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Regime Switching Dynamic Impact of Risk Management on Bank Profitability: Evidence from South Africa

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Abstract

Purpose: This study investigates the regime-switching dynamic impact of key risk management variables (liquidity risk, credit risk, exchange rate risk, and inflation risk) on bank profitability in South Africa, measured by return on equity (ROE) from 2000Q1 to 2024Q4. The aim is to determine whether these relationships differ between two economic regimes: regime 1 (stable) and regime 2 (crisis).

Design/Methodology/Approach: The study employs a Markov Switching Means Vector Autoregressive (MSM-VAR) model using quarterly data to capture nonlinear and state-dependent dynamics in the risk–profitability relationship. The model distinguishes between low-risk (stable) and high-risk (crisis) regimes, accounting for structural breaks and changing macroeconomic conditions.

Findings: The results reveal strong evidence of regime-dependent dynamics. Liquidity risk has a significant positive impact on ROE during crises but is insignificant during stable periods. Credit risk positively influences profitability during stable periods but has a strong negative effect during crises. Conversely, exchange rate risk and inflation risk do not show statistically significant effects in either regime. The results validate the importance of incorporating non-linear modelling approaches when assessing risk–performance linkages in volatile emerging market contexts.

Practical Implications: The findings highlight the need for state-contingent risk management strategies. Banks should enhance liquidity buffers and implement countercyclical credit risk practices during stable periods to mitigate the adverse effects of downturns. Policymakers and regulators should consider macroprudential tools that adapt to shifting economic conditions to sustain the banking sector's resilience.

Originality/Value: This study applies a regime-switching framework to evaluate the risk–profitability nexus in South African banking. It provides empirical evidence on how risk management effectiveness varies across macroeconomic regimes, offering insights into financial stability, risk management, and banking regulation in emerging markets.

Paper Type: Research Paper

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INTRODUCTION

After the 2008 global financial crisis, risk management became essential to banking sector reform. The crisis revealed vulnerabilities in financial institutions' risk management, particularly in emerging markets (Cardoso and Cardoso 2024). In South Africa, banks have had to implement strict credit evaluation and risk mitigation strategies to maintain profitability and ensure stability amid macroeconomic volatility and political uncertainty (Strauss-Kahn 2008).

The financial sector is vital for economic development as it mobilizes savings, allocates capital, and facilitates trade and investment (Eklemet et al. 2024). Its stability and performance depend on effective risk management systems. Tursoy (2018) argues that a bank's long-term viability relies on its ability to mitigate risk exposures. Bessis (2011) defines risk as any uncertain event that can negatively impact profitability, emphasizing the need for comprehensive risk governance frameworks.

Numerous studies have explored the relationship between risk management and bank performance, yielding mixed results. Zhongming et al. (2019) and Siddique et al. (2022) found that strong risk management practices can reduce the negative impact of non-performing loans (NPLs) on profitability. Fadun and Silwimba (2023) and Mamari et al. (2022) indicate that while risk management improves returns on assets (ROA), its effect on return on equity (ROE) is often limited. Mohamed and Onyiego (2018) emphasize the significance of credit and operational risks in influencing bank performance in East Africa. Chenga et al. (2020) and Kolapo et al. (2012) demonstrate that effective risk controls enhance profitability and financial stability.

In South Africa, evidence on the factors influencing bank profitability is fragmented. Chiyengerere (2021) and Chenga et al. (2020) highlight the impact of liquidity risk, while Razermera et al. (2024), Munangi (2020), Fombang and Maseko (2024) stress the importance of credit risk, particularly non-performing loans (NPLs). Some studies indicate a positive relationship between the Capital Adequacy Ratio (CAR) and bank performance (Chiyengerere 2021; Chin'Anga 2015), while others argue that excessively high capital buffers may hinder profitability by restricting more aggressive lending strategies (Munangi 2020).

Despite these contributions, a significant limitation persists. Most existing studies depend on static linear models, such as fixed-effects panel regressions or the generalized method of moments (GMM), which assume that relationships remain stable over time. These methods fail to account for structural breaks or regime shifts caused by financial crises, policy shocks, or economic turbulence. As Harb et al. (2023) point out, the impact of risk on bank profitability is likely non-linear and time-varying, influenced by the broader economic environment. However, this dynamic aspect remains largely unexamined in the South African context.

This study examines the regime-switching impact of risk management on bank profitability in South Africa, focusing on Return on Equity (ROE) as the key performance indicator. The study employs a Markov Switching Means Vector Autoregressive (MSM-VAR) model to analyse relationships across low-risk (stable) and high-risk (volatile) periods, capturing how the relationship between risk and performance evolves with changing macroeconomic conditions.

The main research question guiding this study is:

How do changes in economic regimes affect the relationship between risk management factors and bank profitability (ROE) in South Africa?

To unpack this further, the study addresses the following sub-questions:

- What is the impact of liquidity risk on ROE during low-risk and high-risk regimes?
- How does credit risk influence ROE under different economic conditions?
- What is the effect of exchange rate risk on ROE across economic regimes?
- How does inflation risk affect ROE in varying economic states?

The study has two main objectives. First, it seeks to evaluate the relationship between core risk management factors and bank profitability using a regime-sensitive model, which is underutilized in the South African literature. Second, it aims to provide insights for banks and regulators on how to adjust their risk management strategies during economic stability compared to financial distress.

This research enhances the discussion on banking resilience and performance optimization in emerging markets. It fills a methodological gap by advancing beyond static models and focusing on an under-researched emerging economy.

The paper is organized as follows: Section 2 presents the literature review, Section 3 discusses the theoretical framework and variables development, Section 4 outlines the research methodology, Section 5 reports and discusses the empirical findings, and Section 6 concludes.

LITERATURE REVIEW

The study examines the relationship between risk management practices, credit, liquidity, operational, and market risks and the financial performance of banks in various regions using different econometric methods. The following section focuses on international studies on the relationship between risk management and bank ROE.

Credit Risk Management: Harb et al. (2023) found that credit risk management does not impact accounting performance but has a non-linear relationship with market performance in the MENA region. In Nigeria, Fadun and Silwimba (2023) reported mixed effects: non-performing loans (NPLs) negatively impact financial performance, while expected credit losses (ECL) have a positive effect. Zhongming et al. (2019) demonstrate that NPLs hinder bank performance in China, whereas bank size and net income positively influence it. Siddique et al. (2022) found negative effects of NPLs but positive effects of capital adequacy (CAR) on South Asian banks' performance using the GMM estimator. In Kenya, Mohamed and Onyiego (2018) emphasize that effective credit risk management is crucial to bank performance.

*Operational Risk Management***:** Von Tamakloe et al. (2023) and Mohamed and Onyiego (2018) both demonstrate a strong positive effect of operational risk on bank performance in Ghana and Kenya, respectively. Von Tamakloe et al. (2023) performed a panel regression analysis with seven banks, finding that operational risk accounts for 99.24% of the impact on bank performance. Similarly, Mohamed and Onyiego (2018) used regression analysis to identify operational risk as the strongest driver in Kenya. Additionally, Fadun and Oye (2020) conducted a 15-year panel data study, concluding that effective operational risk management practices are vital for improving bank performance in Nigeria.

Liquidity Risk Management: Harb et al. (2023) conducted a panel regression analysis of 51 banks in 10 MENA countries from 2010 to 2018, finding mixed results for liquidity risk. While liquidity risk alone was not significant, its interaction with credit risk showed a significant inverted U-shaped effect on bank performance. Similarly, Siddique et al. (2022) used a GMM estimator and found that liquidity ratios (LR) were negatively related to performance in South Asia.

Risk Management Moderation: Eklemet et al. (2024) conducted a study using a Dynamic Panel (System GMM) with 20 banks from 2013 to 2022. They found that risk management moderated the negative relationship between risk exposure and bank performance in Ghana, indicating that improved governance leads to better performance outcomes.

Overall Risk Management: Mamari et al. (2022) in Oman and Muhammad et al. (2018) in Pakistan showed that comprehensive risk management practices, monitoring, assessment, and governance, positively affect financial performance. Mamari et al. (2022) used Structural Equation Modeling (PLS-SEM) and found that risk management positively impacts return on assets (ROA) but does not significantly affect return on equity (ROE). In contrast, Muhammad et al. (2018) employed regression and correlation analysis, revealing that understanding, assessing, and monitoring risk positively influences risk management practices.

The following section focuses on South African studies on the relationship between risk management and bank ROE.

Credit Risk: Credit risk is a critical determinant of bank profitability. Research by Razermera et al. (2024) and Babatunde et al. (2020) emphasize the importance of effective credit risk management, especially regarding non-performing loans (NPLs). Razermera et al. (2024) used a panel regression model to analyze the six largest commercial banks in South Africa from 2013 to 2020, finding that NPLs were the primary determinant of profitability during the COVID-19 pandemic. Babatunde et al. (2020) examined a panel dataset of 14 commercial banks and discovered that NPLs and the capital adequacy ratio significantly influenced the performance of smaller banks, suggesting variations in risk management practices. Fombang and Maseko (2024) also highlighted the positive impact of credit loss ratios on profitability, indicating differing credit management practices across banks and market conditions. Their analysis from 2013 to 2022 revealed a positive effect of credit loss ratios on profitability, while the ratio of loss allowances to total loans had a negative impact. Munangi and Sibindi (2020) documented a negative relationship between credit risk (NPLs) and bank profitability using panel data techniques, reinforcing earlier findings. Munangi (2020) confirmed this negative correlation, illustrating that inadequate credit risk management can lead to reduced profitability.

Capital Adequacy: Both the capital adequacy ratio (CAR) and the loan-to-deposit ratio (LTDR) are widely recognized as critical indicators of financial performance. Research conducted by Chiyengerere (2021) and Munangi (2020) confirms the positive impact of capital adequacy on profitability. For instance, Chiyengerere (2021) utilized a fixed effects model alongside Panel EGLS (cross-section SUR) and found that risk factors, including CAR and liquidity ratios, significantly influence bank performance. This study reinforces the notion that effective risk management practices can enhance profitability, aligning with other research that underscores the importance of managing financial risk. Munangi (2020) examined the negative correlation between credit risk, specifically non-performing loans (NPLs), and financial performance using panel data techniques, including pooled ordinary least squares (OLS), fixed effects, and random effects estimators. This further illustrates how inadequate credit risk management can lead to diminished profitability. Notably, Munangi (2020) also indicates that excessive capital may adversely affect returns, complicating the relationship between capital adequacy and profitability. This finding aligns with the conclusions of Razermera et al. (2024) and Munangi and Sibindi (2020), while emphasizing a direct focus on capital adequacy as a mitigating factor. The study supports the growing consensus that a robust capital base is essential for bank stability, yet it cautions that excessively high capital adequacy ratios could hinder returns. Additionally, Chin'Anga (2015) conducted a panel regression analysis from 2002 to 2013, examining credit risk management in four major South African banks, and found that both capital adequacy and NPLs were critical determinants of profitability.

Bank Size: Several studies, including those by Babatunde et al. (2020) and Munangi (2020), indicate that smaller banks are more vulnerable to credit risk than larger banks. Larger banks can capitalize on economies of scale, leading to more effective risk management. This suggests that a bank's size significantly influences how risk affects profitability.

Operational and Liquidity Risks: From 2012 to 2018, Chenga et al. (2020) used Smart PLS-SEM to study the interactions between credit risk, operational risk, liquidity risk, and profitability. Their research found a positive relationship between liquidity risk and profitability, while operational risk negatively impacted profitability.

GENERAL HYPOTHESES

H_1: The effect of liquidity risk on ROE differs significantly between low-risk and high-risk economic regimes.

H_2: The impact of credit risk on ROE varies across different economic regimes.

H_3: The influence of exchange rate risk on ROE is contingent upon the prevailing economic regime.

H_4: The effect of inflation risk on ROE is regime-dependent, with varying impacts during stable and volatile periods.

METHODS

Data Source

Historical time series data from 2000Q1 to 2024Q4 on ROE, liquidity risk, credit risk, exchange rate risk, and inflation risk was obtained from the World Bank and the South African Reserve Bank (SARB).

Variables Description

Dependent Variable

ROE (Return on Equity): A key indicator of bank performance, ROE measures the net income returned as a percentage of shareholders' equity. It reflects how effectively a bank uses equity capital to generate profits. A higher ROE indicates greater efficiency in generating returns for investors.

Independent Variables (Risk Factors)

Liquidity Risk (LR): Liquidity risk, measured by the Loan-to-Deposit Ratio (LDR), reflects a bank's ability to meet its short-term obligations. It occurs when a firm cannot fulfil its short-term financial commitments due to a mismatch between liquid assets and liabilities (see Mohamed and Onyiego 2018; Harb et al. 2023). For banks, this risk may manifest itself as the inability to secure funding or sell assets quickly at a reasonable price. Liquidity risk is crucial for financial stability, especially during financial stress, and its impact on a bank's ROE is expected to vary with economic conditions.

Credit Risk (CR): Credit risk is assessed by measuring Non-Performing Loans (NPLs) as a percentage of total loans, indicating the proportion of loans not being repaid. It refers to the potential for a borrower to default, leading to financial losses for the lender or investor (see Razermera et al. 2024). This risk arises from a borrower's inability or unwillingness to repay the debt. It is crucial for lenders, including banks and financial institutions. The effect of credit risk on a bank's ROE is expected to vary based on economic conditions.

Exchange Rate Risk (ER): ZAR/USD volatility measures exchange rate risk, which arises from fluctuations affecting a bank's foreign currency assets and liabilities. This risk represents the potential for losses due to changes in exchange rates, particularly for companies in international trade or investment, as fluctuations can influence profitability and asset values. The impact of exchange rate risk on a bank's ROE is expected to vary based on economic conditions.

Inflation Risk (IR): Inflation risk is assessed using Consumer Price Index (CPI) inflation rates, which indicate the overall rise in prices. This risk highlights the decrease in purchasing power, potentially diminishing the real value of financial assets and income. Banks may experience varying impacts on profitability based on their ability to adjust interest rates in response to inflation (Tan and Floros 2012). Thus, the influence of inflation risk on ROE is expected to vary across different economic regimes.

Stationarity Tests: ADF and PP

Before model estimation, we assess the stationarity of the time series data using the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller 1979) and the Phillips-Perron (PP) test (Phillips and Perron 1988) to prevent spurious regressions. The test equation is:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{k} \delta\, i^{\Delta} Y_{t-i} + \epsilon_t \tag{1}$$

where the null hypothesis H_0 is that the series has a unit root (i.e., it is non-stationary).

Phillips-Perron (PP) Test: The PP test improves the ADF test by correcting for serial correlation and heteroskedasticity in the error terms, without requiring lagged difference terms. It evaluates the same null hypothesis as the ADF test.

Both tests will confirm the stationarity of each variable (ROE, LR, CR, ER, IR). If any variable is non-stationary at levels but stationary at first difference (I(1)), appropriate transformations will be applied.

The Johansen Cointegration Test

The Johansen Cointegration Test assesses the long-run equilibrium relationship between non-stationary variables integrated in the same order, usually I(1). Since unit root tests (ADF and PP) confirmed that all variables in this study (ROE, LR, CR, ER, and IR) are I(1), the Johansen test is suitable for investigating a stable long-term relationship among these variables.

The Johansen method relies on a Vector Error Correction Model (VECM), which extends the VAR model to I(1) variables. It offers two test statistics to identify the number of cointegrated relationships (r):

Trace Statistic – Tests the null hypothesis that the number of cointegrating vectors is ≤ r against the alternative r ≥ 1.

Maximum Eigenvalue Statistic – Tests the null hypothesis of r cointegrating vectors against the alternative of r + 1.

Hypotheses:

- H_0 (Null): No cointegration exists among the variables.
- H_1 (Alternative): One or more cointegrating relationships exist.

Markov Switching Means Vector Autoregressive (MSM-VAR)

This study employs the Markov Switching Means Vector Autoregressive (MSM-VAR) model to investigate the regime-dependent relationship between risk management factors and bank performance in South Africa. Economic relationships can undergo structural breaks and nonlinearities due to regime changes, such as financial crises or economic booms. As a result, risk-return dynamics in the banking sector are expected to differ across various economic phases. The model transitions between regimes based on the current economic state, considering structural changes in the relationship between risk factors and bank performance. The dependent variable is ROE, which measures bank performance. The independent variables (LR, CR, ER, and IR) are expected to behave differently in high-risk versus low-risk regimes. Effective management of risks (liquidity, credit, market, and macroeconomic) directly influences bank performance (Bessis, 2011).

The general form of the MSM-VAR(1) model can be specified as:

$$Y_t = \mu S_t + \Phi S_t Y_{t-1} + \epsilon_t \tag{2}$$

where:

Y_t = vector of endogenous variables at time t (ROE, LR, CR, ER, IR)
μS_t = regime-dependent intercept term
ΦS_t = regime-dependent autoregressive coefficient matrix
S_t = unobserved state variable governed by a first-order Markov chain with a finite number of regimes (e.g., two regimes: high-risk and low-risk regimes)

$\epsilon_t \sim N(0, \Sigma s_t) =$ regime-dependent error term

The state variable S_t follows a Markov process where the probability of transitioning between regimes depends only on the current regime:

Where are the transition probabilities from state i to state j.

In the context of this study:

- Regime 1 may represent a stable or low-risk environment.
- Regime 2 may represent a crisis or high-risk environment.

Thus, the relationship between risk variables and ROE is allowed to differ across these regimes.

RESULTS AND DISCUSSION

Descriptive Statistics

Table 1 summarizes all variables used in this study. The average ROE is 14%, with a standard deviation of 5.92%, indicating moderate variability. A positive skewness of 0.62 shows that some banks significantly outperform others. The kurtosis value of 3.26 suggests a distribution that is nearly normal but has a heavy tail. The Jarque-Bera statistics indicate a slight deviation from normality, with a p-value of less than 0.05.

Liquidity risk had an average value of 16.30, indicating a moderate level of risk across the sample. The standard deviation of 4.31 shows some variation in liquidity risk among the observations. The negative skewness of -0.89 indicates that most observations are clustered at the higher end, with a few extremely low values. Additionally, a kurtosis value of 3.56 suggests a leptokurtic distribution characterized by a sharper peak and heavier tails compared to a normal distribution. This finding is further supported by the Jarque-Bera statistic, which reveals a significant departure from normality.

Table 1. A Summary of Descriptive Statistics

	ROE	LR	CR	ER	IR
Mean	14.19213	16.29929	3.518000	85.37510	115.0518
Median	14.05752	17.02667	3.550000	81.46500	110.9800
Maximum	28.91479	22.09582	5.900000	108.9900	176.9000
Minimum	4.570380	2.871920	1.100000	64.68000	58.14000
Std. Dev.	5.915355	4.313345	1.221804	11.86229	38.04785
Skewness	0.616236	-0.892524	-0.036508	0.342619	0.121627
Kurtosis	3.264140	3.564015	2.356829	1.890415	1.553033
Jarque-Bera	6.619819	14.60212	1.745834	7.086378	8.970352
Probability	0.036519	0.000675	0.417731	0.028921	0.011275
Sum	1419.213	1629.929	351.8000	8537.510	11505.18
Sum Sq.	23605.81	28408.58	1385.420	742821.4	1467008.
Sum Sq. Dev.	3464.151	1841.889	147.7876	13930.67	143316.3
Observations	100	100	100	100	100

Source: Authors' Estimation using Eviews 14.

Credit risk has a mean of 3.52, indicating that it is relatively contained. The standard deviation of 1.22 shows variability in risk levels. A skewness of -0.04 indicates a nearly symmetric distribution around the mean. A kurtosis of 2.36 suggests lighter tails than a normal distribution. The Jarque-Bera test indicates that credit risk is probably normally distributed since the p-value exceeds 0.05.

The average exchange rate risk is 85.38, with a standard deviation of 11.86, indicating considerable variability. Positive skewness of 0.34 suggests fewer extremely high values compared to ROE. The kurtosis of 1.89 indicates a platykurtic distribution, which is flatter than normal. The Jarque-Bera statistic shows a slight deviation from normality, with a p-value of less than 0.05.

Inflation risk has an average value of 115.05, indicating significant overall risk. The highest standard deviation of 38.05 reflects considerable variability. A skewness of 0.12 shows that the distribution is nearly symmetrical, with a slight inclination towards higher values. The kurtosis of 1.55 suggests a platykurtic distribution, characterized by lighter tails and a lower peak compared to a normal distribution. The Jarque-Bera statistics indicate a significant deviation from normality.

Root Test Results

Both the ADF and PP unit root tests were conducted to assess the stationarity of the variables *ln*ROE, *ln*LR, *ln*CR, *ln*ER, and *ln*IR. Stationarity is crucial for validating inferences in time-series econometric models, including MSM-VAR. The results of the tests are presented in Table 2.

Table 2. ADF and PP Unit Root Test Results

Variables	ADF Test			PP Test		
	Critical Value (1%)	t-statistic	Status	Critical Value (1%)	t-statistic	Status
*ln*ROE	-3.499167	-5.374720***	I(1)	-3.498439	-10.87213***	I(1)
*ln*LR	-3.499167	-7.036089***	I(1)	-3.498439	-14.46061***	I(1)
*ln*CR	-3.499167	-5.378499***	I(1)	-3.498439	-12.89015***	I(1)
*ln*ER	-3.498439	-9.088144***	I(1)	-3.498439	-9.083835***	I(1)
*ln*IR	-3.499167	-3.459281***	I(1)	-3.498439	-13.73425***	I(1)

Note: (***), (**), and (*) indicate significant at 1%, 5% and 10%. All the variables are log linearized.
Source: Authors' Estimation using EViews 14.

The ADF and PP unit root tests indicate that all variables (*ln*ROE, *ln*LR, *ln*CR, *ln*ER, and *ln*IR) are non-stationary at their levels but become stationary after first differencing (I(1)). The t-statistics are significantly lower than the 1% critical values, allowing rejection of the null hypothesis of a unit root at the 1% significance level for all variables.

Cointegration Test Results

A cointegration test determines if a long-term relationship exists between variables in a multivariate time series. It includes the trace test and the Max-eigenvalue test, which assess the number of cointegrated equations. The optimal lag length was determined using several selection criteria. The AIC and the LR test favoured lag 5, while FPE and HQ identified lag 2 as optimal. Lag 2 was selected for the cointegration analysis due to its balance between model fit and simplicity. The results are presented in Table 3.

Table 3. Johansen cointegration tests

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized		Trace	0.05	Prob.**
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Critical Value
None *	0.337060	73.39818	69.81889	0.0252
At most 1	0.164185	33.52438	47.85613	0.5279
At most 2	0.100331	16.12763	29.79707	0.7033
At most 3	0.033391	5.872026	15.49471	0.7106
At most 4	0.026225	2.577800	3.841465	0.1084
Unrestricted Cointegration Rank Test (Max-eigenvalue)				
Hypothesized		Max-Eigen	0.05	Prob.**
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Critical Value
None *	0.337060	39.87380	33.87687	0.0086
At most 1	0.164185	17.39676	27.58434	0.5460
At most 2	0.100331	10.25560	21.13162	0.7203
At most 3	0.033391	3.294226	14.26460	0.9252
At most 4	0.026225	2.577800	3.841465	0.1084

Trace test and Max-eigenvalue test indicates 1 cointegrating equation(s) at the 0.05 level * denotes rejection of the hypothesis at the 0.05 level **MacKinnon-Haug-Michelis (1999) p-values
Source: Authors' Estimation using Eviews 14

The null hypothesis of "no cointegration" is rejected at the 0.05 significance level because the Trace statistic (73.39818) exceeds the critical value (69.81889) and the p-value (0.0252) is less than 0.05. This indicates one cointegrating equation, as the subsequent null hypothesis ("At most 1 cointegrating equation") is not rejected (p-value = 0.5279). The null hypothesis for "no cointegration" is also rejected at the 0.05 level based on the Max-Eigenvalue statistic, which is 39.87380, greater than the critical value of 33.87687, and a p-value of 0.0086, which is less than 0.05. Like the Trace test, the Max-Eigenvalue test suggests one cointegrating equation, since the "At most 1 cointegrating equation" hypothesis is not rejected (p-value = 0.5460). Both the Trace and Max-Eigenvalue tests indicate a single cointegrating relationship at the 0.05 significance level, suggesting a stable long-term relationship between the variables in the system.

MSM-VAR

Following Agyemang-Badu et al. (2024) and Pamba (2024), this study employs a two-regime model. Regime one is characterized by a Stable Environment, while regime two represents a Crisis Environment.

Table 4. MSM-VAR

	C	LR	CR	ER	IR
	Regime 1 (Stable Environment)				
ROE	3.088640	-0.063834	0.782946	0.016883	0.051853
	(6.56109)	(0.12608)	(0.39619)	(0.03715)	(0.03525)
	[0.47075]	[-0.50631]	[1.97617]	[0.45448]	[1.47122]
	Regime 2 (Crisis Environment)				
ROE	-14.31430	2.167812	-2.277629	0.013330	0.016585
	(11.0692)	(0.31958)	(0.68506)	(0.06387)	(0.03929)
	[-1.29316]	[6.78327]	[-3.32470]	[0.20871]	[0.42214]
	Common				
ROE(-1)	0.379071	ROE(-2)	0.506368	SIGMA-ROE	2.256320
	(0.10013)		(0.09749)		(0.35145)
	[3.78569]		[5.19422]		[6.42007]
	Transition Matrix Parameters				
Variable	Coefficient	Std. Error	z-Statistic	Prob.	
P11-C	3.374666	0.788031	4.282400	0.0000	
P21-C	-2.279681	0.694249	-3.283663	0.0010	
Determinant resid covariance		3.732026			
Log likelihood		-191.3081			
Akaike info criterion		4.210370			
Schwarz criterion		4.606028			
Number of coefficients		15			

Note: ( ) represents standard error, [ ] represents test statistics
Source: Authors' Estimation using Eviews 14.

The relationship between liquidity risk and bank ROE among South African banks shows a clear regime-dependent pattern. In Regime 1 (stable economic conditions), liquidity risk has a negative but statistically insignificant effect on ROE (coefficient = –0.0638; z = –0.5063; p = 0.4708), indicating that under normal economic conditions, liquidity risk does not materially influence bank profitability. In contrast, Regime 2 (crisis conditions) reveals a strong positive and statistically significant relationship between liquidity risk and ROE (coefficient = 2.1678; z = 6.7833). This indicates that during financial stress, higher liquidity risk exposure is associated with improved profitability. This outcome can be explained by a crisis-driven risk re-pricing mechanism, where banks maintaining higher loan-to-deposit ratios can charge higher risk premiums on lending. These elevated lending spreads, combined with wider interest margins during uncertainty, can outweigh liquidity costs and lead to higher returns on equity. Additionally, the crisis regime reflects a strategic intermediation and market reallocation channel, where banks extending credit more aggressively during downturns consolidate market share as risk-averse institutions reduce lending. This counter-cyclical behaviour strengthens income generation and enhances profitability in stressed conditions. These findings align with the broader empirical literature. Siddique et al. (2022) document a weaker or negative relationship between liquidity risk and bank performance in South Asia under stable conditions, highlighting the limited role of liquidity risk in non-stress environments. In contrast, Chenga et al. (2020) find that proactive liquidity management improves profitability in South African banks, particularly during adverse conditions, supporting the view that liquidity risk becomes more significant under stress. Overall, the results provide strong evidence of state-dependent effects in the liquidity risk–profitability nexus, demonstrating that the impact of liquidity risk on ROE varies significantly across economic regimes. While liquidity risk is largely neutral in stable periods, it becomes a key determinant of profitability during crises through its influence on pricing behaviour and competitive dynamics in the banking sector.

The relationship between credit risk and bank ROE in South African banks shows a clear regime-dependent pattern, emphasizing the importance of economic context in determining risk–return dynamics. In regime 1 (stable economic conditions), credit risk positively affects ROE (coefficient = 0.7829; Z = 1.9762). This suggests that during economic stability, banks may benefit from high credit risk through risk-based pricing strategies that increase interest margins. This aligns with findings by Fombang and Maseko (2024), who report a similarly positive relationship in the South African banking sector under stable conditions. Conversely, in regime 2 (crisis conditions), the relationship shifts: Credit risk negatively impacts ROE (coefficient = –2.2776; z = –3.3247). This indicates that during financial stress or economic downturns, increased credit risk, evidenced by higher default rates and non-performing loans, harms bank profitability. Studies by Siddique et al. (2022) and Fadun and Silwimba (2023) support these findings, noting similar negative effects in South Asia and Nigeria, respectively. Additionally, Munangi and Sibindi (2020) document the adverse effects of credit risk on profitability during turbulent periods in South Africa. These results underscore that credit risk management is crucial to bank performance in South Africa, with its effects significantly influenced by macroeconomic conditions. While greater credit exposure may enhance returns in stable times, it can quickly diminish profitability during downturns. The consistency of these findings with existing literature highlights the urgent need for dynamic credit risk strategies, including forward-looking provisioning, credit scoring adjustments, and stress testing, to adapt to changing economic regimes. Overall, the findings emphasize the necessity of regime-sensitive risk management practices to ensure long-term profitability and financial stability. South African banks must monitor economic signals and adjust credit exposure accordingly to maintain resilience throughout the business cycle.

The analysis shows a positive yet statistically insignificant relationship between exchange rate risk and ROE across both economic regimes. In Regime 1 (stable conditions), the coefficient is 0.0169 ($z = 0.4545$), and in Regime 2 (crisis conditions), it is 0.0133 ($z = 0.2087$). The low Z-statistics indicate that exchange rate risk does not significantly affect bank profitability. This suggests that South African banks may be insulated from exchange rate volatility, potentially due to effective hedge strategies, regulatory limits on foreign currency exposure, or low dependence on foreign-denominated assets and liabilities. The findings align with Bartram et al. (2010), who noted the insignificant effects of exchange rate volatility on firm-level profitability in emerging markets. Overall, exchange rate risk has a minimal influence on ROE in South Africa, indicating that other financial risks, such as credit and liquidity risk, are more critical determinants of bank profitability. Banks should manage currency risk prudently while focusing on more impactful, regime-sensitive risks.

The relationship between inflation risk and bank ROE in South African banks is positive but statistically weak across both economic regimes. In Regime 1 (stable conditions), inflation risk has a marginally positive effect on ROE (coefficient = 0.0519; $z = 1.4712$), just falling short of significance. In Regime 2 (crisis conditions), the effect remains positive (coefficient = 0.0166), but is statistically insignificant ($z = 0.4221$), indicating a limited influence on bank profitability during economic stress. These results suggest that while inflation may have some potential to enhance bank returns, particularly through interest rate adjustments and increased lending margins, its impact is not strong or consistent across regimes. This weak and regime-insensitive relationship implies that banks can pass on inflation-related costs to borrowers, but the benefits do not significantly affect profitability, especially during crises when credit demand may decline. These findings align with Tan and Floros (2012), who identified a positive link between inflation and bank profitability in China, indicating that banks in emerging markets might exploit inflationary conditions to boost returns. However, the lack of statistical strength in the South African context suggests that other macroeconomic variables or institutional factors may influence this relationship. In conclusion, while inflation risk may provide some upside to bank profitability, particularly during stable periods, it does not consistently or significantly drive ROE in South Africa. This underscores the need for bank managers and analysts to regard inflation risk as a secondary performance driver and to integrate it into a broader, regime-aware risk management strategy for sustainable profitability.

ROE(-1) and ROE(-2): Both lagged values of ROE show strong, positive, and statistically significant coefficients, indicating that past performance effectively predicts current performance, a common trend in the banking sector.

SIGMA-ROE: The coefficient of 2.256320 is statistically significant, indicating volatility in ROE and is crucial for evaluating risk management practices.

P11-C (Transition from Regime 1 to Regime 1): The coefficient of 3.374666 is significant, with a z-statistic of 4.282400, indicating a strong tendency to remain in the stable regime.

P21-C (Transition from Regime 2 to Regime 1): The coefficient of -2.279681 is significant, with a z-statistic of -3.283663, suggesting that the transition from high-risk to low-risk environments is less likely.

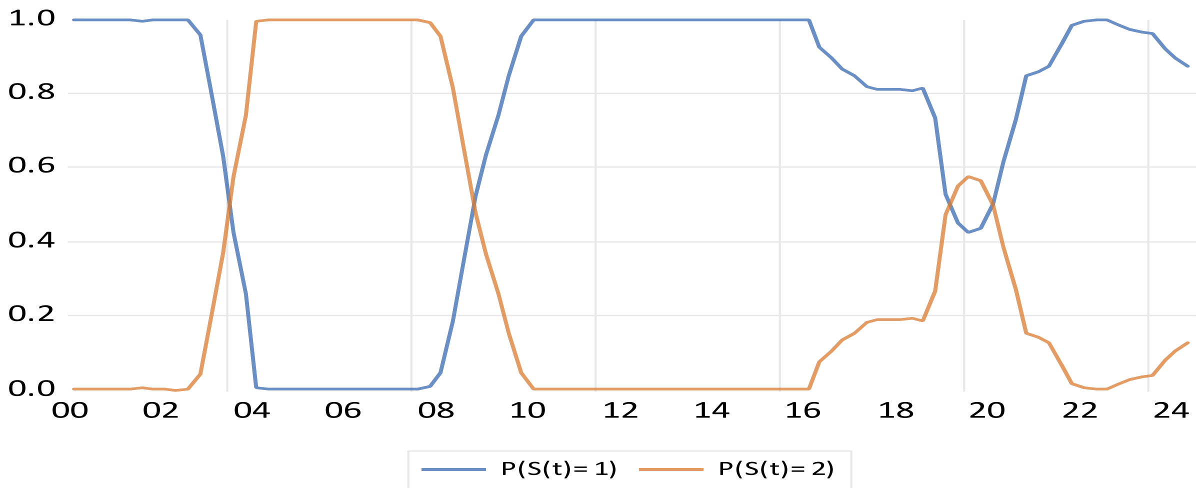
Table 5. Summary of Hypothesis Testing

Hypothesis	Result	Evidence
H_1: Liquidity risk's effect on ROE is regime-dependent	Supported	Positive and significant in crisis; insignificant in stability
H_2: Credit risk's impact on ROE varies by regime	Supported	Positive in stable periods; significantly negative in crises
H_3: Exchange rate risk has regime-dependent impact	Not supported	Insignificant in both regimes
H_4: Inflation risk effect is regime-dependent	Not supported	Statistically insignificant in both regimes

Probability Plot

In Figure 1, the Smoothed Regime Probabilities show the likelihood of the economy being in either

Regime 1 (stable) or Regime 2 (crisis) at any moment.

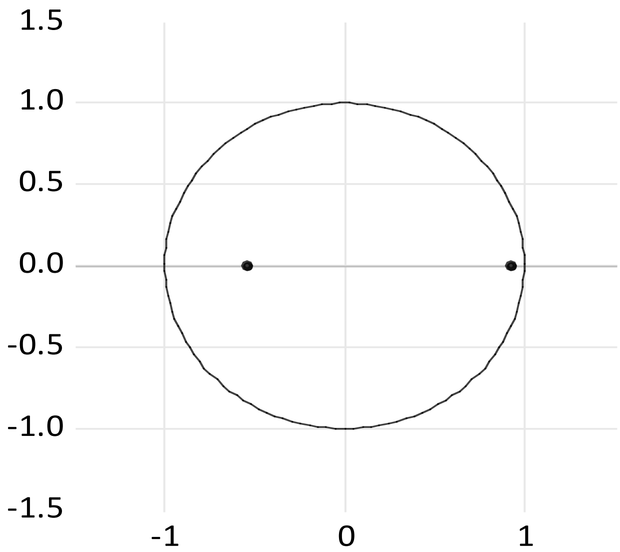


Source: Authors' Estimation using Eviews 14.
Figure 1. ROE Smoothed Probabilities in the MSM-VAR model.

There is strong evidence of regime switching in the system. On average, it spends 72% of its time in Regime 1 (stable) and 28% in Regime 2 (crisis). While stable environments predominate, crisis periods are statistically significant. Regime 1 (stable) is more frequent and certain, as indicated by a high transition probability (P(1|1) = 0.967). The clear transitions between regimes demonstrate that the model effectively distinguishes between them. Non-normality suggests that regime shifts occur abruptly, which is beneficial for planning policy responses and conducting stress tests. Overall, the analysis of regime probabilities and transition dynamics provides insights into the system's behaviour, aiding decision-making for optimal risk management strategies.

Inverse Root of AR

The roots of a characteristic polynomial test the stability of a VAR model, specifically ROE with two lags and multiple exogenous variables. In VAR or MSM-VAR models, all the roots must lie within the unit circle (modulus less than 1) for dynamic stability. Figure 2 illustrates the inverse roots of the AR characteristic polynomial.



Source: Author`s calculation using Eviews 14.
Figure 2. ROE Inverse Roots of AR Characteristic Polynomial

All the roots lie within the unit circle, confirming that the VAR model meets the stability condition. A stable VAR model leads to meaningful impulse response functions and reliable forecasting. Conversely, unstable systems can exhibit nonstationary behaviour, rendering their inferences invalid. Thus, shocks to the system will diminish over time rather than escalate.

Transition Probability

The transition probability matrix shows the likelihood of switching between regimes, like stable and crisis environments. The expected duration indicates how long the system typically remains in each regime before transitioning.

Table 6. Transition Probability.

South Africa	Regime 1	Regime 2
Regime 1	0.966903	0.033097
Regime 2	0.092820	0.907180
Durations	30.21452	10.77356

Source: Authors' Estimation using EViews 14

$P(1|1) = 0.9669$: There is a 96.69% probability that the system remains in Regime 1 (stable environment) if it is currently in Regime 1. $P(2|1) = 0.0331$: The chance of switching from Regime 1 to Regime 2 is 3.31%. $P(2|2) = 0.9072$: If the system is in Regime 2 (a crisis environment), there is a 90.72% probability that it will remain there. $P(1|2) = 0.0928$: There is a 9.28% chance of switching back to Regime 1 from Regime 2. Both regimes exhibit high persistence, with Regime 1 being slightly more persistent than Regime 2. The model reflects realistic dynamics: stability lasts longer, while crises are more likely to revert. Risk strategies should be tailored to the current regime. Banks should focus on credit risk management during stable periods and maintain liquidity buffers during crises. Policymakers and banks can use the high persistence of Regime 1 to develop long-term strategies but must remain agile to respond to potential transitions to Regime 2. Early warning systems based on macro indicators could aid in detecting transitions from Regime 1 to Regime 2, despite their low likelihood.

CONCLUSION

This study investigates the regime-switching dynamic impact of risk management on bank profitability in South Africa. Using an MSM-VAR model, it analyses how key financial risks such as liquidity, credit, the exchange rate, and inflation affect bank ROE across different economic environments. The findings indicate that credit and liquidity risks have significant regime-dependent effects on bank profitability. Specifically, credit risk positively influences ROE during stable periods but negatively impacts it during crises, illustrating its dual role based on macroeconomic conditions. Liquidity risk, insignificant in normal times, becomes a critical driver of profitability during high-risk regimes, highlighting the importance of liquidity management in stressful situations. Conversely, exchange rate and inflation risks exhibit positive but statistically insignificant effects in both regimes, suggesting limited influence on ROE in the South African banking context. These results emphasize the need for adaptive risk management strategies that respond to evolving economic conditions. Banks should enhance their credit risk frameworks and maintain strong liquidity buffers, especially in anticipation of financial downturns. Additionally, regulators and policymakers should adopt regime-sensitive approaches to supervision and macroprudential regulation. Overall, the study contributes to the literature on financial risk and performance by shedding light on the non-linear and state-dependent nature of risk–return relationships in emerging markets. It provides practical insights into improving the resilience and profitability of the banking sector in South Africa.

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Data Available Statement
The data used in this study were sourced from the South African Reserve Bank and the Johannesburg Stock Exchange. These data are publicly accessible through their respective databases, subject to applicable access conditions.
Data can be accessed at:
South African Reserve Bank: https://www.resbank.co.za
Johannesburg Stock Exchange: https://www.jse.co.za

Conflict of interest
The author declares no conflict of interest.

AI Tools Statement
AI-based language editing tools were used to improve grammar and clarity. All intellectual content, interpretation, and conclusions are solely the responsibility of the author.

Author contribution (as applicable):
All aspects of the study, including conceptualization, methodology, analysis, and writing, were conducted solely by Dumisani Pamba.

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