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Climate change and systemic risk: The intermediary role of asset volatility

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Background: The escalating impact of climate change on financial systems signals an urgent need to enhance risk management within the banking sector. Addressing this challenge is particularly critical for South Africa, where climate-induced systemic risks are increasingly evident.

Aim: This study investigates the role of climate change in driving systemic risk within South Africa's banking sector, focussing on asset volatility as a mediating factor.

Setting: Quarterly data for South Africa from 2002 to 2020 were used in this study.

Method: The study utilises Bayesian Model Averaging and Structural Equation Modelling along with the Baron and Kenny mediation approach.

Results: The findings reveal a positive relationship between climate change and bank systemic risk, with asset volatility acting as a partial mediator suggesting that climate-induced risk elevates bank systemic risk in South Africa

Conclusion: The study underscores the need for cohesive risk management strategies that integrate both macro-prudential regulatory perspectives and micro-risk management practices to mitigate climate-induced systemic risks.

Contribution: This study contributes to the understanding of the impact of climate change on systemic risk in South Africa's financial system by using the component expected shortfall method to quantify risk. By using asset volatility as a mediator and the ND-GAIN Climate Vulnerability Index, the study offers a nuanced, multidimensional view of how climate risks affect financial stability.

Keywords: climate change; systemic risk; asset volatility; CES; South African banking sector.

Introduction

The global climate system has dramatically changed in recent decades, resulting in heightened frequency, severity and effects of extreme weather across many regions around the world. Both empirical research and scientific knowledge purport the idea that despite efforts to reduce impact and build resilience, climate change will continue to have negative ramifications on the global economy in the coming decades (Goswami et al. 2006). There is a growing consensus that climate change is no longer just an environmental issue but a significant driver of systemic risk, with far-reaching implications on financial stability and economic resilience (Battiston, Dafermos & Monasterolo 2021). De Bandt et al. (2022) assert that risks stemming from climate change can have profound and wide-ranging consequences, potentially leading to systemic risk within the financial system in extreme cases. Systemic risk, according to Manguzvane and Muteba Mwamba (2019), is the risk of a financial system-wide failure, as opposed to risks linked to individual institutions.

From a theoretical perspective, this study draws on traditional asset pricing theories including the Efficient Market Hypothesis (EMH) (Fama 1970) and the Adaptive Market Hypothesis (AMH) (Lo 2004, 2017) to explore how climate risks influence systemic risk in banking. Complementing these, the financial contagion theory (Forbes & Rigobon 2002; Raddant & Kennett 2021) reveals how localised climate shocks ripple through interconnected financial networks, amplifying market instability. This integrated framework offers a robust theoretical lens to understand the complex pathways linking climate-driven asset volatility to systemic risk thereby informing improved risk management practices and macro-prudential policies. Climate change is widely understood to have a dual effect on economic systems. Volz et al. (2022) state that direct physical and transition risks are interlinked and have the potential to contribute to systemic risk within a financial system. Climate risk manifests through physical risks such as extreme weather events damaging assets and disrupting economic activity and transition risks such as policy shifts, carbon pricing and stranded assets, all of which affect asset valuations, creditworthiness and liquidity conditions (Battiston et al. 2021; Stolbova, Monasterolo & Battiston 2018).

A key transmission mechanism through which climate-related risks contribute to systemic risk is asset volatility (Wu et al. 2023). As cited by Volz et al. (2020), Monasterolo and De Angelis (2020) and Dafermos, Nikolaidi and Galanis (2018), physical risks such as climate-related disasters and transition risks like regulatory and policy changes lead to the depreciation of real and financial assets. This often triggers capital flight from climate-sensitive sectors, leading to large and unpredictable fluctuations in asset prices (Volz et al. 2020). For example, Sasol's exposure to climate transition risks has led to heightened asset volatility, dampening investor confidence and posing broader financial stability concerns. In 2020, its stock price plunged by over 80%, reaching a record low of ZAR 21.88 on 23 March 2020, as markets reacted to the growing risk of stranded assets and capital outflows from fossil fuel investments (Mikhaylov et al. 2020; Sharenet 2025). Given this context, South Africa is quite a unique case. According to the Notre Dame Global Adaptation Initiative (ND-GAIN) data, South Africa's climate risk profile is among the highest globally, largely because of its environmental exposure, economic fragility and governance-related challenges (World Bank 2021). South Africa's economy relies significantly on climate-sensitive industries such as agriculture, mining, energy, transport and tourism (Gray, Taraz & Halliday 2023). The energy sector, in particular, remains coal-dominated, with coal accounting for 80% of the energy mix. As one of the largest coal producers and exporters globally, South Africa faces heightened risks from shifting international demand and tightening climate regulations (Department of Minerals Resources and Energy 2023). As expected, South Africa's financial system is significantly exposed to climate-sensitive industries, with the South African Reserve Bank (SARB) estimating that around 35% of total corporate bank credit is extended to these sectors (Monnin, Sikhosana & Singh 2024). This substantial exposure underscores the importance of understanding how climate change influences systemic risk through the lens of asset volatility. Empirical research suggests that climate change does not serve as a direct trigger for systemic risk. Instead, it manifests as increased asset volatility, which subsequently disrupts the banking sector by tightening credit markets, reducing liquidity and threatening overall financial stability (Bolton et al. 2020; Curcio, Gianfrancesco & Vioto 2023; Naseer et al. 2024; Wu et al. 2023). Recent historical episodes, including the Global Financial Crisis (GFC) and coronavirus disease 2019 (COVID-19), demonstrate that asset volatility plays a crucial mediating role, significantly impacting the broader economy through its influence on real economic activity and investor sentiment. Therefore, the puzzle here is to understand the mechanism through which climate change influences systemic risk.

Given South Africa's high exposure to climate-sensitive sectors, the country's concentrated banking sector further amplifies systemic risk through interconnected financial channels. The five largest banks in South Africa namely Standard Bank, FirstRand, Absa, Nedbank and Capitec dominate the banking sector, collectively holding over 90% of total assets (South African Reserve Bank [SARB], 2024). Given their market capitalisation and extensive financial influence, the International Monetary Fund (IMF 2022) classifies them as systemically important institutions. This concentration heightens financial fragility because shocks to climate-sensitive sectors can lead to correlated stress across multiple banks, exacerbating systemic vulnerability (Wu et al. 2024). If climate-induced asset volatility results in sharp devaluations in climate-sensitive industries, banks with large loan books in these sectors may experience higher default rates, liquidity pressures and capital adequacy concerns, exacerbating financial instability (Bolton et al. 2020). Furthermore, climate risk transmits to the financial system through asset repricing and increased volatility, rising default probabilities in exposed industries and capital flight from climate-vulnerable sectors, which are particularly concerning given South Africa's highly concentrated financial system (Battiston et al. 2021; Bolton et al. 2020; Monasterolo & De Angelis 2020; Stolbova et al. 2018). Given South Africa's weaker growth prospects, fiscal challenges and structural constraints, climate-induced financial shocks pose an even greater threat to banking stability. Therefore, understanding the impact of climate change is significant as it underscores the urgent need for macro-prudential climate stress testing, scenario analysis and policy interventions to mitigate systemic risk arising from climate-related disruptions in South Africa.

The macroeconomic impacts of climate change are well documented, with evidence showing that climate-induced risks disrupt economic growth, inflation dynamics and labour productivity, with repercussions on the broader economy (Capasso, Gianfrate & Spinelli 2020; Kumar & Maiti 2024; Oikonomou, Brooks & Pavelin 2012; Tol 2024). There is a growing consensus that climate change is no longer just an environmental issue, but rather it has direct economic and financial consequences. As such there is an emerging body of literature that explores the link between climate change and financial stability (Battiston et al. 2021; Dafermos et al. 2018; Hua 2023; Lamperti et al. 2021; Nand & Bardsley 2020). Despite this, research quantifying the impact of climate change on bank systemic risk remains scarce, with key contributions from Wu et al. (2024) and Song and Fang (2023). Notably, most studies focus on the Eurozone, the United States and China, while research on South Africa and the broader sub-Saharan Africa (SSA) region despite being highly vulnerable to climate change remains limited.

Against this background, this study contributes to the literature fourfold. Firstly, rather than viewing climate change as a peripheral issue, we examine it as a systemic risk driver. Understanding this relationship is crucial for policymakers, regulators and financial institutions in mitigating climate-induced financial shocks. Secondly, rather than looking at a broad index, we detangle systemic risk which allows us to understand how climate change threatens the stability of the entire financial system, not just individual firms or sectors. Systemic risk analysis helps identify cascading effects, where climate-induced shocks can spread through banking networks, amplifying economic distress and financial crises. Thirdly, this study establishes the intermediary role of asset volatility in the transmission of climate risk into financial distress. Recent events such as COVID-19 and the 2008 financial crisis highlight the profound effects of asset price fluctuations on real economic activity via macroeconomic stability and investor confidence. By exploring this pathway, this study provides a novel perspective on how climate risk transitions into systemic financial risk within the South African context, emphasising the importance of integrating asset volatility into climate risk assessments.

Furthermore, we employ the component expected shortfall (CES) method to quantify systemic risk, addressing gaps in how climate risks translate into financial vulnerabilities (Abbass et al. 2022; Rocha et al. 2022; Tol 2009; Volz et al. 2020). Unlike MES and SRISK, CES enables the aggregation of systemic risk contributions across banks, addressing limitations in alternative approaches (Derindere Köseoğlu 2023; Manguzvane & Ngobese 2023). Lastly, the study introduces a novel dataset to proxy climate change, a move away from the use of isolated metrics such as carbon emissions and rises in temperature, which does not fully capture the intrinsic nature of climate change. By utilising ND-GAIN's comprehensive climate change vulnerability index (CCVI), this research captures the multidimensional nature of climate risks, providing a detailed view of climate susceptibility through factors such as exposure, sensitivity and adaptive capacity (ND-GAIN n.d.).

The remainder of this study is organised as follows: The first part presents the literature review, followed by the methodology. Next, the empirical results are discussed and finally, the conclusions and recommendations are presented.

Literature review

Systemic risk rose to prominence after the 2008 financial collapse. According to Kaufman and Scott (2003), systemic risk is the possibility that one event could create significant ripple effects within the financial networks. Given the growing influence of climate change on the financial sector and the broader economy, examining how it impacts systemic risk is crucial for developing reliable risk frameworks, especially considering banks' substantial role in global economic stability. Research suggests that climate risks affect systemic stability by influencing asset price trends and credit quality (Wu et al. 2023; Zhai et al. 2023). These dynamics impact financial markets.

Theoretical literature

Climate risks, broadly classified as physical and transition risks, play a crucial role in shaping asset price volatility and consequently, systemic risk in banking (Volz et al. 2020). Physical risks arise from climate-related events such as extreme weather, rising sea levels and changing rainfall patterns, directly impacting business operations and supply chains (Battiston et al. 2021). Transition risks stem from the economic shifts required to transition to a low-carbon economy, affecting industries reliant on fossil fuels, regulatory policies and investor preferences (Zhai et al. 2023). These risks manifest across macro-, meso- and microeconomic levels, amplifying market risk, liquidity constraints and financial instability (Bolton et al. 2020; Sato, Tasca & Isogai 2019; Wu et al. 2023), making climate change a significant driver of systemic risk in banking.

The theoretical framework linking climate change and bank systemic risk is grounded in traditional asset pricing theories including EMH (Fama 1970) and AMH (Lo 2004, 2017). Fama's EMH (1970) suggests that asset prices fully integrate all available information, implying that climate risks should be immediately priced into financial markets. In the context of systemic risk, an efficient market would, in theory, signal any impending financial instability as a result of climate change by adjusting asset prices accordingly (Yusuf, Araoye & Afolabi 2024). However, given the uncertainty and long-term nature of climate risks, markets often struggle to fully incorporate these factors, leading to mispricing (Naseer et al. 2024). This failure can result in financial institutions, particularly banks exposed to climate-sensitive sectors, underestimating risks until a systemic crisis unfolds (Battiston et al. 2021; Bolton & Kacperczyk 2021).

The AMH extends from the EMH by proposing that markets adjust and evolve as investors respond to new risks and competitive forces (Lo 2004). Applied to climate change, this framework suggests that market participants incrementally refine their understanding of climate risks, integrating them into pricing and decision-making processes. However, cognitive biases and the unpredictable nature of climate-related disruptions may slow this adjustment, leading to mispricing and potential financial instability (Lo 2017). Complementing this is the financial contagion and risk transmission framework, which explains how climate-related shocks propagate through the banking system (Battiston et al. 2021). Forbes and Rigobon (2002) argue that what appears to be contagion in stock markets may be the result of inherent interdependence among these markets. In the context of climate risks, localised disruptions such as severe climate-related disasters and abrupt policy changes can trigger stress in one segment of the financial sector, which may then spread through these interlinked networks. Supporting this notion, Raddant and Kenett (2021) illustrates how market disruptions during the GFC underscored the vulnerabilities inherent in interconnected markets. These studies collectively suggest that even when individual financial institutions employ robust risk management practices, the interconnected nature of the financial system can amplify the adverse effects of climate-induced shocks, thereby escalating systemic risk.

These theories provide an integrated framework to understand how climate-driven asset volatility influences systemic risk. Market inefficiencies, adaptive investor behaviour and contagion dynamics amplify volatility, affecting financial stability, particularly in climate-vulnerable economies like South Africa.

Empirical literature

Numerous studies have investigated the relationship between climate change and financial stability, with research spanning multiple regions, including the global, Eurozone, United States and Chinese contexts. For instance, Wu et al. (2023) found that temperature deviations negatively impact financial stability in China, with delayed effects and regional disparities. Similar studies in China found that climate change exacerbates financial instability, with Meng, Wang and Ding (2023) showing that carbon tax policies enhance stability over time, while An et al. (2022) found that climate risks pressure markets, threatening financial stability. Wu et al. (2023) further highlight climate deviations, particularly temperature changes, weaken financial resilience and increase market instability.

Addressing methodological gaps, Battiston et al. (2021) emphasised the unique characteristics of climate-related financial risks, such as deep uncertainty, non-linearity and endogeneity. The authors advocated for innovative approaches, including network modelling and dynamic macroeconomic frameworks, to better understand the macrofinancial implications of climate change. Their work provides a foundation for central banks and financial supervisors to integrate climate risks into their policies and risk assessments, ensuring a more comprehensive approach to financial stability.

On a global scale, Mandel et al. (2021) developed a model assessing how climate-induced shocks, such as floods, propagate through financial networks, finding that systemic risk depends on countries' exposure to natural hazards and financial leverage. Monasterolo and De Angelis (2020) analysed financial market reactions to the Paris Agreement, showing a decrease in systematic risk for low-carbon indexes, while carbon-intensive assets remained largely unaffected. Giuzio et al. (2021) similarly examine the impact of climate risk on financial stability in the Eurozone banking sector. The study finds that climate-related financial risks amplify systemic risk, primarily through credit deterioration and market volatility, underscoring the need for climate-adjusted stress testing and regulatory interventions. Dietz et al. (2016) found that high-emission scenarios significantly reduce global financial asset values, linking climate risk to asset depreciation and financial instability. Expanding on this, Dafermos et al. (2018) show that climate change increases bank leverage, firm defaults and financial instability, suggesting that climate-targeted monetary policies could mitigate these risks.

While the relationship between climate change and financial stability has been widely studied, few studies have specifically examined the effect of climate change on systemic risk. Building on the discussion with the same geographic sphere, this section isolates systemic risk as a distinct area of focus, exploring the growing body of literature that investigates how climate change amplifies systemic risks. By detangling systemic risk from broader financial stability concerns, this discussion highlights the unique mechanisms through which climate change threatens the stability of interconnected financial networks.

Wu et al. (2024) investigate the relationship between climate risk and systemic risk in the global banking sector, analysing how different transmission channels amplify financial vulnerabilities. Using cross-country data from 120 countries between 2007 and 2020, the study finds that higher climate risk exposure significantly elevates systemic risk in banks, primarily through deteriorating credit quality rather than asset devaluation. The results also suggest that banks with stronger profitability and capital adequacy are better positioned to mitigate climate-induced financial instability, underscoring the importance of resilience-enhancing policies in the banking sector.

Wu et al. (2023) examine the impact of climate change on systemic risk in the banking sector, using quarterly panel data from 16 listed commercial banks in China. The study employs a CoVaR (Conditional Value-at-Risk) approach to measure systemic risk and uses temperature and precipitation data as proxies for climate change. The findings reveal that climate change significantly increases systemic risk spillovers, with non-state-owned banks being more vulnerable than state-owned banks. The study highlights the differential effects of climate change on systemic risk across bank ownership types, emphasising the need for tailored risk management strategies to address these vulnerabilities.

Curcio et al. (2023) focussed on the systemic risks linked to extreme climate events in the financial sector in the banking and insurance sectors of the United States. The study found a positive relationship between climate risks and systemic instability, particularly under more intense weather conditions. The use of green indexes was found to reduce systemic risks more effectively than brown indexes, suggesting an advantage for sustainable policies in risk management. The potential of climate events to drive systemic risks reflects a need for more research into how these impacts shape financial stability across interconnected sectors.

Aevoae et al. (2023) analysed the role of ESG factors in assessing the systemic risk posed by climate change in the banking industry. The study, which utilised data from 67 publicly listed banks across 47 countries between 2007 and 2020, found a negative correlation between ESG factors and bank-specific systemic risk. This suggests that prioritising environmental, social and corporate governance factors can mitigate specific banking risks, helping reduce the interconnectedness of banks and promoting broader financial stability.

In a 2020 study, Liu et al. (2020) investigated the impact of climate-induced risks on systemic banking risk in China, focussing on the relationship between rising temperatures and financial stability. Using temperature data as a proxy for climate change over the period of 2005–2018, the study found that higher temperatures were associated with increased systemic risk exposure in the banking sector. This suggests that climate-related physical risks, such as extreme heat, can amplify vulnerabilities within financial systems, particularly in regions heavily reliant on climate-sensitive industries. Building on this research, Song and Fang (2023) further explored the link between temperature shifts and systemic risk in China's banking sector. Employing the CoVaR methodology to measure systemic risk, the study analysed data from 2010 to 2020 and found a positive association between temperature variability and systemic risk. These empirical findings reinforce the notion that climate change poses significant threats to financial stability, particularly in economies with high exposure to climate-sensitive sectors. Together, these studies highlight the growing importance of integrating climate risk assessments into financial stability frameworks, especially in regions like China where climate change impacts are increasingly pronounced.

Despite growing interest in the relationship between climate change and financial stability, several critical gaps remain in the literature. Firstly, while studies such as Aevoae et al. (2023), Wu et al. (2023), Song and Fang (2023), Liu et al. (2020) and Curcio et al. (2023) have begun to explore climate change and bank systemic risk, empirical research in this area remains limited. Moreover, a review of existing research reveals a significant gap in studies examining the impact of climate change on both financial stability and systemic risk in South Africa or the broader sub-Saharan African region. While global and multiregional studies provide valuable insights, the lack of localised research limits our understanding of how climate risks impact financial systems in regions with unique economic structures, such as South Africa, which is widely recognised as highly vulnerable to the impacts of climate change.

Secondly, climate change is viewed as a peripheral issue in financial stability literature and this limits understanding of its role in systemic risk literature. Moreover, financial stability literature relies on broad indicators like the FSI which, while useful, aggregate multiple financial risks and fail to isolate the specific impact of climate risks on systemic risk within banking systems (Diallo & Ouoba 2024; Ozili & Iorember 2024; Park & Mercado 2014). Furthermore, many studies use single-metric proxies like climate deviation and carbon emissions, which may not fully capture the impact of climate change (Song & Fang 2023; Zhang et al. 2021). Conversely, broader measures like ESG indicators (Aevoae et al. 2023) lack specificity and standardisation, limiting their effectiveness in assessing climate risk. Lastly, few studies establish transmission mechanisms through which climate risk affects systemic risk, despite evidence suggesting that climate change influences systemic risk through channels such as asset volatility, credit risk exposure and financial contagion (Battiston et al. 2017).

Given South Africa's high exposure to climate risks, this study is both topical and relevant. Our research addresses these gaps by examining asset volatility as a mediating factor, leveraging a localised dataset for South Africa, and applying the CES model, which allows for the aggregation of bank-level systemic risk, a key variable required for this study but one that alternative approaches such as MES and SRISK do not permit (Manguzvane & Ngobese 2023). This provides a more precise understanding of how climate risk exacerbates bank systemic risk. By addressing these gaps, the study seeks to contribute to both the global discourse and the development of region-specific policies and risk management strategies tailored to South Africa's financial system.

Methods

Empirical model

This study follows closely the work of Wen and Ye (2014) and Wu et al. (2023). To examine the impact of climate change on bank systemic risk specified as (Equation 1):

$$\begin{aligned} SR_t = \alpha CC_t + \beta_1\, GDPG_t + \beta_2\, IR_t + \beta_3\, DCG_t + \beta_4\, EX_t + \\ \beta_5\, BCTA_t + \beta_6\, LDR_t + \beta_7\, ROA_t + \beta_8\, NIM_t + \\ \beta_9\, BCR_t + \varepsilon_t \end{aligned} \quad \text{[Eqn 1]}$$

where systemic risk (SR) represents the dependent variable and climate change (CC) is the main predictor variable in the model. Gross domestic product growth (GDPG), interest rates (IR), domestic credit growth (DCG) and exchange rates (EX) represent macroeconomic control variables used in the model. Bank capital to total assets (BCTA), loan-to-deposit ratio (LDR), return on assets (ROA), net interest margin (NIM) and the bank concentration ratio (BCR) represent the bank-specific control variables used in the model.

Data and sources

This study utilises quarterly data for South Africa, spanning from Q1 2000 to Q1 2020. The primary variables of interest include SR, CC indicators, asset volatility and a set of control variables. The data are sourced from credible databases, including the IMF, S&P Capital IQ, SARB for economic indicators and financial data, and CC metrics derived from the ND-GAIN website.

The rest of the explanatory variables were selected based on their significance in explaining SR and asset volatility, data availability across BRICS and insights from both theory and empirical literature (Adenuga et al. 2021; Schleer & Semmler 2015; Song & Fang 2023; Wu et al. 2023, 2024).

Systemic risk

The study calculates SR for six JSE-listed banks – Absa, Capitec, FirstRand, Investec, Nedbank and Standard Bank covering 2000 to 2020, using CES as a risk index. As a result of data limitations, other banks were excluded. The study used CES as an index for bank SR. According to Derindere Köseoğlu (2023), CES measures a bank's expected addition to the aggregate capital shortfall during a systemic crisis. To calculate CES, we assume that the banking sector in South Africa consists of n banks, such that the value-weighted (r_{mt}) for the South African banking system is given as (Equation 2):

$$r_{mt} = \sum_{i=1}^{n} w_{it} r_{it} \quad \text{[Eqn 2]}$$

where r_{mt} represents the total returns for the banking sector as a whole and r_{it} denotes the returns for each individual institution i on a day t and w_{it} represents the weight of the ith bank in the banking sector at time t. The weights are assigned based on the financial institution's comparative market capitalisation.

The conditional expected shortfall (ES) is represented by (Equation 3):

$$ES_{m,t-1}(C) = -E_{t-1}(r_{mt} \mid r_{mt} < C) \quad \text{[Eqn 3]}$$

where the distressing event is specified by a threshold C such as the VaR. To calculate the role of each bank in the aggregated risk of the entire system, Acharya, Engle and Richardson (2010) developed a technique called the MES. This relates to the bank's marginal contribution to the aggregated risk of the entire financial system as measured by ES (Acharya et al. 2010). To determine the institution's marginal contribution to the aggregated banking sector risk through ES, we compute the MES through the following (Equation 4):

$$MES_{it}(C) = \frac{\partial ES_{m,t-1}(C)}{\partial w_{it}} = -E_{t-1}(r_{it} \mid r_{mt} < C) \quad \text{[Eqn 4]}$$

Utilising the approach by Banulescu and Dumitrescu (2015), we derive the CES as follows (Equation 5):

$$CES_{it} = w_{it} \frac{\partial ES_{m,t-1}(C)}{\partial w_{it}} = -w_{it} E_{t-1}(r_{it} \mid r_{mt} < C) \quad \text{[Eqn 5]}$$

The CES is expressed in the same measurement unit as ES and is equivalent to the product of MES and the institution's weight in the system.

The fact that the total of all financial institutions' CES is equivalent to the anticipated loss of the financial system on each date is an enticing feature of CES. As such, it is simple to express CES as a percentage of ES (Equation 6):

$$(C) = \frac{CES_{it}(C)}{ES_{m,t-1}(C)} \text{ x } 100 = \frac{w_{it} E_{t-1}(r_{it} \mid r_{mt} < C)}{\sum_{i=1}^{n} w_{it} E_{t-1}(r_{it} \mid r_{mt} < C)} \text{ x } 100 \quad \text{[Eqn 6]}$$

Figure 1 provides insights into the SR profiles of Absa, Capitec, Firstrand, Investec, Nedbank and Standard Bank. Systemic risk within the South African banking system appears to be heavily influenced by external factors, as evidenced during periods of global economic instability such as the financial crisis and the COVID-19 pandemic. This suggests that despite the country's economic fundamentals, external events play a significant role in shaping SR levels (Foggitt et al. 2017).

According to Figure 1, Firstrand and Standard Bank are the largest contributors, exerting substantial influence on the overall risk landscape. Absa and Nedbank fall within the mid-range of SR contributors, while Investec and Capitec are the least contributors. Notably, a significant shift occurs after 2016, with Capitec's contribution to SR witnessing a notable increase. After taking the daily SR based on the CES of the selected banks in South Africa from February 2000 to December 2020, we aggregate these to get the quarterly CES of the South African banking industry. Our findings of these systemically important banks align with the findings of Manguzvane and Ngobese (2023).

Predictor variable

This study applies the CCVI to measure climate vulnerabilities using quarterly data from Q1 2000 to Q1 2020, assessing exposure, sensitivity and adaptive capacity across key sectors. Traditional climate risks proxies, such as temperature increases and carbon emissions, focus narrowly on physical or transition risks, overlooking socioeconomic and financial vulnerabilities (Collender et al. 2023; Klusak et al. 2023). Similarly, ESG scores suffer from subjectivity and inconsistencies, limiting comparability Anyfantaki et al. (2024). Unlike these, ND-GAIN's CCVI integrates environmental, economic and social dimensions, offering a more comprehensive and robust measure of systemic climate risks within financial systems.

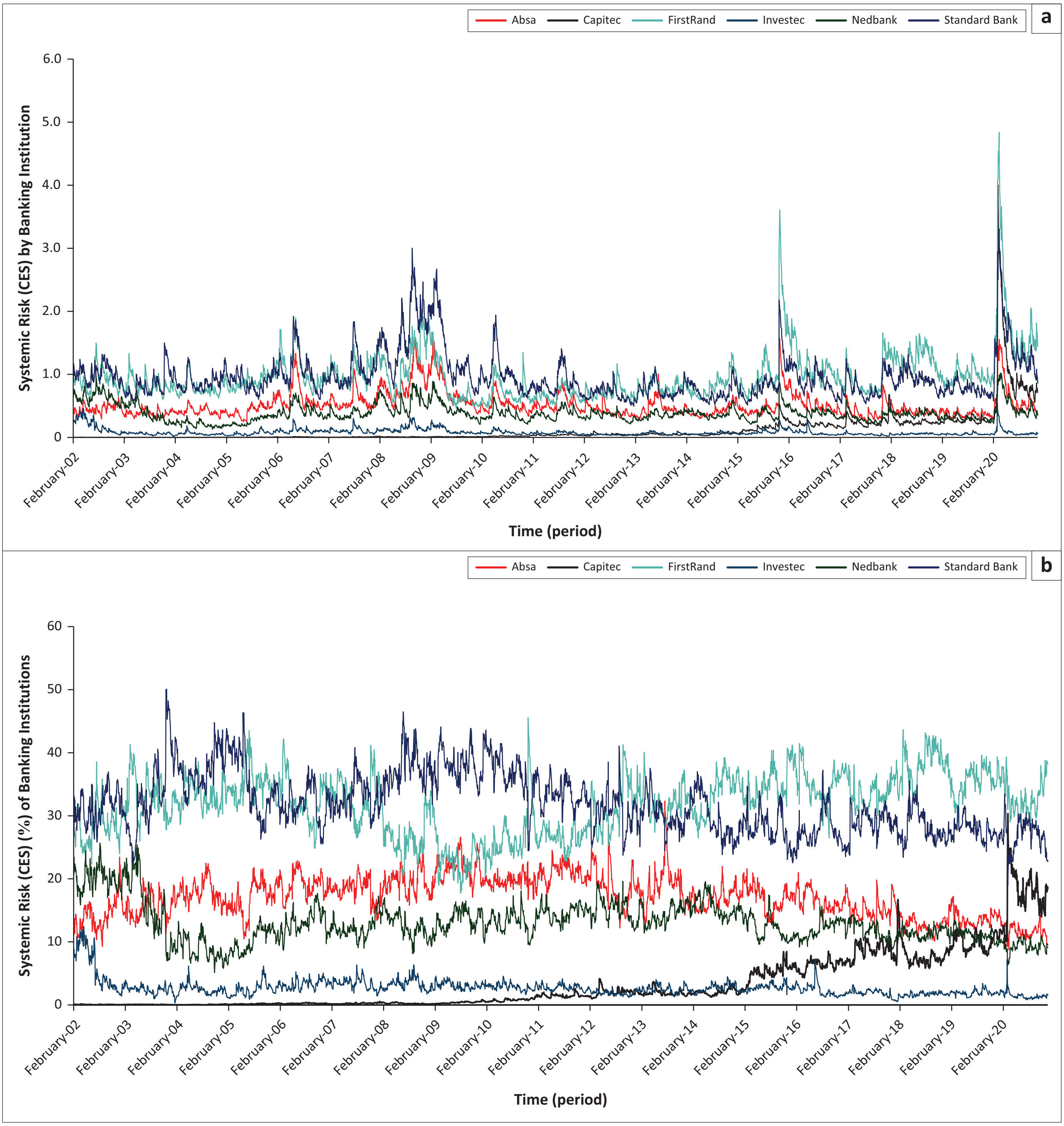
Mediating variable

To proxy asset price volatility, the study utilises the Johannesburg All Share Index (JSE ALSI) as a basis for calculating the volatility index. Duncan (2022) highlights that this index encompasses a broad and diversified range of South African equities. Its volatility can serve as a reliable indicator of market sentiment and overall economic stability, making it a relevant choice for gauging asset price fluctuations in the South African context. The index, which serves as a proxy for asset price volatility, is calculated as the 360-day standard deviation of the return on the national stock market index (Federal Reserve Bank of St. Louis [FRED] 2024). This metric captures the degree of fluctuation or variability in the index over the specified period. The data are collected from the S&P Cap IQ.

Estimation techniques

Stepwise regression for mediation testing

Wen and Ye (2014) propose a stepwise regression approach to explore the link between climate-related risks and SR. The mediating effect is tested through the following steps. Firstly, the dependent variable is regressed on the independent variable along with the control variables. Secondly,



CES, component expected shortfall.

FIGURE 1: (a) Component expected shortfall and (b) component expected shortfall per cent by banking institutions.

the relationship between the independent variable and the mediator is assessed, as described in Equation 2. Finally, the dependent variable is regressed on both the independent and mediating variables, as outlined in Equation 3.

To establish if asset volatility mediates the effect of CC on SR, we consider these criteria: significant results for CC in Equation 2 and for asset volatility in Equation 3 suggest mediation. If, however, CC's coefficient in Equation 3 becomes insignificant but asset volatility remains significant, this denotes full mediation. If both coefficients are significant in Equation 3, this signals partial mediation, where CC affects SR both directly and through asset volatility (Equation, 7, 8, 9):

$$SR_t = \alpha CC_t + \beta_1\, GDPG_t + \beta_2\, IR_t + \beta_3\, DCG_t + \beta_4\, EX_t + \beta_5\, BCTA_t + \beta_6\, LDR_t + \beta_7\, ROA_t + \beta_8\, NIM_t + \beta_9\, BCR_t + \varepsilon_t \quad \text{[Eqn 7]}$$

$$AV_t = \alpha CC_t + \beta_1\, GDPG_t + \beta_2\, IR_t + \beta_3\, DCG_t + \beta_4\, EX_t + \beta_5\, BCTA_t + \beta_6\, LDR_t + \beta_7\, ROA_t + \beta_8\, NIM_{it} + \beta_9\, BCR_t + \varepsilon_t \quad \text{[Eqn 8]}$$

$$SR_t = \alpha CC_t + \beta_1 AV_t + \beta_2 GDPG_t + \beta_3 IR_t + \beta_4 DCG_t + \beta_5 EX_t + \beta_6 BCTA_t + \beta_7 LDR_t + \beta_8 ROA_t + \beta_9 NIM_t + \beta_{10} BCR_t + \varepsilon_t \quad \text{[Eqn 9]}$$

Systemic risk is the dependent variable, and CC is the main predictor variable in our analysis. Asset volatility (AV) is the mediating variable used in the model. The rest of the variables are our control variables.

Bayesian model averaging

This section presents the Bayesian Model Averaging (BMA) approach, which mitigates model uncertainty by evaluating multiple models, enhancing robustness and reducing overfitting (Zhang, Cao & Wei 2016; Zhang & Yang 2015).

To describe the dataset, a set of possible models denoted by M_j for $j = (1, 2, 3 \ldots J)$ are considered within the model space M. By averaging across a broad set of models, it becomes possible to identify which variables are relevant to the data generation process based on a given set of priors. Each model (representing a combination of variables) is assigned a weight, and the final estimates are calculated as a weighted average of the parameter estimates from each model. While BMA includes all variables in the analysis, it reduces the influence of less important variables by assigning them lower weights. The weights play a crucial role in BMA estimation and depend on various factors, including the specified priors and the features of the averaging process.

We consider a linear regression with constant term β_0 and k potential independent variables $X_1, X_2, X_3, \ldots, X_k$. That model is specified in Equation 10:

$$Y = \beta X + \varepsilon \quad \text{[Eqn 10]}$$

The term β represents an $nx1$ parameter vector, X is an $nx1$ matrix of explanatory variables and $\varepsilon = (\varepsilon_1, \varepsilon_2, \varepsilon_3, \ldots, \varepsilon_T)$ is the disturbance vector, where T refers to the sample size.

Posterior inclusion probabilities

The posterior distribution for each coefficient of interest β_i given the data D, is (Equation 11):

$$\Pr(\beta_i \mid D) = \sum_{i=1}^{2^k} \Pr(\beta_i \mid M_i) \Pr(\beta_i \mid M) \quad \text{[Eqn 11]}$$

Posterior model probabilities

The posterior model probability $(\beta_i|M)$ of M is calculated as the ratio of its marginal likelihood to the total sum of marginal likelihoods across the entire model space, expressed as (Equation 12):

$$\Pr(M_i \mid D) = \frac{\Pr(D \mid M_i)\Pr(M_i)}{\Pr(D)} = \frac{\Pr(D \mid M_i)\Pr(M_i)}{\sum_{i=1}^{2^k} \Pr(D \mid M_j)\Pr(M_j)} \quad \text{[Eqn 12]}$$

Integrated likelihood

The likelihood function of model M_i, $\Pr(D \mid \beta_i, M_i)$ captures all the information about β_i provided by data D. The marginal likelihood is the probability density of the data, given the model M_i which equals the likelihood of times the prior density $\Pr(\beta_i \mid M_i)$ integrated over the parameter space. This equation stems from the law of total probability and provides a measure of how well the model M_i fits the observed data (Equation 13):

$$\Pr(D|M_i) = \int \Pr(D \mid \beta_i, M_i) \Pr(\beta_i \mid M_i)\, dB_i \quad \text{[Eqn 13]}$$

The integrated likelihood plays a key role in determining the model weights used in BMA. It reflects the probability of the observed data given the model M_i accounting for all possible values of the parameters.

β_i represents the vector parameters associated with the model M_i. These parameters are specific to the model and can vary within the parameter space. $Pr(D \mid M_i)$ is the marginal likelihood of the data given model M_i which is integrated over the parameter space. $Pr(D \mid \beta_i, M_i)$ is the likelihood function, representing how well the data fit the model given a specific parameter β_i. $Pr(\beta_i \mid M_i)$ is the prior distribution of the parameter β_i given the model M_i reflecting prior knowledge or assumptions about the parameter. dB_i indicates the integration over the parameter space for β_i summing over all possible values of the parameter.

Prior specifications and assigning model priors

One of the most challenging aspects of BMA is assigning appropriate prior distributions for both the model parameters and the model space (Clyde 2000). A key issue in setting priors for BMA Model parameters is that using noninformative (improper) priors can lead to problematic predictive distributions, $Pr(D \mid M)$ which cannot be interpreted as model probabilities. Furthermore, these priors do not allow the use of Bayes Factors, which are essential for model comparison. In this analysis, we focus on the simple case of normal linear regression, where a uniform prior is assigned to each model because of the lack of prior information. This approach follows the 'rule of thumb'. While many researchers have proposed various informative priors for models, this study uses a uniform prior, defined as (Equation 14):

$$\Pr(M_i) = {}^{1}\!/_{2^k} \quad \text{[Eqn 14]}$$

where $\Pr(M_i) > 0$ and $\sum_{i=1}^{M} \Pr(M_i)$.

Posterior mean and variance

The posterior mean and variance estimates of β_i are expressed as (Equation 15, 16):

$$E(\beta \mid D) = \sum_{i=1}^{2^k} \hat{\beta}_l \Pr(M_i \mid D) \quad \text{[Eqn 15]}$$

$$V(\beta \mid D) = \sum_{i=1}^{2^k} \hat{\beta}_l \left(\text{var}[\beta \mid D, M_i] + \hat{\beta}_1^{\,2}\right) \Pr(M_i \mid D) - E[\beta \mid D]^2 \quad \text{[Eqn 16]}$$

where $\hat{\beta}_l = E[\beta \mid D, M_i]$.

Bayesian model averaging predictive performance

Bayesian Model Averaging enhances predictive accuracy, as shown by improvements in out-of-sample prediction error. Predictive performance can be assessed using the Log Predictive Score (LPS), introduced by Good (1952), which measures how well a model predicts unseen data. This involves splitting data into a training set for model fitting and a prediction set for out-of-sample evaluation. For BMA, the LPS is weighted by each model's posterior probability, with lower values indicating better predictive accuracy, making it a valuable tool for model comparison.

In particular, we assess the predictive performance of a single model M as follows (Equation 17, 18):

$$-\sum_{\beta \in D^P} \log\{pr(\beta \mid M, D^T)\} \quad \text{[Eqn 17]}$$

$$-\sum_{\beta \in D^P} [\log\{\sum_{i=1}^{I} pr(\beta \mid M_i, D^T)\ pr(M_i \mid D^T)\}] \quad \text{[Eqn 18]}$$

Ethical considerations

This article followed all ethical standards for research without direct contact with human or animal subjects.

Results

The descriptive statistics in Table 1 show that SR has an average of 7.38 with a broad range, indicating varied risk levels across observations, while CC exhibits minimal variation, averaging 8.52. Asset volatility is relatively high, with a mean of 18.60, suggesting significant fluctuations. Overall, the rest of the variables show limited variation, with IR, DCG and BCR displaying more stability.

Overall impact of climate change on bank systemic risk: Bayesian model averaging empirical results

Table 2 displays the empirical findings of the baseline model, assessing the impact of CC on bank SR using the BMA approach based on stepwise regression. All models, as shown in Table 2, show that the mean coefficient of CC is positive and remains significant across all models, even as additional explanatory variables are introduced. This suggests that CC is a consistent and influential driver of SR within the banking industry. Each variable's mean coefficient estimates its impact on SR, with relevance measured by Posterior Inclusion Probability (PIP). A PIP above 90% indicates high significance, while credible intervals excluding zero confirm statistical significance at the 95% level.

Table 2 shows a positive and statistically significant relationship between CC and bank SR in Model 3, with a mean coefficient of 2.91. This suggests that as climate-related risks intensify, SR increases. The findings align with Wu et al. (2023), reinforcing that CC is a key driver of SR within the banking sector. The PIP for CC is 0.96, reinforcing that it is an important factor in most models generated by BMA.

Macroeconomic explanatory variables

The findings indicate that macroeconomic variables such as economic growth, IR and exchange rates significantly influence SR. Economic growth exhibits a negative and statistically significant relationship with SR with a negative coefficient of (0.73), suggesting that higher economic expansion mitigates financial instability. This is consistent with Wu et al. (2024) and

TABLE 1: Descriptive statistics.

Variable	Obs	Mean	SD	Min	Max
Systemic risk	76	7.38	1.48	5.72	13.26
Climate change	76	8.51	0.49	7.56	9.38
Asset volatility	76	18.59	4.56	12.98	34.11
Economic growth	76	2.37	2.16	-5.96	5.60
Interest rates	76	11.21	2.22	7.71	15.75
Domestic credit growth	76	10.39	6.16	-0.12	25.84
Exchange rate	76	9.82	3.04	5.63	15.54
Bank capital to total assets	76	7.90	0.78	5.70	9.30
Loan-to-deposit ratio	76	113.41	6.55	97.51	128.11
Return on assets	76	1.08	0.32	0.58	1.63
Net interest margin	76	3.45	0.43	2.71	4.19
Bank concentration ratio	76	86.29	9.21	76.69	99.53

SD, standard deviation; Obs, observations; Min, minimum; Max, maximum.

TABLE 2: Stepwise regression – Total effects of climate change on bank systemic risk.

Variable	Systemic risk		
	BMA model 1	BMA model 2	BMA model 3
Climate change	0.01	3.54**	2.91**
CI	-0.16, 0.29	2.10, 4.98	0.02, 4.76
PIP	0.10	1.00	0.96
Economic growth	-	-0.84**	-0.72**
CI	-	-0.99, -0.68	-0.85, -0.59
PIP	-	1.00	1.00
Interest rates	-	0.32**	0.63**
CI	-	0.23, 0.40	0.49, 0.77
PIP	-	1.00	1.00
Domestic credit growth	-	0.1003**	0.08**
CI	-	0.0570, 0.1441	0.01, 0.13
PIP	-	0.9999	0.98
Exchange rates	-	0.22**	0.16**
CI	-	0.10, 0.34	0.17, 0.29
PIP	-	0.99	0.93
Bank capital to total assets	-	0.51**	1.11**
CI	-	0.00, 1.12	0.00, 1.81
PIP	-	0.87	0.96
Bank concentration ratio	-	0.05**	0.06**
CI	-	0.02, 0.07	0.03, 0.08
PIP	-	0.99	1.00
Loan-to-deposit ratio	-	-	-0.05
CI	-	-	-0.11, 0.00
PIP	-	-	0.88
Return on assets	-	-	-0.15
CI	-	-	-0.91, 0.41
PIP	-	-	0.56
Net interest margin	-	-	-2.28**
CI	-	-	-3.23, -1.37
PIP	-	-	1.00
Constant	7.33	-36.16**	-25.36**
CI	4.90, 8.75	-54.40, -17.68	-44.82, 5.64
PIP	1.00	1.00	1.00

BMA, Bayesian model averaging; CI, confidence interval; PIP, posterior inclusion probability.
**, denotes a 5% significance level, respectively.

Liu, Sun and Tang (2021), who found that higher GDP growth stabilises financial systems by improving borrower repayment capacity and reducing default rates. Conversely, IR shows a positive and statistically significant relationship with SR, reinforcing the notion that higher borrowing costs elevate credit risk, thereby amplifying systemic instability. Our results align with the findings by Tian and Li (2024) and Wu et al. (2023, 2024), who found that rising IR exacerbate financial fragility by increasing the cost of capital and reducing firms' ability to service debt. Exchange rate volatility also significantly affects SR, with depreciation increasing financial stress, as demonstrated by Della Corte et al. (2022), who found that currency depreciation heightens credit risk exposure in emerging markets.

Bank-specific explanatory variables

Among the bank-specific factors, the NIM is negative and significant, suggesting that higher bank profitability enhances resilience to SR, aligning with Song and Fang (2023). In contrast, DCG is positive and significant, indicating that excessive credit expansion amplifies SR, consistent with Tian and Li (2024) and Wu et al. (2024). Similarly, higher bank concentration increases SR through interconnectedness and contagion effects (Wu et al. 2024). The bank capital-to-assets ratio is also positive and significant, implying that higher capitalisation does not necessarily mitigate SR but may encourage riskier lending, as observed by Wu et al. (2023). This challenges the Basel III framework, which advocates for higher capital buffers to enhance financial stability (Basel Committee on Banking Supervision [BCBS] 2011). Loan-to-deposit ratio and ROA are insignificant, indicating no measurable impact on SR. Instead, broader structural factors like credit expansion and profitability are more relevant. While some studies (Song & Fang 2023; Wu et al. 2023) link loan-to-deposit ratios to banking risks, our findings show they are not significant in South Africa's context.

Overall, the results demonstrate that CC is a significant and economically meaningful driver of SR, with a larger impact than traditional macroeconomic factors like economic growth and IR as well as bank-specific variables. This suggests that while traditional macroeconomic and bank-specific variables contribute to SR, CC is a more substantial driver. The greater magnitude of climate risk effects can be attributed to its long-term, structural and systemic nature, which differentiates it from cyclical macroeconomic fluctuations (Volz et al. 2020). Unlike traditional factors, climate risk introduces persistent disruptions, policy-induced financial volatility and asset revaluations that have far-reaching consequences beyond short-term economic cycles (Bolton et al. 2020; Dafermos et al. (2018); Scott, Van Huizen & Jung 2017). This supports the findings by Tian and Li (2024), who highlight that climate risks are not only persistent but also magnify existing financial vulnerabilities. Consequently, policymakers and financial institutions must prioritise climate risk as a central component of SR management, as its impact increasingly outweighs traditional economic and financial determinants of banking stability.

Predictive performance using log predictive score

Table 3 presents the predictive performance of the BMA models which were evaluated using the LPS, which measures the out-of-sample accuracy. Detailed results for both BMA Model 4a and 4b are provided in Table 4. Among the three models compared the BMA Model 3 from Table 2, with flexible priors, BMA Model 4a and BMA Model 4b.

BMA Model 3 with flexible priors performed best, yielding the smallest mean LPS of 1.12. This suggests that the BMA Model 3 is the most reliable model for predicting SR in future scenarios, indicating that a balance between flexibility and model parsimony is important. The model with informative priors, BMA Model 4a showed a slightly higher mean LPS of 1.21, suggesting that while informative priors helped focus on key predictors, they did not improve overall predictive accuracy. The fully specified model, BMA Model 4b, which included all predictors, had a mean LPS of 1.13, showing that including all variables does not necessarily enhance predictive accuracy. These findings highlight that models that focus on key drivers without overfitting can offer superior predictive performance when forecasting SR, especially when driven by factors like CC and economic conditions.

TABLE 3: Log predictive score summary.

Model	Mean	Min	Max
BMA model 3	1.11	0.22	4.47
BMA model 4a	1.21	0.42	5.65
BMA model 4b	1.13	0.16	6.39

BMA, Bayesian model averaging; Min, minimum; Max, maximum.

TABLE 4: Bayesian model averaging model 4a and 4b results.

Variables	Dependent variable: Systemic risk		
	Mean	SD	PIP
Model 4a			
Economic growth	-0.54	0.09	1.00
Interest rates	0.44	0.15	0.99
Return on assets	0.92	0.88	0.55
Climate change	0.50	0.56	0.54
Bank concentration	0.03	0.03	0.46
Net interest margin	-1.32	1.47	0.46
Domestic credit growth	0.04	0.05	0.46
Loan-to-deposit ratio	-0.00	0.02	0.09
Bank capital to total assets	-0.01	0.13	0.05
Exchange rates	0.00	0.01	0.01
Model 4b			
Constant	-23.00	9.47	1.00
Climate change	2.68	0.87	1.00
Economic growth	-0.56	0.08	1.00
Interest rates	0.67	0.08	1.00
Domestic credit growth	0.04	0.03	1.00
Exchange rates	0.14	0.06	1.00
Bank capital to total assets	1.09	0.36	1.00
Loan-to-deposit ratio	-0.06	0.02	1.00
Return on assets	-0.25	0.45	1.00
Net interest margin	-2.63	0.72	1.00
Bank concentration ratio	0.08	0.01	1.00

SD, standard deviation; PIP, posterior inclusion probability.

The intermediary effects

Asset volatility was incorporated to explore the intermediary mechanism. As noted in the methodology section, we employed two models aligned with Equation 2 and Equation 3, representing steps 2 and 3, respectively. Step 2 results are shown in BMA Model 5 while BMA Model 6 displays the third step's mediation outcomes in Table 5.

Model 5 regresses AV as the dependent variable on CC and other control variables such as economic growth, IR and bank-specific factors. The objective here is to understand how CC and other factors impact the volatility of asset prices within the banking sector. On the other hand, Model 6 regresses SR as the dependent variable on CC, AV (which is included as a mediator) and the same control variables. This model aims to explore how both CC and AV, along with other factors, influence the overall SR in the banking system.

Table 5 shows that the coefficient of CC is significant in both models. In Model 5, CC has a positive and significant coefficient of 3.90, indicating that an increase in CC significantly heightens AV. This suggests that greater climate-related risks lead to increased volatility in the value of assets held by banks. This finding aligns with findings by Wu et al. (2024) supporting the notion that CC can create economic disruptions by affecting energy, agriculture and real estate sectors, reducing asset values. Additionally, the transition risks posed by shifting policies, regulations and market preferences because of climate concerns could further harm the valuations of firms in carbon-intensive industries (Barnett 2019; Battiston et al. 2021). Investor behaviour also plays a role as short-term fluctuations in climate risks can drive market pessimism, amplifying downside risks in the stock market, and thereby increasing AV (Lu et al. 2019; Monasterolo & De Angelis 2020).

TABLE 5: Intermediary effects of asset volatility on systemic risk.

Variable	Model 5	Model 6
	Asset volatility	Systemic risk
Climate change	3.89**	2.12**
CI	0.03, 6.62	0.06, 3.77
PIP	0.96	0.95
Economic growth	-2.22**	-0.25**
CI	-2.50, -1.96	-0.51, -0.01
PIP	1.00	0.92
Interest rates	0.58**	0.53**
CI	0.33, 0.83	0.38, 0.66
PIP	0.99	1.00
Domestic credit growth	-0.01	0.08**
CI	-0.11, 0.02	0.04, 0.12
PIP	0.24	1.00
Exchange rates	-0.81**	0.34**
CI	-1.09, -0.57	0.20, 0.48
PIP	1.00	1.00
Bank capital to total assets	-0.04	1.21**
CI	-1.42, 0.86	0.53, 1.83
PIP	0.23	0.99
Bank concentration ratio	0.00	0.06**
CI	-0.01, 0.05	0.04, 0.08
PIP	0.25	1.00
Loan-to-deposit ratio	0.26**	-0.10**
CI	0.17, 0.35	-0.16, -0.05
PIP	1.00	0.99
Return on assets	0.77	-0.53
CI	0.00, 2.52	-1.26, 0.00
PIP	0.58	0.84
Net interest margin	0.30	-2.60**
CI	0.00, 2.56	-3.46, -1.71
PIP	0.27	1.00
Asset volatility	-	0.20**
CI	-	0.11, 0.31
PIP	-	0.99
Constant	-39.56**	-17.18
CI	1.41, 2.70	-35.01, 5.12
PIP	1.00	1.00

CI, confidence interval; PIP, posterior inclusion probability.
**, denotes a 5% significance level, respectively.

In Model 6, the coefficient for AV is positive and statistically significant, suggesting that higher AV is associated with increased SR in the banking sector. As AV rises, SR within the industry escalates, aligning with findings by Wu et al. (2023) and Bartram and Bodnar (2009). These results reinforce the idea that fluctuations in asset values can destabilise the banking system, making it more vulnerable to broader financial risks (Bolton et al. 2020; Dafermos et al. 2018). In the same equation, CC has a positive and significant coefficient of 2.12, highlighting that CC directly contributes to SR in the banking sector. As both variables are significant, the results, therefore, confirm that AV partially mediates the relationship between CC and SR. This means that CC affects SR both directly and through AV.

Robustness test

In this section, we conduct a robustness test to validate the reliability of our baseline model, which examines the relationships between CC, AV and bank SR. To ensure that model-specific assumptions or particular estimation techniques do not drive the baseline findings, we utilise both the Structural Equation Model (SEM) and the Baron and Kenny (1986) approach for mediation analysis.

Structural equation modelling

The SEM is particularly useful for testing complex relationships involving multiple paths and indirect effects, allowing us to account for the mediating role of AV between CC and SR. On the other hand, the Baron and Kenny (1986) approach provides a simpler stepwise method to determine whether AV is a significant mediator in this relationship. By using both approaches, we strengthen the credibility of our findings and ensure that our results are robust across different methodologies.

The results of the SEM, as shown in Table 6, provide significant empirical results into the relationships between CC, AV and SR. The bottom results in Table 6 show that the path from CC to AV is positive and statistically significant. This indicates that as CC intensifies, it directly leads to increased AV (Wu et al. 2024). This suggests that the risks posed by CC result in greater fluctuations in asset values, potentially as a result of

TABLE 6: Structural equation model results.

Structural	Coefficient	$P > \|z\|$	95% CI (Upper)
Dependent variable: Systemic risk			
Constant	-19.67**	0.01	-35.13, -4.20
Asset volatility	0.20***	0.00	0.11, 0.28
Climate change	2.35***	0.00	0.91, 3.79
GDP growth	-0.27**	0.01	-0.50, -0.05
Interest Rates	0.54***	0.00	0.42, 0.67
Domestic credit growth	0.08***	0.00	0.04, 0.12
Exchange rates	0.35***	0.00	0.23, 0.48
Bank capital to total assets	1.29***	0.00	0.76, 1.83
Loan-to-deposit ratio	-0.11***	0.00	-0.15, -0.06
Return on assets	-0.62***	0.04	-1.23, -0.01
Net interest margin	-2.64***	0.00	-3.43, -1.85
Bank concentration ratio	0.06***	0.00	0.04, 0.09
Dependent variable: Asset volatility			
Constant	-49.83***	0.00	-87.188, -12.48
Climate change	4.91***	0.00	1.45, 8.37
GDP growth	-2.27***	0.00	-2.54, -2.00
Interest rates	0.58***	0.00	0.30, 0.86
Domestic credit growth	-0.06	0.22	-0.16, 0.04
Exchange rates	-0.81***	0.00	-1.06, -0.56
Bank capital to total assets	-0.05	0.93	-1.40, 1.28
Loan-to-deposit ratio	0.23***	0.00	0.13, 0.34
Return on assets	1.47**	0.05	-0.03, 2.98
Net interest margin	1.49	0.13	-0.47, 3.44
Bank concentration ratio	0.00	0.76	-0.04, 0.06

CI, Confidence interval; GDP, gross domestic product.
*, ** and *** denote 10%, 5% and 1% significance levels, respectively.

the changes in economic conditions, regulatory responses or investor behaviour linked to climate-related risks (Lei & Shcherbakova 2015; Monasterolo & De Angelis 2020).

The top results in Table 6 show that the path from CC to bank SR is also positive and statistically significant. This suggests that CC directly affects increasing SR within the banking sector. Climate change exacerbates the financial system's vulnerabilities, making the banking sector more susceptible to crises and instability. Additionally, the path from AV to SR is positive and statistically significant. This finding indicates that SR in the banking sector rises as AV increases. In other words, asset value fluctuations contribute to the banking sector's overall instability.

The SEM results demonstrate that CC has both direct and indirect (through AV) effects on SR in the banking sector. The positive and significant paths suggest that CC increases AV, which in turn raises SR, while also contributing to SR directly.

Baron and Kenny approach to testing mediation

Having estimated the SEM equation, we test for the indirect effects of AV in the relationship between CC and SR. Table 7a and Table 7b present the Baron and Kenny mediation approach, which involves three steps to establish mediation by examining the relationships between CC (independent variable), AV (mediator) and SR (dependent variable). Following Iacobucci, Saldanha and Deng (2007), who adopted Baron and Kenny's (1986) framework for SEM, this approach uses the Sobel test to assess the significance of indirect effects.

TABLE 7a: Significance testing of indirect effects.

Estimates	Delta	Sobel	Monte Carlo
Indirect effect	0.99	0.99	0.96
Standard error	0.42	0.42	0.43
z-value	2.37	2.37	2.30
p-value	0.02	0.01	0.02
Confidence interval	0.17, 1.80	0.17, 1.80	0.23, 1.93

TABLE 7b: Significance testing of indirect effects.

Baron and Kenny approach to testing mediation	Coefficient	p-value
Step 1: Asset volatility: Climate change (X ->M)	4.91**	0.005
Step 2: Systemic risk: Asset volatility (M ->Y)	0.20***	0.000
Step 3: Systemic risk: Climate change (X ->Y)	2.35**	0.014

Note: Ratio of indirect effect to total effect = (0.99/3.34) with coefficient = 0.296. Ratio of indirect effect to direct effect = (0.99/2.353) with coefficient = 0.420.
*, ** and *** denote 10%, 5% and 1% significance levels, respectively.

The first step checks if CC (X) significantly affects AV (M), showing that CC increases AV as risks escalate. The second step examines if AV (M) impacts SR (Y), with results indicating that higher AV amplifies SR, reinforcing its role in magnifying financial risks. The third step tests if CC directly influences SR without the mediator, and results confirm that CC independently increases SR. The mediation effect is quantified by multiplying the path from CC to AV (Step 1) with the path from AV to SR (Step 2). As all steps are significant, the Sobel test indicates partial mediation, showing that while CC directly impacts SR, AV also mediates part of this effect. Mediation accounts for about 30% of the total effect and is approximately 0.4 times the direct effect, consistent with the main empirical findings.

Conclusion

This study examines the impact of CC on SR in South Africa's systemically important banks from Q1 2000 to Q1 2020. Findings reveal that climate-induced risk significantly amplifies SR, with a greater magnitude than traditional macroeconomic factors such as economic growth and IR, as well as bank-specific factors. Furthermore, AV partially mediates this effect, underscoring the need for banks to incorporate climate risk assessments into SR management frameworks to prevent underestimating financial vulnerabilities.

The findings of this study consistently demonstrate that CC exerts a greater influence on SR than traditional macroeconomic and bank-specific factors across all models. This reinforces the notion that climate risk is not merely an environmental challenge but a dominant financial risk driver with long-term structural implications. Given its outsized impact, the South African banking sector must transition from exploratory climate risk assessments to enforceable regulatory frameworks that integrate climate risk into SR models. Without such measures, the financial system remains vulnerable to climate-induced instability, increasing the likelihood of climate-driven financial crises in the future.

From a policy perspective, regulatory responses and climate risk disclosures play a critical role in mitigating systemic financial vulnerabilities. Given the rising emphasis on climate-related financial risks, regulators have begun integrating climate risk into financial stability assessments. The SARB has taken initial steps in this direction, including climate stress testing and exploratory scenario analyses. However, these measures remain largely voluntary and exploratory, lacking the enforcement mechanisms necessary to drive meaningful SR mitigation. Stricter regulatory requirements, such as integrating climate risk into capital adequacy assessments and risk-weighted asset calculations, should be prioritised. Internationally, frameworks such as the Task Force on Climate-Related Financial Disclosures (TCFD) and the Network for Greening the Financial System (NGFS) provide a foundation for climate-related financial risk assessments. While some South African financial institutions are beginning to adopt these standards, a regulatory mandate requiring comprehensive climate risk disclosures and stress testing would enhance transparency and resilience across the banking sector.

Moreover, given that AV mediates the relationship between climate change and SR, banks in South Africa must integrate climate-adjusted volatility measures into their risk management frameworks to better capture potential financial disruptions. In the case of South Africa, where the economy is heavily reliant on climate-sensitive sectors, diversification within these sectors rather than being away from them becomes critical. Banks should prioritise financing sustainable initiatives, such as renewable energy investments and climate-resilient agricultural practices. Expanding financial exposure to booming, less climate-sensitive sectors such as technology and telecommunications can help mitigate SR in South Africa's climate-vulnerable economy. These industries are growing rapidly and are facing lower exposure to physical climate risks than mining, agriculture and energy. Investing in them diversifies risk, enhances financial stability and reduces reliance on climate-volatile sectors. Supporting innovation-driven industries also strengthens long-term economic resilience and sustainable growth. Climate stress testing should explicitly incorporate volatility shocks to assess resilience to abrupt asset revaluations and regulators, particularly the SARB, should integrate AV into capital adequacy assessments to ensure climate-exposed assets are appropriately weighted. Additionally, financial institutions should explore hedging strategies and innovative instruments such as green bonds and sustainability-linked loans to mitigate exposure to climate-induced volatility.

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R.P.S. and J.H.E. contributed equally to this research article.

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Data availability

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