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-RESEARCH ARTICLE-

ANALYSING CLIMATE CHANGE AND BANKING SYSTEM STABILITY IN SELECTED SUB-SAHARAN ECONOMIES

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—Abstract—

This research is significant as it examines a crucial yet underexplored intersection between climate change and the stability of the banking system in Sub-Saharan Africa. Although extensive studies have addressed the economic consequences of climate change across various sectors worldwide, the interaction between climate dynamics and financial system stability, particularly in developing regions, has received comparatively little attention. This study assesses the impact of climate change on banking sector stability in 29 selected Sub-Saharan African nations, utilising annual

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data spanning from 1996 to 2017. The analysis employs the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) methodology and incorporates essential control variables, including net interest margin, bank concentration, money supply, and regulatory quality, to ensure the robustness of the estimates. The empirical results reveal no statistically significant short-term or long-term influence of climate change on banking stability within the sampled countries. Nonetheless, the findings underscore the importance of governments proactively integrating climate-related policies into the regulatory and operational frameworks of the banking sector to mitigate potential systemic risks in the future. These conclusions provide valuable guidance for policymakers and financial regulators seeking to enhance the resilience of the financial system amid growing climate uncertainties.

Keywords: Climate Change, Banking System Stability, Sub-Saharan Economies, Climate Financial Econometrics, CS-ARDL.

INTRODUCTION

The banking system constitutes a network of financial intermediaries that facilitate the provision of financial services within an economy. These services encompass loan issuance, investment operations, deposit mobilisation, savings management, and payment system functions, among others. Functionally, the banking system enables the circulation of money between firms, individuals, and other financial institutions. Notably, in Sub-Saharan Africa, the banking system reflects the prominence of financial assets and activities across the region (Mlachila & Yabara, 2013). Correspondingly, the economic standing of the banking system exhibits substantial variation across countries within SSA (Mlachila & Yabara, 2013). The stability of the banking sector is therefore a critical component of the broader financial system, as an economy lacking a stable banking sector is inherently susceptible to systemic collapse.

Climate change has emerged as a profound threat to global economic structures, with substantial evidence of its detrimental effects on sectors including agriculture, infrastructure, and public health (Diffenbaugh & Burke, 2019; IPCC, 2018; Mazzocchetti, et al 2025). This research addresses a significant gap by extending the analysis beyond traditional macroeconomic or environmental frameworks to consider the potential for climate change to compromise financial sector soundness, an area that remains underrepresented in both academic and policy discussions. Given the structural vulnerabilities of many Sub-Saharan banking systems and their exposure to climate-related disruptions—such as droughts, floods, veld fires, and agricultural volatility—this study offers timely, region-specific insights for informing financial regulation, climate policy, and sustainable development strategies.

Despite global recognition of climate change as a pressing concern, its mitigation remains inconsistent, with some state actors and policymakers expressing scepticism

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regarding its existence (Agbloyor et al., 2022). According to the Intergovernmental Panel on Climate Change (IPCC), climate change refers to long-term alterations in climatic conditions, measurable through statistical properties such as means or variability over extended periods. Although climate change is a persistent phenomenon, recent variations are largely attributed to anthropogenic activities (Dlugolecki & Lafeld, 2005). While Sub-Saharan Africa is regarded as one of the most vulnerable regions globally, climate change is increasingly identified as a significant threat to financial stability within the region (African Development Bank, 2021). Broadly, climate change represents an undiversifiable, or systemic, risk to the banking sector, with the potential to disrupt core banking functions and exert substantial adverse effects on the real economy (Hu & Borjigin, 2025).

The IPCC (2018) and Giuzio, et al (2019) suggest that climate change impacts the banking system through two principal channels: physical risk and transition risk. Conversely, Carney (2015) identifies three channels through which climate change may influence financial stability: physical risk, liability risk, and transition risk. Physical risk arises from economic and financial losses induced by extreme climatic events, such as heatwaves, storms, floods, and landslides (Settlements, 2021). Transition risk, as defined by Carney (2015), refers to the risks associated with the shift towards a low-carbon economy. Transition risks may also generate secondary risks, including liability, market, policy, legal, liquidity, credit, operational, and reputational risks (Fabris, 2020; Settlements, 2021).

Sub-Saharan Africa is particularly susceptible to climate-induced shocks (African Development Bank, 2019). For example, a few studies demonstrate the impact of climate disturbances on SSA banking systems, macroeconomic stability and monetary policy dynamics. A 2019 World Bank report highlights both the opportunities and challenges facing the region, including those associated with climate change. The United Nations (UN) (2023) notes that over 110 million individuals in SSA were adversely affected by climate-related events, resulting in approximately USD 8.5 billion in economic damages. SSA remains one of the least resilient regions globally in terms of withstanding climate-related adversities (UN, 2023). The continual variation in climatic conditions in the region poses a growing threat to banking system stability. Historical data underscores the economic cost of climate events. Allianz Group and the Worldwide Fund for Nature (WWF, 2005) reported that floods and storms in 1999 incurred losses of 13 billion Euros, while heatwaves in 2003 resulted in losses of 10 billion Euros. The European Commission projects that, without effective mitigation, global damage from climate change could amount to 74 trillion Euros in present-day value. Within Africa, UN (2021) reports estimate that annual climate-related investments for SSA will range between USD 30–50 billion over the coming decade. Puig et al. (2016) further suggest that adaptation costs in developing countries may reach USD 140–300 billion by 2030 and USD 280–500 billion by 2050.

The importance of this research is heightened by the recognition that SSA banking sectors constitute a substantial portion of the continent's financial system. Achieving sustainable banking operations requires that financial and monetary authorities develop a comprehensive understanding of climate change and implement policies aligned with its challenges. A critical research question is: what are the effects of climate change on the banking sector? Addressing this question is essential to promoting banking system stability in SSA. Evidence from developed economies indicates that climate change can negatively impact banking sector stability (Klomp, 2014; Schüwer et al., 2019; Noth & Schüwer, 2023; Laborda, et al 2026). This study aims to deepen understanding of the relationships between climate change variables and banking system stability. The Sub-Saharan region is of particular interest due to its high vulnerability to climate-related risks and its bank-based financial architecture. Additionally, the study introduces methodological innovations that are underutilised in existing literature, including the application of econometric techniques such as the CS-ARDL model. The robustness of empirical findings is highly contingent on the methodological approaches employed (Ibrahim, 2017). Finally, the development of a climate change index provides a further contribution to studies examining the interface between climate change and banking system stability.

LITERATURE REVIEW

This study draws upon theoretical frameworks relevant to the subject matter as foundational guidance for the research. Additionally, empirical evidence concerning CC and the broader financial system is critically examined to address the research question. Li et al. (2020) note that relatively few studies have investigated systemic CC risk in relation to the banking sector. The China Expert Panel on Climate Change (CEPCC) and the United Kingdom Committee on Climate Change (UKCCC) classify climate-induced systemic risks into two categories: emergency climate risk and incremental climate risk. Emergency climate risk pertains to severe, immediate threats arising from climate-related events that require rapid management and intervention. Manifestations of such risks include natural disasters and extreme weather events, which have the potential to inflict substantial harm on economies, ecosystems, and communities.

CC can also generate concentration effects, spillovers, and interconnections within the financial system, amplifying economic and financial repercussions (Monasterolo, et al 2019; GAR, 2023). Systemic risks threaten financial sector stability, arising from both exogenous and endogenous shocks (Choudhury, 2021). Liu et al. (2021) examine the relationship between CC and banking stability in China using monthly data from 2002–2008, finding that both positive and negative temperature shocks compromise financial stability. Similarly, Le et al. (2023) report that elevated CC risk reduces bank stability, based on a study of 6,433 banks across 109 countries for 2015–2019 employing panel system GMM estimation. Do et al. (2023) find that natural disasters diminish bank stability, analysing 907 US domestic banks and data from the Spatial Hazards Events and Losses Database for 2010–2019 using panel GMM. Agbloyor et al. (2022) investigate the effect of carbon dioxide (CO2) emissions on BS stability globally for 2000–2013 across 122 countries, revealing that low levels of CO2 emissions positively influence BS stability, whereas higher emissions exert the opposite effect. Semieniuk et al. (2021), in a literature survey, argue that transition costs associated with implementing environmental regulations may elevate non-performing loans, thereby reducing bank profitability.

Bovari et al. (2018) employ a Stock-Flow model grounded in Lotka-Volterra logic to test bank stability, concluding that CC negatively affects financial stability. Dafermos et al. (2018) utilise a stock-flow-fund ecological macroeconomic model with global data spanning 2016–2120 to illustrate multiple pathways through which CC impacts financial stability. They show that CC diminishes firms' capital and profitability, creates liquidity pressures that elevate default rates, reallocates financial resources through declining corporate bond prices, and ultimately hinders credit expansion. Additionally, the authors suggest that green quantitative easing strategies may mitigate CC-induced financial instability. Evidence of the adverse relationship between CC and financial systems is also provided by Battiston et al. (2017 & 2021), who demonstrate that a significant portion of investors' equity is directly and indirectly exposed to CC risk, using network-technique stress testing on a large Euro area bank. Aglietta and Espagne (2016) further support the view that CC constitutes a systemic risk within the financial system and functions as a negative externality, which economic agents may hedge via carbon taxation and emissions trading. Their study concludes that CC and financial fragility reinforce each other. Liu et al. (2024), using panel data from 53 countries (2007–2019) with fixed-effects estimation, confirm the negative association between CC and financial stability.

Chabot and Bertrand (2023) analyse the effects of physical and transition risks on the European financial system (2011–2020) using panel data techniques, concluding that greenhouse gas emissions, chronic and acute climate risks undermine financial stability, with temperature anomalies, heatwaves, wildfires, and droughts identified as significant factors. Likewise, Blickle et al. (2021), assessing weather disasters' effects on US banks via regression analysis from 1995–2018, report that weather-related shocks have an insignificant effect on banking stability, suggesting that stability may be endogenous. Brown et al. (2021), employing a two-stage least squares approach with 102,742 observations for 2012–2016, provide evidence that bank valuations are elevated in relation to physical CC risk. Noth and Schüwer (2023) contend that property damages from natural disasters erode US banks' stability, based on fixed-effects analysis of 66,766 banks (1994–2012). In Nigeria, Oguntuase (2017) documents that bank exposure to CC shocks is significant, analysing annual loan portfolios for 14 commercial banks as of December 2016. Fabris (2020) posits that CC constitutes a financial risk capable of disrupting the balance sheets of financial institutions while simultaneously creating opportunities, based on panel GMM analysis of 6,433 commercial banks across 109 countries (2005–2019).

Saliya & Wickrama (2021) employ Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) to examine CC's impact on financial stability in Fiji using survey data, concluding that CC preparedness requires multi-level strategies. Roncoroni et al. (2021), using climate stress-testing on Mexican supervisory data from Banco de México, report that robust market conditions are essential for effective CC policy implementation within financial risk frameworks. Fontana and Sawyer (2016) argue that CC increases operational uncertainty and hinders financial stability, analysing interdependencies between economic and biophysical systems. Nand & Bardsley (2020) emphasise that losses from CC-induced disasters amplify financial risks, drawing on narrative reviews and contemporary media reports. Contrastingly, Cavallo et al. (2013) find that natural disasters exert an insignificant effect on financial stability, analysing 196 economies (1970–2008) using panel data methods. Lamperti et al. (2019), employing an agent-based approach, suggest that CC intensifies global banking crises. Conversely, Caby et al. (2022), using panel GMM on 137 banks across emerging and advanced economies (2011–2019), observe a positive relationship between CC ramifications and BS profitability.

METHODOLOGY

The study adopts a contemporary panel data approach that accounts for cross-sectional dependence and integrates multiple econometric model variants. To investigate the effect of CC on BS stability in selected SSA economies, the analysis utilises a comprehensive set of CC variables and constructs a climate change index for estimation purposes through the application of principal component analysis (PCA). Accordingly, the study posits the following hypotheses:

H1: *Climate change has a significant impact on banking system stability in selected Sub-Saharan economies.*

A panel dataset was constructed with annual observations spanning 1996 to 2017 for 29 SSA economies. It should be noted that the data pertaining to bank-specific parameters are national aggregates. The selection of countries was guided strictly by data availability, and the complete list of countries included in this study is provided in Appendix 1. Given the nuanced nature of CC data, and to mitigate potential limitations in assessing its impact on BS stability, the study sourced CC information from two data portals: the ClimateWatch Online platform and the World Bank Climate Change Knowledge Portal. ClimateWatch is an online platform that supports the Paris Agreement by utilising open-access data to enhance transparency and accountability regarding CC issues. Greenhouse gas (GHG) emissions were obtained from ClimateWatch, while temperature and precipitation data were extracted from the World Bank Climate Change Knowledge Portal.

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Furthermore, a Climate Change Index (CCI) was developed using PCA based on the three aforementioned CC variables—temperature, precipitation, and GHG emissions—to strengthen the methodological contribution of the study. Consistent with finance and economic literature, the bank Z-score is employed as a proxy for BS stability. Previous studies, including Le et al. (2023), Do et al. (2023), Dutta and Saha (2021), Cobbinah et al. (2020), Rupeika-Apoga et al. (2018), Ijtsma et al. (2017), Leroy and Lucotte (2017), and Louati and Boujelbene (2015), have all utilised the bank Z-score as an indicator of BS stability. The inclusion of control variables enhances statistical precision (Cobbinah et al., 2020). Bank-specific controls, such as Net Interest Margin (NIM) and Bank Concentration, were obtained from the World Bank Global Finance Database. Macroeconomic indicators, including money supply, were sourced from the World Development Indicators platform. Additionally, regulatory quality was included as a control variable. It is noteworthy that the selection of these controls was not arbitrary; Demirgüç-Kunt (1997) indicate that governance (institutional) indicators can significantly influence BS stability. Governance variables were sourced from the World Governance Indicators (WGI) database. Table 1 presents a detailed description of the data, including notation, sources, and the expected signs.

Table 1: Data Description, Notion and Sources

Variable	Notation	Data Source	Expected Sign
Banking System Stability	BS	Global Finance Development Database	
Temperature	TEMPT	Climate Change Knowledge Portal	-
Precipitation	PPT	Climate Change Knowledge Portal	-
Greenhouse Gas	GHG	ClimateWatch Database	-
Climate Change Index	CCI	Principal Component Analysis (PCA)	
Bank Concentration	BC	Global Finance Development database	+
Net Interest Margin	NIM	Global Finance Development Database	+
Money Supply	MS	World Development Indicators (WDI)	+
Regulatory Quality	RQ	World Governance Indicators (WGI)	+

Source: Author's Construct, 2024.

The study adopts a four-step panel data approach to examine the aforementioned impact. To express the relationships in a panel data framework, the equations are formulated as follows:

$$BS_{it} = \text{f(CLIMATE CHANGE,CONT)it} \qquad (1)$$

CLIMATE CHANGE (CC) denotes the specific climate-related variable(s) incorporated into the regression model, namely temperature (TEMPT), precipitation (PPT), GHG, and the CCI constructed for this study. The vector of control variables comprises bank-specific factors, including Net Interest Margin (NIM) and Bank Concentration (BC), as well as macroeconomic indicators such as Money Supply (MS). Additionally, governance factors, represented by Regulatory Quality (RQ), are incorporated as control variables. Based on these specifications, the following

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econometric models are formulated to address the research objectives:

$$BS_{it} = f(TEMPT_{it}, NIM_{it}, BC_{it}, MS_{it}, RQ_{it}) \tag{2}$$

$$BS_{it} = f(PPT_{it}, NIM_{it}, BC_{it}, MS_{it}, RQ_{it}) \tag{3}$$

$$BS_{it} = f(GHG_{it}, NIM_{it}, BC_{it}, MS_{it}, RQ_{it}) \tag{4}$$

$$BS_{it} = f(CCI_{it}, NIM_{it}, BC_{it}, MS_{it}, RQ_{it}) \tag{5}$$

Econometrically, Models 1–5 can be expressed as follows. In line with the methodology adopted by Kadanali (2020), various parameters employed in Models 6–9 are transformed using natural logarithms to mitigate issues of heteroscedasticity, address the influence of outliers, and establish elasticity relationships among the variables. As noted by Breusch and Pagan (1979) and Cook and Weisberg (1983), heteroscedasticity represents a significant concern in regression analyses, as results derived from models affected by heteroscedasticity may be unreliable. Consequently, the equations for Models 6–9 are normalised through logarithmic transformation. The normalised equations are therefore specified as follows:

$$\ln BS_{it} = \phi_{it} + \delta BS_{i,t-k} + \delta_1 \ln TEMPT_{i,t-k} + \delta_2 \ln NIM_{i,t-k} + \delta_3 \ln BC_{i,t-k} + \delta_4 \ln MS_{i,t-k} + \delta_5 \ln RQ_{i,t} + \mu_{it} \tag{6}$$

$$\ln BS_{it} = \theta_{it} + \beta \ln BS_{i,t-k} + \beta_1 \ln PPT_{i,t-k} + \beta_2 \ln NIM_{i,t-k} + \beta_3 \ln BC_{i,t-k} + \beta_4 \ln MS_{i,t-k} + \beta_5 \ln RQ_{i,t-k} + \mu_{it} \tag{7}$$

$$\ln BS_{it} = \varphi_{it} + \lambda \ln BS_{i,t-k} + \lambda_1 \ln GHG_{i,t-k} + \lambda_2 \ln NIM_{i,t-k} + \lambda_3 \ln BC_{i,t-k} + \lambda_4 \ln MS_{i,t-k} + \lambda_5 \ln RQ_{i,t-k} + \mu_{it} \tag{8}$$

$$\ln BS_{it} = \sigma_{it} + \alpha \ln BS_{i,t-k} + \alpha_1 \ln CCI_{i,t-k} + \alpha_2 \ln NIM_{i,t-k} + \alpha_3 \ln BC_{i,t-k} + \alpha_4 \ln MS_{i,t-k} + \alpha_5 \ln RQ_{i,t-k} + \mu_{it} \tag{9}$$

Where, $\phi_{it}, \theta_{it}, \varphi_{it}, \sigma_{it}$ are the respective intercepts from model 6 to 9. In addition, $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5$ are the coefficients for model 6. Further, the coefficients of model 7 are shown as $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$. $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$ denotes the coefficients of model 8. For model 9, the coefficients are $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$. i and t shows the cross-section units indicated in the panel and the time period of the panel respectively. μ is the error term with zero mean and constant variance. Also, k is a series of lag values.

Cross-Sectional Autoregressive Distributed Lag (CS-ARDL)

The study employs the CS-ARDL model developed by Chudik and Pesaran (2015) to examine the research objective. Unlike conventional linear panel ARDL models, CS-

ARDL effectively accounts for cross-sectional dependence and allows heterogeneity across units, providing more efficient and consistent estimates. Its suitability is reinforced by prior applications in economics, finance, social sciences, and environmental studies (Erülgen et al., 2020; Li et al., 2020). The model captures dynamic relationships and addresses endogeneity through its specification, while controlling for cross-sectional dependence and accommodating instrumental variables. Designed for variables integrated of order I(0) or I(1), CS-ARDL produces pooled long-term estimates (Chakraborty & Mazzanti, 2021). Its use is particularly appropriate for macroeconomic data across multiple countries, where methods such as system GMM, fixed effects, or random effects may inadequately capture interdependencies. Chudik and Pesaran (2015) further advise that both the Mean Group (MG) and Pooled Mean Group (PMG) estimators should be employed within CS-ARDL to address parametric estimation concerns. Building upon the foundational ARDL I(1) model and incorporating a multifactor error structure, the CS-ARDL methodology is elaborated in the following equation, which provides a step-by-step representation of the modelling approach proposed by Chudik and Pesaran (2015).

$$\gamma_{it} = \alpha_{it} + \theta\gamma_{it-1} + \alpha'_{0i}\,\chi_{it} + \alpha'_{1i}\,\chi_{it-1} + \varepsilon_{it} \tag{10}$$

$$\varepsilon_{it} = \delta_{it} f_t + \mu_{it} \tag{11}$$

$$\varpi_{it} = \begin{pmatrix} \chi_{it} \\ \kappa_{it} \end{pmatrix} = \alpha_{\varpi_{it}} + \beta_i \gamma_{it-1} + \Gamma_i^{i} f_t + \upsilon_{it} \tag{12}$$

$i = 1....N$; $t = 1.....T$, $\chi_{it} = k_x$ x 1, thus, vector of regressors in cross-sectional units i at time period t. α_{it} and $\alpha\varpi_i$, κ_{it} is k_k x 1 is covariates vector to the i^{th} cross-sectional unit. μ_{it} denotes the idiosyncratic errors. f_t represent m x 1 vector of unobserved factors. Preliminary diagnostic tests, including assessments of cross-sectional dependence, correlation analyses, and unit root evaluations using the Cross-Sectionally Augmented Dickey-Fuller (CADF) and Cross-Sectional Augmented IPS (CIPS) tests, as well as examinations of slope homogeneity, yielded satisfactory results, as presented in the Appendix.

PRESENTATION OF RESULTS AND DATA ANALYSIS

Descriptive Statistics

The statistical properties of the variables are summarised in Table 2. The table indicates that, with the exception of temperature, the CCI, and RQ, all variables included in the descriptive statistical analysis exhibit positive mean values over the sample period. The lowest mean is observed for the CCI, while the highest mean is recorded for precipitation, followed by RQ and BC. A detailed presentation of the descriptive statistics is provided in Table 2.

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Table 2: Descriptive Statistics of Variables

VARIABLE	MEAN	MEDIAN	MAX	MIN	SD	SKEWNESS	KURTOSIS	JARQUE -BERRA
lnBS	3.2975	3.3503	6.5282	-0.5276	1.5607	0.0970	2.0686	24.0607
lnTEMPT	-0.5651	-0.4231	1.0296	-4.6051	0.7418	-1.4546	6.6136	572.139
lnPPT	6.7490	6.9163	7.9207	4.9437	0.6134	-0.9873	3.3219	106.4262
lnGHGAS	3.3420	3.3624	6.3409	0.5364	1.4007	-0.1682	2.4151	12.1026
lnCCI	-2.41E-15	-0.0105	2.8972	-4.5795	1.1629	0.0162	3.0515	0.0986
lnNIM	0.5697	0.6193	2.9865	-4.2436	0.8394	-0.8893	6.7685	461.6456
InBC	3.9309	4.3472	6.5963	0.0000	1.3914	-2.0567	6.7278	819.2211
lnMS	3.0630	3.1072	4.2944	0.0000	0.7111	-1.9363	9.7661	1615.719
lnRQ	-0.3925	-0.4068	1.1272	-1.7993	0.5065	0.1295	3.1855	2.7012

The table shows the summary statistics of variables which consist of dependent, independent and control variables. BS is banking system stability, TEMPT is temperature, PPT is precipitation, GHGAS is greenhouse gas, CCI is climate change index, NIM is net interest margin, BC is bank concentration, MS is money supply and RQ depicts regulatory quality. ln is the natural logarithm.
Source: Author's computations in EViews 10.

Co-Integration Test Results

It is essential to note that, once the order of integration has been determined, the study proceeds to examine co-integration among the CC variables, BS stability, and the control variables included in the analysis. Considering the panel structure and temporal dimension of the dataset, the Kao residual co-integration test is applied across all econometric models, specifically Models 6–9. The results of the Kao residual co-integration test are presented in Table 3.

As indicated in Table 3, all models demonstrate significance at the 1 percent level, suggesting that the variables under consideration are co-integrated. Consequently, the null hypothesis of no co-integration is rejected, implying the existence of a long-run equilibrium relationship across all specified models. These findings confirm the appropriateness of employing the CS-ARDL model to examine both the short- and long-term dynamics between CC and BS stability. The detailed outcomes of the Kao residual co-integration tests are provided in Table 3.

Table 3: Kao Residual Co-Integration Test Results

Model	T-Statistics	P-Value
6	-9.6605***	0.0000
7	-9.1098***	0.0000
8	-10.0136***	0.0000
9	-9.5995***	0.0000

*** indicate the significance level at 1 percent.

CS-ARDL Findings

The study specifically investigates the long-term and short-term impact of CC on BS stability in selected SSA economies by employing the CS-ARDL model. Following the works of Chudik and Pesaran (2015) and Eberhardt and Presbitero (2015), a lag length of two periods is adopted, as recommended for cross-sectional averages in CS-ARDL estimation. The results of the CS-ARDL model are reported in Table 4. Across Models 6–9, the CC variables consistently exhibit negative coefficients with BS stability, although these relationships are statistically insignificant. The convergence coefficients (error terms) are negative and significant in all models, confirming that the system returns swiftly to equilibrium after any deviations. The convergence coefficients for Models 6, 7, 8, and 9 are −0.9692, −0.9999, −0.9695, and −0.9862, respectively, further affirming the existence of a stable long-run relationship. Table 4 depicts the long-term and short-term results using the CS-ARDL estimation technique:

In Model 6, temperature exhibited a positive but statistically insignificant relationship with banking system stability in the long term, contrasting with Liu et al. (2021), who reported a significant negative association, highlighting a novel insight given the limited quantitative literature on this specific relationship. A 1 percent increase in net interest margin in the long term raised banking system stability by 0.3098 percent, while bank concentration reduced stability by 0.2782 percent at the 5 percent significance level. Conversely, money supply decreased banking system stability by 0.1760 percent at the 6 percent relevant level. Regulatory quality demonstrated a positive relationship with stability, although it remained statistically insignificant even at the 10 percent level. In the short term, temperature continued to exhibit a positive but insignificant effect, whereas net interest margin maintained a positive and significant influence, increasing stability by 0.2935 percent at the 1 percent significance level. Bank concentration remained negatively and significantly associated with banking system stability, with a 1 percent rise reducing stability by 0.2702 percent at the 5 percent level.

Table 4: Estimates of Long-Term and Short-Term Impact of Climate Change on Banking System Stability

Models	**6**		**7**		**8**		**9**	
Long-Term Impact								
Variables	**Coefficient**	**Std. Err**	**Coefficient**	**Std.Err**	**Coefficient**	**Std.Err**	**Coefficient**	**Std.Err**
lnTEMPT	0.0195	0.0027 (0.5421)	-	-	-	-	-	-
lnPPT	-	-	-0.0842	0.3373 (0.803)	-	-	-	-
lnGHGAS	-	-	-	-	-0.2123	-0.3373 (0.803)	-	-
lnCCI	-	-	-	-	-	-	-0.0080	0.0243 (0.742)
lnNIM	0.3098	0.0390*** (0.000)	0.2827	0.0435*** (0.000)	0.2900	0.0430*** (0.000)	0.2857	0.0389*** (0.000)

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Table 4: Estimates of Long-Term and Short-Term Impact of Climate Change on Banking System Stability (cont…)

Models	6		7		8		9	
lnBC	-0.2782	0.1176** (0.018)	-0.1627	0.0939* (0.083)	-0.1848	0.0951 (0.052)	-0.2257	0.1020** (0.027)
lnMS	-0.1760	0.1016* (0.083)	-0.4662	0.1376 (0.735)	-0.0578	0.1016 (0.569)	-0.1359	0.0922 (0.141)
lnRQ	0.0882	0.0882 (0.840)	-0.0975	0.0956 (0.308)	-0.0924	0.0961 (0.336)	-0.0711	0.1159 (0.539)
Short-Term Impact								
Δ lnTEMPT	0.0219	0.0230 (0.341)	-	-	-	-	-	-
Δ lnPPT	-	-	-0.0271	0.2408 (0.910)	-	-	-	-
Δ lnGHGAS	-	-	-	-	-0.1987	-0.2305 (0.389)	-	-
Δ lnCCI	-	-	-	-	-	-	-0.0008	0.0266 (0.973)
Δ lnNIM	0.2935	0.0387*** (0.000)	0.2900	0.0430*** (0.000)	0.2827	0.0435*** (0.000)	0.2762	0.0406*** (0.000)
Δ lnBC	-0.2702	0.1237** (0.029)	-0.1723	0.1004* (0.086)	-0.1862	0.0971* (0.055)	-0.2263	0.1069** (0.034)
Δ lnMS	-0.1629	0.0917* (0.076)	-0.0235	0.1525 (0.877)	-0.1017	0.0988 (0.270)	-0.1465	0.0898 (0.103)
Δ RQ	0.0573	0.0793 (0.470)	-0.0550	0.1013 (0.587)	-0.0973	0.9880 (0.325)	-0.0471	0.1106 (0.670)
ECT(-1)	-0.9692	0.0319*** (0.000)	-0.9999	0.0423*** (0.000)	-0.9695	0.0371*** (0.000)	-0.9862	0.0359*** (0.000)

***, ** and * indicate the significance level at 1 percent, 5 percent and 10 percent, respectively. The value in brackets (.) measures the respective probability values (P-Values) of the variables. Where BS is banking system stability, TEMPT represents temperature, PPT denotes precipitation, GHGAS represents greenhouse gas, CCI signifies climate change index, NIM implies net interest margin, BC is bank concentration, MS is money supply and RQ depicts regulatory quality. ln is the natural logarithm.
Source: Author's construct from computations in STATA 17.

Similarly, money supply exerted a negative and statistically significant effect in the short term, with a 1 percent increase reducing stability by 0.1629 percent at the 10 percent significance level. Regulatory quality retained a positive yet statistically insignificant relationship with banking system stability in the short-term analysis.

- For model 7, Table 4 indicates that the coefficient for precipitation, representing the climate change explanatory variable, is negative and statistically insignificant with respect to banking system stability in the long term.

Aligned with expectations, net interest margin exhibited a positive and statistically significant effect on banking system stability. Specifically, a 1 percent increase in net interest margin corresponds to a 0.2827 percent rise in banking system stability at the 1 percent significance level. Regarding the long-term effects in model 7, bank concentration negatively influenced banking system stability, with an elasticity of 0.1627. This relationship is significant at the 10 percent level, indicating that a 1 percent increase in bank concentration diminishes banking system stability by 0.1627 percent. In contrast, the long-term impacts of money supply and regulatory quality on banking system stability were statistically insignificant, although both exhibited negative associations. The short-term analysis of both explanatory and control variables on banking system stability is subsequently examined.

- It is evident that precipitation exhibited a negative association with banking system stability, although this relationship was not statistically significant even at the 10 percent level. Overall, precipitation aligns with the expected directional effect in both the short-term and long-term analyses.

Net interest margin demonstrated a modest yet positive influence on banking system stability, where a 1 percent increase in net interest margin corresponds to a 0.2900 percent improvement in banking system stability across the selected Sub-Saharan economies. In the context of short-term impacts, bank concentration exerted a significantly detrimental effect on banking system stability, with a 1 percent rise in bank concentration reducing stability by 0.1723 percent. Conversely, money supply and regulatory quality showed negative but statistically insignificant effects on banking system stability in the short term. Extending the discussion to model 8, the subsequent interpretations of the variables' statistical performance are summarised in Table 4.

- Expectedly, greenhouse gas had a negative relationship with banking system stability in the long-term, however, the link was insignificant.

As shown in Table 4, net interest margin maintained a positive and statistically significant association with banking system stability, achieving significance at the 1 percent level. Controlling for other variables, a 1 percent increase in net interest margin corresponds to an enhancement of banking system stability by 0.2900 percent. Similarly, bank concentration and money supply exhibited consistent directional effects in the long-term for model 8. Specifically, the relationship between bank concentration and banking system stability was negative and statistically significant. This indicates that an increase in bank concentration results in a decline in banking system stability, with the marginal effect estimating a reduction of 0.1848 percent at the 10 percent significance level. In contrast, the negative association between money supply and banking system stability was not statistically significant. Additionally, regulatory quality demonstrated a negative but insignificant impact on banking system stability in the long-term.

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For the Short-Term Impact on Model 8

- Greenhouse gas reported a negative and insignificant nexus with banking system stability.

Furthermore, net interest margin exhibited a positive and statistically significant effect on banking system stability. The marginal interpretation of this relationship indicates that a 1 percent increase in net interest margin enhances banking system stability by 0.2827 percent at the 1 percent significance level. In contrast, bank concentration displayed a negative and statistically significant association with banking system stability, significant at the 10 percent level. This implies that a 1 percent rise in bank concentration reduces banking system stability by 0.1862 percent, highlighting its relevance for the study. Conversely, money supply and regulatory quality showed no statistically significant effect on banking system stability in the short-term for model 8.

For Model 9

- The results reveal that climate change index is insignificantly ruinous to banking system stability as the coefficient of climate change index is negative and statistically insignificant in the short- and long-term.

It is noteworthy that net interest margin in model 9 demonstrates a stabilising influence on the banking system in both the long-term and short-term, as indicated by the positive and statistically significant relationships observed across the two temporal dimensions. As reflected in Table 4, these results were expected; specifically, a 1 percent increase in net interest margin corresponds to an augmentation of banking system stability by 0.2857 percent in the long-term and 0.2762 percent in the short-term. Conversely, bank concentration exhibits a negative and significant association with banking system stability in both the short- and long-term. Table 4 highlights that bank concentration diminishes stability by 0.2257 percent in the short-term and 0.2263 percent in the long-term, both significant at the 5 percent level. It is pertinent to note that money supply does not act as a stabilising factor in either temporal dimension, and regulatory quality similarly demonstrates a negative and statistically insignificant effect on banking system stability within model 9.

According to Zhang et al. (2022), the banking sector functions primarily as a vehicle for capital management, with banks acting as institutions that mobilise deposits and extend loans. Consequently, the authors contend that rising temperatures appear to exert no direct influence on banking stability when considering this operational definition of the sector. Complementing this view, Alagidede et al. (2016) suggest a "Laffer Effect" of temperature, wherein it may yield both beneficial and adverse outcomes depending on contextual conditions. Despite these theoretical perspectives, the influence of temperature, greenhouse gas emissions, precipitation, and the climate change index on banking stability in Sub-Saharan Africa remains highly uncertain. Wen and Chang

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(2015) emphasise that individuals deposit funds and obtain loans for investment purposes, while firms utilise bank loans for expansion, research, and development. Similarly, Cortés and Strahan (2017) argue that both households and businesses encountering economic losses may rely on banks for financial support. Given the statistically insignificant effects of all climate change variables in this study, it is inferred that climate change does not exert a meaningful short-term or long-term impact on banking system stability in the selected Sub-Saharan economies.

With respect to the control variables, net interest margin consistently demonstrates a positive influence on banking system stability across all four models (6–9). This finding aligns with Ali et al. (2018), who reported a significant positive association between net interest margin and financial stability. Net interest margin is widely recognised as a key indicator for assessing banking efficiency. Saksonova (2014) observes that it provides a comprehensive measure of how banks manage interest-bearing assets, calculated as the difference between interest earned on loans and interest paid on deposits. Endri et al. (2020) similarly note that net interest margin reflects the real interest spread, influenced by macroeconomic conditions. In Sub-Saharan economies, weak macroeconomic structures often prompt central banks to raise interest rates in response to monetary policy tightening and rising inflation. During periods of high interest rates, borrowers face elevated repayment obligations, which reduces future purchasing power, while banks benefit from higher interest income, thereby enhancing their capital position and lending capacity. While this may strengthen banks' capital portfolios, it could also increase risk-taking behaviour, potentially leading to higher non-performing loans.

Bank concentration demonstrates a negative effect on banking system stability across all models in both the short- and long-term, deviating from the a priori expectations presented in Table 1. This outcome indicates that higher concentration levels may destabilise the banking sector in selected Sub-Saharan economies. The finding corroborates the studies of Kombo et al. (2021) and Berger et al. (2008), which identify bank concentration as a factor contributing to financial instability. However, these results contrast with Nyangu et al. (2022), who argue that both high and low concentration can enhance financial stability, and also differ from Zomo Yobe (2017), which suggests that concentration supports banking system stability.

CONCLUSION

Climate change has become a pivotal concern in global financial markets, yet its implications for financial system stability remain underexplored. Sub-Saharan Africa's financial system is predominantly bank-based, contrasting with the more diversified structures of developed economies. While some countries have advanced climate-related risk frameworks within their banking sectors, others lag, resulting in fragmented evidence on the impact of climate change on banking stability in SSA. Addressing this

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gap, the study examines both short- and long-term effects of climate change on banking system stability in selected Sub-Saharan economies from 1996 to 2017, employing the CS-ARDL model. Key explanatory variables include temperature, precipitation, greenhouse gas emissions, and a composite CCI, with bank Z-score as the proxy for stability. Control variables comprise NIM, BC, MS, and RQ. Empirical findings reveal that climate change indicators exert no significant short- or long-term effects on banking system stability in the sampled economies. NIM consistently demonstrates a strong positive influence, underscoring its role in strengthening banking resilience. In contrast, BC and MS generally show negative effects, some statistically significant, while RQ exhibits inconsistent and insignificant impacts. The negative and significant error correction terms across models confirm long-run equilibrium and the robustness of the estimations.

Based on these findings, it is recommended that policymakers focus on reinforcing the internal dynamics of the banking system. This includes promoting competitive banking environments, ensuring prudent liquidity management, and continuously developing frameworks for monitoring climate-related financial risks. Although this study did not find direct effects of climate variables on banking system stability, the potential for indirect vulnerabilities remains, especially as climate risks intensify over time. Consequently, integrating climate considerations into macroprudential and banking sector policies remains a critical priority. This study makes a significant contribution by empirically assessing the relationship between climate change and banking system stability in Sub-Saharan Africa, yet it is not without limitations. The restricted availability of consistent data constrained the analysis to 29 countries, leaving room for future research to expand the scope to encompass all SSA economies. Furthermore, subsequent studies could adopt alternative methodological frameworks capable of addressing heterogeneity and endogeneity issues, such as the panel system generalized method of moments (Sys-GMM). Future research might also investigate indirect transmission channels through which climate change could influence banking system stability, including sectoral credit risk, deterioration in asset quality, or fiscal pressures within climate-sensitive economic sectors.

REFERENCES

African Development Bank, (2019). Climate Change in Africa. Assessed on March 4,2023 from https://www.afdb.org/en/cop25/climate-change-africa

African Development Bank, (2021). Climate risk regulation in Africa’s financial sector and related private sector initiatives. Retrieved on May 6, 2023 from https://www.unepfi.org/wordpress/wp-content/uploads/2021/11/Climate-risk-regulation-in-Africas-financial-sector-and-related-private-sector-initiatives-Report.pdf

African Development Bank, (2021). *Climate change in Africa*. Retrieved on March 14, 2023, from https://www.afdb.org/en/cop25/climate-change-africa

Agbloyor, E. K., Kusi, B. A., Abor, P. A., & Ntim, C. G. (2022). Corporate Governance, Regulations and Banking Stability in Africa. *Palgrave Macmillan Studies in Banking and Financial Institutions*, 605-657. https://doi.org/10.1007/978-3-031-04162-4_19

Aglietta, M., & Espagne, E. (2016). *Climate and finance systemic risks, more than an analogy? The climate fragility hypothesis*. https://ideas.repec.org/p/cii/cepidt/2016-10.html

Alagidede, P., Adu, G., & Frimpong, P. B. (2016). The effect of climate change on economic growth: evidence from Sub-Saharan Africa. *Environmental Economics and Policy Studies*, *18*(3), 417-436. https://link.springer.com/article/10.1007/s10018-015-0116-3

Allianz Group and WWF, (2005). Climate Change & the Financial Sector: An Agenda for Action. Retrieved on May 1, 2023 from https://www.wwf.org.uk/sites/default/files/2005-01/allianz_rep_0605.pdf

Ali, H., Fowler, H. J., & Mishra, V. (2018). Global observational evidence of strong linkage between dew point temperature and precipitation extremes. *Geophysical Research Letters*, *45*(22), 12,320-312,330. https://doi.org/10.1029/2018GL080557

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. https://doi.org/10.1038/nclimate3255

Battiston, S., Dafermos, Y. and Monasterolo, I., (2021). Climate risks and financial stability. *Journal of Financial Stability*, *54*, p.100867. https://doi.org/10.1016/j.jfs.2021.100867

Berger, A. N., Klapper, L. F. and Turk-Ariss, R., 2008. Bank competition and financial stability. In Handbook of competition in banking and finance (pp. 185-204). *Edward Elgar Publishing*. https://doi.org/10.4337/9781785363306.00018

Blickle, K. S., Hamerling, S. N., & Morgan, D. P. (2021). *How Bad Are Weather Disasters for Banks?* https://fedinprint.org/item/fednsr/93339

Bovari, E., Giraud, G., & Mc Isaac, F. (2018). Coping With Collapse: A Stock-Flow Consistent Monetary Macrodynamics of Global Warming. *Ecological Economics*, *147*, 383-398. https://doi.org/10.1016/j.ecolecon.2018.01.034

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica: Journal of the econometric society*, 1287-1294. https://doi.org/10.2307/1911963

Brown, J. R., Gustafson, M. T., & Ivanov, I. T. (2021). Weathering cash flow shocks. *The Journal of Finance*, *76*(4), 1731-1772. https://doi.org/10.1111/jofi.13024

Caby, J., Ziane, Y., & Lamarque, E. (2022). The impact of climate change management on banks profitability. *Journal of Business Research*, *142*, 412-422. https://doi.org/10.1016/j.jbusres.2021.12.078

Carney, M. (2015). Breaking the tragedy of the horizon–climate change and financial stability. (29), 220-230. https://www.bankofengland.co.uk/-/media/boe/files/speech/2015/breaking-the-tragedy-of-the-horizon-climate-change-and-financial-stability.pdf

Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, *95*(5), 1549-1561. https://doi.org/10.1162/REST_a_00413

Chabot, M., & Bertrand, J.-L. (2023). Climate risks and financial stability: Evidence from the European financial system. *Journal of Financial Stability*, *69*, 101190. https://doi.org/10.1016/j.jfs.2023.101190

Chakraborty, S. K., & Mazzanti, M. (2021). Renewable electricity and economic growth relationship in the long run: Panel data econometric evidence from the OECD. *Structural Change and Economic Dynamics*, *59*, 330-341. https://doi.org/10.1016/j.strueco.2021.08.006

Choudhury, B. (2021). Climate Change as Systemic Risk. *Berkeley Business Law Journal*, *18*(2). https://doi.org/10.15779/Z381J9783Q

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

Cobbinah, J., Zhongming, T., & Ntarmah, A. H. (2020). Banking competition and stability: evidence from West Africa. *National Accounting Review*, *2*(3), 263-284. https://doi.org/10.3934/NAR.2020015

Cook, R. D., & Weisberg, S. (1983). Diagnostics for heteroscedasticity in regression. *Biometrika*, *70*(1), 1-10. https://doi.org/10.1093/biomet/70.1.1

Cortés, K. R., & Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics*, *125*(1), 182-199. https://doi.org/10.1016/j.jfineco.2017.04.011

Dafermos, Y., Nikolaidi, M., & Galanis, G. (2018). Climate change, financial stability and monetary policy. *Ecological Economics*, *152*, 219-234. https://doi.org/10.1016/j.ecolecon.2018.05.011

Demirgüç-Kunt, A., & Detragiache, E. (1997). The determinants of banking crises-evidence from developing and developed countries . World Bank Publications., *106*. https://www.imf.org/external/pubs/ft/wp/wp97106.pdf

Diffenbaugh, N. S., & Burke, M. (2019). Global warming has increased global economic inequality. *Proceedings of the National Academy of Sciences*, *116*(20), 9808-9813. https://doi.org/10.1073/pnas.1816020116

Dlugolecki, A., & Lafeld, S. (2005). Climate change and the financial sector. an agenda for action. https://inis.iaea.org/records/7ygwb-cg564

Do, Q. A., Phan, V., & Nguyen, D. T. (2023). How do local banks respond to natural disasters? *The European Journal of Finance*, *29*(7), 754-779. https://doi.org/10.1080/1351847X.2022.2055969

Dutta, K. D., & Saha, M. (2021). Do competition and efficiency lead to bank stability? Evidence from Bangladesh. *Future Business Journal*, *7*(1), 1-12. https://doi.org/10.1186/s43093-020-00047-4

Eberhardt, M., & Presbitero, A. F. (2015). Public debt and growth: Heterogeneity and non-linearity. *Journal of international Economics*, *97*(1), 45-58. https://doi.org/10.1016/j.jinteco.2015.04.005

Endri, E., Marlina, A., & Hurriyaturrohman, H. (2020). Impact of internal and external factors on the net interest margin of banks in Indonesia. *Banks and Bank Systems. Dec*, *15*(4), 99-104. https://doi.org/10.21511/bbs.15(4).2020.09

Erülgen, A., Rjoub, H., & Adalıer, A. (2020). Bank characteristics effect on capital structure: evidence from PMG and CS-ARDL. *Journal of Risk and Financial Management*, *13*(12), 310. https://doi.org/10.3390/jrfm13120310

Fabris, N. (2020). Financial Stability and Climate Change. *Journal of Central Banking Theory and Practice*, *9*(3), 27-43. https://doi.org/10.2478/jcbtp-2020-0034

Fontana, G., & Sawyer, M. (2016). Towards post-Keynesian ecological macroeconomics. *Ecological Economics*, *121*, 186-195. https://doi.org/10.1016/j.ecolecon.2015.03.017

Governor's Annual Report (GAR). (2023). *Restored confidence in the greek economy amid international uncertainty – Continuation of reforms.* https://www.bankofgreece.gr/en/news-and-media/press-office/news-list/news?announcement=c9f09196-c4fd-4a0c-98ac-018f93c70351

Giuzio, M., Krusec, D., Levels, A., Melo, A.S., Katrin, M. and Radulova, P., 2019. Climate change and financial stability (financial stability review). *European central bank*. https://www.sbp.org.pk/FSR/2021/Box-4.1.pdf

Hu, Z. and Borjigin, S., (2025). Climate information disclosure quality and systemic risk in the US banking industry. *Journal of Financial Stability*, p.101420. https://doi.org/10.1016/j.jfs.2025.101420

Ibrahim, M. (2017). *Studies on financial development and economic growth in sub-Saharan Africa*. University of the Witwatersrand, Johannesburg (South Africa). https://www.proquest.com/openview/5c28f7fe29e6b6fb8e842edb1c7f4a14/1?pq-origsite=gscholar&cbl=2026366&diss=y

Ijtsma, P., Spierdijk, L., & Shaffer, S. (2017). The concentration–stability controversy in banking: New evidence from the EU-25. *Journal of Financial Stability*, *33*, 273-284. https://doi.org/10.1016/j.jfs.2017.06.003

IPCC. (2018). Summary for Policymakers" in Global warming of 1.5° C. An IPCC Special Report on the impacts of global warming of 1.5° C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty. Sustainable Development, and Efforts to Eradicate Poverty. Geneva, Switzerland: World Meteorological Organization, 32. https://www.ipcc.ch/sr15/chapter/spm/

Kadanali, E., & Yalcinkaya, O. (2020). Effects of Climate Change on Economic Growth: Evidence from 20 Biggest Economies of the World. *Journal for Economic Forecasting*, *23*(3), 93-118. https://ideas.repec.org/a/rjr/romjef/vy2020i3p93-118.html

Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. *Journal of Financial Stability*, *13*, 180-192. https://doi.org/10.1016/j.jfs.2014.06.001

Kombo, P., Hakizimana, J., & Bouity, C. (2021). Impact of Market Concentration on the Stability of the Banking Sector in the Central African Economic and Monetary Community (CEMAC). *Modern Economy*, *12*(5), 960-975. https://doi.org/10.4236/me.2021.125049

Laborda, J., Suárez, C., Fernández, A., Wang, H., Cerdá, E., Ricci, L. and Quiroga, S., (2026). Unveiling how financial markets could intensify climate change risks. *Ecological Economics*, *239*, p.108773. https://doi.org/10.1016/j.ecolecon.2025.108773

Lamperti, F., Bosetti, V., Roventini, A. and Tavoni, M., (2019). The public costs of climate-induced financial instability. *Nature Climate Change, 9*(11), 829-833. https://doi.org/10.1038/s41558-019-0607-5

Le, A.-T., Tran, T. P., & Mishra, A. V. (2023). Climate risk and bank stability: International evidence. *Journal of Multinational Financial Management*, *70*, 100824. https://doi.org/10.1016/j.mulfin.2023.100824

Leroy, A., & Lucotte, Y. (2017). Is there a competition-stability trade-off in European banking? *Journal of International Financial Markets, Institutions and Money*, *46*, 199-215. https://doi.org/10.1016/j.intfin.2016.08.009

Li, A. S., Ingham, J. F., & Lennon, R. (2020). Genetic disorders of the glomerular filtration barrier. *Clinical Journal of the American Society of Nephrology*, *15*(12), 1818-1828. https://doi.org/10.2215/CJN.11440919

Liu, X., Liu, J., & Hao, Y. (2024). Climate change shocks and credit risk of financial institutions: evidence from China's commercial banks. *Emerging Markets Finance and Trade*, *60*(7), 1392-1406. https://doi.org/10.1080/1540496X.2023.2278659

Liu, Z., Sun, H., & Tang, S. (2021). Assessing the impacts of climate change to financial stability: evidence from China. *International Journal of Climate Change Strategies and Management*, *13*(3), 375-393. https://doi.org/10.1108/IJCCSM-10-2020-0108

Louati, S., & Boujelbene, Y. (2015). Banks' stability-efficiency within dual banking system: a stochastic frontier analysis. *International Journal of Islamic and Middle Eastern Finance and Management*, *8*(4), 472-490. https://doi.org/10.1108/IMEFM-12-2014-0121

Mazzocchetti, A., Monasterolo, I., Dunz, N. and Essenfelder, A.H., (2025). Breaking the economy: How climate tail risk and financial conditions can shape loss persistence and economic recovery. *Ecological Economics*, *237*, 108685. https://doi.org/10.1016/j.ecolecon.2025.108685

Mlachila, M. M., & Yabara, M. M. (2013). *Banking in sub-Saharan Africa: the macroeconomic context*. International Monetary Fund. https://www.imf.org/en/Publications/Departmental-Papers-Policy-

Papers/Issues/2016/12/31/Banking-in-Sub-Saharan-Africa-the-Macroeconomic-Context-40622

Monasterolo, I., Roventini, A. and Foxon, T. J., (2019). Uncertainty of climate policies and implications for economics and finance: An evolutionary economics approach. *Ecological Economics*, *163*, 177-182. https://doi.org/10.1016/j.ecolecon.2019.05.012

Nand, M. M. and Bardsley, D. K., (2020). Climate change loss and damage policy implications for Pacific Island Countries. Local Environment, 25(9), pp.725-740. https://doi.org/10.1080/13549839.2020.1825357

Noth, F., & Schüwer, U. (2023). Natural disasters and bank stability: Evidence from the US financial system. *Journal of Environmental Economics and Management*, *119*, 102792. https://doi.org/10.1016/j.jeem.2023.102792

Nyangu, M., Marwa, N., Fanta, A., & Minja, E. J. (2022). Bank concentration, competition and financial stability nexus in the East African Community: is there a trade-off? *Cogent Economics & Finance*, *10*(1), 2082026. https://doi.org/10.1080/23322039.2022.2082026

Oguntuase, O. J. (2017). Climate Fragility Assessment of Nigerian Bank. https://www.academia.edu/36913944/Climate_Fragility_Assessment_of_Nigerian_Commercial_Banks

Puig, D., Olhoff, A., Bee, S., Dickson, B. and Alverson, K., (2016). The adaptation finance gap report. https://backend.orbit.dtu.dk/ws/portalfiles/portal/198610751/Adaptation_Finance_Gap_Report_2016.pdf

Rupeika-Apoga, R., Zaidi, S., Thalassinos, Y., & Thalassinos, E. (2018). Bank stability: The case of Nordic and non-Nordic banks in Latvia. https://www.um.edu.mt/library/oar/handle/123456789/43729

Roncoroni, A., Battiston, S., Escobar-Farfán, L. O. and Martinez-Jaramillo, S., (2021). Climate risk and financial stability in the network of banks and investment funds. *Journal of Financial Stability, 54*, 100870. https://doi.org/10.1016/j.jfs.2021.100870

United Nations, (2023). African perspectives of a just transition to low-carbon economies. Online available at: https://uneca.org/sites/default/files/ACPC/2024/African_perspectives_of_a_just_transition_to_Low_Carbon_economies.pdf

United Nations (UN) News Global Perspective Human Stories, (2021). UN-backed report reveals rising climate change risk across Africa. Online available https://news.un.org/en/story/2021/10/1103362

Saliya, C.A. and Wickrama, K.A.S., (2021). Determinants of financial-risk preparedness for climate change: Case of Fiji. *Advances in Climate Change Research*, *12*(2), 263-269. https://doi.org/10.1016/j.accre.2021.03.012

Saksonova, S. (2014). The role of net interest margin in improving banks' asset structure and assessing the stability and efficiency of their operations. *Procedia-social*

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and behavioral sciences, *150*, 132-141. https://doi.org/10.1016/j.sbspro.2014.09.017

Schüwer, U., Lambert, C., & Noth, F. (2019). How do banks react to catastrophic events? Evidence from Hurricane Katrina. *Review of Finance*, *23*(1), 75-116. https://doi.org/10.1093/rof/rfy010

Semieniuk, G., Campiglio, E., Mercure, J. F., Volz, U., & Edwards, N. R. (2021). Low-carbon transition risks for finance. *Wiley Interdisciplinary Reviews: Climate Change*, *12*(1), e678. https://doi.org/10.1002/wcc.678

Settlements, B. f. I. (2021). Climate-Related Risk Drivers And Their Transmission Channels. Retrieved on March 26,2023. https://www.bis.org/bcbs/publ/d517.pdf

Wen, J. and Chang, C.P., (2015). Government ideology and the natural disasters: a global investigation. *Natural hazards*, *78*(3), 1481-1490. https://doi.org/10.1007/s11069-015-1781-z

Zhang, W. L., Chang, C. P., & Xuan, Y. (2022). The impacts of climate change on bank performance: What's the mediating role of natural disasters?. *Economic Change and Restructuring*, *55*(3), 1913-1952. https://doi.org/10.1007/s10644-021-09371-3

Zomo Yobe, G. (2017). Structure du marché bancaire et stabilité bancaire: Le cas de la Communauté Economique de l'Afrique Centrale. *Global Journal of Human-Social Science Economic*, *12*. https://www.scirp.org/reference/referencespapers?referenceid=2993155

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APPENDIX

Table A1: Sub Saharan Economies

List of Countries

Angola	Namibia
Benin	Senegal
Burkina Faso	Rwanda
Cote D'Ivoire	Tanzania
DR. Congo	Sudan
Gabon	Zambia
Kenya	Botswana
Lesotho	Burundi
Malawi	Eswatini
Mali	Ghana
Mozambique	Madagascar
Nigeria	Mauritius
South Africa	Cameroon
The Gambia	Niger
Togo	

Source: Author's Construct, 2024

Following the framework of Chudik and Pesaran (2015) the CSA used to limit the cross-sectional correlations in our study are specified as:

$$\ln BS_{it} = \alpha_0 + \sum_{k=1}^{q_x} \lambda_{ik} \ln BS_{(i,t-k)} + \sum_{k=0}^{q_y} \delta_{1k} \ln TEMPT_{(i,t-k)} + \sum_{k=0}^{q_y} \delta_{2k} \ln NIM_{(i,t-k)} + \sum_{k=0}^{q_y} \delta_{3k} \ln BC_{(i,t-k)} + \sum_{k=0}^{q_y} \delta_{4k} \ln MS_{(i,t-k)} + \sum_{k=0}^{q_y} \delta_{5k} \ln RQ_{(i,t-k)} + \sum_{k=0}^{q_y} \psi_k \Delta \ln \overline{BS}_{(i,t-k)} + \sum_{k=0}^{q_y} \psi_{1k} \Delta \ln \overline{TEMPT}_{(i,t-k)} + \sum_{k=0}^{q_y} \psi_{2k} \Delta \ln \overline{NIM}_{(i,t-k)} + \sum_{k=0}^{q_y} \psi_{3k} \Delta \ln \overline{BC}_{(i,t-k)} + \sum_{k=0}^{q_y} \psi_{4k} \Delta \ln \overline{MS}_{(i,t-k)} + \sum_{k=0}^{q_y} \psi_{5k} \Delta \ln \overline{RQ}_{(i,t-k)} + \mu_{it} \quad \textbf{(17)}$$

$$\ln BS_{it} = \theta + \sum_{k=1}^{q_x} \rho_{ik} \ln BS_{(i,t-k)} + \sum_{k=0}^{q_y} \beta_{1k} \ln PPT_{(i,t-k)} + \sum_{k=0}^{q_y} \beta_{2k} \ln NIM_{(i,t-k)} + \sum_{k=0}^{q_y} \beta_{3k} \ln BC_{(i,t-k)} + \sum_{k=0}^{q_y} \beta_{4k} \ln MS_{(i,t-k)} + \sum_{k=0}^{q_y} \beta_{5k} \ln RQ_{(i,t-k)} + \sum_{k=0}^{q_y} \gamma_k \Delta \ln \overline{BS}_{(i,t-k)} + \sum_{k=0}^{q_y} \gamma_{1k} \Delta \ln \overline{PPT}_{(i,t-k)} + \sum_{k=0}^{q_y} \gamma_{2k} \Delta \ln \overline{NIM}_{(i,t-k)} + \sum_{k=0}^{q_y} \gamma_{3k} \Delta \ln \overline{BC}_{(i,t-k)} + \sum_{k=0}^{q_y} \gamma_{4k} \Delta \ln \overline{MS}_{(i,t-k)} + \sum_{k=0}^{q_y} \gamma_{5k} \Delta \ln \overline{RQ}_{(i,t-k)} + \mu_{it} \quad \textbf{(18)}$$

$$\ln BS_{it} = \varphi + \sum_{k=1}^{q_x} \upsilon_{ik} \ln BS_{(i,t-k)} + \sum_{k=0}^{q_y} \lambda_{1k} \ln GHGAS_{(i,t-k)} + \sum_{k=0}^{q_y} \lambda_{2k} \ln NIM_{(i,t-k)} + \sum_{k=0}^{q_y} \lambda_{3k} \ln BC_{(i,t-k)} + \sum_{k=0}^{q_y} \lambda_{4k} \ln MS_{(i,t-k)} + \sum_{k=0}^{q_y} \lambda_{5k} \ln RQ_{(i,t-k)} + \sum_{k=0}^{q_y} \varpi_{k} \Delta \ln \overline{BS}_{(i,t-k)} + \sum_{k=0}^{q_y} \varpi_{1k} \Delta \ln \overline{GHGAS}_{(i,t-k)} + \sum_{k=0}^{q_y} \varpi_{2k} \Delta \ln \overline{NIM}_{(i,t-k)} + \sum_{k=0}^{q_y} \varpi_{3k} \Delta \ln \overline{BC}_{(i,t-k)} + \sum_{k=0}^{q_y} \varpi_{4k} \Delta \ln \overline{MS}_{(i,t-k)} + \sum_{k=0}^{q_y} \varpi_{5k} \Delta \ln \overline{RQ}_{(i,t-k)} + \mu_{it} \tag{19}$$

$$\ln BS_{it} = \sigma + \sum_{k=1}^{q_x} \vartheta_{ik} \ln BS_{(i,t-k)} + \sum_{k=0}^{q_y} \alpha_{1k} \ln CCI_{(i,t-k)} + \sum_{k=0}^{q_y} \alpha_{2k} \ln NIM_{(i,t-k)} + \sum_{k=0}^{q_y} \alpha_{3k} \ln BC_{(it-k)} + \sum_{k=0}^{q_y} \alpha_{4k} \ln MS_{(i,t-k)} + \sum_{k=0}^{q_y} \alpha_{5k} \ln RQ_{(i,t-k)} + \sum_{k=0}^{q_y} \pi_{ik} \Delta \ln \overline{BS}_{(i,t-k)} + \sum_{k=0}^{q_y} \pi_{1k} \Delta \ln \overline{CCI}_{(i,t-k)} + \sum_{k=0}^{q_y} \pi_{2k} \Delta \ln \overline{NIM}_{(i,t-k)} + \sum_{k=0}^{q_y} \pi_{3k} \Delta \ln \overline{BC}_{(i,t-k)} + \sum_{k=0}^{q_y} \pi_{4k} \Delta \ln \overline{MS}_{(i,t-k)} + \sum_{k=0}^{q_y} \pi_{5k} \Delta \ln \overline{RQ}_{(i,t-k)} \tag{20}$$

Table A2: Correlation Matrix of Variables

	lnBS	lnTEMPT	lnPPT	lnGHGAS	lnCCI	lnNIM	lnBC	lnMS	lnRQ
lnBS	1.0000								
lnTEMPT	0.0557	1.0000							
lnPPT	-0.2583*	-0.1820	1.0000						
lnGHGAS	0.5768*	0.1545	-0.1883	1.0000					
lnCCI	0.4430	0.6536	-0.6958	0.6624	1.0000				
lnNIM	-0.0569*	0.0283	0.0777	-0.1539	-0.1018	1.0000			
lnBC	0.0198	0.0647	0.0542	0.0115	0.0090	-0.0006	1.0000		
lnMS	-0.0569	0.2009	-0.2278	0.1967	0.3112	0.0677	0.0306	1.0000	
lnRQ	-0.0944**	-0.1596	-0.0750	-0.0243	-0.0505	0.1023	0.0206	0.1835	1.0000

*and** indicate 5 percent and 10 percent significance level, respectively. Climate change variables include; lnTEMPT (Temperature), lnPPT (Precipitation), lnGHGAS (Greenhouse Gas) and lnCCI (Climate Change Index).

Source: Author's computation in EViews 10

Table A3: Cross-sectional Dependence Test Results on Individual Variables

Test Statistics	
Variable	**Pesaran CD Test**
lnBS	9.1447***(0.0000)
lnTEMPT	21.5583***(0.0000)
lnPPT	7.3640***(0.0000)
lnGHGAS	17.3121***(0.0000)
lnCCI	22.3074***(0.0000)
lnNIM	5.4142***(0.0001)
lnBC	10.3161***(0.0000)
lnMS	50.0729***(0.0000)
lnRQ	26.4205***(0.0000)

*** indicate 1 percent significance level. Null Hypothesis: no cross-section dependence (correlation). BS is banking system stability, TEMPT is temperature, PPT is precipitation, GHGAS denotes greenhouse gas, CCI implies climate change index, NIM symbolises net interest margin, BC signifies bank concentration, MS is money supply and RQ is regulatory quality. ln indicates natural logarithm.
Source: Author's construct, 2024

Table A4: Cross-sectional Dependence Test Results on Models

Test Statistics	
Model	**Pesaran CD Test**
6	18.3637*** (0.0000)
7	14.1335*** (0.0000)
8	15.1938*** (0.0000)
9	27.1777*** (0.0000)

*** indicate significance level at 1 percent. H0: No cross-section dependence (correlation) in model.
Source: Author's construct,2024

Table A5: Pesaran and Yamagata (2008) Slope Homogeneity Test Results

Model	Test	Value	P -Value
6	Delta Tilde (Δ) Adj Delta Tilde (Δ)	9.460 11.456	0.000*** 0.000***
7	Delta Tilde (Δ) Adj Delta Tilde (Δ)	9.464 11.461	0.000*** 0.000***
8	Delta Tilde (Δ) Adj Delta Tilde (Δ)	8.875 10.749	0.000*** 0.000***
9	Delta Tilde (Δ) Adj Delta Tilde (Δ)	9.043 10.951	0.000*** 0.000***

'***'depicts significance level at 1 percent.
Source: Author's construct,2024

Table A6: Hsiao (1986) Slope Homogeneity Test Results

Model	Hypothesis	F-Statistics	P-Value
6	H_1 H_2 H_3	29.4404 5.5190 72.7966	8.2E-174*** 2.15E-44*** 3.5E-173***
7	H_1 H_2 H_3	26.7492 5.4439 65.6514	2.5E-165*** 1.09E-43*** 5.5E-163***
8	H_1 H_2 H_3	29.3414 9.4411 43.5786	1.6E-173*** 2.25E-76*** 2.2E-125***

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9	H_1 H_2 H_3	22.9097 5.6836 52.2823	7.6E-152*** 6.27E-46*** 1.6E-141***

'***'depicts significance level at 1 percent.
Source: Author's construct, 2024.

Table A7: CIPS Panel Unit Root Test Results

Variables		**Test Statistics**		**Critical Values**		
	Constant	**Constant +Trend**	**Constant (1%)**	**Constant (5%)**	**Constant +Trend (1%)**	**Constant +Trend (5%)**
$\ln BS$	-1.735	-2.375***	-2.30	-2.15	-2.81	-2.66
$\Delta \ln BS$	-4.647***	-4.780***	-2.30	-2.15	-2.81	-2.66
$\ln TEMPT$	-4.022***	-5.761***	-2.30	-2.15	-2.81	-2.66
$\Delta \ln TEMPT$	-5.727***	-5.761***	-2.30	-2.15	-2.81	-2.66
$\ln PPT$	-4.456***	-4.658***	-2.30	-2.15	-2.81	-2.66
$\Delta \ln PPT$	-5.766***	-5.859***	-2.30	-2.15	-2.81	-2.66
$\ln GHGAS$	-1.842	-2.086***	-2.30	-2.15	-2.81	-2.66
$\Delta \ln GHGAS$	-4.766***	-5.056***	-2.30	-2.15	-2.81	-2.66
CCI	-3.929***	-4.181***	-2.30	-2.15	-2.81	-2.66
ΔCCI	-5.672***	-5.705***	-2.30	-2.15	-2.81	-2.66
$\ln NIM$	-2.805***	-3.132***	-2.30	-2.15	-2.81	-2.66
$\Delta \ln NIM$	-5.004***	-5.053***	-2.30	-2.15	-2.81	-2.66
$\ln BC$	-2.650***	-2.864***	-2.30	-2.15	-2.81	-2.66
$\Delta \ln BC$	-4.576***	-4.656***	-2.30	-2.15	-2.81	-2.66
$\ln MS$	-2.414***	-2.585***	-2.30	-2.15	-2.81	-2.66
$\Delta \ln MS$	-4.321***	-4.430***	-2.30	-2.15	-2.81	-2.66
RQ	-2.587***	-3.313***	-2.30	-2.15	-2.81	-2.66
ΔRQ	-5.073***	-5.023***	-2.30	-2.15	-2.81	-2.66

*** and ** depicts stationarity at 1 percent and 5 percent significant levels. CIPS statistical critical values in reference to T and N conditions are the found from the study of Pesaran (2007).

Table A8: CIPS Panel Unit Root Test Results

Variables	**T-Statistics (t-bar)**	**T-Statistics (t-bar)**	**P-Value**	**P-Value**
	Constant	**Constant+Trend**	**Constant**	**Constant+Trend**
$\ln BS$	-1.630	-2.298	0.745	0.527
$\Delta \ln BS$	-3.056***	-3.271***	0.000	0.000
$\ln TEMPT$	-3.310***	-3.562***	0.000	0.000
$\Delta \ln TEMPT$	-4.771***	-4.679***	0.000	0.000

$\ln PPT$	-3.277 ***	-3.538***	0.000	0.000
$\Delta \ln PPT$	-5.766***	-5.859***	0.000	0.000
$\ln GHGAS$	-1.537	-1.716	0.879	1.000
$\Delta \ln GHGAS$	-2.967***	-3.319***	0.000	0.000
CCI	-3.255***	-3.521***	0.000	0.000
ΔCCI	-4.617***	-4.545***	0.000	0.000
$\ln NIM$	-2.184***	-2.508***	0.009	0.000
$\Delta \ln NIM$	-3.542***	-3.730***	0.000	0.000
$\ln BC$	-2.674***	-2.796***	0.000	0.002
$\Delta \ln BC$	-3.488***	-3.488***	0.000	0.000
$\ln MS$	-2.466***	-2.719***	0.000	0.009
$\Delta \ln MS$	-3.542***	-3.730***	0.000	0.000
RQ	-1.749	-2.454	0.501	0.203
ΔRQ	-3.739***	-3.942***	0.000	0.000

*** and ** depicts stationarity at 1 percent and 5 percent significant levels

Table A9: Augmented Mean Group (AMG) Results for Model 6

Variables	Coefficient	Std. Error	Z-statistics	P-Value
lnTEMPT	0.0391	0.0279	1.40	0.161
lnNIM	0.2687***	0.0613	4.38	0.000
lnBC	-0.2649*	0.1481	-1.79	0.074
lnMS	-0.0636	0.1246	-0.51	0.610
lnRQ	0.1289	0.1146	1.12	0.261
C	3.5334***	0.8488	4.16	0.000

*** and * indicate significance level at 1 percent and 10 percent, respectively. TEMPT is temperature, NIM denotes net interest margin, BC symbolises bank concentration, MS implies money supply, RQ is regulatory quality. C signifies the intercept. ln is the natural logarithm.
Source: Author's construct,2024

Table A10: Augmented Mean Group (AMG) Results for Model 7

Variables	Coefficient	Std. Error	Z-Statistics	P-Value
lnPPT	-0.0159	0.1381	-0.12	0.908
lnNIM	0.2681***	0.0584	4.59	0.000
lnBC	-0.2432	0.1598	-1.52	0.128
lnMS	-0.0728	0.1161	-0.63	0.530
lnRQ	0.7567	0.1106	1.68	0.494
C	3.6177***	1.3725	2.64	0.008

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*** indicate significance level at 1 percent. PPT is precipitation, NIM denotes net interest margin, BC symbolises bank concentration, MS implies money supply, RQ is regulatory quality. C signifies the intercept. ln is the natural logarithm.
Source: Author's construct, 2024

Table A11: Augmented Mean Group (AMG) Results for Model 8

Variables	Coefficient	Std. Error	Z-statistics	P-Value
lnGHGAS	-0.0727	0.1685	-0.43	0.666
lnNIM	0.2745***	0.0615	4.46	0.000
lnBC	-0.2733	0.1775	-1.54	0.124
lnMS	-0.0293	0.1014	-0.29	0.773
lnRQ	0.0792	0.1181	0.67	0.502
C	3.4387***	1.2168	2.84	0.005

*** indicate significance level at 1 percent. GHGAS is greenhouse gas, NIM denotes net interest margin, BC symbolises bank concentration, MS implies money supply, RQ is regulatory quality. C signifies the intercept. ln is the natural logarithm.
Source: Author's construct, 2024

Table A12: Augmented Mean Group (AMG) Results for Model 9

Variables	Coefficient	Std. Error	Z-statistics	P-Value
lnCCI	-0.0354	0.0334	-1.06	0.289
lnNIM	0.2681***	0.0610	4.39	0.000
lnBC	-0.2628*	0.1549	-1.70	0.090
lnMS	-0.0709	0.1236	-0.57	0.566
lnRQ	0.1220	0.1137	1.07	0.283
C	3.5174***	0.8807	3.99	0.000

*** and * indicate significance level at 1 percent and 10 percent, respectively. CCI is climate change index, NIM denotes net interest margin, BC symbolises bank concentration, MS implies money supply, RQ is regulatory quality. C signifies the intercept. ln is the natural logarithm.
Source: Author's construct,2024