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Bridging Growth and Sustainability: How Financial Development Shapes the GDP-Climate Finance Nexus

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Abstract
This study investigates the impact of GDP growth on climate finance and the moderating role of financial development in this relationship. It analyses a panel dataset from 2001 to 2021, encompassing the top 25 contributors and affected countries. Employing GMM, static, and dynamic panel techniques, the study presents descriptive statistics, correlation matrices, and regression results. Findings indicate a strong negative association between GDP growth and climate finance, with significant cross-sectional dependence across countries. While GDP per capita shows a linear relationship with climate finance, financial development exhibits a non-linear relationship. The GMM results reveal that GDP growth positively influences climate finance in wealthier economies (Panel A), whereas in lower-income countries, the relationship is negative and quadratic (Panel B), indicating reduced access to climate finance as income rises. Financial development moderates these negative effects by enhancing resource allocation and risk management for climate initiatives. The study emphasizes the need for policies that align economic growth with climate objectives, improve financial systems, promote diverse financial instruments like green bonds, and continuously adapt strategies to ensure effective and sustainable climate finance.

Keywords: Climate finance, financial development, GDP growth, carbon emitter countries, affected countries, quadratic relationship, non-linear relationship

JEL Classification: Q54, O16, E22, G32

1. Introduction

Climate financing, often known as financing for climate-related initiatives, is a broad notion without a well-defined definition or scope. Over the past few decades, climate finance has grown to be a vital tool for shaping how nations communicate with each other, considering ways to cooperate in the development and define common strategies to deal with global warming catastrophe on a national, regional, local, and international level (Mahat et al. 2019). Climate change represents one of the most significant challenges of this century, affecting global ecosystems, economies, and societies on an unprecedented scale (Štreimikienė 2021). Recently, climate change has caused unprecedented economic and human losses (Mumtaz 2018). People's livelihoods and economic growth rate are thought to be severely impacted by climate change and global warming, particularly in industrialized nations (Nath and Behera 2011). Unpredictable rainfall, increased cyclones, and their destructive power, increased extreme weather events, and glacier melting events are already signs of the effects of climate change (Reddy and Gangle 2015). The poor countries of the Global South are most affected by climate change because of their extremely limited capacity for adaptation and mitigation (Satterthwaite 2008).

Various governance and institutional initiatives have been launched at both local and global levels to address climate change, with many additional actions and strategies still being proposed to mitigate its impacts and adapt to its consequences (Buchner et al. 2014). However, addressing climate change is inherently complex, necessitating both innovative strategies and proactive measures to effectively manage its multifaceted challenges and mitigate its far-reaching impacts. Climate change is a global issue that requires coordinated international efforts to effectively address its widespread impacts and achieve meaningful results (Lundsgaarde, Dupuy, and Persson 2018). Countries around the world, especially developing nations, are grappling with the effects of climate change, prompting the creation of international frameworks aimed at collectively addressing this global challenge and mitigating its impact on vulnerable regions. Developed countries should extend financial support, known as climate finance, to assist developing economies in both adapting to and mitigating the adverse impacts of climate change, thereby facilitating their capacity to manage and respond to these environmental challenges effectively (Chowdhury & Jomo, 2022; Khan et al., 2022; Pauw, 2017). According to the Paris Agreement, developing countries are encouraged to utilize climate finance to invest in renewable energy sources, aiming to reduce greenhouse gas emissions, and enhance their preparedness for the impacts of extreme weather events such as droughts and floods (Banga 2019).

Being a worldwide public good, climate poses special challenges for preserving and protecting it because the effectiveness of initiatives to slow down climate change depends on international cooperation and cannot be accomplished unilaterally (Nath and Behera 2011). As nations begin to change, the direction of climate action can be greatly influenced by climate finance because they are transforming these targets into actual mitigation measures (Newell and Bulkeley 2017). Kirikkaleli and Kalmaz (2020), noted that to achieve a high standard of living, developing nations seek to increase their "economic growth," which can be accomplished by increasing production output. These nations' higher output leads to higher levels of energy consumption and urbanization, which in turn fuels high carbon emissions and inefficient use of energy resources. The majority of people in developing countries are poor and dependent on agriculture, but they do not have access to better farming technology, climatic information, other employment opportunities, or institutional support systems. As a result, the situations there are very different. Because of their dependence on climate change-sensitive resources, they may experience significant impacts on their way of life (Nanda 2009).

Because of disparities in geographical position and economic strength, there are major variances in the extent to which developed and developing nations are exposed to environmental degradation (Angelsen and Dokken 2018). To support low-income countries in achieving development that is both climate-resilient and low-carbon, climate finance is a crucial initiative, providing the necessary resources and funding to foster sustainable growth and mitigate environmental impacts (Lundsgaarde et al. 2018; Xue et al., 2022). To maximize profits, wealthy economies seek to invest in emerging economies that have stricter environmental regulations and lower environmental levies, capitalizing on the more favorable financial conditions while adhering to their environmental standards (Quynh et al. 2022). Governments are essential in utilizing financial resources to promote the low-carbon transition and the fight against climate change (Buchner et al. 2014). According to Ellis and Moarif (2017), transparency regarding the type and amount of climate funding offered, mobilized, as well as received by developing countries from developed is essential for both domestic and international purposes. International climate financing providers seek to fund national mitigation efforts that can demonstrate not just their immediate impact on emissions reduction, but also their capacity for self-sustained implementation and "transformational change" in light of their limited financial resources (Betsill et al. 2015). Chaudhry (2017) reaching the goal to reduce emission levels will cost the economy in terms of decreased productivity or the need to switch to cleaner inputs, which may be more expensive for current and future energy sector production of products and services.

The research investigates the interplay between financial development, GDP growth, and climate finance, particularly in the context of low-income countries that are disproportionately affected by climate change despite their minimal contributions to global warming. Existing literature has primarily focused on the distribution and efficiency of climate funds, leaving a gap in understanding the role of financial development as a moderating variable. This study aims to fill that void by examining how financial development influences climate finance while also assessing the impact of GDP growth. The research questions focus on the effects of GDP growth and financial development on climate finance, as well as the moderating role of financial development in the relationship between GDP growth and climate finance. A comparative analysis between high carbon emitter countries and vulnerable nations will further illuminate the differing dynamics of these variables.

The significance of this study lies in its potential contributions to both theoretical and empirical knowledge in the field of climate finance. By focusing on the top 25 most affected countries and the top 25 leading contributors to climate change, the research aims to provide valuable insights into how financial development can enhance climate finance effectiveness across different contexts. This study also seeks to identify which specific factors are most effective in addressing climate finance challenges, emphasizing the growing interest in the relationship between financial development and GDP growth by offering empirical evidence and developing a policy framework, this research intends to support future scholars and practitioners in understanding the critical role of financial development in climate finance. Ultimately, the study stands as a pioneering effort in comparative analysis using these variables, enhancing both the theoretical and practical understanding of climate finance dynamics. Furthermore, there are some control variables in the study as well.

2. Literature Review

2.1 GDP Growth and Climate Finance

Similar to the finance-growth nexus, the literature on finance's impact on environmental degradation or improvement is interesting but shows mixed and inconclusive results (Salahuddin et al., 2018; Bekhet et al., 2017). Hariharan et al. (2022) gave an example in their study that in 2017 a team of economists and scientists in the United States mapped out the potential financial harms that the government might experience which is that by the end of the century, global warming could reduce the GDP of the country by three to six percentage points if it continued at its current rate. As Weiler et al. (2018) stated in their study the rationale behind employing GDP per capita is to account for the possibility that the world's poorest nations will only receive a small amount of aid because they are either unable to accept it or are thought to be unable to do so. However, once GDP reaches a certain level, nations can increasingly handle adaptation-related issues domestically. Thus, the expectation is to identify a positive linear coefficient and a negative quadratic coefficient in the analysis. The results suggest that the probability of receiving adaptation aid diminishes as GDP per capita increases, indicating a decreasing likelihood of receiving such aid with higher levels of economic development. Furthermore, Robinson and Dornan (2017) studied population, GDP, vulnerability, and governance impact on adaptation funds, and the outcomes revealed that population, vulnerability, and governance have a statistically significant relationship with adaptation funds. In contrast, GDP has negatively correlated with adaptation funds.

Robertsen et al. (2015) observed that the majority of climate funds were allocated to lower-middle-income countries, highlighting a significant distribution trend in climate finance towards these economies. Halimanjaya's (2015) research has demonstrated that developing nations are more likely to be chosen to receive climate mitigation funding and to receive more funding overall if they have greater carbon intensity, lower GDP per capita, effective governance, and a larger carbon sink. Islam (2022) investigated the impact of GDP per capita, vulnerability, readiness, HDI, population, CO2 emissions, and import index ODA per capita on adaptation funding, mitigation funding, and overlap funding by using the dynamic panel regression method based on the GMM, the results revealed that vulnerability has no significant impact on funding for mitigation, but has a considerable impact on funding for overlap and adaptation but GDP per capita, and greenhouse gas emissions, one of the control variables, unexpectedly revealed funding for mitigation was significantly impacted negatively, but funding for adaptation or overlap was not significantly impacted. Lee et al. (2022) empirical findings reveal that developing countries receiving climate finance experience substantial reductions in carbon emissions, with mitigation finance demonstrating a more pronounced effect compared to adaptation finance.

To analyze climate financing, Quynh et al. (2022) took three elements together: The analysis of FDI inflows as a percentage of GDP, R&D expenditures as a percentage of GDP, and renewable energy consumption as a percentage of total energy demand for N-11 countries reveals that there is a negative relationship between carbon emissions and the use of renewable energy. In contrast, the relationship between carbon emissions and R&D expenditure is inverse, indicating a different pattern in how R&D investments impact carbon emissions. On the other hand, FDI inflows and carbon emissions are positively correlated. Furthermore, Zhao et al. (2022) study investigates the impact of climate finance, including financing for adaptation and mitigation, on economic risks in developing nations. To quantify climate finance, they used the ratio of the GDP of the logarithm of the three distinct funding types to the recipient nation. The information was gathered from the OECD-DAC database. Masud et al. (2023) collected climate finance data from the Joint Report on MDBs from the year 2011 up to 2021 for South Asia regions and the GCF website. The results showed that global climate finance initiatives are greatly influenced by the climate finance provided by MDBs. Doku et al. (2021) employed DAC donors' financing data for various development projects, categorized under the OECD Rio Marker Creditor Reporting System, to provide a detailed analysis of climate finance (OECD 2018). Two categories can be used to categorize climate finance: While mitigation financing principally aims to reduce greenhouse gas emissions by, for example, investing in renewable energy sources and reducing deforestation, adaptation finance promotes adaptation to real or anticipated climate change and its repercussions (Pickering, Betzold, and Skovgaard 2017). Furthermore, there are some control variables in the study as well.

H1: GDP growth has a significant positive/negative impact on climate finance.

2.2 Financial Development and Climate Finance

Financing for climate change mitigation and adaptation, mobilized by private financial institutions and investors, plays a critical role in achieving global climate change targets, as it supplies the essential resources and investment necessary to support and implement effective strategies for reducing greenhouse gas emissions and adapting to the impacts of climate change (Kawabata 2019). Financial markets and economic systems are increasingly affected by climate change events, as the impacts of climate-related phenomena begin to alter market dynamics and economic stability (Pagnottoni et al. 2022). These approaches have been further expanded to explore the nexus between climate change and finance from a diverse array of perspectives, encompassing various analytical frameworks and methodological approaches (Roncoroni et al., 202; Battiston et al., 2021). Various public actors, such as governments, aid agencies, Climate Funds, and Development Finance Institutions (DFIs), drive public climate finance. They aim to lower the costs and risks of climate investments, boost knowledge and skills, and build a strong track record to build confidence in these investments (Buchner and Clark 2019). Closing the climate finance gap could become more affordable if governments effectively influence policy and market signals, ensure predictable and stable profits, and enhance the strategic potential of investments, all of which are crucial factors in attracting private climate finance (Jin and Kim 2017).

Richardson (2009) argued that the financial sector has emerged as an increasingly prominent stakeholder due to its capacity to serve as a key financier for clean development, particularly given the international urgency to address climate change. Transforming into a low-carbon economy will be unattainable without a robust and supportive private financial sector, as it is crucial for providing the necessary capital and investment required to drive the transition to sustainable energy sources and technologies (Sullivan 2014). Companies need to consider climate change risks more as financial institutions now include clients' climate considerations in their investment decisions (Chiu 2015). Therefore, private climate finance significantly influences the achievement of global climate change targets by providing critical funding and resources necessary for implementing effective mitigation and adaptation strategies (Kawabata 2019). The study was conducted by Kawabata (2019) to identify the determinants influencing financial institutions' mobilization of climate finance, the results indicate that institutions that participate in more climate finance initiatives demonstrate a higher level of engagement in climate finance, with this relationship being statistically significant at the 1% level. Additionally, if a financial institution primarily functions as a debt financier, it is expected to show a greater degree of involvement in climate finance. This is supported by a positive coefficient that is statistically significant at the 5% level, highlighting a strong association between debt financing activities and climate finance participation.

H2: Financial development has a significant positive impact on climate finance.

2.3 Financial Development moderates GDP growth and Climate Finance

Financial development (FD) is essential for economic growth as it facilitates the connection between surplus and deficit sectors of the economy, thereby enhancing the mobilization, utilization, and monitoring of funds. This interconnectedness improves the efficiency of financial transactions and resource allocation, which supports broader economic advancement (Raheem and

Oyinlola 2015). Similarly, the financial sector plays a pivotal role in encouraging firms and industries to adopt modern, environmentally friendly technologies by providing the necessary funding and incentives that facilitate the transition to sustainable practices (Nasreen, Anwar, and Ozturk 2017). Shujah-ur-Rahman et al. (2019) examine how financial development moderates the relationship between carbon emissions, real income, and energy usage in the case of Pakistan. By applying the ARDL technique in short-run and long-run estimations. The results show that carbon emissions are positively and statistically significantly connected with energy consumption and real income, but negatively and statistically significantly correlated with both financial development and GDP per capita. Ehigiamusoe et al. (2021) study demonstrates that the GDP positively affects financial development across the board for the panel.

The high- and middle-income groups have profited when splitting the panel into different income categories, but the low-income group has seen negligible effects. The role of financial development is significant in influencing both carbon emissions and energy consumption, as it affects the allocation of resources towards cleaner technologies and sustainable practices, thereby impacting the overall environmental and energy efficiency of economic activities (Guo, Hu, and Yu 2019). As Guo et al. (2019) stated financial development can help organizations access more R&D money by broadening financing sources. They can help low-carbon businesses and projects raise the necessary capital to support technological innovation that is free of carbon emissions. According to Wang et al. (2012), Carbon-free technological innovation has the potential to significantly reduce carbon emissions. Financial development has the potential to boost economic growth and significantly influence the modernization of the industrial structure, which in turn affects energy use and carbon emissions (Nasreen et al., 2017; Ziaei, 2015). Furthermore, Katircioğlu and Taşpinar (2017) conducted a study for Turkiye from 1960 to 2010 time period using DOLS, VECM, and the Granger Causality test outcomes revealed that financial development moderates the effects of GDP on CO2 emissions, a finding that aligns with the results reported by Jalil and Feridun (2011), who discovered similar results in China inside a Chinese environment. Nevertheless, the moderating effect changes to a positive value when the output is doubled, suggesting that there may be a rise in carbon emissions later in development. The Autoregressive distributed lag model was used by Shahbaz et al. (2013) study to assess if Malaysia's CO2 emissions were reduced by financial development between 1971 and 2011, and it was found that long-run correlations exist among the variables

H3: Financial development moderates the positive/negative impact between GDP growth and climate finance.

2.4 ND-GAIN Index for Readiness and Vulnerability

The current study used the ND-GAIN index for readiness and vulnerability as control variables which has been widely used by many pieces of research previously (Mori et al., 2019; Betzold & Weiler, 2017; Weiler et al., 2018). The ND-GAIN vulnerability index included six sectors infrastructure, ecosystem services, food, water, health, and human habitat. Whereas the ND-GAIN readiness index includes governance readiness, social readiness, and economic readiness indicators. From the study, by Doku et al. (2021) Governance Readiness is assessed using four key indicators: rule of law, regulatory quality, control of corruption, and political stability and non-violence. Higher-quality governments are better at using funds effectively, so they might receive more adaptation aid. On the other hand, if a government is of lower quality, it might struggle more with adaptation and be more vulnerable, which could mean it gets less aid (Weiler et al., 2018). The Social Readiness Index is compiled using four main indicators: Information Communication Technology (ICT) infrastructure, education, social inequality, and innovation. Additionally, Economic Readiness is assessed through the "Ease of Doing Business (DB)" indicator provided by the World Bank, which measures various aspects of the business environment. This illustrates how varying strategies and conditions in different countries can influence their ability to attract investment for adaptation, highlighting the complex interplay between national policies and investment attractiveness (Chen et al. 2015). Barrett (2014) discovered that vulnerability does not significantly influence the ability to attract climate finance, suggesting that other factors may be more critical in determining the flow of financial resources for climate initiatives. As Samuwai and Hills (2018) study investigating the impact of readiness in Asian-Pacific countries on climate finance, it was revealed that readiness serves as a more significant determinant of attracting climate finance compared to factors such as population size, per capita GDP levels, and governance quality.

Similarly, institution and governance weaknesses and violence and conflicts, which are common in many developing nations, may deter investors as a result of increased perceived investment risks. The study demonstrates the significant impacts of these factors on funding allocations for both mitigation and adaptation efforts, highlighting how variations in these elements can influence the distribution and effectiveness of climate finance (Bagchi, Castro, and Michaelowa 2016). According to Nakhooda et al. (2015), the institutional strength of recipient countries determines the flow of climate funds; higher-income nations have better institutions and more developed economies.

2.5 Population

Population is included for two reasons: first, larger countries attract greater geopolitical interest, which can influence the volume of aid they receive, and second, population size impacts the level of aid per capita, with smaller countries generally receiving relatively more aid per capita compared to their larger counterparts (Weiler et al. 2018b). Furthermore, Doku et al. (2021) empirical evidence indicates that both population size and readiness are significant determinants of climate finance in Sub-Saharan Africa, suggesting that these factors play a crucial role in influencing the allocation and effectiveness of climate-related funding in the region.

3. Data and Methodology

This is quantitative research. We are using secondary data. This study includes a panel dataset from the period 2001 to 2021 on 50 countries. We divided our study into two parts to make a comparison as it is one of the important objectives of this study; panel A: 25 carbon-emitter countries include 525 observations and panel B: 25 carbon-affected countries include 525 observations as shown in Table 1. They were drawn from various geographical regions. The list of countries is sorted according to their contribution to emitting carbon and their vulnerability. The dependent variable is climate finance. GDP growth as an independent variable. Whereas financial development is taken as a moderator variable. Also, some of the control variables are readiness, population, and the country's vulnerability to climate change as shown in Table 2 below. We have unbalanced panel data. The equation (1) is as follows;

$$Y_{it} = \alpha + \beta_1 X_{it} + \beta_2 M_{it} + \beta_3 (X * M)_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots (1)$$

Where;
Y_{it} = Dependent Variable
α = Constant.
β = Slope
X_{it} = Independent Variable
M_{it} = Moderator variable
*X*M* = Interaction term
ε = Error term

Table 1: Countries list

Emitter Countries	Affected Countries
China, USA, India, Russia, Japan, Iran, Germany, Saudi Arabia, Indonesia, South Korea, Canada, Brazil, Turkiye, South Africa, Mexico, Australia, UK, Italy, Poland, Thailand, Malaysia, Spain, France, Qatar, Argentina	Afghanistan, Philippines, Chad, Haiti, Kenya, Pakistan, Bangladesh, Malawi, Niger, Ethiopia, Somalia, Sudan, Nepal, Zimbabwe, Vietnam, Uganda, Srilanka, Madagascar, Nigeria, Cambodia, Rwanda, Yemen, Egypt, Tunisia, Libya

3.1 Econometric Techniques

This section outlines the econometric procedures employed in the study to achieve its objectives. The study utilizes several estimation techniques, including cross-sectional dependency analysis, and static panel models (both fixed and random effects), as well as dynamic panel methods incorporating the Generalized Method of Moments (GMM). Within GMM, both system GMM and difference GMM are applied. For a comprehensive understanding, descriptive statistics and pairwise correlation matrices will be analyzed. Based on these results, the study will determine the acceptance or rejection of hypotheses and provide relevant policy implications.

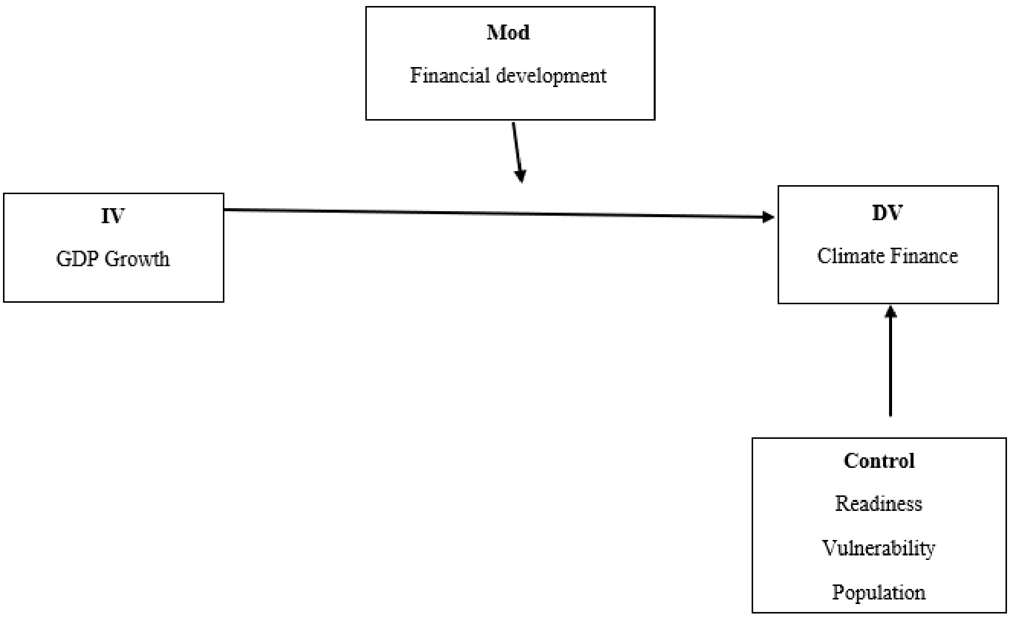


Figure 1: Theoretical framework

Table 2: Operalization of Variables

Variable Type	Symbol	Indicator Name	Measurement scale	Source	References
Dependent variable	*CF*	Climate Finance	Three indicators: (1) FDI inflows in terms of % of GDP. (FDI) (2) R & D expenditures in terms of % of GDP. (RDE) (3) Renewable energy in terms of % of total energy demand Natural resources depletion (% of GNI). (REC)	WB-WDI	(Quynh et al. 2022)
Independent variable	*GDPpc*	GDP Growth	GDP per capita Constant 2015 $ US	WB-WDI	(Robinson and Dornan 2017)
Moderator variable	*FD*	Financial development	Three indicators: (1) Domestic credit to private sectors by banks (% of GDP). (DC) (2) Domestic credit to the private sector (% of GDP). (DCP) (3) Broad money (% of GDP). (M2) (4) Liquid Liabilities (% of GDP). (M3)	WB-WDI	(Rjoub et al., 2021;Katircioğlu & Taşpinar, 2017;Shujah-ur-Rahman et al., 2019)
Control variable	*Read*	Readiness	Three indicators: (1) Economic Readiness (Ease of Doing Business) (2) Governance Readiness (Political stability, control of corruption, regulatory quality, and the rule of law) (3) Social Readiness (Education, Social inequality, Information Communication Technology infrastructure, and Innovation) scoring (higher scores are better) 0-100	ND-GAIN	(Doku et al. 2021a)
	Vuln	Vulnerability	Country vulnerability Scores (infrastructure, ecosystem services, food, water, health, and human habitat) Scoring (lower scores are better) 0-100	ND-GAIN	(Weiler et al. 2018a)
	Pop	Population	Total Population	WB-WDI	(Weiler et al., 2018)

Note: ND-GAIN is the Notre Dame Global Adaptation Index, WB is the World Bank, and WDI is the World Development Indicator.

3.2 Constructing a Principal Composite Analysis (PCA):

Principal component analysis (PCA) is a statistical tool that helps simplify data or statistical methods to reduce the size of large datasets. It helps to transform several correlated variables into fewer uncorrelated variables. It maintains most of the original data's variability (Kherif and Latypova 2020). In this study, a composite financial development index was extracted through the application of a principal component factor analysis, which was subsequently refined using a varimax rotation to achieve a more interpretable factor structure (Katircioğlu and Taşpinar 2017), and also a climate finance index (see Appendix I).

The construction of composite financial development and climate finance in this study can be elucidated through the following functional relationship. It integrates multiple variables and their interactions to provide a comprehensive framework for understanding the dynamics between financial development and climate-related investments.

$FD = f(DC, DCP, M2, M3)$ …………… (2)

$CF = f(FDI, RDE, REC)$…………..(3)

The process of converting original variables into uncorrelated variables is delineated below, involving a series of transformations designed to orthogonalize the variables and eliminate any existing correlations, thereby facilitating more accurate analysis and interpretation.

$Final_{index} = W_1FS_1 + W_2FS_2 + \cdots + W_mFS_m = \sum_i^m W_i * FS_i$………… *(4)*

Where $Final_{index}$ represents the final composite index developed, FS_i denotes the factor scores of respective constituting indicators, and W_i signifies the assigned weights determined for each of the indicators (Yasin, Ahmad, and Chaudhary 2021). The assigned weights are derived through a specific process that takes into account the relative importance and contribution of each indicator to the overall index.

$w_i = (\frac{v_i}{\sum_{i=1}^n v_i}) \times 100$………… (5)

Where w_i represents the weight assigned to each *i*th factor for the financial indicator, v_i denotes the variance explained by each *i*th actor, and n signifies the total number of factors included in the analysis (Katircioğlu and Taşpinar 2017) The empirical model specification for this study is expressed as an equation:

$CF_{it} = \alpha_0 + \alpha_1 CF_{it-1} + \alpha_2(GDPpc)_{it} + \alpha_3(FD)_{it} + \alpha_4(FD * GDPpc)_{it} + \alpha_5(Read)_{it} + \alpha_6(Vuln)_{it} + \alpha_7(Pop)_{it} + \varepsilon_{it}$……………………….. *(6)*

Where α_0, α_1, α_2, α_3, α_4, α_5, α_6, and α_7 denote the coefficients of the predictor variables under investigation, εit' signifies the error term,' i 'signifies the individual country effect, and t indicates the time-specific effect. It is essential to decide between Special GMM (SGMM) and Difference (DGMM) as the most suitable estimator for this study.

4. Empirical Results and Discussion

4.1 Descriptive statistics

The study presents descriptive statistics for several variables over a 21-year period, detailed in Table 3. Panel A shows means for CF, GDPpc, FD, Read, Vuln, and Pop, with notable values of 6.77e-08, 22509.28, -1.60e-07, 0.5136281, and 1.83e+08, respectively. The standard deviations for CF, FD, Read, and Vuln are low, indicating data clustering around the mean, while GDPpc and Pop show larger deviations, suggesting more variability. GDPpc and Read are positively skewed (mean > median), whereas CF, FD, Vuln, and Pop are negatively skewed (mean < median). Skewness and kurtosis analyses reveal that CF and Read are nearly symmetrical, while GDPpc, FD, and Vuln exhibit moderate skewness. Pop is significantly non-normal. Kurtosis indicates that GDPpc, FD, and Read are platykurtic (close to normal), while CF, Vuln, and Pop are leptokurtic, with heavier tails and sharper peaks.

Table 3: Descriptive statistics

Panel A: Carbon Emitter Countries									
Variable	N	Mean	Median	Std. Dev	Var	Min	Max	Skew	Kurtosis
CF	455	6.77e-08	0.0021	0.5167	0.26698	-1.4243	1.1927	-0.1203	3.0197
GDPpc	525	22509.28	13567.9	18384.42	3.38e+08	777.734	73493.3	0.7093	2.3038
FD	390	-1.60e-07	-0.3148	0.9880	0.976262	-1.3352	3.2606	0.8037	2.9880
Read	525	0.5136	0.5001	0.1273	0.016213	0.2872	0.7584	0.2337	1.7525
Vuln	525	0.3632	0.3724	0.0552	0.00305	0.2695	0.5339	0.6352	3.3128
Pop	525	1.83e+08	6.60e+07	3.39e+08	1.15e+17	678831	1.40e+09	2.9042	9.9529
Panel B: Affected Countries									
Variable	N	Mean	Median	Std. Dev	Var	Min	Max	Skew	Kurtosis
CF	120	1.91e-08	0.1757	0.7513	0.5645	-1.62004	1.1354	-0.4300	1.9424
GDPpc	525	1762.612	1208.68	2114.95	4473050	255.1	13729.2	3.5058	17.117
FD	447	7.79e-09	-0.3558	0.9898	0.9797	-1.0492	5.1994	1.7743	6.8374
Read	525	0.3027	0.2828	0.0657	0.0043	0.1609	0.4604	0.3702	2.7940
Vuln	525	0.5336	0.5334	0.0718	0.0052	0.3658	0.6940	-0.0994	2.8964
Pop	525	4.97e+07	2.50e+07	5.38e+07	2.89e+15	5300000	2.30e+08	1.5510	4.4265

Source: Author's Stata version 14.2 Computation

Panel B presents different means for the same variables: 1.91e-08, 1762.612, 7.79e-09, 0.3027, 0.5336, and 4.97e+07. The patterns of skewness and kurtosis are similar, with GDPpc, Read, and Pop remaining positively skewed, and CF and FD negatively skewed. Vuln displays a normal distribution. Overall, the results highlight variations in distribution and normality across the analyzed variables. Log transformation is a valuable technique in statistics for addressing skewed data and non-constant variance. Converting data to a logarithmic scale helps improve the validity of statistical analyses and leads to more accurate conclusions. The equation is written as:

$lnCF_{it} = \alpha_0 + \alpha_1(lnGDPpc)_{it} + \alpha_2(lnFD)_{it} + \alpha_3(lnFD * lnGDPpc)_{it} + \alpha_4(Read)_{it} + \alpha_5(Vuln)_{it} + \alpha_6(lnPop)_{it} + \varepsilon_{it}$……………………….. *(7)*

Where α_0, α_1, α_2, α_3, α_4, α_5, α_6, and α_7 denote the coefficients of the predictor variables under investigation, εit' signifies the error term,' i 'signifies the individual country effect, and t indicates the time-specific effect. Read and Vuln cannot be logged because they are measured in percentage points.

4.2 Pairwise Correlation Matrix

In addition, the correlation approach was used to assess the relationships between variables. From Table 4, Panel A, the results indicate a strong negative correlation between lnGDPpc, lnFD, and Read, meaning that as one variable increases, the other decreases, reflecting a downward-sloping negative linear relationship. Specifically, as lnGDPpc, lnFD, and Read increase, lnCF tends to decrease. However, there is a strong positive association between lnGDPpc and lnFD with the control variable Read. It means (upward sloping) positive linear relationship between variables. All variables are statistically significant at a 0.01, 0.05, and 0.10 level of significance.

Table 4: Pairwise correlation

Panel A: Carbon Emitter Countries						
Variables	lnCF	lnGDPpc	lnFD	Read	Vuln	lnPop
lnCF	1.0000					
lnGDPpc	-0.5534***	1.0000				
	0.0000					
lnFD	-0.4591***	0.3275***	1.0000			
	0.0000	0.0000				
Read	-0.6310***	0.7417***	0.6097***	1.0000		
	0.0000	0.0000	0.0000			
Vuln	0.2667***	-0.7774***	-0.2011***	-0.6441***	1.0000	
	0.0000	0.0000	0.0001	0.0000		
lnPop	0.1520***	-0.5412***	0.1217***	-0.0889**	0.3609***	1.0000
	0.0011	0.0000	0.0162	0.0418	0.0000	
Panel B: Affected Countries						
Variables	lnCF	lnGDPpc	lnFD	Read	Vuln	lnPop
lnCF	1.0000					
lnGDPpc	-0.6985***	1.0000				
	0.0000					
lnFD	-0.5042***	0.4647***	1.0000			
	0.0000	0.0000				
Read	-0.5616***	0.3288***	0.4895***	1.0000		
	0.0000	0.0000	0.0000			
Vuln	0.7984***	-0.8140***	-0.6510***	-0.3882***	1.0000	
	0.0000	0.0000	0.0000	0.0000		
lnPop	0.0006	0.0832*	0.2834***	0.1741***	-0.1028***	1.0000
	0.9945	0.0567	0.0000	0.0001	0.0185	

Note: significance level of 10% (*), 5% (**), and 1% (***)

In Panel B, the results reveal a strong negative association between lnGDPpc, lnFD, and Read, indicating that as one variable increases, the other variables decrease. This relationship demonstrates a downward-sloping negative linear correlation among the variables. It indicates that as lnGDPpc increases, lnCF decreases and as lnFD and Read increases, lnCF decreases. However, there is a strong positive association between Vuln and lnCF. It means (upward sloping) positive linear relationship between variables. These two variables tend to increase and decrease together. All variables are statistically significant at a0.01, 0.05, and 0.10 significance level.

4.3 Cross-Sectional Dependence (CSD)

H_0: weak cross-section dependence

H_1: strong cross-section dependence

From the outcomes presented in Table 5, both Panel A and Panel B demonstrate that most probability values are below the 0.05 significance level. Consequently, we reject the null hypothesis, indicating a strong presence of cross-sectional dependence, which implies that the data across countries exhibit a significant correlation.

Table 5: Cross-Sectional Dependence (CSD)

Panel A: Carbon Emitter Countries				
Variables	CD	CDw	CDw+	CD*
lnCF	5.13***	-0.08	208.94***	5.68***
	(0.000)	(0.938)	(0.000)	(0.000)
lnGDPpc	54.15***	5.18***	1058.35***	0.13
	(0.000)	(0.000)	(0.000)	(0.899)
lnFD	17.91***	-0.11	356.29***	-1.86*
	(0.000)	(0.916)	(0.000)	(0.062)
Read	34.28***	6.53***	739.62***	1.20

	(0.000)	(0.000)	(0.000)	(0.231)
Vuln	43.73***	6.50***	961.16***	-0.98
	(0.000)	(0.000)	(0.000)	(0.329)
InPop	53.65***	6.87***	931.36***	-0.75
	(0.000)	(0.000)	(0.000)	(0.454)
Panel B: Affected Countries				
Variables	CD	CDw	CDw+	CD*
lnCF	3.64***	-0.28	46.7***	2.1**
	(0.000)	(0.782)	(0.000)	(0.036)
lnGDPpc	38.15***	0.43	915.64***	-0.01
	(0.000)	(0.670)	(0.000)	(0.995)
lnFD	11.98***	0.65	485.28*	-1.11
	(0.000)	(0.513)	(0.000)	(0.268)
Read	2.46***	-2.04**	687.17***	3.35***
	(0.014)	(0.041)	(0.000)	(0.001)
Vuln	24.44***	3.03***	818.44***	6.27***
	(0.000)	(0.002)	(0.000)	(0.000)
InPop	77.99***	-1.89*	1349.02***	-0.98
	(0.000)	(0.059)	(0.000)	(0.328)

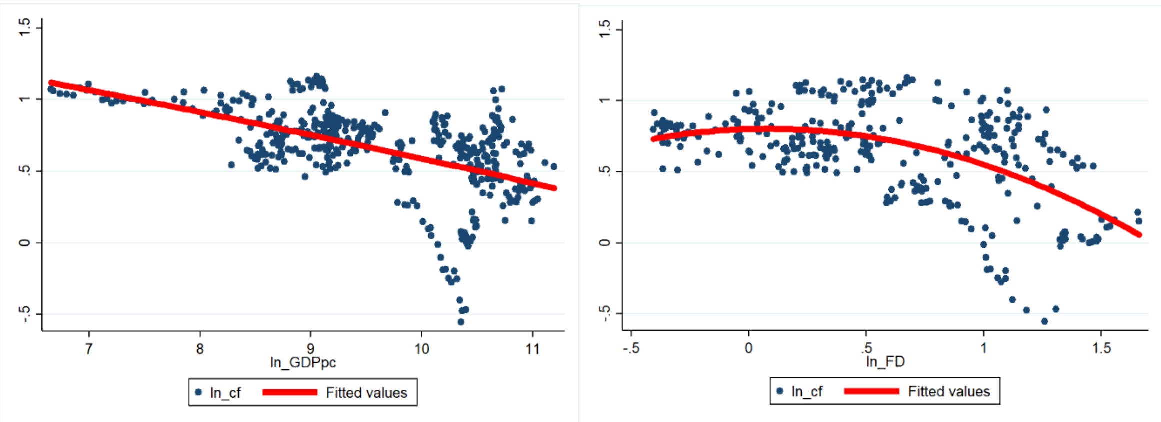
Note: p-values in parenthesis. A significance level of 10% (*), 5% (**), and 1% (***).

4.4 Two-way scatter plot (Qfit)

Figure 2 below Panel A (a) shows that there is a straight line. It is linear. (b) show that the line is bending. It means it is not straight so there is a quadratic association it means when we do the regression, we should add a square of lnFD. By converting Eq 7 into a quadratic equation.

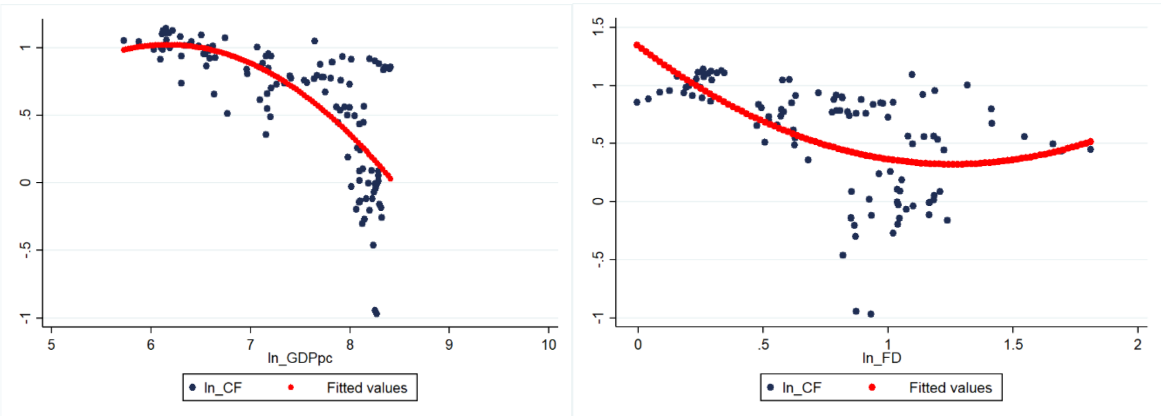
$$lnCF_{it} = \theta_0 + \theta_1(lnGDPpc)_{it} + \theta_2(lnFD)_{it} + \theta_3(lnFD)^2 + \theta_4(lnFD_{it} * lnGDPpc_{it}) + +\theta_5 (lnFD^2 * lnGDPpc_{it}) + \theta_6(Read)_{it} + \theta_7(Vuln)_{it} + \theta_8(lnPop)_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots \text{(8a)}$$

Panel A: Carbon Emitter Countries



(a) **Qfit of lnCF and lnGDPpc** **(b) Qfit of lnCF and lnFD**

Panel B: Affected Countries



(A)Qfit of lnCF and lnGDPpc **(b) Qfit of lnCF and lnFD**

Figure 2: Two-way scatter plot (Qfit)

Figure 2 Panel B (a) and (b) show that the line is bending. It means it is not straight so there is a quadratic association it means when we do the regression, we should add a square of this variable that is lnGDPpc and lnFD. By converting Eq 7 into a quadratic equation.

$$lnCF_{it} = \theta_0 + \theta_1(lnGDPpc)_{it} + \theta_2(lnGDPpc)^2 + \theta_3(lnFD)_{it} + \theta_4(lnFD)^2 + \theta_5(lnFD_{it} * lnGDPpc_{it}) + \theta_6(lnFD_{it} * lnGDPpc^2) + \theta_7 (lnFD^2 * lnGDPpc_{it}) + \theta_8(lnFD^2 * lnGDPpc^2) + \theta_9(Read)_{it} + \theta_{10}(Vuln)_{it} + \theta_{11}(lnPop)_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots (8b)$$

4.5 Static Panel Model

4.5.1 Estimating the Fixed-Effects Model with Moderation

When employing fixed effects, we assume that certain characteristics, which may affect or influence the predictor or outcome variables, are present and need to be accounted for, thus allowing us to control for these individual-specific effects and better isolate the impact of the variables of interest. So, we assume there's a connection between entity errors and the predictor variables. Fixed Effects help us to eliminate the impact of these traits that don't change over time. Then, we can see clearly how much the predictors affect the outcome variable. Table 6 below shows the fixed effect regression with the interaction term. In Panel A, the coefficients reveal that a one-unit increase in lnGDPpc is associated with a decrease of -0.04525 in lnCF. However, the two-tailed p-value for lnGDPpc indicates that this effect is not statistically significant at the 0.05 level. Conversely, for the moderator variable lnFD, a one-unit increase results in a 3.337909 increase in lnCF; yet, this positive effect diminishes at a rate of -1.83536, reflecting a diminishing marginal effect of lnFD on lnCF. The interaction variables lnFD*lnGDPpc and lnFD²*lnGDPpc have a less p-value (< 0.05) so it is statistically significant. So, there is a moderation effect. The F-test is <0.05 its mean model is a good fit and all the predictor variables are jointly significant.

Table 6: Fixed-effects regression

Panel A: Carbon Emitter Countries						
lnCF	Coef.	Std. Err.	t	P > l t l	[95% Conf.	Interval]
lnGDPpc	-0.04525	0.061249	-0.74	0.461	-0.16578	0.075273
lnFD	3.337909	0.914315	3.65	0.000***	1.538698	5.137121
lnFD²	-1.83536	0.779423	-2.35	0.019**	-3.36913	-0.30159
lnFD_GDPpc	-0.35176	0.101409	-3.47	0.001***	-0.55131	-0.1522
LnFD²_GDPpc	0.177192	0.080231	2.21	0.028**	0.019312	0.335072
Read	-0.15774	0.144441	-1.09	0.276	-0.44197	0.126499
Vuln	2.006029	1.693039	1.18	0.237	-1.32557	5.337633
lnPop	-0.11717	0.135314	-0.87	0.387	-0.38344	0.149108
_cons	2.67392	3.020357	0.89	0.377	-3.26961	8.617451
Sigma_u	0.29228					
Sigma_e	0.103173					
rho	0.8892	(fraction of variance due to u_i)				
F test that all u_i =0: F (20, 303) = 55.55					Prob > F=0.0000	
Panel B: Affected Countries						
lnCF	Coef.	Std. Err.	t	P > l t l	[95% Conf.	Interval]
lnGDPpc	16.04651	5.012595	3.2	0.006***	5.362418	26.7306
lnGDPpc²	-1.15215	0.357195	-3.23	0.006***	-1.91349	-0.39081
lnFD	100.5448	43.61435	2.31	0.036**	7.582974	193.5066
lnFD²	-73.2412	44.0905	-1.66	0.117	-167.218	20.7355
lnFD_GDPpc	-27.5477	10.8093	-2.55	0.022**	-50.5872	-4.50821
lnFD_GDPpc²	1.9186	0.670195	2.86	0.012***	0.490112	3.347088
lnFD²_GDPpc	19.03691	11.12749	1.71	0.108	-4.68077	42.75458
lnFD²_lnGDPpc²	-1.25126	0.700483	-1.79	0.094*	-2.7443	0.241785
Read	-2.73176	1.071853	-2.55	0.022**	-5.01636	-0.44716
Vuln	1.301793	6.292518	0.21	0.839	-12.1104	14.71398
lnPop	-0.98597	1.02318	-0.96	0.351	-3.16683	1.194886
_cons	-38.1279	21.62118	-1.76	0.098*	-84.2124	7.956541
Sigma_u	1.075041					
Sigma_e	0.166223					
rho	0.976651	(fraction of variance due to u_i)				
F test that all u_i =0: F (11, 15) = 56.76					Prob > F=0.0000	

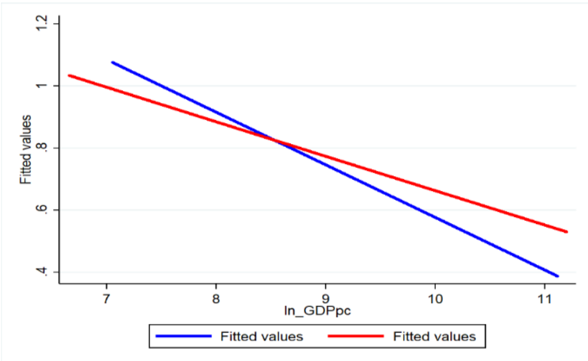
Note: significance level of 10% (*), 5% (**), and 1% (***)

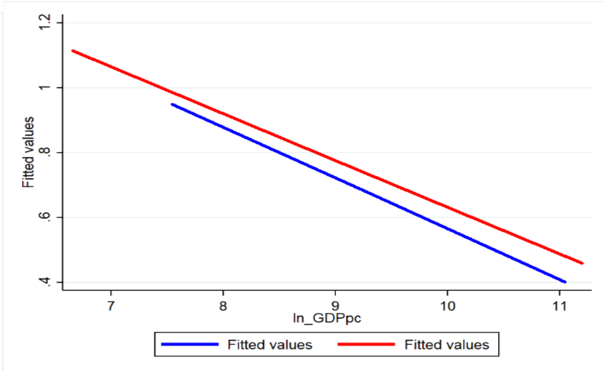
In Panel B the coefficients result shows that if there is one unit increase in lnGDPpc, lnCF increases by 16.04651 but this increasing effect is diminishing by the rate of -1.15215. The two-tailed p-value for the independent variable lnGDPpc is significant at the 0.05 level, indicating a meaningful effect. For the moderator variable lnFD, a one-unit increase results in a substantial 100.5448 increase in lnCF; however, this effect diminishes at a rate of -73.2412. Additionally, the interaction terms—lnFD*lnGDPpc, lnFD*lnGDPpc², and lnFD²*lnGDPpc²—exhibit p-values below 0.05 and 0.10, signifying their statistical significance at both the 5% and 10% levels. So, there is a moderation effect. The F-test is <0.05 its mean model is a good fit and all the predictor variables are jointly significant.

4.5.2 Dummy Variable

From Table 10, In Panel A and Panel B, the outcome shows that there is moderation among variables. So, for this, we have to make a graph. To generate the graph, each component was converted into a dummy variable, where values exceeding the mean were categorized as high (equal to 1), and values at or below the mean were categorized as low (equal to 0). The resulting graphs illustrate a moderation effect among the interaction terms, as evidenced by the intersecting lines, which indicate that the relationships between variables change at the point of intersection.

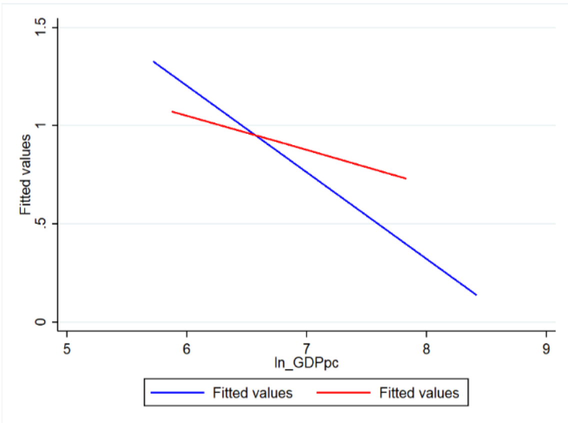
Panel A: Carbon Emitter Countries

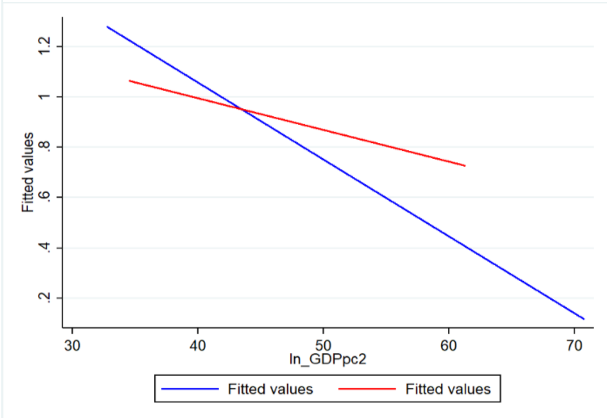




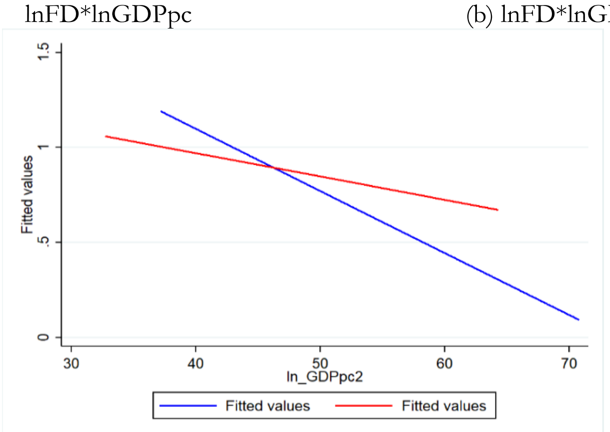
(a) lnFD*lnGDPpc (b) lnFD²*lnGDPpc

Panel B: Affected Countries





(a) lnFD*lnGDPpc (b) lnFD*lnGDPpc²



(c) lnFD²*lnGDPpc²

Figure 3: Graph of the fixed-effects regression interaction term

4.5.3 Estimating the Random-Effects Model with Moderation

The Random Effects model is a way that researchers often use to look at how certain characteristics specific to each affect the outcome we're interested in, like in a set of panel data.

Table 7 below shows the random effect regression with the interaction term. In Panel A the coefficients result shows that if there is one unit increase in lnGDPpc, lnCF decreases by -0.09089. A two-tailed p-value of the independent variable lnGDPpc is significant at 0.10 level of significance. The moderator variable lnFD shows that if there is one unit increase in lnFD there is a 2.973529 increase in lnCF but this increasing effect is diminishing by the rate of -1.61162. The interaction variables lnFD*lnGDPpc and $lnFD^2$*lnGDPpc have a less p-value (< 0.05) so it is statistically significant. So, there is a moderation effect. The F-test is <0.05 its mean model is a good fit and all the predictor variables are jointly significant.

Table 7: Random-effects regression (GLS regression)

Panel A: Carbon Emitter Countries						
lnCF	Coef.	Std. Err.	t	P > l z l	[95% Conf.	Interval]
InGDPpc	-0.09089	0.053131	-1.71	0.087*	-0.19502	0.013245
InFD	2.973529	0.873112	3.41	0.001**	1.262262	4.684796
$InFD^2$	-1.61162	0.728943	-2.21	0.027**	-3.04032	-0.18292
InFD_GDPpc	-0.31608	0.096454	-3.28	0.001***	-0.50513	-0.12704
$InFD^2$_GDPpc	0.155195	0.075387	2.06	0.04**	0.007439	0.302951
Read	-0.12685	0.142347	-0.89	0.373	-0.40585	0.152144
Vuln	-0.12493	1.014877	-0.12	0.902	-2.11406	1.864189
InPop	-0.05189	0.039139	-1.33	0.185	-0.1286	0.024827
_cons	2.693046	1.089552	2.47	0.013***	0.557563	4.828529
Sigma_u	0.239965					
Sigma_e	0.103173					
rho	0.843982	*(fraction of variance due to u_i)*				
Wald chi2 (8) = 133.26					Prob > F=0.0000	
Panel B: Affected Countries						
lnCF	Coef.	Std. Err.	t	P > l z l	[95% Conf.	Interval]
InGDPpc	9.50923	4.804928	1.98	0.048**	0.091745	18.92672
$lnGDPpc^2$	-0.72625	0.370379	-1.96	0.05**	-1.45218	-0.00033
InFD	44.79577	19.79211	2.26	0.024**	6.003941	83.5876
$InFD^2$	-30.856	21.71461	-1.42	0.155	-73.4158	11.7039
InFD_GDPpc	-13.2127	5.555744	-2.38	0.017**	-24.1018	-2.32364
$lnFD\_GDPpc^2$	0.979074	0.387013	2.53	0.011***	0.220542	1.737606
$InFD^2$_GDPpc	8.58973	5.657017	1.52	0.129	-2.49782	19.67728
$lnFD^2\_GDPpc^2$	-0.59856	0.366203	-1.63	0.102	-1.31631	0.119183
Read	-1.92455	0.631111	-3.05	0.002***	-3.1615	-0.68759
Vuln	1.931731	2.658175	0.73	0.467	-3.2782	7.141659
InPop	-0.00025	0.147063	0	0.999	-0.28848	0.287993
_cons	-30.6159	15.36468	-1.99	0.046**	-60.7301	-0.50165
Sigma_u	0.292883					
Sigma_e	0.166223					
rho	0.756372	*(fraction of variance due to u_i)*				
Wald chi2 (11) = 147.26					Prob > F=0.0000	

Note: significance level of 10% (*), 5% (**), and 1% (***).

In Panel B the coefficients result shows that if there is one unit increase in lnGDPpc, lnCF increases by 9.50923 but this increasing effect is diminishing by the rate of -0.72625. The two-tailed p-value for the independent variable lnGDPpc is significant at the 0.05 level, indicating a statistically meaningful effect. For the moderator variable lnFD, a one-unit increase results in a 44.79577 increase in lnCF, although this effect diminishes at a rate of -30.856. Additionally, the interaction terms lnFD*lnGDPpc and lnFD*$lnGDPpc^2$ exhibit p-values less than 0.05, confirming their statistical significance at the 5% level. This suggests the presence of a moderation effect, as evidenced by the significant interactions altering the relationship between the variables. The F-test is <0.05 its mean model is a good fit and all the predictor variables are jointly significant.

4.6 Hausman Test

The Hausman test is employed to determine whether a fixed effects or random effects model is more appropriate. Table 8 presents the results of the Hausman test, where Panel A shows a p-value of 0.3031, which exceeds the 5% threshold (> 0.05), indicating that the Random Effects model is preferred. Similarly, Panel B reports a p-value of 0.0569, also above the 5% level (> 0.05), leading to the conclusion that the Random Effects model should be used in this case as well.

b = Consistent under H0 and Ha;
B = Inconsistent under Ha, efficient under H0
H_0: Random effects as the selected model
H_1: Fixed effect as the chosen model

Table 8: Hausman test

Panel A: Carbon Emitter Countries				
	----------Coefficients-----------			
Variables	(b) Fixed	(B) Random	(b-B) Difference	Sqrt (diag (V_b -V_B)) S.E.
InGDPpc	-0.04525	-0.09089	0.045636	0.030764
InFD	3.337909	2.973529	0.364381	0.278632
$InFD^2$	-1.83536	-1.61162	-0.22374	0.281141
InFD_GDPpc	-0.35176	-0.31608	-0.03567	0.032088
$InFD^2$_GDPpc	0.177192	0.155195	0.021997	0.028007
Read	-0.15774	-0.12685	-0.03088	0.026456
Vuln	2.006029	-0.12493	2.130964	1.360175
lnPop	-0.11717	-0.05189	-0.06528	0.129867
Chi2 (8) = (b – B)' [(V_b-V_B) ^ (-1)] (b – B) = 9.48				
Prob > Chi 2 = 0.3031				

Panel B: Affected Countries				
	----------Coefficients-----------			
Variables	(b) Fixed	(B) Random	(b-B) Difference	Sqrt (diag (V_b -V_B)) S.E.
InGDPpc	13.5409	10.74452	2.796377	5.437818
$lnGDPpc^2$	-1.03067	-0.80022	-0.23045	0.376152
InFD	65.50333	67.42581	-1.92248	34.38826
$InFD^2$	-52.6695	-46.4859	-6.18362	23.3566
InFD_GDPpc	-18.8963	-19.0841	0.187781	9.446886
lnFD_$GDPpc^2$	1.384457	1.344597	0.03986	0.64066
$InFD^2$_GDPpc	14.1281	12.78476	1.343332	6.078638
$lnFD^2$_$GDPpc^2$	-0.95759	-0.8729	-0.08469	0.394931
Chi2 (6) = (b – B)' [(V_b-V_B) ^ (-1)] (b – B) = 12.24				
Prob > Chi 2 = 0.0569				

Source: Author's Stata version 14.2 Computation

4.7 Breusch and Pagan Lagrangian Multiplier Test for Random Effects

Now to exclude pooled OLS we have to run the LM test. LM test is used to choose a regression model best among the Random Effect Model (REM) with the pooled OLS. Table 9 In both Panel A and Panel B below, the p-values are below the 0.05 level of significance. Consequently, the null hypothesis (H0) is rejected and the alternative hypothesis (H1) is accepted, indicating that the Random Effects model is the appropriate choice for the regression analysis in this study.

l*nCF [Country1, t] = Xb + u [Country1] + e [Country1, t]*
H_0: Random effects are insignificant
H_1: Random effects are significant

Table 9: Breusch and Pagan Lagrangian multiplier test for random effects

Panel A: Carbon Emitter Countries		
	Var	Sd = Sqrt (var)
lnCF	0.1068181	0.3268304
e	0.106448	0.1031735
u	0.0575832	0.239965
Test: var(u) = 0		
Chibar2 (01) = 1147.12		
Prob > chibar2 = 0.0000		
Panel B: Affected Countries		

	Var	Sd = Sqrt (var)
lnCF	0.228917	0.478452
e	0.02763	0.166223
u	0.085781	0.292883
Test: var(u) = 0		
Chibar2 (01) = 12.22		
Prob > chibar2 = 0.0002		

Source: Author's Stata version 14.2 Computation

4.8 Dynamic Panel Model

4.8.1 Generalized Method of Moments

The coefficients were estimated using system GMM and difference GMM techniques. The results of the estimation are presented in Table 10a and Table 10b. According to Panel A, the one-step GMM analysis reveals that the coefficient for lnCF with a lag of 2 is significant at the 5% level. The moderator variable lnFD exhibits positive coefficients, indicating that a 1% increase in lnFD results in a 16.93854 increase in lnCF, although this effect diminishes at a rate of -14.06034, and this effect is statistically significant at the 5% level. Additionally, the interaction term lnGDPpc*lnFD shows negative coefficients, and it is also significant at the 5% level. The Sargan test assesses whether the instruments are uncorrelated with the error term in the model, which is crucial for ensuring the validity of the instruments. Meanwhile, the Hansen test evaluates the overall validity of the instruments, providing a broader measure of the robustness of the instrument set used in the model.

H_0: The instruments are valid

H_1: The instruments are not valid

In Panel A, the Sargan test results for both DGMM and SMM models show p-values greater than 0.05, failing to reject the null hypothesis (H0) and suggesting that the instruments are valid and the model is correctly specified. Conversely, the Hansen test results for both DGMM and SMM models exhibit significant p-values greater than 0.05, indicating that the instruments are uncorrelated with the error term and that the model is correctly specified. Additionally, the Arellano-Bond test for autocorrelation reveals that both AR (1) and AR (2) are not significant with p-values greater than 0.05, providing no evidence of first-order or second-order autocorrelation, which supports the validity of the model.

Table 10a: GMM (System GMM and Difference GMM) for carbon emitter countries

Panel A: Carbon Emitter Countries				
	Difference GMM		System GMM	
	One Step	Two Step	One Step	Two Step
	Coefficients	Coefficients	Coefficients	Coefficients
InCF				
lnCF_Lag1	-0.32188 (0.119)	-0.324916 (0.422)	0.048546 (0.904)	0.114077 (0.835)
InCF _Lag 2	-0.40660*** (0.008)	-0.4025495 (0.115)	-0.240057** (0.052)	-0.06738 (0.892)
lnGDPpc	0.12747 (0.615)	0.518689** (0.019)	0.1859043* (0.069)	0.032136 (0.945)
InFD	14.52467** (0.029)	16.27246** (0.032)	16.93854** (0.019)	11.72788 (0.199)
$InFD^2$	-12.3998** (0.031)	-10.51515 (0.182)	-14.06034*** (0.014)	-8.76562 (0.166)
InFD_GDPpc	-1.53523** (0.033)	-1.723419** (0.032)	-1.907925** (0.021)	-1.3694 (0.186)
$InFD^2$_GDPpc	1.25790** (0.032)	1.071786 (0.176)	1.507405*** (0.013)	0.977952 (0.170)
Read	0.01939 (0.926)	-0.321748 (0.297)	-0.6454341 (0.158)	0.006283 (0.990)
Vuln	6.7776** (0.027)	12.83237 (0.358)	-5.963743 (0.138)	-5.72953 (0.294)
lnPop	-.1356547 (0.493)	-0.553514 (0.687)	0.2290645 (0.118)	0.207122* (0.069)

No. of groups	19	19	19	19
No. of instruments	19	19	19	19
AR (1) Pr > z	0.967	0.975	0.346	0.558
AR (2) Pr > z	0.288	0.653	0.609	0.593
Sargan test	0.176	0.265	0.342	0.236
Hansen test	0.617	0.563	0.0.66	0.438

Note: p-values in parenthesis. A significance level of 10% (*), 5% (**), and 1% (***).

In Table 14b, Panel B, the two-step system GMM analysis indicates that lnCF with a lag of 1 is significant at the 5% level. The coefficient for lnGDPpc is positive, suggesting that a 1% increase in lnGDPpc results in a 0.895238 increase in lnCF, although this effect diminishes at a rate of -0.11722, with both effects being statistically significant at the 5% level. Additionally, the interaction term lnGDPpc*lnFD exhibits negative coefficients and is statistically significant at the 5% level. In Panel B, the Sargan test results for both DGMM and SGMM models do not show significant p-values (> 0.05), which means the null hypothesis (H0) is not rejected, implying that the instruments are valid and the model is correctly specified. Conversely, the Hansen test results for both DGMM and SGMM models present significant p-values (> 0.05), indicating that the instruments are uncorrelated with the error term and supporting the correct specification of the model. The Arellano-Bond test for autocorrelation shows that both AR (1) and AR (2) are not significant with p-values greater than 0.05, suggesting that there is no evidence of first-order or second-order autocorrelation, which is a positive indicator for the model's validity.

Table 10b: GMM estimation (System GMM and Difference GMM) for affected countries

Panel B: Affected Countries				
	Difference GMM		System GMM	
	One Step	Two Step	One Step	Two Step
	Coefficients	Coefficients	Coefficients	Coefficients
InCF				
lnCF_Lag1	0.86936*** (0.001)	3.921323 (0.510)	0.842438*** (0.000)	1.206157** (0.05)
InCF _Lag 2	0.033175** (0.052)	-2.11302*** (0.070)		
lnGDPpc	81.5558 (0.413)		39.01628 (0.273)	0.895238** (0.035)
lnGDPpc²	-6.08025 (0.402)	0.878956 (0.609)	-2.96634 (0.269)	-0.11722** (0.043)
InFD	1219.285** (0.034)		341.1618 (0.327)	
InFD²	-1535.897** (0.028)		-248.896 (0.339)	
InFD_GDPpc	-328.5374** (0.045)		-102.145 (0.319)	-1.85622* (0.066)
lnFD_GDPpc²	22.18527 (0.068)	-0.48025 (0.652)	7.619001 (0.310)	0.286388* (0.068)
InFD²_GDPpc	387.7377 (0.284)		72.61744 (0.331)	1.184106 (0.612)
lnFD²_GDPpc²	-24.56877 (0.282)	0.230184 (0.661)	-5.27611 (0.323)	-0.18005 (0.623)
Read	-5.783358 (0.606)		-3.32304 (0.598)	
Vuln	-6.346685 (0.577)		-0.09419* (0.085)	
lnPop	-2.210107 (0.459)		-0.40016 (0.177)	-0.06446 (0.850)
No. of groups	8	8	8	8
No. of instruments	8	8	8	8
AR (1) Pr > z	0.148	-	0.205	0.090
AR (2) Pr > z	0.224	0.569	0.230	0.240
Sargan test	0.248	0.78	0.77	0.77
Hansen test	0.436	0.87	0.65	0.65

Note: p-values in parenthesis. A significance level of 10% (*), 5% (**), and 1% (***).

4.8.2 The decision to select between SGMM and DGMM

Blundell and Bond (2002) suggest using SGMM over DGMM if DGMM's estimate is close to or below the fixed effect estimator, as it may indicate weak instrumentation and downward bias. Therefore, SGMM is chosen for this analysis as it is likely to provide better estimates than Pooled OLS and fixed effects.

H_1: GDP growth has a significant positive/negative impact on climate finance

In panel A the results estimated in the Table 10 fixed effects and Table 11 random effect model show a significant negative linear relationship between economic growth and climate finance. In Panel B, there is a significant negative quadratic relationship between economic growth and climate finance. On the other hand, System GMM for Panel A shows a positive impact of GDP growth on climate finance this is because the wealthy economies have a larger pool of financial resources, thereby making more funds available for investment in climate-related projects and initiatives. Furthermore, higher GDP usually leads to more tax revenue for governments, which can be used to support climate finance and promote sustainable development and environmental protection. High-income countries drive innovation and new technologies, better infrastructure, and transportation including cleaner and more efficient ones, which can help with climate finance. Poor countries are more likely to be selected for aid than relatively richer developing countries. This is consistent with the findings of (Weiler et al. 2018) for donor-recipient countries.

In panel B, the System GMM shows a negative quadratic relationship between GDP growth and climate finance. Low-income countries are very vulnerable to climate change, but their access to climate finance decreases in a non-linear way as their income rises, initially improving slightly but then dropping more sharply at higher income levels. Furthermore, they suffer because they often have fewer resources to invest in climate-related projects. Secondly, their high vulnerability to climate impacts can strain their finances, reducing the funds available for climate finance. Thirdly their poor infrastructure can reduce the effectiveness of climate investments, and limited financial stability and higher risks can deter private investors from supporting climate finance in these countries. Moreover, low-income countries due to low GDP growth, tend to redirect their resources towards sectors deemed more urgent or profitable, which can reduce the funds available for climate finance. This makes affected countries more dependent on carbon-emitter countries to help them with this issue. This is consistent with the findings of (Weiler et al. 2018) for donor-recipient countries.

H_2: Financial development has a significant positive impact on climate finance.

In Panel A and Panel B, the results estimated in Table 10 (fixed effects), Table 11 (random effects), Table 16, and Table 17 (System GMM) all reveal a significant positive quadratic relationship between financial development and climate finance. This indicates that as financial development increases, access to climate finance initially improves; however, this improvement occurs at a diminishing rate. Specifically, while higher levels of financial development lead to enhanced access to climate finance, the incremental benefits of further increases in financial development become progressively smaller over time. This suggests that, although greater financial development fosters better access to climate finance, the rate of improvement in access diminishes as financial development continues to advance. Financial development improves climate finance by providing more funding channels, offering diverse investment options like green bonds, enhancing risk management, increasing market efficiency, and including experts who support climate investments.

H_3: Financial development moderates the positive/negative impact between GDP growth and climate finance.

In panel A the results estimated in Table 10 fixed effects and Table 11 random effect model and Table 16 System GMM results show that financial development moderates the negative impact between GDP growth and climate finance. Because GDP growth has a linear relationship with climate finance, meaning that as GDP increases, climate finance changes proportionally. Financial development, however, affects climate finance in a non-linear way, with initial improvements leading to significant benefits but diminishing returns at higher levels. Financial development moderates the negative effects of GDP growth on climate finance by enhancing financial system efficiency, providing risk management tools, and offering diverse investment options.

In panel B, the results estimated in Table 10 fixed effects Table 11 random effect model, and Table 17 System GMM results show that the relationship between GDP growth and climate finance is non-linear, meaning its impact varies with different levels of GDP growth. Financial development also affects climate finance in a non-linear manner, with initial improvements having a significant impact but diminishing returns at higher levels. Financial development moderates the negative impact of GDP growth on climate finance because improved financial systems enhance the ability to channel resources effectively into climate-related projects, even in the face of challenges posed by GDP growth; additionally, it introduces advanced tools and mechanisms for managing risks associated with climate investments, making such investments more viable despite adverse economic conditions, and a well-developed financial sector further ensures efficient resource allocation, thereby mitigating the detrimental effects of GDP growth on climate finance and maintaining funding for climate initiatives.

5. Conclusion

The study explores the impact of GDP growth on climate finance. The moderating role of financial development for a panel data set of the top 25 contributors and the top 25 affected countries over the period 2001–2021. Although several studies have recently been conducted on climate finance, this study makes the first attempt to make a comparative study using these variables. The reported results are robust and reliable since we employ multiple tests. The objective of climate finance is to foster green growth and subsequently reduce carbon emissions. To achieve this, we aim to investigate whether systematic differences exist between the groups of countries in Panel A and Panel B concerning a range of climate finance, financial development, and economic target variables. Should such differences be identified, we seek to quantify their magnitude through a comparative analysis. This analysis will compare the outcomes of carbon emitter countries with those of the affected countries, all within a specific theoretical framework, to better understand the impact and effectiveness of climate finance initiatives across different contexts.

The empirical evidence of panel A and panel B of the correlation matrix shows that Panel A and Panel B show a strong negative association. There is strong cross section dependence which means the data across countries is correlated. Panel A shows a linear relationship between GDPpc and CF but a non-linear relationship between FD and CF. whereas the Panel has a non-linear relationship with CF. Further GMM result shows that GDP growth exhibits a complex relationship with climate finance, offering both potential benefits in terms of increased resources and challenges due to potential shifts in focus and resource allocation**.** GDP growth can affect climate finance by changing the availability of resources for climate initiatives. While higher GDP can lead to increased funding for climate finance due to greater wealth and revenue, rapid growth may also divert focus from long-term sustainability, potentially reducing climate finance if it leads to increased demand in other sectors. Financial development helps mitigate the adverse effects of GDP growth by enhancing financial system efficiency, offering advanced risk management tools, and offering diverse investment options, such as green bonds. This ensures better allocation of resources to climate finance and maintains funding for climate initiatives even amid economic fluctuations. The significant increase in climate finance, reflects developed nations' commitment to helping developing countries tackle global warming. However, developed nations must continue this support to effectively reduce carbon emissions.

For some policy implications Carfora and Scandurra (2019) stated that to ensure efficient allocation of funding, policymakers must systematically monitor the outcomes of financed projects, rigorously analyze these results, and make informed adjustments. This approach is essential for enhancing the effectiveness of future investments and ensuring that resources are utilized optimally. Policies should be crafted to foster economic growth in a manner that is congruent with climate goals, ensuring that economic development efforts are harmonized with environmental sustainability objectives. Enhance financial systems to improve resource allocation and risk management for climate projects, support the development and use of diverse financial instruments such as green bonds, and continuously review and adjust strategies to ensure that climate finance remains effective and sustainable.

Data on climate finance and financial development can be limited, complicating accurate analysis. The complex, non-linear interactions between GDP growth, financial development, and climate finance make it hard to pinpoint specific effects and causality. The impact of these factors can differ by region and country, affecting the generalizability of results. Policy differences and varying institutional capacities can influence how financial development moderates GDP growth's impact on climate finance, and evolving conditions may affect the relevance of findings over time.

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Appendix I

Table 1: PCA of Climate Finance Index for 25 Carbon Emitter Countries

Panel A: Carbon Emitter Countries				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp 1	1.30218	0.398493	0.4341	0.4341
Comp 2	0.903685	0.109546	0.3012	0.7353
Comp 3	0.794138	-	0.2647	1.0000
Orthogonal Varimax				
Component	Variance	Difference	Proportion	Cumulative
Comp 1	1.00001	3.75167e-06	0.3333	0.3333
Comp 2	1	7.76213e-06	0.3333	0.6667
Comp 3	0.999994	-	0.3333	1.0000
Eigenvectors				
Variable	Comp 1	Comp 2	Comp 3	Unexplained
FDI	0.4917	0.8706	0.0169	0
REC	0.6142	-0.3605	0.7020	0
RDE	-0.6173	0.3348	0.7119	0
Factor Loadings				
Variable	Factor 1	Uniqueness	KMO	
FDI	0.2751	0.9243	0.5993	
REC	0.3675	0.8649	0.5460	
RDE	-0.3698	0.8632	0.5453	
		Overall 0.5558		

Note: The number of principal components (or factors) extracted is 1. The KMO is a measure of sampling adequacy known as Kaiser–Meyer–Olkin.

Table 2: PCA of Climate Finance Index for 25 Affected Countries

Panel B: Affected Countries				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp 1	1.58983	0.620002	0.5299	0.5299
Comp 2	0.96983	0.529492	0.3233	0.8532
Comp 3	0.440338	-	0.1468	1.0000
Orthogonal Varimax				
Component	Variance	Difference	Proportion	Cumulative
Comp 1	1.00002	2.13E-05	0.3333	0.3333
Comp 2	0.999999	1.75E-05	0.3333	0.6667
Comp 3	0.999981	-	0.3333	1.0000
Eigenvectors				
Variable	Comp 1	Comp 2	Comp 3	Unexplained
FDI	0.2218	0.9748	-0.0248	0
REC	0.6913	-0.1392	0.709	0
RDE	-0.6877	0.1744	0.7048	0
Factor Loadings				
Variable	Factor 1	Uniqueness	KMO	
FDI	0.1421	0.9798	0.7588	
REC	0.6631	0.5603	0.5082	
RDE	-0.6593	0.5654	0.5083	
		Overall 0.5129		

Note: The number of principal components (or factors) extracted is 1. The KMO is a measure of sampling adequacy known as Kaiser–Meyer–Olkin.

Table 3: PCA of Financial Development Index for 25 carbon emitter countries

Panel A: Carbon Emitter Countries					
Component	Eigenvalue	Difference	Proportion	Cumulative	
Comp 1	3.43218	3.09232	0.8580	0.8580	
Comp 2	0.339859	0.130282	0.0850	0.9430	
Comp 3	0.209577	0.191195	0.0524	0.9954	
Comp 4	0.0183824	-	0.0046	1.0000	
Orthogonal Varimax					
Component	Variance	Difference	Proportion	Cumulative	
Comp 1	1.00002	5.35779e-06	0.2500	0.2500	
Comp 2	1.00001	0.0000189302	0.2500	0.5000	
Comp 3	0.999993	0.0000172118	0.2500	0.7500	
Comp 4	0.999976	-	0.2500	1.0000	
Eigenvectors					
Variable	Comp 1	Comp 2	Comp 3	Comp 4	Unexplained
DC	0.4922	0.2741	-0.8260	0.0166	0
DCP	0.4754	0.7024	0.5185	0.1085	0
M2	0.5226	-0.3669	0.1747	-0.7495	0
M3	0.5085	-0.5449	0.1353	0.6529	0
Factor Loadings					
Variable	Factor 1	Factor 2	Uniqueness	KMO	
DC	0.8553	0.1660	0.2409	0.9203	
DCP	0.8226	0.2494	0.2611	0.7893	
M2	0.9824	-0.1210	0.0203	0.6680	
M3	0.9543	-0.2392	0.0321	0.6748	
				Overall 0.7434	

Note: The number of principal components (or factors) extracted is 1. The KMO is a measure of sampling adequacy known as Kaiser–Meyer–Olkin.

Table 4: PCA of Financial Development Index for 25 Affected Countries

Panel B: Affected Countries					
Component	Eigenvalue	Difference	Proportion	Cumulative	
Comp 1	3.23595	2.59061	0.809	0.809	
Comp 2	0.645343	0.526712	0.1613	0.9703	
Comp 3	0.118631	0.118557	0.0297	1.0000	
Comp 4	7.45E-05	-	0.0000	1.0000	
Orthogonal Varimax					
Component	Variance	Difference	Proportion	Cumulative	
Comp 1	1.00001	5.57E-06	0.25	0.25	
Comp 2	1	5.27E-07	0.25	0.5	
Comp 3	1	1.2E-05	0.25	0.75	
Comp 4	0.999989	-	0.25	1.00	
Eigenvectors					
Variable	Comp 1	Comp 2	Comp 3	Comp 4	Unexplained
DC	0.5228	-0.4095	0.2474	0.7055	0
DCP	0.5237	-0.4041	0.2455	-0.7087	0
M2	0.5269	0.1737	-0.832	0.0021	0
M3	0.4181	0.7993	0.4317	0.0027	0
Factor Loadings					
Variable	Factor 1	Factor 2	Uniqueness	KMO	
DC	0.9622	-0.2763	-0.0022	0.6488	
DCP	0.9637	-0.2707	-0.002	0.6495	
M2	0.9105	0.2388	0.114	0.8094	
M3	0.67	0.4617	0.338	0.6837	
				Overall 0.6931	

Note: The number of principal components (or factors) extracted is 1. The KMO is a measure of sampling adequacy known as Kaiser–Meyer–Olkin