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The Stability of the Financial Cycle: Insights from a Markov Switching Regression in South Africa

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Abstract: The stability of the financial cycle is paramount for the effective formulation and implementation of macroprudential policy in South Africa. The South African Reserve Bank (SARB) and the Prudential Authority strive to mitigate excessive fluctuations in the financial cycle, recognising that a stable cycle provides more reliable signals for financial sector activity and anchors macroprudential policy decisions. However, the tightening of macroprudential policy by the SARB and the Prudential Authority during the post-2009 recovery period, despite mild signs of recovery from the global financial crisis, raises concerns about the stability of the South African financial cycle. This study aims to construct a financial cycle volatility index to assess its stability and identify the key macroeconomic drivers of financial instability in South Africa. Employing monthly data from 1970 to 2024, the study utilises a dynamic conditional correlation model and a Markov switching regression model to analyse the relationship between macroeconomic variables and financial stability. The findings reveal heightened financial cycle volatility around crisis periods and demonstrate that macroeconomic variables such as exchange rate fluctuations, price level changes, and implementing monetary and macroprudential policies can significantly increase financial instability. These results suggest a need for proactive and aggressive macroprudential policy measures in the years preceding potential crises. Moreover, the study's findings emphasise the importance of considering macroeconomic conditions when calibrating financial cycle policies.

Keywords: financial cycle; financial stability; macroprudential policy; Markov switching regression

JEL Classification: E32; E44; E52; E58

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1. Introduction

A stable financial cycle is pivotal for maintaining financial stability and is essential for formulating and implementing effective macroprudential policy. The financial cycle measures systemic risk over time (Jing et al., 2022; O'Brien & Velasco, 2025). When the financial cycle is stable and authorities have successfully managed it, systemic risk is mitigated, which in turn contributes to a stable financial environment (Meuleman & Vander Vennet, 2020). A stable financial cycle ensures that shifts in macroprudential policy accurately reflect underlying developments within the financial system, which in turn increases the credibility of prudential authorities (Zhang et al., 2020). Conversely, an unstable financial cycle can lead to misleading signals about financial sector conditions, making macroprudential policy adjustments less reliable as indicators of actual financial sector developments (Nyati et al., 2021). Due to its critical role, many authorities consider the financial cycle a primary anchor for financial stability and macroprudential policy. This study is motivated by the above critical roles of the financial cycle in maintaining financial stability and shaping macroprudential policies. A thorough examination of the financial cycle's stability is essential to identify potential vulnerabilities, mitigate systemic risks, and enhance the effectiveness of policy measures to safeguard the financial system.

Economic theory suggests that systemic risk accumulates during the expansion phase of the financial cycle and materialises into financial crises during downturns (Borio et al., 2020a; Das et al., 2022; Danthine, 2012). During expansions, financial agents often become overly optimistic, leading to increased borrowing, lending, and investment in riskier assets, which appear less dangerous in a booming economy. In downturns, however, heightened debt levels result in higher default rates, and investments in riskier assets frequently lead to substantial losses, potentially triggering financial crises. Recognising these dynamics, the South African Reserve Bank (SARB) and the Prudential Authority (PA) aim to stabilise the financial cycle to enhance financial stability by mitigating excessive credit and asset price growth (Nyati et al., 2024). In line with this approach, the Committee on the Global Financial System (CGFS) suggests that macroprudential policy should respond to changes in the financial cycle (Forbes, 2021). Specifically, it recommends tightening macroprudential measures during a financial boom in a strong real economy, unchanging macroprudential measures during a downturn without a crisis, and releasing policy buffers during a financial expansion in a weak economy (Mishra, 2019). Similarly, macroprudential buffers should also be released in a downturn coupled with a weak economy, particularly during a crisis.

Theoretical and policy perspectives assume that each financial expansion foreshadows a potential crisis in the subsequent downturn. Moreover, following the CGFS guidelines, one would expect macroprudential policy adjustments to align with financial cycle developments. However, not all financial cycle booms pose a threat (Borio et al., 2018, 2020b), and not all macroprudential policy changes correspond to phases of the financial cycle. In South Africa, for example, between 2002 and 2007, South African banks' credit extension increased at an average annual rate of 19.2%, a sharp contrast to the late 1990s, when credit growth hovered around 0% before reaching approximately 15% by the end of 2007 (*see* Figure 1). This period of rapid credit expansion coincided with favourable economic conditions, with output growing at an annual average of 4.5% and inflation remaining within the target range of 3% to 6%. Notably, no internal financial crisis occurred in South Africa during this period. Absent the global financial crisis originating in the United States, credit and economic growth would likely have continued, improving the living standards for many South Africans (Hollander & Havemann, 2021).

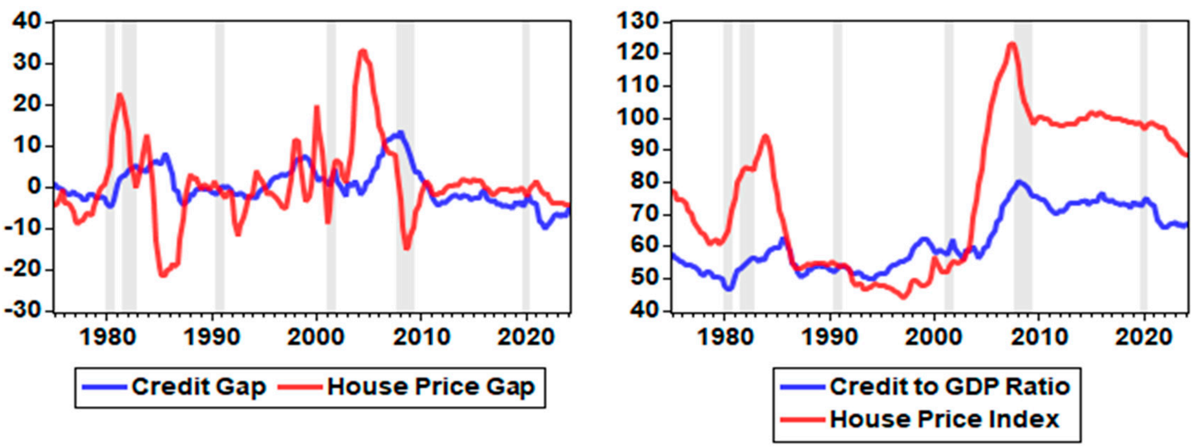

Figure 1. Evolution of credit and housing markets in South Africa. *Source:* own estimates.

Another example is the 2007–2009 global financial crisis to 2019, during which South Africa's financial cycle showed only mild signs of recovery without a discernible boom (*see* Figure 1). Economic conditions suggested that macroprudential policy should have been relaxed or, at the very least, left unchanged. However, the SARB and PA continued to tighten macroprudential policy tools, such as the countercyclical capital buffer (CCyB), capital conservation buffer (CCB), and capital requirements. For instance, CCyB requirements were introduced in January 2016, and the CCB progressively increased from 0.625% in 2017 to 1.25% in 2018 and 2.5% in 2019 (Magubane, 2024a). Additionally, even as the financial cycle had yet to recover from the impacts of the COVID-19 pandemic, the Pillar 2A minimum capital requirement was reinstated to 1% from 0% in January 2022 (Magubane, 2024a).

This phenomenon, where not all financial cycle booms are detrimental, implies that the financial cycle can exhibit stability even during expansion phases. However, strict actions taken by the SARB and the PA in South Africa between 2018 and 2022 reflect an assumption of inherent instability within the financial cycle. This creates a notable contradiction where macroprudential policy tightening does not always align with financial cycle expansion. This raises critical research questions: How stable is the financial cycle across its various phases? What are the key determinants of this stability? To address these questions, this study's objective is to construct a dynamic conditional correlation (DCC) model to develop the financial cycle volatility index (FCVIX), which is used to measure the stability of the financial cycle over time. However, the point of departure for the study is to apply a Markov Switching Autoregression (MSAR) model to examine the drivers of the FCVIX. The financial cycle is represented through the total domestic credit, the house price index, and the all-share price index, with monthly data from 1970-M1 to 2023-M4. Explanatory variables include the macroprudential policy index (MPI), policy rate (PR), real GDP (Y), consumer price index (CPI), and the real effective exchange rate (ER).

2. Literature Review

The stability of the financial cycle is essential for two reasons. The financial cycle traces systemic risk's evolution over time and signals when to activate and deactivate macroprudential policy. The financial cycle often reflects the accumulation of systemic risk as credit grows rapidly and asset prices inflate beyond sustainable levels, followed by market corrections that usually manifest as crises (Adarov, 2023). Risk in this context refers to systemic risk, which is the risk of threats to financial stability that can impair the functioning of a significant portion of the financial system, resulting in adverse effects on the broader economy (Agénor & Pereira da Silva, 2023; Freixas, 2018; Galati & Moessner, 2018). This type of risk comprises two distinct aspects: the cross-sectional and time-varying dimensions (Mieg, 2022). The cross-sectional dimension focuses on the distribution of risks across different institutions or sectors at a given time, highlighting systemic vulnerabilities due to interconnectedness or exposure concentrations. In contrast, the time-varying dimension examines how risks evolve, emphasising cyclical patterns and the impact of macroeconomic conditions on the overall risk profile. The financial cycle is primarily concerned with the time-varying aspect of systemic risk. In this dimension, systemic risk often appears as cyclical deviations in credit, asset prices, and leverage from long-term trends, leading to financial imbalances (Adarov, 2022; Sato et al., 2019). On the other hand, the financial cycle is measured as the co-movement of cyclical fluctuations in the growth of credit and asset prices (Tian, 2024). The definition of the financial cycle and systemic risk shows that these concepts are closely interconnected.

For example, the debt-deflation theory proposed by Fisher (1933) and the general theory proposed by Keynes (1936) were the first theoretical frameworks to emphasise that activity in financial markets could be characterised by financial booms followed by busts

(Ma et al., 2019). Fisher (1933) argued that this behaviour of financial markets affected the real economy through debt deflation. During a business cycle boom, financial markets are flooded with liquidity, searching for yield, which in turn triggers a rise in investments into riskier assets that seem safe during good times (Dimand, 2019). The increased investment in assets initiates a surge in asset prices, which, in turn, improves the net worth of businesses and enables them to acquire more debt to fund additional investments (Hryhoriev, 2024). The increased investments in riskier assets and rising debt levels build financial imbalances. The higher levels of debt, in turn, reduce currency deposits and the rate at which they occur due to an inflow of bank loan repayments. The contraction in currency deposits causes a slowdown in the velocity of money, reducing aggregate spending and shrinking the price level (Metrah, 2017). Furthermore, the fall in the price level will trigger an appreciation of debt in real terms, thereby causing a further fall in aggregate spending and further reducing the price level (Metrah, 2017).

Keynes (1936), on the other hand, argued that financial markets could affect real economic activity through the 'State of Credit', which is influenced by how much confidence lenders have in financing borrowers (Thakor & Merton, 2024). Lenders' confidence depends on their perceptions of how well borrowers' incentives are aligned with their own and, subsequently, how well secured borrowers' liabilities are. Keynes contended that a collapse in the confidence of either borrowers or lenders is enough to induce a downturn (Carlsson Hauff & Nilsson, 2020). A fall in either lenders' or borrowers' confidence reduces the amount of credit available in the economy, thereby reducing spending and, consequently, reducing aggregate output (Herreno, 2020; Angeletos & Lian, 2022). Indeed, recent evidence suggests that credit can either spur or retard aggregate spending (Kim & Mehrotra, 2022). In addition, evidence suggests that credit and output tend to move pro-cyclical with each other (Leroy & Lucotte, 2019). Put simply, credit and output rise and fall together. The predictions of the debt-deflation theory and the general theory were helpful in explaining the Great Depression; they became popular with scholars such as Gurley and Shaw (1955), Kindleberger (1978), Goldsmith (1969), McKinnon (1973), and Minsky (1977).

For instance, Minsky (1977) argued that the pro-cyclical nature of credit supply creates fragile financial systems and leads to financial crises. This is because, during credit expansion, economic agents accumulate more risk, which then becomes an ingredient for financial disruption (see Herrera et al., 2020). Kindleberger (1978), on the other hand, provided a historical account of how the mismanagement of money and credit creates financial fragility and causes financial disruptions, while Gurley and Shaw (1955) linked economic development and finance. According to economies could grow by accumulating more debt, provided proper debt management is in place. These scholars provided insight into how the strength or weakness of the financial system can affect economic conditions. However, these studies are theoretical and were overshadowed by the 'irrelevance theorem' of d.

Nevertheless, financial cycles lost favour for most postwar periods (Adarov, 2022). The main factor behind the decline in the popularity of financial cycles was the irrelevance theorem proposed by Modigliani and Miller (1958). The irrelevance theorem posited that capital financing did not affect a firm's value, which could bear on its ability to accumulate more capital and invest more (Modigliani & Miller, 1958). In contrast, a firm's value is determined by what the firm does with its profits (Al-Kahtani & Al-Eraij, 2018). This is because, according to Modigliani and Miller, when firms acquire debt to fund more investment, the value of outstanding equity falls as the selling of cash flows to debtholders lowers equity value. This implies that the gains from acquiring finance are offset by the cost of finance (Al-Kahtani & Al-Eraij, 2018). Hence, firms do not base their investment decisions on capital financing. Based on these arguments, it was accepted that since finance did not matter in a firm's decision to invest, it also did not affect the macroeconomy (Gersbach & Papageorgiou, 2024). Consequently, scholars became less concerned with studying financial factors and financial cycles. Financial cycles progressively disappeared from the macroeconomists' radar screen and became a sideshow to macroeconomic fluctuations (Drehmann et al., 2012).

In the late 1990s, other mature theories of financial cycles emerged from large macroeconomic models. For instance, Bernanke (1999) and Gertler and Karadi (2011) developed the financial–economic cycle theory, which stipulated that the macroeconomy depends on credit conditions. When credit conditions deteriorate, there may be substantial increases in bankruptcies, debt burdens, and bank failures, including a severe fall in asset prices. This sequence of events works to depress economic activity. Furthermore, Bernanke (1999) and Gertler and Karadi (2011) argued that the macroeconomy depends on the interaction of credit shocks with credit interventions. A financial crisis emerges during a disturbance in credit, which depresses the whole economy. In reaction to a financial crisis, central banks tightened monetary policy, causing banks to raise their lending standards, thereby improving credit conditions. As credit conditions improve, the economy is rescued from the crisis and enters an upward phase. These interactions offer a mechanism for how credit conditions cause business fluctuations.

Consistent with Bernanke (1999), Kiyotaki and Moore (1997) developed the credit cycle theory. In this framework, lenders cannot force borrowers to repay their debt; instead, lenders rely on several assets, such as land or buildings, to secure debt. Hence, assets have a dual role: (i) they affect credit constraints through variations in their prices; (ii) assets are part of the factors of production. Kiyotaki and Moore (1997) postulated that the dual role of assets implies that an increase in asset prices eases credit constraints and triggers an expansion in investment and production. Put differently, an increase in asset prices improves the net worth of companies, thereby causing them to acquire more credit, invest more, and produce more. Furthermore, the rise in production and investment stimulates demand for assets and further puts upward pressure on asset prices, accelerating credit accumulation, investment, and production (Bordalo et al., 2018). The conclusions of Kiyotaki and Moore (1997) suggest that the interaction between asset prices and credit constraints can amplify macroeconomic fluctuations and lead to large business cycles. Krishnamurthy and Muir (2017) reached a similar conclusion and found that credit constraints and asset prices can lead to large swings in the business cycle. These advances by Kiyotaki and Moore (1997) and Bernanke (1999) support the arguments of Keynes (1936) and Fisher (1933) by identifying channels through which financial cycles could affect the real sector.

The credit cycle and the financial–economic cycle theories had significant flaws. Borio et al. (2015) argued that these theories reduced the importance of financial cycles to nominal frictions that only marginally affect the speed of real activity adjustments to equilibrium in an otherwise stable economy. This has proved limiting as it ignored the role of financial cycles as instigators and drivers of fluctuations in real activity. Not surprisingly, as a result of the global financial crises of 2007/09 and the failure of the above theories to foresee it, research has emerged focusing on analysing financial cycles as "self-reinforcing interactions between perceptions of value and risk, attitudes towards risk, and financing constraints, which translate into booms followed by busts" (Borio, 2014). These studies include Schüler et al. (2020), Aldasoro et al. (2020), Coimbra and Rey (2024), Jordà et al. (2018), Bai et al. (2019), Strohsal et al. (2019), Potjagailo and Wolters (2023), and Qin et al. (2021), amongst others.

These studies focus on estimating financial cycles and analysing their stylised facts. They rarely examine the association between the financial cycle and systemic risk. Some studies have focused on advanced economies. For instance, Drehmann et al. (2012), Jordà et al. (2018), Strohsal et al. (2019), and Schüler et al. (2020) have examined the United States, United Kingdom, and Germany. Strohsal et al. (2019) found that the length of the financial cycle phases is roughly 15 years. Moreover, financial cycles in these economies are characterised by high amplitude, indicating sharp and volatile turning points. Indeed, financial cycles in advanced economies have been the primary source of global financial instability in recent years. International financial crises, such as the Asian Financial Crisis, Black Monday, the Dot-com Bubble Burst, the Global Financial Crisis, and the Euro-Zone Debt Crisis, among others, were triggered by peak turning points in these cycles. According to Borio (2014), a few years before each crisis, these financial cycles tend to enter zones of unsustainable development. Jordà et al. (2018) focused on 17 advanced economies and estimated that financial cycles last 2 to 32 years. However, the main contribution of their study was to show that U.S. monetary shocks drove variations in risk appetite along the financial cycle. Drehmann et al. (2012), focusing on the G7 countries, found that from 1990 onwards, financial cycles typically last up to 20 years but have sharp amplitude around turning points. These findings imply that financial cycle peaks tend to occur at or around times of financial crisis. Moreover, the study found that business cycle recessions coinciding with financial downturns tend to be deeper and longer-lasting. These findings suggest that financial cycles in advanced economies are characterised by instability, though the evolution of this instability takes time to manifest.

Some studies have focused on global financial cycles, combining both advanced and emerging market economies (see Bai et al., 2019; Adarov, 2022; Aldasoro et al., 2020; Ha et al., 2020; Claessens et al., 2011). Bai et al. (2019) concentrated on the United States and 23 emerging market economies. The main aim of their study was to examine the influence of variations in financial cycles, measured by spreads and stock prices. The study found that the duration of financial cycles was longer than that of business cycles. However, the study's point of departure was to show that the standard deviation of financial cycles in emerging market economies was more significant compared to the United States, indicating that financial cycles are more volatile in emerging market economies. The study also highlighted that emerging market economies depend on the U.S. for financial resources, which creates uncertainty and instability in these financial systems as these markets lack complete control over financial developments. Aldasoro et al. (2020), focusing on both emerging and advanced economies, found no significant difference in the duration of financial cycles, suggesting that the time it takes for systemic risk to evolve is similar in both advanced and emerging market economies. Adarov (2022) found that financial cycles in advanced and developing economies last up to 15 years and are driven by the volatility index (VIX) and U.S. Treasury bills.

These results suggest that although there may be differences in the stability of financial cycles between advanced and emerging market economies, these differences are minor. As a result, the sources of instability can be expected to be similar across these economies. However, it is essential to note that there is a gap in studies focusing solely on emerging market economies and individual countries in particular. Therefore, the above findings are generalisations and must be applied to individual countries with caution. For instance, Prabheesh et al. (2021) found that the Indian financial cycle is more volatile than global financial cycles, whereas the Indonesian financial cycle is more stable. Krznar and Matheson (2017) found that the financial cycle in New Zealand lasts up to 20 years, while the financial cycle in South Africa is approximately 17 years (Bosch & Koch, 2020). These differences merit investigations that focus on individual economies, which is the focus of this study.

This study makes significant contributions to the existing theoretical and empirical literature on the financial cycle and systemic risk. Theoretically, the study expands the understanding of the factors that drive systemic risk within the financial cycle, mainly focusing on exchange rates, price levels, the business cycle, the repo rate, and macroprudential policy. Economic theory suggests that exchange rates play a crucial role in systemic risk, especially in open economies, as they influence capital flows and external debt, thereby impacting financial stability (Ali, 2022). Fluctuations in the exchange rate can lead to capital flight or sudden shifts in investor sentiment, increasing volatility and systemic risk. On the other hand, the price level is an essential factor in understanding inflationary pressures and their effects on the economy. According to the Quantity Theory of Money, rising prices can lead to higher interest rates, which may trigger financial instability if there are imbalances in debt (Benati, 2021).

The business cycle is another critical driver of systemic risk, as economic expansions and contractions affect the availability of credit and overall economic growth. During boom periods, excessive borrowing can lead to financial bubbles, while credit becomes more constrained during recessions, amplifying systemic risk (Minsky, 1977). The repo rate, set by central banks, serves as a tool to control inflation and stabilise the economy. Changes in the repo rate can influence borrowing costs and liquidity in financial markets, thus impacting financial stability (Taylor, 1993). Finally, macroprudential policy, which aims to mitigate risks to the financial system, is essential in regulating systemic risk. Central banks aim to reduce the likelihood of financial crises by imposing capital buffers and other financial stability measures.

Empirically, the study contributes to the literature by constructing a financial cycle volatility index, which allows the study to track and quantify the systemic risk present at different phases of the financial cycle. This index integrates the aforementioned factors and provides a comprehensive tool to measure the fluctuations in systemic risk over time. Applying this index can help us better understand how these theoretical factors interact to shape financial stability and assess the potential for crisis in emerging market economies. This study, therefore, not only advances theoretical insights but also provides empirical evidence to support the role of these factors in driving systemic risk within the financial cycle.

3. Econometric Methods

The study sample is from the first month of 1970 to the ninth month of 2024. This is a sufficient period to capture any changes in the stability of the financial cycle and changes in variables that might affect the stability of the financial cycle. To address the objective of the study, two variables must be constructed. The first is the financial cycle, and the second is the FCVIX. According to the existing literature, the financial cycle can be represented by a common factor between credit, house prices, and share prices (Farrell & Kemp, 2020; De Wet, 2020; Adarov, 2022; Pahla, 2019; Menden & Proaño, 2017). The primary motivation for choosing these variables is that they are the primary sources of systemic risk, which the financial cycle aims to trace over time (Borio, 2014). In the credit market, over-indebtedness and defaulting on debt repayments of households and government debt repayments contribute to instability. In the asset markets, price volatility creates uncertainty about the housing and equity markets in South Africa (Magubane, 2024b). Besides this motivation, credit, house, and share prices represent the most significant financial markets in South Africa, which account for a significant share of the financial system's resources and developments (Magubane, 2024b). Hence, in this study, the variables total domestic credit, house price index, and all-share price index were used.

The study utilised principal component analysis (PCA) to combine these variables into a financial cycle. One significant benefit of using PCA over dynamic factor models is its capability to manage large datasets like those utilised in this research (Jawadi et al., 2021). Conversely, dynamic factor models become less effective as the number of variables grows (Khoo et al., 2024). Another reason for selecting PCA is that it possesses time-varying parameters, unlike simple correlation (Lever et al., 2017). This characteristic enables the study to follow and depict the progression of financial cycles over time. The initial step is to find a linear function $\theta 1' \ z$ of the elements of $z = n$ financial indicators that have the maximum variance. $\theta 1$ is a vector of m variables $\theta_{11}, \theta_{12}, \ldots, \theta 1$ m, and $'$ denotes transpose such that

$$\theta_1' x = \theta_{\ 11} z_1 + \theta_{12} z_2 + \ldots + \theta x_m = \sum_{j=1}^{m} \theta z_j. \tag{1}$$

Subsequently, a linear function, denoted as $\alpha_2' x$ should be sought, which is uncorrelated with $\alpha_1' x$, and exhibits maximum variance. At the kth stage, it is necessary to identify a linear function of $\alpha_k' x$ that also has maximum variance and remains uncorrelated with $\theta_1' z, \theta_2' z \ldots, \theta_{k-1} z$. The variable derived at the kth stage is referred to as $a_k x$, and is among the principal components that account for variations in financial variables. This study is conducted with eigenvalues exceeding one to identify financial cycles from financial indicators. As demonstrated by Brave et al. (2019), the derived principal components will serve as the financial cycle index, which can then be used to construct the financial cycle.

Constructing the financial cycle involves removing the principal trend of the principal component, leaving only the cyclical component indicative of the financial cycle. The literature offers several filtering techniques, each with unique characteristics. For the sake of comparability, the study uses the Hodrick–Prescott filter (HP filter), which is extensively utilised in the financial cycle literature (Bosch & Koch, 2020; Adarov, 2022). The HP filter was selected because it is the favoured method for estimating financial cycles, and it is more effective than other techniques at predicting financial expansions and contractions (Hamilton, 2020). Additionally, as shown in Bosch and Koch (2020), it has produced dependable financial cycles in South Africa's context. For the scope of the study, presume that the principal components from the first equation can be depicted in the following manner:

$$z_t = v_t + w_t l = 1, 2 \ldots, T \tag{2}$$

In this context, z_t represents the observed principal component, with v_t and $w_t l$ denoting the cyclical and trend components of the observed series, respectively. Additionally, it is assumed that the secular component is difference stationary, while the cyclical component is level stationary. The trend is estimated by minimising Equation (4).

$$\min_{[g_t]_{t=1}^{T}} \sum\nolimits_{t=1}^{T} c_t^2 + \lambda \sum\nolimits_{t=1}^{T} [(g_{t+1} - g_t) - (g_{t-1} - g)]^2 \tag{3}$$

Assume, z_t represents the observed principal component of the data, while v_t and w_{tl} denote the cyclical and trend components, respectively. A key assumption underlying the HP filter is that the trend component w_{tl} is difference stationary, implying that changes in the trend follow a predictable, smooth path. In contrast, the cyclical component, v_t, is assumed to be level stationary, which allows for short-term deviations around the trend that revert to a long-run mean over time. These assumptions ensure that the HP filter captures both the persistent, long-term dynamics and the transient fluctuations characteristic of financial cycles.

The HP filter estimates the trend by minimising a loss function, as represented in Equation (3). This loss function balances the trade-off between the smoothness of the trend component and the fidelity of the cyclical component to the observed series. The first term, $\sum_{t=1}^{T} c_t^2$, penalises deviations of the cyclical component, c_t, from zero, while the second term, $\lambda \sum_{t=1}^{T} [(g_{t+1} - g_t) - (g_{t-1} - g)]^2$, penalises variations in the second difference in the trend component, g_t. The penalty parameter λ plays a crucial role in determining the smoothness of the estimated trend, with higher values of λ yielding a smoother trend and lower values allowing for more pronounced short-term fluctuations.

For financial cycle analysis, the choice of λ is critical, as it governs the temporal resolution of the decomposition. According to Drehmann et al. (2012) and Bosch and Koch (2020), for quarterly financial cycles, λ is set to 400,000. If the trend component is removed, Equation (3) can be reformulated as a financial cycle equation as seen in Equation (4)

$$FC_t = q_t \tag{4}$$

In order to construct the FCVIX, Equation (4) is re-estimated as a DCC model in order to extract time-varying conditional variance between the financial cycle and its lags. The DCC is chosen because studies such as Engle (2002) demonstrated the versatility of the DCC model in capturing correlations, volatility dynamics, and systemic risk in modern financial markets. In particular, the choice of the DCC is influenced by its ability to estimate time-varying correlation and volatility (Kovacic & Vilotic, 2017). Firstly, the DCC model, proposed by Engle (2002), offers a flexible and computationally efficient framework for modelling time-varying correlations while maintaining a parsimonious structure. It allows for the estimation of dynamic correlations between multiple time series without requiring the estimation of a large number of parameters, as is the case with BEKK models (Bollerslev et al., 1988). This makes the DCC model particularly advantageous in studies with large datasets or when the number of variables is relatively high, as it mitigates issues related to overfitting and computational complexity.

Secondly, while the BEKK model provides a more detailed specification by modelling the full conditional covariance matrix, it can be computationally intensive, especially with multiple variables, due to the need for estimating a large number of parameters (Bollerslev & Engle, 1993). In contrast, the DCC model offers a simpler structure that still captures time-varying correlations effectively, making it a preferred choice for our study. Furthermore, Copula-GARCH models, while useful in capturing non-linear dependencies and tail risk, can be difficult to estimate and require assumptions about the joint distribution of the data (Patton, 2006). The DCC model, on the other hand, allows for a more straightforward estimation of time-varying correlations without relying heavily on distributional assumptions, making it more suitable for our study's objectives.

The study estimates the following model:

$$y_t = Cx_t + \epsilon_t \tag{5}$$

$$\epsilon_t = H_t^{\frac{1}{2}} v_t \tag{6}$$

$$H_t = D_t^{\frac{1}{2}} R_t \tag{7}$$

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}} \tag{8}$$

$$Q_t = (1 - \lambda_1 - \lambda_2) R_t + \lambda_1 \widetilde{\epsilon_{t-1}} \widetilde{\epsilon'_{t-1}} + \lambda_2 Q_{t-1} \tag{9}$$

where y_t is the financial cycle; x_t is the lags of dependent variables; $H_t^{\frac{1}{2}}$ is the Cholesky factor of the time-varying conditional covariance matrix H_t; v_t is an $(m\ x\ 1)$ vector of (iid) innovations; and D_t is a diagonal matrix consisting of conditional variances:

$$D_t = \begin{pmatrix} \sigma_{1,t}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{2,t}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{m,t}^2 \end{pmatrix} \tag{10}$$

In which $\sigma^2_{i,t}$ evolves according to a univariate GARCH model of the form $\sigma^2_{i,t} = s_i + \sum_{j=1}^{p_i} \alpha_j \epsilon^2_{i,t-j} + \sum_{j=1}^{q_i} \beta_j \sigma^2_{i,t-j}$ by default, where α_j and β_j are the ARCH and GARCH parameters, respectively.

R_t is a matric of conditional quasicorrelation,

$$R_t = \begin{pmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1m,t} \\ \rho_{12,t} & 1 & \cdots & \rho_{2m,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1m,t} & \rho_{2m,t} & \cdots & 1 \end{pmatrix} \tag{11}$$

$\widetilde{\epsilon_t}$ is an m x 1 vector of standardised residuals, $D_t^{-\frac{1}{2}} \epsilon_t$, and λ_1 and λ_2 are non-negative parameters that govern the dynamics of conditional quasicorrelation and satisfy $0 \leq \lambda_1 + \lambda_2 < 1$. If Q_t is stationary, the R matrix in Equation (11) is a weighted average of the unconditional covariance matrix of the standardised residuals $\epsilon^{\sim}$, denoted by $\overline{R}$, and the unconditional mean of Q_t, denoted by $\overline{Q}$. Since $\overline{R} \neq \overline{Q}$, as shown by Aielli (2013), R is neither the unconditional matrix nor the unconditional mean of Q_t. For this reason, the parameters in R are known as quasicorrelation (Aielli, 2013; Engle, 2002). The study is interested in the estimated time-varying conditional covariance used to represent the FCVIX.

In order to assess which variables drive the stability of the financial cycle, the following variables were used in the study: the ER, CPI, Y, PR, and MPI. We considered Equation (12) which expresses the FCVIX in an MSAR:

$$Y_t = \mu_{s_t} + X_t \beta_{s_t} + \delta_{i,s_t} \left(Y_{t-i} - \mu_{s_{t-i}} - K_{t-i} B_{s_{t-i}} \right) + \epsilon_{s_{t-i}} \tag{12}$$

where Y_t is the growth of the FCVIX, X_t is a vector of covariates containing the explanatory variables with state-dependent parameters β_{s_t}, δ_{i,s_t} is the ith autoregressive term in state s_t, and ϵ_{s_t} is the normal, independent, and identically distributed normal error term with mean zero and state-dependent variance, σ^2. $\mu_{s_{t-i}}$ is the state-dependent mean at time $t - i$. The MSAR is used in this study in analysing the stability of financial cycles because it effectively captures the non-linear and regime-dependent dynamics inherent in financial data (Hamilton, 1989; Krolzig, 1997). Financial cycles often exhibit distinct phases, such as expansions and contractions, corresponding to underlying structural regimes (Claessens et al., 2011). Unlike threshold autoregressive models, which require the a priori specification of the transition threshold, the MSAR model probabilistically determines regime transitions based on the data, thus reducing model specification bias and enhancing its robustness for analysing complex financial systems (Ang & Timmermann, 2011). Additionally, MSAR models accommodate the potential persistence of states and the asymmetric effects of shocks across regimes, features that are critical for understanding financial cycle dynamics (Borio, 2014). Empirical studies have demonstrated that MSAR models outperform other regime-switching approaches, such as smooth transition autoregressive models, in capturing the abrupt regime changes typical of financial cycles. Using monthly data, the MSAR framework also enables the identification of short-term fluctuations and long-term trends, ensuring a comprehensive understanding of the factors affecting financial cycle stability, such as macroeconomic policies and external shocks (Gadea Rivas & Perez-Quiros, 2015). Hence, the MSAR model's flexibility and suitability for regime-dependent financial analysis justify its application in this study.

The MSAR model is predicated on several key assumptions that enable it to analyse the regime-dependent dynamics of financial cycles effectively. At its core, the MSAR framework assumes that the observed time series, Y_t, in this case representing the growth of the FCVIX, is governed by latent regimes, denoted by s_t, which follow a discrete-time Markov process. This assumption underpins the probabilistic nature of regime transitions, where a state transition matrix determines the probability of transitioning from one state to another. Such a framework allows the model to capture the non-linear and regime-switching behaviour typical of financial cycles, such as expansions and contractions, without requiring an explicit threshold specification for regime changes (Hamilton, 1989; Krolzig, 1997).

The model further assumes that Y_t is influenced by a vector of covariates, X_t, with state-dependent parameters, β_{s_t}, reflecting how explanatory variables vary across different regimes. Additionally, the autoregressive structure of the model, encapsulated by δ_{is_t}, allows for state-dependent dynamics, where the influence of lagged values of Y_t changes according to the prevailing regime. This assumption is critical for capturing the persistence and path-dependency of financial cycles, which often exhibit prolonged phases of stability or instability (Claessens et al., 2011). The inclusion of a regime-dependent mean, $\mu_{s_{t-i}}$, and variance, $\sigma^2_{s_t}$, ensures that both the central tendency and volatility of Y_t adapts to the specific characteristics of each regime. The model also assumes that the error term, ϵ_{s_t}, is normally distributed, independent, and identically distributed, with a mean of zero, providing a robust framework for handling stochastic variations in the data.

These assumptions collectively allow the MSAR model to probabilistically determine regime transitions, minimising model specification bias compared to threshold autoregressive models (Ang & Timmermann, 2011). By accommodating the asymmetric effects of shocks and capturing abrupt regime changes, the MSAR model aligns with empirical observations of financial cycles, which often display sudden shifts in behaviour due to external shocks or policy interventions. The model's capacity to incorporate both short-term fluctuations and long-term trends further enhances its utility in understanding the factors influencing financial cycle stability, including macroeconomic variables and external shocks (Gadea Rivas & Perez-Quiros, 2015). Moreover, the MSAR framework's flexibility and robustness make it particularly well suited for studying the inherently non-linear and regime-dependent nature of financial systems, justifying its application in this study.

Financial cycles are widely recognised to exhibit two distinct phases: expansion and contraction. The expansion phase is characterised by rising credit growth, increased asset prices, and overall economic optimism, while the contraction phase reflects declining credit availability, falling asset prices, and heightened financial distress (Borio, 2014; Drehmann et al., 2012; Schüler et al., 2020; Magubane, 2024b; Nyati et al., 2024). These alternating phases align with the dynamics of financial market behaviour, which often oscillate between risk appetite and risk aversion periods. Given this cyclical nature, the study adopts a two-state MSAR model to effectively capture the financial cycle's non-linear dynamics and regime-dependent properties. The choice of two states is well suited to reflect the inherent dichotomy of expansion and contraction, ensuring that the model provides a parsimonious yet robust framework for analysing shifts in financial conditions while maintaining interpretability (Hamilton, 1989). The study applies a simple two-state FCVIX growth model with state variant variance. It means to estimate the impact of the macroprudential policy index (MPI), policy rate (PR), real GDP (Y), consumer price index (CPI), and the real effective exchange rate (ER) on the stability of the financial cycle in both the instability and stability states in South Africa as follows:

$$Y_t = \mu_{s_t} + \epsilon_{s_t} \tag{13}$$

where

$$Y_t = \begin{bmatrix} \mu_1 + \epsilon_{1t} \; if \; s_t = 1 \\ \mu_2 + \epsilon_{2t} \; if \; s_t = 2 \end{bmatrix} \tag{14}$$

Before discussing the results of the study, it is important to outline the sources of the variables used. The policy rate, total domestic credit, and house price index were obtained from the Bank for International Settlements (BIS). The Organisation for Economic Co-operation and Development (OECD) sourced the real effective exchange rate and all-share price index. The gross domestic product (GDP) and consumer price index (CPI) variables were retrieved from the South African Reserve Bank (SARB). Finally, the macroprudential policy index (MPI) was obtained from the International Monetary Fund (IMF).

4. Results and Discussion

The following hypotheses are proposed to achieve the study's objectives. First, the study hypothesises that the financial cycle volatility index (FCVIX) effectively captures the stability of the financial cycle in South Africa. The null hypothesis (H_0) asserts that the FCVIX does not provide a reliable measure of financial cycle stability. In contrast, the alternative hypothesis (H_1) contends that the FCVIX is a valid and reliable measure. Furthermore, the study investigates the influence of macroeconomic and policy variables on the FCVIX. For each determinant, the null hypotheses (H_0) state that the variable—such as exchange rate volatility, consumer price index, output, financial cycle dynamics, repo rate, and macroprudential policies—has no significant effect on financial cycle stability, while the alternative hypotheses (H_1) propose that each variable significantly impacts the FCVIX. Finally, the overarching null hypothesis (H_0) posits that macroeconomic and policy variables do not collectively or interactively influence financial cycle stability. In contrast, the alternative hypothesis (H_1) suggests that these factors play a significant and interactive role in shaping the stability of the financial cycle in South Africa. This results and discussion section delves into the study's empirical findings, addressing these hypotheses and shedding light on the key determinants and dynamics of financial cycle stability.

Figure 2 plots the FCVIX against the financial cycle. The FCVIX is derived as the conditional standard deviation of the financial cycle, calculated using the DCC model. Since the index is based on standard deviation, a commonly used rule of thumb is that a standard deviation more significant than one signifies higher volatility, while a standard deviation below one indicates lower volatility (Ahmed et al., 2020). A visual inspection of Figure 2 reveals that the FCVIX exceeds the value of one around financial crisis periods. During these times, the FCVIX displays sharp spikes, signalling elevated levels of volatility. In terms of financial cycle stability, this suggests that the financial cycle tends to exhibit greater instability during crisis events. In contrast, the financial cycle shows more stability when no crises exist.

Figure 2 highlights several significant financial turmoil events that coincide with moments of instability in the financial cycle. These include the financial crash caused by the COVID-19 pandemic in 2019/20, the Euro-debt crisis in 2010, the global financial crisis from 2007 to 2009, the Dotcom bubble burst in 2002, and the Asian financial crisis in 1997. Most of these crises originated internationally; South Africa, a smaller economy highly dependent on the international financial system, is particularly vulnerable to external adverse shocks (De Waal & Van Eyden, 2016; Gumata & Ndou, 2019). However, some crises were domestic, such as the Banking Crisis of 2002 (Hollander & Havemann, 2021). This observation indicates that instability in the financial cycle reflects vulnerabilities within the country and captures external shocks, demonstrating the interconnectedness of the global and local financial systems.

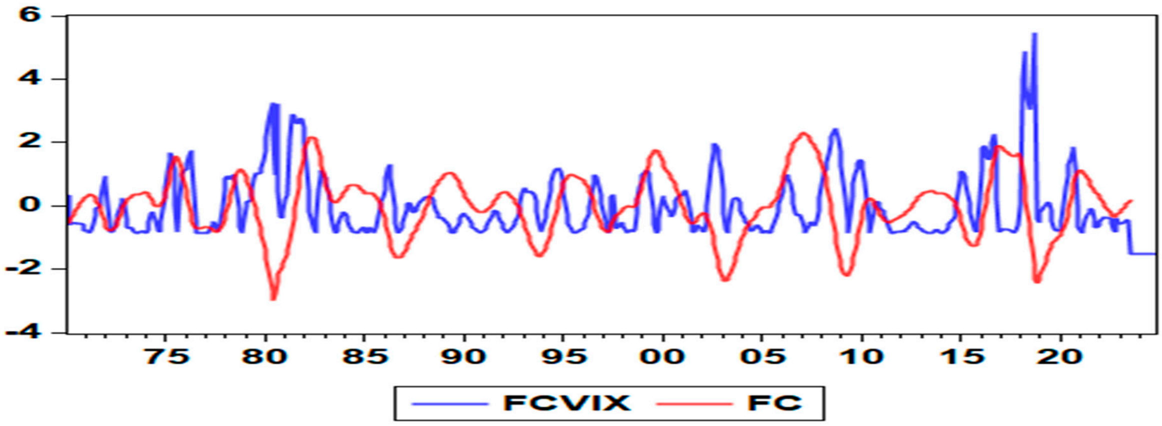

Figure 2. Evolution of the South African financial cycle and the FCVIX (1970–2023). *Source:* own estimates.

Economic theory posits that systemic risk develops during the expansion phase of the financial cycle, implying that we should expect greater instability in the financial cycle during this phase (Ma et al., 2019; Dimand, 2019). However, some of the study's results contradict this theory. The findings suggest that between the 1970s and 1980s, the financial cycle exhibited more instability during its expansionary phases. This is reflected in the FCVIX, which experienced sharper spikes during the expansion phases of this period. In contrast, from the late 1990s to the present, findings indicate that the financial cycle exhibits more instability during its downturn phases. Sharper spikes in the FCVIX have been observed during downturns in recent years. In other words, the study finds that in recent years, the financial cycle has shown more stability during its expansionary phase and greater instability during its downturn phase. This pattern, however, can only be observed from a time-line graph, and formal testing is necessary to verify these findings.

To further investigate this, we conducted a crosscorrelation analysis between the financial cycle and the FCVIX, as presented in Figure 3. A visual inspection of Figure 3 indicates that maximum correlation occurs at a positive lag 5. This suggests that the FC volatility index and the financial cycle are leading each other, but the sign of the maximum correlation is negative, indicating that these variables move countercyclically. In simpler terms, during a financial cycle expansion, the FCVIX tends to decline, while it rises during an economic cycle downturn. These results align with the observations made in Figure 2, further supporting our findings.

Before presenting the study's primary results, a model fit test was conducted to validate the results of the DCC model and assess the reliability of the FCVIX. The Ljung–Box Q test was employed to determine whether the residuals exhibited heteroscedasticity or homoscedasticity. The model's residuals are normally distributed with a slight left tail (*see* the bell-shaped histogram in Figure A1A in Appendix A). The null hypothesis of the test Ljung–Box Q is that the residuals are heteroscedastic, while the alternative hypothesis posits homoscedasticity. A key advantage of the Ljung–Box Q test is its ability to evaluate dependencies across multiple lags rather than a single lag. Following the approach of Ramsey (1999), the test was performed at lags 6, 12, 18, 24, 30, and 36. The results, presented in Table 1, reveal that the autocorrelation (AC) and partial autocorrelation (PAC) parameters are statistically significant at all the tested levels (as indicated by the Prob* values). This significance suggests that the null hypothesis of heteroscedasticity is rejected in favour of the alternative hypothesis of homoscedasticity. These findings indicate that the DCC model and FCVIX results are reliable.

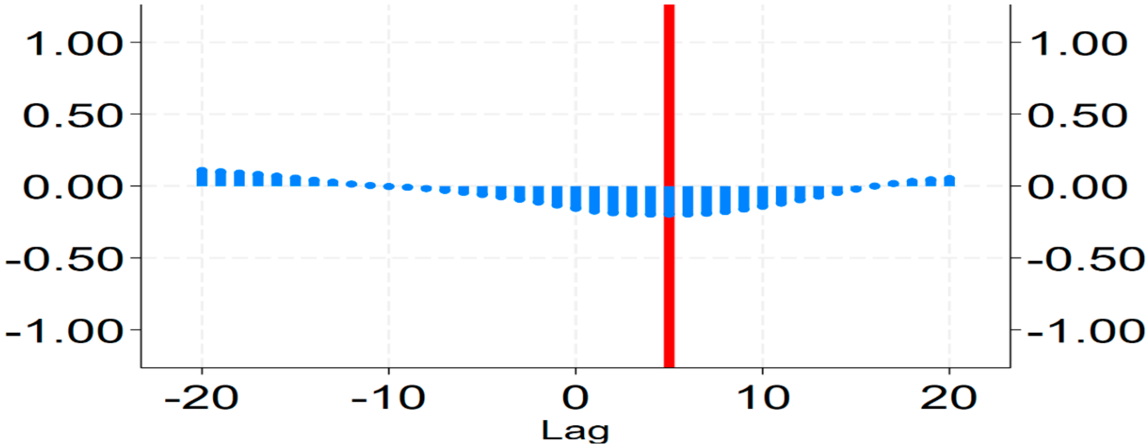

Figure 3. Cross-correlogram of the South African financial cycle and the FCVIX. *Source:* own estimates.

Table 1. Ljung–Box Q autocorrelation test—DCC.

Lag	AC	PAC	Q-Stat	Prob*
6	0.215	0.123	260.04	0.000
12	0.175	0.096	298.03	0.000
18	0.171	0.092	351.49	0.000
24	0.185	0.098	395.67	0.000
30	−0.002	−0.030	415.13	0.000
36	0.091	0.055	421.99	0.000

Sources: own estimates.

The study next applied the Augmented Dickey–Fuller (ADF) unit root test to evaluate the stationarity of the variables used in the MSAR model. Additionally, the Phillips–Perron (PP) unit root test was conducted to confirm the findings of the ADF test. This step is critical to ensure that all variables are of the same order of integration before estimating the MSAR model (Hall et al., 1999). Table 2 presents the test results. For both the ADF and PP tests, the null hypothesis posits that the series contains a unit root (non-stationary), while the alternative hypothesis suggests that the series is stationary. The results in Table 2 demonstrate that in almost all the cases, the null hypothesis is rejected at all the significance levels for both the level and first difference versions of the variables. The only exceptions are the ADF test results at the level, where the null hypothesis fails to be rejected for FCVIX, CPI, and MPI.

When variables are stationary at both levels and first differences as in the study, using the first differences is often preferred in econometric models like MSAR due to considerations of stability and interpretability. Econometric theory suggests that differencing stationary variables can mitigate potential overfitting issues in models designed to capture regime-switching behaviour (Hamilton, 1989). Since the MSAR model focuses on identifying shifts in underlying states or regimes, using first differences minimises the risk of spurious state transitions caused by level-based fluctuations unrelated to regime dynamics (Krolzig, 1997). Moreover, differencing adheres to the principle of parsimony, which advocates for simpler models that effectively capture the data's structural properties (Lütkepohl, 2005). Empirical evidence demonstrates that this approach improves the model's ability to identify structural shifts, particularly in financial and economic time series with high-frequency variations (Kim & Nelson, 1999). Given these considerations, the study proceeded to estimate the MSAR model using the differenced variables to ensure clearer inferences and more robust regime identification.

Table 2. ADF and PP unit roots test.

	UNIT ROOT TEST TABLE (PP)						
At Level							
	FCVIX	ER	CPI	Y	FC	MPI	PR
t-Statistic	−6.534	−9.208	−15.675	−9.487	−4.799	−1.212	−3.538
Prob.	0.000	0.000	0.0000	0.000	0.000	0.000	0.000
	***	***	***	***	***	***	***
At First Difference							
	d(FCVIX)	d(ER)	d(CPI)	d(Y)	d(FC)	d(MPI)	d(PR)
t-Statistic	−7.983	−4.645	−14.417	−8.693	−5.893	−7.345	−9.057
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	UNIT ROOT TEST TABLE (ADF)						
At Level							
	FCVIX	ER	CPI	Y	FC	MPI	PR
t-Statistic	−1.445	−1.731	−1.364	−1.981	−7.054	−1.602	−1.836
Prob.	0.138	0.079	0.160	0.045	0.000	0.102	0.063
	no	*	no	**	***	no	*
At First Difference							
	d(FCVIX)	d(ER)	d(CPI)	d(Y)	d(FC)	d(MPI)	d(PR)
t-Statistic	−9.925	−10.811	−9.080	−10.098	−8.474	−8.179	−9.494
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Sources: own estimates. *Notes:* (*) significant at the 10%; (**) significant at the 5%; (***) significant at the 1%; and (no) not significant; lag length based on SIC; probability based on MacKinnon (1996) one-sided p-values.

Next, the study discusses the main results of the MSAR. Table 3 below displays the results. The results of this study reveal important dynamics that drive financial stability and instability in South Africa. These findings provide a nuanced understanding of how various macroeconomic and financial variables interact with the FCVIX. The high persistence of changes in the FCVIX, evidenced by autoregressive parameters ($\delta_1 = 0.974$ and $\delta_2 = 0.822$) being close to 1, suggests that fluctuations in financial stability (instability) are deeply embedded in the system. Economic theory posits that high persistence in financial volatility often stems from structural weaknesses or entrenched cyclical behaviours within the financial system (Jain, 2007; Caporale et al., 2018; James, 2021). For South Africa, this persistence reflects an economic landscape shaped by recurring crises, such as the prolonged impacts of the global financial crisis of 2008, the sovereign credit rating downgrades in 2017 and 2020, and the economic disruptions caused by the COVID-19 pandemic (Bond, 2018). This also reflects a system that is vulnerable to the excessive debt of households and the government, rapid loadshedding, and high price levels (Mothibi & Mncayi, 2019). Each of these events introduces systemic shocks that heighten financial instability, amplifying the volatility observed in the financial cycle.

The exchange rate and price levels contribute significantly and positively to the FCVIX in both the states of stability and instability, underscoring their pivotal role in influencing financial cycle dynamics. This is indicated by the positive sign in parameters corresponding to ER and CPI. This finding is similar to Moyo and Tursoy (2020), Trecy et al. (2024), and Olamide et al. (2022) who also found the exchange rate and the price level to be significant drivers of financial market behaviour in South Africa. In the context of South Africa, the exchange rate is particularly volatile, reflecting the country's susceptibility to global capital flows, commodity price fluctuations, and domestic political risks. The depreciation of the rand, such as the sharp decline observed during the political turmoil surrounding the "Nenegate" crisis in 2015, has historically been linked to periods of heightened financial instability (Potgieter, 2021). From a theoretical perspective, the Mundell–Fleming model suggests that exchange rate volatility transmits external shocks into the domestic economy, thereby destabilising financial markets (Okotori & Ayunku, 2020; Egilsson, 2024). Moreover, inflationary pressures, as captured by the price level, exacerbate this instability. During episodes of high inflation, such as the energy-driven price hikes in 2022, financial markets react adversely, with increased uncertainty feeding into greater volatility (Miyajima, 2020).

Table 3. MSAR main results.

	Instability State		Stability State	
	Coefficient	**P > z**	**Coefficient**	**P > z**
ER	0.013	0.004	0.155	0.000
CPI	0.009	0.000	−0.010	0.281
Y	−0.029	0.159	0.753	0.001
FC	−0.008	0.168	−0.011	0.056
PR	0.008	0.020	0.059	0.128
MPI	0.019	0.082	0.250	0.002
μ	0.015	0.000	0.010	0.000
δ_1	0.974	0.000		
δ_2	0.822	0.000		

Source: own estimates. *Notes:* P > z refers to p-values.

Interestingly, the financial cycle's contribution to the FCVIX is negative in both the states of instability and stability, though the effects are statistically insignificant. Put differently, the financial cycle reduces volatility. The negative impact of the financial cycle is because credit and asset price growth contribute to economic development in South Africa. Borio (2014) argues that financial cycles often act as stabilising mechanisms, dampening volatility during expansions and contractions. However, in South Africa, inefficiencies in credit markets—such as limited access to credit for marginalised groups—may weaken the stabilising role of financial cycles. This is further supported by the SARB's Financial Stability Review (2023), which highlights structural barriers within South Africa's financial sector, such as high levels of inequality and limited financial inclusion. These challenges may explain the weak and statistically insignificant impact of the financial cycle on volatility.

The business cycle exhibits contrasting effects on the FCVIX, contributing negatively during instability and positively during stability. This dichotomy reflects the dual role of economic activity in shaping financial stability. In periods of instability, economic downturns suppress financial volatility by reducing speculative activities and dampening risk appetite, consistent with Minsky's (1977) financial instability hypothesis. Conversely, in stable periods, economic growth fosters increased risk-taking and financial market activity, amplifying volatility. This dynamic is particularly evident in South Africa, where periods of economic recovery, such as the post-2020 rebound from COVID-19 lockdowns, have been accompanied by heightened credit extensions and asset price inflation (Fotso et al., 2022; van Seventer et al., 2021). The statistically significant positive effect of the business cycle during stability highlights the pro-cyclicality of South Africa's financial system, a feature commonly observed by studies such as Bergman and Hutchison (2020), Rothert (2020), and Saini et al. (2024), in emerging markets.

Both the repo rate and the macroprudential policy index contribute positively and significantly to the FCVIX in both states of stability and instability, highlighting their strong influence on financial volatility. Studies such as Martinez-Miera and Repullo (2019), Laeven et al. (2022), and Agur and Demertzis (2019) have already demonstrated that the contractionary effects of monetary and macroprudential policy can heighten financial risk by dampening the growth of credit and asset prices below the accepted levels. The positive effect of the repo rate reflects the cost-of-credit channel, wherein higher interest rates increase borrowing costs, reduce liquidity, and heighten financial market volatility. For instance, the SARB's aggressive interest rate hikes in 2022 to combat inflation significantly strained household and corporate balance sheets, contributing to increased financial instability. Similarly, the macroprudential policy index's positive contribution underscores the impact of regulatory measures on market behaviour. While these policies are designed to enhance stability, their implementation can initially increase volatility by restricting credit growth and curbing speculative activities. Recent research by Nyati et al. (2024) demonstrates the trade-offs associated with macroprudential policies, particularly in contexts like South Africa's, where financial inclusion remains a challenge.

Next, the study discusses the regime features of the FCVIX in different states. Table 4 presents the results. The variance results, which show slow growth in the FCVIX during instability and high growth during stability, reflect the fundamental behaviour of financial markets in response to different economic conditions. Instability often results in risk aversion, characterised by reduced speculative activity, constrained credit markets, and suppressed financial transactions. This dynamic aligns with Minsky's (1977) financial instability hypothesis, which posits that during crises, market participants retreat into defensive postures to preserve capital. For instance, during the apartheid era, South Africa faced international sanctions that severely restricted access to global financial markets (Davis, 2018). The instability induced by these sanctions forced the financial system to adopt cautious strategies, resulting in subdued volatility growth (Davis, 2018). In contrast, the high growth of the FCVIX during stable periods reflects heightened financial activity fuelled by optimism and increased risk-taking. Theoretically, this dynamic aligns with Borio's (2014) argument that stability often fosters conditions that sow the seeds of future instability. For example, following the end of apartheid in 1994, South Africa entered a period of relative political and economic stability. This newfound optimism drove significant foreign investment inflows, boosting financial market activity and volatility. However, unchecked growth in financial activity also contributed to subsequent vulnerabilities, exemplified by the 2002 banking crisis, during which smaller banks like Saambou and Regal Bank collapsed under the weight of poor risk management and overexposure to unsecured lending (Hollander & Havemann, 2021).

Table 4. Features of the FCVIX in different states.

	Instability	**Stability**
σ	0.001	0.013
θ	28.113	19.837
ρ_1	0.964	0.739
ρ_2	0.036	0.261

Source: own estimates. *Notes:* ρ_1 and ρ_2 refer to the probability of remaining and switching between states, respectively. θ refers to the duration of each state whereas σ is the variance of each state.

The finding that instability lasts up to 28 months, compared to 19 months of stability, underscores the entrenched nature of financial volatility in South Africa. The prolonged periods of instability reflect deep-rooted structural challenges, such as persistent unemployment, inequality, and political uncertainty. Reinhart and Rogoff (2009) argue that emerging markets often experience extended instability due to their reliance on external financing and vulnerability to global shocks. In South Africa, this dynamic has been observed during events like the 1998 Asian Financial Crisis, which triggered capital outflows and currency depreciation, prolonging instability in the domestic financial system. The relatively shorter duration of stability reflects the fragility of South Africa's financial system, where stable periods are often disrupted by exogenous or domestic shocks (Pretorius & De Beer, 2014). For instance, the optimism that followed the democratic transition in 1994 was cut short by fiscal crises and governance failures in the subsequent decades (Sachs, 2021; Gumata, 2022). Recent examples include the economic stagnation caused by rolling blackouts (load-shedding) since 2007, exacerbated by operational inefficiencies at Eskom, and the sharp depreciation of the rand in 2015 due to a sudden change in finance ministers, colloquially referred to as "Nenegate" (Naidoo, 2023; Walsh et al., 2021).

The strong likelihood of the FCVIX remaining in its current state, whether stability or instability, underscores the inertia present in South Africa's financial system. However, the finding that the likelihood of remaining in the instability state is higher than in the stability state signals a systemic bias toward prolonged financial instability. This persistence can be explained through Hamilton's (1989) regime-switching theory, which posits that structural and cyclical factors reinforce the continuity of a given state. In South Africa, factors such as weak economic growth, high public debt levels, and policy uncertainty act as anchors, preventing transitions to stability. Historical events support this interpretation. During the apartheid era, sanctions and exclusion from global markets entrenched financial instability, as the economy relied heavily on domestic financing and faced constrained capital flows. Similarly, the 2002 banking crisis, though isolated to smaller banks, reflected systemic issues such as weak regulatory oversight and limited financial inclusion, which perpetuated instability in the broader financial system. More recently, the COVID-19 pandemic reinforced the persistence of instability by exacerbating structural weaknesses, such as high unemployment and limited fiscal space for stimulus.

The transition probabilities also reflect the challenges policymakers face in shifting the economy toward stability. The SARB has historically employed monetary policy tools, such as adjustments to the repo rate, to stabilise the financial system. For example, during the 2020 pandemic, the SARB cut the repo rate by 300 basis points to support liquidity and financial stability. However, such measures often have limited effectiveness in addressing the underlying structural issues, such as governance failures and inadequate infrastructure investment, which perpetuate financial instability. These findings underscore the need for a multifaceted policy approach to address the drivers of financial volatility in South Africa. The slow growth of the FCVIX during instability suggests that policymakers must prioritise structural reforms to enhance resilience and reduce systemic vulnerabilities. This includes improving governance at state-owned enterprises, increasing investment in infrastructure, and fostering financial inclusion. For example, addressing Eskom's operational inefficiencies and stabilising the energy supply could reduce the economic uncertainty that fuels financial instability. The high growth of the FCVIX during stability highlights the importance of counter-cyclical policies to prevent overheating and mitigate the risks of excessive financial activity. Strengthening macroprudential regulations, such as capital buffers and loan–value ratios, could curb excessive risk-taking during stable periods, reducing the likelihood of subsequent instability. Empirical studies, such as those by Aikman et al. (2015), have shown that robust macroprudential frameworks can mitigate the pro-cyclical effects of financial activity, particularly in emerging markets.

As with the DCC model, the Ljung–Box Q test was used to assess the validity of the MSAR results. The findings are presented in Table 5. According to the table, there is no evidence of heteroscedasticity in the residuals of the MSAR, indicating that the model is well specified. Moreover, the results are normally distributed as indicated by the bell-shaped histogram in Figure A1B in Appendix A. Therefore, the results can be considered reliable.

Table 5. Ljung–BOX Q autocorrelation test—MSAR.

Lag	AC	PAC	Q-Stat	Prob*
6	0.148	0.109	134.42	0.000
12	0.134	0.070	162.48	0.000
18	0.116	0.093	176.60	0.000
24	0.168	0.078	203.79	0.000
30	0.129	0.091	227.55	0.000
36	0.054	0.021	256.97	0.000

Source: own estimates.

In addition to the Ljung–Box Q test, the variance inflation factor (VIF) test was conducted to determine whether multicollinearity could have affected the results of the MSAR. Addressing multicollinearity is crucial in regression analysis, as it can distort the reliability of coefficient estimates and weaken the interpretability of the model. Multicollinearity inflates standard errors, making it difficult to determine the unique contribution of each explanatory variable, which can lead to misleading inferences about the relationships between variables (Gujarati, 2021). VIF is widely used as a diagnostic tool to detect and quantify multicollinearity due to its simplicity, interpretability, and robustness in empirical research (Mansfield & Helms, 1982; Kutner et al., 2005; Hair et al., 2012; Montgomery et al., 2021). A VIF of 1 indicates no multicollinearity, values between 1 and 5 suggest moderate multicollinearity, and a VIF exceeding 10 is widely regarded as a strong indication of high multicollinearity that requires intervention (Gujarati, 2021; O'Brien, 2007).

Table 6 presents the findings of the VIF analysis. According to the table, the VIF parameters (logσ = 1.030 and logσ = 1.024) for all the variables combined are closer to one, suggesting that overall, the parameters of the MSAR model are not significantly inflated. This indicates that when the variables are considered as a group, there is no multicollinearity in the model. However, Table 5 shows that for each individual variable, the VIF values range between 1 and 5, suggesting moderate inflation. This indicates the presence of a small level of multicollinearity in the model.

A small level of multicollinearity is unavoidable when analysing variables such as the repo rate, macroprudential policy, exchange rate, consumer price index, output, and the financial cycle due to the inherent interdependence of these economic indicators. The economic literature consistently highlights that such variables are structurally and dynamically linked as a part of the broader macroeconomic and financial systems. For instance, the repo rate, which represents the central bank's monetary policy stance, directly influences borrowing costs, aggregate demand, and inflation. Similarly, macroprudential policy measures are designed to stabilise the financial system and often respond to shifts in output and financial cycles, further linking these variables (Borio, 2014). The exchange rate is also intertwined with monetary policy and inflation dynamics, as changes in interest rates affect capital flows and currency values. Likewise, the consumer price index, which measures inflation, is closely linked to both the exchange rate (through import prices) and monetary policy (via inflation targeting frameworks). Output, as a measure of economic activity, is influenced by all the aforementioned variables, including the financial cycle, which captures fluctuations in credit growth and asset prices that feed into aggregate demand (Drehmann et al., 2012). These interconnections are a natural feature of macroeconomic systems and reflect their co-movement in response to shocks or policy interventions.

Table 6. Variance inflation factor test.

Variable	Coefficient Variance	Uncentered VIF	Cantered VIF
Regime 1			
ER	0.000	1.348	1.309
CPI	0.001	3.497	1.949
Y	0.121	4.030	1.880
FC	0.002	5.176	1.666
PR	0.006	5.931	2.169
MPI	0.024	5.148	2.577
Regime 2			
ER	0.024	1.079	1.079
CPI	0.013	3.125	3.123
Y	0.022	3.804	3.773
FC	0.003	5.857	5.828
PR	0.017	4.336	4.329
MPI	0.004	5.421	5.365
Common			
Log(σ)	0.001	1.030	1.024
	Probability Parameters		
P1-C	0.039	1.272	1.164

Source: own estimates.

In our study, the VIF results for all the variables combined were close to 1, suggesting that there is no significant multicollinearity at the aggregate level. When the variables were considered individually, the VIF parameters ranged from 1 to 5, indicating a small level of multicollinearity. However, as emphasised in the literature, a small degree of multicollinearity within this range is generally considered acceptable and does not undermine the validity of the model (Gujarati, 2021). These interconnections between the variables are not only expected but also necessary for reflecting the real-world complexity of economic systems. Therefore, the small level of multicollinearity in our model is inherent to the nature of the economic variables being studied and does not detract from the reliability of the MSAR results. Given these theoretical and empirical justifications, we conclude that the MSAR results are robust and valid for analysing the dynamics of the financial cycle and related economic indicators.

Next, the threshold autoregressive model (TAR) was estimated as an additional test to corroborate the findings of the MSAR. Table 7 presents the findings. In the table, there are three states identified by the model. The three states represent different levels of financial cycle volatility. State 1 corresponds to a period of stability, where the FCVIX is low, indicating a more stable financial environment. State 2 is an intermediate state, where the FCVIX is moderate, reflecting a transitional period between stability and instability. State 3 represents instability, with high FCVIX indicating a more volatile financial environment.

In state 1, where the FCVIX is low, CPI and PR are statistically significant with positive coefficients, indicating that higher inflation and stronger macroprudential policies are associated with higher financial cycle volatility. Y is also significant, with a positive coefficient, suggesting that stronger economic activity is linked to increased financial cycle volatility. On the other hand, FC and MPI are not statistically significant, indicating their limited impact in this state.

In state 2, where the FCVIX is in an intermediate range, ER, CPI, and Y remain significant and positive, suggesting that higher exchange rates, inflation, and economic activity are associated with higher volatility in the financial cycle. FC, PR, and MPI continue to show mixed results, with FC and MPI being non-significant, and PR showing marginal significance at a higher threshold.

Table 7. Threshold autoregression results.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FCVIX < 0.014 -- 339 obs				
ER	0.053	0.032	1.667	0.096
CPI	0.069	0.026	2.645	0.008
Y	0.583	0.258	2.252	0.024
FC	−0.386	0.001	−0.023	0.981
PR	0.101	0.037	2.683	0.007
MPI	0.039	0.051	0.769	0.441
0.014 <= FCVIX < 0.027 -- 202 obs				
ER	0.055	0.019	2.848	0.004
CPI	0.044	0.016	2.680	0.007
Y	0.528	0.166	3.170	0.001
FC	0.153	0.001	0.364	0.716
PR	0.029	0.022	1.337	0.181
MPI	−0.012	0.053	−0.236	0.813
0.027 <= FCVIX -- 101 obs				
ER	0.111	0.013	8.313	0.000
CPI	0.060	0.016	3.694	0.000
Y	0.596	0.150	3.974	0.000
FC	−0.013	0.002	−5.438	0.000
PR	0.124	0.026	4.614	0.000
MPI	0.412	0.111	3.689	0.000

In state 3, where the FCVIX is high, the relationship between the variables and financial cycle volatility becomes even more pronounced. ER, CPI, Y, PR, and MPI are all statistically significant with positive coefficients, indicating strong associations with higher financial cycle volatility. However, FC has a negative coefficient and is highly significant, suggesting that a higher financial cycle might be associated with lower FCVIX in this state. This could reflect a reversal effect where, as the financial cycle becomes more volatile, certain economic measures begin to stabilise or diminish the impact of further volatility on the financial cycle.

The results from the TAR model show both corroboration and contrast with the findings from the MSAR model. A key area of agreement between the two models is the positive relationship between the FCVIX and the ER. The TAR model suggests that the exchange rate is positively associated with the FCVIX across all the states, with the effect being most pronounced in the high volatility state. This finding aligns with the MSAR model, which also demonstrated a positive linear relationship between the FCVIX and ER. Both models support the argument made in the literature, such as by Borio et al. (2016), that external shocks—like exchange rate movements—can drive financial cycle fluctuations. Higher exchange rates can exacerbate financial market volatility, especially in economies such as South Africa, with open capital accounts or those heavily dependent on imported goods and capital flows. The pronounced effect in the high volatility state found in the TAR model emphasises the amplifying role that exchange rate shocks can have during periods of financial instability, corroborating the findings of Chinn and Ito (2007) who discuss the link between exchange rate volatility and economic risk.

Similarly, the relationship between the FCVIX and the PR is consistent across both models. In the TAR model, the repo rate is positively correlated with the FCVIX in both the low and high volatility states. This finding is consistent with the MSAR model, where a positive linear relationship was also observed. This suggests that stronger financial policies, such as increases in the repo rate, are associated with higher financial cycle volatility. These results support the notion that higher interest rates, intended to stabilise the economy, may have the unintended effect of exacerbating financial volatility, especially in times of heightened uncertainty. This is consistent with Cerutti et al. (2017), who show that monetary policies—while designed to dampen financial cycle fluctuations—can also have counter-cyclical effects that intensify market volatility in certain conditions.

The relationship between the FCVIX and the MPI is another area where the models converge. The TAR model shows a significant positive relationship between the FCVIX and MPI, particularly in the high volatility state. This finding reinforces the idea that more robust macroprudential measures, such as higher capital requirements or counter-cyclical buffers, may be associated with greater financial volatility in certain conditions. Similarly, the MSAR model suggests a positive and linear relationship between the FCVIX and MPI. This corroborates the broader literature, including Borio (2014), which highlights that while macroprudential policies can stabilise financial markets in the long run, they may also lead to unintended consequences in the short term, particularly when financial markets are already in a state of flux.

The relationship between the FCVIX and the FC shows divergence between the two models. The TAR model reveals a negative and highly significant relationship between the FCVIX and FC in the high volatility state, suggesting that as the financial cycle becomes more volatile, it actually contributes to reducing the FCVIX. This contrasts with the MSAR model, which consistently shows a negative relationship between the FCVIX and FC. The reversal effect in the TAR model can be interpreted as a dynamic adjustment mechanism, whereby the heightened volatility of the financial cycle may act as a corrective force that stabilises financial conditions in the long run. This result is in line with the theory of dynamic financial stability (Schinasi, 2010), which suggests that periods of high volatility in financial markets may eventually lead to market corrections and stabilisation. However, the MSAR model does not capture this stabilisation effect and instead implies that a negative relationship between FC and the FCVIX persists regardless of the state of volatility. This highlights the TAR model's ability to account for non-linear relationships and regime-dependent dynamics, a feature that is less prominent in MSAR models.

The results regarding CPI also show both corroboration and contrast. In the TAR model, CPI has a positive and significant impact on the FCVIX in the low-volatility state and a negative impact in the high-volatility state. This suggests that inflation behaves differently depending on the level of financial volatility, supporting the argument made in the literature that inflation's effects on financial instability are state-dependent (see Woodford, 2012). The MSAR model similarly shows that CPI contributes positively to the instability state and negatively to the stability state, which directly corroborates the findings from the TAR model. This result highlights the context-dependent role of inflation in influencing financial cycle volatility, with inflationary pressures potentially amplifying volatility during periods of economic instability, but helping to stabilise financial markets in periods of low volatility.

Finally, the results for Y exhibit some notable contrasts between the two models. The TAR model shows a positive and significant relationship between output and the FCVIX in the low volatility state, but a negative contribution in the high volatility state. In contrast, the MSAR model shows a negative relationship between output and the FCVIX in both the instability and stability states. This discrepancy can be explained by the different assumptions underlying each model. The TAR model, by allowing for state-dependent changes in the relationship between output and the FCVIX, provides a more dynamic view of how economic growth interacts with financial volatility, while the MSAR model imposes a linear structure that does not account for possible non-linearities. This highlights the potential benefit of the TAR model in capturing the more complex interactions between output and financial cycle volatility in different states of the economy, as discussed by Filardo (2012), who emphasises that output and financial volatility are not always inversely related, especially when financial conditions are at extreme points.

While the TAR model and the MSAR model generally align in their findings about the relationships between the FCVIX and variables like ER, PR, and MPI, they differ in their treatment of CPI and output. The TAR model provides a more nuanced understanding of how these relationships change depending on the level of financial cycle volatility, offering insights into regime-dependent effects. On the other hand, the MSAR model assumes linearity, providing a more straightforward analysis of these relationships. Despite these differences, the overall conclusions about the impact of key macroeconomic variables on financial cycle volatility remain similar across the two models. Therefore, in conclusion, the study accepts the results of the MSAR as robust, since they align with the TAR in most cases.

5. Conclusions

The primary aim of this study was to construct a measure for assessing the stability of the financial cycle (FCVIX) in South Africa and identify the key drivers of its fluctuations. To achieve this, the study utilised the MSAR model to analyse monthly time-series data spanning from 1970 to 2024. Key variables, including exchange rates, inflation, the business cycle, and macroprudential policies, were considered to investigate how these factors interact with the financial cycle volatility index. This method allowed for the identification of distinct phases of financial stability and instability, providing insights into the structural and cyclical dynamics that influence financial volatility in the South African context. By employing this approach, the study aimed to uncover both the persistence and the drivers of financial instability, contributing to a deeper understanding of South Africa's economic resilience.

The results of the study highlight that financial instability in South Africa exhibits significant persistence, primarily driven by exchange rate volatility, inflationary pressures, and the business cycle. The study found that exchange rate fluctuations and inflationary pressures exacerbate financial instability, aligning with the existing literature, such as the work of Aye et al. (2024), which underscores the importance of these variables in emerging markets. The high persistence of financial volatility observed in the study is also consistent with the findings of Reinhart and Rogoff (2009), who argue that emerging markets often experience prolonged instability due to their reliance on external financing and vulnerability to global shocks. Furthermore, the study revealed that while financial cycles could have stabilising effects in certain contexts, such as in the work of Borio (2014), the weak and statistically insignificant relationship between the financial cycle and volatility in South Africa indicates that factors like limited financial inclusion and structural weaknesses undermine the stabilising potential of financial cycles. The results suggest that South Africa's financial system is prone to prolonged periods of instability, with exogenous and domestic shocks often interrupting stable periods. These findings also support the view that financial instability is deeply rooted in South Africa's structural challenges, such as high inequality and political uncertainty, which reinforce the cyclical nature of financial volatility.

The findings from this study have several key implications for South Africa's economic and financial policy. First, the study underscores the importance of aggressively employing macroprudential policies during periods of economic turmoil to maintain the stability of the financial cycle. Given the persistence of financial instability in South Africa, it is crucial to adopt proactive regulatory measures to contain volatility and mitigate systemic risks. The study's results emphasise that macroprudential policies should not be seen as supplementary, but rather as essential tools for managing financial cycles and reducing the likelihood of prolonged instability. Second, the study highlights the need for better coordination between monetary and macroprudential policies to ensure that the monetary policy does not inadvertently destabilise the financial cycle. In South Africa, the effects of the repo rate and macroprudential policy index on financial volatility illustrate the need for the careful calibration of both policies to avoid exacerbating instability. As seen during the 2020 pandemic, while aggressive interest rate cuts provided immediate liquidity relief, they did little to address the underlying structural weaknesses that contributed to long-term instability. Third, the findings suggest that when calibrating macroprudential policies, real economic factors, such as price levels, exchange rates, and business cycles, must be carefully considered. By accounting for these key variables, policymakers can better align macroprudential interventions with the broader economic context, reducing the risk of policy-induced financial imbalances and fostering a more stable financial environment.

To enhance the stability of the financial cycle in South Africa, several policy recommendations are proposed. First, it is critical to employ macroprudential policy more aggressively during periods of economic turmoil to safeguard the financial system from excessive risk-taking and instability. In times of economic uncertainty, such as during external shocks or domestic crises, the authorities should implement stricter regulations to mitigate credit expansion and speculative activities, thereby reducing the risk of financial instability. Second, a more coordinated approach between monetary and macroprudential policies is essential. While monetary policy typically aims to control inflation and manage interest rates, it can have unintended consequences for the financial cycle if not aligned with macroprudential measures. For example, aggressive interest rate hikes may exacerbate volatility in times of economic instability, as seen in the study. Therefore, a careful balance between both policies is crucial for achieving long-term financial stability. Finally, when formulating and calibrating macroprudential policies, policymakers must give due consideration to real economic factors, including the price level, exchange rate, and business cycle. These variables play a central role in determining financial stability, and their inclusion in policy frameworks can allow for more targeted and effective interventions. By ensuring that macroprudential policies are calibrated with a thorough understanding of these economic dynamics, South Africa can reduce financial volatility and foster a more resilient financial system.

One of the primary limitations of this study lies in its geographical focus on South Africa. By concentrating solely on South Africa, the analysis excludes other countries that may also benefit from an FCVIX-based assessment of financial cycle stability. The findings and implications drawn from the South African context may not be directly generalisable to economies with different financial structures, regulatory frameworks, or levels of economic development. Expanding the scope to include a broader range of countries in future research could provide a more comprehensive understanding of the relationship between financial cycles and stability across diverse economic settings. A cross-country analysis would also allow for comparative insights and a deeper investigation into the varying impacts of macroprudential policies and other factors on financial cycles globally.

Another notable limitation is the relatively narrow selection of financial variables included in the construction of the FCVIX. The financial sector is complex and comprises hundreds of variables, each of which could play a significant role in influencing financial cycle volatility. However, due to data availability and methodological constraints, only a handful of variables were incorporated into the analysis. This limited scope may overlook critical interactions and dynamics within the financial system. Addressing this limitation would involve broadening the dataset to include additional financial indicators, equity market performance, and banking sector stability metrics. Incorporating a wider range of variables could enhance the robustness of the model and provide a more nuanced understanding of the determinants of financial cycle volatility.

To address these limitations, future research could adopt a multi-country framework that incorporates diverse economic and financial systems to improve the external validity of the findings. Additionally, advances in data collection and computational methods could allow for the integration of a larger number of financial variables without compromising the efficiency and accuracy of the analysis. By addressing these limitations, subsequent studies could strengthen the theoretical and practical contributions of FCVIX analysis and provide policymakers with more robust tools for enhancing financial stability.

Future research could explore innovative methodologies to refine the measurement of financial cycle stability, such as incorporating machine learning techniques to model complex interactions among financial variables. Additionally, future studies could investigate the dynamic interplay between financial cycle stability and non-traditional factors, such as climate risks, technological innovations, and geopolitical shocks, which are increasingly relevant in shaping global financial systems. Research could also delve into the long-term impacts of sustained macroprudential interventions on financial cycle dynamics, providing a more comprehensive understanding of their effectiveness over extended time horizons. Lastly, applying the FCVIX framework in real-time policy simulations could offer valuable insights into the practical application of findings, enabling policymakers to test the efficacy of proposed interventions under varying economic scenarios.

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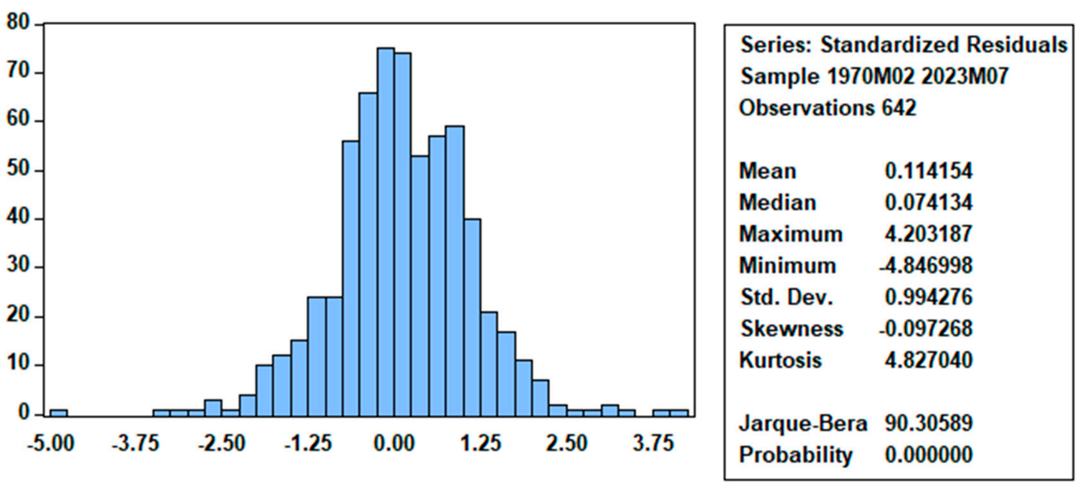
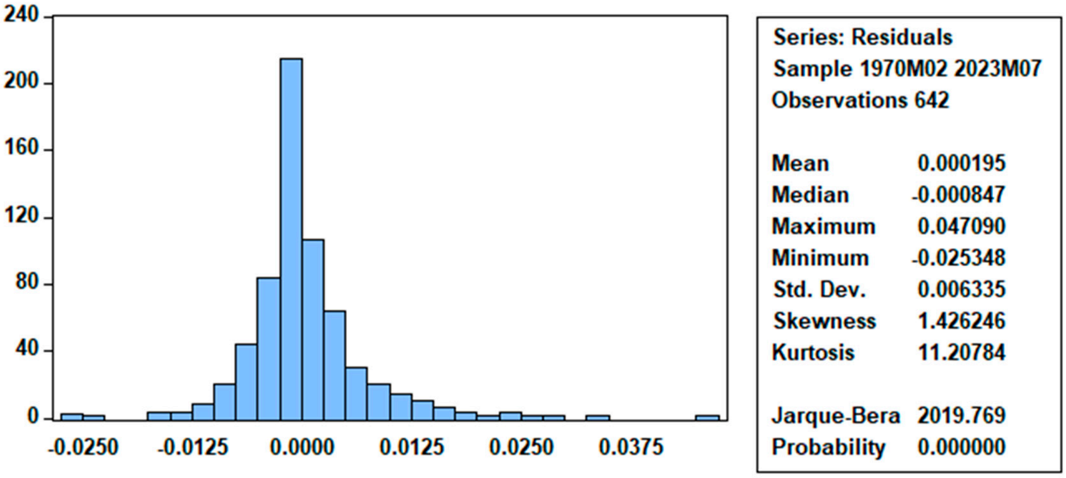
Appendix A



(A)

Figure A1. *Cont.*



(**B**)

Figure A1. (**A**) Histogram normality test—DCC model. (**B**) Histogram normality test—MSAR model.

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