Financial stability under climate stress: Empirical evidence from Namibia

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Abstract

Climate change has emerged as one of the defining risks in recent years. These risks are associated with economic losses and, eventually, the financial system's stability. This paper empirically examines the impact of climate change on financial stability in Namibia. This study employs a Nonlinear Autoregressive Distributed Lag (NARDL) approach to examine how climate change asymmetrically affects the stability of Namibia's financial system, using quarterly data from 2009 to 2023. The findings reveal that both increases and decreases in rainfall patterns negatively affect financial stability in the long run. Moreover, an increase in temperature has a negative asymmetric effect on financial stability. Interestingly, increases in CO2 emissions are associated with improvements in financial stability. Therefore, the study recommends the integration of climate-related risks into financial institutions' risk assessment frameworks and the adoption of long-term risk monitoring and mitigation strategies. Furthermore, the study also recommends that regulators should conduct climate stress testing to assess the resilience of the financial system stability under varying climate scenarios.

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1. Introduction

Climate change has emerged as a defining challenge of the 21st century, bringing about many environmental, social, and economic transformations. According to the Intergovernmental Panel on Climate Change (IPCC, 2021), the global average surface temperature increased by approximately 1.1°C between 2011 and 2020 compared to the period from 1850 to 1990. Abnormal shifts in the climate system have led to a rising frequency and intensity of extreme weather and climate events worldwide. These events significantly impact the real economy. Given that finance plays a pivotal role in economic development, such events can also affect the financial sector through various channels, potentially threatening the value of assets and income sources of borrowers. Consequently, regulators are increasingly focusing on climate-related risks. For instance, central banks and the Network for Greening the Financial System (NGFS) have initiated efforts to integrate climate-related risks into supervision and financial stability monitoring. Dietz et al. (2016) noted that climate change could lead to losses in global financial assets estimated at approximately USD 24 trillion. Liu et al., (2024) contended that climate change generates a sequence of financial fluctuations, which could potentially cause system risk and affect the safety and stability of the financial sector. As a result, climate change has become a growing concern and a source of risk for financial stability.

Risks to financial stability from climate change are notably uncertain, both in severity and time horizon, as emphasized by the Financial Stability Board (2020). The future trajectory of climate change and its impact on the financial system is highly uncertain and could exhibit nonlinear dynamics over time, often contingent on policy measures. While research on the effect of climate change on financial stability is still evolving, existing literature indicates that climate change primarily affects the financial system through physical and transition risks. This heightened attention gained momentum following the Governor of the Bank of England, Mark Carney's, 2015 speech titled "Breaking the Tragedy of the Horizon - Climate Change and Financial Stability". Physical risks refer to disruptions in economic activity or decline in asset values resulting from the direct impact of climate change, such as droughts, flooding, hurricanes, and wildfires. Transition risks refer to the financial risks associated with the shift to a lower-carbon economy aimed at mitigating climate change. Against this backdrop, the financial sector, a linchpin in the country's economic landscape, faces a range of challenges emanating from both physical and transition risks associated with climate change.

Namibia experiences climate-related challenges that extend beyond its impact on agriculture, adversely influencing household income levels. According to the World Bank

(2021), Namibia suffered its most severe drought in 2013, affecting nearly 37 percent of the population. Table 1 shows that although flooding is a frequent phenomenon in Namibia, drought episodes tend to be more devastating, costing the country an estimated USD 175 million annually. Besides drought and floods, wildfires have become a growing concern for the country as it witnessed a staggering 499 344 hectares of land consumed by uncontrolled fires between January and April 2023 (BoN, 2024).

Table 1: Climate events in Namibia between 1900 and 2023

Climate events	Number of events	Total Affected	Total Damage ('000 USD)
Drought	8	2,143,200 Aggregate headcount	175,000
Flood	12	1,094,450 Aggregate headcount	40,980
Wildfire	3	3 million Hectares (2021) 2.4 million Hectares (2022) 499,344 Hectares (2023)	Estimate not available

Source: World Bank

Given that economic activities ultimately underpin financial assets, climate-related risks can therefore affect the financial system. Despite Namibia's Nationally Determined Contributions (NDC) Implementation Strategy and Action Plan, there is limited empirical literature providing a quantitative understanding of the impact of climate risks on the financial sector. Such evidence is crucial to facilitate efficient adjustment of business models, policy adaptation, and mitigation strategies. This is especially pressing in light of the *principles for the effective management and supervision of climate-related financial risks,* published by the Bank for International Settlements (BIS) in June 2022, which aim to enhance banks' risk management and supervisory practices related to climate risks.

Climate change presents growing risks to financial systems, particularly in climate-vulnerable developing economies (IMF, 2019; FSB, 2020). In Namibia, where the economy is highly exposed to climate variability through sectors such as agriculture, mining, and energy, the financial system faces increasing vulnerability to both physical and transition risks. While the existing literature on climate-related financial risks is expanding, it remains limited for developing economies and is largely focused on linear transmission mechanisms. This paper addresses this gap by developing climate risk scenarios tailored to the Namibian context and applying a Nonlinear Autoregressive Distributed Lag (NARDL) model to examine the asymmetric short-run and long-run effects of climate change on financial stability over the period 2009Q1 to 2023Q4. By decomposing climate variables into positive and negative shocks, the paper contributes novel empirical evidence on the transmission of climate risks in a developing economy context. While Amo-Bediako et al. (2023) employed the NARDL approach in a regional panel setting compromising of 29 sub-Saharan economies and solely focusing on the banking sector, the current study is distinct in its country-specific application to Namibia and, more importantly, its broader focus on financial stability. The findings will strengthen the evidence base for integrating climate risk into financial regulation and macroprudential policy in vulnerable developing economies.

The study's key findings are as follows. The results indicate the presence of a long run cointegrating relationship between climate variables and financial stability, characterised by significant asymmetric effects. Both increases and decreases in rainfall are found to negatively affect financial stability, highlighting the systemic risks posed by climate extremes such as floods and droughts. Temperature shocks display asymmetric effects as well, with increases in temperature having a more pronounced adverse impact. The asymmetric cumulative dynamic multipliers plots reveal that positive temperature shocks trigger volatile negative responses in financial stability up to the mid-horizon, before gradually stabilising, while negative temperature shocks exert more muted but persistent positive effects. In terms of rainfall, the plot confirms an overall negative impact on financial stability, regardless of the direction of the shock.

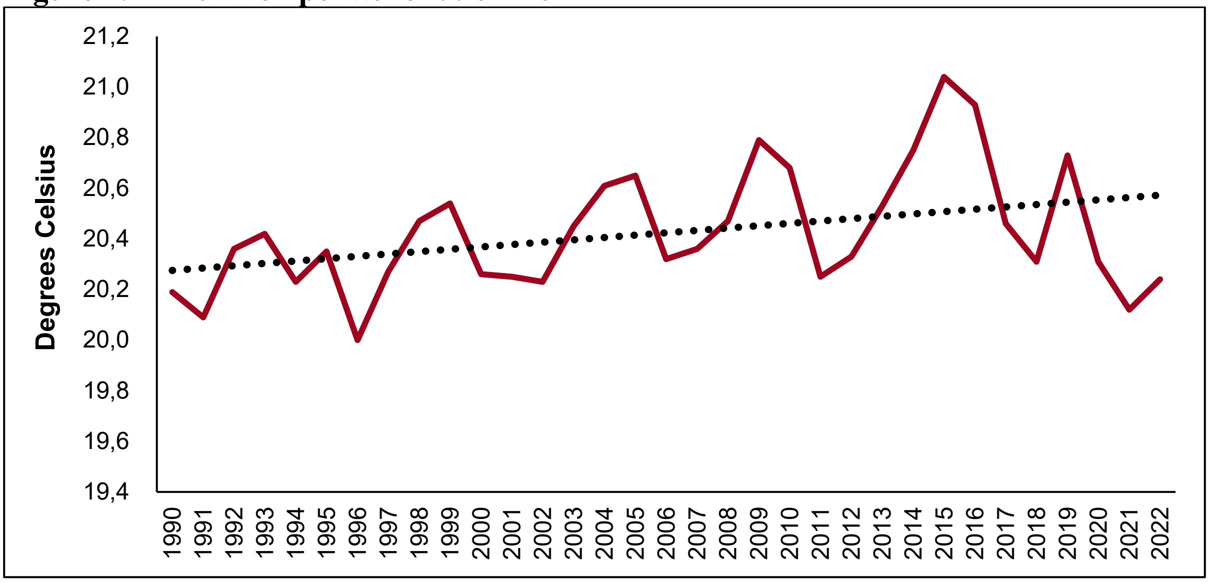
Contrary to the climate transition risk theory, particularly those emphasized by the NGFS (2020), the results indicate that increases in CO2 emissions are associated with improvements in financial stability. This outcome likely reflects short-term economic expansion driven by high-emission activities such as industrial output and energy consumption, which may temporarily support credit growth, asset valuations, and profitability. The dynamic multiplier plots reinforce this pattern, showing that positive CO2 shocks consistently produce stronger and more persistent improvements in the financial stability index than negative shocks. However, this apparent stability may conceal long-term vulnerabilities, as prolonged exposure to high-emission trajectories increases susceptibility to future policy shifts, stranded asset risks, and abrupt market repricing, all central to the transition risk narrative. Overall, the findings highlight the complex and time-varying nature of climate-finance linkages and underscore the urgency of integrating forward-looking climate risk assessments into macroprudential regulation, financial supervision, and early warning frameworks.

The remainder of this paper is organised as follows. Section 2 explores key stylized facts that highlight the nature and scope of climate-related risks in Namibia. Section 3 synthesizes the existing literature relevant to these risks. Section 4 introduces the empirical framework adopted for the analysis. In Section 5, the variables and data sources are described in detail. Section 6 presents the estimation results along with an interpretation of the key findings. The paper concludes in Section 7, offering a summary of insights and related policy recommendations.

2. Climate related risk stylized facts in Namibia

Namibia's climate change is characterised by a distinct upward trend in temperature as depicted in Figure 1. The mean annual temperature in Namibia has remained broadly unchanged over the years, hovering around 20.4 degrees Celsius. In this regard, the mean annual temperature reached its highest level of 21.0 degrees Celsius in 2015 and has been drifting downwards since then, reporting an average of 20.2 degrees Celsius during 2022. However, temperature is projected to increase by an average of 0.6 degrees Celsius to 1.8 degrees Celsius between 2020 and 2039 (World Bank, 2021). This sort of increase in temperature is likely to affect the agricultural sector, particularly crop and livestock production, which will ultimately impact the country's GDP.

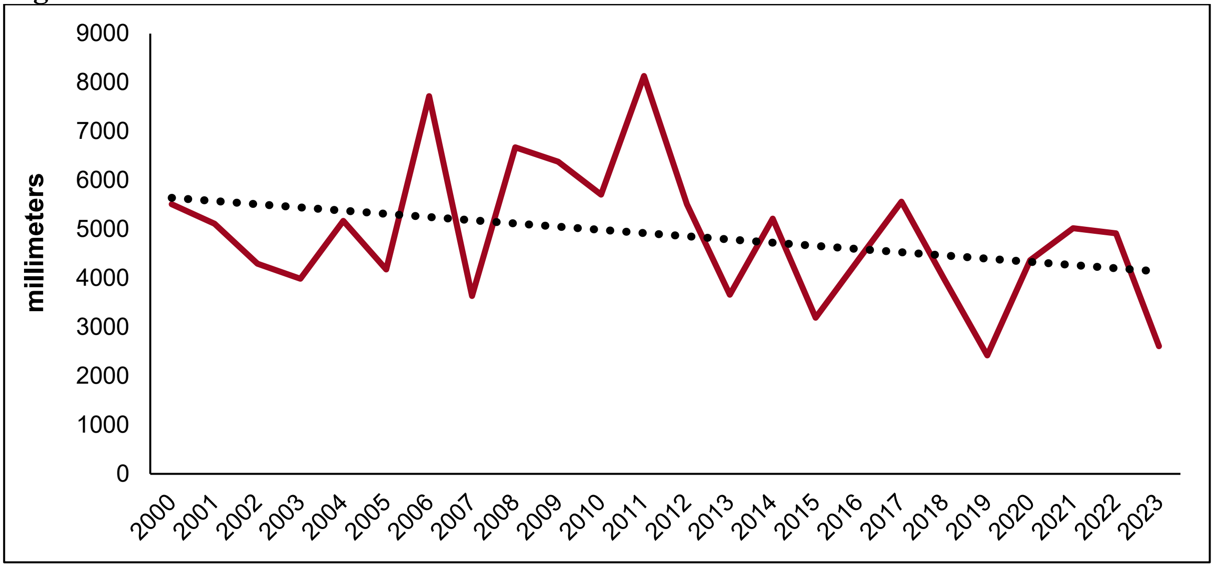
Figure 1: Annual temperature 1990 – 2022



Source: World Bank

Precipitation levels in Namibia have been erratic, with variable rainfall patterns over the years. The accumulated annual rainfall stands at a modest 4890mm over the period 2000 to 2023, exhibiting considerable diversity across the country (Figure 2). Rainfall levels range from 750mm in the northeast to less than 110mm in the southwest and coastal areas. Such disparities in precipitation have increased extreme weather phenomena, including droughts and floods, which pose substantial pressure on pressure on Namibia's socio-economic development. The climatic conditions of Namibia, particularly rainfall and temperature, are notably influenced by the El Niño–Southern Oscillation (ENSO)[2] effect. During El Niño episodes, rainfall tends to be below average, exacerbating the challenges faced by the country (World Bank, 2021).

Figure 2: Annual Rainfall level



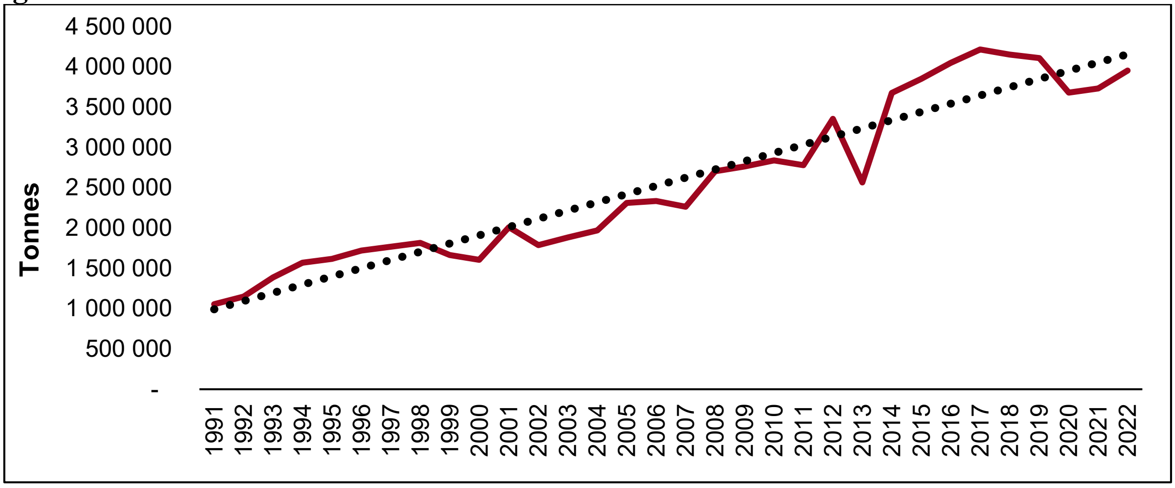
Source: Climate Hazards Group Infrared Precipitation (CHIRP)

Although carbon emission levels have increased over the years, Namibia remains a net carbon sink according to Climate Analytics. Namibia's carbon emission levels have tripled, increasing from 1.1 million metric tons of carbon dioxide in 1990 to 3.9 million metric tons in 2022 (Figure 3). However, Namibia is a net carbon sink with a negligible contribution accounting for less than 0.01 percent of global emissions. Nevertheless, although current emission levels are comparatively low by global standards, they are on an upward trajectory and are projected to reach 90.713 Mt CO2e in 2030 under the business-as-usual scenario[3] (Government of Namibia (GRN), 2023). The Agriculture, Forestry, and Other Land Use (AFOLU) sector is the predominant source of greenhouse gas emissions in Namibia, accounting for approximately 81.5 percent of total national emissions. This is primarily due to fertilizer application, fossil fuel use, and the open burning of agricultural residues. The transport and energy sectors follow, contributing around 8.3 percent (Figure 4). In line with the Paris Agreement, Namibia's Nationally Determined Contribution (NDC) under the United Nations Framework Convention on Climate Change outlines mitigation commitments across key sectors, including AFOLU, energy, and industrial processes and product use. These efforts are complemented by the

[2] El Niño is a cyclical event that consistently ravages the region's economies and agricultural sectors with droughts and water scarcity.
[3] The business-as-usual scenario is projected based on observed emission trends during the baseline period 2000-2010 and the currently available socio- economic information and development plans, inclusive of the impact of the Covid-19 pandemic. The projections are done on an individual category basis and aggregated to arrive at sector and eventual national levels.

promotion of climate-smart technologies, such as renewable energy, sustainable energy systems, and improved waste management practices (GRN, 2023).

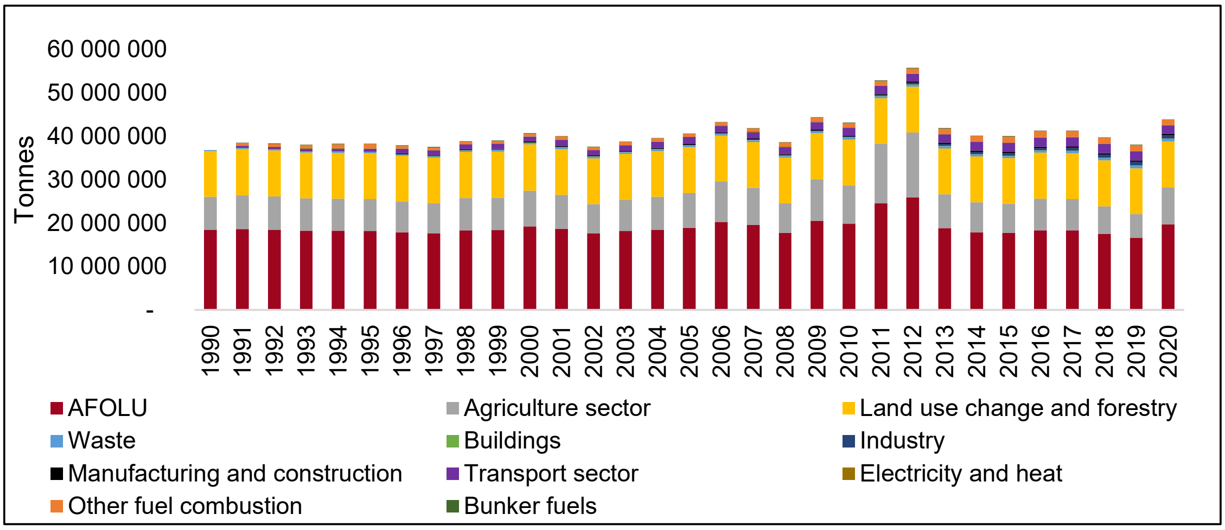
Figure 3: Annual CO2 emissions



Source: Climate Watch (2023)

Namibia has committed to reducing emissions, despite its low levels of greenhouse gas emissions. In this regard, Namibia aims to mitigate a total of 11.902 Mt CO2 e, comprised of a 7.669 Mt CO2 e reduction in projected emissions and an additional 4.233 Mt CO2 e from enhanced removals (GRN, 2023). Key sectoral interventions include the expansion of renewable and sustainable energy sources, the implementation of improved waste management technologies, the promotion of low-carbon transport systems, and the adoption of climate-smart practices (GRN, 2023).

Figure 4: Greenhouse gas emissions by sector



Source: Climate Watch

Namibia's sectoral loan distribution is centred on the individual sub-sector. The concentration of commercial bank lending is mainly geared toward the individual sub-sector, accounting for an average of 42.1 percent for the period 2019-2023 (Table 2). It is important to note that in the individual sub-sector, mortgage advances account for over 60 percent of total credit advanced to the sub-sector. These mortgage advances are exposed to climate change through physical risks such as wildfires and floods and may have an impact on property values. Over the years, banks have gradually increased their credit allocation to the agriculture sector, rising from an average of 3.0 percent during 2004–2008 to 4.9 percent between 2019 and 2023. Although the proportion of credit extended to agriculture remains relatively modest, the sector continues to serve as the primary source of staple food production and sustains the livelihoods of many rural communities in Namibia.

Agriculture remains a fundamental component of Namibia's economy and serves as a key foundation for agri-based industries. In 2023, the sector contributed approximately 7 percent to Namibia's GDP. It is closely integrated with other vital sectors such as manufacturing, trade, tourism, and transport through both input and output linkages (GRN, 2023). The banking sector may face financial exposure through its lending to households and businesses that are dependent on agricultural activity. Climate-related physical risks, including prolonged droughts and erratic rainfall, can reduce agricultural output and consequently undermine the financial positions of borrowers. This impact may be direct through diminished production and income levels, or indirect through broader macroeconomic effects such as lower GDP growth. As a result, credit risk may increase due to higher default rates, declining asset values, reduced availability of funding, and increased reliance on existing credit facilities (Bank of Namibia (BoN), 2024). In addition, physical damage to collateral assets resulting from extreme weather events can elevate risks associated with collateralised lending (European Systemic Risk Board, 2021).

Table 2: Bank Lending in Namibia per sector (Percentage Share)

	2004-2008	2009-2013	2014-2018	2019-2023
Agriculture, hunting & forestry	3.0	3.8	4.1	4.9
Fishing	3.8	2.0	0.8	1.7
Mining & quarrying	1.6	1.6	1.9	1.8
Manufacturing	2.4	2.4	2.2	2.9
Construction	2.6	2.7	4.4	3.6
Electricity, oil, gas & water	0.6	0.6	1.1	2.9
Trade & accommodation	5.4	15.5	18.5	7.5
Transport, storage & communication	2.3	2.3	1.5	2.1
Finance & insurance	6.2	3.8	4.1	7.4
Real estate & Business services	9.5	14.6	6.3	6.9
Government services	2.5	1.3	3.0	4.4
Individuals	54.3	46.9	43.3	42.1
Other	5.7	2.4	2.4	4.7

Source: BoN

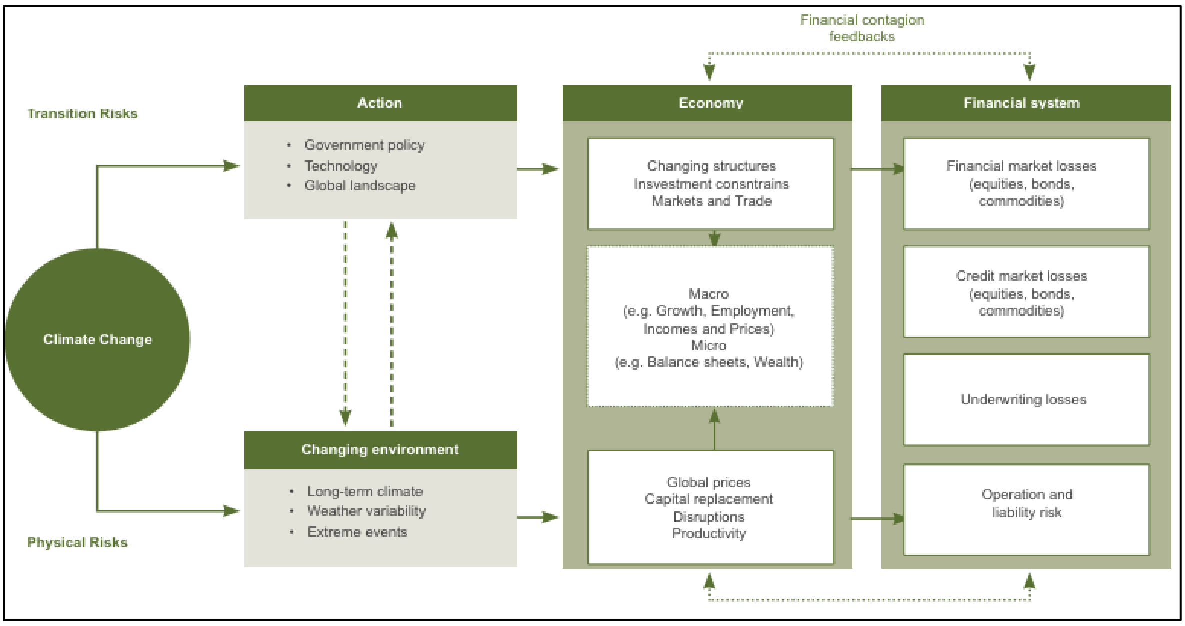
Financing needs for climate change mitigation have increased globally, particularly for emerging and developing economies (EMDEs). It is estimated that in the EMDEs, climate mitigation investment needs are expected to increase from US$0.3 trillion of total investment needs in 2020 to around US$2.1 trillion of the total US$17.2 trillion investment needs in 2030 (GFSR, 2023). Furthermore, private finance is critical for EMDEs to meet their climate investment requirements for both mitigation and adaptation, as public investments will not be sufficient to meet climate investment needs (GFSR, 2023). In Namibia, the Green, Social and Sustainability (GSS) bond issuance by the banking sector has increased from a value of N$66.6 million observed in 2018 to around N$1.2 billion at the end of 2023. Nonetheless, there is a pressing need to scale up both public and private climate finance to achieve the targets set out in the NDC. The financial sector is anticipated to play a critical role in mobilising and directing investments toward sustainable development and climate-resilient initiatives. As indicated by GRN (2023), the estimated financial resources required for the implementation of climate mitigation and adaptation measures are around USD15.1 billion, of which USD13.6 billion (90 percent) is to be sourced internationally, implying that the remaining USD1.5 billion will be funded domestically through various initiatives such as the Environmental Investment Fund.

3. Literature Review

3.1 Theoretical Literature

Physical and transition risks constitute a key theoretical framework for analysing the impact of climate change on financial stability. Physical risks directly affect infrastructure and economic assets as a result of climate-related phenomena, including temperature fluctuations, a rise in sea levels, and extreme weather. Conversely, transition risks are associated with the shift to a low-carbon economy, including policy changes, technological developments, and shifts in consumer preferences (NGFS, 2019). These risks can lead to stranded assets, asset revaluations, and sudden changes in market conditions (Carney, 2015). According to Fabris (2020), the key problem is that the financial system generally considers these risks in the short run, whereas transition risks tend to materialise in the long run, thus creating a mismatch. Figure 5 below demonstrates in detail how physical and transition risks can affect the financial system.

Figure 5: Potential financial stability risks associated with climate change



Source: NGFS

3.2 Empirical Literature

Nur et al. (2023) conducted an empirical investigation into how climate related risks influence both financial access and stability within G20 economies. Using a panel dataset spanning from 2006 to 2017, the authors applied a fixed effects model that accounts for variations across countries and potential heterogeneity in the relationships studied. Climate risk was proxied using the Global Climate Risk Index (CRI) developed by German watch. The study's results demonstrate that heightened climate risks significantly constrain financial access, while efforts to reduce such risks appear to facilitate improved access to financial services. Conversely, the analysis found no statistically significant link between climate risk and financial fragility among G20 nations. The authors emphasize the importance of integrating climate risk considerations into financial regulatory frameworks. They further argue that, in the pursuit of a low-carbon transition, policymakers must ensure that financial resource distribution does not exacerbate environmental harm.

The impact of climate risk on financial stability is more pronounced in developing and emerging economies than it is for developed countries. Liu et al., (2024) conducted panel analysis on yearly data sets for 53 countries ranging from developed to developing and emerging economies to investigate the impact of climate change on financial stability. The global climate risk index, as constructed by the German watch, was used to measure climate risk, with bank specific and relevant macroeconomic variables used as covariates in the study. The findings of the study reveal that climate risk has a negative impact on financial stability although the impact is heterogenous among countries due to different levels of economic development, financial development, and competition. It is noted that while macroprudential policies have proven effective in safeguarding financial stability in climate vulnerable countries, it is important to recognise that various instruments differ in their effectiveness when addressing climate related financial risks.

Based on the European Central Bank (2021) climate risks pose a potential systemic threat to financial stability that extends beyond the individual risks faced by specific institutions. Due to the distinct characteristics and broad-reaching impact of climate-related risks, addressing them may necessitate a macroprudential approach to enhance the banking system's resilience and mitigate climate-related vulnerabilities. The inherent complexity, long time horizons, tipping points, and partial irreversibility of these risks lead to significant uncertainty regarding their timing and impact, making risk quantification and forward-looking projections particularly challenging. This uncertainty often results in the systematic underestimation or underpricing of climate risks, as financial markets and institutions may discount these risks, assuming they will only materialise in the distant future (European Central Bank, 2021). Furthermore, climate-related systemic risks are exacerbated by interconnectedness, spillover effects, and second-round consequences, which are common in other types of financial risks as well. Since these systemic dimensions are typically not captured by banks' individual risk management strategies, a combination of microprudential and macroprudential measures, including enhanced disclosure requirements, capital-based policies, and climate stress-testing, is necessary to maintain financial stability (European Central Bank, 2021).

Noth and Schüwer (2023) concluded that natural disasters matter for bank stability. The study adopted the fixed effects Ordinary Least Squares (OLS) regression model on 6136 US banks over the period 1994-2012 to analyse the natural disaster and bank stability in the US financial system. The findings of the paper reveal that weather-related natural disasters significantly weaken the stability of banks in affected regions. In the short term, it is noted that due to natural disasters, the banks' z-scores decreased, probabilities of default increased, non-performing assets ratios and foreclosure ratios increased, and the return on assets and equity ratios decreased. Furthermore, the results also show that the negative effects of weather-related disasters die out after some years if no further disasters occur in the process.

Diallo et al., (2023) examined the causal relationship between climate risk and financial stress in 15 Economic Community of West African States (ECOWAS) over the period 2000-2019. Employing the Multivariate Threshold Autoregressive Vector model (MTVAR) to estimate this relationship, the empirical evidence strongly supports the non-linear relationship between climate risk and financial stress. Specifically, the findings of the study revealed the existence of an optimal temperature threshold, below and above which a complex interplay occurs between climate risk and financial stress.

Amo-Bediako et al., (2023) assessed how climate change impacts the banking systems' resilience in 29 Sub-Saharan African (SAA) economies, employing a two-step empirical approach. First, a Generalized Auto-Regressive Conditional Heteroskedascity (GARCH) model is used to forecast climate change variables. Thereafter, a panel ARDL is estimated for the period 1996-2017. The study found that despite a temperature shock, the SSA banking system maintained its resilience in the long run. In contrast, the banking system does not maintain its resilience when faced with precipitation and greenhouse gas shocks in the long run. The short-term impact indicates that the banking systems in SSA are resilient to only precipitation shocks. Based on these findings, the study advocates for robust climate related stress testing and the formulation of proactive strategies and risk management frameworks to address emerging climate related financial vulnerabilities. In addition to ensuring long-term financial stability and confidence, good and efficient macroeconomic policy creation and execution require a thorough grasp of the factors that shape a country's financial sector, thus making research tailored to individual nations essential.

Dafermos et al., (2018) found that climate change is likely to increase the rate of default on corporate loans, which could harm the stability of the banking system. This would be after eroding the capital of firms and reducing their profitability and liquidity. To reach this conclusion, the paper examined climate change, financial stability, and monetary policy using a stock-flow-fund ecological macroeconomic model. The model is estimated and calibrated using global data and simulations conducted for the period 2016–2120. The findings of the study further highlight that climate change could lead to a reallocation of portfolios which will result in a gradual decline in the prices of corporate bonds. Thus, revealing that climate-induced financial instability might adversely affect the credit intermediation in the financial system.

Fabris (2020) developed a comprehensive nine-step framework for managing climate-related risks and demonstrated that climate change can adversely affect the balance sheets of financial institutions. The study revealed that climate-related impacts raise the probability of credit defaults, thereby posing risks to overall financial stability. An increase in nonperforming loans as a result of climate disruptions can constrain lending activities within the financial sector, which may subsequently slow economic growth, reduce employment opportunities, and adversely affect social welfare.

Liu et al. (2021) investigated the effects of climate change on financial stability in China using a two-step empirical approach. Initially, they applied a vector autoregression (VAR) model to capture the dynamic impact of climate variables on financial stability. Subsequently, they employed a nonlinear autoregressive distributed lag (NARDL) model to explore the asymmetric and nonlinear responses of financial stability to climate shocks, based on monthly data spanning 2002 to 2018. Their findings reveal that both positive and negative climate shocks negatively affect financial stability. Notably, in the short run, positive climate shocks have a stronger immediate effect on financial stability compared to negative shocks; however, in the lagged periods, the impact of negative shocks becomes more pronounced.

In summary, Section 3 focuses on theoretical and empirical analysis of climate change. Section 3.1 identifies two approaches through which climate change can affect financial stability. Within the empirical literature in Section 3.2, it is observed that climate change does have an impact on financial stability; however, country preparedness in terms of policy implementation concerning climate risk can determine the ability to cushion against climate shocks. To the best of the authors' knowledge, no empirical study has been done in the context of Namibia to investigate the effects of climate change on financial stability. This study addresses this gap by investigating the nonlinear and asymmetric effects of climate change on financial stability, considering both short-term and long-term dynamics.

4. Data, model specification and method

The paper provides new insight into the relationship between climate change and financial stability in Namibia by adopting a nonlinear and asymmetric analytical framework. The study employed a nonlinear autoregressive distributive lag (NARDL) methodology to estimate the asymmetric relationship between climate change and financial stability, using quarterly data covering the period 2009Q1 to 2023Q4 sourced from Bank of Namibia (BoN), the Namibia Statistics Agency (NSA), the World Bank, Climate Watch and the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data (Table 3). The selection of the study period is guided by the availability of quarterly data on key banking sector indicators.

Table 3: Description of variables

Variable	Expected Relationship	Source
Dependent Variable: Financial Stability Index (FSI)		
Financial Market Indicators (FMI)		
Stock Market Cap to GDP	+	NSX and NSA
Government Domestic Debt to GDP	-	BoN and NSA
Interest Rate Spread	-	BoN and NSA
Financial Vulnerability Indicators (FVI)		
Ratio of current account deficits to GDP	+	BoN and NSA
Real effective exchange rate	+	BoN and NSA
Public debt to GDP ratio	-	BoN and NSA
Import cover	+	BoN
Non-government credit to total credit	-	BoN
Financial Soundness Indicators (FS)		
Return on assets	+	BoN
Liquid assets to total assets	+	BoN
Bank regulatory capital to risk-weighted assets	+	BoN
Non-performing loans to total loans	-	BoN
Independent Variables		
Rainfall	-	CHIRPS
Carbon emissions (CO2)	-	Climate Watch
Temperature (Temp)	-	World Bank

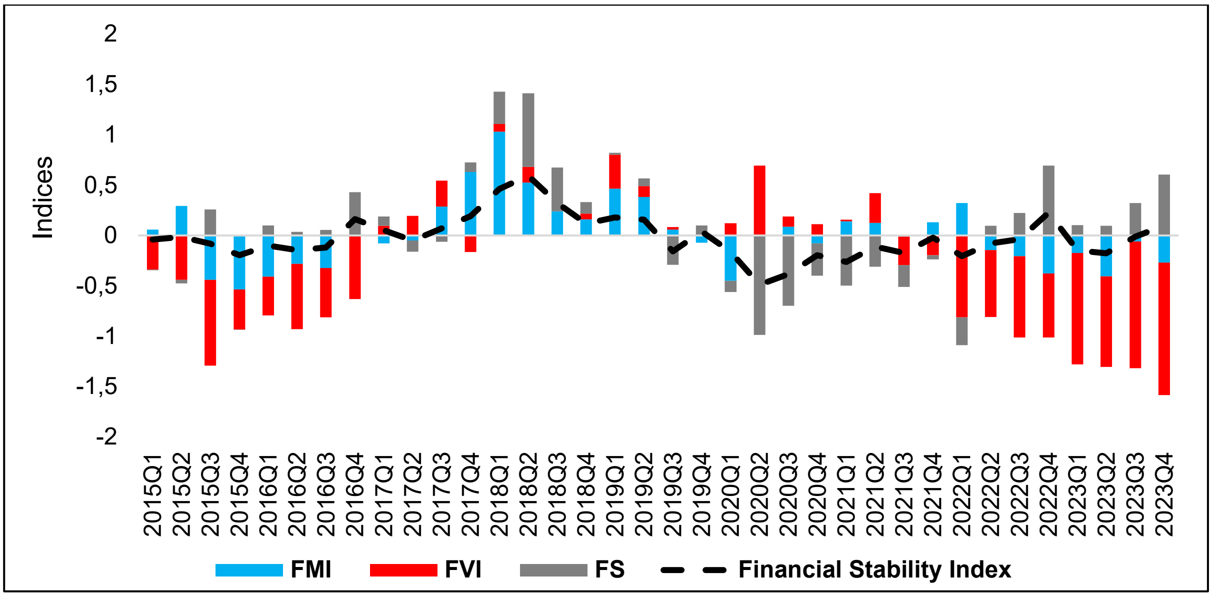
Note: The signs reflect the expected relationship between each partitioned variable and financial stability. A positive (+) sign indicates a strengthen financial stability, while a negative (−) sign suggests a weakened financial stability.

4.1 Measurements of Variables

To facilitate the nonlinear and asymmetric impact of climate change on financial stability, the study derives the financial stability index following the study conducted by Liu, Sun and Tang (2021). This paper selects various indicators representing various dimensions affecting financial stability in Namibia. Three broad dimensions in the form of Financial Market Indicators, Financial Vulnerability Indicators, and Financial Soundness Indicators were selected (Table 3). Each dimension consists of a set of indicators that are first standardized using z-score normalization to account for differing units and scales. To ensure consistency in interpretation, all indicators that are negatively associated with financial stability (such as non-performing loans) are inverted so that higher values uniformly indicate improved stability. Within each category, indicators are equally weighted to construct their respective sub-indices. These sub-indices are then aggregated into the overall FSI using expert-assigned weights: 25 percent for Financial Market Indicators, 15 percent for Financial Vulnerability Indicators, and 60 percent for Financial Soundness Indicators. This weighting reflects the relative importance of each dimension, with a strong emphasis on financial soundness given its role in institutional resilience. Furthermore, given the limited depth and activity in capital markets the authors opted for a higher weight to be assign for Financial Soundness Indicators. However, to validate the robustness of the results, an alternative specification using equal weights was also employed.

A higher value of the FSI indicates greater financial system stability, while a lower value signal increased systemic risk or vulnerability.

Figure 6: Namibia's Financial Stability Index



Source: Authors own computation using data obtained from BoN

Figure 6 above illustrates the quarterly movements of the Financial Stability Index (FSI), represented by the black line, alongside its decomposed sub-indices. The overall FSI remained broadly stable around zero for most of the sample period, reflecting a relatively resilient financial system. However, notable episodes of instability are evident, particularly during the Covid-19 pandemic (grey shaded area), when the index dipped sharply into negative territory. The post-pandemic period reflects gradual recovery, with the FSI sub-index being the key driver behind the rebound in the overall index.

In terms of the control variables, climate change is measured by three indicators, namely, temperature and rainfall levels as well as carbon emissions. Following the paper by Odongo (2022), this study uses rainfall data measured in millimeters as well as temperature measured in Degrees Celsius. Theoretically, the transmission of climate change to the financial system is through physical and transition risks. Depending on the exposure of banks to households and businesses, the combined impact of the physical and transition risk results in losses related to market, credit, and underwriting as well as operational risks (BoN, 2023). As a result, lower asset valuations and debt defaults may have a negative impact on investor confidence and cause systemic bank losses (Batten, et al., 2016; Bovari et al., 2018; Dafermos et al., 2018; Fabris, 2020). Thus, there is an anticipated negative relationship between temperature, rainfall variability, and financial stability. A similar impact is expected for carbon emissions, which is likely to influence the financial system through its impact on carbon tax and its consequent effect on business operations. It is worth noting that the data on carbon emissions is usually reported as tonnes of carbon. However, the figures have been recalculated as tonnes of carbon dioxide, thus applying a conversion factor of 3.664[4].

The descriptive statistics presented in Table 4 reveal notable differences in the distribution and variability of the variables. The Financial Stability Index (FSI) has a mean of 0.05 and a standard deviation of 0.28, indicating modest variation around a relatively neutral average. It ranges from -0.37 to 0.64 and shows a slight right-skewness of 0.43, with a kurtosis of around -1.17, suggesting fewer extreme values than a normal distribution. Temperature (measured in Celsius) has a tight distribution, with a mean of 20.52°C and a standard deviation of 0.29, indicating relatively stable temperature levels across the sample spanning from 2009 until 2023. Rainfall exhibits the highest dispersion among the variables, with a standard deviation of 1.64, suggesting significant variability in precipitation levels. Carbon emissions are relatively stable, with a mean of 13.69, a narrow range of 0.55, and a low standard deviation of 0.17. The negative skewness of -0.76 and negative kurtosis of -0.97 imply a distribution with slightly more frequent lower values and lighter tails than a normal distribution. Overall, these statistics highlight the relatively stable behaviour of temperature and carbon emissions, in contrast to the more volatile patterns observed in rainfall and financial stability. The correlation matrix shows that financial stability index is moderately associated with carbon emissions and inversely related to temperature, while rainfall exhibits weak correlations with all variables (Table 4).

Table 4: Summary Statistics and Correlations

	Mean	**Maximum**	**Minimum**	**Std dev**	**Skewness**	**Kurtosis**
FSI	0.05	0.64	-0.37	0.28	0.43	-1.17
TEMP	20.52	21.08	20.11	0.29	0.36	-1.15
RAINFALL	6.14	8.55	3.46	1.64	-0.36	-1.31
CO2	13.69	13.87	13.32	0.17	-0.76	-0.97
Correlations	**FSI**	**TEMP**	**RAINFALL**	**CO2**		
FSI	1					
TEMP	-0.5115	1				
RAINFALL	-0.0342	0.0032	1			
CO2	0.5398	-0.0276	0.0872	1		

Source: Author's computation using R version 4.4.2. Note: FSI denotes financial stability index; Temp signifies the temperature; Rainfall denotes the log of rainfall; CO2 represents the log of the carbon emission.

Prior to estimating the empirical model, the Augmented Dickey-Fuller (ADF) and Dickey-Fuller Generalized Least Squares (DF-GLS) unit root tests were conducted to ascertain the

[4] This is the conversion factor recommended by the Global Carbon Project. It comes from the fact that an average CO_2 molecule has a mass 3.664 times that of a carbon atom.

variables order of integration. The unit root test results presented in Table 5 indicate that all the variables are non-stationary at in levels, however, becoming stationary after first differencing. This implies that all variables are integrated of order one, I(1). As a result, the NARDL estimating method has been used to estimate asymmetric effects of both the long-run and short-run coefficients, which is a practical consequence of the observed mixed order of integration.

Table 5: Unit Root Test Results

	ADF Test			DF-GLS			Order of integration
Variables	**Levels**	**First diff**	**5% CV**	**Levels**	**First diff**	**5% CV**	**Decision**
FSI	-1.3314	-3.6636**	-3.4639	-1.5123	-5.4616***	-3.0300	I(1)
TEMP	-2.4278	-4.4314***	-3.4639	-2.1695	-4.1574***	-3.0300	I(1)
RAINFALL	-2.4880	-5.9739***	-3.4639	-1.7077	-3.9521***	-3.0300	I(1)
CO2	-1.4565	-6.1679***	-3.4639	-1.1969	-6.7957***	-3.0300	I(1)

*Note: ***, **, * denotes significance at 1%, 5%, and 10% level, respectively. CV stands for critical values.*

4.2 Model specification

This study adopts the nonlinear autoregressive distributed lag (NARDL) approach as outlined by Liu, Sun, and Tang (2021), presented in Equation 1. The NARDL framework offers several advantages over traditional linear specifications. One of its key strengths is its flexibility regarding the integration order of variables, provided none are integrated beyond first order. Additionally, it is well-suited for use with small sample sizes, making it a robust option for empirical analysis. Importantly, the model allows for the simultaneous estimation of both long-run and short-run asymmetries, facilitating a straightforward approach to testing for symmetry across different time horizons.

$$FSI_t = f(Rainfall_t, CO2_t, TEMP_t) \ldots\ldots\ldots(1)$$

Where: FS_t designates the financial stability indicator as explained under the measurement of variables. $Rain_t$ represents rainfall while $CO2_t$ and $TEMP_t$ denotes carbon emissions and temperature, respectively. To investigate the asymmetric relationship between climate change and financial stability in Namibia, Equation 1 is adapted to capture the differential effects of climate variables on financial stability. This adaptation involves decomposing the explanatory variables into their positive and negative partial sum components, following the methodology proposed by Shin et al. (2014), thereby allowing for the identification of asymmetric dynamic responses. The independent variables in the model are separated into their respective partial sums, capturing both positive and negative changes, as outlined below:

$$lnRain_t^+ = \sum_{t=1}^{t} \Delta lnRain_i^+ = \sum_{t=1}^{t} \max(\Delta lnRain_i^+, 0)$$

$$lnRain_t^- = \sum_{t=1}^{t} \Delta lnRain_i^- = \sum_{t=1}^{t} min(\Delta lnRain_i^-, 0)$$

$$lnCO2_t^+ = \sum_{t=1}^{t} \Delta lnCO2_i^+ = \sum_{t=1}^{t} max(\Delta lnCO2_i^+, 0)$$

$$lnCO2_t^- = \sum_{t=1}^{t} \Delta lnCO2_i^- = \sum_{t=1}^{t} min(\Delta lnCO2_i^-, 0)$$

$$TEMP_t^+ = \sum_{t=1}^{t} \Delta TEMP_i^+ = \sum_{t=1}^{t} max(\Delta TEMP_i^+, 0)$$

$$TEMP_t^- = \sum_{t=1}^{t} \Delta TEMP_i^- = \sum_{t=1}^{t} min(\Delta TEMP_i^-, 0) \ldots (3)$$

The modified long run form of Equation 1 is given as Equation 4 below:

$$FSI_t = \delta_0 + \delta_1 FS_{t-i} + \delta_2^+ lnRain_{t-i}^+ + \delta_2^- lnRain_{t-i}^- + \delta_3^+ lnCO2_{t-i}^+ + \delta_3^- lnCO2_{t-i}^- + \delta_4^+ TEMP_{t-i}^+ + \delta_4^- TEMP_{t-i}^- + e_t) \ldots\ldots\ldots (4)$$

In this specification, the superscripts denote the partial sums of positive and negative changes in the explanatory variables. The summation terms, $\sum_{i=0}^{4} \delta$, represent the long run coefficients to be estimated. Consistent with the main objective of this study, Equation 2 is finally transformed fully into a NARDL model capturing both short and long run dynamics taking the form:

$$\Delta FSI_t = \beta_0 + \sum_{i=1}^{p0} \left(\beta_{1,i} \Delta FS_{t-i}\right) + \sum_{j=0}^{q_2^+} (\beta_{2,i}^+ \Delta lnRain_i^+) + \sum_{j=0}^{q_2^-} (\beta_{2,j}^- \Delta lnRain_i^-) + \sum_{k=0}^{q_3^+} (\beta_{3,i}^+ \Delta lnCO2_i^+) + \sum_{k=0}^{q_3^-} (\beta_{3,j}^- \Delta lnCO2_i^-) + \sum_{l=0}^{q_4^+} (\beta_{4,i}^+ \Delta TEMP_i^+) + \sum_{l=0}^{q_4^-} (\beta_{4,j}^- \Delta TEMP_i^-) + \delta_1 FS_{t-i} + \delta_2^+ lnRain_{t-i}^+ + \delta_2^- lnRain_{t-i}^- + \delta_3^+ lnCO2_{t-i}^+ + \delta_3^- lnCO2_{t-i}^- + \delta_4^+ TEMP_{t-i}^+ + \delta_4^- TEMP_{t-i}^- + \varepsilon_t \ldots (5)$$

Equation 5 presents the final asymmetric specification of the NARDL model applied to assess financial stability in the context of Namibia. In this formulation, the coefficients β and δ represent the short-run and long-run parameters, respectively. The long run effects of positive and negative shocks in the explanatory variables on financial stability are measured by $\left(\frac{\sum_{i=2}^{+} \delta_i^+}{\delta_1}\right)$ and $\left(\frac{\sum_{i=2}^{-} \delta_i^-}{\delta_1}\right)$, respectively.

Additionally, $\sum_{i=1}^{p_j} p$ and $\sum_{i=1}^{q_j} q$ represent the lag orders.

Lastly, similar to the linear ARDL method, Shin et al., (2014) introduce the bound test for identifying asymmetrical cointegration in the long run. The null hypothesis states that the effect is symmetrical in the long run if the below holds:

$$H0 = \delta_0 = \delta_1^+ = \delta_1^- = \delta_2^+ = \delta_2^- = \delta_3^+ = \delta_3^- = \delta_4^+ = \delta_4^- = 0$$

In contrast, the alternative hypothesis posits the existence of a long-run asymmetric relationship, which holds true if the following condition is satisfied:

$$H1 = \delta_0 \neq \delta_1^+ \neq \delta_1^- \neq \delta_2^+ \neq \delta_2^- \neq \delta_3^+ \neq \delta_3^- \neq \delta_4^+ \neq \delta_4^- \neq 0$$

The F statistics and critical values are also used in the NARDL to reach a conclusion about H0. If H0 is rejected, it indicates that there is a long-term nonlinear equilibrium relationship between climate change and financial stability. In order to ensure the fitness and stability of the estimated model, it is typical, when dealing with time-series models, such as the ARDL/NARDL, to carry out numerous diagnostic tests (Pesaran and Shin, 1999). Therefore, this paper includes a number of diagnostic tests, including the Lagrange multiplier test for serial correlation, Wald test for testing asymmetry, and functional form. The cumulative sum of recursive residuals (CUSUM) and cumulative sum of squares (CUSUMSQ) plots are also used to verify model stability.

5. Results

5.1 Nonlinear Autoregressive Distributed Lag (NARDL)

Prior to estimating the NARDL model, the unit root properties of the series were conducted to determine the order of integration of the variables. The unit root test results show that all variables are integrated of order one, I(1). Given this, the NARDL framework remains appropriate for the analysis, as it accommodates I(1) variables provided none of the series is integrated of order two, I(2), which would violate the model's assumptions. Before proceeding with the bounds test for cointegration, it is essential to identify the appropriate lag length for the model. As noted by Yesigat et al. (2018), lag selection is particularly important in time series analysis, given that economic variables often exhibit delayed responses. Appropriately chosen lags help capture dynamic adjustments and mitigate potential autocorrelation in the residuals. Based on the AIC, the optimal lag length selection for the NARDL model is (1,1,1,2,2,0,1).

After determining the optimal lag length, the bounds testing approach was applied to examine the presence of cointegration among the variables. The results of the bounds test presented in Table 6 indicate the presence of a long-term nonlinear relationship between climate variables (temperature, rainfall, and CO2 emissions) and financial stability as proxied by the

Financial Stability Index. This is evident from the F-statistics value, which exceeds the upper and lower critical bounds at the 5 percent level of significance, as specified by Pesaran et al (2001).

Table 6: Bounds Test Results for Financial Stability Climate Nexus Model

Test statistics	Value	Lag	
F-statistic	5.9966***	2	
Bounds Test Critical Value: Case 5 – Unrestricted Intercept and Unrestricted Trend			
Significance level	Lower bound	Upper bound	
10%	2.724	3.893	
5%	3.197	4.460	K = 6
1%	4.230	5.713	

Source: Authors' computation using eviews
*Note: ***,**,* indicates significance at the 1%,5%,10% level.*

In addition, the study applies Wald-type coefficient symmetry tests to assess both the long-run and short-run asymmetries between the explanatory variables and the financial stability index. As presented in Table 7, the null hypothesis assumes that positive and negative changes in each climate-related variable (CO2 emissions, rainfall, and temperature) exert symmetric effects on financial stability index. The results reveal that the null hypothesis is strongly rejected for CO2 and rainfall, suggesting significant asymmetric transmission effects. This implies that increases and decreases in these variables impact financial stability index differently. In contrast, temperature shows no statistically significant asymmetry in the long run, indicating that its effects are largely symmetric. However, the short-run test results show that temperature exhibits a significant asymmetric effect, while rainfall displays weak evidence of asymmetry, significant at the 10 percent level.

Table 7: Results of the Symmetric test

Variable	F-statistics	P-value	Decision (is there asymmetry?)
	Long run		
CO2	9.7560***	0.0040	Yes
Rainfall	7.7746***	0.0093	Yes
Temperature	24.9499	2.5722	No
	Short run		
CO2	9.0096***	0.0047	Yes
Rainfall	3.5553*	0.0668	Yes
Temperature	4.4009**	0.0424	Yes

Source: Authors' computation using EViews
*Note: ***,**,* indicates significance at the 1%,5%,10% level.*

Following the confirmation of a nonlinear relationship between climate variables and financial stability, the study proceeds to estimate the short-run and long-run coefficients within the NARDL framework. The estimation results, presented in Table 8, are based on the NARDL (1,1,1,2,2,0,1) specification, which reflects the optimal lag structure determined for the variables included in the model. Overall, the covariates accord with the a priori expectations as highlighted earlier on.

Table 8: Asymmetric short run and long run regression results

Dependent Variable: Financial Stability Index (FSI)				
Short run results: D (A_FSI)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-0.228809	0.058254	-3.927758	0.0003
$\Delta LnRain\_Pos_t$	-0.032192	0.019092	-1.686111	0.0984
$\Delta LnRain\_Neg_t$	0.088305	0.027305	3.233999	0.0022
$\Delta Temp\_Pos_t$	-1.722644	0.672226	-2.562596	0.0137
$\Delta Temp\_Pos_{t-1}$	2.520205	0.742405	3.394652	0.0014
$\Delta Temp\_Neg_t$	-2.104650	0.657738	-3.199829	0.0025
$\Delta Temp\_Neg_{t-1}$	1.930931	0.639247	3.020632	0.0041
$\Delta LnCO2\_Neg_t$	1.220190	0.894046	1.364795	0.1788
ECM_{t-1}	-0.749884	0.108103	-6.936782	0.0000
Long run results				
$LnRainfall\_pos$	-0.202898	0.062188	-3.262643	0.0019
$LnRainfall\_neg$	0.210466	0.066193	3.179571	0.0025
$Temp\_pos$	-2.626644	0.474781	-5.532329	0.0000
$Temp\_neg$	-0.358870	0.293587	-1.222360	0.2272
$LnCO2\_pos$	1.536241	0.473523	3.244277	0.0020
$LnCO2\_neg$	-0.504565	0.620851	-0.812698	0.4202

Diagnostic Tests	**Test Statistic**	**Probability Value**
Normality	4.2722	0.1181
Heteroscedasticity	1.2201	0.2964
ARCH LM (χ^2)	1.2727	0.2642
Serial Correlation (Breusch-Godfrey LM Test)	2.3110	0.1125
RAMSEY	0.1373	0.7130
CUSUM	Stable	
CUSUMSQ	Stable	

Source: Authors' computation using EViews
*Note: ***,**,* indicate significance at the 1%,5%,10% level.*

The findings indicate that temperature exerts a negative asymmetric effect on financial stability, consistent with the empirical evidence reported by Liu et al. (2021). In this regard, Table 8 indicates that a 1°C increase in average temperature leads to a decline of approximately 2.63 index points in the financial stability index, suggesting that rising temperatures significantly weaken financial resilience. Conversely, a 1°C decline in average temperature increases the index by 0.36 points, implying that colder-than-usual temperatures improve financial stability resilience, ceteris paribus. This suggests that lower temperatures are more beneficial to financial stability than rising temperatures. One possible explanation is improved business conditions in sectors such as agriculture, where cooler temperatures help mitigate the risks associated with extreme heat. A decline in temperature can enhance crop-growing conditions by improving soil moisture retention and reducing heat stress ultimately boosting agricultural productivity. As a result, this eases financial stress for farmers and lenders actively involved in agricultural financing and related business ventures, contributing to resilient financial stability.

As shown in Table 8, the short-run results indicate that all four coefficients of temperature have a statistically significant impact on financial stability in Namibia. Both positive and negative shocks to temperature in the current period exhibit similar directional effects as their long-run counterparts, although the magnitude of these short-run impacts is comparatively lower. At the first lag, a clear asymmetry is observed. A positive shock to temperature increases the financial stability index by approximately 2.52 points, while a negative shock at the same lag decreases the index by about 1.93 points, holding other factors constant. The positive and significant coefficient on the first lag of a negative temperature shock supports the findings of Liu et al. (2021) and aligns with a priori expectations. Importantly, unlike the long-run case, the null hypothesis of coefficient symmetry is rejected in the short run based on the Wald test. This suggests that positive and negative temperature shocks exert asymmetric effects on financial stability even over shorter horizons.

In terms of CO2 emissions, the results indicate that a positive shock to CO2 emissions does have a significant positive effect on the financial stability index. More specifically, a 1 percent increase in CO2 emissions leads to a 0.0154 index point increase in the financial stability index. These findings on carbon emissions accord with the findings by Agbloyor et al. (2021). The findings show that an increase in CO2 through increased activity in the energy use industry, agriculture, and land use can result in a resilient financial system. Improved industrial activity leads to an enhanced financial stability index as financial sectors' profitability improves and supports lower default risks. Similarly, although statistically insignificant, a negative shock to CO2 emissions is associated with an improvement in financial stability. Specifically, a 1 percent decline in CO2 emissions increases the index by 0.005 points, suggesting that reduced emissions may also contribute to a more resilient financial system, possibly through increased focus on green financing and reduced environmental risks. These findings highlight the complex interplay between carbon-intensive sectors and financial stability and underscore the need to balance economic growth with environmental sustainability. What is encouraging about the results on CO2 emissions is the fact that Namibia is a net carbon sink with a negligible contribution to global emissions.

Although statistically insignificant, the short-run results for CO2 emissions indicate that the model selected only the negative partial sums, with a coefficient sign opposite to that observed in the long run. Nonetheless, consistent with the long-run findings, the null hypothesis of symmetry is rejected in the short run based on the Wald test, as shown in Table 7.

The results on rainfall patterns indicate that a positive shock to rainfall levels reduces the financial stability index, implying a weakening of financial system resilience. This finding aligns with studies such as Amo-Bediako et al. (2023), which highlight the adverse effects of extreme weather events, including floods, on the sub-Saharan banking system stability. What these results mean for Namibia is that higher rainfall may be associated with increased risks of flooding, which can disrupt economic activities, particularly in agriculture, a key sector of the economy. Floods can lead to crop failures, damage to infrastructure, and higher insurance claims, all of which strain financial institutions by reducing loan repayment capacity and increasing non-performing loans. These results underscore the importance of climate adaptation measures, such as improved flood management systems and diversification of economic activities, to mitigate the adverse impacts of extreme rainfall on financial stability.

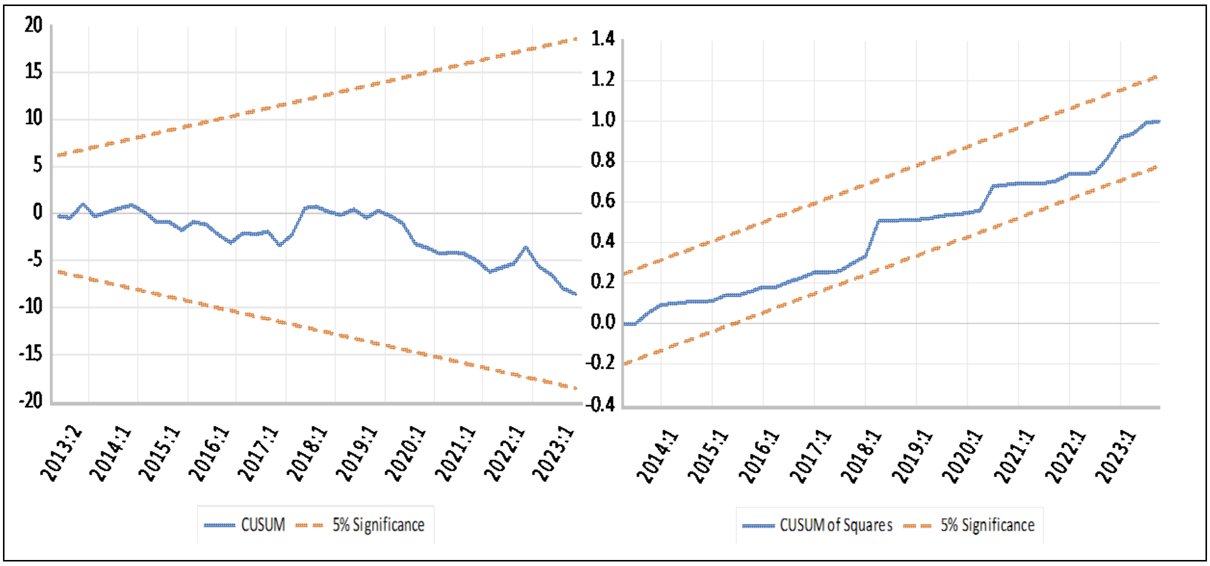
On the other hand, a negative shock to rainfall patterns significantly reduces the financial stability index, an expected outcome given Namibia's high vulnerability to recurrent droughts. Namibia is highly susceptible to recurrent drought episodes, with the recent drought, especially those experienced since 2019, being ranked among the worst in recent history. The severity of these conditions has prompted the Bank of Namibia to issue a determination to provide drought relief for the agricultural sector during 2024. Prolonged droughts adversely impact agricultural productivity, reduce household incomes, and increase credit risk for banks, particularly those with significant exposure to the agricultural sector. These findings highlight the vulnerability of Namibia's financial system to climate-related shocks, reinforcing the need for policies that enhance resilience, such as climate risk stress testing and financial sector support mechanisms during extreme weather events.

Over the short run, the coefficients of positive and negative shocks in rainfall behave in a similar fashion to their long run counterparts, although the magnitude of the impact is notably lower. Contrary to the long run, the null hypothesis of symmetry from the Wald test cannot be rejected at the 5 percent level of significance in the short run, suggesting that the short run coefficients of positive and negative partial sums of rainfall are statistically symmetric. This short-run symmetry may reflect the lagged economic impacts of slow-onset hazards like droughts, as well as the limited immediate transmission of fast-onset shocks such as floods into financial system dynamics.

To assess the statistical adequacy of the model, a series of diagnostic tests were conducted. As shown in Table 8, the model satisfies key diagnostic criteria, with test statistics yielding p-values greater than the 5 percent threshold. These results suggest that the residuals exhibit normality, homoscedasticity, and no serial correlation, thereby confirming the model's appropriate specification.

To assess the structural stability of the estimated NARDL model, both the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) plots were employed. As illustrated in Figure 7, the plots remain within the 5 percent significance boundaries, indicating that the model is structurally stable over the sample period.

Figure 7: CUSUM and CUSUMSQ plots of recursive residuals



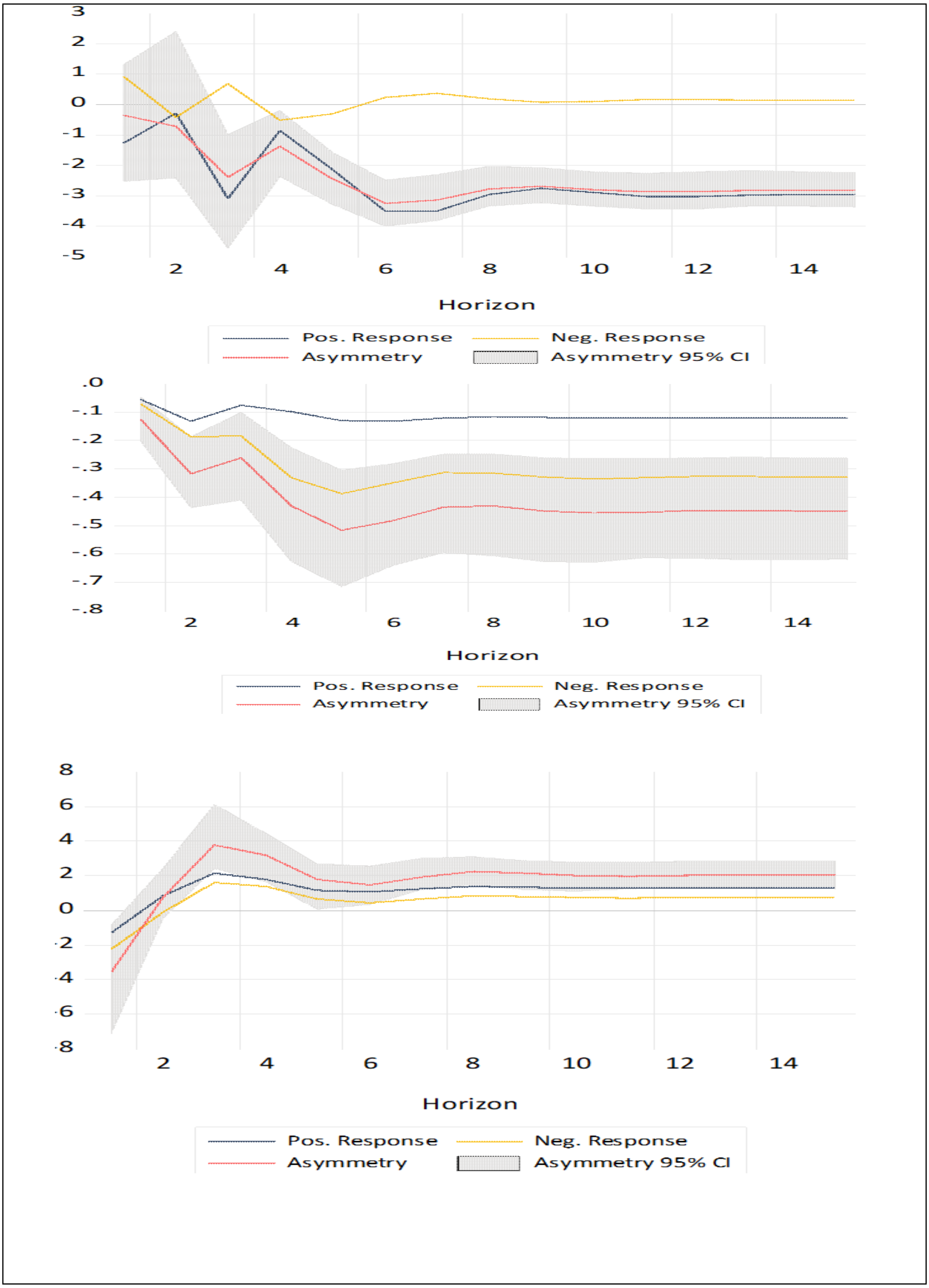
Source: Authors own computation using Eviews

To gain further insight into the adjustment dynamics, the study examines the asymmetric cumulative dynamic multipliers derived from the estimated NARDL model selected based on the lowest Akaike Information Criterion (AIC). These multipliers trace the evolution of the financial stability index in response to positive and negative shocks to CO2 emissions, rainfall, and temperature over a 15-quarter forecast horizon. The trajectories of the responses are depicted using distinct color-coded lines, where the blue and yellow lines represent positive and negative climate shocks, respectively. The divergence between these paths illustrates the extent of asymmetry in the adjustment process. In addition, the red line highlights the net difference between the two responses, while the surrounding shaded grey areas indicate the 95 percent bootstrap confidence intervals, as presented in Figure 8.

As shown in Figure 8, all the graphs validate the significant asymmetric response of FSI to shocks in CO2, rainfall, and temperature. The empirical findings show that the cumulative effects of easing temperature or a negative change in temperature dominate the cumulative effects of a positive change in temperature. In particular, the positive temperature shock has a very volatile negative effect on FSI until period 6, which stabilises after period 10. However, the negative temperature shock has the greatest muted positive effects on FSI throughout the horizon. In terms of rainfall, an overall negative relationship is observed between shocks in rainfall and FSI. In contrast, CO2 exhibits an overall positive association with financial stability, primarily driven by the stronger influence of positive shocks compared to the effects of negative shocks.

To assess the robustness of the estimation results, the model was re-estimated using an FSI constructed by applying equal weights to the three broad categories originally used in its compilation. The findings remain broadly consistent with the baseline results, reinforcing the validity of the main conclusions. However, two notable differences emerged. First, in the long run, the coefficient on the negative CO2 shock, though still statistically insignificant, turned positive, implying that lower emissions are associated with a decline in the financial stability index. This result is contrary to the transition risk theory, which suggests that a long-term reduction in emissions should strengthen financial system resilience by mitigating climate-related risks. Second, the previously insignificant long-run coefficient on negative temperature shock became statistically significant, while retaining the same sign but with a smaller magnitude. This finding highlights the importance of temperature-driven physical risks even under alternative FSI constructions. In the short run, the results are largely unchanged, except that CO2 was excluded from the final specification due to a lack of statistical relevance. These outcomes affirm the robustness of the primary findings to alternative specifications of the FSI. The full set of robustness results is reported in Appendix Table A1.

Figure 8: Cumulative effects of temperature, rainfall, and CO2 on FSI in Namibia



Source: Authors own computation using Eviews

6. Conclusion and Recommendations

Challenges posed by climate change have become one of the greatest concerns in recent years, particularly its impact on financial stability. This paper uses the NARDL approach to cointegration to examine the potential impact of climate change on financial stability in Namibia using quarterly time series data from the period 2009 to 2023. The study constructs a financial stability index (FSI) used as a proxy for financial stability. This index is used to empirically test the relationship of financial stability against climate variables such as CO2, temperature, and rainfall. The findings indicate a long-term equilibrium relationship between the FSI and climate-related variables. The study finds a negative asymmetric impact of temperature on financial stability. It also reveals that both negative and positive shocks to rainfall patterns reduce the financial stability index, as extreme weather conditions, whether it is droughts or floods, disrupt agricultural activity and strain the broader financial system. The study further finds that both negative and positive shocks to CO2 emissions improve the financial stability index, suggesting that higher emissions may be associated with increased economic activity, which temporarily supports financial conditions despite potential long-term environmental risks.

The results of this research suggest important policy implications. Firstly, the short-term immediate impact of climate-related shocks highlights the importance of integrating climate-related risks into financial institutions' risk assessment frameworks. These frameworks should clearly define procedures for identifying vulnerabilities and outline response strategies for managing climate-related shocks. Secondly, the study recommends that financial institutions adopt a long-term risk monitoring and mitigation strategy. This would involve developing adaptive policies that allow for the gradual adjustment of portfolios and investment strategies in response to changes in these variables. Thirdly, financial institutions should aim to actively explore early warning systems that will assist in identifying and mitigating the potential idiosyncratic risks to their institutions stemming from systemic climate disasters. Finally, for fast-moving hazards, such as floods and storms, regulators should conduct climate stress testing to assess the resilience of the financial system stability to sudden and unpredictable climate events. As this work represents the first step in addressing climate risks to financial stability, further research is necessary in assessing the impact of climate change on specific sectors in the financial system, such as insurance and investment fund managers. Such efforts would ensure a comprehensive approach to understanding and mitigating climate-related risks across the entire financial system.

References

Agbloyor, E. K., Dwumfour, R. A., Pan, L., & Yawson, A. (2021). Carbon emissions and banking stability: Global evidence.

Amo-Bediako, E., Takawira, O., & Choga, I. (2023). The impact of climate change on the resilience of banking systems in selected Sub-Saharan economies. International Journal of Applied Economics, Finance and Accounting, 17(2), 469-482.

Bank of Namibia (BoN). (2024). Financial Stability Report, 2023, Bank of Namibia, Windhoek, Namibia

Batten, S., Sowerbutts, R., & Tanaka, M. (2016). Let's talk about the weather: the impact of climate change on central banks.

BIS. (2022). Principles for the effective management and supervision of climate-related financial risks. BIS, Basel, Switzerland

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.

Carney, M. (2015). Breaking the tragedy of the horizon–climate change and financial stability. *Speech given at Lloyd's of London*, *29*, 220-230.

Climate Risk Profile: Namibia (2021): The World Bank Group.

Dafermos, Y., Nikolaidi, M., & Galanis, G. (2018). Climate change, financial stability and monetary policy. *Ecological Economics*, *152*, 219-234.

Diallo, M. N., Bah, M. M., & Ndiaye, S. N. (2023). Climate risk and financial stress in ECOWAS. *Journal of Climate Finance, 5, 100025.*

Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). 'Climate value at risk' of global financial assets. *Nature Climate Change*, *6*(7), 676-679.

European Central Bank. (2021, October). Climate-related risks to financial stability. ECB Macroprudential Bulletin, 15.

European Central Bank/European Systemic Risk Board Project Team on climate risk monitoring. (July 2021). Climate-related risk and financial stability. *European Central Bank*

Fabris, N. (2020). Financial stability and climate change. *Journal of Central Banking Theory and Practice*, *9*(3), 27-43.

Financial Stability Board (FSB). (2020). The implications of climate change for financial stability. https://www.fsb.org/2020/11/fsb-examines-financial-stability-implications-of-climate-change/

Government of Namibia (GRN). (2023). Namibia's Nationally Determined Contribution (NDC) Second Update of Namibia's Emission Baseline Projections and Impact on NDC Target

International Monetary Fund. (2019). The economics of climate change: Fiscal risks and opportunities. IMF Fiscal Monitor. https://www.imf.org/en/Publications/fandd/issues/2019/12/climate-change-central-banks-and-financial-risk-grippa

International Monetary Fund. (2023). Global financial stability report: Financial and Climate Policies for a High-Interest-Rate Era. International Monetary Fund. https://www.imf.org/en/Publications/GFSR/Issues/2023/10/10/global-financial-stability-report-october-2023

IPCC. (2021). *Summary for policymakers*. In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, & B. Zhou (Eds.), *Climate change 2021: The physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (In Press). Intergovernmental Panel on Climate Change.

Liu, Z., He, S., Men, W., & Sun, H. (2024). Impact of climate risk on financial stability: Cross-country evidence. *International Review of Financial Analysis*, *92*, 103096.

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.

Network for Greening the Financial System (NGFS). (2019). Technical supplement to the First NGFS Comprehensive Report: Macroeconomic and financial stability impacts of climate change. https://www.ngfs.net/en/publications-and-statistics/publications/technical-supplement-first-ngfs-comprehensive-report

Noth, F., & Schüwer, U. (2023). Natural disasters and bank stability: Evidence from the US financial system. *Journal of Environmental Economics and Management*, *119*, 102792.

Nur, T., Sahin, S., Topaloglu, E. E., & Ege, I. (2023). Evaluating the impact of climate risk on financial access and stability in G20 countries: A panel data approach (2006-2017).

Odongo, M. T., Misati, R. N., Kamau, A. W., & Kisingu, K. N. (2022). Climate change and inflation in Eastern and Southern Africa. *Sustainability*, *14*(22), 14764.

Pesaran, M. H., & Shin, Y (1999). An autoregressive distributed lag modelling approach to cointegration analysis (Vol. 9514). Cambridge, UK: Department of Applied Economics, University of Cambridge.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of applied econometrics, 16(3), 289-326.

Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. *Festschrift in honor of Peter Schmidt: Econometric methods and applications*, 281-314.

Yesigat, A., Rao, T. K. & Nagaraja, G., 2018. Determinants of Demand for Money and its Stability in Ethiopia. International Journal of Research and Analytical Reviews, 5(4), pp. 349-360.

Appendix

Table A1: Asymmetric short run and long run regression results

Dependent Variable: Financial Stability Index (FSI)				
Short run results: D (A_FSI)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-0.035074	0.049704	-0.705668	0.4838
$\Delta LnRain\_Pos_t$	-0.006160	0.014995	-0.410837	0.6830
$\Delta LnRain\_Neg_t$	0.061703	0.022490	2.743575	0.0085
$\Delta Temp\_Pos_t$	-0.519867	0.581824	-0.893512	0.3760
$\Delta Temp\_Pos_{t-1}$	2.098742	0.707085	2.968162	0.0047
$\Delta Temp\_Neg_t$	-2.447823	0.614785	-3.981593	0.0002
$\Delta Temp\_Neg_{t-1}$	1.412690	0.571724	2.470928	0.0171
ECM_{t-1}	-0.746860	0.124901	-5.979636	0.0000
Long run results				
$LnRainfall\_pos$	-0.126528	0.055676	-2.272580	0.0273
$LnRainfall\_neg$	0.188015	0.056176	3.346896	0.0015
$Temp\_pos$	-1.682273	0.395428	-4.254307	0.0001
$Temp\_neg$	-1.032363	0.264230	-3.907060	0.0003
$LnCO2\_pos$	1.883836	0.390676	4.821993	0.0000
$LnCO2\_neg$	0.192406	0.463104	0.415471	0.6795

Diagnostic Tests	**Test Statistic**	**Probability Value**
Normality	1.1091	0.5743
Heteroscedasticity	0.8593	0.6049
ARCH LM (χ^2)	0.4001	0.5297
Serial Correlation (Breusch-Godfrey LM Test)	0.9308	0.4026
RAMSEY	0.1135	0.9102
CUSUM	Stable	
CUSUMSQ	Stable	

Source: Authors' computation using EViews