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ARTICLE

Climate shock, exchange rate market pressure, and banking sector fragility: Proposing the climate augmented currency and banking crisis model

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Abstract

Considering the multifaceted complexity of systemic risk and lack of predictive power of the current Financial Soundness Indicators, the authors intend to develop a new banking sector fragility index as an early warning signal for systemic risks; but also examine how climate shocks and exchange rate pressures affect the fragility of the banking sector. Furthermore, we propose the Climate Augmented Currency and Banking Crisis (CACB) model which is an extension of the second and third generation-type speculative attack model. The Augmented Autoregressive Distributed Lag (A-ARDL) is applied on monthly data from 2007M1-2023M12 in The Gambia. The analysis reveals that temporary climate shocks increase banking sector vulnerability in the long run. On the other hand, long term climate shock decreases banking sector fragility both in the short and long run. Likewise, a surge in exchange rate market pressure decreases banking sector vulnerability both in the short and long run. However, exchange volatility and exchange rate overvaluations increase the potential of a systemic risk in the banking sector. The CACB analysis identified four determinants of currency crisis: fragile banking sector, low level of international reserves, climate shock and state-contingent exchange rate overvaluation.

Keywords: Banking Sector Fragility Index, Climate Shock, Exchange Rate Market Pressure, Exchange Rate Volatility, Augmented ARDL, The Gambia

1. Introduction

Before the 2008 financial crisis (GFC), financial stability was primarily considered from a microprudential viewpoint. The objective of supervision was to reduce the risks of individual bank failures, and not their impact on the overall financial system (Altunbas, et al., 2017). When the crisis hit, it was clear that macroprudential was the missing part of the puzzle within global financial framework (Loloh, 2015). A macroprudential framework that is able to identify, analyze, and tackle threats such as systemic buildups and structural fragilities within the financial system due to interlinkages, common exposures, and the critical role of individual intermediaries in key financial markets that can render institutions "too-big-to-fail". This triggered Bank for International Settlement (BIS) and the International Monetary Fund (IMF) to craft the foundations for a macroprudential policy framework.

Therefore, this study investigates effect of exchange rate market pressure, exchange rate volatility and overvaluation on banking sector fragility in The Gambia, using a modified version of the currency crisis model developed by Sachs et al. (1996). The Sachs et al. (1996) model highlights that a country is more likely to experience a currency crisis if the economy has bad fundamentals- exchange rate overvaluation, low level of foreign reserves relative to liquid liabilities and a fragile banking sector. Furthermore, exchange rate pressures and overvaluation may undermine the stability of the banking sector via various channels. Primarily, exchange rate overvaluation leads to cheaper imports and less exports competitiveness, thus deteriorating the current account balance and depleting foreign reserves, which increases the risk of currency depreciation. If banks have negative net open positions (hold significant foreign currency liabilities or lend to firms with such exposures), an abrupt depreciation can raise the cost of debt servicing, starring higher non-performing loans (NPLs). Furthermore, exchange rate market pressures can shrink investor confidence, leading to capital flight and liquidity squeeze in the banking system. These dynamics can impact banks' balance sheets, impair asset quality, and erode capital buffers, thus increasing systemic fragility.

In this regard, we modified this framework by incorporating climate shock and explicit state-contingent exchange rate overvaluation. This is motivated by the increasing episodes of climate events or shocks that have exacerbated the vulnerability of the economy and the financial system. These climate shocks may affect financial stability via two channels- physical and transition risk.

Physical risk may arise due to natural disasters- causing damage to fixed capital (buildings, machinery, and infrastructure), disrupt coastline operations due to storms, and decline in agricultural yield as a result of droughts (Farbotko, 2019; Kedward et al., 2023; Joof and Adaoglu, 2024); consequently, it increases the insurance liability, default risk and decreases the profitability of affected corporations. These can then feedback into the financial system through depreciated asset valuations, reputational risks, or legal costs, liquidity and debt servicing bottlenecks or via macroeconomic factors (shocks to exchange rates, volatile commodity prices, or the sustainability of sovereign debt) (Pinzón et al., 2020; Rudgley & Seega, 2021). Contrarily, transition risk may stem from shifts in policy, regulation, technology, trade, and consumer preferences geared to the mitigation of climate-related financial risks and or scaling the transition to a low-carbon economy. Thus, a sudden policy shift or technological breakthrough could trigger a "Minsky moment" that's stranded assets and substantial financial losses of businesses in fossil fuel-related or environmentally unfriendly industries. Therefore, the authors intend to:

i. develop a banking sector fragility index as an early warning signal for systemic risks
ii. examine how climate shocks and exchange rate dynamics could affect the banking sector fragility in The Gambia
iii. propose a fourth generation-typecurrency crises model

The Gambia has experienced various climate shocks and exchange rate volatilities. According to a World Bank report for The Gambia between 1980-2022, floods constituted over 45% of natural disasters, storms 22.7% whilst drought constitutes 13.6%[1]. Moreover between 2002 and 2003, the country suffered a drought causing a 3% contraction of GDP in 2003 and subsequently, the Dalasi (GMD) depreciated by 45% against the US dollar and 60% against the Euro by end December 2003 (Joof, 2024). This was followed by a similar effect between 2011-2012 which resulted in a crop failure, causing GDP to contract by 4.1% in 2011 alone and currency depreciation of 30% against the US dollar at the end of 2012 (Joof, 2024).

The literature on exchange rate pressures has been widely documented, for instance (Kaminsky et al., 1998; Frankel and Rose, 1996; Moreno, 1995; Nag and Mitra 1999; Jeanne and Masson 2000;

1. https://climateknowledgeportal.worldbank.org/country/gambia/vulnerability:~:text=Climate%20hazards%20in%20The%20Gambia,l

Parlaktuna, 2005). However, only a few studies linked exchange rate market pressures to banking sector fragility, Feridun (2009) for the case of Türkiye, Shen and Chen (2008) for a panel of 51 countries, Shang et al. (2024) for the case of China. Therefore, the current literature is limited on various grounds; none of these studies was conducted in The Gambia and their analysis do not incorporate climate shock and exchange rate volatility. Moreover, these studies mostly rely on the Granger Causality and Autoregressive Distributed Lag model.

Thus, we intend to bridge the gap in the literature as follows: first, the literature on currency and banking crises has substantially evolved over the past three decades, ranging from the first-generation models which focused on fiscal imbalances (Salant and Henderson, 1978; Krugman, 1979) to second generation models centered on policy credibility (Sachs et al., 1996; Obstfeld, 1996), and ultimately the third generation models which incorporate balance sheet effects and banking sector fragility (Krugman, 1999; Jeanne and Zettelmeyer, 2002). These approaches have provided critical insights into the dynamics of currency and banking crises; however, they ignore the implication of climate-related macro-financial risk. This research offers a novel extension by propounding a fourth-generation model called the Climate Augmented, Currency, and Banking Crises (CACB) Model. The CACB framework incorporates the second-generation structures of speculative attacks caused by shifts in credibility and expectations, the third generation features of banking sector fragility and capital flow reversals, and an exogenous climate shock component (floods, droughts, or extreme weather events) that acts as an amplifier of macroeconomic distress by weakening the macroeconomic fundamentals and financial stability. This holistic approach allows a better understanding of the dynamic of crisis, especially in economics that are highly vulnerable to climate shocks. Secondly, although Sachs et al. (1996) implicitly accounted for "state-contingent behavior of investors" via the logic of multiple equilibria, however they did not model interactions between overvaluation and banking fragility or reserve coverage. Therefore, another extension of the CACB model is the addition of an explicit state-contingent effects of exchange rate overvaluation, which posits that the effect of overvaluation depends on the underlying economic fundamentals (the stability of the banking sector, and level of international reserve) not unambiguously bad as assumed by Sachs et al. (1996). Thirdly, this is the first study to incorporate the effect of climate and exchange rate shocks on banking sector vulnerability and currency crises framework in The Gambia. Furthermore, as opposed to the banking sector fragility index (BSFI) use in previous studies such as Kibritcioglu (2003; Feridun, 2009), which uses equally weighting, we proposed a new BSFI using the precision approach which accounts for the varying contributions of each indicator, where distinct weights are assigned to each of the indicators in the index based on their perceived contribution or importance. This ensures that the assigned weights reflect the impact of the indicators in the index to improved accuracy; the index is constructed using credit risk, liquidity risk and market risk. Fourthly, in measuring climate shocks studies using various proxies Joof and Isiksal (2024) frequency of natural disasters, Assi et al. (2024) climate-driven hazard and exposure and climate-driven INFORM risk index, ND-GAIN index, Chen and Chu (2022) to proxy climate shock. Unlike the aforementioned studies, we use the Hodrick-Prescott filter (HP filter) to decompose the frequency of natural disaster into a cyclical component of (temporary climate shock) and long-term trend (long term climate shock). This is done to prevent misattributing the frequency of natural disasters to climate change, given that climate change unfolds over a longer horizon. Fifthly, the study uses the novel Augmented Autoregressive Distributed Lag (A-ARDL) from 1993-2022. This test added one additional F-statistics to the two F-statistics in the traditional bound test to help avoid inclusiveness in cointegration. Finally, to measure the exchange rate vulnerability the authors computed the exchange rate conditional volatility the Glosten-Jagannathan-Runkle GARCH (GJR) model, and the exchange rate market pressure index (EMPI) developed by (Joof, 2024).

The structure of study includes the following parts: Section 2 represents the literature review; Section 3 shows the research design and method; Section 4 presents the findings of this research.

Finally, the research has been concluded with recommendations.

2. Literature review

2.1 Theoretical Review and Conceptual Framework of BSFI

The research builds on the second-generation speculative attack model pioneered by Sachs et al. (1996), which propounded on how weak economic fundamental (overvalued exchange rate, low level of foreign reserves relative to liquid liabilities and a fragile banking sector) is likely to trigger a currency crisis through self-fulfilling prophecy and multiple equilibria. In this paper, we develop a fourth-generation model by incorporating climate shocks as an exogeneous factor that impacts banking sector fragility, investor confidence and exchange rate market pressure. The real exchange rate (RER) is denoted as:$RER = E_0/P$, where P = 1 implies $RER = E_0.E_0$ is the nominal exchange rate, P is ration of domestic price to foreign prices levels. The condition of a devaluation is determined by the level of capital outflow (K) and level of foreign reserve (R), as long as $K \leq R$, devaluation will not occur. If the reverse happened, a devaluation would occur, and the government will set a new exchange rate target (E^T), where E_1 is the next-day exchange rate Eq.1:

$$E_0 = \begin{cases} E_0 & \text{if } K \leq R \\ E^T & \text{if } K > R, \end{cases} \tag{1}$$

Therefore, based on Sachs et al. (1996), the size of the devaluation (in the absence of climate shock) is determined as:

$$D = \left(\frac{E^T}{E_0}\right) - 1 \tag{2}$$

Thus,

$$D = \begin{cases} 0 & \text{if } K \leq R \\ \dfrac{E^T - E_0}{E_0} & \text{if } K > R, \end{cases} \tag{3}$$

where D is the expected devaluation, and E^T mirrors the stability of the banking system. When the banking system is stable and sound, the government sets $E^T = e$, where e represents the long-term RER. On the other hand, when the banking sector is fragile, the real exchange rate is allowed to depreciate more than e. This is being done to prevent or reduce the rate of bankruptcy within the banking sector. The revised devaluation size with a climate shock:

$$D = \frac{E^T - E_0}{E_0}\left(\frac{e}{E_0} f(BSF, CS)\right) - 1 \quad (3) \tag{4}$$

where BSF is banking sector fragility and CS is climate shock. When the banking sector is fragile ($f(BSF) > 1$) or the current rate E_0 is unusually appreciated relative to e, the function $f(BSF)$ exceeds unity and $D > 0$: the larger that ratio, the larger the devaluation. In our extended model, we simply incorporated $f(CS)$ to depend on a climate-shock term–so that extreme weather events amplify the same mechanism Sachs et al. (1996) describe, raising the gap between what the government "should" set (E_T) and where the market currently is (E_0), and hence increasing D. The function

$f(BSF, CS)$ depicts how a fragile banking sector and climate shock exacerbate the level of exchange rate devaluation. Therefore, a higher exchange rate depreciation will be experienced in the event of a more fragile banking sector and severe climate shock, thereby raising the risk of capital reversal.

Where E^T therefore, depends on:

$$E^T = ef(BSF, CS), \quad f'(BSF, CS) > 0, \quad f(0) = 1 \tag{5}$$

Therefore, capital outflow decision rule is shown in equation 6; investor j withdraws if:

$$D > \theta_j \Leftrightarrow \left\{ \frac{e}{E_0} f(BSF, CS) \right\} - 1 > \theta_j \tag{6}$$

where θ_j is investor j's threshold–the maximum devaluation they are willing to tolerate before a capital reversal. The magnitude of the devaluation depends on a high $\frac{\theta}{x}$ or large $f(BSF, CS)$.

The occurrence of multiple equilibria arises due to expected exchange rate behavior (Sachs et al. 1996). Therefore, when the anticipated devaluation or loss is > the θ (risk aversion cutoff or threshold), investors will withdraw their funds vice-versa. This threshold effect underpins the "self-fulfilling prophecy" of a crisis, where capital reversal depends on anticipated devaluation, while devaluation depends on capital reversal. To sketch the multiple equilibria scenario, Sachs et al. (1996) assume that N denotes the number of small investors and each holding assets k in the banking sector of a given country. Therefore, the size of the receiving capital reversal when investors flee with all their funds will be $K = Nk$. Investor decision rule depends on: withdraw funds when $D > \theta$ and maintain funds when $D \leq \theta$.

The total capital reversal is demonstrated as:

$$K = \begin{cases} 0 & \text{if } D \leq \theta \\ Nk & \text{if } D > \theta. \end{cases} \tag{7}$$

Sound fundamentals:

$$\left(\frac{e}{E_0} \right) f(BSF, CS) - 1 \leq \theta \tag{8}$$

Although Sachs et al. (1996) implicitly accounted for "state-contingent behavior of investors" through the logic of multiple equilibria, however they did not model interactions between overvaluation and structural buffers (banking fragility or reserve coverage). Therefore, another extension of our model is the inclusion of an explicit state-contingent effects of exchange rate overvaluation, which posits that the effect of overvaluation depends on the underlying economic fundamentals (the stability of the banking sector, and level of international reserve) not unambiguously bad as assumed by Sachs et al. (1996). The State-Contingent Effects of Exchange Rate Overvaluation (Eq.10):

$$\begin{aligned} f(BSF, CS, RER) = 1 + \alpha BSF + \beta CS + \eta_1 (RER \times BSF) \\ - \eta_2 \left(RER \times \frac{NFA}{N\pi} \right) \end{aligned} \tag{10}$$

where $\eta_1 > 0$ represents the amplifying effect when the banking sector is fragile and $\eta_2 > 0$ is the mitigating effect when there is high international reserves buffers. Thus, equation (10) suggests that overvaluation amplifies crisis risk only during episodes of fragility in the banking sector and is offset during periods of high international reserves buffers.

In summary, we argue that bad economy fundamentals (exchange rate overvaluation, low level of foreign reserves relative to liquid liabilities and a fragile banking sector) coupled with extreme weather events or climate shocks are a recipe for currency crises. Though the framework assumes a fixed exchange rate regime, however it is applicable under a manage float regime. This is because the often-declared official exchange rate regimes barely reflected the actual policies of the central banks, which always intervened to maintain the exchange rate within certain bands irrespective of the prevailing regime (Feridun, 2009). In light of this, we apply the exchange market pressure index that holds under all forms of exchange rate regimes.

2.2 Climate Risk and Financial Stability

Regulatory authorities are increasingly giving utmost importance to the threats posed by climate to the financial system. However, little has been done to empirically examine these risks. Most of the recent studies applied scenario or stress-testing approach. For instance, using the VaR (Value-At-Risk model), Dietz et al. (2016) computed the exposure of worldwide financial assets to climate risk, they found an exposure level (a tail risk loss) of $24.2 trillion or 16.9% of total assets. Similarly, examining the Dutch financial system using scenario analysis, Vermeulen et al. (2018) found a probable EURO 159 billion (11% of assets) loss exposure to climate risk. Roncoroni et al. (2021) examined the link between transitional risk and financial stability using a “stress-test framework under supervisory policy scenarios and market conditions”. Their analysis revealed that if the low-carbon economy transition is done in a disorderly manner, a strong market environment will permit more aspiring policies to be implemented while maintaining the same level of financial risk. Dunz et al. (2021) explored climate risk sentiments and financial stability by developing a “Stock-Flow Consistent model using global carbon tax and a revision of the macroprudential banking framework via a Green Supporting Factor (GSF)”. The results showed that both carbon tax and GSF help in scaling-up green finance in the short term, however, CSF has probable trade-offs with the financial stability of banks. Nieto (2019) “quantified the (syndicated) loan exposure to elevated environmental risk sectors of the banking system in the USA, European Union, China, Japan and Switzerland using European Central Bank (ECB) database on December 31, 2014”. The stress-testing approach suggests that the loan exposures of these countries is US$1.6 trillion. Faiella & Lavecchia (2022) in the case of Italian banks, explored the loan exposures to climate risk using a “climate-scenario framework”. The findings suggest a range of 8-10.2% exposure to their total assets.

Only a few applied econometric analyses: Sun et al. (2020) examined the effect of climate risk on the performance of quoted mineral firms in China using five proxies of climate risk. They found that these firms have varying degrees of sensitivity to climate risk, depending on the nature of their operations. Furthermore, climate risk has twin effects on firm performance (positive and negative). Li (2022) investigated the link between climate risk and the profitability of banks in Vietnam between 1990-2020 using the ARDL. The findings revealed that green investment and ecological sustainability enhances financial stability, whereas climate risk adversely affects financial stability. Similarly, applying the Generalized Methods of Moments (GMM), Sun et al. (2022) explored the co-movement of financial stability and climate risk in G-5 nations from 2009-2018. Their analysis indicated climate risk and financial stability are significant at 21%, whereas the connectedness between emission drift and financial stability stood at 19.5%. Spyros Alogoskoufis et al. (2021) uses the climate stress test scenario analysis regarding the future macroeconomic development until 2050. Their analysis reveals that the probability of default for the most impacted sectors could increase up to11% to 37.5% comparative to the orderly transition scenario by the Network for Greening the Financial System (NGFS). Using scenario analysis of the NGFS, Clerc et al. (2021) conducted a stress test for “75% of the technical insurance provisions and 85% of the total assets of

French banks based on the three NGFS scenarios until 2050”. The result for the physical risk analysis reveals two to five times increase loss ratios related to claims on natural disasters and a surge of premiums (to compensate for these losses) by 130–200%. Using Fourier Bootstrap ARDL model, Joof and Isiksal (2024) examined the effect of physical risk (frequency of natural disaster) and transition risk (environmental taxes and technologies) on financial stability in Türkiye from 1980-2020. The authors found physical risk reduces financial stability in Türkiye, whilst transition risk improves financial stability.

3. Methodology

3.1 Data

The paper explores the effect of climate risk, exchange rate pressure, exchange rate overvaluation and exchange rate volatility on banking sector fragility in The Gambia using a monthly data from 2007M1-2023M12. The study uses banking sector fragility as a dependent variable, whereas climate risk as an independent variable proxied by the frequency of natural disaster, exchange rate market pressure index, exchange rate overvaluation, exchange rate volatility and net foreign assets are used as independent variables. To avoid misattribution of natural disaster occurrences to climate change, we use the Hodrick-Prescott filter (HP filter) with a smoothing parameter (Lamda) λ=14440 which is commonly used for monthly data. This was done to separate the cyclical component of natural disaster occurrences from its long-term trend; these two components are used as measures of climate risk.

$$BSFI_t = f(CS, HPtrend, EMPI, RER, EXCVOL, NFA) \tag{9}$$

$$BSFI_t = \beta_0 + \beta_1 CY_t + \beta_2 HPtrend_t + \beta_3 EMPI_t + \beta_4 RER_t + \beta_5 EXCVOL_t + \beta_6 \frac{NFA}{M2_t} + \mu_t \tag{12}$$

Where BSFI is banking sector fragility index, CS denotes cyclical component of climate shock (temporary climate shock), HPtrend is the long run trend of climate shocks, EMPI is the exchange rate market pressure index, RER is exchange rate overvaluation, VOL is exchange rate volatility and NFA/M2 denotes ratio of international reserve to money supply.

Table 1. Variables and data source

Variable	Description	Source
$BSFI_t$	Banking sector fragility index	CBG
CS_t	Cyclical components of climate shock	EM-DAT
$HPtrend_t$	Long run trend of climate shocks	EM-DAT
$EMPI_t$	Exchange market pressure index	(Joof, 2024)
RER_t	Exchange rate overvaluation	IMF
VOL_t	Exchange rate volatility	CBG
$\frac{NFA}{M2_t}$	Ratio of international reserve to money supply	CBG

Note: CBG = Central Bank of The Gambia, IMF-FS = International Monetary Fund Financial Statistics and EM-DAT = Emergency Event Database.
3.2 Explanation of the variables.

3.1.1 Frequency of Natural Disasters

The frequency of natural disasters was obtained from EM-DAT[2] . To avoid misattribution of natural disaster occurrences to climate change, we use the Hodrick-Prescott filter (HP filter) with a smoothing parameter (Lamda) $\lambda = 14440$ (which is commonly used for monthly data) to separate the cyclical component of natural disaster occurrences from its long-term trend. Thus, we used the cyclical and long term trend components to proxy extreme weather events (temporary climate shocks) and climate change, respectively.

3.1.2 EMPI

The exchange rate market pressure index data[3] developed by Joof (2024) is used in the paper. The EMPI was computed as weighted averages of normalized changes in the exchange rate, interest rate differentials and ratio of international reserves to narrow money (M1). According to Feridun, (2009) a positive value of the EMPI signifies heightened pressure in the exchange market, which may result from a combination of factors such as currency devaluation, a widening interest rate spread, or a decline in international reserves.

$$EMPI = \alpha\Delta e_t + \beta\Delta t_t - \gamma\Delta r_t \tag{13}$$

Where:

$$\Delta e_t = \frac{exc_t - exc_{t-1}}{e_{t-1}}, \quad \Delta i_t = (i - i^*), \quad \text{and} \quad \Delta r_t = \frac{NFA_t - NFA_{t-1}}{NFA_{t-1}}$$

$$\alpha = \frac{1}{\sigma_e}, \quad \beta = \frac{1}{\sigma_t}, \quad \text{and} \quad \gamma = \frac{1}{\sigma_r}$$

In the above equations: α, β, γ are the weights, the monthly percent changes are denoted as Δ, e_t is the nominal exchange rate of the Gambian dalasi/United States dollar, t is the 13-month T-bill rate (domestic interest rate), t^* is the USA 3-month T-bill rate, t_t is interest rate differential between The Gambia and USA[4], and r_t is the ratio of net foreign asset (NFA) to narrow money (M1) ... "to confirm that the assigned weights represent the variables' impact in the index, the precision weighting method (i.e. the inverse of the standard deviation of Δe_t, Δt_t, and Δr_t, respectively)" (Joof, 2024, p. 3).

3.1.3 Banking Sector Fragility Index (BSFI)

The purpose of the BSFI is to detect or predict systemic risks in the national banking sector. In constructing the BSFI, Kibritcioglu (2003) uses three indicators to develop a banking sector fragility index: bank deposits as a proxy to changes in liquidity (DP), domestic private sector credit or claims on private sector as a proxy of changes in credit risk (CPS) and foreign liabilities as a proxy of change in exchange rate or market risk (FL). The volatility of these three indexes denotes variation in the fragility of banking sector in The Gambia. The BSFI by (Kibritcioglu, 2003):

$$BSFI_t = \left(\frac{\Delta CPS_t - \mu_{cps}}{\sigma_{cps}}\right) + \left(\frac{\Delta DP_t - \mu_{dp}}{\sigma_{dp}}\right) + \left(\frac{\Delta FL_t - \mu_{fl}}{\sigma_{fl}}\right) \tag{14}$$

Equation (14) above describes the BSFI as a mean of standardized values of CPS, DP and FL, where μ and σ denote the arithmetic mean and standard deviation of the three indicators, respectively.

2. https://www.emdat.be/
3. The exchange rate market pressure index data can be obtained from: 10.13140/RG.2.2.34617.38248
4. https://fred.stlouisfed.org/series/TB3MS

The annual changes of all the three indicators are used; the intuition of applying 12-month percentage changes in the monthly data rather than applying monthly changes is to prevent seasonality in the data. Moreover, a banking crisis is usually caused by longer-term factors and thus cannot be signaled by monthly fluctuations (Kibritcioglu, 2003).

However, Kibritcioglu (2003) assumes that all the indicators contribute equally to the banking fragility, thus it ignores the variations caused by each of the indicators. For instance, the Gambian commercial banks are more sensitive to liquidity and credit risk than exchange rate exposures. Thus, we proposed a new BSFI using the precision approach which accounts for the varying contributions of each indicator. The approach involves assigning distinct weights to each of the indicators in the index based on the perceived contribution or importance. More important Indicators are given the highest weights vis-à-vis; this ensures that the assigned weights reflect the impact of the indicators in the index to improved accuracy. We employed data from the 12 commercial banks in The Gambia; the data was obtained from Central Bank of The Gambia (CBG). The new BSFI is computed as:

$$BSFI = \alpha \Delta DP_t + \beta \Delta CPS_t + \gamma \Delta FL_t \tag{15}$$

Where

$$\alpha = \frac{1}{\sigma_{DP}}, \quad \beta = \frac{1}{\sigma_{CPS}}, \quad \text{and} \quad \gamma = \frac{1}{\sigma_{FL}}$$

where α, β, and γ are the weights (the inverse of the standard deviation of ΔDP_t, ΔCPS_t, and ΔFL_t, respectively).

3.1.4 Exchange Rate Overvaluation

To compute exchange rate overvaluation in The Gambia, we use the real effective exchange rate computed by the International Monetary Fund Financial Statistics Database[5] which is measured as the ratio of the data to a trade-weighted basket of the currencies of 20 industrial and developing trading partner countries. We compute the exchange rate overvaluation as follows:

$$RER_t = \frac{REER_t - REER_{t-1}}{REER_{t-1}} \tag{16}$$

Where RER denotes exchange rate overvaluation, REER is the real effective exchange rate computed by the International Monetary Fund[6], as the ratio of the data to a trade-weighted basket of the currencies of 20 industrial and developing trading partner countries.

3.2 Exchange Rate Volatility

The nominal exchange rate of GMD/USD obtained from the Central Bank of The Gambia[7] is used in computing the exchange rate volatility: we transform it into monthly returns (i.e., $100 \times \ln(p_t/p_{t-1})$; where p_t is the monthly value at time t) and then returns were converted into monthly volatilities measured by absolute returns. In computing conditional volatility, we estimated eleven univariate GARCH models[8] and based on the information criteria statistics (Akaike Information Criterion) from the estimated models, the Glosten–Jagannathan–Runkle GARCH (GJR) developed by Glosten et al. (1993) was selected as the most appropriate model. The GJR-GARCH extends the GARCH model to capture asymmetric effects (i.e., positive and negative shocks on volatility). It also captures "leverage effects"—where negative shocks tend to increase volatility more than positive shocks of the same magnitude.

5. https://data.imf.org/regular.aspx?key=63140098
6. https://data.imf.org/regular.aspx?key=63140098
7. https://app.datawarehousepro.com/go/cbg
8. For the sake of brevity, we do not report the estimation results for the univariate GARCH models.

3.2.1 Ratio of international reserve to money supply

We obtained net international reserve and broad money supply (M2) from The Central Bank of The Gambia Macroeconomic Datawarehouse . We use this because according to Calvo (1995) in an event of a capital outflow, the central bank must cover all its "liquid liabilities with its international reserves" to prevent a large depreciation (Calvo 1995) .... "M2 is a broad measure of liquid liabilities, which include not only direct liabilities—monetary base and short-term government bonds—but also the liquid liabilities of banks" (Feridun, 2009: p 73).

3.3 Model Specification

3.3.1 Augmented Autoregressive Distributed Lag (A-ARDL)

We applied The Augmented Dickey Fuller (ADF) (1979) unit root test, but since it does not account for structural breaks, it may give inaccurate conclusions. To resolve these issues, we also use the Perron-Vogelsang (1992) which accounts for breaks in the data. Depending on the unit root test, the appropriate cointegration techniques are applied, the ARDL is applied when the variables are integrated at order I(0) and/or I(1). In this study, the A-ARDL cointegration test by (Sam et al., 2019) is employed to resolve the drawbacks (small sample size problems and inclusiveness of results when the F-statistics is between the upper and lower bound) of the traditional bound test. The A-ARDL added one additional F-statistics to the two F-statistics in the traditional bound test to help avoid inclusiveness in cointegration. Furthermore, the A-ARDL introduced bootstrap critical values to determine the level of significance and these critical values suitable for small sample sizes (Jin et al., 2024). Furthermore, the Bayer and Hanck (2013) joint cointegration test is applied, this approach jointly assesses the p-values of fisher's single equation test:

$$EG - J = -2[\ln(P_{EG}) + \ln(P_J)] \tag{17}$$

$$EG - J - B - BDM = -2[\ln(P_{EG}) + \ln(P_J) + \ln(P_B) + \ln(P_{BDM})] \tag{18}$$

Where EG, J, B, and BDM are the p-values of Engle and Granger (1987), Johansen (1988), Boswijk (1994), and Banerjee et al. (1998), respectively, as shown in Eq. (17) and (18). The presence of cointegration is affirmed when the Fisher statistic is higher than the critical values.

4. Data Presentation and Discussion

4.1 Summary Statistics

Figure 1 represents the absolute return and conditional volatility obtained from the GJR-GARCH model. The highest exchange rate volatility observed over the same period was in February 2016. This event can be attributed to the 80% decline in the country's foreign reserve between January and February 2016 (Joof, 2024). Furthermore, an executive directive was issued to peg the Gambian dalasi (GMD) at D35–40 against the USD; however, owing to the low level of foreign reserve, the peg could not be sustained and subsequently collapsed, resulting in this substantial depreciation of the GMD (Joof, 2024).

Table 2. Descriptive statistic outcomes

	Mean	Median	Maximum	Minimum	Std.Dev	Skewness	Kurtosis
BSFI	0.001984	0.061085	2.015164	-1.332470	0.637906	0.139380	2.468190
CS	0.000446	-0.101750	0.982677	-0.637810	0.363700	0.946055	3.270025
EMPI	-0.029360	-0.005090	7.579715	-9.620970	1.667387	-0.614180	10.690930
HPTREND	0.250786	0.179606	0.699751	0.014157	0.205803	0.876814	2.522179
NFA	8.694404	8.410643	10.273430	5.599125	0.937781	0.001511	2.791871
RER	0.005905	0.000000	0.285589	-0.166860	0.093165	0.996874	4.299025
VOL	1.489979	0.715622	15.200380	-3.327320	2.301478	2.776046	13.102070

Note: BSFI is banking sector fragility index, CS denotes cyclical component of climate shock, HPtrend is the long run trend of climate shocks, EMPI is the exchange rate market pressure index, RER is exchange rate overvaluation, VOL is exchange rate volatility and NFA/M2 denotes ratio of international reserves to broad money.

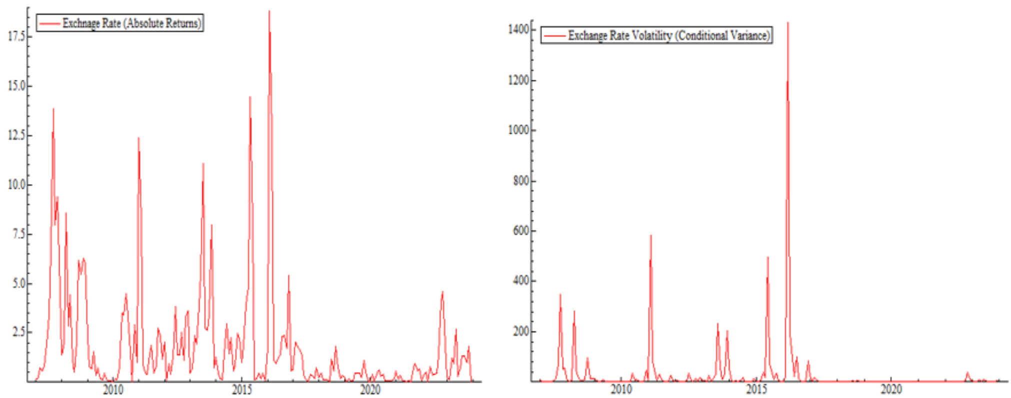

Figure 1. Absolute Return and Conditional Variance of Exchange Rate from GJR Garch model

4.2 *Unit Root Test*

To test for the stationarity process, we used the ADF unit root analysis, however it does not account for structural breaks; thus, we also use the PV for structural breaks. The outcome of the ADF banking sector fragility, exchange rate market pressure, temporary climate shock and exchange rate overvaluation are stationary at level I(0) whilst exchange rate volatility, long term climate shocks and net foreign assets are stationary at I(1). The PV reveals that the variables are I(1) beside temporary climate shock and banking sector fragility. Based on both the ADF and PV, we can conclude the presence of I(0) and I(1)) variables. Thus, the ARDL models are appropriate for our estimations.

Table 3. Outcomes of PV and ADF tests

Variables	PV_{test}		ADF_{test}
Level	$Test_{Statistics}$	D_{SB}	$Test_{Statistics}$
BSFI	-4.457754***	2007M12	-3.321421**
CS	-8.197806***	2022M10	-8.023287***
EMPI	-14.82397***	2016M2	-13.96657***
HPTREND	-3.576391	2013M10	-0.649370
NFA	-3.232132	2017M05	-2.084223
RER	-3.220713	2014M07	-3.220713**
VOL	-10.68188***	2009M12	-2.877363
First difference			
BSFI	-	-	-
CS	-	-	-
EMPI	-	-	-
HPTREND	-13.69775***	2013M01	-9.921589***
NFA	-19.44163***	2007M12	-6.640983***
RER	-17.20805***	2017M3	-
VOL	-	2016M13	-6.576836***

,*indicates the level significance at '1 and 5' percent. D_{SB} implies dates of structural-break. Note: BSFI is banking sector fragility index, CS denotes cyclical component of climate shock, HPtrend is the long run trend of climate shocks, EMPI is the exchange rate market pressure index, RER is exchange rate overvaluation, VOL is exchange rate volatility and NFA/M2 denotes ratio international reserves to broad money.

4.3 Cointegration Results

In Table 4 and 5, the augmented ARDL cointegration and the Bayer-Hanck test are reported, respectively. This technique solves the weak power, size problem and inclusiveness faced by the traditional ARDL bound test which occurs when the F-statistics fall between the upper and lower bounds, by introducing an additional F-statistics. The analysis shows the presence of long run relationships among the series; hence the three F-statistics are higher than the critical values 1% level of significance. Similarly, the Bayer-Hanck results confirmed the presence of cointegration among the variables, hence the F-statistics are higher than the critical values at 1% significance level.

Table 4. Augmented ARDL analysis

			Test stat				
F-overall			T-dependent			F-independent	
12.58411			-9.272181			5.049525	
CV	1%		5%		10%		
Statistics	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	Reference
F overall	3.15	4.43	2.45	3.61	2.12	3.23	Narayan(2005)
T dependent	-3.43	-4.99	-2.86	-4.38	-2.57	-4.04	Pearsan(2001)
F independent	2.84	4.69	2.12	3.72	1.78	3.25	Sam et al. (2019)

Table 5. The outcomes of the B-H test

Fisher F static		
Model (LCF)	EG-J	EG-J-Ba-Bo
	55.285378	110.56591
CV at 1%	8.301	15.938

4.4 Short and Long run ARDL

After confirming the stationarity and cointegration, the ARDL is applied to capture the short and long run dynamics (Table 6). Based on the analysis, the lagged error correction term (ECT (−1)) is negative and significant, indicating that the system convergence from the short term towards the long-term at a speed of adjustment of 48%. The outcome shows that temporary climate shocks have a positive association with banking sector vulnerability in the long run. A percentage increase in temporary climate shocks increases banking sector vulnerability by 0.42% in the long run; it suggests that temporary climate shocks increase the probability of systemic risk. On the other hand, after decomposing frequency of natural disasters, its long-term trend has a negative relationship with banking sector vulnerabilities both in the short and long run. Thus, long term climate shock decreases banking sector fragility both in the short and long run.

Similarly, an increase in net foreign asset strengthens and improves the resilience of the baking sector. A percentage increase in net foreign assets increased the stability of the banking sector by 0.18% and 0.34% respectively. Likewise, a surge in exchange rate market pressure was found to exhibit a negative association with the banking sector fragility, this implies that an increase in exchange rate market pressure decreases banking sector vulnerability both in the short and long run. However, exchange volatility and exchange rate overvaluations exhibited positive relationships with banking sector fragility, this implies that an increase in both exchange volatility and exchange rate overvaluations increase the potential of a systemic risk in the banking sector. Moreover, to assess the validity and stability of our model, we conducted diagnostics test (ARCH test of serial correlation, heteroskedasticity, Ramsey for stability, CUSUM and CUSUMSQ). The diagnostic assessment reveals that our model did not suffer from serial correlation, heteroskedasticity and the series normally distributed. Similarly, the CUSUM and CUSUMSQ in Figure 2 reveals that our model is stable, hence the blueline is within the 5% confidence bound.

Table 6. ARDL method analysis

Variable	Coefficient	k-Statistic	Prob.
Short run			
CS	0.2022	1.1930	0.2360
EMPI	−0.0769*	−1.7887	0.0771
HPTREND	−1.4835**	−2.1927	0.0309
NFA	−0.1515*	−1.8820	0.0631
RER	1.6785	1.6289	0.1069
VOL	0.0152	0.3820	0.7033
Long run			
CS	0.4215***	10.6494	0.0000
EMPI	−0.1603***	−11.5242	0.0000
HPTREND	−3.0910***	−9.16279	0.0000
NFA	−0.3783***	−10.8856	0.0000
RER	3.4974***	13.1825	0.0000
VOL	0.0318*	1.6755	0.0973
Diagnostic analysis			
ECT	−0.4799***	−5.8730	0.0000
Heteroskedasticity		0.9181	0.4964
ARCH		0.6248	0.4314
Ramasy		0.5870	0.5587

“ *, and **, *** indicates the significance of the explored variables at "1 and 5%" levels”. Note: BSFI is banking sector fragility index, CS denotes cyclical component of climate shock, HPtrend is the long run trend of climate shocks, EMPI is the exchange rate market pressure index, RER is exchange rate overvaluation, VOL is exchange rate volatility and NFA/M2 denotes ratio international reserves to broad money.

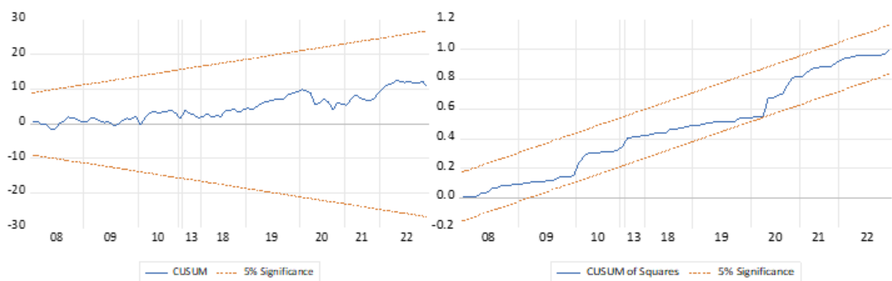

Figure 2. CUSUM and CUSUM -SQ of LCF model

4.5 *Empirics for the Climate Augmented Currency and Banking Crisis (CACB) Model*

The CACB framework incorporates speculative attacks caused by shifts in credibility and expectations, banking sector fragility and capital flow reversals, and an exogenous climate shock component that acts as an amplifier of macroeconomic distress. This section provides an empirical lens of the CACB model.

$$\mathrm{EMPI}_t = \beta_0 + \beta_1\mathrm{BSF}_t + \beta_2\mathrm{CS}_t + \beta_3(\mathrm{BSF}_t \times \mathrm{CS}_t) + \beta_4\mathrm{NFA}_t + \beta_5\mathrm{RER}_t + \beta_6\mathrm{VOL}_t + \varepsilon_t \tag{19}$$

where $EMPI_t$ is the exchange rate market pressure index, BSF_t is banking sector fragility, CS is temporary climate shock, $BSF_t * CS_t$ is the interactive term or amplifier, NFA_t is net foreign assets,

REF_t is exchange rate overvaluation and VOL_t is the exchange rate volatility. To test the applicability of the CACB model, we use the Fully Modified Ordinary Least Square (FMOLS) of (Phillips and Hansen, 1990). The analysis reveals that banking sector fragility has a positive effect on exchange rate market pressure, implying that a weak banking sector may trigger currency crisis. Similarly, the interactive term between banking sector fragility and climate shock has a positive impact on EMP; this supports the validity of the CACB model which posits that an exogenous climate shock component acts as an amplifier of macroeconomic distress and eventually contributing to currency crisis. Furthermore, the ratio of international reserve to money supply also exhibited a positive effect on EMP. This is because in the event of a capital reversal central bank must cover all liquid liabilities to avoid depreciation (Calvo, 1995). Thus, a surge in the ratio of international reserve to M2 suggests an increase potential of a crisis (Feridun, 2009). Furthermore, exchange rate volatility also increases the probability of a crisis. However, overvaluation has a negative effect on EMP, suggesting that an increase in exchange rate overvaluation reduces the exchange rate pressures.

However, exchange rate overvaluation has a negative relationship with EMPI, implying that an increase in overvaluation reduces exchange rate pressures. This is inconsistent with the CACB theoretical underpinning which posits that overvaluation signals weak fundamentals and creates devaluation pressures. Therefore, our results suggest the presence of "state-contingent effect"- the effect depends on the underlying fundamentals (the stability of banking sector and the level of international reserves). Specifically, the analysis reveals that the interaction between overvaluation and level of international reserves has a negative on exchange rate pressure whereas the interaction between overvaluation and banking sector fragility shows a positive effect on exchange rate pressures. This suggests that overvaluation amplifies crisis risk only during episodes of banking sector fragility and is offset during periods of high international reserves buffers. Thus, we refine our framework to capture the interaction between overvaluation and these economic fundamentals, which underpins the importance of taking into account the heterogeneity of economic realities crisis prediction models.

$$f(\mathrm{BSF}, \mathrm{CS}, \mathrm{RER}) = 1 + \alpha \mathrm{BSF} + \beta \mathrm{CS} + \eta_1(\mathrm{RER} \times \mathrm{BSF}) - \eta_2\left(\mathrm{RER} \times \frac{\mathrm{NFA}}{\mathrm{M2}}\right) \tag{20}$$

Where $\eta_1 > 0$ represents the amplifying effect when the banking sector is fragile and $\eta_2 > 0$ is mitigating effect when there is high international reserves buffers. The revised empirical model:

$$\begin{aligned}\mathrm{EMP}_t = {} & \beta_0 + \beta_1\mathrm{BSF}_t + \beta_2\mathrm{CS}_t + \beta_3(\mathrm{BSF}_t \times \mathrm{CS}_t) + \beta_4\mathrm{NFA}_t + \beta_5\mathrm{RER}_t \\ & + \beta_6(\mathrm{RER}_t \times \mathrm{BSF}_t) + \beta_7\left(\mathrm{RER} * \frac{\mathrm{NFA}_t}{\mathrm{M2}_t}\right) + \beta_8\mathrm{VOL}_t + \varepsilon_t\end{aligned} \tag{21}$$

Table 7. FMOLS

Variable	Coefficient	Std. Error	Prob.
VOL	0.1070^{***}	0.0379	0.0052
BSF	0.0101^{***}	0.0065	0.00087
RER	-2.1733^{*}	1.1077	0.0512
NFA/M2	0.6063^{*}	0.3089	0.0560
BSF * CS	0.8670	0.0762	0.2567
RER * BSF	0.8059^{*}	0.4558	0.0580
RER * $\frac{NFA}{M2}$	-4.7564^{**}	2.7745	0.0209

Note: *’**’*** denotes 1%, 5% and 10% significant level. VOL is exchange rate volatility, BSF is banking sector fragility, RER is exchange rate overvaluation, NFA/M2 is the ratio of international reserve to broad money and BSF*CS is the interactive term between banking sector fragility and climate shock.

5. Discussion, Conclusion and Policy Options

Climate risk is arguably one of the most contemporary issues in financial stability policy dialogue globally. The increasing climate-related physical risk on banking sector stability has raised concern among central banks and supervisory authorities, and they are increasingly acknowledging fact that tackling these risks aligns with their core mandates to maintain price and financial stability (ECB, 2020; NGFS, 2020). However, the impact of climate shocks on the banking sector fragility is still not fully understood. Similarly, exchange rate stability is also a major concern for small-open imported dependent country like The Gambia, which has experienced various currency crises (Joof, 2024). The literature on exchange rate pressures has been widely documented, for instance (Moreno, 1995; Nag and Mitra 1999; Jeanne and Masson 2000; Parlaktuna, 2005). However, only a few studies linked exchange rate market pressures to banking sector fragility, Feridun (2009) for the case of Türkiye, Shen and Chen (2008) for a panel of 51 countries, Shang et al. (2024) for the case of China. Furthermore, these studies do not account the effect of climate shocks. Thus, we intend to bridge the gap by examining the impacts of climate shocks and exchange rate pressures on the banking sector fragility of The Gambian using the Augmented Autoregressive Distributed Lag (A-ARDL) from 2007M1-2023M12. Moreover, we propose a novel speculative attack-type (CACB) model that incorporates an exogenous climate shock and state contingent of exchange rate.

The analysis from the A-ARDL revealed that temporary climate shock increases the fragility of the banking sector and could trigger systemic risks. However, the long-term trend of climate shock reduces the vulnerability in the banking sector. Furthermore, exchange rate market pressure promotes banking sector stability, whilst exchange rate volatility and overvaluation contribute to high banking sector vulnerability. On the other hand, the CACB identified four factors that triggers currency crisis: low level of international reserve, a weak banking system, climate shock and a state contingent overvaluation of exchange rate.

This research offers remarkable policy implications. The positive relationship between temporary climate shocks and banking fragility can be explained by the fact that natural disasters may cause damage to bank’s fixed capital (buildings and infrastructure), due to storms, which consequently affect operational risk and insurance underwriting. Moreover, banks can incur losses arising from decrease in asset quality (credit risk) due to a decline in agricultural yield or services of clients whose activities depends on the ecosystem, and such losses can impact the profitability, and credit risk of the banking sector (Joof and Adaoglu, 2024). This is also supported by Joof and Adaoglu (2024: p6), who highlighted that … "physical risk may trigger major categorical risks such as insurance underwriting, credit, market, and operational risks through their adverse impacts on cash flows, balance sheet and operations. For instance, climate-related physical risks can increase the level of nonperforming loans (i.e., decrease in asset quality) in financial institutions due to potential profitability decline in companies impeding their ability to pay back their debt obligations." On the other hand, long term trend of climate shock is negatively related to banking sector fragility in The Gambia; this because it allows the economy, banks and supervisory authorities to adapt and mitigate climate shocks via various mechanisms. For instance, in the long run, banks may diversify their portfolios and develop sustainable instruments such as green credits to reduce their exposure from climate susceptible sectors but also integrating climate-related risk assessments such as scenario analysis and stress testing to better evaluate transmission channels. Similarly, this relationship could also be explained by the fact that authorities will have time to initiate and implement sustainable taxonomies like Environment, Social and Government considerations (ESG) and promote adaptation infrastructure. All of which will contribute to reducing banking sector fragility in The Gambia.

Similarly, the negative relationship between exchange rate market pressure and banking sector fragility implies that a decline in market pressures tends to increase the fragility of the banking sector. This is because banks tend to increase their risk-taking behaviors (increasing lending to riskier sectors, expanding exposure to foreign-currency-denominated loans, or reducing their focus on hedging strategies) when there appears to be no currency crisis ahead or during episodes of exchange rate stability. For an import-dependent country like The Gambia, such behaviors may exacerbate the fragility of the banking sector and the likelihood of a currency crises, especially due external shocks. Furthermore, in the long run, these risk-taking behaviors can accumulate and trigger a currency crisis, and consequently, aggravate banking sector fragility through rising non-performing loans, liquidity shortages, and foreign exchange mismatches. This is in line with the twin-crises hypothesis which posits currency crisis is usually accompanied by a banking crisis, which also affirms the study of (Feridun, 2009). This outcome also confirms the studies by Kibritcioglu et al. (1998) who highlighted that exchange rate pressure is the leading determinant of the 1994 crisis via the signaling approach. Likewise, using the Markov regime-switching approach, Mariano et al. (2004) identified foreign reserves and exchange rate as the leading indicators 2001 crises in Türkiye. Özkan (2005), indicated fragility of the financial system is among the causes of the 2001 crises in Türkiye.

On the other hand, the positive effect of exchange rate volatility and exchange overvaluation on banking sector fragility can be attributed to the fact that real exchange rate overvaluation increases the fragility in of the banking sector by affecting the net open position (NOP) of banks in short positions, thus decreasing the profitability and debt-servicing capacity, leading to a higher default risk. This episode deteriorates the banks' asset quality, raising systemic risks, particularly in an economy like The Gambia, with imperfect financial system and externalities in the lending process ... "Imperfect because banks loans are sources of external financing for nonfinancial firms and deposits are the most important forms of household savings. Externality arises because individual banks do not internalize the effect of their lending decisions about the quality of information potential borrowers received from other banks and therefore extend more credit than they otherwise would" (Sobolev, 2000; p9).

Furthermore, overvaluation often promotes excessive foreign borrowing due to seemingly low costs of capital, exposing banks and borrowers to foreign exchange risks. Thus, a sudden depreciation in the dalasi (The Gambia's currency) to correct the overvaluation will raise the cost of servicing foreign-denominated debt rises and consequently woresning banking sector fragility. This was observed when an executive directive from the office of the President was issued in The Gambia between May 2015-January 2016 targeting the exchange rate between the range of GMD35-40 while the market rate is at GMD 50 per USD. After rescinding the decision in February 2016, the GMD experienced its highest crisis/pressure. According to Joof (2024) this was due to a decrease in foreign reserves by 80% between January to February 2016. Moreover, the decline in foreign reserve was accompanied by deteriorating balance of payment and debt servicing, causing the peg ultimately collapsed, leading to highest exchange rate crises in decades. Furthermore, during this period, the banks incurred heavy losses due to their foreign liability exposures. Likewise, high currency volatility compounds these challenges by establishing uncertainties in the FX market. This uncertainty raises the cost for both banks and borrowers in managing their foreign exchange exposures, thus worsening default risks. Similarly, volatility also triggers speculative attacks and capital outflows, thus straining liquidity in the banking system. We suggested the following policy options: (i) The Central bank of The Gambia (CBG) should consider formulating and incorporating climate-related financial risk guideline for the banking sector including ESG considerations. (ii) The investment decisions of banks should incorporate the financing of the transition to a greener economy. (iii) Banks should assess their climate-related physical risk exposures using scenario analysis and stress testing to ensure resilience to climate shocks. (iv) Banks may diversify their portfolios and develop sustainable instruments such as green credits to reduce their exposure from climate susceptible sectors. (v) CBG and financial institution should establish an exchange rate monitoring mechanism or use the exchange rate market pressure index by Joof (2024), developed for The Gambia to provide real-time analysis on the exchange rate pressures. (vi) CBG should ensure independence and transparency, to enhance credibility in managing exchange rate policies. (vii) Encourage investment in sectors that can leverage exchange rate depreciation for competitive advantage, such as tourism and agriculture. (viii) Promote domestic resource mobilization to reduce exposure to exchange rate pressures.

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