Financial Management, 52*(2), 231–251. https://doi.org/10.1111/fima.12417

Kedward, K., Ryan-Collins, J., & Chenet, H. (2023). Biodiversity loss and climate change interactions: Financial stability implications for central banks and financial supervisors. *Climate Policy, 23*(6), 763–781. https://doi.org/10.1080/14693062.2022.2107475

Khan, I., Hou, F., & Le, H. P. (2021). The impact of natural resources, energy consumption, and population growth on environmental quality: Fresh evidence from the United States of America. *Science of the Total Environment, 754*, Article 142222. https://doi.org/10.1016/j.scitotenv.2020.142222

Khan, M. I., Rahman, S. U., & Hussain, J. (2025). Green finance and ecological outcomes: A

quantile approach to biodiversity and carbon emissions in OECD countries. *Journal of Economic Studies*. Advance online publication. https://doi.org/10.1108/JES-06-2025-0408

Lange, S., Pohl, J., & Santarius, T. (2020). Digitalization and energy consumption. Does ICT reduce energy demand? *Ecological Economics, 176*, Article 106760. https://doi.org/10.1016/j.ecolecon.2020.106760

Levine, R. (1997). Financial development and economic growth: Views and agenda. *Journal of Economic Literature, 35*(2), 688–726.

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

Maneejuk, P., & Yamaka, W. (2025). Green complexity and its dual threshold effects: Balancing environmental impact and economic growth. *Environmental Economics and Policy Studies, 28*(2), 565–592. https://doi.org/10.1007/s10018-025-00443-6

Mealy, P., & Teytelboym, A. (2022). Economic complexity and the green economy. *Research Policy, 51*(8), Article 103948. https://doi.org/10.1016/j.respol.2020.103948

Mehmood, U., Tariq, S., Aslam, M. U., Agyekum, E. B., Uhunamure, S. E., Shale, K., Kamal, M., & Khan, M. F. (2023). Evaluating the impact of digitalization, renewable energy use, and technological innovation on load capacity factors in G8 nations. *Scientific Reports, 13*. https://doi.org/10.1038/s41598-023-36373-0

Mies, M. (2025). Biodiversity finance: Sovereign biodiversity loss drivers and financial stability. *Journal of Industrial Ecology, 29*(3), 937–954. https://doi.org/10.1111/jiec.70017

Mol, A. P. J., & Spaargaren, G. (2000). Ecological modernisation theory in debate: A review. *Environmental Politics, 9*(1), 17–49. https://doi.org/10.1080/09644010008414511

Neagu, O., Neagu, M.-I., & Gavurova, B. (2022). How green is the economic complexity in the Central and Eastern European Union countries? *Frontiers in Environmental Science, 10*, Article 910454. https://doi.org/10.3389/fenvs.2022.910454

NGFS. (2022). *Central banking and supervision in the biosphere: An agenda for action on biodiversity loss, financial risk and system stability* (Final report of the NGFS-INSPIRE Study Group on Biodiversity and Financial Stability). Network for Greening the Financial System.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica, 49*(6), 1417–1426. https://doi.org/10.2307/1911408

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

Özbay, F., Tekin, B., Shah, S. A. R., & Abbas, N. (2024). Is the load capacity curve a true phenomenon for OECD economies? Hidden behavior of financial institutions and markets in environmental sustainability. *Journal of Environmental Management, 370*, Article 122812. https://doi.org/10.1016/j.jenvman.2024.122812

Ozkan, O., Adeshola, I., Usman, O., & Adebayo, T. S. (2025). The asymmetric role of resource efficiency and alternative energy on load capacity factor in India. *Environmental Quality Management, 35*(1), Article e70144. https://doi.org/10.1002/tqem.70144

Pata, U. K., & Isik, C. (2021). Determinants of the load capacity factor in China: A novel dynamic ARDL approach for ecological footprint accounting. *Resources Policy, 74*, Article 102313.

https://doi.org/10.1016/j.resourpol.2021.102313

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics, 61*(S1), 653–670. https://doi.org/10.1111/1468-0084.0610s1653

Pedroni, P. (2004). Panel cointegration: Asymptotic and finite sample properties of pooled time series test with an application to the PPP hypothesis. *Econometric Theory, 20*(3), 597–625. https://doi.org/10.1017/S0266466604203073

Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels* (Cambridge Working Papers in Economics No. 0435). University of Cambridge.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica, 74*(4), 967–1012. https://doi.org/10.1111/j.1468-0262.2006.00692.x

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., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics, 142*(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

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. https://doi.org/10.1257/jep.9.4.97

Pörtner, H.-O., Scholes, R. J., Arneth, A., Barnes, D. K. A., Burrows, M. T., Diamond, S. E., et al. (2023). Overcoming the coupled climate and biodiversity crises and their societal impacts. *Science, 380*(6642), Article eabl4881. https://doi.org/10.1126/science.abl4881

Poyser, A. (2026). Does financing biodiversity reduce biodiversity loss? Evidence from EU funding of science and innovation. *Review of Finance, 30*(1), 273–319. https://doi.org/10.1093/rof/rfaf064

Romero, J. P., & Gramkow, C. (2021). Economic complexity and greenhouse gas emissions. *World Development, 139*, Article 105317. https://doi.org/10.1016/j.worlddev.2020.105317

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal, 9*(1), 86–136. https://doi.org/10.1177/1536867X0900900106

Seidl, A., Mulungu, K., Arlaud, M., van den Heuvel, O., & Riva, M. (2020). Finance for nature: A global estimate of public biodiversity investments. *Ecosystem Services, 46*, Article 101216. https://doi.org/10.1016/j.ecoser.2020.101216

Siche, R., Pereira, L., Agostinho, F., & Ortega, E. (2010). Convergence of ecological footprint and emergy analysis as a sustainability indicator of countries: Peru as case study. *Communications in Nonlinear Science and Numerical Simulation, 15*(10), 3182–3192. https://doi.org/10.1016/j.cnsns.2009.10.027

Song, Y., & Dong, J. (2024). Impact of climate policy uncertainty on corporate green investment: Examining the moderating role of financing constraints. *Frontiers in Marine Science, 11*, Article 1456079. https://doi.org/10.3389/fmars.2024.1456079

Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of Management Review, 20*(3), 571–610. https://doi.org/10.2307/258788

Waldron, A., Miller, D. C., Redding, D., Mooers, A., Kuhn, T. S., Nibbelink, N., Roberts, J. T.,

Tobias, J. A., & Gittleman, J. L. (2017). Reductions in global biodiversity loss predicted from conservation spending. *Nature, 551*(7680), 364–367. https://doi.org/10.1038/nature24295

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics, 69*(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Yang, M., Magazzino, C., Awosusi, A. A., & Abdulloev, N. (2024). Determinants of load capacity factor in BRICS countries: A panel data analysis. *Natural Resources Forum, 48*(2), 525–548. https://doi.org/10.1111/1477-8947.12331

Yıldırım, M., Destek, M. A., & Manga, M. (2024). Foreign investments and load capacity factors in BRICS: The moderating role of environmental policy stringency. *Environmental Science and Pollution Research, 31*. https://doi.org/10.1007/s11356-023-31814-9

Zeraibi, A., Zhao, X., & Liu, Y. (2026). Exploring economic green complexity in the load capacity of G20 countries: Do environmental policy and public debt matter? *International Journal of Environmental Research, 20*(1), Article 18. https://doi.org/10.1007/s41742-025-00939-9.