

The Diverse Nature of Financial Institutions Development in Environmental Degradation: Evidence from Developed Economies

Abstract

Purpose

This study empirically examines the impact of financial institutions (mutual funds, pension funds, banks and insurance firms) on the ecological footprint of six developed economies.

Design/methodology/approach

Using data from 2001 to 2020, we employed robust econometric techniques, including CS-ARDL, FMOLS, and the Dumitrescu & Hurlin (2012) panel causality test, to estimate the environmental impact of the development of both bank and non-bank financial institutions.

Findings

The findings report that banking development, mutual funds and pension funds reduce the ecological footprint. Whilst the insurance market's development enhances the ecological footprint, suggesting heterogeneous and diverse impacts of financial institutions on environmental quality. On the disintegration of insurance funds, we found that both non-life and life insurance market development increases the ecological footprint (depicted in Fig. 1). The findings suggest comprehensive integration of ecological footprint quality in the investment/lending practices of financial institutions to mitigate environmental degradation in developed economies.

Originality/value

This study is the first of its kind to explore the impact of both financial (banks) and non-financial institutions' development on environmental degradation.

Financial institution development

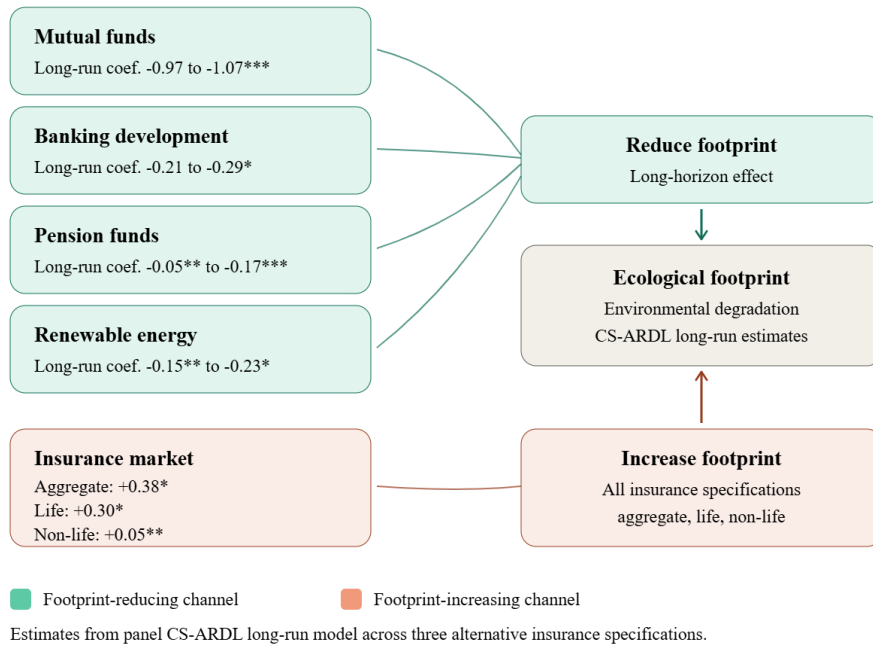


Figure 1: Graphical abstract (CS-ARDL results)

Source: Authors' own work

Keywords: *Ecological Footprint, Insurance Market, Pension Funds, Mutual Funds, Banking Development*

1. Introduction

Humanity is currently consuming the equivalent of roughly 1.7 Earths each year. It is reported that 80% of the world's inhabitants face an ecological deficit and consume more natural resources than their regeneration, causing harm to the global ecosystem and sustainability (Ecological Footprint Network, 2024; Nketiah et al., 2024; Shahbaz et al., 2023). The imbalance is noticeable in advanced economies. Particularly, the six developed countries (France, Germany, Japan, Italy, the United Kingdom and the United States) together represent nearly one-tenth of the world's energy consumption-based ecological footprint. Because these economies have the world's most advanced financial systems, understanding whether their financial development can ease or intensify environmental pressure is a critical point towards achieving the global sustainability objectives.

Based on the Environmental Kuznets Curve (EKC) framework, literature has widely examined the role of financial development (FD) in shaping environmental outcomes (Grossman & Krueger, 1995); however, the empirical findings remain inconclusive. Some studies suggest that FD promotes environmental degradation by facilitating industrial expansion and energy-intensive activities (Baloch et al., 2019; Ashraf & Doytch, 2023). Whereas, others argue that it enhances environmental quality by supporting renewable energy infrastructure, green innovation and cleaner technologies (Ahmad et al., 2022; Fakher & Ahmed, 2023). A strand of literature documents insignificant effects (Ridzuan et al., 2017). Gök (2020) attributes these inconsistencies mainly to the different proxies used for FD, the estimation techniques employed and the attributes of sample size. The current study explicitly addresses these methodological and empirical concerns.

The main limitation of the existing literature is its tendency to conceptualizing the "FD" mainly through domestic credit to the private sector, total deposits, broad money supply or composite index (Svirydzenka, 2016; Caglar et al., 2021; Xiong et al., 2017). The composite index or relying only on banking development does not cover the environmental role of other non-financial institutions, such as insurance companies (both life and non-life), pension funds and mutual funds. The aggregation of FD generates both empirical and policy-oriented limitations. In terms of an empirical perspective, institution-specific environmental effects may offset one another when combined into aggregate indicators, thereby contributing to the inconsistent and unstable coefficient estimations in the literature. From a policy perspective, the aggregated evidence lacks the precision necessary to inform institution-specific regulatory strategies for reducing

environmental degradation. As a result, disintegrating FD into its banking and non-banking components and treating institutional heterogeneity is the main theme of the study. These institutions are economically large, invest in long-term projects, increase engagement with environmental, social and governance (ESG) investment and are pivotal to economic growth (Kayhan et al., 2021). These non-banking institutions carry critical implications for the environment (Shahbaz et al., 2024), which remain substantially underexplored in the literature. Considering this may not only be a methodological contribution but a vital policy-oriented contribution for producing evidence to inform policymakers of effective and targeted environmental policies.

Moreover, these institutions are fundamentally different from banks and from one to another, in the context of maturity, structure, functions, regulatory frameworks, risk orientation and investment preferences. Insurance companies invest in conventional fixed and short-term securities for high returns to meet the insurance claims without consideration of where the funds are used (Appiah-Otoo & Acheampong, 2021). Both life and non-life insurance companies invest significantly in mining, transportation and energy sectors, and produce carbon emissions (Popescu et al., 2024). These collective funds (non-bank financial institutions) can use their financial leverage to convince the finance-receiving entities to adopt environmentally friendly practices and may decide to invest only in firms with a good ESG score. For instance, pension funds managed to reduce investment in fossil fuel commodities drastically in the OECD countries (Rempel & Gupta, 2020). Also, insurance companies provide incentives to their customer who follow sustainable business practices and invest more in green financial products (Taylor & Tollin, 2009).

Given the varying nature and investment preferences, this study explores a critical and previously ignored research gap. Specifically, the comparative environmental impact of bank-based versus non-bank financial institutions, and the further disintegration of life and non-life insurance companies, has not been investigated previously, to the best of our knowledge. Consequently, this study uses both banks and non-financial institutions (insurance sector, mutual funds, and pension funds) to impact the ecological footprint in six developed economies. These countries have high urbanization (75% on average compared to 54% of the world, along with Canada), represent approximately 46% of the world's GDP, consume 23% of the world's energy (along with Canada) and fall within the top 15 contributors to the global ecological footprint (consumption). Figure 2

below illustrates the trends of greenhouse gas emissions per person in the six highly developed countries.

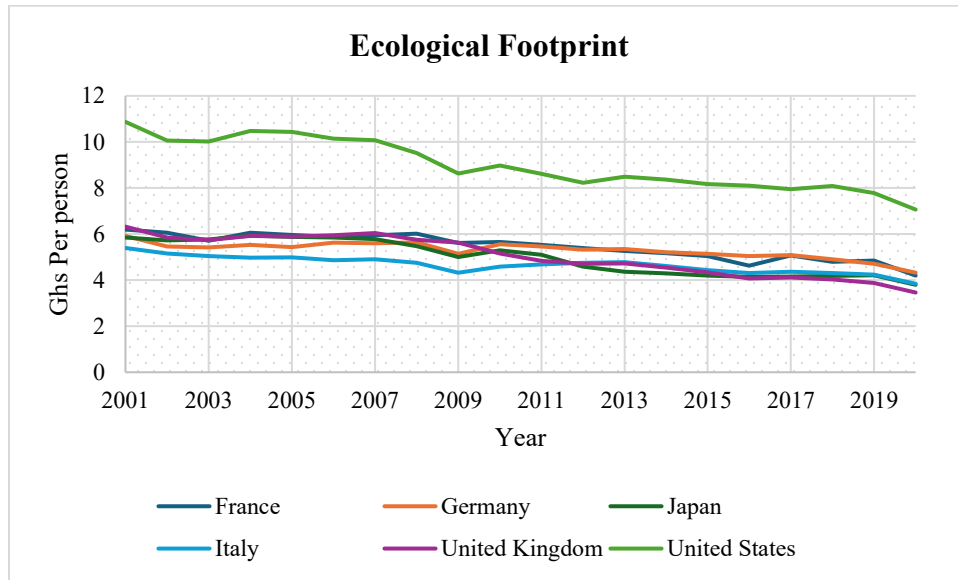


Figure 2: Ecological Footprint in six highly developed countries
Source: Authors' own work

Accordingly, the current study investigates the following questions: (a) Do bank and non-bank financial institutions' development exert a differential impact on ecological footprint? (b) Do life and non-life insurance institutions' development have different environmental effects? Moreover, to answer these questions, the study pursues the following objectives: (a) To estimate the impact of both banking, mutual funds, pension funds and insurance companies on ecological footprint across a panel of six developed economies. (b) To identify and explore a potential disintegrating impact of the development of life and non-life insurance institutions on the ecological footprint.

By achieving these objectives, the study contributes to literature in several ways. First, to the best of our knowledge, this study is the first to empirically examine the environmental consequences of both banks and non-bank financial institutions within developed countries. The study directly addresses Gök's (2020) concern, considering alternative proxies for FD to cover both bank and non-bank financial institutions' development. Second, the study disintegrates the insurance sector into life and non-life insurance market development to examine their environmental impact. Finally, the study uses second-generation econometric techniques, including CS-ARDL and the

Dumitrescu-Hurlin causality test, which are robust and control the cross-sectional dependency (CSD) and slope heterogeneity effect in the panel countries.

Moreover, the study

2. Literature Review

2.1. Theoretical framework

Theoretically, this study is based on two complementary theories. Firstly, the Environmental Kuznets Curves (EKC) frame how income level (economic growth) shapes environmental outcomes through scale, composition and technique effects (Grossman & Krueger, 1995). FD enters this framework and introduces the Financial Kuznets Curve (FKC), discussing that the financial sector mobilize funds and capital, which enhances economic activities and thereby environmental outcomes (Patrick, 1966; Rahman et al., 2024; Rashid et al., 2025). Secondly, the innovation diffusion theory explains the gradual and society-wide adoption of renewable energy through which the adverse environmental impact of the financial sector can be balanced (Rogers, 1963). The main theoretical proposition is that financial institutions' development plays a dual role in environmental outcomes. On the one hand, it reduces the cost of credit and capital, facilitating industrial expansion and infrastructure, which increases energy consumption and hence affects the ecological footprint (Baloch et al., 2019; Boutabba, 2014). On the other hand, financial institutions can replace energy-intensive technology with renewable energy ones and can channelize the funds to green and renewable energy projects (Tamazian & Bhaskara Rao (2010).

Beyond this, the impact of financial institutions on the environment operates through two more specific channels. Firstly, the ESG-driven portfolio reallocation channel, in which long-term institutional investors, including pension and mutual funds, are mainly exposed to transition and stranded-asset risk. This may encourage divestment from carbon-intensive holdings and reallocation toward environmentally friendly financial instruments (Flammer, 2021; Krueger et al., 2020). By changing the relative cost of capital, this transition may facilitate investment in environmentally friendly firms while limiting financing opportunities for polluting firms. Secondly, institutional investors may influence firms' decisions by proxy voting, board engagement and stewardship activities (corporate governance channel). This may promote stronger environmental disclosures and lower emissions intensity in investee firms (Azar et al., 2021). On the contrary, the banking sector operates through a more diffuse credit-allocation

channel, while insurance markets retain underwriting and asset exposure to fossil-fuel sectors. These differences provide the theoretical basis for expecting heterogeneous environmental effects across institution types.

Critically, the role and direction of environmental outcomes depend on the type of financial institution. Both bank and non-bank institutions are different in terms of structure, functions and investment (Svirydzenka, 2016), and can have different environmental consequences (Gök, 2020). Based on this institution's heterogeneity, it is why and how financial development is disintegrated into different financial institutions, rather than being seen as a single or composite measure.

2.2. Financial development and environmental degradation

Literature highlights a significant impact of FD on environmental degradation, but the results remain inconclusive. Tamazian & Bhaskara Rao (2010) report that financial liberalization improves environmental quality, subject to the presence of a strong institutional framework. Lee et al. (2015) and Al-Mulali et al. (2015) observe a significant role of FD in mitigating environmental degradation in a few OECD countries. Dogan & Turkekul (2016) find no evidence to support the presence of EKC in the USA. However, the study explores that FD and carbon emissions are positively associated. Moreover, the country-wise findings remain mixed, such as negative for Indonesia (Shahbaz, Hye, et al., 2013) and no relationship for Turkey (Ozturk & Acaravci, 2013) and China (Jalil & Feridun, 2011).

By further disintegrating FD, Hao et al. (2016) finds a positive impact of financial markets' depth and efficiency, but a negative impact on environmental degradation, respectively. In a way forward, Shahbaz et al. (2016) conclude that banking sector development impedes environmental degradation by supporting environmentally harmful technology production in Pakistan. On the contrary, Dogan & Seker (2016) and Dar & Asif (2017) propose a negative relationship between banking development and carbon emissions due to sustainable technological development. Further, Pan et al. (2016) suggest that after exceeding a threshold GDP, financial scaling, and efficiency—dynamics of FD—increase carbon intensity in China. Xing et al. (2017) find that the financial sector's depth, structure, openness, growth, efficiency, and ecology can significantly but differently affect carbon emissions at the regional and state level.

Furthermore, Dizaji & Ousia (2017) finds a U-shaped relationship between FD, especially stock market development, and carbon emissions. On the contrary, Ridzuan et al. (2017) suggest that the financial sector is not significantly related to environmental degradation. Tong et al. (2018) explore that, along with the spillover effect from other countries, industrial structure, and banking development, the upsurge in carbon emissions in China. Ganda (2019) report a negative impact of banking development on environmental quality across different quantiles in the OECD countries. Moreover, Khan et al. (2020) and Ibrahiem (2020) report that FD supports technological innovation, which reduces emissions and ecological footprint. Whilst, Kartal et al. (2023) report a positive association between FD and environmental quality across quantiles. More recently, Rashid et al. (2025) explored a U-shaped relationship between money supply and carbon procyclicality, suggesting that money supply negatively affects carbon procyclicality in the short-run but positively in the long-run.

Studies report that overall FD (both institutions and markets) promotes environmental quality through the channel of renewable energy (Kirikkaleli & Adebayo, 2021; Usman et al., 2022; Aluko & Obalade, 2020; Andrew et al., 2024). In contrast, literature argues that overall FD deteriorates environmental quality by increasing ecological footprint and reducing renewable energy demand (Usman & Makhdum, 2021; Wang et al., 2023). Furthermore, Zhang & Umair (2023) find a dynamic spillover effect (inter-dependency) between green bonds, green stocks and carbon markets. Table 1 provides a brief literature review.

Table 1: Literature review about FD and ecological footprint

Study	Sample	FD proxy	Methodology	Relationship between FD and environmental degradation
Tamazian et al. (2009)	BRIC	Stock & banking development	ARDL	—
Shahbaz et al. (2013)	Indonesia	Domestic credit to the private sector	ARDL and VECM	—
Boutabba, (2014)	India	Domestic credit to the private sector	ARDL	—
Dogan & Turkekul, (2016)	USA	FD composite index	ARDL	+

Study	Sample	FD proxy	Methodology	Relationship between FD and environmental degradation
Shahbaz et al. (2016)	Pakistan	Stock market & banking development	ARDL	+
Halkos & Polemis (2017)	OECD panel	Banking-sector deposits	Panel regression	+
Baloch et al., (2019)	59 BRI countries, panel	FD composite index	Fixed effects	+
Aluko & Obalade (2020)	Panel	FD composite index	Panel methods	—
Gök (2020)	Meta-analysis	Multiple FD proxies	Meta-regression	Mixed
Ahmed et al. (2021)	Panel	FD composite index	Panel cointegration	+
Ashraf et al. (2022)	124 economies, panel	FD composite index	Two-step system GMM	Mixed
Pata & Yilanci, (2020)	G7 panel	FD composite index	Bootstrap rolling window	Mixed
Raggad et al. (2024)	Saudi Arabia	Financial institutions vs. markets	Nonlinear ARDL	Asymmetric
Rashid et al. (2025)	Panel	Money supply	Nonlinear panel	U-shaped (mixed)
This study	6 developed countries	Mutual funds, pension funds, banks, life & non-life insurance (disaggregated)	CS-ARDL, FMOLS and DOLS	not previously examined for developed economies

Source: Authors' own work

According to the available literature, the impact of FD on environmental degradation is mixed, depending on different proxies, sample and methodology. However, the impact of non-bank

institutions, such as insurance companies (life and non-life), mutual funds and pension funds, has largely been ignored. Particularly, to the best of the author's knowledge, the ecological impact of the insurance sector has not been investigated so far. To fill this gap in the literature, this study investigates the impact of banking development, mutual funds, pension funds, life insurance and non-life insurance companies in developed countries to determine whether these financial institutions affect ecological footprint in developed economies. Accordingly, the study develops and tests the following hypotheses:

H1: Banking sector, mutual funds and pension funds development significantly affect the ecological footprint.

H2: Aggregate insurance, life insurance and non-life insurance market development affect the ecological footprint.

3. Methodology

3.1. Data and variables

The study selected a sample of G7 countries. However, due to missing observations for some of the selected variables, Canada is excluded, reducing the sample to six countries. The period of our empirical examination spans 2001 to 2020, given the availability of yearly data for each variable and country. The study uses proxies to measure the study variables. The study controlled the effect of renewable energy and environmental policy stringency, considering the former's significant effects on environmental quality (Andrew et al., 2024; Bhowmik et al., 2024).

For environmental degradation, the ecological footprint is used, since it covers carbon emissions (a primary greenhouse gas) and the human pressure on natural resources, such as forestry, fishing, agriculture, mining, and manufacturing (Ecological Footprint Network, 2024). Further, Table 2 presents variable details, symbols, definitions and data sources. The graphical illustration in Figure 3 demonstrates the trend in the selected variable data over the study period.

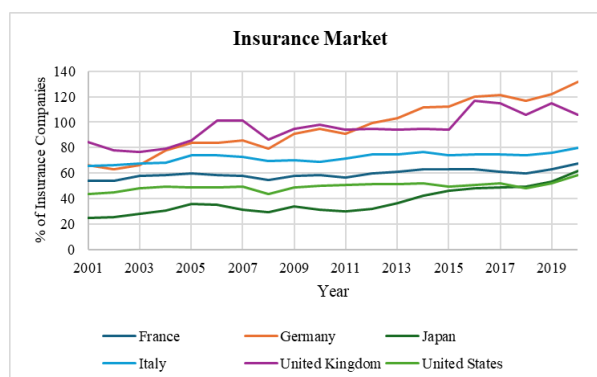
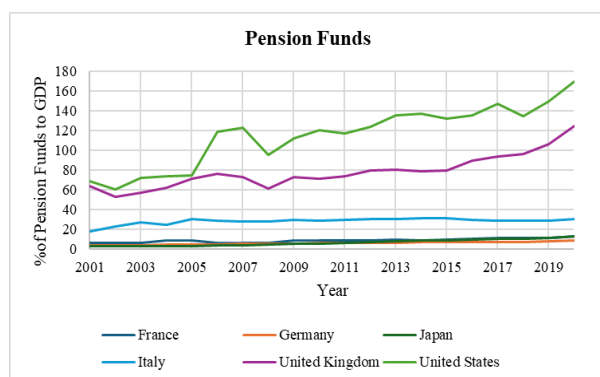
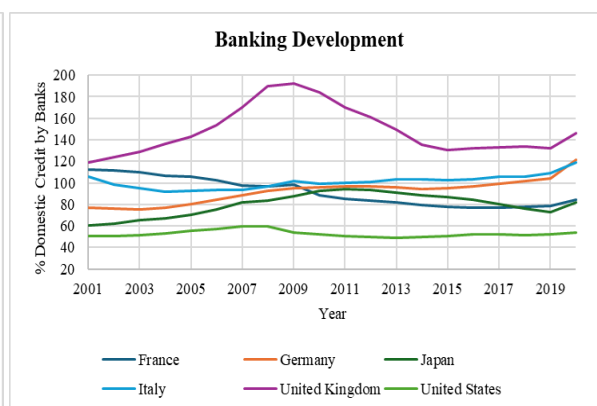
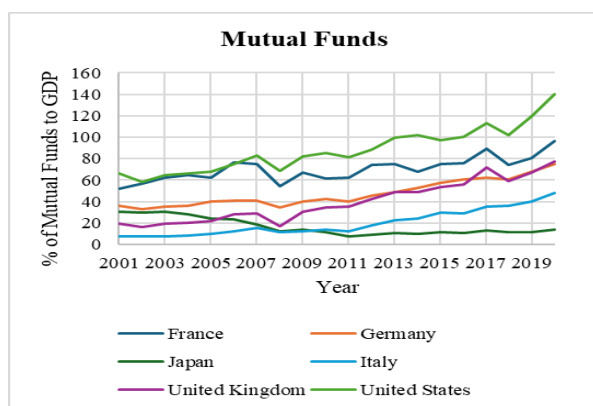
Table 2: Variables and data detail

Variables	Symbol	Definition	Sources
Ecological Footprint	EF	Ecological Footprint (gha per person)	EFN
Mutual Funds	MF	Mutual Fund Assets to GDP (%)	WB
Pension Funds	PF	Pension Fund assets to GDP (%)	WB

Insurance Companies	IC	Insurance Companies' assets to GDP (%)	WB
Non-life Insurance Companies	NLFI	Premium Volume to GDP (%)	WB
Life-Insurance Companies	LFI	Premium Volume to GDP (%)	WB
Banking Development	BD	Domestic Credit to Private Sector by banks to GDP (%)	WB
Environmental Policy Stringency	EPS	Score (0-6)	OECD
Renewable Energy	RE	Renewable energy consumption, % of total energy	WB

Note: Ecological Footprint Network (EFN), World Bank (WB)

Source: Authors' own work



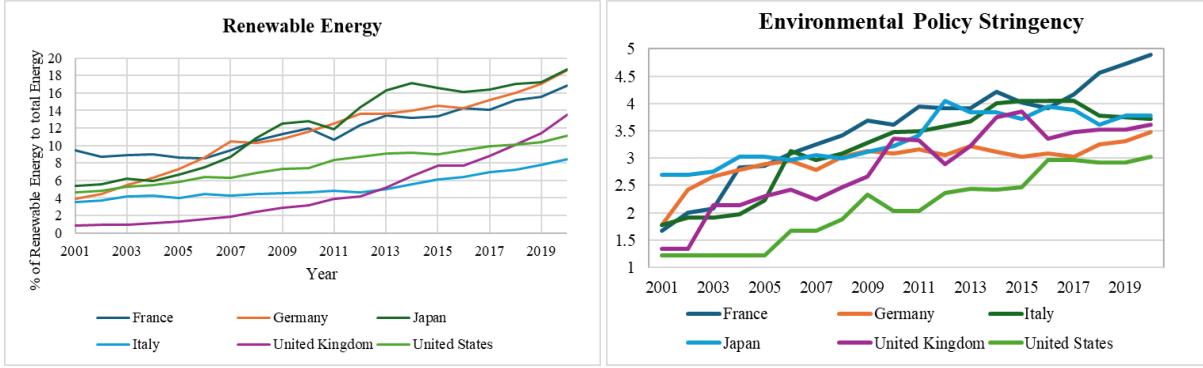


Figure 3: Time trend in variable
Source: Authors' own work

3.2. Empirical modelling

We develop empirical models in equations 1, 2 & 3 to examine the impact of financial institutions development, renewable energy and environmental policy stringency on the ecological footprint in the sample countries.

$$\ln EF_{it} = \alpha_{it} + \beta_1 \ln MF_{it} + \beta_2 \ln PF_{it} + \beta_3 \ln IC_{it} + \beta_4 \ln BD_{it} + \beta_5 \ln EPS + \beta_6 \ln RE_{it} + e_{it} \dots \dots \dots (1)$$

$$\ln EF_{it} = \alpha_{it} + \beta_1 \ln MF_{it} + \beta_2 \ln PF_{it} + \beta_3 \ln LIC_{it} + \beta_4 \ln BD_{it} + \beta_5 \ln EPS + \beta_6 \ln RE_{it} + e_{it} \dots \dots \dots (2)$$

$$\ln EF_{it} = \alpha_{it} + \beta_1 \ln MF_{it} + \beta_2 \ln PF_{it} + \beta_3 \ln NLIC_{it} + \beta_4 \ln BD_{it} + \beta_5 \ln EPS + \beta_6 \ln RE_{it} + e_{it} \dots \dots \dots (3)$$

Whereas $\ln EF$, $\ln MF$, $\ln PF$, $\ln IC$, $\ln LIC$, $\ln NLIC$, $\ln BD$, $\ln EPS$ and $\ln RE$ represent the logarithm form of ecological footprint, mutual funds, pension funds, insurance companies, life insurance companies, non-life insurance companies, banking development, environmental policy stringency and renewable energy. In the above equations, α_{it} is the intercept, $\beta_{1it} \dots \dots \dots \beta_{nit}$ indicates the coefficients of slope due to regressors in the sample countries (i) in the time period (t) and e_{it} is the error term.

3.2.1. Econometric techniques

The econometrics techniques of this study are presented below in Fig. 4. We applied a series of preliminary tests to estimate robust results. We run the descriptive statistics to analyze the data characteristics, followed by the variance inflation factor (VIF) test to estimate the multicollinearity. The VIF determines the inflated variance in the regression model (coefficients of the regressors)

due to the explanatory variables. Afterwards, we run the Pesaran Cross-Sectional Dependency (CSD) test to identify cross-sectional dependence between the error terms of each cross-section.

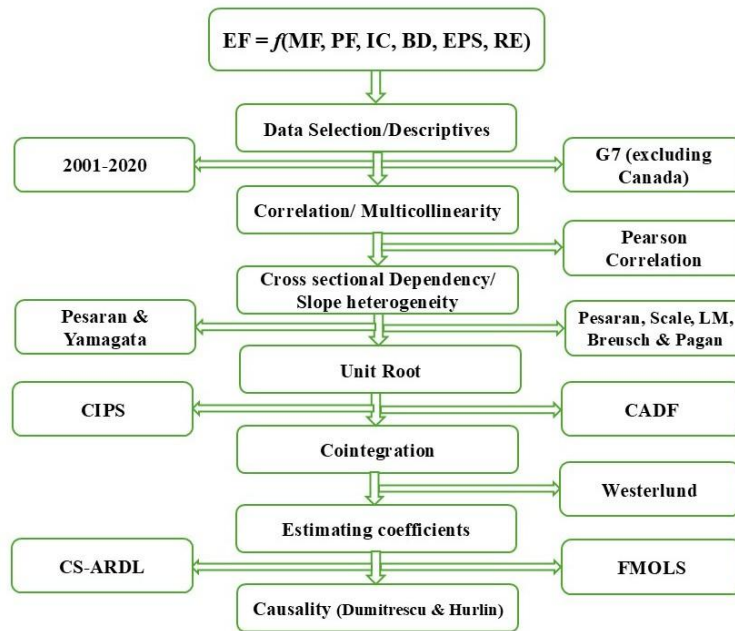


Figure 4: Econometric techniques

Source: Authors' own work

a) Cross-sectional dependency test

The test for CSD is important considering the interconnectedness of economic, financial, environmental and geographical indicators in the developed countries (Ertur & Musolesi, 2017). Without controlling for CSD, the results can be biased and inconsistent (Blomquist & Westerlund, 2013). We applied Breusch & Pagan (1980), Pesaran (2006) scaled-LM and Pesaran et al. (2008) Bias-corrected scaled LM and CSD tests to examine the possible CSD among the variables.

The Breusch test does not apply to this study due to $N \rightarrow \infty$. Therefore, Pesaran (2004) proposed a scaled version of the LM test and is numerically expressed as follows;

$$CSD_{LM} = \sqrt{\frac{I}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N (T_{ij} \hat{\rho}_{ij}^2 - 1) \rightarrow N(0,1) \dots \dots \dots (4)$$

However, this test is asymptotically distributed as chi-squared with $\frac{N(N-1)}{2}$ degrees of freedom if $N \rightarrow \infty$ and finite T . However, with a larger N , this test is not centred at the mean (zero), and the normal approximation leads to distortion.

In response, Pesaran et al. (2008) proposed the bias-corrected scaled LM test for detecting CSD in a larger T and smaller N , and is illustrated below.

$$LM_{adj} = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\Psi}_{ij} \right) \left[\frac{(T-K)\hat{\Psi}_{ij}^2 - (T-K)\hat{\Psi}_{ij}^2}{Var(T-K)\hat{\Psi}_{ij}^2} \right] \dots \dots \dots (5)$$

In equation (4), μT_{ij} and $v T_{ij}$ represent the mean and variance and is used to estimate normally distributed t-statistics.

b) Slope heterogeneity test

In the next step, we applied Pesaran & Yamagata (2008) slope of heterogeneity test, grounded on the economic variables characteristics of highly skewed and structural breaks due to external events (Dong et al., 2024). Moreover, the presence of a heterogeneity test can lead to biased and inconsistent results. This test was originally adopted from Swamy (1970) and is described as follows:

$$\tilde{\Delta}_{adj} = \sqrt{N} \frac{N^{-1}\hat{S} - E(\check{Z}_{it})}{\sqrt{Var}(\check{Z}_{it})} \dots \dots \dots (6)$$

$$\tilde{\Delta}_{adj} = \sqrt{N} \frac{N^{-1}\hat{S} - E(\check{Z}_{it})}{\sqrt{Var}(\check{Z}_{it})} \sim N(0,1) \dots \dots \dots (7)$$

Equation (6) is modelled for a larger data set, and Equation (7) is for a smaller data set. N represents the number of cross-sections, S indicates the Swamy t-statistics, E indicates the number of explanatory variables, and $Var(t,k)$ is the standard error in the sample countries in the specified time.

c) Unit root tests

Afterwards, we employed CIPS and CADF panel unit root tests for cross-sectionally dependent and slope-heterogeneous series. The panel unit root test guides us in using appropriate statistical

techniques to achieve consistent results (Dong et al., 2024). Equation (8) illustrates the CADF unit root test that considers slope heterogeneity and CSD.

$$\Delta X_{it} = \beta_i + \pi_i x_{i,t-1} + \lambda_i \bar{x}_{t-1} + \delta_i \Delta \bar{x}_t + e_{it} \dots (8)$$

The addition of one lag led to the formation of equation 9.

$$\Delta X_{it} = \beta_i + \pi_i x_{i,t-1} + \lambda_i \bar{x}_{t-1} + \sum_{j=0}^P \delta_i \Delta \bar{x}_{t-j} + \sum_{j=1}^P \varphi_{ij} \Delta x_{i,t-j} + e_{it} \dots (9)$$

Whereas \bar{x}_{t-1} indicates cross-section, $\Delta x_{i,t-j}$ represent the mean of the lagged value at first difference. CIPS is mathematically presented as follows:

$$CIPS = N^{-1} \sum_{i=1}^N CADF_i \dots \dots \dots (10)$$

d) Cointegration test

Further, we applied Westerlund (2007) cointegration tests to identify the existence of long-run association among the variables. It is an efficient cointegration test and considers CSD and slope heterogeneity in the model. This test offers four t-statistics, comprising of two groups (Gt, Ga) and two panels (Pt, Pa) components. The group statistics (Gt, Ga) and panel (Pt, Pa) are described as follows:

$$G_t = \frac{1}{N} \sum_{i=1}^N \frac{a'_i}{SE(a'_i)} \dots \dots \dots (11)$$

$$G_a = \frac{1}{N} \sum_{i=1}^N \frac{T a'_i}{a'_i(1)} \dots \dots \dots (12)$$

Panel cointegration is estimated as follows.

$$P_s = \frac{a'_i}{SE(a'_i)} \dots \dots \dots (13)$$

$$P_a = T a'_i \dots \dots \dots (14)$$

e) Relationship estimations

The existence of CSD, slope heterogeneity and long-run cointegration guides us to employ a second-generation test to estimate the coefficients of slope for the relationship. Chudik & Pesaran, (2015) proposes the Cross-Sectionally Augmented ARDL (CS-ARDL), which addresses both CSD and pooled slope heterogeneity problems. The CS-ARDL augments the ARDL specification with cross-sectional averages of the variables to proxy the unobserved common factors that generate cross-sectional dependence, while estimating country-specific coefficients that are then averaged (mean-group), thereby accommodating slope heterogeneity. It provides both short-run and long-run estimations at mixed integration order ($I(0)$ and $I(1)$) panels. This technique is robust to weak endogeneity and structural breaks, making it appropriate for interdependent developed economies in our sample (C.-C. Lee et al., 2023).

For robustness, the study also employs the FMOLS test to estimate long-run relationship amongst the variables in line with (Shahbaz et al., 2021; Kaushal et al., 2024). Pedroni (1999, 2000) argues that FMOLS is more robust than OLS to estimate parameters of long-run relationship, if long-run cointegration exists among the variables. Moreover, FMOLS controls the potential bias in estimation due to variance, autocorrelation and endogeneity (Balsalobre-Lorente et al., 2023). The FMOLS is numerically illustrated as follows in line with (Pedroni, 2000).

$$y_{it} = \alpha_i + \beta x_{it} + \mu_{it} \dots \dots (15)$$

$$x_{it} = x_{it-1} + e_{it} \dots \dots (16)$$

Where y_{it} , and x_{it} , α_i , e_{it} , (i) and (t) represent the dependent and independent variables, intercept, error term, sample countries and time period. in the time

f) Causality test

Lastly, we employ Dumitrescu and Hurlin's (2012) (DH) panel causality test to determine the direction of the relationship. This technique controls the potential heterogeneity in the data and estimates Z-bar and W-bar statistics. The W-bar provides the average statistics, and the Z-bar estimates a standard normal distribution.

4. Empirical results and discussion

4.1. Descriptive, multicollinearity and correlation

Table 3 presents the descriptive statistics and normal distribution parameters of the selected variables for the sample countries. Pension funds (lnPF) development recorded the highest standard deviation, followed by non-life insurance market development (lnNLIC), suggesting high variations in the pension funds and non-life insurance market development of the sample countries. On the other hand, banking development (lnBD) has the lowest standard deviation. The kurtosis values of the variables exceed the threshold value (± 1.96) and suggest a non-normal distribution of data. Moreover, the correlation values are reported in Table 4, indicating a significant relationship among the variables.

Table 3: Descriptive statistics

	lnEF	lnMF	lnPF	lnBD	lnIC	lnNLIC	lnLIC	lnEPS	lnRE
Mean	1.71	3.61	2.96	4.49	4.16	1.27	0.57	1.056	2.01
Median	1.68	3.73	2.69	4.54	4.17	1.67	0.65	1.121	2.16
Maximum	2.39	4.94	5.13	5.26	4.88	2.85	1.19	1.587	2.93
Minimum	1.24	1.98	0.77	3.89	3.20	-1.78	-0.37	0.201	-0.16
Std. Dev.	0.25	0.77	1.28	0.33	0.38	1.13	0.34	0.316	0.66
Skewness	0.98	-0.51	0.13	-0.02	-0.36	-1.46	-0.77	-1.083	-1.18
Kurtosis	3.48	2.10	1.62	2.72	2.76	4.13	3.05	3.741	4.58
Jarque-Bera	20.54	9.17	9.93	0.40	2.95	49.09	11.76	26.22	40.42

Source: Authors' own work

Table 4: Correlation test

Variables	lnEF	lnBD	lnIC	lnMF	lnPF	lnEPS	lnRE	lnNLFI	lnLFI
lnEF	1								
lnBD	-0.647	1							
lnIC	-0.376	0.622	1						
lnMF	0.435	-0.31	0.177	1					
lnPF	0.348	-0.011	0.238	0.264	1				
lnEPS	-0.756	0.323	0.253	-0.11	-0.22	1			
lnRE	-0.216	-0.318	-0.134	0.296	-0.378	0.532	1		
lnNLFI	0.33	-0.772	-0.527	0.179	-0.192	0.039	0.562	1	
lnLFI	0.552	-0.772	-0.493	0.439	-0.28	-0.189	0.516	0.848	1

Source: Authors' own work

4.2. Cross-sectional dependency and slope heterogeneity test

Table 5 confirms the existence of CSD amongst the variables of the selected economies. The results suggest that economic or political shocks in one sample country can spread into another

country. Table 6 documents the Pearson & Yamagata (2008) heterogeneity test and reports the existence of slope heterogeneity for the selected variables

Table 5: CSD test

Variables	Breusch-Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
lnEF	246.90***	42.34***	42.18***	15.7***
lnMF	206.46***	34.96***	34.79***	7.19***
lnPF	193.17***	32.53***	32.37***	13.7***
lnIC	198.73***	33.54***	33.39***	13.99***
lnBD	72.16***	10.44***	10.28***	0.58
lnEPS	223.633***	38.091***	37.933***	14.902***
lnNLIC	59.59***	8.14***	7.98***	1.84**
lnLIC	68.32***	9.74***	9.58***	0.83
lnRE	260.236***	44.78***	44.62***	16.11***

Note: ***, ** and * represent P-values < 0.01, <0.05 and 0.1, respectively.

Source: Authors' own work

Table 6: Slope heterogeneity test

	Model 1	Model 2	Model 3
Delta	3.737***	3.337***	3.117***
Adj. Delta	4.825***	4.386***	4.024***

Note: ***, ** and * represent P-values < 0.01, <0.05 and 0.1, respectively.

Source: Authors' own work

4.3. Panel unit root test

In the next step, the study applied CADF and CIPS unit root tests to examine the cointegration order to avoid using spurious regression. Results in Table 7 indicate that the variables are non-stationary (unit root problem) at the level. However, all the variables turn stationary at the first difference and accept the alternative hypothesis that the variables are integrated at order $I(1)$. The stationarity among the variables is a condition to examine the integration among the variables. Moreover, the results in Table 8 reject the null hypothesis of no cointegration and report the long-run cointegration among the variables at 1% level of significance.

Table 7: Unit root tests

Variables	CADF		CIPS	
	Level	First Difference	Level	First Difference
lnEF	-2.253	-4.219***	-2.253	-4.219***

lnMF	-1.592	-4.064***	-1.592	-4.064***
lnPF	-2.015	-2.634***	-3.12	-4.397***
lnIC	-2.243	-3.107***	-1.978	-3.107***
lnNLIC	-1.716	-3.316***	-1.716	-3.316***
lnLIC	-1.57	-2.886***	-1.57	-2.886***
lnBD	-0.427	-4.567***	-0.686	-2.269***
lnEPS	-3.316***	-4.5***	-3.316	-4.501***
lnRE	-1.955	-4.664*	-1.955	-4.664***

Note: ***, ** and * represent P-values < 0.01, <0.05 and 0.1, respectively.

Source: Authors' own work

Table 8: Westerlund cointegration test

Model with aggregate insurance market development				
Statistic	Value	Z-value	P-value	Robust P-value
Gt	-2.198	0.547	0.708	0.000
Ga	-5.761	2.377	0.991	0.000
Pt	-5.126	0.068	0.527	0.000
Pa	-5.556	1.245	0.894	0.000
Model with life-insurance market development				
Gt	-2.169	0.617	0.731	0.000
Ga	-4.565	2.729	0.997	0.000
Pt	-4.469	0.618	0.732	0.000
Pa	-4.531	1.532	0.937	0.000
Model with non-life insurance market development				
Gt	-1.674	1.806	0.965	0.143
Ga	-4.094	2.867	0.998	0.000
Pt	-3.334	1.569	0.942	0.000
Pa	-4.959	1.412	0.921	0.000

Source: Authors' own work

4.4. Panel long-run estimations

Following the existence of CSD and slope heterogeneity, the long-run and short-run results are estimated through CS-ARDL, providing consistent results, as reported in Table 9. The results show a negative impact of mutual funds on the ecological footprint in the long-run. A 1% increase in mutual funds reduces the ecological footprint by 0.97% to 1.07% across the three models (the aggregate, life and non-life insurance). Pension funds also reduce the ecological footprint in the long-run by 0.05% to 0.17%. These findings suggest that both mutual funds and pension funds have a significant, favourable impact on the environmental quality, in line with the findings of Kirikkaleli & Adebayo (2021) and Usman & Hammar (2021). Moreover, the results demonstrate a negative impact of banking sector development on ecological footprint, showing that the banking sector plays a significant role in reducing environmental pollution. The findings support the study's

hypothesis *H1* for banking development, pension funds and mutual funds and suggest that these financial institutions are inclined towards environmentally friendly investments. Moreover, the findings indicate a positive impact of aggregate, life and non-life insurance market development on ecological footprint, in line with the previous findings of [Altarhouni et al. \(2021\)](#) and [Appiah-Otoo & Acheampong \(2021\)](#). In particular, a 1% increase in the aggregate, life insurance and non-life insurance market development significantly increases the ecological footprint in the long run by 0.38%, 0.3% and 0.05%, respectively. A possible explanation for this might be investment by insurance companies in polluted economic activities, and cause increase in ecological footprints. Expectedly, the renewable energy coefficient is found in a negative relationship with ecological footprint. Specifically, a 1% increase in renewable energy reduces the ecological footprint by 0.15% to 0.23%. Hence, it can be conceivably hypothesized that renewable energy significantly reduces fossil fuel consumption and overall ecological footprint.

Moreover, in the short-run, pension funds and banking sector development are negatively associated with the ecological footprint. The convergence of the short-run and long-run estimations indicates stability in the environmental impact of both bank and non-bank institutions. However, aggregate and life-insurance market development are negatively related to the ecological footprint. Overall, the CS-ARDL results reinforce the central findings that financial institutions have heterogeneous impacts on the ecological footprint. Long-run and pool investment horizons have a negative impact, while insurance sector development has a positive impact on environmental degradation.

For robustness, the study employs the FMOLS estimator, and the results are presented in Table 10. These findings are almost parallel to the CS-ARDL findings, as banking sector development, mutual funds and pension funds reduce ecological footprint, while insurance sector development upsurges. Renewable energy also retains its negative impact and significance across three estimations.

The consistency of the CS-ARDL and FMOLS findings is validated by estimating country-wise FMOLS presented in Appendix 1. As can be shown, mutual and pension funds are negatively associated with an ecological footprint in almost all countries. This indicates that the broader results from the aggregated sample are not driven by a single economy but hold consistently across the panel. The most striking result is the negative relationship of insurance market development

with the ecological footprint in France and the United States, substantially different from the positive coefficients observed in Germany, Italy and the United Kingdom. The discrepancy could be attributed to the deeper integration of insurance and capital-market intermediaries into environmentally oriented investment in France and the United States, while in the other countries these channels still finance carbon-intensive sectors. It can therefore be assumed that German, Japanese and French banks are significant financiers of green projects, whereas the banking sectors in the latter three countries continue to channel credit toward more pollution-intensive industries.

The environmental policy stringency variable exhibits heterogeneous effects across countries: it negatively and significantly affects ecological footprint in Germany and the United States, suggesting that stricter environmental regulation in these economies substantially reduces environmental degradation. In contrast, it carries a positive and significant coefficient in France, Italy, Japan and the United Kingdom, which could be attributed to the slow translation of regulatory stringency into binding industrial outcomes, the presence of carbon leakage to less regulated sectors, or compliance costs that have not yet matured into emission-reducing structural change. Overall, the country-wise findings (Appendix 1) corroborate the aggregated sample findings in Tables 9 and 10.

Table 9: CS-ARDL estimations

Variables	Model with aggregate insurance market development		Model with life- insurance market development		Model with non-life insurance market development	
	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
Short-run estimations						
lnMF	0.082	0.127	-0.042	0.048	-0.071	0.11
lnBD	-0.27*	0.158	-0.2***	0.137	-0.25***	0.109
lnPF	-0.049**	0.024	-0.081**	0.039	-0.192**	0.074
lnRE	-0.175	0.116	-0.161**	0.076	-0.273*	0.142
lnEPS	0.027	0.122	0.069	0.064	0.162	0.161
lnIC	-0.340*	0.184	—	—	—	—
lnLIC	—	—	-0.355***	0.131	—	—
lnNLIC	—	—	—	—	0.051**	0.022
Long-run estimations						
lnMF	-0.968***	0.062	-1.042***	0.048	-1.074***	0.052
lnBD	-0.292*	0.17	-0.205*	0.119	-0.237*	0.132
lnPF	-0.049**	0.025	-0.083**	0.04	-0.171***	0.061
lnRE	-0.176	0.115	-0.152**	0.078	-0.225*	0.132
lnEPS	0.032	0.066	0.059	0.062	-0.003	0.097
lnIC	0.379*	0.202	—	—	—	—

lnLIC	—	—	0.303*	0.184	—	—
lnNLIC	—	—	—	—	0.045**	0.02

Note: Value in parentheses shows t-stat.

***, ** and * represent significance level at 1%, 5% and 10%, respectively.

Source: Authors' own work

Table 10: FOMLS estimations

Variables	Model with aggregate insurance market development		Model with life-insurance market development		Model with non-life insurance market development	
	Coef.	Std. Err	Coef.	Std. Err	Coef.	Std. Err
lnMF	-0.09***	0.005	-0.11***	0.005	-0.15***	0.004
lnBD	-0.10***	0.01	-0.17***	0.016	-0.11***	0.008
lnPF	-0.14***	0.009	-0.14***	0.01	-0.05***	0.004
lnRE	-0.14***	0.011	-0.17***	0.014	-0.14***	0.012
lnEPS	-0.02***	0.007	0.01	0.008	0.001	0.001
lnIC	0.05***	0.014	—	—	—	—
lnLIC	—	—	0.09***	0.006	—	—
lnNLIC	—	—	—	—	0.06***	0.009

Note: Value in parentheses shows t-stat.

***, ** and * represent significance level at 1%, 5% and 10%, respectively.

Source: Authors' own work

4.5. Panel causality

Table 11 documents the DH causality test to determine the causal relationships among the selected variables and to validate the central findings. The DH results are quite revealing in several ways. First, a bidirectional causality is reported for mutual funds, pension funds and non-life insurance market development with ecological footprint. These findings suggest these financial institutions are interrelated to ecological footprints. Moreover, a unidirectional causality is reported for renewable energy with the ecological footprint and mutual and pension funds market with banking development. The findings validate CS-ARDL results that mutual funds, pension funds and renewable energy can mitigate ecological footprint in the selected countries, and the practice should be adopted across the globe.

Table 11: D-H causality

Variables	lnEF	lnMF	lnPF	lnBD	lnIC	lnLFI	lnNLFI	lnEPS	lnRE
lnEF	—	6.69***	4.78**	3.51	4.44*	6.70***	4.79**	1.91	2.82
lnMF	10.89***	—	2.81	5.47***	2.37	8.17***	4.92**	3.48	2.41
lnPF	6.19***	3.94	—	4.34*	5.46***	2.77	3.07	3.08	5.22**
lnBD	3.45	4.27*	2.67	—	6.29***	2.76	8.49***	3.21	5.15**
lnIC	3.80	5.10**	1.10	3.11	—	3.81	1.98	3.42**	1.96
lnLFI	2.12	3.78	2.64	2.59	2.74	—	3.46	1.87	2.39
lnNLFI	4.00**	3.44	4.91*	2.73	3.24	2.65	—	3.63	4.15
lnEPS	3.40	5.10**	3.86	1.13	4.94**	3.91	2.00	—	4.74**
lnRE	6.03***	6.13***	5.20**	2.57	5.62***	3.29	3.14	4.09	—

Note: The test considers the null hypothesis of no causality. Values in parentheses show t-stat. ***, ** and * represent significance level at 1%, 5% and 10%, respectively.

Source: Authors' own work

5. Conclusion and policy recommendations

Environmental degradation is a global reality, and the literature suggests that diverting finance and technological development can mitigate the ecological footprint. We conducted an empirical study to examine the impact of the insurance market, banking development, mutual and pension funds, and pension funds on the ecological footprint. The study makes several important contributions to literature; first, we contribute to the growing literature on the significant role of non-banking institutions, such as mutual and pension funds, in mitigating the ecological footprint. Second, this is the first study of its kind that investigates the role of financial institutions from a banking and non-banking perspective on the ecological footprint. Third, we conduct both aggregate and country-wise analyses to confirm the consistency and robustness of the findings. Fourth, this study has implications for policymakers, practitioners and academics.

We report robust evidence on the relationship between ecological footprints and financial institutions' development. Firstly, we find that banking development, mutual funds and pension funds significantly reduce the ecological footprint. Similar results were also reported in the country-wise analysis, thereby validating the significant role of mutual and pension funds in reducing the ecological footprint. Secondly, the insurance market development increases the ecological footprint. But country-wise results reported discrepancies for both life and non-life insurance market development, which must be interpreted with caution. Thirdly, the supplementary analysis of the DH causality test confirms the bi-directional relationship of non-life

insurance, mutual and pension funds; a uni-directional relationship of renewable energy with ecological footprint.

5.1. Policy implications

Policymakers can use the findings to reformulate the policies and regulations for insurance market development at the country level. Based on the heterogeneous environmental impact of financial institutions, a uniform green finance policy is recommended; instruments should instead be targeted at the institutions that are likely to promote degradation. For the insurance sector, supervisors must ensure ESG screening of the short-duration investment horizons that back technical reserves and underwriting frameworks, which could price environmental risk premiums to discourage the insurance of highly polluting activities. Finally, policymakers may condition R&D incentives on environmental performance and channelize funds towards sustainable and clean energy projects.

5.2. Limitations and future research

This study is limited to only six developed countries and uses data from 2001 to 2020. Extending the study to institutional-level disintegration and considering developing and emerging countries may expand the scope of the current findings. Moreover, due to data limitations, this study uses asset and premium-based proxies; future studies could employ alternative proxies, such as portfolio-based and ESG-backed assets, to explore the channels through which non-bank institutions decrease environmental degradation.

Appendix 1: Country-wise FMOLS results

Country	Variable	Model with aggregate insurance market development	Model with life-insurance market development	Model with non-life insurance market development
France	lnMF	-0.09*** (-4.93)	-0.14*** (-4.69)	-0.20*** (-26.35)
	lnPF	-0.02 (-1.60)	-0.07*** (-2.88)	-0.08*** (-10.77)
	lnIC/lnLFI/lnNLFI	-0.58*** (-10.51)	-0.40*** (-4.05)	0.06*** (5.49)
	lnBD	-0.03 (-0.93)	-0.16*** (-2.74)	-0.03 (-1.60)
	lnEPS	0.10*** (7.54)	0.13*** (4.32)	0.08*** (8.53)
	lnRE	-0.38*** (-19.66)	-0.46*** (-11.26)	-0.35*** (-27.13)
Germany	lnMF	-0.32*** (-36.29)	-0.33*** (-35.17)	-0.23*** (-33.26)
	lnPF	-0.23*** (-16.22)	-0.14*** (-7.79)	-0.16*** (-12.54)
	lnIC/lnLFI/lnNLFI	0.21*** (11.36)	0.21*** (15.45)	0.07*** (5.99)
	lnBD	-0.40*** (-25.23)	-0.48*** (-24.58)	-0.49*** (-35.23)
	lnEPS	-0.31*** (-19.21)	-0.19*** (-8.49)	-0.30*** (-17.43)
	lnRE	0.28*** (38.01)	0.21*** (15.74)	0.31*** (45.92)
Italy	lnMF	-0.07*** (-3.84)	-0.10*** (-9.46)	-0.03*** (-3.11)
	lnPF	-0.29*** (-10.31)	-0.39*** (-20.06)	-0.24*** (-18.44)
	lnIC/lnLFI/lnNLFI	0.09*** (3.16)	0.24*** (11.04)	-0.05*** (-5.85)
	lnBD	0.07* (1.64)	0.11*** (3.28)	0.04 (1.46)
	lnEPS	0.23*** (8.00)	0.07*** (2.77)	0.26*** (15.47)
	lnRE	-0.20*** (-6.29)	-0.08*** (-3.41)	-0.20*** (-10.27)
Japan	lnMF	0.01 (1.02)	-0.02 (-1.21)	0.02*** (2.74)
	lnPF	-0.34*** (-15.36)	-0.06** (-1.96)	-0.25*** (-10.82)
	lnIC/lnLFI/lnNLFI	0.27*** (5.98)	0.07 (1.05)	-0.03 (-1.31)
	lnBD	-0.52*** (-15.98)	-0.79*** (-17.31)	-0.51*** (-14.84)
	lnEPS	0.14*** (8.60)	0.16*** (8.79)	0.16*** (6.59)
	lnRE	-0.23*** (-13.87)	-0.10*** (-4.10)	-0.24*** (-13.65)
United Kingdom	lnMF	-0.03* (-1.94)	0.06*** (2.98)	-0.20*** (-5.72)
	lnPF	-0.18*** (-7.87)	-0.25*** (-7.77)	0.23*** (4.25)
	lnIC/lnLFI/lnNLFI	0.26*** (8.81)	0.02 (0.46)	0.25*** (7.49)
	lnBD	0.20*** (12.33)	0.25*** (12.60)	0.23*** (12.53)
	lnEPS	0.07*** (4.11)	-0.13*** (-3.63)	0.03* (1.68)
	lnRE	-0.18*** (-24.90)	-0.14*** (-10.91)	-0.27*** (-18.27)
United States	lnMF	-0.05* (-1.82)	-0.14*** (-8.68)	-0.25*** (-17.69)
	lnPF	0.24*** (14.62)	0.09*** (7.43)	0.17*** (14.55)
	lnIC/lnLFI/lnNLFI	-0.53*** (-9.81)	0.42*** (12.23)	0.05*** (5.43)
	lnBD	0.08*** (2.62)	0.07*** (3.39)	0.12*** (4.41)
	lnEPS	-0.34*** (-16.49)	-0.02 (-0.85)	-0.22*** (-18.66)
	lnRE	-0.11*** (-4.19)	-0.47*** (-14.79)	-0.09*** (-4.55)

*Notes: t-statistics in parentheses. **, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.
Source: Authors' own work

References

- Ahmad, M., Ahmed, Z., Yang, X., Hussain, N., & Sinha, A. (2022). Financial development and environmental degradation: Do human capital and institutional quality make a difference? *Gondwana Research*, *105*, 299–310.
- Ahmed, Z., Zhang, B., & Cary, M. (2021). Linking economic globalization, economic growth, financial development, and ecological footprint: Evidence from symmetric and asymmetric ARDL. *Ecological Indicators*, *121*, 107060.
- Al-Mulali, U., Ozturk, I., & Lean, H. H. (2015). The influence of economic growth, urbanization, trade openness, financial development, and renewable energy on pollution in Europe. *Natural Hazards*, *79*(1), 621–644.
- Altarhouni, A., Danju, D., & Samour, A. (2021). Insurance Market Development, Energy Consumption, and Turkey's CO2 Emissions. New Perspectives from a Bootstrap ARDL Test. *Energies*, *14*(23), 7830.
- Aluko, O. A., & Obalade, A. A. (2020a). Financial development and environmental quality in sub-Saharan Africa: Is there a technology effect? *Science of The Total Environment*, *747*, 141515.
- Aluko, O. A., & Obalade, A. A. (2020b). Financial development and environmental quality in sub-Saharan Africa: Is there a technology effect? *Science of The Total Environment*, *747*, 141515.
- Andrew, A. A., Adebayo, T. S., Lasisi, T. T., & Muoneke, O. B. (2024). Moderating roles of technological innovation and economic complexity in financial development-environmental quality nexus of the BRICS economies. *Technology in Society*, *78*, 102581.
- Appiah-Otoo, I., & Acheampong, A. O. (2021). Does insurance sector development improve environmental quality? Evidence from BRICS. *Environmental Science and Pollution Research*, *28*(23), 29432–29444.
- Ashraf, A., & Doytch, N. (2023). Does investing abroad reduce the ecological footprints at home? Analysis of outward GFDI and M&A from developed and developing countries. *Environment, Development and Sustainability*, *25*(7), 6689–6710.
- Ashraf, A., Nguyen, C. P., & Doytch, N. (2022). The impact of financial development on ecological footprints of nations. *Journal of Environmental Management*, *322*, 116062.
- Azar, J., Duro, M., Kadach, I., & Ormazabal, G. (2021). The Big Three and corporate carbon emissions around the world. *Journal of Financial Economics*, *142*(2), 674–696.
- Baloch, M. A., Zhang, J., Iqbal, K., & Iqbal, Z. (2019). The effect of financial development on ecological footprint in BRI countries: Evidence from panel data estimation. *Environmental Science and Pollution Research*, *26*(6), 6199–6208.
- Balsalobre-Lorente, D., Nur, T., Topaloglu, E. E., & Evcimen, C. (2023). Assessing the impact of the economic complexity on the ecological footprint in G7 countries: Fresh evidence under human development and energy innovation processes. *Gondwana Research*, S1342937X23000941.
- Bhowmik, R., Sharif, A., Anwar, A., Raza Syed, Q., The Cong, P., & Ha, N. N. (2024). Does environmental policy stringency alter the natural resources-emissions nexus? Evidence from G-7 countries. *Geoscience Frontiers*, *15*(5), 101874.

- Blomquist, J., & Westerlund, J. (2013). Testing slope homogeneity in large panels with serial correlation. *Economics Letters*, 121(3), 374–378.
- Boutabba, M. A. (2014). The impact of financial development, income, energy and trade on carbon emissions: Evidence from the Indian economy. *Economic Modelling*, 40, 33–41.
- Breusch, T. S., & Pagan, A. R. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies*, 47(1), 239.
- Caglar, A. E., Mert, M., & Boluk, G. (2021). Testing the role of information and communication technologies and renewable energy consumption in ecological footprint quality: Evidence from world top 10 pollutant footprint countries. *Journal of Cleaner Production*, 298, 126784.
- Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2), 393–420.
- Dar, J. A., & Asif, M. (2017). Is financial development good for carbon mitigation in India? A regime shift-based cointegration analysis. *Carbon Management*, 8(5–6), 435–443.
- Dogan, E., & Seker, F. (2016). An investigation on the determinants of carbon emissions for OECD countries: Empirical evidence from panel models robust to heterogeneity and cross-sectional dependence. *Environmental Science and Pollution Research*, 23(14), 14646–14655.
- Dogan, E., & Turkekul, B. (2016). CO2 emissions, real output, energy consumption, trade, urbanization and financial development: Testing the EKC hypothesis for the USA. *Environmental Science and Pollution Research*, 23(2), 1203–1213.
- Ertur, C., & Musolesi, A. (2017). Weak and Strong Cross-Sectional Dependence: A Panel Data Analysis of International Technology Diffusion. *Journal of Applied Econometrics*, 32(3), 477–503.
- Fakher, H. A., & Ahmed, Z. (2023). Does financial development moderate the link between technological innovation and environmental indicators? An advanced panel analysis. *Financial Innovation*, 9(1), 112.
- Faraji Dizaji, S., & Ousia, N. A.-S. (2017). The Effects of Economic, Financial and Political Developments on Iran's CO2 Emissions. *Iranian Economic Review*, 21(4).
- Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*, 142(2), 499–516.
- Ganda, F. (2019). The impact of innovation and technology investments on carbon emissions in selected organisation for economic Co-operation and development countries. *Journal of Cleaner Production*, 217, 469–483.
- Gök, A. (2020). The role of financial development on carbon emissions: A meta regression analysis. *Environmental Science and Pollution Research*, 27(11), 11618–11636.
- Grossman, G. M., & Krueger, A. B. (1995). Economic Growth and the Environment. *The Quarterly Journal of Economics*, 110(2), 353–377.
- Halkos, G. E., & Polemis, M. L. (2017). Does Financial Development Affect Environmental Degradation? Evidence from the OECD Countries. *Business Strategy and the Environment*, 26(8), 1162–1180.
- Hao, Y., Zhang, Z.-Y., Liao, H., Wei, Y.-M., & Wang, S. (2016). Is CO2 emission a side effect of financial development? An empirical analysis for China. *Environmental Science and Pollution Research*, 23(20), 21041–21057. h
- Hashem Pesaran, M., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, 142(1), 50–93.
- Ibrahiem, D. M. (2020). Do technological innovations and financial development improve environmental quality in Egypt? *Environmental Science and Pollution Research*, 27(10), 10869–10881.

- Jalil, A., & Feridun, M. (2011). The impact of growth, energy and financial development on the environment in China: A cointegration analysis. *Energy Economics*, 33(2), 284–291.
- Kartal, M. T., Samour, A., Adebayo, T. S., & Kılıç Depren, S. (2023). Do nuclear energy and renewable energy surge environmental quality in the United States? New insights from novel bootstrap Fourier Granger causality in quantiles approach. *Progress in Nuclear Energy*, 155, 104509.
- Kaushal, L. A., Chauhan, A. S., Dwivedi, A., & Bag, S. (2024). The governance factor: Mitigating carbon emissions through FDI and financial development in emerging Asian economies. *Journal of Environmental Management*, 367, 121740. h
- Kayhan, F., Turgut, M., & İslamoglu, M. (2021). A Comparative Overview Of Mutual Funds, Pension Funds, Real Estate Investment Funds And Venture Capital Investment Funds. *Aksaray Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 13(3), 117–126.
- Khan, A., Muhammad, F., Chenggang, Y., Hussain, J., Bano, S., & Khan, M. A. (2020). The impression of technological innovations and natural resources in energy-growth-environment nexus: A new look into BRICS economies. *Science of The Total Environment*, 727, 138265.
- Kihombo, S., Ahmed, Z., Chen, S., Adebayo, T. S., & Kirikkaleli, D. (2021). Linking financial development, economic growth, and ecological footprint: What is the role of technological innovation? *Environmental Science and Pollution Research*, 28(43), 61235–61245.
- Kirikkaleli, D., & Adebayo, T. S. (2021). Do renewable energy consumption and financial development matter for environmental sustainability? New global evidence. *Sustainable Development*, 29(4), 583–594.
- Krueger, P., Sautner, Z., & Starks, L. T. (2020). The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies*, 33(3), 1067–1111.
- Lee, C.-C., Yahya, F., & Razzaq, A. (2023). Greening South Asia with Financial Liberalization, Human Capital, and Militarization: Evidence from the CS-ARDL Approach. *Energy & Environment*, 34(6), 1957–1981.
- Lee, J.-M., Chen, K.-H., & Cho, C.-H. (2015). THE RELATIONSHIP BETWEEN CO₂ EMISSIONS AND FINANCIAL DEVELOPMENT: EVIDENCE FROM OECD COUNTRIES. *The Singapore Economic Review*, 60(05), 1550117.
- Nketiah, E., Song, H., Adjei, M., Obuobi, B., & Adu-Gyamfi, G. (2024). Assessing the influence of research and development, environmental policies, and green technology on ecological footprint for achieving environmental sustainability. *Renewable and Sustainable Energy Reviews*, 199, 114508.
- Ozturk, I., & Acaravci, A. (2013). The long-run and causal analysis of energy, growth, openness and financial development on carbon emissions in Turkey. *Energy Economics*, 36, 262–267.
- Pan, X., Yan, Y., Peng, X., & Liu, Q. (2016). Analysis of the Threshold Effect of Financial Development on China's Carbon Intensity. *Sustainability*, 8(3), 271
- Pata, U. K., & Yilanci, V. (2020). Financial development, globalization and ecological footprint in G7: Further evidence from threshold cointegration and fractional frequency causality tests. *Environmental and Ecological Statistics*, 27(4), 803–825.
- Patrick, H. T. (1966). Financial Development and Economic Growth in Underdeveloped Countries. *Economic Development and Cultural Change*, 14(2), 174–189.
- Pedroni, P. (1999). Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors. *Oxford Bulletin of Economics and Statistics*, 61(s1), 653–670.
- Pedroni, P. (2000). Fully modified OLS for heterogeneous cointegrated panels. In *Advances in Econometrics* (Vol. 15, pp. 93–130). Emerald (MCB UP).

- Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels. *IDEAS Working Paper*.
- Pesaran, M. H. (2006). Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. *Econometrica*, 74(4), 967–1012.
- Pesaran, M. H., Ullah, A., & Yamagata, T. (2008). A bias-adjusted LM test of error cross-section independence. *The Econometrics Journal*, 11(1), 105–127.
- Popescu, I.-S., Schaubroeck, T., Gibon, T., Petucco, C., & Benetto, E. (2024). Investment funds are responsible for substantial environmental and social impacts. *Communications Earth & Environment*, 5(1), 355.
- Raggad, B., Ben-Salha, O., Zrelly, H., & Jbir, R. (2024). How do financial institutions and markets impact the ecological footprint in Saudi Arabia? A nonlinear cointegration approach. *Stochastic Environmental Research and Risk Assessment*, 38(3), 1099–1119.
- Rahman, S. U., Faisal, F., Ali, A., Mansor, N. N. A., Ul Haq, Z., Sulimany, H. G. H., & Ramakrishnan, S. (2024). Assessing Country Risk in the Stock Market and Economic Growth Nexus: Fresh Insights from Bootstrap Panel Causality. *The Quarterly Review of Economics and Finance*, 94, 294–302.
- Rashid, A., Yahya, F., & Hussain, M. (2025). Money supply and carbon procyclicality under the financial Kuznets curve. *Journal of Economic Studies*, 1–20.
- Rempel, A., & Gupta, J. (2020). Conflicting commitments? Examining pension funds, fossil fuel assets and climate policy in the organisation for economic co-operation and development (OECD). *Energy Research & Social Science*, 69, 101736.
- Ridzuan, A., Ismail, N., & Che Hamat, A. (2017). Does Foreign Direct Investment Successfully Lead to Sustainable Development in Singapore? *Economies*, 5(3), 29.
- Shahbaz, M., Dogan, M., Akkus, H. T., & Gursoy, S. (2023). The effect of financial development and economic growth on ecological footprint: Evidence from top 10 emitter countries. *Environmental Science and Pollution Research*, 30(29), 73518–73533.
- Shahbaz, M., Hye, Q. M. A., Tiwari, A. K., & Leitão, N. C. (2013). Economic growth, energy consumption, financial development, international trade and CO2 emissions in Indonesia. *Renewable and Sustainable Energy Reviews*, 25, 109–121.
- Shahbaz, M., Patel, N., Du, A. M., & Ahmad, S. (2024). From black to green: Quantifying the impact of economic growth, resource management, and green technologies on CO2 emissions. *Journal of Environmental Management*, 360, 121091.
- Shahbaz, M., Shahzad, S. J. H., Ahmad, N., & Alam, S. (2016). Financial development and environmental quality: The way forward. *Energy Policy*, 98, 353–364.
- Shahbaz, M., Solarin, S. A., Mahmood, H., & Arouri, M. (2013). Does financial development reduce CO2 emissions in Malaysian economy? A time series analysis. *Economic Modelling*, 35, 145–152.
- Shahbaz, M., Topcu, B. A., Sarıgül, S. S., & Vo, X. V. (2021). The effect of financial development on renewable energy demand: The case of developing countries. *Renewable Energy*, 178, 1370–1380.
- Svirydzenka, K. (2016). *Introducing a new broad-based index of financial development*. International Monetary Fund. <https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Introducing-a-New-Broad-based-Index-of-Financial-Development-43621>
- Swamy, P. A. V. B. (1970). Efficient Inference in a Random Coefficient Regression Model. *Econometrica*, 38(2), 311.

- Tamazian, A., & Bhaskara Rao, B. (2010). Do economic, financial and institutional developments matter for environmental degradation? Evidence from transitional economies. *Energy Economics*, 32(1), 137–145.
- Tamazian, A., Chousa, J. P., & Vadlamannati, K. C. (2009). Does higher economic and financial development lead to environmental degradation: Evidence from BRIC countries. *Energy Policy*, 37(1), 246–253.
- Taylor, R. J., & Tollin, H. M. (2009). Insurance Market for Global Warming Heats Up: Old Products and New Policies Respond to Climate Change Risks. *Environmental Claims Journal*, 21(3), 247–261.
- Tong, X., Li, X., Tong, L., & Jiang, X. (2018). Spatial Spillover and the Influencing Factors Relating to Provincial Carbon Emissions in China Based on the Spatial Panel Data Model. *Sustainability*, 10(12), 4739.
- Usman, M., & Hammar, N. (2021). Dynamic relationship between technological innovations, financial development, renewable energy, and ecological footprint: Fresh insights based on the STIRPAT model for Asia Pacific Economic Cooperation countries. *Environmental Science and Pollution Research*, 28(12), 15519–15536.
- Usman, M., Jahanger, A., Makhdum, M. S. A., Balsalobre-Lorente, D., & Bashir, A. (2022). How do financial development, energy consumption, natural resources, and globalization affect Arctic countries' economic growth and environmental quality? An advanced panel data simulation. *Energy*, 241, 122515.
- Usman, M., & Makhdum, M. S. A. (2021). What abates ecological footprint in BRICS-T region? Exploring the influence of renewable energy, non-renewable energy, agriculture, forest area and financial development. *Renewable Energy*, 179, 12–28.
- Wang, R., Usman, M., Radulescu, M., Cifuentes-Faura, J., & Balsalobre-Lorente, D. (2023). Achieving ecological sustainability through technological innovations, financial development, foreign direct investment, and energy consumption in developing European countries. *Gondwana Research*, 119, 138–152.
- Westerlund, J. (2007). Testing for Error Correction in Panel Data*. *Oxford Bulletin of Economics and Statistics*, 69(6), 709–748.
- Xing, T., Jiang, Q., & Ma, X. (2017). To Facilitate or Curb? The Role of Financial Development in China's Carbon Emissions Reduction Process: A Novel Approach. *International Journal of Environmental Research and Public Health*, 14(10), 1222.
- Xiong, L., Tu, Z., & Ju, L. (2017). Reconciling Regional Differences in Financial Development and Carbon Emissions: A Dynamic Panel Data Approach. *Energy Procedia*, 105, 2989–2995.
- Zhang, Y., & Umair, M. (2023). Examining the interconnectedness of green finance: An analysis of dynamic spillover effects among green bonds, renewable energy, and carbon markets. *Environmental Science and Pollution Research*, 30(31), 77605–77621.