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The Load Capacity Curve Hypothesis: Natural Resource Rent, Financial Inclusion, and the Pathways to Global Environmental Sustainability

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Abstract

The load capacity factor (LCF) hypothesis extends the environmental Kuznets curve (EKC) framework by incorporating both the demand and supply sides of natural resources. This study investigates the LCF hypothesis and the environmental impacts of the natural resources, financial inclusion, population density, and energy consumption on LCF globally and across income groups. The Driscoll-Kraay standard error approach is employed on the panel data from 1995 to 2021. For robustness analysis, the system GMM estimation approach is also utilized. The results reveal the validity of the LCF hypothesis. Natural resource rent negatively affects LCF across all panels except the low-income group, where an insignificant relationship is observed. Financial inclusion reveals mixed findings; it improves LCF in high-income and high-middle-income economies whereas reducing LCF in low-middle-income economies. Comparatively, financial inclusion measures reflect mixed effects. An increase in domestic credit and bank branches leads to environmental degradation by reducing LCF across all panels. The proliferation of ATMs tends to improve LCF in global, high-income, and upper-middle-income economies, whereas diminishing it in low-middle-income and low-income economies. This research suggests the importance of developing an inclusive financial system, along with adopting cleaner energy technologies to improve the load capacity of the planet.

Keywords: Energy consumption, natural resource rent, financial inclusion, load capacity factor.

1. Introduction

Environmental disruption is one of the major world issues. There is mounting evidence of climate change, greenhouse emissions, biodiversity loss, rise in temperatures, and deforestation. These changes highlight the limits of mainstream economic growth models

(Portner et al., 2023). Such changes have led to a 73% average decline in wildlife populations since 1970 (Worldwide Fund for Nature, 2024). Recently, the United Nations (UN) report revealed that more than half of the Sustainable Development Goals (SDGs) targets will likely miss the deadline. Besides, biodiversity loss has direct impact on the lives of 3.2 billion people globally (United Nations, 2025). These trends and alarming findings underscore the basic point that economic progress alone cannot translate into long-term well-being. Therefore, global agendas such as SDGs emphasize aligning economic progress with environmental preservation (Polasky et al., 2019). Now a debate has started among policy makers and economists on how economies can be expanded while keeping the planet within environmental capacity (Basheer et al., 2022). Similarly, the environmental Kuznets curve (EKC) is one of the most widely discussed frameworks to understand environmental changes. According to the EKC hypothesis, at a lower stage of economic expansion, countries experience environmental loss, followed by improvement as income rises after a turning point, forming a U-shaped pattern (Majeed & Mazhar, 2020; Farooq et al., 2022; Leal & Marques, 2022; Dinda, 2004). Although this hypothesis has an appealing narrative, it is critiqued for having a narrow understanding of sustainability as it only focuses on tracking pollution. It overlooks the key dimensions such as ecological balance and resilience of the ecological system (Armeanu et al., 2018).

It remains fundamental to understand the key dimensions of ecological balance. Particularly, how economic growth and financial systems support or undermine the ecological balance. Economic activity is shaped by many factors, including resource extraction and financial inclusion (FI). It is essential to understand whether these factors force economies towards or push them beyond from sustainability. Addressing this question is merely academic but a central issue for the policy makers and answering it will help in knowing how to achieve SDGs. To move beyond the narrow dimensions of environmental degradation and capture the broader dimension of ecological sustainability, scholars have turned towards a concept called “load capacity”. This framework helps to measure the balance between ecological supply (biocapacity) and ecological demand (ecological footprint). Thus, it suggests a more nuanced analysis of environmental conservation and ecological capacity. It is a comprehensive indicator accounting for both demand (pressure imposed by humans) and supply and reflecting the ability of the ecosystem to absorb human pressure (Jahanger et al., 2023). A sustainable balance is achieved by a country when its load capacity factor (LCF) is greater than one. Whereas a value below one indicates a gap in ecological balance. The nonlinear relationship, as suggested by LCF, show that economic growth at first weakens the sustainability and then improves through the adoption of technologies that promote sustainability (Fang et al., 2024).

Within the broader perspective of LCF, natural resource rent (NRR) and FI are considered two of the most crucial factors that influence environmental outcomes. While natural resource extraction is known to drive economic growth, it can also lead to environmental deterioration (Duan & Liu, 2023). Likewise, FI can shape environmental outcomes through multiple channels. For instance, on the one hand, through the expanded access to financial services and resources, businesses and industries can be empowered to invest in green and sustainable technologies, which ultimately enhance environmental sustainability and improve LCF (Qing et al., 2024; Samour et al., 2024; Mazhar et al., 2025). For example, in Europe and G20 countries, FI is aligned with technological innovation, therefore promoting sustainable development (Qing et al., 2024). Similarly, it may also support a transition towards low-carbon economies through the adoption of clean and sustainability-oriented technologies (Feng et al., 2022; Ghouse et al., 2025; Murtaza et al., 2025).

On the contrary, FI can also exacerbate environmental degradation. Increased access to financial services leads to a negative effect on environment through channels like higher consumption, resource exploitation, and industrial expansion. These factors intensify environmental degradation (Anu et al., 2023; Liu et al., 2023). However, the impact of FI is not certain, as it varies across income groups, the degree of integration of green policies, and the structure of governance. For example, high-income economies have higher FI and, as a result, increased carbon emissions, particularly when financial access is not directed towards environmentally sustainable investments (Anu et al., 2023; Hussain et al., 2021).

Despite the growing literature on FI and ecological sustainability, the following research gaps remain unaddressed in the existing literature. First, the earlier studies have extensively used narrow indicators of environmental sustainability, such as CO2 emissions, and not much focused on LCF, which is a broader measure, integrating biocapacity and ecological footprint. Second, the past literature has not examined the role of FI and comparative assessment of FI indicators for global and across different income groups and not provided comprehensive results on how the relationship of FI, FI indicators and LCF differs across different income groups.

To fill these gaps, we investigate the validity of LCF hypothesis along with examining the impact of NRR, population density (PD) and energy consumption (EC) on LCF. This research has following objectives: First, to examine the existence of LCF hypothesis globally and across income groups, second, how does NRR, FI, PD and EC impact the LCF globally and across different income levels? And does the effect of these variables vary by income group. Finally, how FI variables: domestic credit (DC) to private sector by banks, commercial bank branches (BB), and number of ATMs (ATM) impact the LCF globally and across income groups? The study addresses these questions to deepen understanding of the economic-environmental dynamics shaping sustainable development. The aim is to inform targeted policy strategies to enhance the ecological load capacity of the planet.

Next section 2 will review the existing literature on the LCF hypothesis, FI, and natural resource dependence in relation to environmental sustainability. Section 3 will cover the econometric model, data sources, and empirical methodology. It also includes panel data techniques for global and income-group analyses. Section 4 will discuss the empirical results, robustness checks, and heterogeneity across income levels. Finally, Section 5 will conclude the study along with policy implications.

2. Literature Review

The concept of global warming was introduced in the late 1970s and 1980s. Resultantly, ecological degradation gained global prominence. Several notable efforts were made to combat global warming. For instance, the Intergovernmental Panel on Climate Change (IPCC) institution was set up by UN in 1989. Furthermore, many global agreements were approved. For example, the Kyoto Protocol and the Paris Climate agreements were approved in 1997 2015, respectively. These global efforts aim to mitigate carbon emissions and to control temperature within the limit of 1.5 °C.

In line with these international agreements, researchers and environmental economists investigated the link between the economic and the ecological systems. Early research focused on industrialization, urbanization, and energy consumption as the potential factors affecting the environment. A rise in environmental deterioration directed the argument towards identifying the theoretical linkage between economic expansion and environmental changes. This led to famous theories like ecological modernization theory, EKC, and lately, the load capacity curve (LCC).

2.1 Theoretical Foundation

The theoretical foundation of the LCC emerged from the idea of sustainable development, initially presented in the Brundtland report of 1987. This report focused on developed and developing economies for the effective exploitation of natural resources while maintaining the ecological balance (World Commission on Environment and Development, 1987). This theory led to the evolution of ecological footprint theory, encompassing both human demand and nature's supply (Wackernagel & Rees, 1996) in terms of area.

Ecological footprint (EF) theory serves as a broad yet practical measure to determine whether a human's needs exceed nature's regenerative capacity or biocapacity (Majeed & Mazhar, 2019). EF provided a numerical value of the human impact on the biosphere, but it failed to include economic growth or income. The EKC hypothesis, presented as an inverted U-shaped curve, showing a nonlinear association between economic expansion and environmental degradation (Grossman & Krueger, 1991).

EKC gained prominence but it also received criticism for its limited ecological scope, ignoring important pollutant indicators and assuming a universal developmental path for each nation. This led to the quest for a broader sustainability measure, introduced as LCC by Siche et al. (2010). The introduction of LCC solved the issue of traditional indicators by indicating ecological surplus if $LCF > 1$ whereas ecological deficit is shown by $LCF < 1$. LCF was integrated into EKC by Pata & Kartal (2023). The initial phase of growth shows low LCF, illustrating low environmental quality with the increase in per capita while environmental quality improves as LCF exceeds a certain income limit.

2.2 Empirical Evidence on the Determinants of LCF

Building on a strong theoretical foundation of the economic-environmental nexus, researchers have made significant contributions through empirical research to understand the factors that can influence the environment. This empirical review across global, regional, and different income categories highlights the contributions of the existing literature and the gaps that can be better explained within the dynamic framework of LCC.

2.2.1 Economic Growth and EKC

The foundational theory of EKC gained immense attention in the 1990s and is supported by adequate empirical studies (Beckerman, 1992; Panayotou, 1993; Selden & Song, 1995; Dinda, 2004; Majeed & Mazhar, 2020; Farooq et al., 2022). Among the atmospheric and environmental indicators, CO2 emissions and GDP are the most used (Haseeb et al., 2018; Aslam et al., 2021).

However, the study of Shafik & Bandyopadhyay (1992) conditions the applicability of the EKC on the existence of strong governing bodies. The literature also consists of studies that completely nullify the presence of EKC in various regions. A recent study by Bekun et al. (2025) for MINT economies found EKC to be invalid in these nations. The validity of EKC was challenged when broader metrics of ecology were employed (Majeed & Mazhar, 2019; Massagony & Budiono, 2023).

2.2.2 Ecological Footprint, Bio Capacity, and LCF

EF soon became the central focus of researchers, as it reflects the human consumption demand in the form of a biologically productive area comprising six sub-components of grazing land, carbon footprint, and forest area, fishing grounds, cropland and built-up land (Unvan, 2020). This automatically takes into account the regenerative capacity of nature to provide these resources, termed bio capacity (Toderoiu, 2010). LCF emerged as a quantifiable metric, expressed as a ratio of bio capacity, and EF indicates ecological surplus and deficit (Siche et al, 2010). Numerous research papers have used LCF as the main indicator of environmental performance (Pata & Isik, 2021; Pata & Samour, 2022; Jin & Huang, 2023; Liu et al., 2024; Sun & Qamruzzaman, 2025).

2.2.3 LCF and LCC

The use of LCF as a static indicator led to the creation of a dynamic LCC curve, which explores the trajectories of countries along with economic growth. An increment in the numerical figure of LCF indicates a move towards a healthy environment, while a decline in it shows a deteriorating ecosystem (Pata & Samour, 2022; Deng et al., 2024). Fang et al. (2024) employed the ARDL method from 1984 to 2018 for ASEAN countries to test the LCC hypothesis. The study verifies the presence of LCC, but its findings differ from the earlier research as the key variables like natural resources, urbanization and political risk cause a decrease in LCF, whereas biomass consumption increases it.

Liu et al. (2024) utilizing MMQR for G-20 nations found that the factors of LCF have a disproportionate effect on environment. High economic growth, renewable energy (RE), and natural resources improve LCF, whereas low economic growth, financial globalization, and existing technology degrade environmental quality. Wang et al. (2024) conducted a study for BRICS economies to analyze the effect of economic expansion, nuclear energy, RE, and financial development (FD) from 1990 to 2018. The results align with EKC and LCC hypotheses. However, FD shows a contrasting result as it lowers LCF and increases carbon emissions in selected countries. Using a sample of middle-income countries from 2006 to 2022, Pata et al. (2025) investigated the roles of fintech, RE, and government effectiveness in ecological sustainability. Their findings supported the presence of the LCC hypothesis in middle-income countries.

Degirmenci & Aydin (2024) explored the role played by Annex II nations in environmental sustainability from 1994 to 2018 under the framework of LCC. The study employs CS-ARDL and AMG estimators, which show contrasting results, indicating that LCC does not apply to these economies except Finland. Pata & Karlilar Pata (2024) integrates economic, demographic, energy, resources, and financial aspects to calculate LCF and test the LCC hypothesis. Their findings also demonstrated the invalidity of LCC in the top 5 biofuel-consuming nations over 2002-2021.

2.2.4 Economic Growth, Population Density, Energy Consumption, and Natural Resources

One of the key components of the LCC hypothesis is economic growth, as it directly influences environmental quality. Increased income leads to increased expenditures that put upward pressure on resources, but once a threshold is reached, this high resource usage can finance green investments and innovations that promote environmental well-being (Grossman & Krueger, 1991; Pata & Balsalobre-Lorente, 2022).

PD measures the number of people living on a piece of land. High PD corresponds to more resource demand by the residents, which decreases the biocapacity, thus lowering LCF and increasing environmental stress (Erdogan, 2024).

The inevitable effect of energy, its sources, and consumption on ecological sustainability cannot be denied. Deng et al. (2024) explored the effect of economic complexity, energy security, and RE for the top 10 emitter countries over 1998-2010. The findings validate the hypothesis of LCC in the short and long run, as well as a U-shaped relationship between GDP and LCF.

The availability, abundance, and exploitation of natural resources like forests, wildlife, sunlight, water, and minerals aid in determining the biocapacity of a region. In Russia, Caglar et al. (2024) explored the resource-environment nexus by using N-ARDL from 1992 to 2021. The results illustrate that increased natural resource extraction lowers LCF, while a reduction in natural resource extraction improves LCF.

2.2.5 Financial Inclusion

FD has an important role in determining a nation's ecological health. On the one hand, FD supports in mobilizing credit, lending activities, leading to high energy consumption, which pushes emission-based manufacturing activity. This gives rise to negative externalities and a lower LCF (Annor et al., 2024; Javed et al., 2025). On the other hand, FD supports investment in green technologies, research, and development that leads to energy-efficient innovations, positively influencing the environment with a higher LCF (Raihan et al., 2023; Degirmenci et al., 2025). This contrast arises as FD is a narrow measure that focuses only on depth or volume, ignoring the distributional aspects, accessibility, and potential misallocation of resources.

This limitation served as a basis for FI. It provides easier, affordable, and more equitable access to credit, encouraging people to use and invest in green technologies. It aids in upscaling environmental quality and a high LCF, especially in the presence of strict environmental laws (Abir et al., 2024; Samour et al., 2024; Mehmood et al., 2024). On the contrary, FI also augments environmental stress by increased resource consumption, high emissions, and a low LCF, specifically in regions where environmental regulations are weak (Arshad & Parveen, 2024; Ridwan et al., 2024).

In Turkiye, the effect of FI on environmental sustainability was examined by Yurtkuran & Güeneysu (2023) by using ARDL, and the results report a decrease in LCF. Conversely, Kurniawati et al. (2025) did not find any significant correlation between FI and environmental sustainability. This lack of empirical consensus on whether FI enhances environmental sustainability or not integrating the framework of LCC hypothesis needs an in-depth investigation.

2.3 Literature Gap & Significance of the Study

Regardless of the growing focus of researchers on environmental sustainability, the literature still exhibits significant gaps. First, only a small number of few studies have employed LCF to examine the LCC hypothesis. Second, a scarce and inconclusive literature on the environmental impact of FI on LCF demands further analysis. Third, there is no comprehensive study that has analyzed the role of these important economic and demographic variables across the globe and in different income groups.

This study is designed to critically evaluate the effects of economic growth, PD, EC, natural resources, and FI on environmental sustainability through LCF. This study differs from the existing ones as it encompasses a comprehensive assessment of global and different income groups that have not been studied yet. Incorporating FI helps us assess if income group heterogeneity responds differently to the availability of financial services and, consequently, ecological stability. Additionally, a comprehensive data set from 1995 to 2021 is used by employing dynamic methods like Driscoll-Kraay standard errors approach and system GMM provide robust results.

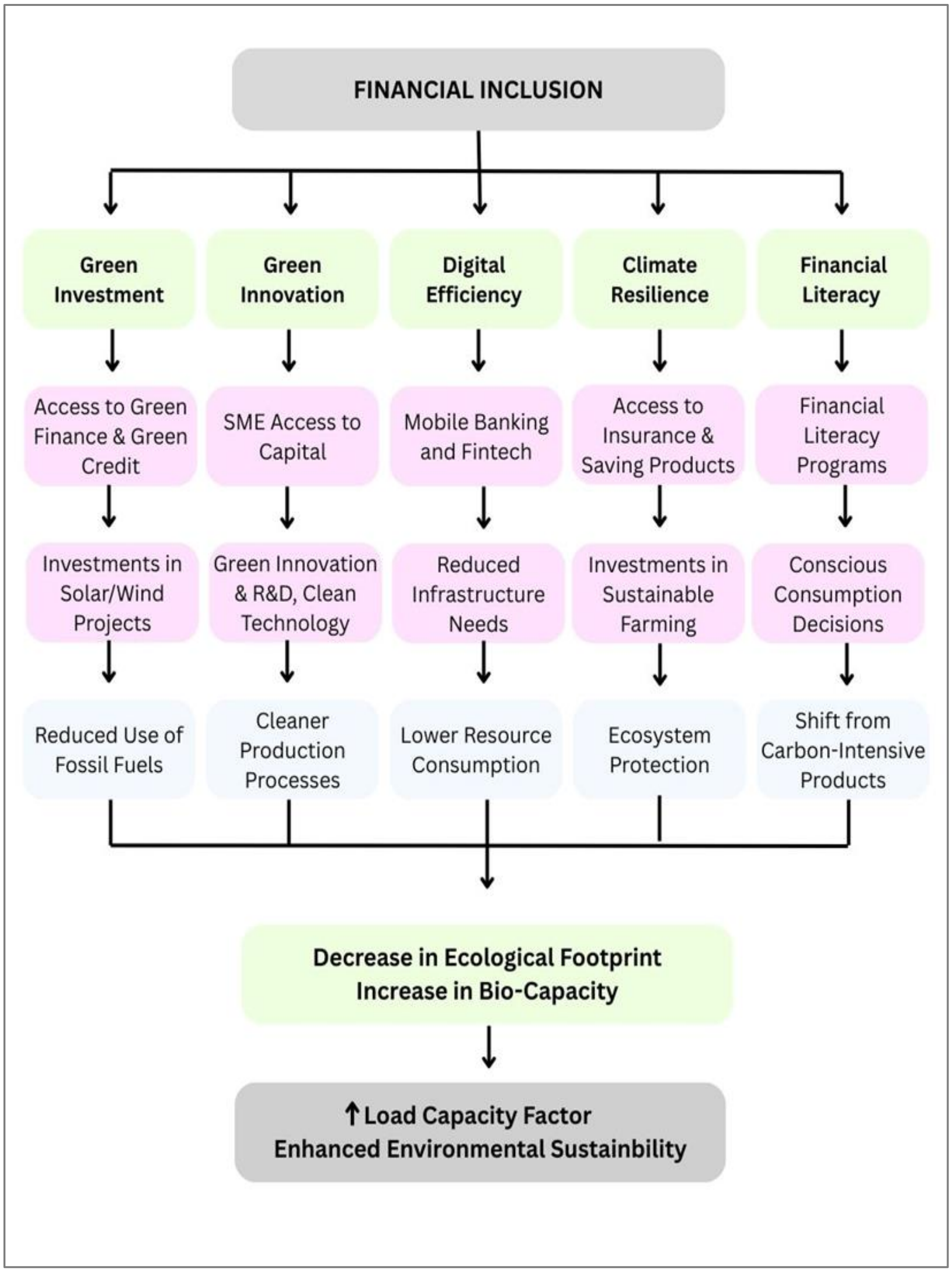

Figure 1: Financial Inclusion and Environmental Quality (Positive Impact)

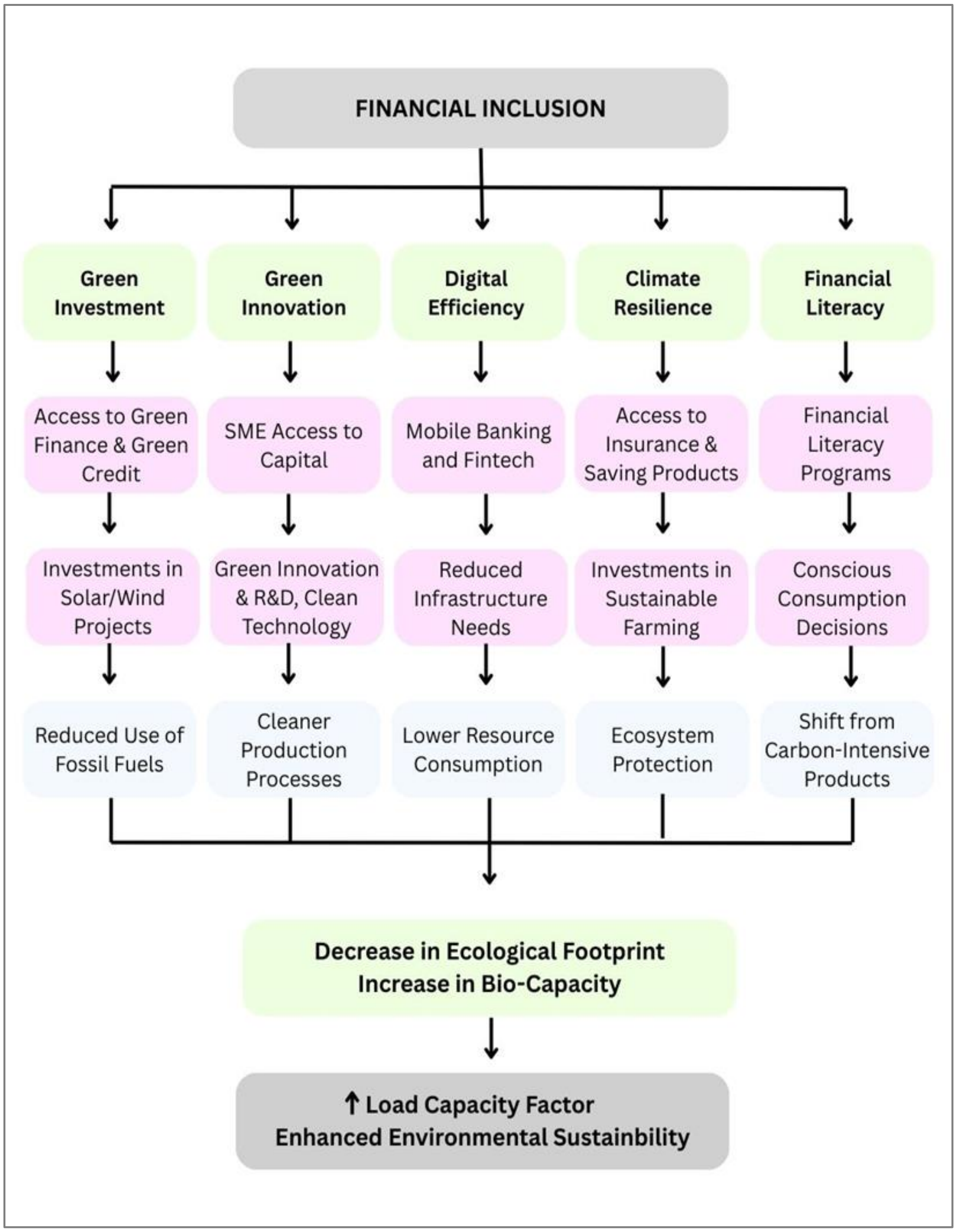

Figure 2: Financial Inclusion and Environmental Quality (Negative Impact)

3. Model, Data, and Empirical Methodology

3.1 Model and Data

The present research examines the LCF hypothesis globally and across income groups with a particular focus on the roles of NRR and FI in environmental quality. The empirical model is based on the model given by Erdogan (2024). The study of Erdogan (2024) only examined the impact of NRR, PD and EC on LCF while this study incorporates FI as important determinant of LCF. The panel data is used from 1995 to 2021. The empirical evidence is provided for a global panel and four income groups.

$$lnLCF_{it} = \gamma_0 + \gamma_1 lnGDP_{it} + \gamma_2 lnGDP_{it}^2 + \gamma_3 PD_{it} + \gamma_4 EC_{it} + \gamma_5 NRR_{it} + \gamma_6 FI_{it} + \varepsilon_{it} \quad (1)$$

Based on the research objective, the equation 1 is extend as equation 2:

$$lnLCF_{i,t} = \gamma_0 + \gamma_1 lnGDP_{i,t} + \gamma_2 lnGDP_{i,t}^2 + \gamma_3 PD_{i,t} + \gamma_4 EC_{i,t} + \gamma_5 NRR_{i,t} + \gamma_6 DC_{i,t} + \gamma_7 BB_{i,t} + \gamma_8 ATM_{i,t+}\varepsilon_{it} \quad (2)$$

where LCF, GDP, GDP^2, NRR, PD, EC and FI, DC, BB, and ATM indicates load capacity factor, economic growth, population density, energy consumption, natural resource rent, financial inclusion index, domestic credit to private sector by banks, commercial bank branches, and number of ATMs, respectively. ln, γ_{1-8} and ε_{it} indicate the log function, regression coefficients, and residuals, respectively.

As countries differ in terms of income levels and different income groups differ in terms of natural resources and FI (Table 2), their comparison is crucial. The LCF hypothesis is investigated for 161 countries across the world and across income groups, including high-income (56), high-middle-income (42), low-middle-income (43), and low-income (20) economies over 1995-2021. The explanations of the data origin of the utilized indicators are reported in Table 1.

Table 1: Description of Variables

Variables	**Symbols**	**Definition of variable**	**Source**
Load capacity	LCF	“Biocapacity per capita /EF per capita”	[1]
GDP per capita	GDP	“GDP per capita is gross domestic product (constant 2015 US$)”	[2]
Population	PD	“Population density (people per sq. km of land area)”	[2]
Energy Consumption	EC	“Energy use (kg of oil equivalent) per $1,000 GDP (constant 2021 PPP)”	[2]
Natural resource rent	NRR	“Total natural resources rents (% of GDP)”	[2]
Financial Inclusion	FI Index	“Commercial bank branches (per 100,000 adults); Domestic credit to private sector by banks (% of GDP); Automated teller machines (ATMs) (per 100,000 adults).”	[3]

Data Sources: [1] Global Footprint Network https://www.footprintnetwork.org

[2] World Development Indicators https://databank.Worldbank.org [3] Authors’ own calculations

3.2 Empirical Methods

This data is collected by utilizing a panel setup. Because the frequency of countries (N) is greater than that of the time period (T), the panel techniques suitable for short panels are utilized. First, the second-generation static panel model is used when cross-section dependence (CD) is present in the model. Reporting Driscoll-Kraay standard errors is the best strategy to augment CD in the static panel model.

Driscoll-Kraay (1998) standard errors by using the fixed effects estimation method are also reported for the global panel and income groups. Driscoll Kraay (1998) is the second-generation static panel technique, suitable when N > T. If it is assumed that CD is created due to unobserved common factors, and error term captures their effect, and the errors are uncorrelated with independent regressors. Then, the standard fixed and random effects models are consistent though not efficient. Besides, the estimated standard errors are not unbiased.

In this case, a better choice is to correct standard errors by Driscoll and Kraay (1998). It produces standard errors for the coefficient estimated by fixed effect, OLS, and GLS regressions. We have used the fixed effects method, reporting Driscoll-Kraay standard errors. The error structure is considered autocorrelated up to some lags and robust to heteroskedastic disturbances and CD. We implement Driscoll-Kraay standard errors in two steps. First, all model variables $Z_{it} \in \{Y_{it}, X_{it}\}$ are within transformed as follows:

$$\bar{Z}_{it} = Z_{it} - \bar{Z}_{l} + \bar{\bar{Z}}$$

Where,

$$Z_i = T_i^{-1} \sum\nolimits_{t=t_{i1}}^{T_1} . \ and$$

$$\bar{\bar{Z}} = (\Sigma\, T_i) - 1\Sigma_i \Sigma_t Z_{it}$$

Given that the Fixed Effects estimator of the within-estimator as below

$$\tilde{Y}_{it} = \tilde{x}'\theta + \tilde{\varepsilon}_{it}$$

The estimates are transformed in the second step by fixed effects estimation with Driscoll-Kraay standard errors. Before estimating CD corrected standard errors, we have checked the presence of CD in individual variables.

A variety of tests are available to check CD. Here, we have applied test of CD that is suitable for a case of N > T proposed by Pesaran (2004). Pesaran CD test is as follows:

$$Pesaran\ CD_1 = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=I+1}^{N} \hat{\rho}\, ij \right)$$

Where $\hat{\rho}ij$ is the pairwise correlation of residuals of the sample estimate.

Although Driscoll-Kraay is a second-generation static panel technique and does not handle the problem of endogeneity, it is more common in samples having more cross-sections than time. In the second step, the study also utilizes system GMM. The selection among different dynamic panel data techniques depends on the number of cross sections (N) versus the number of time periods (T). We proceed with one step system GMM estimates reported in Table 4.

System GMM uses an equations approach (level equation and first difference equation) with additional moment conditions (additional instruments), and additional instruments yield more efficient parameter estimates. The two-equation approach with additional instruments improves efficiency (Greene, 2002, p.308).

The generalized panel autoregressive model is:

$$Y_{it} = \alpha Y_{it-1} + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \omega_i + \varepsilon_{it}$$

The level equation and first difference equations for model 1 are constructed as:

The level equation is a standard regression in levels but uses lagged differences as instruments to address endogeneity (Blundell and Bond, 1998).

$$LCF_{it} = \beta_0 + \alpha LCF_{i,t-1} + \beta_1 GDP_{i,t} + \beta_2 GDP_{i,t}^2 + \beta_3 EC_{i,t} + \beta_4 PD_{i,t} + \beta_5 NRR_{i,t} + \beta_6 FI_{i,t} \ (1.1)$$

The instruments used in level equation (1.1) are:

$$\Delta LCF_{i,t-2} \Delta GDP_{i,t-1} \Delta GDP_{i,t-1}^2 \Delta EC_{i,t-1} \Delta PD_{i,t-1} \Delta NRR_{i,t-1} \Delta FI_{i,t-1}$$

The first difference equation is a standard first-difference regression but uses lagged levels as instruments (Blundel and Bond, 1998).

$$\Delta LCF_{i,t} = \beta_0 + \alpha\Delta LCF_{i,t-1} + \beta_1\Delta GDP_{i,t} + \beta_2\Delta GDP_{i,t}^2 + \beta_3\Delta EC_{i,t} + \beta_4\Delta PD_{i,t} + \beta_5\Delta NRR_{i,t} + \beta_6\Delta FI_{i,t} \ (1.2)$$

The instruments used in the difference equation (1.2) are:

$$LCF_{i,t-2}GDP_{i,t-1}GDP_{i,t-1}^2\, EC_{i,t-1}PD_{i,t-1}NRR_{i,t-1}FI_{i,t-1}$$

System GMM is robust to residual correlation and heteroscedasticity. Serial correlation is tested on AR (2). Internal instruments (lagged differences and lagged levels) are suitable (Roodman, 2009). Similarly, the level and first difference equations for model 2 are extended to see the individual impact of FI indicators on LCF as:

$$LCF_{it} = \beta_0 + \alpha LCF_{i,t-1} + \beta_1 GDP_{i,t} + \beta_2 GDP_{i,t}^2 + \beta_3 EC_{i,t} + \beta_4 PD_{i,t} + \beta_5 NRR_{i,t} + \beta_6 DC_{i,t} + \beta_7 BB_{i,t} + \beta_8 ATM_{it} \ (2.1)$$

The level equation (2.1) is estimated using following instruments:

$$\Delta LCF_{i,t-2}\Delta GDP_{i,t-1}\Delta GDP_{i,t-1}^2\Delta EC_{i,t-1}\Delta PD_{i,t-1}\Delta NRR_{i,t-1}\Delta DC_{i,t-1}\ \Delta BB_{i,t-1}\Delta ATM_{i,t-1}$$

and,

$$\Delta LCF_{i,t} = \beta_0 + \alpha\Delta LCF_{i,t-1} + \beta_1\Delta GDP_{i,t} + \beta_2\Delta GDP_{i,t}^2 + \beta_3\Delta EC_{i,t} + \beta_4\Delta PD_{i,t} + \beta_5\Delta NRR_{i,t} + \beta_6\Delta DC_{i,t} + \beta_7\Delta BB_{i,t} + \beta_8\Delta ATM_{it} \ (2.2)$$

The first difference equation (2.2) is estimated using following instruments:

$$LCF_{i,t-2}GDP_{i,t-1}GDP_{i,t-1}^2\, EC_{i,t-1}PD_{i,t-1}NRR_{i,t-1}\, DC_{i,t-1}\, BB_{i,t-1}ATM_{i,t-1}$$

The GMM estimator is found by minimizing a quadratic form of the sample moment conditions:

$$\hat{\theta}_{gmm} = \arg min\, h(\theta)'\hat{\Omega}^{-1}h(\theta)$$

The moment conditions are derived from the orthogonality conditions between the instruments and the errors:

$$E[Z'\epsilon] = 0$$

Where Z is the matrix of instruments and ϵ is a vector of errors.

In a system GMM context, the moment conditions are combined from both the level and difference equations. The system GMM estimator combines these moment conditions into a single system to achieve more efficient and less biased estimates compared to the difference GMM. The empirical results are obtained using Stata 17.

4. Results and Discussion

The summary statistics of variables is reported in Table 2.

Table 2: Descriptive Statistics

Variables	Statistics	Global	HIC	UMIC	LMIC	LIC
LCF	Mean	1.3206	1.184	1.170	1.229	1.989
	Std. dev	2.6722	3.593	2.139	1.383	2.634
	Minimum	0.0058	0.0058	0.1468	0.0847	0.2801
	Maximum	34.253	34.253	24.2465	9.292	17.374
GDP per capita	Mean	12210.91	29963.5	5273.6	1865.4	659.9
	Std. dev	17532.5	20179.2	2634.1	1256.9	371.35
	Minimum	211.2656	3312.65	932.36	211.27	212.09
	Maximum	112417.9	112417.9	14040.6	8955.5	2356.2
Energy Consumption	Mean	106.2789	101.254	105.645	101.69	145.68
	Std. dev	73.20618	57.632	54.481	68.637	143.32
	Minimum	3.937672	23.0050	30.673	3.938	5.346
	Maximum	1124.29	426.79	429.62	572.73	1124.29
Population	Mean	174.23	296.557	97.337	134.89	95.45
	Std. dev	568.23	937.91	110.27	198.07	111.43
	Minimum	1.437	2.3437	1.438	1.946	5.374
	Maximum	7965.8	7965.8	634.1	1287.9	541.4
Natural Resources	Mean	7.430	5.39	8.17	6.54	12.16
	Std. dev	10.98	10.88	12.28	8.38	8.43
	Minimum	0.0002	0.0002	0.0023	0.0011	0.306
	Maximum	88.592	59.069	66.05	79.43	41.41
Financial Inclusion	Mean	1.22	1.67	1.21	0.92	0.65
	Std. dev	0.81	0.97	0.62	0.51	0.43
	Minimum	0.17	0.3	0.19	0.20	0.17
	Maximum	7.24	7.24	4.76	4.76	1.22
Domestic Credit	Mean	44.40	76.36	39.13	27.95	10.27
	Std. dev	38.92	41.47	29.69	22.61	6.62
	Minimum	0.38	4.66	1.15	1.36	0.38
	Maximum	254.6	254.6	179.1	124.3	34.7
Bank Branches	Mean	16.36	27.30	16.29	9.11	2.61
	Std. dev	15.63	17.60	12.04	9.03	1.57
	Minimum	0.040	2.15	0.382	0.479	0.040
	Maximum	110.86	110.86	71.92	71.95	6.95
ATMs	Mean	43.61026	81.36	39.89	12.29	3.032
	Std. dev	48.02134	51.22	26.71	12.71	2.80
	Minimum	0.00026	4.097	0.295	0.011	0.00026
	Maximum	403.2105	403.39	128.56	74.04	13.84

Notes: High-Income Countries (HIC); Upper-Middle-Income Countries (UMIC); Lower-Middle-Income Countries (LMIC); Low-Income Countries (LIC)

Table 2 reports that the highest mean value of LCF is attributed to low-income countries while the lowest values is associated with upper-middle-income countries. Similarly, the highest mean value of NRR is linked to low-income countries. In the case of FI the highest mean value is linked to high-income countries while the lowest mean value is ascribed to low-income countries, respectively, indicating that financial accessibility on average is high in high-income countries as compared to other income groups. Table 3 shows the findings of the CD test. The test results suggest the presence of CD.

Table 3: Cross-sectional Dependence of the Variables

	Pesaran (2004)				
	Global	**HIC**	**UMIC**	**LMIC**	**LIC**
LCF	143.85^{***}	40.48^{***}	41.49^{***}	86.28^{***}	39.06^{***}
GDP per capita	324.02^{***}	113.07^{***}	100.56^{***}	112.46^{***}	13.78^{***}
Population	63.31^{***}	67.30^{***}	55.71^{***}	152.14^{***}	69.08^{***}
Energy consumption	26.87^{***}	97.19^{***}	24.15^{***}	59.93^{***}	40.98^{***}
Natural resources	123.76^{***}	234.87^{***}	111.75^{***}	28.68^{***}	13.46^{***}
Financial inclusion	38.81^{***}	61.76^{***}	14.34^{***}	64.01^{***}	67.70^{***}
Domestic credit	160.65^{***}	34.50^{***}	53.76^{***}	51.73^{***}	39.65^{***}
Bank branches	42.74^{***}	81.44^{***}	25.33^{***}	38.79^{***}	37.13^{***}
ATMs	223.50^{***}	39.52^{***}	88.63^{***}	101.52^{***}	49.36^{***}

Note: ***p<0.01

Due to the presence of CD in variables, the study proceeds with second-generation static Driscoll-Kraay fixed effects estimates suitable for short panel data, and the results are reported in Table 4.

Table 4: Driscoll- Kraay FE Estimates of Model 1

Variables	**Global**	**HIC**	**UMIC**	**LMIC**	**LIC**
GDP per capita	-0.7850*** (0.0792)	-0.86244*** (0.225)	-0.9111*** (0.576)	0.5867*** (0.363)	-0.1128 (0.4024)
GDP Sq. per capita	0.6171** (0.1773)	0.3161*** 0.1710	0.28476 *** (0.242)	-0.0750*** (0.0252)	0.1323 (0.1064)
Population	-0.0003* (0.0047)	-0.0002** (0.00001)	-0.008*** (0.002)	0.0022*** (0.0004)	0.00048 (0.00019)
Energy consumption	-0.00281*** (0.00043)	-0.0089*** (0.00167)	-0.0052** (0.0002)	-0.0018*** (0.0003)	-0.0006*** (0.00038)
Natural resource	-0.0256*** (0.0101)	-0.0026*** (0.0075)	-0.0264*** (0.0102)	-0.0006*** (0.0053)	0.00264 (0.0018)
Financial inclusion	0.0533 (0.0354)	0.2971*** (0.0696)	0.0742*** (0.0456)	-0.0504*** (0.0706)	-0.1291 (0.0408)
Constant	7.879*** (0.7188)	2.240*** (0.6580)	10.2363 (0.0875)	1.4312*** (0.9698)	8.167 (0.6637)
Observations	3696	1387	969	974	343

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

The results in Table 4 show the existence of the LCF hypothesis in the global panel, high-income and upper middle-income group, while we found an inverted U-shaped relationship for the lower middle-income group, and it is not valid for the low-income group. For the low-income group, we have found an insignificant relationship between LCF and all selected variables. It can be due to the smaller cross-sectional dimensions than the time. As load capacity incorporates both demand-side and supply-side ecological indicators, it is considered a more comprehensive indicator of ecological sustainability.

The U-shaped relationship found in the global, high, and upper middle-income panel indicates that at low levels of economic development, LCF tends to decrease as GDP increases, thus indicating environmental deterioration due to a focus on economic growth. Until income per capita reached to specific threshold, further increase in GDP led to an increase in LCF, indicating improvement in environmental performance by promoting eco-friendly activities, increase awareness for clean environment, and technological advancement (Erdogan et al., 2024). The findings are aligned with the empirical results of Hakkak et al. (2023).

Energy consumption has adverse impact on LCF across all panels except the low-income group, having an insignificant relationship. It is considered that most of the environmental problems are caused due to increase in energy use, especially fossil fuel-based energy sources. All forms of traditional energy have negative environmental impact in the form of deterioration in the sustainability of life on land and below water, and an increase in solid waste due to increasing input use for fossil fuel-based industrialization and a rise in greenhouse gas emissions levels. It can be argued that an increase in traditional energy sources can raise the human impact on ecology (ecological footprint) in sample countries, while natural regeneration rate (biological capacity) may not match with the increasing demand from ecology that led to decrease in LCF, and result in environmental degradation. The empirical findings are consistent with those of Akhayere et al. (2023).

PD has a decreasing impact on the LCF. It can be suggested that due to increasing provision of education, jobs, health, and developed infrastructure opportunities (Sapkota & Bastola, 2017) in urban areas, migrants generally concentrate in the industrial urban areas. Rahman and Alam (2021) also noted that a rise in the number of individuals living in a particular area leads to an increase in consumption and production activities there. Therefore, negative externalities are generated due to rising PD, such as waste management issues, inadequate sanitation services, higher air pollution, rising energy demand, increasing CO2 levels due to increase in private car use, and a rise in ecological footprint due to increase in urban infrastructure investment at all levels, and so forth (see, for details, Majeed & Tauqir, 2020). While biological regeneration capacity cannot be sustained due to the urban population, and LCF decreases. Thus, the anthropogenic effect of economic activities is concentrated in a particular area, causing depletion of resources that lead to decrease in environmental quality due to reduction in biocapacity. This finding is supported by Sapkota and Bastola (2017) and Rahman and Alam (2021).

Natural resources like fossil fuel resources are used as the main input in energy supply, and have historically become an integral part of economic development by promoting economic activities at an unprecedented rate since the industrial revolution (Pata et al., 2023). The extensive use of natural resources not only causes their depletion but also degrades the environment. The empirical literature also indicates that non-renewable resource extraction, indicating extensive use of non-renewable natural capital, has negative ecological consequences (Bashir et al., 2024), and natural resource extraction is known to drive economic growth; it can also lead to environmental degradation (Duan & Liu, 2023; Caglar et al., 2024).

Downey et al. (2010) emphasized that although natural resources served as basic consumption and production inputs can lead to environmental degradation due to the extraction of rare earth minerals, generating up to 2000 tons of solid waste. The United Nations Environment Program (2023) emphasized that increased natural resource and minerals demand has enhanced environmental damage and threats to human life in some SSA regions. These findings are aligned with Adebayo et al. (2022) and Li et al. (2023).

FI means an increase in financial accessibility. The expansion of the financial sector due to an increase in inclusiveness makes new credit facilities, provides a variety of financial products, and attracts new customers that not only increase the income stream but also the whole economy (Koomson & Danquah, 2021; Javeid et al., 2025). The relationship between FI and LCF depends on which measures of FI are used. This study utilizes three indicators of FI: commercial bank branches (per 100,000 adults), domestic credit to private sector by banks (% of GDP), and automated teller machines (ATMs) (per 100,000 adults), following Gul et al. (2018).

The empirical literature has found mixed findings of the relationship between FI and LCF, which is sensitive to the indicators used as a proxy for FI. The variable of FI is insignificant in the global panel. While a 1% increase in FI increases LCF in the high and upper middle-income panels by 0.2972 and 0.0742%, respectively. Empirical literature also investigates that if FI means to enable green investments and environmentally conscious entrepreneurship, then the impact is positive (Trabelsi & Fhima, 2024), and if FI facilitates increased consumption and pollution, then the impact is environmental degradation (Guan & Zhao, 2024).

Access to financial services can promote ecological sustainability. For instance, it can empower entrepreneurs and individuals to invest in environmentally friendly technologies and businesses. The results are supported by (Samour et al., 2024), who found the positive impact of FI on LCF in European countries using the number of ATM per 10000 individuals as an indicator of FI. Qing et al. (2024) also report that FI improves LCF. On the contrary, a 1% increase in FI decreases LCF in the lower middle-income and low-income groups by 0.0504 and 0.1291%, respectively. FI can decrease the LCF, potentially by increasing consumption and pollution. Yurtkuran and Güneysu (2023) have found that the LCF is valid in Türkiye, and FI reduces LCF in the long run. Kurniavati et al. (2025) found that the LCC hypothesis was not present in the ASEAN-5 region. While Yurtkuran & Güneysu (2026) also found the validity of LCF in Türkiye and an increase in financial technologies that capture accessibility and efficiency of financial services reduces pollution in Türkiye. Financial technologies improve environmental quality by increasing access to green finance and enabling more efficient utilization of resources (Ahmad et al., 2024).

Literature also reports that negative impacts of FI that include higher consumption, resource exploitation, and industrial expansion exacerbate environmental degradation (Hussain et al., 2021; Anu et al., 2023; Liu et al., 2023). Pata et al. (2025) investigated the existence of a U-shaped curve between GDP and LCF, validated the LCF hypothesis, also found that enhancing fintech and supporting RE development leads to ecological well-being. The study also analyzed the individual impact of FI indicators on LCF across the global panel and all income groups, and the results are reported in Table 5.

Table 5: Driscoll- Kraay FE Estimates of Model 2

Variables	Global	HIC	UMIC	LMIC	LIC
GDP per capita	-0.272*** (0.133)	-0.1371*** (0.1193)	-0.061*** (0.126)	0.0194*** (0.1526)	0.7892 (0.4818)
GDP Sq. per capita	0.055*** (0.009)	0.077 *** (0.0571)	0.0221*** (0.069)	-0.0431*** (0.0107)	-0.1033 (0.1148)
Population	-0.00008*** (0.00004)	-0.00016*** (0.00004)	-0.0002 (0.0008)	-0.0002*** (0.00029)	0.0016 (0.0041)
Energy consumption	-0.0019*** (0.00026)	-0.0043*** (0.0007)	-0.0026*** (0.00043)	-0.0019*** (0.0004)	-0.0004** (0.0002)
Natural resource	-0.0051*** (0.0015)	-0.01196** (0.00403)	0.00125 (0.0017)	-0.0047* (0.00156)	-0.0014** (0.0006)
Domestic credit	-0.0011*** (0.0004)	-0.0010 (0.0005)	-0.0025*** (0.0009)	-0.0003*** (0.00053)	-0.0038 (0.0020)
Bank Branches	-0.0044*** (0.00078)	-0.0037*** (0.0008)	-0.0025*** (0.0009)	-0.00204** (0.00096)	0.0087 (0.010)
ATMs	0.00067*** (0.00012)	0.00069*** (0.0002)	0.0007*** (0.0002)	-0.0036*** (0.00075)	-0.0198*** (0.0031)
Constant	6.494*** (0.496)	4.1026 (0.4829)	1.1390 (0.6745)	5.042 (0.560)	4.702 (0.798)
Observations	2435	914	641	640	223

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 5 shows that DC and BB tend to reduce LCF across all panels, while proliferation of ATMs improves LCF in global, high-income, and upper middle-income economies, consistent with Samour et al. (2024), who found the positive impact of an increase in the number of ATM per 10000 individuals on LCF in European countries. On the contrary, an increase in the number of ATM per 10000 individuals reduces LCF in lower-middle-income and low-income economies, consistent with Yurtkuran and Güneysu (2023). Moreover, Tables 6 and 7 report system GMM estimates by using the FI index and individual components of FI, respectively, to check the robustness of our findings.

Table 6: GMM Estimates of Model 1

Variables	Global	HIC	UMIC	LMIC	LIC
L.LCF	0.8521*** (0.0579)	0.5325*** (0.0330)	0.7330*** (0.3938)	0.8690*** (0.0687)	0.3870*** (0.3921)
GDP per capita	-0.2165*** (0.0173)	-0.5169*** (0.8694)	-0.0314*** (0.0083)	0.3216*** (0.2172)	0.3967 (0.2827)
GDP Sq. per capita	0.5478*** (0.6220)	0.0182*** (0.0843)	0.4497*** (0.0172)	-0.0265*** (0.0168)	-0.547 (0.4923)
Population	-0.0034 (0.0051)	-0.0009*** (0.00007)	-0.0077 *** (0.00175)	-0.0002*** (0.00011)	0.00851 (0.0073)
Energy consumption	-0.0034*** (0.00028)	-0.0307*** (0.0025)	-0.00814** (0.0018)	-0.0004*** (0.0002)	0.0112 (0.0082)
Natural resource	-0.0294 (0.0024)	-0.1066*** 0.0089)	-0.0193*** (0.0042)	-0.0042*** (0.0021)	0.3774 (0.2807)
Financial inclusion	0.0029* (0.0119)	0.4778*** (0.0443)	0.1270*** (0.0313)	-0.0406*** (0.0171)	-0.3052 (0.0059)
Sargan	0.598	0.561	0.358	0.625	0.321
AR (1)	0.000	0.019	0.023	0.000	0.034
AR (2)	0.315	0.642	0.095	0.623	0.348

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 7: GMM Estimates of Model 2

Variables	Global	HIC	UMIC	LMIC	LIC
L.LCF	0.6266*** (0.0475)	0.75009*** (0.0381)	0.5295*** (0.1472)	0.6882*** (0.1045)	0.0374 (0.0384)
GDP per capita	-0.1732*** (0.0271)	-0.1098*** (0.49093)	-0.352 (0.3661)	0.8223*** (0.6305)	0.252 (0.2652)
GDP Sq. per capita	0.0061*** (0.0012)	0.1474*** (0.0234)	0.0256 (0.0215)	-0.1354*** (0.0464)	-0.0157 (0.0193)
Population	-0.00024*** (0.00003)	-0.00015*** (0.000023)	-0.00208*** (0.00058)	-0.0004*** (0.00013)	0.00018 (0.00013)
Energy consumption	-0.00098*** (0.00013)	-0.00034*** (0.00008)	-0.0024*** (0.0006)	-0.00118*** (0.00039)	-0.0006 (0.00069)
Natural resources	-0.00176*** (0.00022)	-0.00759*** (0.00104)	-0.00401*** (0.00153)	-0.0104*** (0.0033)	-0.0005 (0.0014)
Domestic Credit	-0.0018*** (0.00018)	-0.00058*** (0.0009)	0.0018*** (0.00057)	-0.00134*** (0.0005)	0.0016 (0.0014)
Bank Branches	-0.00220*** (0.00031)	-0.00526*** (0.0008)	-0.0037*** (0.00092)	-0.0029*** (0.00095)	-0.004 (0.0076)
ATMs	0.00073*** (0.00015)	0.0001* (0.0007)	0.00095*** (0.00041)	-0.0078*** (0.0025)	0.0004 (0.0036)
Sargan	0.531	0.913	0.053	0.215	0.420
AR (1)	0.000	0.000	0.092	0.000	0.000
AR (2)	0.849	0.098	0.604	0.320	0.429

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

The GMM estimates in Table 6 are consistent with Table 4, except that the coefficient of FI in the global panel is improved and has a positive impact on LCF, which also validates the robustness of our findings. Moreover, Sargan test examines the overall validity of the instrument, and the null hypothesis that all over-identifying restrictions are valid is accepted. AR (1) probability indicates the correlation of the lagged dependent variable, and AR (2) probability shows that the null hypothesis of no second-order serial correlation is accepted in all panels, indicating that moment conditions are correctly specified. Tables 8 and 9 show the sensitivity of our findings by including renewable energy consumption as the proxy variable.

Table 8: Sensitivity of Driscol-Kraay Estimates of Model 1

Variables	**Global**	**HIC**	**UMIC**	**LMIC**	**LIC**
GDP per capita	-0.2306 (0.1708)	-0.3928*** (0.0029)	-0.0458*** (0.7543)	0.69393*** (0.4417)	-0.368 (0.901)
GDP Sq. per capita	0.0035 (0.0110)	0.1561*** (0.0486)	0.3095*** (0.0427)	-0.2047*** (0.0294)	0.2652 (0.1410)
Population	-0.00016*** (0.00003)	-0.0018*** (0.0005)	-0.0037*** (0.00014)	-0.0015*** (0.0009)	-0.0037 (0.0009)
Energy consumption	-0.00083*** (0.00018)	-0.0005*** (0.00041)	-0.0016*** (0.00061)	-0.0031*** (0.00035)	-0.0004* (0.0001)
Natural resource	0.0040 (0.0026)	-0.0056*** (0.0028)	-0.0058*** (0.0008)	-0.0325*** (0.0018)	0.0029 (0.0017)
Financial inclusion	0.00540 (0.0079)	0.0787*** (0.0111)	0.0946*** (0.0130)	-0.32044*** (0.0459)	-0.1215* (0.039)
Renewable energy	0.0124*** (0.0006)	0.0414*** (0.0010)	0.02392*** (0.00053)	0.0067*** (0.0009)	0.0046 (0.0021)
Constant	1.3925*** (0.6578)	16.8751*** (0.2279)	20.076*** (3.3570)	9.2765*** (1.6947)	7.1326 0.5447
Observations	3696	1387	969	974	343

Standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1

Table 9: Sensitivity of Driscol-Kraay Estimates of Model 2

Variables	Global	HIC	UMIC	LMIC	LIC
GDP per capita	-0.6215*** (0.0597)	-0.5362*** (0.0577)	-0.1413*** (0.2524)	0.889*** (0.747)	-0.999 (0.588)
GDP Sq. per capita	0.0907*** (0.0035)	0.3541*** (0.0524)	0.3689*** (0.0718)	-0.4296*** (0.0508)	0.1182 (0.1228)
Population	-0.0005*** (0.0003)	-0.0004*** (0.0034)	-0.0030*** (0.0004)	-0.001*** (0.0001)	0.0018 (0.004)
Energy consumption	-0.0018*** (0.00014)	-0.0015*** (0.0005)	-0.0012 (0.001)	-0.0039*** (0.0004)	-0.0046 (0.0003)
Natural resource	-0.0041*** (0.0009)	-0.0099*** (0.0021)	-0.0041*** (0.0015)	-0.0380*** (0.0025)	0.0013 (0.0006)
Domestic credit	-0.0033*** (0.0002)	-0.0005* (0.00029)	-0.0034*** (0.0085)	-0.0027* (0.0009)	-0.0023 (0.0016)
Bank branches	-0.0008*** (0.0008)	-0.00752*** (0.0079)	0.0043*** (0.0008)	0.0176*** (0.0031)	0.0054 (0.0098)
ATMs	0.00264*** (0.0005)	0.00203*** (0.00014)	0.0042*** (0.0005)	0.0272*** (0.0067)	-0.0198*** (0.0032)
Renewable energy	0.0206*** (0.0005)	0.0407*** (0.0018)	0.0249*** (0.0005)	0.0098*** (0.0017)	0.0046*** (0.0013)
Constant	7.9261*** (0.2923)	38.398*** (5.4188)	24.908*** (5.4991)	20.894 *** (2.9112)	1.797 (0.198)
Observations	2435	914	641	640	223

Standard errors in parentheses ***$p<0.01$, **$p<0.05$, *$p<0.1$

Tables 8 and 9 show that an increase in RE consumption improves LCF across all panels, while the relationship between FI, NRR, and LCF in Table 8 and the relationship between DC, BB, ATMs, NRR, and LCF in Table 9 is unaffected (as in Tables 4 and 5) due to the inclusion of RE in models 1 and 2.

5. Conclusion

Environmental sustainability is one of the most pressing challenges in today's time, with growing evidence of climate change, biodiversity loss, and environmental degradation weakening the planet's capacity to support future generations. The past literature has employed environmental indicators like CO2 and GHG emissions to explain the connection between economic expansion and environmental disruption. These indicators represent demand side of the environment. The findings based on these indicators are limited in their scope. This study addresses this critical gap by utilizing LCF, which captures both supply side (bio-capacity) as well as the demand side (ecological footprint) of the ecology. This study investigates the validity of the LCF hypothesis across 161 countries from 1995 to 2021.

The empirical analysis, in this study, includes Driscoll-Kraay standard errors and system GMM that yield significant results to contribute to the environmental literature. First of all, the study provides substantial evidence to support the LCF hypothesis globally and in high-income and upper-middle-income economies as it reveals a U-shaped relationship between GDP growth and environmental sustainability, consistent with prior studies (Fang et al., 2024; Jahanger et al., 2023). The results suggest that at first, LCF declines as GDP increases due to the environmental degradation that is driven by resource-intensive activities. However, after a certain income threshold, LCF improves with economic growth, signifying adoption of cleaner technologies, enhanced regulations, and adoption of cleaner technologies. However, in line with previous studies (Dinda, 2004; Armeanu et al., 2018), this study also identifies an inverted U-shaped relationship between LCF and GDP for lower-middle-income countries and an insignificant relationship for low-income countries, which reflects limited institutional capacity.

Furthermore, the study reveals a negative impact of NRR on LCF for all income regions except low-income countries. This finding emphasizes the cost of extractive industries, due to which the EF increases, and the bio-capacity of the planet depletes. This detrimental impact of resource exploitation is also referred to as “resource curse”, without proper management, resource abundance fails to promote environmental sustainability (Duan & Liu, 2023). EC is yet another factor that exhibits a negative relationship with LCF for global, high-income, upper-middle, as well as lower-middle-income countries, reflecting the dominance of fossil fuel-based systems that increase pressure on the environment through emissions and externalities. Similarly, PD exhibits a negative impact on LCF, and the impact is more prominent in high-income panels. This relationship shows the human-induced environmental pressure in urban areas. The increase in population density in urban areas increases resource consumption which may strain waste management and elevate pollution in urban settings.

The findings of this study provide important insights for the contextual relationship between FI and environmental sustainability. The results show mixed effects, both positive and negative. In line with recent studies (Qing et al., 2024; Mazhar et al., 2025; Samour et al., 2024), in high-income as well as upper-middle-income countries, FI has a positive impact on LCF, whereas in lower-middle-income countries, the impact is negative. These results suggest that income levels, regulatory framework, institutional quality, and infrastructure of financial systems can mediate the impact of FI on LCF. In developed countries, for instance, robust environmental regulations, high institutional quality, and green innovation facilitate clean technologies and sustainable entrepreneurship. However, in least developed economies, the governance and environmental regulations are weak, and therefore, FI accelerates environmental degradation due to investments in polluting industries and high consumption of carbon-intensive goods, resonating with past studies of (Anu et al., 2023; Liu et al., 2023).

To provide additional granularity to these findings, the study does a disaggregated analysis of FI. DC and BB have a negative impact on LCF, reflecting financing of resource-intensive activities in the economies and an increase in the ecological footprint. In contrast, ATMs have a positive impact on LCF, suggesting benefits from digital financial structures. However, in lower-middle and lower-income countries, the ATMs have a negative impact due to the increased consumption and infrastructure spending. Finally, the study employs system GMM and sensitivity analysis for robustness checks. It incorporates RE consumption to strengthen results.

5.1 Theoretical Implications

This study theoretically contributes to ecological modernization theory, EF literature and EKC framework in several ways. First the results indicate that income and LCF have a U-shaped relationship in global, high income and upper middle-income countries, which is consistent with EKC mechanism, where environmental sustainability is measured in LCF rather than traditional indicators like CO2. The results indicate that after certain income levels, economic growth can have a same direction as improvements in ecological balance, but only when technology is upgraded and environmental regulations are strong. Secondly, the negative impact of natural resource dependence on LCF emphasizes the need for cleaner technologies to mitigate the environmental degradation. Therefore, growth erodes LCF in regions where technologies are not modern rather than improving. Thirdly, the utilization of LCF hypothesis, in this study, extends the debates of EKC into broader ecological framework. The results indicate that simply improving CO2 indicators does not mean higher load capacity if resource consumption patterns are unsustainable. Finally, heterogeneous impacts of FI in different regions and income groups suggest that FI can either improve or contradict LCF, which highlights the importance of EF within FI strategies.

5.2 Policy Implications

The findings of this study also have several policy implications. First of all, the evidence suggest that policy makers need to be actively work towards the implementation of cleaner technologies and less-resource intensive trajectories instead of simply focusing on economic growth. This will allow economies to move towards the upper segment of the U curve. The requirements include promotion of green technologies, strict environmental regulations and the use of renewable energy sources. Secondly, the negative impact of NRR suggests the urgency to move towards implementation of environmental standards, strengthening governance of resource extraction and transparency in management. Third, the negative impacts of EC on LCF suggest the need for energy transitions which includes fossil fuel subsidies reduction, improving energy efficiency in transport, industry as well as households. Fourth, the detrimental impact of PD on LCF, call for investment in green infrastructure, urban planning and public transport to mitigate the negative impacts of PD, particularly in high income regions. Finally, the dual impact of FI suggest that policy makers should promote and prioritize environmentally clean and responsible projects and discourage polluting activities linked to financial products.

5.3 Limitations and Future Study Directions

This study has several imitations that open the doors for future research possibilities. First, future studies can focus on heterogeneity across regions and different sectors rather than relying on country-level data. By employing sectoral or sub national data, future studies can understand the impact of FI, EC and resource use at a granular level. Secondly, due to data constraints, this study could not include other important mediating variables such as institutional quality, environmental regulation and green finance variables. Future studies can incorporate these variables to better understand the position of FI and its impacts on LCF. Third, theoretical analysis of this study is grounded in EKC and ecological modernization theory, while future research could integrate additional theories such as green finance theory to better understand the role of finance on sustainable development pathways.

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Availability of Data

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Declaration of AI Use

It is declared that no generative AI tools / LLMs were used in writing this manuscript. Only Grammarly was used for correcting the grammatical errors and for clarity of the writing.

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Appendix

Table A1: List of Abbreviations

Abbreviation	**Full Form**
ARDL	Augmented Autoregressive Distributed Lag
ATM	Automated Teller Machine
DC	Domestic Credit
EF	Ecological Footprint
EKC	Environmental Kuznets Curve
FI	Financial Inclusion
GMM	Generalized Method of Moments
LCC	Load Capacity Curve
LCF	Load Capacity Factor
WCED	World Commission on Environment and Development

Table A2: List of Countries

Afghanistan	Cabo Verde	Finland	Kenya	Netherlands	Spain
Albania	Cambodia	France	Korea Rep	New Zealand	Sri Lanka
Algeria	Cameroon	Gabon	Kuwait	Niger	Sweden
Angola	Canada	Gambia	Kyrgyz Rep	Nigeria	Switzerland
Antigua and Barbuda	Central African Republic	Georgia	Lao PDR	Norway	Syrian Arab Republic
Argentina	Chad	Germany	Latvia	Oman	Tajikistan
Armenia	Chile	Ghana	Lebanon	Pakistan	Tanzania
Australia	China	Greece	Lesotho	Panama	Thailand
Austria	Colombia	Grenada	Liberia	Papua New Guinea	Timor-Leste
Azerbaijan	Comoros	Guatemala	Libya	Paraguay	Togo
Bahamas	Congo, Dem. Rep.	Guinea	Lithuania	Peru	Tonga
Bahrain	Costa Rica	Guinea-Bissau	Luxembourg	Philippines	Trinidad and Tobago
Bangladesh	Cote d'Ivoire	Guyana	Madagascar	Poland	Tunisia
Barbados	Croatia	Haiti	Malawi	Portugal	Türkiye
Belarus	Cyprus	Honduras	Malaysia	Qatar	Uganda
Belgium	Czechia	Hungary	Mali	Romania	Ukraine
Belize	Denmark	India	Malta	Russian Federation	United Arab Emirates
Benin	Djibouti	Indonesia	Mauritania	Rwanda	United Kingdom
Bhutan	Dominica	Iran, Islamic Rep.	Mauritius	Samoa	United States
Bolivia	Dominican Republic	Iraq	Mexico	Saudi Arabia	Uruguay
Bosnia and Herzegovina	Ecuador	Ireland	Moldova	Senegal	Uzbekistan
Botswana	Egypt, Arab Rep.	Israel	Mongolia	Siera Leone	Vanuatu
Brazil	El Salvador	Italy	Morocco	Singapore	Viet Nam
Brunei Darussalam	Equatorial Guinea	Jamaica	Mozambique	Slovak Rep	Yemen, Rep.
Bulgaria	Eritrea	Japan	Myanmar	Slovenia	Zambia
Burkina Faso	Estonia	Jordan	Namibia	Solomon Islands	Zimbabwe
Burundi	Fiji	Kazakhstan	Nepal	South Africa	