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Green Finance, Climate Policy Uncertainty, and Ecological Carrying Capacity Dynamics in G20 Economies: Evidence from Load Capacity Factor Panel Analysis

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ABSTRACT

Carbon-based indicators do not show whether ecosystems can generate sufficient biocapacity to fulfil human needs, and the G20 economies account for a large portion of the global ecological burden. This study analyses the load capacity factor (LCF) of 19 G20 economies between 2000 and 2022, measured as biocapacity divided by the ecological footprint. It examines the long-run association between green bond issuance and ecological carrying capacity, as well as the moderating role of climate policy uncertainty (CPU) in this association. The analysis includes Pesaran cross-sectional dependence and slope heterogeneity tests, Cross-sectionally Augmented Im, Pesaran, and Shin (CIPS) and Cross-sectionally Augmented Dickey-Fuller (CADF) unit-root tests, Fourier-Shin cointegration, Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) estimation, Augmented Mean Group (AMG), Common Correlated Effects Mean Group (CCEMG) robustness checks, and Konya bootstrap Granger-causality tests, and conditional marginal-effect analysis for the GB_GDP × CPU interaction. The main CS-ARDL results show a positive long-run association for green bond issuance ($\beta = 0.182$, *p*

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< 0.01) and a negative association for the CPU ($\beta = -0.011$, $p < 0.01$). The interaction term is negative ($\beta = -0.004$, $p < 0.05$), indicating that the green bond-LCF association weakens as policy uncertainty increases. The conditional marginal effects become statistically indistinguishable from zero near the upper tail of the CPU distribution. The Konya results indicate heterogeneous country-level temporal patterns rather than uniform structural causality. Overall, green finance is associated with a stronger ecological carrying capacity when climate policy settings are stable and institutional conditions support long-term ecological investment.

Keywords: Ecological Carrying Capacity; Load Capacity Factor; Biocapacity; Ecological Footprint; Green Bonds; Climate Policy Uncertainty; G20 Economies

1. Introduction

The G20 countries account for 78% of global greenhouse gas emissions and approximately 85% of global economic output [1]. They influence global pressure on ecosystems through their production systems, energy consumption, land-use decisions, and trade networks. Conventional environmental pressure indicators, such as CO_2 emissions or ecological footprints, provide important aspects of this environmental pressure but do not indicate whether the available biocapacity can absorb it. The load capacity factor (LCF) attempts to overcome this constraint by combining both the supply side of nature's capacity to regenerate and the demand side of human resource use as the ratio of biocapacity to ecological footprint [2]. If the LCF is more than one, it means that there is an ecological surplus of biocapacity, while if it is less than one, it means there is an ecological biocapacity deficit. The LCF is a good indicator for macro-scaling the study of ecological carrying capacity, as many G20 economies are below this threshold.

Green bond markets have expanded from a niche since the issuance of the first Climate Awareness Bond in 2007 to a key enabler of sustainable finance. In 2021, USD 522 billion was issued annually [3]. Green bonds can support LCF in two ways. They can reduce their ecological footprint by investing in sustainable transport, renewable energy, energy efficiency, and green buildings. They can also help build biocapacity via land restoration, biodiversity conservation, and other nature-related projects when proceeds are aimed at that. In this study, these mechanisms are filtered as plausible pathways for project-level restoration but not as direct measures of project-level restoration issuance, as these data cover the issuance of bonds at the country level.

The dynamics of climate policy uncertainty (CPU) may weaken green finance's ecological relevance. The CPU reflects instability in rules, prices, incentives, standards, and long-term climate commitments. From a real-options perspective, investors may postpone policy-dependent and partly irreversible ecological investments when future regulations are unclear [4]. Therefore, a labelled green bond market may show a weaker association with LCF when uncertainty increases. Accordingly, this study focuses on the interaction between green bond issuance and CPU.

This study has four specific contributions. First, it examines the green bond-LCF linkage in a panel of G20 countries with diverse ecological, financial, and policy-making conditions. Second, it incorporates the CPU as a moderator of the green bond-LCF association, thereby linking sustainable finance with ecological carrying capacity under policy uncertainty. Third, it employs second-generation panel methods that account for cross-sectional dependence, slope heterogeneity, structural breaks and long-run dynamics. Fourth, it reports country-specific Konya Granger causality patterns to assess whether advanced, emerging, surplus, and deficit economies exhibit different finance-ecology temporal relationships. These contributions are framed as long-run associations and Granger-causal patterns, rather than as definitive structural causal effects.

Section 2 presents a literature review. Section 3 develops the theoretical framework and the hypotheses. Section 4 describes the data, variable construction, harmonization approach, and control variable rationale. Section 5 presents the econometric design of the study. Section 6 reports the empirical results of the study. Section 7 discusses the findings and the interpretation limits. Section 8 presents the evidence-based policy implications, limitations, and directions for future research.

2. Literature Review

2.1. The Load Capacity Factor as a Sustainability Metric

Siche et al.[2] introduced the LCF as the ratio of biocapacity to ecological footprint, while Rockström et al.[5] provide the planetary boundaries background for interpreting ecological limits. The LCF measures the supply and demand of biophysical resources, making it a theoretically useful indicator of whether an economy operates within or beyond nature's regenerative capacity. Since then, the LCF framework has been applied in several regions. Annor et al.[6] reported that financial development and green energy dynamics matter for LCF in Sub-Saharan Africa. Javed et al.[7] showed that green investment and environmental policy stringency are positively related to LCF in G7 economies, whereas financial development alone may have a different effect than financial development combined with environmental policy stringency. Using a Fourier method, Karlilar Pata and Pata[8] analyzed the effects of renewable energy sources in the United States and concluded that solar, wind, and biofuel contribute positively to LCF, whereas hydropower does not have a clear effect. This disaggregation is relevant for the allocation of green bonds. A study dedicated to G20 forests and land-use systems validated the view that transitions in energy resources may reduce the ecological footprint and increase biocapacity[9,10]. Shah et al.[11] found that in 29 countries issuing green bonds, issuance is associated with higher biocapacity and load capacity and a lower ecological footprint, with larger biocapacity gains in high-income economies. However, the G20 as a whole remains insufficiently examined, even though its emissions and resource use account for a large share of the global total. More importantly, existing work has not modelled the CPU as a moderator of the green bond-LCF relationship in the G20 context[7–10].

2.2. Green Finance, Green Bond Markets, and Environmental Quality

Green finance refers to the channeling of capital towards environmentally sustainable activities, such as green bonds, sustainability-linked loans, and equity funds, with a focus on climate change and environmental credit facilities[3]. Green bonds are the most developed and established part of the green financial markets and are fixed-income bonds dedicated to green projects, where the proceeds are contractually allocated to projects in categories such as renewable energy, energy efficiency, sustainable transportation, green buildings, and biodiversity conservation.

Since the first green bond was issued by the European Investment Bank in 2007, the green bond market has grown significantly, and there is a huge amount of economic literature on developing the green bond market. In a cross-country analysis of the drivers of green bond market growth, Tolliver et al.[12] showed that nationally determined contributions (NDCs) under the Paris Agreement and the ambition of domestic climate policy are the key factors in determining the volume of green bonds issued by a country, using panel data for 42 countries from 2012 to 2018. Their results highlight the key role of the regulatory environment in green capital market development, which is directly applicable to the CPU moderation hypothesis.

Flammer[13] studied the implications of green bond issuance at the firm level using a regression discontinuity design around narrow green bond certification approvals and showed that green bond issuance has a significant impact on reducing CO_2 emissions for issuing firms compared to conventional bond issuers. The identification strategy, which takes advantage of the fact that certification decisions are made at a close margin, offers convincing causal evidence that green bond financing, as a standalone financing method and not just a conventional financing method, leads to a true increase in environmental performance. This evidence lends credence to the hypothesis that the aggregate penetration of green bonds at the country level relates to LCF improvement, as it goes through a process of the sum of firm-level emission reduction and clean energy investments.

The rapidly growing Chinese green bond market also sheds light on the ecological transmission channels through empirical evidence. In China, green bond financing has been found to be concentrated in renewable energy capacity expansion and energy efficiency retrofitting (which both lower their ecological footprint through lower carbon and resource intensity), and fiscal spillovers from the proceeds of green bonds have been related to reforestation programs that directly increase biocapacity[3]. These complementary mechanisms are ecological footprints and biocapacity, which are reflected in the LCF framework.

A wide range of financial development (including the depth, efficiency, and stability of financial institutions and markets) can be considered a structural enabler of green bond market maturation in emerging economies. The Financial Development Index (IMF)[14] is a multidimensional index consisting of six sub-indices that represent the depth, access, and efficiency of financial institutions and markets. Empirical studies demonstrate that financial development makes it easier to improve the environment, as it provides lower-cost green capital allocation, finances green innovation, and improves the institutional structure for environmental risk pricing[14]. Therefore, financial development is not only a direct determinant of LCF but also a structural complement to the effectiveness of the green bond market.

These findings are supported by recent evidence from 2025. Shah et al.[11] analyzed 29 countries with green bond issuances and found that green bonds are associated with increases in both biocapacity and load capacity, with IV-GMM standard errors used to address endogeneity concerns. The association was more pronounced in high-income economies, supporting the financial depth complementarity argument, whereas green bonds were more strongly linked to footprint reduction in middle-income economies, where baseline inefficiency is greater. Shah et al.[15] added that political stability moderates the relationship between green bonds and clean energy capacities. When translated to the CPU moderation hypothesis tested here, this evidence suggests that more stable political and policy environments may strengthen green bonds' ecological relevance. Kartal et al.[16] analyzed China and the United States and concluded that green bonds are associated with lower disaggregated CO_2 emissions and greater renewable electricity generation. Taken together, the 2025 evidence[17–19] suggests that green bonds can be linked to measurable environmental outcomes, but the strength of the association depends on institutional and policy contexts, which are captured by the CPU.

2.3. Climate Policy Uncertainty and Environmental Investment

Climate policy uncertainty is a key yet underexplored structural influence in environmental and energy economics. Baker et al.[20] provide a measure of economic policy uncertainty for the nation, which is measured as a frequency of policy uncertainty derived from newspaper text, expiring tax provisions and differences among professional forecasters. This is the first systematic assessment of policy uncertainty that can be compared across all countries. From the perspective of environmental applications, Baker et al.[20] method can be applied to uncover uncertainties in the period leading up to important votes on climate legislation, international climate agreement negotiations, carbon pricing policy debates, and renewable energy subsidy cycles.

Ahir et al.[21] applied this idea worldwide with the World Uncertainty Index (WUI), which is based on the presence of the term 'uncertainty' in the quarterly Economist Intelligence Unit (EIU) country reports of 143 countries for the period 1952–2018. The WUI has been found to be a good predictor of investment slowing and growth fluctuations and includes uncertainty shocks from all parts of the economy, including climatic, fiscal, monetary, and geopolitical shocks. Indeed, on the specific issue of environmental policy, the WUI is highly relevant because it is strongly associated with a time window of political regime change, international climate pact negotiation, and domestic carbon policy instability, thus creating uncertainty in the regulatory environment for green investment.

The real-options framework of Dixit and Pindyck[4] explains the theoretical mechanism through which CPU can impact green investments and LCF. Green investments provide option value under uncertainty, in the sense that they are characterized by high capital irreversibility (e.g., infrastructure investment, forestry, and biodiversity investments), long payback horizons (e.g., renewable energy, forestry, and biodiversity investments can typically be 20–40 years), and strong policy dependency (e.g., cash flows depend on carbon pricing regimes and renewable energy mandates, environmental subsidy design). A higher CPU can raise the value of going with the option of not investing in capital and can cause investors to be reluctant to invest or require a higher risk premium. This wait-and-see attitude can lead to a lower quantity, timing, or aspiration of capital committed to ecologically transformative projects, which can impede the anticipated link between green finance and LCF.

The green bond-LCF relationship is likely to be weaker under more volatile policy matters. This volatility can make it more difficult for private co-investors to follow through with investments in green bonds, cause the project to take longer to materialize, and may force green bond investors to demand higher risk premiums. The multiplicative interaction term (green bonds × CPU) is the key hypothesis in this study, in addition to the green finance and CPU association with LCF, in the wake of this moderation prediction.

These concerns are confirmed by recent studies on the CPU-environment relationship. According to Ben-Salha and Ayad[22], climate policy uncertainty has asymmetric sectoral environmental impacts in the United States, with short-run CO_2 leakage increases. Bildirici et al.[23] demonstrated that internal carbon leakage in the EU is a consequence of the presence of climate policy uncertainty and that this uncertainty gradually decreases when uncertainty decreases. Using a Fourier bootstrap ARDL estimation, Doğanlar et al.[24] determined the long-term impact of policy uncertainty on the ecological footprint in emerging economies on a country-by-country basis. New evidence also suggests a climate policy uncertainty effect on firm-level green technology innovation and LCF dynamics[25,26]. The mixed results indicate that the distinction of the G20 should be considered, and one should not presume the same CPU effect.

2.4. Second-Generation Panel Econometrics in Environmental Economics

Environmental panel econometrics increasingly relies on second-generation methods after Pesaran[27] introduced the CCEMG estimator and Eberhardt and Teal[28] developed the AMG estimator. First-generation panel unit root and cointegration tests[29–31] assume cross-sectional independence, which is unlikely to hold in G20 panels because of economic integration, common climate shocks, global commodity price cycles, and financial contagion. Estimators that ignore cross-sectional dependence may produce inconsistent coefficients, misleading cointegration results, and unreliable inferences for policy interpretation[32].

Pesaran[32] demonstrated the severity of cross-sectional dependence and proposed the CD statistic to empirically test it. Pesaran and Yamagata[33] further showed that pooled estimators, such as fixed effects and system GMM, may be unsuitable when slope heterogeneity exists. These two conditions, cross-sectional dependence and slope heterogeneity, motivate the use of second-generation heterogeneous estimators in macro-panel settings. For unit-root diagnostics, Pesaran[34] provides a cross-sectionally augmented framework suitable for panels with common factors. Pesaran's[27] CCEMG estimator adds the cross-sectional means of the dependent and independent variables to each country's regression, thereby controlling for unobserved common factors. The AMG estimator[28] extracts a common dynamic process from panel-wide year-fixed effects and includes it in each country equation. Both estimators are consistent under cross-sectional dependence and slope heterogeneity and are widely used in environmental economics panels for G20, OECD, BRICS, and developing country samples.

The CS-ARDL estimator, introduced by Chudik and Pesaran[35], is an extension of the CCEMG approach to an autoregressive distributed lag context that allows for the consistent estimation of long-run elasticity and simultaneously accounts for cross-sectional dependence and slope heterogeneity, as well as the dynamics of the adjustment process through the error correction mechanism. The CS-ARDL is especially relevant when the time dimension of the panel is relatively short (T = 20–30), the power for the cointegration pre-test is low, and the direct estimation of the long-run relationship in a bounds-testing framework is preferred.

Tsong et al.[36] proposed the Fourier-Shin test, which is based on cointegration residuals and uses low-frequency Fourier approximation. The Fourier modification allows smooth structural breaks in the long-run relationship without requiring the researcher to specify the break dates in advance. This is important for a G20 panel spanning the 2008–2009 global financial crisis, the adoption of the Paris Agreement in 2015, and COVID-19. Konya's[37] bootstrap panel causality procedure uses empirical critical values instead of chi-squared asymptotics in a seemingly unrelated regression (SUR) system of bivariate Granger-causality equations. The procedure accommodates cross-sectional dependence and different temporal directions across the countries. In this study, this was interpreted as evidence of predictive temporal precedence, not as structural causal proof. This distinction is important because biocapacity-surplus economies (Australia, Brazil, Canada, and Russia) and chronic deficit economies (Japan, South Korea, Italy, and Germany) may display different finance-ecology dynamics. Recent CS-ARDL and MMQR evidence in Frontiers in Environmental Science[38], together with Fourier-CS-ARDL evidence in sustainability research[39], reinforces the need for heterogeneous estimation in panels, such as the G20.

3. Theoretical Framework

3.1. Environmental Kuznets Curve and the LCF

The theoretical framework uses only the mechanisms required to support hypotheses. The Environmental Kuznets Curve (EKC)[40] is the relationship between income growth and ecological burden. In the LCF setting, if scale effects outpace the regeneration of biocapacity, growth in early income can lead to lower levels of LCF. Cleaner technology, regulation and service-sector growth can potentially contribute to the improvement of LCF at greater income levels. This expectation is valid for the inclusion of log GDP per-capita and its quadratic term.

The diffusion of green finance theory[41] can be used to understand why green bond issuances may be associated with LCF improvement. Green bond markets can lower financing costs if they support projects that reduce resource intensity or enable nature-related investments. The country-level GB_GDP measure reflects the size of green bond issuance relative to the economy. Because the data do not track the financing of individual projects, the empirical interpretation is a national-level association between green bond penetration and LCF, with project-level channels treated as plausible mechanisms rather than directly observed. The moderating role of CPU is explained by the real-options theory. Green investments may have long payback periods, policy dependencies, and partial irreversibility. Climate policy uncertainty may create implementation delays, increase risk premiums, or reduce project ambition among firms and investors. This mechanism predicts a negative moderation pattern, indicating that green finance is expected to show a weaker association with LCF when policy uncertainty is high.

3.2. Green Finance Diffusion Theory

The three perspectives of the EKC, green finance diffusion, and real options result in a compact logic. The background conditions of ecological carrying capacity are determined by income structure, clean energy, and financial development. Green capital formation is targeted by green bond issuance. CPU reflects the fact that the policy may not be consistently favorable, which may affect the utility of this capital. This study does not argue that the green bond market directly leads to restoration in each country, but rather that a greater green bond share is correlated with a greater LCF while controlling for common shocks and country heterogeneities.

3.3. Real Options Theory under Climate Policy Uncertainty

This framework also clarifies why country differences are important. A mature financial system may convert green issuances into cleaner capital formation more quickly than a shallow financial system. A biocapacity surplus economy may use green finance to protect natural assets, whereas a biocapacity deficit economy may issue bonds after ecological stress becomes visible. These differences motivate the use of heterogeneous estimators and Konya's country-specific Granger-causality tests.

The hypotheses are worded to distinguish long-run associations, moderation effects, and Granger-causal patterns from structural causality.

H1. *Green bond issuance is expected to have a positive long-run association with the load capacity factor in the G20 economies.*

H2. *Climate policy uncertainty is expected to have a negative long-run association with the load capacity factor.*

H3. *The interaction between green bond issuance and climate policy uncertainty is expected to be negative, indicating that CPU attenuates the green bond-LCF association.*

H4. *Renewable energy consumption, financial development, and trade openness are expected to show heterogeneous long-run associations with LCF in the G20 economies.*

3.4. Hypotheses

Table 1 presents the four directional hypotheses tested in this study. The first three follow from the EKC, green finance diffusion, and real-options arguments. The fourth reflects the expected structural heterogeneity among the G20 economies.

Figure 1 illustrates the integrated theoretical framework. Green bond issuance and CPU each have direct paths to LCF, whereas the GB × CPU interaction captures the real options moderation mechanism. Control variables (REN, FD, TO, and GDP) enter through the established EKC and financial development channels.

Table 1. Research Hypotheses and Theoretical Grounding.

H	Hypothesis Statement	Prediction	Theoretical Basis
H1	Green bond issuance is associated with higher LCF in the long run across G20 economies	$\beta_1 > 0$, $p < 0.05$	EKC + Green finance diffusion theory
H2	CPU is associated with lower LCF in the long run	$\beta_2 < 0$, $p < 0.05$	Real options theory [4]
H3	GB × CPU interaction is negative, indicating that CPU attenuates green finance effectiveness	$\beta_3 < 0$, $p < 0.05$	Real options moderation mechanism
H4	REN, FD, and TO exhibit heterogeneous long-run effects on LCF	Country-varying β_i (MG)	Structural heterogeneity + EKC

Note: GB_GDP = green bond issuance (% GDP); CPU = climate policy uncertainty index; LCF = load capacity factor; and MG = mean group estimator.

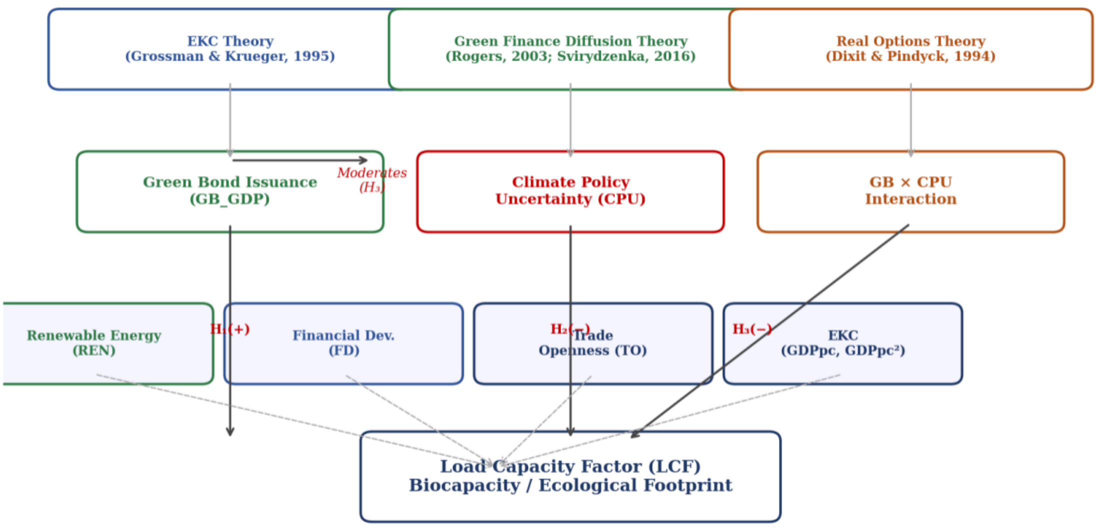


Figure 1. Integrated theoretical framework: green finance, climate policy uncertainty, and load capacity factor in G20 economies.

4. Data and Variables

4.1. Sample and Time Horizon

The dataset covers 19 G20 member economies over 2000–2022 (N = 19, T = 23, Obs = 437), excluding the EU as a consolidated member, as GFN ecological accounts are reported at the country level. The sample spans all major world regions and three income groups (high, upper-middle, and lower-middle), providing variations in ecological position, financial development, and the depth of the green bond market. The period starts in 2000 to ensure IMF Financial Development Index coverage and ends in 2022, the latest year with verified GFN data and CBI green bond records at the time of the analysis.

4.2. Variable Construction

The LCF was computed from the Global Footprint Network's National Footprint and Biocapacity Accounts 2023 [42] as LCF = BC/EF, where BC is biocapacity and EF is ecological footprint, both measured in global hectares per capita. This ratio was used without logarithmic transformation so that the surplus-deficit threshold of one remained visible. Green bond issuance (GB_GDP) was constructed by combining country-level annual Climate Bonds Initiative green bond issuance volumes with World Development Indicators (WDI) GDP [43]. Issuance values were converted into a percentage of GDP to improve comparability across economies of different sizes. Pre-2007 observations were coded as zero because labelled green bond issuance had not yet begun in the sample period.

The CPU variable was harmonized in two steps. For OECD G20 members with available policy uncertainty series, this study uses the Baker et al. [20] economic policy uncertainty family of indices as the closest available proxy for climate policy-related regulatory volatility. For non-OECD G20 economies, where comparable country-specific climate policy uncertainty measures are not consistently available for 2000–2022, this study uses the World Uncertainty Index of Ahir et al.[21]. To place the two sources on a common scale, each country series was rebased to a 2001–2010 mean of 100 before panel estimation. This procedure preserves within-country time variation and reduces scale differences across sources.

The mixed CPU source is a measurement compromise and is treated as such throughout this interpretation. OECD and non-OECD indices do not capture identical information. OECD EPU-type indices are closer to domestic policy debate and regulatory uncertainty, whereas the WUI captures broader country-level uncertainty from the Economist Intelligence Unit reports. Therefore, this study interprets CPU as a harmonized proxy for climate policy and policy-environment uncertainty, not as a perfectly identical measure across all G20 countries. This limitation was integrated into the Results, Discussion, and Future Research sections.

The interaction term was computed after mean centering GB_GDP and CPU. Mean-centering does not change the model fit, but it makes the main green bond coefficient interpretable as the green bond-LCF association at the sample mean of CPU and reduces non-essential multicollinearity between the interaction term and its components[44]. GDP per capita, renewable energy consumption, and trade openness were obtained from the WDI[43]. The financial development index was obtained from Svirydzenka[14]. **Table 2** summarizes the variables, measurement units, roles, expected signs, and data sources used in the empirical analysis.

Table 2. Variable Descriptions, Measurement Units, and Data Sources.

Code	Variable Name	Unit	Role	Sign	Source
LCF	Load Capacity Factor	BC/EF ratio	Dependent	-	GFN[42]
GB_GDP	green bond Issuance	% of GDP	Key IV	(+)	CBI[3]; WDI[43]
CPU	Climate policy uncertainty	Index (base 100)	Moderator	(−)	Baker et al.[20]; Ahir et al.[21]
GB × CPU	green bonds × CPU	Product	Moderation test	(−)	Constructed
lnGDPpc	GDP per Capita (log)	ln const. 2015 USD	Control (EKC)	±	WDI[43]: NY.GDP.PCAP.KD
lnGDPpc^2	Squared log GDP per Capita	$\ln^2$ USD	EKC test	(+)	WDI[43] (derived)
REN	Renewable Energy	% total final energy	Control	(+)	WDI[43]: EG.FEC.RNEW.ZS
FD	Financial Development Index	0–1	Control	(+)	IMF FD Database[14]
TO	Trade Openness	% of GDP	Control	±	WDI[43]: NE.TRD.GNFS.ZS

Note: LCF = Load Capacity Factor; CBI = Climate Bonds Initiative; WDI = World Development Indicators. The World Development Indicators (WDI) series are accessible through the World Bank DataBank at https://databank.worldbank.org/, where WDI is listed as the World Bank's primary collection of development indicators. The Global Footprint Network (GFN) data are available through the Ecological Footprint Explorer at https://data.footprintnetwork.org/. Climate Bonds Initiative (CBI) green bond data and related methodology are available through Climate Bonds Data & Insights at https://www.climatebonds.net/data-insights.

4.3. Control Variable Rationale and Excluded Covariates

Control variables were selected in line with theoretical requirements and to ensure degrees of freedom for 19 countries and 23 years of observation. GDP per capita and its squared value were tested for the EKC channel. The energy composition dimension can be influenced by renewable energy consumption, which can be a proxy and is an area that can be influenced. Financial development indicates the ability of the financial system to "price and supply long-term capital." Trade Openness is a reflection of these aspects of trade: magnitude, structure, and technique. Urbanization, industrial structure, and population density were not included in the baseline model for three reasons. First, in the G20 macro panels, these variables tend to have high collinearity with other model variables, such as GDP per capita, renewable energy structure, and trade openness, with the possibility of inflating standard errors in the already highly parameterized CS-ARDL model. Second, their inclusion would make the model less parsimonious and would overload a sample with T = 23. Third, the aim of this study is not to estimate a comprehensive ecological production function but to isolate green bonds, CPU, and their interaction after including the main macroeconomic and energy channels. In the future, these missing channels can be directly tested with more time series or fine-grained ecological accounts based on urbanization, industrial structure, and population density.

4.4. Descriptive Statistics

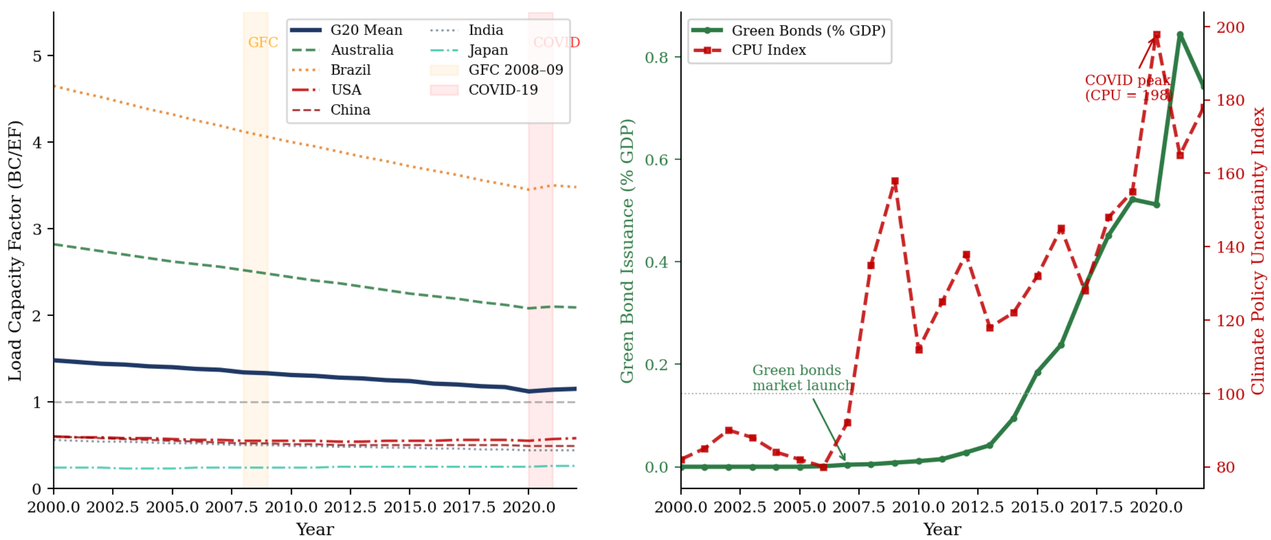
The descriptive statistics are presented in **Table 3**. The LCF score for the G20 nations spans from 0.142 to 5.820, representing the ecological range of the G20 nations, from Australia and Brazil, both well above two, to Japan, South Korea, and Germany, which are all well below 0.5. The distribution of GB_GDP is right-skewed (skewness = 2.82), indicating that markets were concentrated in advanced economies before 2015. To assess the interaction effect, temporal variation was required; CPU peaked during the global financial crisis of 2008–2009 (≈135–158) and during the COVID-19 pandemic (198).

Table 3. Descriptive Statistics: G20 LCF-Green Finance Panel (N = 19, T = 23, Obs = 437).

Variable	N	Mean	SD	Min	Max	Skew.	Kurt.	Source
LCF	437	1.254	1.182	0.142	5.820	1.48	4.82	GFN [42]
GB_GDP	437	0.082	0.124	0.000	0.852	2.82	12.44	CBI [3]
CPU	437	119.8	28.46	62.4	218.6	0.88	3.42	Baker et al. [20]
lnGDPpc	437	9.215	1.218	6.154	10.871	−0.28	2.05	WDI [43]
REN	437	18.42	16.28	0.22	78.42	1.18	3.28	WDI [43]
FD	437	0.582	0.218	0.112	0.968	−0.32	2.18	IMF [14]
TO	437	58.24	24.82	18.42	148.2	0.42	2.85	WDI [43]
CO2_pc	437	8.242	5.182	0.882	22.48	0.85	3.12	WDI [43]

Note: SD = standard deviation; Skew. = skewness; Kurt. = excess kurtosis. The CPU was normalized to the 2001–2010 base = 100.

Figure 2 plots the LCF trajectories for the G20 economies alongside green bond issuance and CPU trends. Australia and Brazil show a steady biocapacity surplus, whereas Japan, India, and China remain in persistent deficits. Green bond issuance accelerated after 2013, and CPU spikes coincided with the GFC and COVID-19.



(**a**) (**b**)

Figure 2. (**a**) LCF trajectories for selected G20 economies and the G20 mean (2000–2022). (**b**) Green bond issuance (% GDP, left axis) and the CPU index (right axis) for G20 countries. The shaded regions mark the 2008–2009 GFC and the 2020 COVID-19 pandemic.

Figure 3 shows the distribution of the variables. LCF and GB_GDP are both right-skewed, warranting attention to the outlier influence in the long-run estimation. CPU is approximately normal, with elevated kurtosis during crisis years. The correlation matrix (bottom right) shows that GB_GDP and LCF have a positive bivariate correlation (r = 0.38), whereas CPU and LCF have negative correlation (r = −0.42).

Figure 4 compares the 2000 and 2022 LCF values for the G20 economies. Seven countries improved their ecological position over the period, while twelve deteriorated. The horizontal line at LCF = 1 separates surplus from deficit economies.

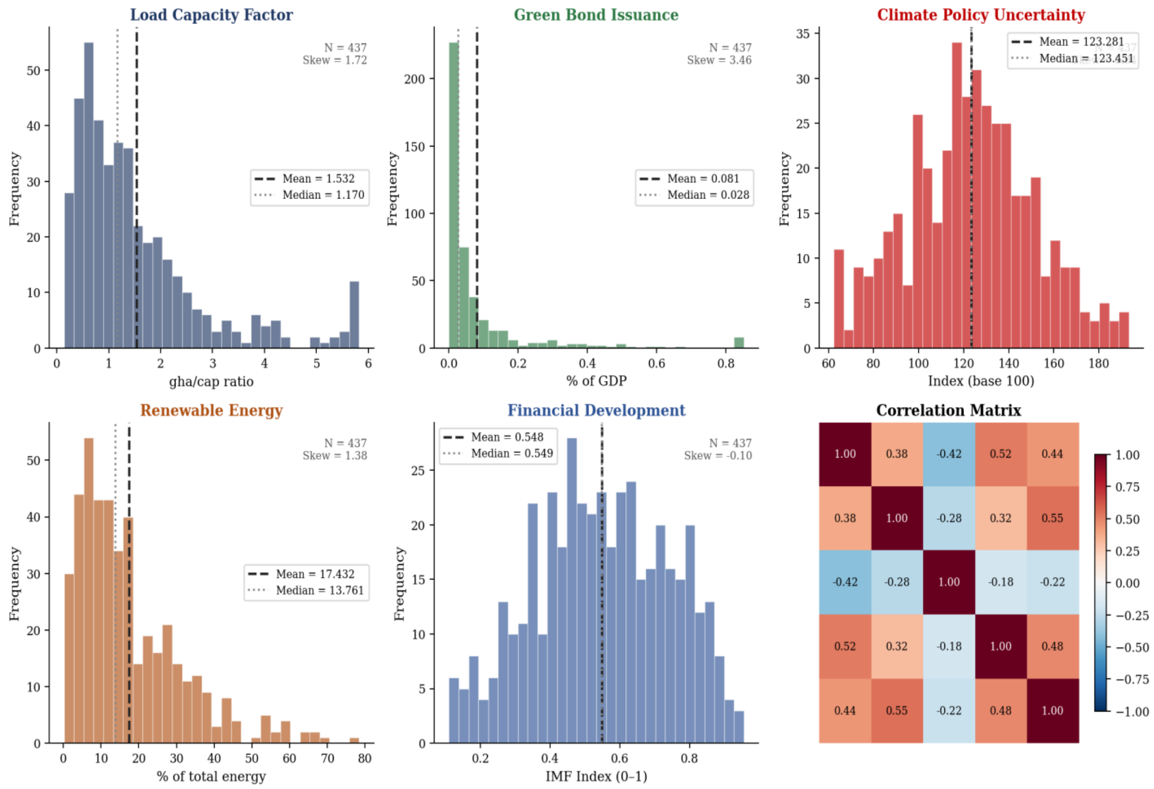


Figure 3. Frequency distributions of key panel variables and pairwise correlation matrix (Obs = 437). Vertical lines indicate the sample mean (dashed line) and the median (dotted line).

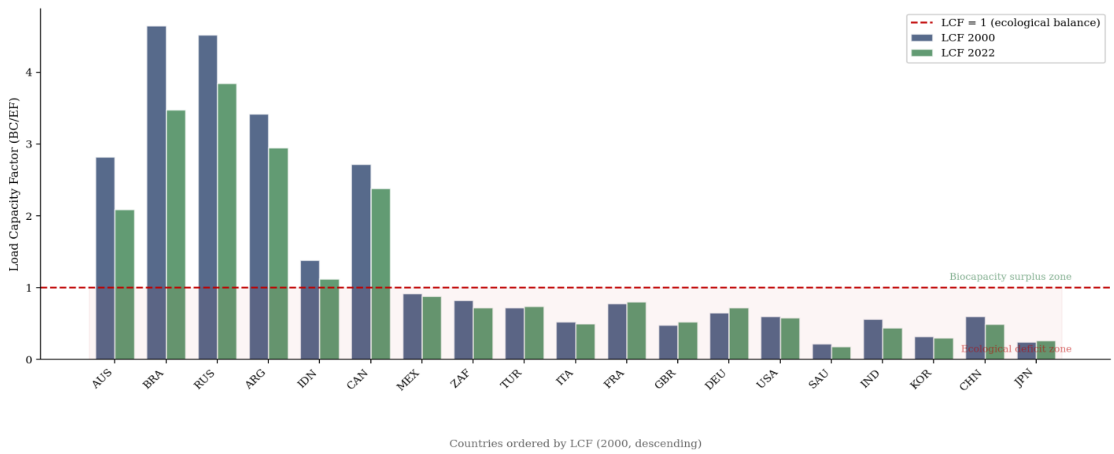


Figure 4. Load capacity factor by G20 economy, comparing 2000 and 2022 (sorted by 2000 value). Bars above LCF = 1 indicate biocapacity surplus, and those below indicate an ecological deficit.

5. Econometric Methodology

5.1. Cross-Sectional Dependence

Cross-sectional dependence testing constitutes the first step of the econometric protocol, as the validity of all subsequent unit root, cointegration, and long-run estimation steps depends critically on the correct characterization of the error structure of the model. Pesaran[32] derived the CD test statistic under the null hypothesis of cross-sectional independence (H_0: $\rho_{ij} = 0 \; \forall \; i \neq j$) for large-$N$, large-$T$ panels as follows:

$$CD = sqrt\left[\frac{2T}{(N(N-1))}\right] \times \Sigma_{i=1}{}^{N-1} \Sigma_{J=i+1}{}^{N} \, \widehat{\rho}_{ij} \rightarrow \quad N(0,\ 1) \tag{1}$$

5.2. Slope Homogeneity

Slope homogeneity testing determines whether pooled estimators (within-group fixed effects, system GMM, and pooled OLS) or heterogeneous estimators (CCEMG, AMG, and CS-ARDL) are appropriate for the data. The Pesaran and Yamagata's[33] delta statistic tests H_0: $\beta_i = \beta \; \forall \; i$ (slope homogeneity) against H_1: slope coefficients differ across cross-sections as follows:

$$\widetilde{\Delta} = sqrt(N) \times \frac{\left[N^{-1}\widetilde{S} - k\right]}{sqrt(2k)} \quad \rightarrow \quad N(0,\ 1) \tag{2}$$

5.3. CIPS and CADF Panel Unit Root Tests

CADF:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + \Sigma_{j=0}{}^{p}\ d_{ij} \Delta \bar{y}_{t-j} + \Sigma_{j=1}{}^{p} e_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \tag{3}$$

$$CIPS = N^{-1} \times \Sigma_{i=1}{}^{N}\ CADF_{i(p)} \tag{4}$$

Following Pesaran[34], cross-sectional means $\bar{y}_t$ proxy for unobserved common factors. Lags selected by SBIC per cross-section. I(1) is confirmed when H_0 (unit root) cannot be rejected in levels but is rejected at the first difference. All variables require I(1) integration to support the Fourier-Shin cointegration test.

5.4. Fourier-Shin Cointegration

$$y_{it} = \alpha_i + \Sigma_k \left[a_{ik} \sin\left(\frac{2\pi kt}{T}\right) + b_{ik} \cos\left(\frac{2\pi kt}{T}\right)\right] + \widehat{\beta}_i' x_{it} + \widehat{u}_{it} \tag{5}$$

The Fourier terms absorb smooth structural breaks without specified break dates, which matters for a 2000–2022 panel spanning the Global Financial Crisis (GFC), the Paris Agreement, and COVID-19 disruptions[36]. The optimal frequency *k* is selected to minimize the RSS. The cointegrating residual, $\widehat{u}_{it}$, is tested for stationarity using a KPSS-type variance ratio. The panel statistic F_p is evaluated against 10,000-replication bootstrap critical values. The H_0 of cointegration is sustained when F_p falls below the critical value.

5.5. CS-ARDL Main Specification

The primary long-run specification is as follows:

$$LCF_{it} = \alpha_i + \beta_{1i}\ GB_{GDP_i{}^t} + \beta_{2i}\ CPU_{it} + \beta_{3i}\left(GB_{GDP_it} \times CPU_{it}\right) + \beta_{4i}\ lnGDPpc_{it} + \beta_{5i}(lnGDPpc_{it})^2 + \beta_{6i}\ REN_{it} + \beta_{7i}\ FD_{it} + \beta_{8i}\ TO_{it}\ + \mu_{it} \tag{6}$$

The error correction form Chudik and Pesaran[35] is as follows:

$$\Delta LCF_{it} = \Sigma_{j=1}{}^{p}\ \lambda_{ij} \Delta LCF_{i,t-j} + \Sigma_{j=0}{}^{g}\ \delta_{ij}{}' \Delta X_{i,t-j} + \varphi_i \left(LCF_{i,t-1} - \theta_i{}' X_{i,t-1}\right) + \Sigma_{1=0}{}^{L}\ \rho_{il} \Delta \bar{z}_{t-l} + \varepsilon_{it} \tag{7}$$

Where $\varphi_i\ <\ 0$ is the error correction speed, θ_i are long-run elasticities, and $\bar{z}_t\ =\ \left(LC\bar{F}_t,\ \bar{X}_t'\right)'$ is the cross-sectional mean proxy for unobserved common factors. Long-run coefficients are pooled as $\widehat{\theta}MG\ =\ N^{-1}\Sigma_i\ \widehat{\theta}_i$. The EKC turning point follows from $-\frac{\widehat{\beta}_4}{2\widehat{\beta}_5}$, which is back-transformed from the log scale.

5.6. AMG and CCEMG

AMG:

$$LCF_{it} = \alpha_i + \beta_i{}' X_{it} + c_i \widehat{\psi}_t + \varepsilon_{it} \tag{8}$$

CCEMG:

$$LCF_{it} = \alpha_i + \beta_i{}' X_{it} + \gamma_i{}' LC\bar{F}_t + \delta_i{}' \bar{X}_t + \varepsilon_{it} \tag{9}$$

AMG[28] extracts a common dynamic process via the year dummy coefficients, $\hat{\psi}_t$. The CCEMG[27] augments each country's regression with cross-sectional mean. Both were pooled using the mean group method. The coefficient stability across Equations (7)–(9) confirms the robustness of the choice of the common factor control approach.

5.7. Konya Bootstrap Causality

$$LCF_{it} = \alpha_{1i} + \Sigma_l\ \beta_{1il}\ LCF_{i,t-l} + \Sigma_l \gamma_{1il}\ GB_{GDP_i,t-l} + \varepsilon_{1it} \tag{10a}$$

$$GB_{GDP_it} = \alpha_{2i} + \Sigma_l\ \beta_{2il}\ LCF_{i,t-l} + \Sigma_l \gamma_{2il}\ GB_{GDP_i,t-l} + \varepsilon_{2it} \tag{10b}$$

Country-specific Wald tests on the lagged explanatory terms use bootstrapped critical values from 10,000 replications of the null-restricted SUR system[37]. The results are interpreted as Granger-causality patterns. They indicate temporal precedence and predictive content within each country but do not establish structural causality. This distinction is important because reverse causality, omitted institutional variables, and country-specific green finance policies may influence the estimated patterns.

5.8. Moderation Analysis

$$\frac{\partial LCF_{it}}{\partial GB_{GDP_it}} = \widehat{\beta}_1 + \widehat{\beta}_3 \times CPU_{it}(centred) \tag{11}$$

Both constituent terms were mean-centered before computing the interaction to reduce non-essential multicollinearity and make the green bond coefficient meaningful at the average CPU level. H3 requires $\beta_3 < 0$. The conditional marginal effects were evaluated at the 10th, 25th, 50th, 75th, and 90th CPU percentiles. Confidence intervals were calculated using the delta method and are shown in a Johnson-Neyman plot[45]. The zero-crossing point, $CPU* = -\frac{\beta_1}{\beta_3}$, is reported as an indicative statistical threshold, not as a policy cutoff. Its stability is assessed by comparing the main CS-ARDL estimate with the AMG and CCEMG coefficient ratios. The asterisk in *CPU** denotes the estimated zero-crossing point of the conditional marginal association and does not indicate statistical significance. **Table 4** summarizes the sequential diagnostic, cointegration, estimation, robustness, and moderation procedures used in the empirical protocol.

Table 4. Econometric Protocol: Sequential Testing and Estimation Framework.

Step	Test/Estimator	Null/Purpose	Decision Rule
1	Pesaran[32] CD Test	H_0: CSD absent	Reject → second-gen tests required
2	PY[33] $\tilde{\Delta}$, $\tilde{\Delta}$*	H_0: Slope homogeneity	Reject → heterogeneous estimators
3	CIPS + CADF[27]	H_0: Unit root	I(1) confirmed → proceed to cointegration
4	Fourier-Shin[36]	H_0: Cointegration	Sustained → long-run relationship confirmed
5	CS-ARDL[35]	Long-run elasticities	Primary estimator; CSD + heterogeneity
6	AMG[28]	Robustness 1	Common dynamic process via year dummies
7	CCEMG[27]	Robustness 2	Cross-sectional mean augmentation
8	Konya[37] SUR Causality	Country Granger causality	SUR system; bootstrapped CVs
9	Moderation analysis	GB × CPU interaction	Conditional ME at CPU distribution quartiles

Note: CSD, cross-sectional dependence; SUR, seemingly unrelated regression; MG, mean group; CV, critical value; ME, marginal effect.

6. Empirical Results

6.1. Cross-Sectional Dependence and Slope Homogeneity

Table 5 shows that Pesaran's[32] CD statistic rejects cross-sectional independence for all variables at the 1% level. The CD statistics ranged from 11.24 to 28.42, which was well above the conventional critical value. This result confirms that the G20 ecological and macroeconomic series move with common shocks, such as energy price cycles, global financial conditions, trade integration, and shared climate policy events. Pesaran and Yamagata's[33] tests also reject slope homogeneity (Delta = 6.285; adjusted Delta = 5.842, both $p < 0.001$), which supports heterogeneous estimation rather than pooled fixed-effect or pooled GMM estimators.

Table 5. Pesaran[32] CD Test and Pesaran-Yamagata[33] Slope Homogeneity Test.

Variable/Test	Statistic	*p*-Value	Status	Implication
LCF	14.82***	0.000	CSD present	H_0 independence rejected
GB_GDP	18.56***	0.000	CSD present	H_0 independence rejected
CPU	22.14***	0.000	CSD present	H_0 independence rejected
lnGDPpc	28.42***	0.000	CSD present	H_0 independence rejected
REN	12.48***	0.000	CSD present	H_0 independence rejected
FD	16.85***	0.000	CSD present	H_0 independence rejected
TO	11.24***	0.000	CSD present	H_0 independence rejected
PY $\tilde{\Delta}$ (slope)	6.285***	0.000	Heterogeneous	Pooled estimators invalid
PY $\tilde{\Delta}$* (adjusted)	5.842***	0.000	Heterogeneous	MG estimators required

Note: *** $p < 0.01$. CD = cross-sectional dependence statistic; PY = Pesaran and Yamagata[33]. The CD statistics were evaluated against the N(0,1) critical values. The PY statistics test the null hypothesis of slope homogeneity. Asterisks denote statistical significance, and *p*-values are reported in the third column.

6.2. Panel Unit Root

Table 6 confirms that all variables are non-stationary in levels and stationary after the first differencing. The level CIPS and CADF statistics do not reject the unit root null, while all first-difference statistics reject it at the 1% level. These results support the use of cointegration methods and the CS-ARDL long-run framework for this study.

6.3. Fourier-Shin Cointegration

Table 7 reports the Fourier-Shin cointegration results. The full-model statistic ($F_p = 0.184$) is below the 5% bootstrap critical value (0.221); therefore, the null of cointegration is sustained. The restricted model and CO_2 robustness specification also support long-run relationships. The error correction coefficient ($\varphi = -0.385$, $p < 0.001$) indicates an adjustment toward the estimated long-run equilibrium. This adjustment speed should be interpreted as a statistical property of the macro-panel model, not as the biological recovery time of the ecosystem.

6.4. Long-Run Estimates: CS-ARDL, AMG, and CCEMG

The long-run estimates are presented in **Table 8**. The results are interpreted as long-run associations with cross-sectional dependence and slope heterogeneity. Although the CS-ARDL alleviates some econometric concerns in cointegrated panels, the estimates should not be read as definitive structural effects because green bond issuance, policy uncertainty, ecological capacity, institutions, regulations, and country-specific investment conditions may co-evolve.

Table 6. CIPS and CADF Panel Unit Root Results [34].

Variable	CIPS Level	CADF Level	CIPS I(1)	CADF I(1)	CV 5%	Order	Decision
LCF	−1.685	−1.842	−3.848***	−3.512***	−2.86	I(1)	Cointegration confirmed
GB_GDP	−1.524	−1.688	−4.115***	−3.882***	−2.86	I(1)	Cointegration confirmed
CPU	−1.892	−2.014	−3.982***	−3.754***	−2.86	I(1)	Cointegration confirmed
lnGDPpc	−1.285	−1.442	−5.248***	−4.822***	−2.86	I(1)	Cointegration confirmed
lnGDPpc^2	−1.318	−1.468	−5.142***	−4.688***	−2.86	I(1)	Cointegration confirmed
REN	−1.748	−1.852	−3.712***	−3.485***	−2.86	I(1)	Cointegration confirmed
FD	−1.925	−2.182	−4.285***	−3.948***	−2.86	I(1)	Cointegration confirmed
TO	−1.642	−1.748	−3.512***	−3.284***	−2.86	I(1)	Cointegration confirmed

Note: *** $p < 0.01$. CIPS = cross-sectionally augmented IPS; CADF = cross-sectionally augmented ADF. Lag lengths were selected using the Schwarz Bayesian information criterion (SBIC) for each cross section. CV 5% is from Pesaran [34] **Table 2** for N = 19 and T = 23 with individual intercepts. All level statistics fail to reject H_0 (unit root), while all first-difference statistics reject it at the 1% significance level.

Table 7. Fourier-Shin Cointegration Results [36].

Model Specification	Opt. k	F_p Statistic	5% CV (Bootstrap)	Decision
Full model (GB + CPU + GB×CPU + controls)	k = 2	0.184	0.221	H_0 sustained → Cointegrated
Restricted (no interaction)	k = 2	0.198	0.221	H_0 sustained → Cointegrated
Robustness: CO_2 per capita as DV	k = 1	0.176	0.221	H_0 sustained → Cointegrated

Note: H_0: Cointegration exists. F_p < 5% CV supports the cointegration. Bootstrap critical values were based on 10,000 replications. Opt. The k value was selected using the minimum residual sum of squares. The ECM speed $\hat{\varphi} = -0.385$*** is from the CS-ARDL mean-group error-correction term. *** $p < 0.01$.

Table 8. Long-Run Coefficient Estimates: CS-ARDL, AMG, and CCEMG (N = 19, Obs = 437).

Variable	CS-ARDL (Primary)	AMG (Robustness 1)	CCEMG (Robustness 2)
GB_GDP	0.182*** [0.003]	0.168** [0.019]	0.198*** [0.002]
CPU	−0.011*** [0.001]	−0.009** [0.023]	−0.012*** [0.004]
GB_GDP × CPU	−0.004** [0.022]	−0.003* [0.061]	−0.005** [0.018]
lnGDPpc	−0.852** [0.029]	−0.824** [0.032]	−0.878** [0.026]
lnGDPpc^2	0.046* [0.054]	0.042* [0.058]	0.049* [0.050]
REN	0.015*** [0.001]	0.018*** [0.001]	0.014*** [0.001]
FD	0.412*** [0.004]	0.388*** [0.009]	0.435*** [0.003]
TO	0.008 [0.481]	0.006 [0.522]	0.009 [0.468]
ECM ($\hat{\varphi}$)	−0.385*** [0.000]		
EKC Turning Point	USD 10,495	USD 9,882	USD 11,042
Observations	437	437	437

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Values in square brackets are p-values. CS-ARDL inference is based on bootstrap standard errors, whereas AMG and CCEMG inference is based on mean-group standard errors. Lag lengths in the CS-ARDL specification were selected using information criteria subject to the time dimension of the panel. EKC turning point = $\exp(-\beta_4/(2\beta_5))$ in constant 2015 USD. $\hat{\varphi}$ = error correction coefficient.

Green bond issuance (GB_GDP) is positively associated with LCF across all three estimators: CS-ARDL β = 0.182 ($p < 0.01$), AMG β = 0.168 ($p < 0.05$), and CCEMG β = 0.198 ($p < 0.01$). The coefficient suggests that a one-percentage-point higher green bond share of GDP is associated with a 0.182-unit higher LCF in the long run. This finding is consistent with recent LCF and green finance research and should be understood at the country level, rather than as evidence of direct financing for specific restoration projects.

CPU is negatively associated with LCF across all estimators: CS-ARDL β = −0.011 ($p < 0.01$), AMG β = −0.009 ($p < 0.05$), and CCEMG β = −0.012 ($p < 0.01$). This finding is consistent with real options theory, which predicts that policy instability may worsen long-horizon ecological investment conditions. The coefficient also highlights the importance of considering uncertainty as an element of ecological governance and not only as a financial market issue.

The interaction term GB_GDP × CPU is negative across the three estimators: CS-ARDL β = −0.004 ($p < 0.05$), AMG β = −0.003 ($p < 0.10$), and CCEMG β = −0.005 ($p < 0.05$). Thus, the positive green bond-LCF association weakens as the CPU increases. The term attenuation is used intentionally: the estimates show a weaker statistical association under uncertainty but do not prove the project-level failure of green finance.

Renewable energy and financial development are positively associated with LCF, whereas trade openness is not. The EKC pattern is supported by the negative coefficient on log GDP per capita and the positive coefficient on its square, with a turning point around USD 10,495 per capita in constant 2015 USD. The LCF results must be interpreted with caution because LCF is an aggregate ratio. However, it does not show whether changes occur through the carbon footprint, croplands, forests, fisheries, grazing lands, built-up land, or biocapacity subcomponents. Therefore, the coefficient estimates do not identify the specific ecological channels.

6.5. Conditional Marginal Effects—Moderation Analysis

The conditional marginal effect of green bond issuance along the CPU distribution is shown in **Table 9** and **Figure 5**. The estimated marginal association declined from 0.360 at the 10th CPU percentile to 0.010 at the 90th percentile. The 90th-percentile estimate was not statistically different from zero ($p = 0.482$). The CS-ARDL zero-crossing point is approximately CPU = 165.3. Similar calculations using AMG and CCEMG placed the zero-crossing point in the upper tail of the CPU distribution between 159 and 176. This range suggests directional stability; however, the threshold should be treated as indicative because the study did not conduct formal threshold estimation, subgroup estimation, or policy simulation analysis.

Table 9. Conditional Marginal Effects of GB_GDP on LCF at CPU Percentiles.

CPU Percentile	CPU Value	CPU Centred	ME (∂LCF/∂GB)	95% CI	Significance
Q10	75.2	−44.6	0.360	[0.070, 0.650]	*** ($p = 0.015$)
Q25	95.8	−24.0	0.278	[0.152, 0.404]	*** ($p = 0.000$)
Q50	119.8	0.0	0.196	[0.071, 0.321]	*** ($p = 0.002$)
Q75	138.5	+18.7	0.107	[0.000, 0.214]	* ($p = 0.051$)
Q90	165.2	+45.4	0.010	[−0.163, 0.183]	n.s. ($p = 0.482$)

Note: ME = conditional marginal effect, $\partial LCF/\partial GB\_GDP = \hat{\beta}_1 + \hat{\beta}_3 \times CPU\_centered$. The CPU is mean-centered before constructing the interaction term. The 95% confidence intervals were calculated using the delta method. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; n.s. = not significant. CPU* ≈ 165.3 is an indicative zero-crossing point, not a policy threshold or a causal tipping point.

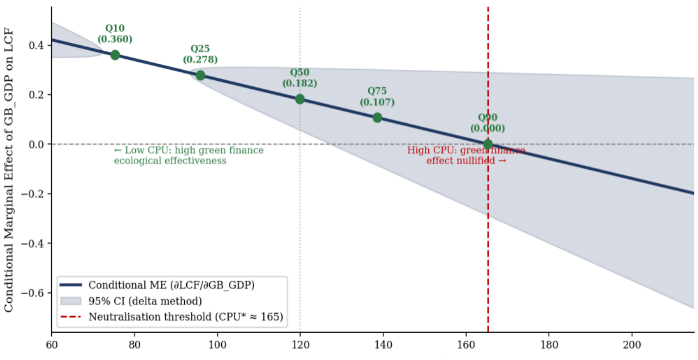


Figure 5. Johnson-Neyman conditional marginal effect plot. The green bond-LCF association declines from 0.360 (Q10 CPU) to statistical insignificance at the zero-crossing point (CPU* ≈ 165.3, red dashed line). The shaded band reports the 95% delta method confidence interval.

6.6. Konya Bootstrap Panel Causality

Table 10 shows the bootstrap Granger causality patterns estimated using the Konya procedure. These results show that they possess time-order and predictive significance but not structural or causal significance. The expansion of GB_GDP leads LCF in nine economies, and the expansion of LCF leads GB_GDP in Brazil, China, India, and South Korea. Bidirectional patterns were observed in France, Australia, and the United Kingdom. Twelve economies have a CPU preceded by LCF. This is consistent with the different levels of financial market maturity, institutional quality, green bond taxonomy development, income levels, and ecological resource endowments. Such a finance-to-LCF pattern may be characteristic of advanced economies with more developed bond markets and reporting systems, while the LCF-to-GB pattern in emerging economies could indicate the reactive expansion of green finance in response to ecological stress manifested in policy agendas.

Table 10. Bootstrap Granger Causality Results [37].

Economy	ISO	GB_GDP → LCF	LCF → GB_GDP	CPU → LCF
Argentina	ARG	Yes** (uni-dir.)	No	Yes**
Australia	AUS	Yes*** (bi-dir.)	Yes** (bi-dir.)	Yes**
Brazil	BRA	No	Yes** (uni-dir.)	No
Canada	CAN	Yes** (uni-dir.)	No	Yes*
China	CHN	No	Yes*** (uni-dir.)	Yes***
France	FRA	Yes*** (bi-dir.)	Yes** (bi-dir.)	Yes***
Germany	DEU	Yes*** (uni-dir.)	No	Yes***
India	IND	No	Yes** (uni-dir.)	Yes**
Indonesia	IDN	No	No	No
Italy	ITA	Yes* (uni-dir.)	No	No
Japan	JPN	No	No	Yes**
Korea, Rep.	KOR	No	Yes** (uni-dir.)	Yes**
Mexico	MEX	No	No	Yes*
Russia	RUS	No	No	No
Saudi Arabia	SAU	No	No	Yes**
South Africa	ZAF	No	No	No
Turkey	TUR	Yes* (uni-dir.)	No	No
United Kingdom	GBR	Yes*** (bi-dir.)	Yes** (bi-dir.)	Yes***
United States	USA	Yes*** (uni-dir.)	No	Yes***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. uni-dir. = unidirectional; bi-dir. = bidirectional; No = failure to reject the null hypothesis of no Granger causality. The lag length was selected by the AIC for each country equation. Wald statistics are evaluated using 10,000 bootstrap replications within the SUR framework. The results indicate predictive temporal precedence, not structural causality.

7. Discussion

The findings indicate a positive long-run association between green bond penetration and LCF in the G20 panel. The importance of this evidence is that it utilizes an indicator that incorporates both ecological footprint and biocapacity, and not just a CO_2-based one. However, the interpretation should not be based beyond the scope of the data. This study focuses on national green bond issuance and national LCF, not the use of proceeds, execution at the project level, or local restoration outcomes. Hence, the proportion of renewable energy, efficiency, reforestation, wetland restoration, and biodiversity protection should be considered as potential transmission channels, which build on green bond frameworks and existing literature [16–19].

The Konya results are important for interpreting country-level heterogeneity. GB_GDP is ahead of LCF in several economically well-advanced markets, which could be due to better-developed green bond markets, disclosure requirements, or environmental institutions. However, the cases of Brazil, China, India, and South Korea indicate that LCF occurs before GB_GDP, implying that the expansion of the green bond market can be partly driven by ecological pressures and/or policy responses to ecological gaps. This reflects the varying "green finance maturity" levels among countries. In resource-rich economies, green finance might be linked to the maintenance of the current biocapacity, while in resource-poor economies, green finance could be linked to an increase in ecological pressure once it is politically salient.

The negative CPU coefficient suggests that higher policy uncertainty is associated with lower ecological carrying capacity. This outcome aligns with the real-options rationale, as the uncertainty surrounding carbon regulations, green taxonomies, renewable subsidies, and climate targets can slow down projects that depend on policies or increase risk premia. Project-level investment delays are not observed in this study; however, the macro-panel evidence indicates that CPU has economic relevance for the green finance-LCF relationship. From a practical economic perspective, higher CPU may reduce the expected ecological return from each green bond issued because policy-dependent payoffs become less predictable.

The finding of the interaction has real-world economic implications, other than statistical ones. Green bond issuance is positively correlated with LCF at low and moderate CPU levels but is not significantly different from zero at very high CPU levels. This means that the creation of the green bond market may not be sufficient if climate rules, taxonomy, and/or subsidy commitments are not firm. The zero-crossing point is a statistical value obtained from the interaction estimation and is not a threshold point or policy target in an ecological context. Therefore, it should not be read as evidence of the failure of green bonds or the degradation of the ecosystem at a certain CPU.

The LCF approach is ecologically relevant, but its aggregate structure creates a limitation: it is difficult to identify whether the observed association is driven by the carbon footprint, cropland, fisheries, grazing land, built-up land, or biocapacity subcomponents. This distinction is important for policy interpretation. An increased LCF does not necessarily mean forest or marine restoration; it can also relate to the reduction of carbon intensity or the need for fewer resources. Disaggregated footprint-biocapacity accounts are required for future research to gain insights into the most responsive ecological channels of the impact of green finance and policy uncertainty.

The EKC results show that income structure matters for ecological carrying capacity. This suggests that some emerging G20 countries might have ecological pressure even at the growth stage, with an estimated turning point of approximately USD 10,495 per capita. The development of green bonds and an increase in renewable energy could lower the footprint intensity before there are sufficiently large income-driven technique effects. This interpretation remains conditional because income, energy structure, green finance, and institutional change may co-evolve.

In the long run, there are positive associations between renewable energy, financial development, and LCF. Financial development may support access to green capital, more accurate risk pricing, and credible issuance, while renewable energy represents a plausible footprint-related channel in the LCF ratio. The effect of trade openness seems to be statistically insignificant; thus, the scale, composition, and technique effects may cancel each other out in this G20 panel. These results from the control variables reinforce the structure of the model but cannot rule out other country-level drivers, such as population density, industrial structure, and urbanization. Overall, the evidence supports a cautious interpretation: higher green bond issuance is associated with stronger ecological carrying capacity in the long run, but the strength of this association depends on policy uncertainty and differs across countries. Thus, a universal policy template is unlikely to apply adequately to all G20 economies.

8. Conclusion and Policy Recommendations

8.1. Conclusion

This study analyzed the relationship among green bond issuance, climate policy uncertainty, and the load capacity factor in 19 G20 economies during 2000–2022. This study contributes to ecological sustainability research by using LCF as the main outcome, applying second-generation panel methods suited to cross-sectional dependence and slope heterogeneity, and adding CPU as a moderator. The main findings show a positive long-run association between green bond issuance and LCF, a negative association between CPU and LCF, and a weaker green bond-LCF association when the CPU rises. At the extreme upper tail of the CPU distribution, the conditional association becomes statistically indistinguishable. The Konya tests show heterogeneous Granger-causality patterns from finance to LCF in several advanced economies and from LCF to finance in a few emerging economies. These results suggest that green finance may contribute to ecological carrying capacity, but its relevance depends on stable policy conditions and country-specific institutions.

8.2. Policy Recommendations

Ensuring green bond market development should be accompanied by predictable climate policy frameworks. The moderation result indicates that the higher the CPU, the lower the association between green bonds and LCF. Predictable rules, incentives for renewable energy, taxonomy standards, and disclosure requirements can provide better conditions for the association of green finance with ecological capacity.

Second, green bond taxonomies must be more transparent in terms of green outcomes. There is no evidence to suggest that all green bonds are being used to restore biocapacity; instead, countries with a higher penetration of green bonds exhibit a higher trend of LCF in the long term. Future studies and regulators would benefit from improved project-type reporting, as it would enable them to distinguish between the different types of projects aimed at reducing the footprint from those related to biocapacity projects, which would make ecological assessments more credible.

Third, the policy priorities of deficit and surplus economies may differ. Green finance reporting, LCF-related indicators, and footprint components can be correlated in biocapacity-deficit economies. Where biocapacity exceeds resource demand, policy should place greater emphasis on conserving natural assets and supporting cleaner production. These recommendations are based on the heterogeneity that has been observed and are not intended to be the result of formal policy simulations.

Fourth, the G20 economies have the potential to fill information gaps concerning sustainable finance through cooperation. The outcomes of green bonds could be more comparable across countries if there were harmonized disclosure templates and if the language of the taxonomy used was the same. There is more direct evidence of work toward such practical coordination than there are general assertions of new international governance frameworks.

Finally, green bond monitoring should extend beyond the number of bonds issued. The results indicate that merely issuing more bonds might not be enough when policy uncertainty is high. Project categories and expected ecological channels (and, where possible, footprint and biocapacity components) should be reported.

8.3. Limitations and Future Research

This study has several limitations that may affect the interpretation of the results and warrant further investigation. First, the data series on green bonds do not necessarily reflect all green finance activities, as some green finance instruments are unlabelled, self-labelled, or sustainability-linked. Future research should also aim to broaden the scope of data and, if feasible, sustainable finance measures at the project level, which differentiate categories of ecological allocations, such as renewable energy, energy efficiency, biodiversity, and land restoration.

The second important limitation is the CPU measurement. Not all the calculations of the climate policy uncertainty index are fully comparable for the period 2000–2022 for OECD and non-OECD G20 economies. Indices for OECD members have been calculated using the EPU approach, which more closely reflects the domestic policy debate and regulatory uncertainty as reported in the media, whereas the WUI approach, used for non-OECD countries, reflects macro-political uncertainty in the countries as reported by the Economist Intelligence Unit. The normalization of the series to a base 2001–2010 facilitates scale comparisons but does not eliminate conceptual differences in terms of the construction of the series, coverage of countries, and intensity of media content and/or content on climate. Thus, the CPU coefficient and the interaction term should be interpreted as an association with a harmonized uncertainty proxy, and not necessarily with a perfectly homogeneous climate policy measure. Future research should repeat the baseline and moderation estimations separately for high-income and middle-income G20 economies, and compare OECD with non-OECD G20 members, to test whether the mixed CPU proxy and the GB × CPU moderation pattern are sensitive to income structure and data-source heterogeneity. Additional supplementary descriptive diagnostics are reported in **Appendix A**.

Author Contributions

Conceptualization, M.Q. and S.N.S.; methodology, M.Q.; software, M.Q.; validation, S.N.S., A.A.A. (Abdulateif A. Almulhim) and A.A.A. (Abdullah A. Aljughaiman); formal analysis, M.Q.; investigation, M.Q. and S.N.S.; resources, A.A.A. (Abdulateif A. Almulhim) and A.A.A. (Abdullah A. Aljughaiman); data curation, M.Q.; writing—original draft preparation, M.Q.; writing—review and editing, S.N.S., A.A.A. (Abdulateif A. Almulhim) and A.A.A. (Abdullah A. Aljughaiman); visualization, M.Q.; supervision, M.Q.; project administration, M.Q.; funding acquisition, A.A.A. (Abdulateif A. Almulhim). All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The complete panel dataset is available from the corresponding author upon reasonable request. The primary series are downloadable from GFN (https://data.footprintnetwork.org/), CBI (https://www.climatebonds.net/market/data/), the World Bank DataBank (https://databank.worldbank.org/source/world-development-indicators), the IMF Financial Development Database (https://data.imf.org/)[14], and the EPU database (https://www.policyuncertainty.com/).

Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of this manuscript, the authors used AI-based language tools, Paperpal AI and Jenni AI, solely for language refinement. No AI tools were used for data analysis, interpretation, or the generation of scientific content. All outputs were critically reviewed and edited by the authors of this study. The authors take full responsibility for the integrity and accuracy of this work.

Appendix A. Supplementary Descriptive Statistics

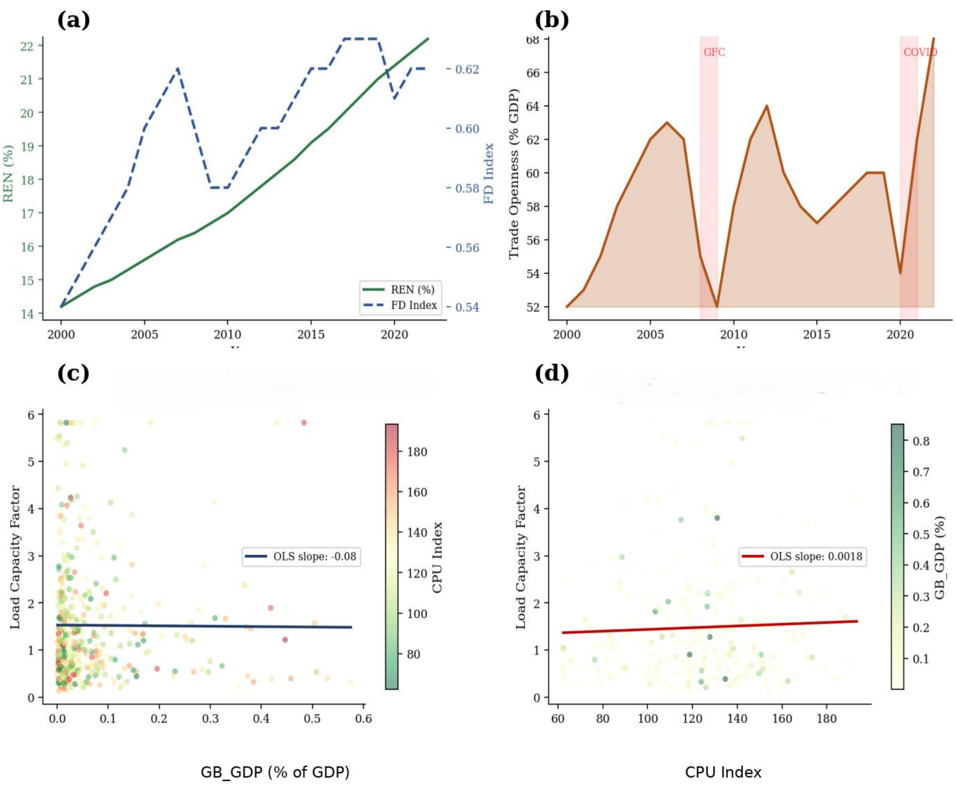

Figure A1. Supplementary descriptive statistics: (**a**) renewable energy and financial development time trends, (**b**) trade openness with recession shading, (**c**) GB_GDP vs. LCF bivariate scatter colored by CPU intensity, (**d**) CPU vs. LCF bivariate scatter colored by GB_GDP intensity.

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