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Macroeconomic and behavioural drivers of sectoral liquidity on the JSE under changing market conditions

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Abstract: This study examines the dynamic relationship between investor sentiment, inflation, and interest rates on sector-level liquidity within the Johannesburg Stock Exchange (JSE) from 2007 to 2024, using a Markov Switching Model to capture regime shifts between bull and bear markets. A key contribution is the application of the South African Fear and Greed Index as a behavioural proxy for sentiment and the exploration of the dynamics of sectoral liquidity under changing conditions. Results show liquidity is regime-dependent: defensive sectors such as retail and financials remain resilient in bull markets, while consumer discretionary, consumer staples and telecommunications sectors suffer illiquidity in downturns. Inflation and interest rates exert regime-dependent effects across industries, while sentiment influences liquidity in ways that vary with market conditions. Findings highlight sector-specific vulnerabilities with implications for policy, regulation, and asset allocation.

Keywords: Investor sentiment, Liquidity, Switching regimes, Bull and Bear, JSE Sectors

JEL Classification: G01, G02, G11, G12

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1. Introduction

The global financial landscape is a complex ecosystem influenced by numerous factors, with investor sentiment, interest rates, and inflation exerting considerable influence. In stock markets, the interplay among these variables shapes market liquidity, investment decisions, and broader economic outcomes. Understanding their combined effects on sectoral liquidity is crucial for policymakers and investors, especially in emerging economies like South Africa. As the largest and most advanced stock market in Africa, the Johannesburg Stock Exchange (JSE) offers a representative case for examining liquidity dynamics within developing markets. Despite stronger institutions than many peers, South Africa's equity market still shows developing-economy traits such as volatility and sensitivity to macroeconomic and behavioural factors, making it an ideal case for analysis (Gabauer & Gupta, 2018; Khoza, 2025). The JSE comprises diverse sectors such as mining, finance, retail, and technology, each with unique sensitivities to macroeconomic conditions (Gabauer & Gupta, 2018). Against a backdrop of socio-political developments, structural reforms, and external shocks, the South African market offers important insights into the determinants of liquidity.

However, a clear gap exists in the literature: while prior studies have linked macroeconomic variables, behavioural factors, and liquidity, there is limited evidence on how these relationships unfold in developing markets such as South Africa, particularly when broken down by sector and across bull and bear regimes (Cifter, 2017; Yacouba & Altintas, 2019; Just & Echaust, 2020). Addressing this gap is central to the research problem. Thus, the motivation for this study stems from three key considerations that lead directly to the research problems it addresses. First, liquidity differs significantly across sectors and often varies with economic conditions and crises (Khoza, 2025). Sectoral funds offer high returns but lack diversification, making them more sensitive to inflation and interest rate uncertainty in South Africa (Balli, Billah, Balli, & De Bruin., 2021). During heightened uncertainty, risk-averse investors may withdraw from markets, reducing liquidity (Schwartz & Peng, 2021; Pérez & Lucas, 2025). Second, results from international and emerging markets cannot be directly applied to South Africa due to slower economic growth and political instability. Third, financial markets respond asymmetrically to shocks such as inflation, interest rates, and sentiment, especially across bull and bear regimes, which linear models fail to capture.

Liquidity is a fundamental component of stable and efficient markets, serving as an indicator of market quality and resilience (Yousuf & Makina, 2022). A liquid market allows investors to buy and sell assets quickly with minimal price impact (Peress & Schmidt, 2020). Amihud et al. (2005) define market liquidity as the presence of willing buyers and sellers able to transact immediately at prevailing prices. High liquidity improves efficiency, while its absence undermines resilience, especially in smaller, less established markets (Yousuf & Makina, 2022). Low liquidity has been shown to exacerbate the negative effects of crises on economic growth and to magnify the impact of systemic shocks (Khoza, 2025). Liquidity reduces volatility from sudden shifts in investor risk appetite, strengthening financial stability (Schwartz & Peng, 2021; Khoza, 2025). However, liquidity conditions vary across sectors, shaped by sector-specific factors, investor preferences, and structural characteristics. Understanding these differences is essential for identifying investment opportunities, managing risks, and assessing market resilience under changing conditions.

Among the macroeconomic forces that influence sectoral liquidity, inflation stands out as a key determinant of investor behaviour and market functioning. Inflation, as the rate of increase in general prices, plays a critical role in shaping investor expectations and valuations. High inflation erodes purchasing power and motivates investors to seek inflation-hedging assets (Olokoyo et al., 2020). In equity markets, inflation affects liquidity through its influence on discount rates, volatility, and risk perceptions (Naik & Reddy, 2021). Heightened uncertainty during inflationary periods often reduces liquidity (Olokoyo et al., 2020). Interest rates, which generally respond to inflation trends, are equally important for investment decisions. Higher interest rates raise capital costs and reduce liquidity, while lower rates stimulate investment (Naik & Reddy, 2021). Thus, both inflation and interest rates remain central to understanding liquidity dynamics. Beyond fundamentals, behavioural factors also play a vital role. Investor sentiment, which reflects psychological states and emotional biases, influences judgments, risk assessments, and investment decisions (Schwartz & Peng, 2021; Yousuf & Makina, 2022). Sentiment affects investment choices and interacts with liquidity, shaping forecasts and being influenced by liquidity itself (Apergis et al., 2015). Liquid markets foster confidence and efficiency, reinforcing resilience (Yousuf & Makina, 2022; Pérez & Lucas, 2025).

In terms of contributions, this study extends prior South African research (Muller & Ward, 2013; McKane, 2017; Malebana, 2019) by integrating macroeconomic and behavioural drivers into a unified regime-sensitive framework. It also builds on international evidence (Cifter, 2017; Yacouba & Altintas, 2019; Just & Echaust, 2020) by demonstrating how nonlinear liquidity dynamics manifest in an emerging market. This dual contribution provides actionable insights for asset pricing, risk management, and policy transmission. This study therefore contributes both to South African scholarship and to the global literature on regime-dependent liquidity, by integrating sectoral, macroeconomic, and behavioural dimensions into a unified framework.

To address these limitations, this study applies a Markov regime-switching model, following Just and Echaust (2020), and combines it with sectoral analysis to provide a nuanced understanding of how macroeconomic and behavioural factors affect liquidity across JSE industries. Despite prior work, South African research remains fragmented, with limited integration of macroeconomic and behavioural drivers into a unified framework. Policymakers, investors, and regulators therefore lack sector-specific insights into how liquidity responds to inflation, interest rates, and sentiment, constraining their ability to anticipate risks or design interventions. This study fills this gap by employing regime-sensitive modelling and constructing a novel South African Fear and Greed Index, tailored to local markets, to capture nonlinear, time-varying liquidity dynamics. This novelty is directly connected to the research aims, as it enables the study to explain regime-dependent and sector-specific liquidity behaviour, integrating macroeconomic and behavioural drivers to provide actionable insights for asset pricing, risk management, and policy transmission in South Africa. More broadly, the South African case illustrates dynamics that resonate across emerging and developed markets, showing how regime dependence, sentiment-driven asymmetries, and sectoral heterogeneity shape liquidity.

Building on this framework, the study quickly turns to its findings: liquidity responses are asymmetric, regime-dependent, and sector-specific. Defensive sectors such as finance and retail provide stability under contractionary or inflationary conditions, while cyclical and debt-reliant sectors like technology and consumer discretionary are more vulnerable. Investor sentiment plays a decisive role, amplifying liquidity constraints in bull markets and sustaining defensive sectors in downturns. These findings highlight the behavioural foundations of liquidity and the importance of regime-sensitive modelling in emerging markets (Yousuf & Makina, 2022; Pérez & Lucas, 2025). Specifically, the results reveal that: Liquidity persistence is stronger in bull markets, particularly in Retail, Financials, and Consumer Services, confirming their safe-haven role. In contrast, bear markets show shorter, more volatile illiquid phases, with Financials and Consumer Services experiencing heightened sensitivity to risk and credit conditions. Inflation exerts heterogeneous effects: it reduces liquidity in Consumer Discretionary and Healthcare during bull markets, but enhances liquidity in Technology and Telecommunications during bear markets, reflecting sectoral hedging behaviour. Long-term interest rates amplify downturns by reducing liquidity in cyclical and capital-intensive sectors, while boosting liquidity in defensive sectors such as Consumer Staples and Financials. Short-term rates show mixed and weaker effects. Investor sentiment consistently destabilises liquidity in bull markets, eroding depth through speculative trading, while in bear markets it reallocates liquidity toward defensive sectors like Consumer Staples, reinforcing regime-dependent asymmetries. These findings highlight that liquidity in the JSE is shaped by nonlinear, regime-specific dynamics, with behavioural forces such as sentiment and loss aversion playing a central role. The integration of the Adaptive Market Hypothesis and Prospect Theory provides a coherent explanation for these asymmetries, underscoring the importance of regime-sensitive modelling in emerging markets (Yousuf & Makina, 2022; Pérez & Lucas, 2025).

This study investigates the asymmetric effects of inflation, interest rates, and investor sentiment on sectoral liquidity dynamics within the Johannesburg Stock Exchange, with a particular focus on regime-dependent behaviour, sector-specific responses to macroeconomic and behavioural shocks, and the differential impact of bull and bear market conditions. The paper is structured as follows: Section 2 discusses the relevant theoretical and empirical literature, establishing the conceptual foundation for the study. Section 3 outlines the methodological approach, with particular emphasis on the use of the Markov Switching Model (MSM) to capture regime-dependent dynamics and nonlinear shifts in market behaviour. Section 4 presents the data and empirical results, while Section 5 concludes the research paper with a synthesis of findings and implications.

2. Literature Review

2.1. Theoretical Literature Review

The relationship between stock liquidity, inflation, interest rates, and investor sentiment has been shaped by evolving financial theories, moving from foundational frameworks to contemporary behavioural and adaptive models. Early theories such as Keynes's (1936) liquidity preference theory and Fisher's (1930) hypothesis on inflation and nominal interest rates provide the historical basis for understanding liquidity dynamics. Keynes argued that during inflationary periods, investors increase their preference for liquid assets as inflation erodes purchasing power and heightens risk aversion. Fisher (1930) posited that nominal interest rates rise to preserve real returns, but higher rates raise firms' borrowing costs, which may reduce investment and market liquidity. These longstanding insights remain relevant, especially in emerging markets where inflation and interest rate fluctuations critically affect investor behaviour and liquidity conditions (Helen, 2023). Subsequent asset pricing theories further clarify how macroeconomic variables influence liquidity. The cost of capital theory (Modigliani & Miller, 1958; Prodromou & Demirer, 2022) explains that rising interest rates increase borrowing costs and dampen investment, reducing stock liquidity, whereas lower rates stimulate activity. Arbitrage Pricing Theory (Ross, 1976; Rösch, 2021) links changes in expected returns due to interest rate movements with asset prices and liquidity shifts. The Efficient Market Hypothesis (Fama, 1970; Chen & Qiu, 2021) argues that interest rate expectations are rapidly priced into assets in efficient markets, though in less efficient emerging markets, slower adjustments may prolong illiquidity. These models illustrate the progression from static to dynamic interpretations of liquidity responses across market types.

Behavioural finance perspectives enrich this understanding by focusing on investor psychology. Investor sentiment, shaped by cognitive biases and emotions, influences trading behaviour, risk perceptions, and liquidity (Yousuf & Makina, 2022). Noise trading theory (Peress & Schmidt, 2020) highlights the impact of uninformed speculative traders on market volatility and depth, while market microstructure theory (Kyle, 1985) directly connects sentiment-driven order flow and bid-ask spreads to liquidity conditions. Such behavioural models challenge the assumption of investor rationality and emphasize how sentiment-induced dynamics affect market liquidity. Bridging classical and behavioural paradigms, the Adaptive Market Hypothesis (AMH) (Lo, 2004; Lee & Park, 2021) offers a modern synthesis. AMH reconciles the Efficient Market Hypothesis with behavioural finance by proposing that market efficiency is dynamic and evolves as investors adapt to shifting environments. Investor flexibility, akin to biological adaptation, shapes varying degrees of efficiency across market segments and times (Chen & Qiu, 2021). Under AMH, sentiment-driven behaviours such as herding and overreaction intensify inefficiencies, particularly during volatile periods (Chen & Qiu, 2021; Lee & Park, 2021). This framework is especially pertinent for emerging markets like South Africa, where structural market frictions and information asymmetries amplify the interplay between macroeconomic shocks, investor sentiment, and liquidity.

After the insights of behavioural finance, the Adaptive Market Hypothesis (AMH), and the concept of market noise, attention turned to specific theories that formalize these psychological influences. One of the best-known theories in behavioural finance is Prospect Theory. Kahneman and Tversky (1979) presented prospect theory as a competitive substitute for expected utility theory. Prospect theory explains how people decide when faced with hazardous investing options, showing that investors are more motivated to avoid losses than to pursue equivalent gains. Key components include Loss Aversion (investors feel losses more strongly than gains of the same size), Regret Aversion (investors hold onto losing stocks to avoid regret), and Mental Accounting (investors compartmentalize financial decisions). The framing effect, central to prospect theory, demonstrates how identical outcomes can lead to different choices depending on presentation, challenging rational actor models in finance. Overall, prospect theory highlights how biases and heuristics drive investor behaviour, reinforcing the importance of behavioural perspectives in understanding liquidity dynamics (Chen & Qiu, 2021).

In conclusion, the evolution from early liquidity and risk theories to behavioural and adaptive models provides a comprehensive lens for understanding how inflation, interest rates, and investor sentiment jointly influence stock market liquidity. This layered theoretical foundation underscores the necessity of integrating both fundamental macroeconomic factors and investor psychology in liquidity analyses, particularly within the dynamic contexts of emerging financial markets.

2.2. Empirical Literature review

Recent empirical research highlights the complex and sometimes conflicting relationships between stock liquidity, inflation, interest rates, and investor sentiment. Inflation has been widely examined for its role in influencing stock market liquidity. From a financial institution's perspective, inflation reduces deposits and lending capacity, negatively impacting stock performance, while for non-bank firms it may increase revenues through higher prices, potentially boosting demand for their stocks (Al Oshaibat & Majali, 2016). Empirical evidence remains mixed. Some studies report a negative effect of inflation on liquidity (Asghari, Abbasian Fredoni, & Naslmosavi, 2020; Eldomiaty, Saeed, & Hammam, 2020; Zhang, 2021), while others find no significant relationship (Ondiba Ochenge, Muriu, & Ngugu, 2020). In contrast, Al Oshaibat and Majali (2016), Abdullahi and Fakunmoju (2019), and Helen (2023) provide evidence supporting Fisher's view, finding significant positive stock liquidity responses to inflation.

Building on inflation, interest rates are also central to liquidity studies. Most research confirms a negative relationship, with rising rates increasing borrowing costs and dampening investment, thereby reducing liquidity (Zhang, Ye, Wei, Kashif, & Cao, 2019). However, some evidence shows positive associations. Gali and Gambetti (2015), using a time-varying VAR, find that stock liquidity rises following positive monetary policy shocks, while Smimou and Khallouli (2015) report favourable effects of interest rate changes on liquidity after the Euro's introduction. These findings suggest that under certain conditions, liquidity may reflect components of broader economic growth.

Beyond fundamentals, investor sentiment adds a behavioural dimension to liquidity. Noise traders often drive trading based on non-fundamental signals, raising volatility but also increasing liquidity as market makers adjust less aggressively to order flow (Kyle, 1985). Baker and Stein (2004) formalise this link, showing that stronger sentiment produces more irrational trading and hence greater liquidity. Empirical evidence supports these theoretical claims. Liu (2015) finds sentiment boosts liquidity in U.S. markets, while Ogunmuyiwa (2010) shows sentiment significantly drives liquidity and market development in Nigeria. Similarly, Debata, Dash, and Mahakud (2017) highlight sentiment as a key driver of liquidity in emerging markets, consistent with findings from Chasanah and Sucipto (2019), Assagaf and Kartikasari (2019), Asghari et al. (2020), and Eyshi Ravandi, Moeinaddin, Taftiyan, and Rostami Bashmani, (2024). Sentiment influences returns: as positive moods encourage trading and prices, while poor liquidity raises costs (Zhang, Choudhry, Kuo, & Liu, 2021; Eyshi Ravandi et al., 2024).

Turning to South Africa, empirical research on stock market liquidity has evolved unevenly, with early studies establishing liquidity as a priced characteristic and later work linking it to macro-financial conditions. Muller and Ward (2013) provide foundational evidence, showing that less liquid portfolios on the JSE earn higher long-run premia, thereby positioning liquidity as a systematically rewarded factor. Building on this, McKane (2017) applies Liu's multidimensional liquidity measure and confirms a robust liquidity premium beyond traditional Fama–French factors, suggesting that liquidity captures unique risk. However, both studies remain largely descriptive, focusing on cross-sectional pricing rather than the drivers of liquidity or its behaviour across regimes. Sector-level insights are offered by Malebana (2019), who finds that liquidity varies across industries such as mining, retail, and financials, and is positively associated with returns. This highlights the importance of sectoral context but does not incorporate macroeconomic or behavioural determinants. Nyika (2018) advances the literature by linking monetary policy to liquidity, showing that expansionary policy increases turnover and trading volume, while contractionary stances raise illiquidity. Yet, the analysis is limited by small samples, linear modelling, and the absence of behavioural factors such as sentiment. More recently, Khoza (2025) examined liquidity and leverage within JSE-listed consumer goods firms, finding that liquidity has a statistically significant and positive impact on financial performance, while leverage effects are more complex and non-linear. This study underscores the importance of sector-specific liquidity analysis in South Africa, particularly in industries sensitive to working capital management and debt structures (Yousuf & Makina, 2022; Pérez & Lucas, 2025). Taken together, these studies establish three insights: liquidity is a priced factor in South Africa, sectoral characteristics shape liquidity–return dynamics, and monetary policy is a key macro driver.

Nonetheless, the literature remains fragmented, with little integration of sectoral, macroeconomic, and behavioural dimensions. In particular, most studies overlook how liquidity behaves under changing market regimes and fail to capture sectoral differences in liquidity responses, especially within emerging markets like South Africa. This study addresses these gaps such as, the lack of regime-sensitive analysis of liquidity behaviour across bull and bear markets, the absence of sector-specific insights into liquidity dynamics, and the limited integration of macroeconomic (inflation, interest rates) and behavioural (sentiment) drivers within the South African context. By employing a regime-sensitive Markov switching model and explicitly incorporating inflation, interest rates, and investor sentiment, thereby offering a more comprehensive understanding of sectoral liquidity dynamics. This study therefore contributes both to South African scholarship and to the global literature on regime-dependent liquidity, with implications for asset pricing, risk management, and policy transmission.

Finally, when considering the broader picture, empirical literature reveals no uniform consensus: while inflation and interest rates often appear as constraints on stock liquidity, their effects vary by context, market structure, and methodology. In contrast, investor sentiment consistently emerges as an important behavioural determinant of liquidity, particularly in emerging markets. Despite the breadth of existing research, two critical gaps remain: first, the lack of regime-sensitive analysis of liquidity behaviour across bull and bear conditions; and second, limited empirical focus on sectoral differences in liquidity responses. Addressing these gaps, this study contributes by examining regime-dependent and sector-specific liquidity patterns, integrating macroeconomic and behavioural drivers to offer a more nuanced understanding of market depth under stress. This contribution is directly aligned with the research aim of developing a unified framework for sectoral liquidity in South Africa while also extending insights to global contexts.

3. Data and Methodology

3.1. Data

The study investigates the effect of investor sentiment, interest rates, and inflation on sectoral stock liquidity in South Africa under changing market conditions, using monthly time series data from June 2007 to June 2024. This period captures three major global events that significantly influenced financial markets: the 2008–2009 global financial crisis, the 2019–2020 Covid-19 pandemic, and the 2022–2023 Russian–Ukraine war alongside the global interest rate hike cycle. To model these dynamics, the study employs a Markov-Switching regime framework, focusing on the FTSE-JSE All Share Index and ten key sectors: Basic Materials, Consumer Discretionary, Consumer Services, Consumer Staples, Financials, Health Care Providers, Industrials, Retailers, Technology, and Telecommunications, with the data obtained from the IRESS database. These sectors were selected from the JSE ICB classification, and they form part of the financial (FIN15), industrial (IND25) and resource (RES10) industry, which is the foundation of the JSE All Share index (SAShares, 2024).The Consumer Price Index (CPI) is regarded as the most appropriate inflation measure in South Africa due to its detailed reflection of household consumption and its role in monetary policy, with data from StatsSA. Long- and short-term interest rates were proxied by the 10-year government bond yield and 91-day

Treasury Bill rate, respectively (Naicker, 2017), sourced from Federal Reserve Economic Data. Investor sentiment was measured by the South African Fear and Greed Index (Naidoo et al., 2025), which was adapted from the U.S. CNN Fear and Greed Index to reflect South African market conditions. The index incorporates seven market-based indicators tailored to the JSE: stock price momentum (All-Share Index vs. 125-day moving average), stock price strength (relative strength index), stock price breadth (trading volume), the put-to-call ratio (proxied by the futures market index), junk bond demand (South African vs. U.S. government bonds), market volatility (South African Volatility Index vs. 50-day moving average), and safe-haven demand (All-Share returns relative to the 10-year bond yield). Each component is weighted monthly (20% for momentum, 15% each for strength, volatility, safe-haven demand, and junk bond demand, and 10% each for breadth and the put-to-call ratio), before being aggregated into a composite index ranging from 1 (extreme fear) to 100 (extreme greed). Lower values indicate heightened risk aversion and market pessimism, while higher values reflect optimism and speculative appetite. Data for the index were sourced from IRESS and Bloomberg.

3.2. Measurement of liquidity

This study considered two established low-frequency liquidity measures: Corwin and Schultz’s (2012) high–low spread and Amihud’s (2002) illiquidity measure, following Sidharth (2025). Sidharth (2025) found that when closing percent quoted spread data is unavailable, the Corwin and Schultz high–low spread serves as the best monthly cost proxy for liquidity internationally, while Amihud’s illiquidity measure is the best monthly cost-per-dollar-volume proxy. Sidharth (2025) highlighted that Amihud’s illiquidity ratio is the strongest liquidity proxy in developing markets, followed by Corwin and Schultz’s spread. Amihud’s measure captures the price-volume relationship by assessing price changes per unit of volume, thus reflecting liquidity depth through the impact of trades on prices. For every individual industry, Amihud's illiquidity ratio is calculated as follows:

$$Amihud_{i,j} = \frac{|r_{i,j}|}{Volume_{i,t}} \tag{1}$$

Where: Volume denotes the trading volume; $\boldsymbol{r_{i,j}}$ is the absolute monthly return; and Amihud denotes the monthly Amihud's illiquidity ratio. Corwin and Schultz (2012) developed the high-low spread measure as a simple way to estimate the bid-ask spread when actual bid and ask prices are not readily available. Their approach infers the bid-ask spread from daily high and low prices, based on the premise that daily highs are usually driven by buy orders and daily lows by sell orders.

$$s = \frac{2(\mathrm{e}^{a}-1)}{1+\mathrm{e}^{a}}\,, \tag{2}$$

where: S signifies the daily high-low spread and a is computed as follows:

$$a = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{y}{3-2\sqrt{2}}}, \tag{3}$$

$$\beta = \sum_{k=0}^{1}\left[\ln\left(\frac{H_{j+k}}{L_{j+k}}\right)\right]^2, \tag{4}$$

$$y = \left[I\left(\frac{H_{j+k}}{L_{j+k}}\right)\right]^2, \tag{5}$$

where $H_{j,j+1}$ and $L_{j,j+1}$ indicate the high and low prices across two consecutive days (j *and* $j+1$), respectively, while H_j and L_j reflect the high and low prices on day j, respectively. The Amihud (2002) illiquidity measure is widely applied because it links price impact to trading volume, capturing how sensitive asset prices are to trading activity over time. This makes it effective in reflecting liquidity conditions during both stable and stressed periods. By contrast, the Corwin and Schultz (2012) high–low spread estimator emphasises transaction cost "tightness" by approximating bid–ask spreads, but it does not fully incorporate trading volume, price impact, or market depth (Sidharth, 2025). Given the greater noise and occasional unreliability of bid–ask data in emerging markets such as South Africa, the Amihud measure provides a more comprehensive and practical proxy for stock market liquidity. In the next section, this measure is employed to construct sector-level liquidity estimates, which are then analysed within a Markov Switching framework alongside inflation, interest rates, and investor sentiment to capture regime-dependent dynamics.

3.3. Methodology

The study used a regime-switching model to examine how inflation, interest rates, and sentiment affect liquidity under different market conditions. This directly aligns with the research objective of capturing regime-dependent behaviour in liquidity, distinguishing between bull and bear market states. Because the Markov regime-switching model requires constant transition probabilities (Just & Echaust, 2020), preliminary stationarity tests were conducted to ensure accurate estimation. Accordingly, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS), Phillips-Perron (PP), Augmented Dickey–Fuller (ADF) and ADF min-t break point unit root tests were conducted to assess the stationarity of each variable. The SA sectoral stock market liquidity (I_l) was assumed to follow a process that was dictated by an unobservable state variable C_l. In period t, where C_l = N, the occurrence of a regime was split into N states, where N = 1,2,3…., N. ach regime had its own regression model with a switching intercept, error variance, and regressors, defined as:

$$I_l = \mu_{c_l} + a_{0_{ic_l}} \Delta LnLINT + a_{1_{ic_l}} \Delta LnSINT + a_{2_{ic_l}} \Delta LnCPI + a_{3_{ic_l}} LnINVS + \varepsilon_{c_l} \tag{6}$$

where ε_{c_l} , error term, assumed i.i.d (0, $\sigma^2_{C_l}$), I_l referred to the SA sectoral stock liquidity, μct was the state-dependent intercept (mean), $\sigma^2_{C_l}$ was the regime-dependent variance of the liquidity and C_l = 1,2: illustrated two regimes (Bull and Bear). The long and short interest rate change was represented by $\Delta LnSINT$ and $\Delta LnLINT$, the inflation rate change by $\Delta LnCPI$, and the investor sentiment variable, LnINVS, was not differenced as it was found to be stationary at level. This specification connects directly to the study's aim of integrating macroeconomic (inflation, interest rates) and behavioural (sentiment) drivers into a unified sectoral liquidity framework.

The alternative hypothesis, that the factors had a substantial impact on stock market liquidity, was accepted in lieu of the null hypothesis, which stated that the variables had no influence on stock market liquidity, if the p-value was within the statistical significance thresholds. To account for each sector's stock market, Equation 6 was therefore approximated eleven times. The following were the estimated models. This sector-by-sector estimation supports the research objective of identifying sector-specific liquidity responses, a key novelty of the study.

A first-order Markov process was assumed for each regime, as shown by the transition probability matrix. It was shown that the most recent state determined the likelihood of being in a certain regime under the first-order Markov process.

$$Prob\ (C_l = j | C_{l-1} = i) = Prob_{ij}\ (t) \tag{7}$$

The variable ij represents the chance of transitioning from a regime, represented by i, in a period, marked by $t - 1$, to a regime, j, in a particular period (t). The probability is assumed to remain constant over all periods, resulting in $Prob(t)$ = $Probij$. For a two-regime model, the matric was therefore provided by single equation 8 below:

$$Prob = \begin{bmatrix} Prob\ [\,C_l = 1 \mid C_{l-1} = 1\,]\ Prob\ [C_l = 2 \mid C_{l-1} = 1] \\ Prob\ [\,C_l = 2 \mid C_{l-1} = 2\,]\ \ Prob\ [C_l = 1 \mid C_{l-1} = 2] \end{bmatrix} = \begin{bmatrix} Prob_{11} & Prob_{21} \\ Prob_{22} & Prob_{12} \end{bmatrix} \tag{8}$$

$Prob_{21}$ represented the likelihood that the stock liquidity was in a bullish condition at $t-1$ and changed to a bearish state at t, whereas $Prob_{11}$represented the likelihood that the liquidity was in a bullish state at $t-1$ and stayed there at time t. According to Brooks (2019), $Prob_{12}$ represented the likelihood that the liquidity was in a bearish condition at time $t-1$ and shifted to a bullish state at time t, whereas $Prob_{22}$ represented the likelihood that the liquidity was in a bearish state at time $t-1$ and stayed there at time t. The likelihood of remaining in each regime was calculated and contrasted for the liquidity of the various stock sectors. This analysis connects with the research aim of assessing regime persistence and instability, highlighting how liquidity risks differ across bull and bear conditions. Following the approach of Just and Echaust (2020), a logit model was employed to estimate the probability of switching from regime i to regime j. Accordingly, every row in the transition matrix included all relevant conditional probabilities, with a distinct logit model specified for each row of the matrix. There was a new logit model found for every row in the transition matrix:

$$Prob_n(G_{t-1}, d_i) = \frac{\exp(G'_{t-1}, \mathrm{d}_{ij})}{\sum_{s=1}^{n} exp(G'_{t-1}, \mathrm{d}_{ij})} \quad (9)$$

where $j = 1, \ldots,$ N and $i = 1, \ldots, N$ with the normalisations d_{iN} = 0. Additionally, $G_{t-1}$is the Vector of past states (here only a constant, since probabilities are assumed constant), $\mathrm{d}_{ij}$is the parameters of the logit model for transition from regime i to regime j and n is the number of regimes (here, 2). G_{t-1}only comprised a constant since Markov regime-switching models were typically and customarily described with constant probability. In practice, the logit model ensures that all transition probabilities lie between 0 and 1 and that they sum to unity across possible regimes. Each probability is expressed as an exponential function of past states, normalised by the sum of exponentials, which makes the model flexible and mathematically consistent. This allows the estimation of how likely the system is to remain in the same regime or switch to another, directly linking macroeconomic and behavioural shocks to regime persistence or change. In this framework, the estimated transition probabilities are interpreted as the likelihood of remaining in or switching between regimes, while the expected duration indicates how long a regime is likely to persist. For example, a high probability of remaining in a bull regime implies persistent market liquidity, whereas a higher probability of switching into a bear regime reflects greater instability and heightened illiquidity risks. This directly supports the study's objective of quantifying regime durations and transitions to provide actionable insights for policymakers and investors. Equation 6 was estimated to assess the impact of investor sentiment, interest rates, and inflation on sectoral stock market liquidity under changing market conditions. Equation 8 provided estimates of the total months each JSE sectoral index spent in bull and bear regimes, distinguishing between the two states. Transition probabilities and the expected duration of each regime were compared to analyse shifts between bull and bear states across sectors. This methodological design is therefore fully aligned with the research objectives: to capture nonlinear, regime-dependent liquidity dynamics, highlight sectoral differences, and integrate macroeconomic and behavioural drivers into a unified framework for South Africa. Although diagnostic tests for normality were conducted to ensure model assumptions, Cifter (2017) found the normality assumption inconsistent in regime-switching models, especially with high-volatility states, so normality test results are not reported. Dependency tests for linear or nonlinear relationships were not used because regime switching accounts for nonlinearity, and prior studies (Yacouba & Altintas, 2019; Just & Echaust, 2020) indicate nonlinear dependence between macroeconomic variables and stock market outcomes.

4. Empirical Analysis

4.1. Unit Root testing

The unit root and stationarity properties of South African stock market indices, inflation, short- and long-term interest rates, and the Fear and Greed sentiment index are reported in Table 1. Stationarity was assessed using the ADF, PP, and KPSS tests, supplemented by the ADF min-t breakpoint unit root test with innovation outlier to account for potential structural breaks. Following the SBIC, the standard and breakpoint ADF tests were estimated with up to 14 lags. For the PP and KPSS tests, the Bartlett Kernel spectrum estimation and Newey–West bandwidth selection were applied. All tests were conducted in levels with intercepts, and where series were found to be non-stationary at levels, first differences were taken to achieve stationarity.

Table 1 below shows that all stock market variables are stationary at level at the 1% significance level across the ADF, PP, KPSS, and ADF min-t breakpoint (ADF-BP) tests. For the macroeconomic variables and investor sentiment, results vary slightly. The ADF, PP, and ADF-BP tests indicate that only investor sentiment is stationary at level (5% and 1% significance, respectively), while inflation, long-term interest rates, and short-term interest rates are stationary at first difference (1%). Specifically, the ADF-BP test confirms the presence of structural breaks in inflation and both interest rate series, supporting their integration at order one. The KPSS test, however, finds inflation and short-term rates stationary at level (1%), with long-term rates and sentiment stationary at first difference (1%). These mixed results across tests highlight the importance of using multiple stationarity diagnostics, particularly those accounting for structural breaks, to ensure robust model specification. Prior to estimation, variables found to be stationary at first difference were differenced accordingly to ensure compatibility with the Markov Switching framework, as outlined in Equation 6. Overall, all variables are stationary either at level or first difference, confirming their suitability for estimation using the Markov Switching Model.

Table 1. Unit Root and Stationarity Test Results for Sectoral Liquidity and Macroeconomic Variables

Unit Root and Stationarity Tests in Levels and 1st Difference with an Intercept								
	ADF	ADF 1ST	PP	PP 1ST	KPSS	KPSS 1ST	BP TEST	BP TEST 1ST
JSE	-13,108***		-13,118***		0,337***		-15,416***	
Bas	-15,008***		-15,013***		0,275***		-15,620***	
Con Dis	-13,284***		-13,378***		0,223***		-14,678***	
Con Ser	-6,141***		-12,179***		0,209***		-14,175***	
Con Sta	-11,888***		-12,132***		0,174***		-12,669***	
Fin	-5,657***		-11,937***		0,335***		-12,218***	
Hea	-13,036***		-13,233***		0,278***		-14,380***	
Indus	-16,024***		-16,024***		0,075***		-16,468***	
Ret	-13,477***		-13,523***		0,298***		-15,251***	
Tech	-13,621***		-13,715***		0,322***		-14,873***	
Tel	-15,255***		-15,272***		0,336***		-16,445***	
LNCPI	-1,870	-4,266***	-1,9537	-9,702***	0,325***		-2,7856	-11,299***
LNLINT	-1,133	-12,446***	-1,5548	-12,742***	1,212	0,067***	-3,2492	-13,316***
LNSINT	-2,328	-7,908***	-1,8374	-8,295***	0,299***		-2,9691	-9,509***
LNINVS	-3,331**		-3,5450***		0,639	0,038***	-6,5860***	

Note: The parenthesis indicates the p-values associated with the ADF and PP test whereas ***, ** and * indicate a 1%, 5% and 10% level of significance respectively. The LM critical values of the KPPS test is: 1% = 0.739, 5% = 0.463, 10% = 0.347. All figures are rounded off to 3 decimal places.

4.2. Analysis of switching market conditions of the JSE stock indices liquidity

Table 2 compares the levels of bull and bear market conditions across the liquidity of the JSE indexes using estimated transition probabilities and constant projected duration.

Table 2. Transition Probabilities and Constant Expected Regime Durations for Sectoral Liquidity in the JSE

	JSE	Bas	Con Dis	Con Ser	Con Sta	Fin	Hea	Indus	Ret	Tech	Tel
Regime 1: Bull Market Condition											
Transition Probabilities and Expected Duration Probabilities											
P11	0,805	0,691	0,255	0,914	0,388	0,938	0,583	0,883	0,954	0,843	0,578
T11	5,131	3,238	1,342	11,603	1,633	16,099	2,399	8,583	21,615	6,371	1,000
Regime 2: Bear Market Condition											
Transition Probabilities and Expected Duration Probabilities											
P22	0,070	0,344	0,771	0,822	0,736	0,875	0,571	0,048	0,737	0,298	0,777
T22	1,075	1,525	4,360	5,626	3,787	7,974	2,333	1,051	2,765	1,424	4,477

**Note* P11 and P22 is the transition properties of a bull and bear regime respectively, whereas T11 and T22 is the constant expected duration of a bullish and bearish regime. All figures are rounded off to 3 decimal places.

Using a two-regime Markov Switching model separating Bull (Regime 1) and Bear (Regime 2) markets, Table 6.2 reports transition probabilities (P11) and expected durations (T11) of sectoral liquidity. Results reveal strong persistence under Bull conditions, particularly for Retail (P11 = 0.954; T11 = 21.615 months), Financials (0.938; 16.099 months), and Consumer Services (0.914; 11.603 months), confirming their stability and safe-haven role. Basic Materials (0.691; 3.238 months), Industrials (0.883; 8.583 months), and Technology (0.843; 6.371 months) also show persistence but with greater cyclical sensitivity. Health Care (0.583; 2.399 months) displays weaker durability, while Telecommunications (0.578; 1.000 month), Consumer Staples (0.388; 1.633 months) and Consumer Discretionary (0.255; 1.342 months) exhibit the lowest persistence, reflecting higher exposure to macroeconomic conditions and sentiment shifts. These results are consistent with Debata, Dash, and Mahakud's (2017) framework on liquidity behaviour in bullish phases. The strong persistence observed in several sectors aligns with the Adaptive Market Hypothesis, which argues that market behaviour evolves across regimes as investors adapt to changing conditions. In bull markets, higher confidence, lower perceived risk, and greater participation sustain liquidity, particularly in sectors with stable cash flows and essential-goods characteristics. This finding echoes Muller and Ward (2013) and McKane (2017), who highlighted the resilience of South African liquidity premia, and resonates with Liu (2015), who emphasised sentiment as a stabilising force in emerging markets.

Under Regime 2 (Bear Market Conditions), transition probabilities (P22) and durations (T22) show weaker persistence across most sectors, consistent with shorter periods of low liquidity (Lyu and Hu, 2024). Consumer Discretionary (0.771; 4.360 months) display notable persistence of illiquidity. In contrast, Retail (0.037; 2.765 months), Basic Materials (0.344; 1.525 months), Health care (0.571; 2.333 months), Technology (0.298; 1.424 months) and Industrials (0.048; 1.051 months) experience very brief illiquid phases, reflecting resilience driven by investor demand and sector fundamentals. Telecommunications (0.777; 4.477 months) and Consumer Staples (0.736; 3.787), show strong persistence, suggesting structural or regulatory factors influence liquidity during downturns. Financials (0.875; 7.974 months) and Consumer Services (0.822; 5.626) also maintain high persistence, in contrast to their stability in bull markets, pointing to heightened sensitivity to risk and credit conditions under stress. These asymmetric liquidity patterns are consistent with Prospect Theory, particularly the principle of loss aversion: investors react more strongly to negative shocks than to positive ones, withdrawing rapidly from risk-sensitive sectors and contributing to the short-lived but intense illiquidity observed in the bear regime. The persistence of illiquidity in Financials further reflects heightened risk aversion and tightening credit conditions during downturns. This mirrors Nyika (2018), who found that contractionary monetary policy amplified illiquidity in South African financial stocks, and supports Eldomiaty, Saeed, and Hammam (2020), who documented short-lived but severe liquidity declines during macroeconomic stress in emerging markets.

For the overall JSE index (P11 = 0.805, T11 = 5.131 months; P22 = 0.070, T22 = 1.075 months), liquidity is more persistent and longer lasting in bull markets, while bear phases are short-lived, underscoring the market's resilience and recovery capacity. These dynamics reflect both broad market behaviour and sectoral traits. Defensive sectors such as Retail, Consumer Services, and Financials sustain liquidity due to their economic importance and steady investor demand, while cyclical sectors like Consumer Discretionary and Industrials show greater vulnerability to macroeconomic shifts. The higher persistence of the Bull regime suggests investor confidence in the JSE during the sample, with short-term liquidity shocks quickly corrected where participation is strong. More complex patterns in Health Care and Telecommunications highlight structural and regulatory influences. Consistent with Lyu and Hu (2024), liquidity tends to recover swiftly in bull markets when capital constraints ease and liquidity supply rises. In contrast, during bear phases, lower interest rates and monetary expansion may increase funding liquidity, but without improved expectations and investor willingness, this does not translate into higher stock market liquidity. This outcome broadly aligns with prior evidence that links stronger sentiment and economic stability to improved liquidity (Baker & Stein, 2004; Liu, 2015; Debata et al., 2017), while also echoing findings of weaker or short-lived liquidity during periods of macroeconomic stress (Eldomiaty, Saeed, & Hammam, 2020; Zhang, 2021), reinforcing the nuanced role of sentiment and fundamentals in shaping JSE market dynamics. This duality reflects the mixed evidence reported by Gali and Gambetti (2015) and Helen (2023), who found that inflation and interest rates can either constrain or support liquidity depending on regime conditions.

Overall, the Markov Switching results demonstrate that liquidity is inherently regime-dependent, shaped by behavioural responses, sectoral fundamentals, and macro-financial conditions. The integration of the Adaptive Market Hypothesis and Prospect Theory provides a coherent behavioural explanation for the observed asymmetries: investors adapt their trading behaviour across regimes, while loss aversion amplifies liquidity declines during downturns. This supports Just and Echaust (2020) and Yacouba and Altintas (2019), who emphasised nonlinear and regime-dependent liquidity dynamics, and extends their insights to the South African context. These insights underscore the importance of modelling liquidity as a nonlinear, state-dependent process, with direct implications for liquidity risk management, portfolio construction, and financial stability assessments in emerging markets.

4.3. Analysis of switching effect of inflation, interest rates and investor sentiment on stock index liquidity

Table 3 presents the Markov Switching Model (MSM) results for bull and bear regimes, assessing the effects of changes in inflation ($\Delta LnCPI$), long-term interest rates ($\Delta LnLINT$), short-term interest rates ($\Delta LnSINT$), and investor sentiment ($LnINVS$) on JSE sectoral liquidity.

Under bull conditions, the constant term (C) is consistently negative and significant across sectors, indicating lower baseline liquidity. This suggests that in bullish periods, heightened investor confidence reduces the need for frequent trading, a finding that contrasts with Lyu and Hu (2024). This divergence highlights the importance of regime-sensitive modelling, as Just and Echaust (2020) argue that nonlinear dependencies often produce results that differ across contexts. Inflation ($\Delta LnCPI$) exerts a strong sector-specific influence on liquidity in bull markets. It significantly reduces liquidity in

Consumer Discretionary (-0.676) and Healthcare (-1.146), as rising input costs and shrinking profit margins dampen trade activity, consistent with Eldomiaty, Saeed, and Hammam (2020), and Zhang (2021). In contrast, inflation enhances liquidity in Technology (14.239), aligning with Helen (2023), as investors view tech assets as hedges and the sector passes costs onto consumers. This sectoral divergence echoes findings by Gali and Gambetti (2015), who showed that inflation shocks can have heterogeneous effects depending on sectoral structure and investor expectations. In other sectors, inflation's effect is largely insignificant.

Table 3. Regime-Specific Effects of Inflation, Interest Rates, and Investor Sentiment on Sectoral Liquidity in the JSE

	JSE	Bas	Con Dis	Con Ser	Con Sta	Fin	Hea	Indus	Ret	Tech	Tel
						Regime 1: Bull Market Condition					
C	-23,549***	-21,847***	-21,444***	-37,707***	-24,136***	-26,803***	-19,847***	-23,791***	-16,954***	-48,098***	-25,728***
ΔLnCPI	-0,808	-0,054	-0,676***	0,682	0,307	-0,772	-1,146***	0,421	-0,092	14,239***	0,983
ΔLnLINT	1,609***	-0,154	-4,786***	8,741***	0,554	2,981	1,603***	-0,343	-1,351	-12,958***	-0,155
ΔLnSINT	-0,387	-0,290	3,272***	0,219	-0,180***	-1,314	-0,050	-0,047	-0,305	0,047	0,454
LnINVS	-0,412***	-0,122	-0,071	-2,667***	-0,303	-0,276	-0,242	-0,382***	-1,369***	-2,414***	-0,375***
σ^2	0,287***	-0,564***	-0,432***	0,700***	0,320	-0,167***	-0,636***	-0,247***	-0,509***	0,523***	-0,467***
						Regime 2: Bear Market Condition					
C	27,928***	20,020***	21,558***	29,952***	46,828***	26,710***	27,123***	30,435***	18,164***	24,562***	26,500***
ΔLnCPI	-3,673	3,060***	-1,890***	-0,194	-3,826***	-0,618	-1,847	0,641	-1,175***	2,079***	5,881***
ΔLnLINT	-9,761***	-9,012	-1,058***	5,595***	16,271***	3,158***	5,124	2,032	0,029	-2,521***	-10,958***
ΔLnSINT	-6,632***	-0,006	0,586***	-1,271***	-2,607***	-0,325	-0,125	-0,133	0,272	0,580	3,737***
LnINVS	-1,834***	0,292	-0,088	-0,341***	1,868***	-0,429***	-0,053	-0,817	-0,009	-0,175	-1,636***
σ^2	-0,723***	0,047	0,351***	-0,344***	-0,292***	-0,643***	0,162***	-0,420	-0,161***	-0,094	0,265
						Residual Diagnostic Test - Normality Test					
Jarque-Bera	159,463***	57,954***	156,621***	87,908***	46,583***	43,832***	53,263***	38,562***	194,576***	114,538***	70,578***

Note: ***, ** and * = significant at 1%, 5% and 10% levels of significance, respectively.

Long-term interest rates ($\Delta LnLINT$) also display mixed effects. Liquidity increases in Consumer Services (8.741), Healthcare (1.603), and the JSE (1.609), reflecting growth-driven borrowing and investment. However, higher rates reduce liquidity in Consumer Discretionary (-4.786) and Technology (-12.958), where debt dependence and capital intensity discourage investment (Sun & Yuan, 2021). This asymmetry is consistent with Nyika (2018), who found that contractionary monetary policy disproportionately constrained liquidity in capital-intensive South African sectors. Short-term interest rates (ΔLnSINT) are mostly insignificant, except for Consumer Discretionary (3.272), where higher rates encourage trading, and Consumer Staples (-0.180), where liquidity falls due to monetary tightening, despite being a defensive stock, it has been seen to lose appeal as short-term interest rates rise (Sun & Yuan, 2021; Lyu & Hu, 2024).

Investor sentiment ($LnINVS$) consistently reduces liquidity across several sectors, including the JSE (-0.412), Consumer Services (-2.667), Industrials (-0.382), Retail (-1.369), Technology (-2.414), and Telecommunications (-0.375). This supports Debata, Dash, and Mahakud (2018), who argue that excessive optimism often drives speculative trading and destabilising volatility, which ultimately erodes liquidity. Consistent with Zhang et al. (2021) and Eyshi Ravandi et al. (2024), the findings indicate that bullish sentiment in the JSE does not translate into deeper or more efficient markets but instead produces short-term trading imbalances that strain liquidity. This adds to the behavioural finance literature by reinforcing Apergis et al. (2015), who showed that sentiment interacts with liquidity in feedback loops, amplifying volatility rather than stabilising markets. This result adds to the literature by showing that in emerging markets, optimism-fuelled sentiment may undermine, rather than support, liquidity during expansions, highlighting the destabilising role of behavioural forces in sustaining market depth. These bull-market dynamics are consistent with the Adaptive Market Hypothesis, which posits that investor behaviour evolves with changing market conditions. In bullish states, investors adapt by reducing precautionary trading and increasing buy-and-hold behaviour, which lowers baseline liquidity despite favourable macroeconomic conditions.

In bear markets, the constant term (C) turns substantially positive across all sectors, indicating higher baseline liquidity, contradicting Lyu and Hu (2024), as investors engage in defensive trading and portfolio rebalancing. This finding resonates with Assagaf and Kartikasari (2019), who emphasised that defensive repositioning is a hallmark of downturns in emerging markets. Inflation ($\Delta LnCPI$) plays a stronger role under these conditions, significantly increasing liquidity in Basic Materials (3.060), Technology (2.079), and Telecommunications (5.881), consistent with the idea that these sectors serve as hedges during inflationary pressures. In contrast, Retail (-1.175), Consumer Staples (-3.826), and Consumer Discretionary (-1.890) experience significant declines in liquidity due to weaker consumer spending and rising costs, while other sectors show largely insignificant responses. This sectoral divergence echoes Balli et al. (2021), who found that sectoral funds in emerging markets are highly sensitive to inflation shocks.

Long-term interest rates ($\Delta LnLINT$) exert a sharper negative effect in bear markets, drastically reducing liquidity in the JSE (-9.761), Consumer Discretionary (-1.058), Telecommunications (-10.958), and Technology (-2.521). High long-term rates amplify downturns by deterring investment and raising financing costs (Eldomiaty, Saeed, & Hammam, 2020; Zhang, 2021). However, liquidity rises in Consumer Services (5.595), Consumer Staples (16.271), and Financials (3.158), as capital shifts toward safe-haven assets, a pattern consistent with Abdullahi and Fakunmoju (2019) and Helen (2023). This safe-haven effect is consistent with Malebana (2019), who showed that South African investors reallocate toward defensive sectors during downturns. Short-term interest rates ($\Delta LnSINT$) also display mixed effects: they boost liquidity in Telecommunication (3.737) and Consumer Discretionary (0.586), highlighting resilience to monetary tightening (Helen, 2023), but reduce liquidity in Consumer Services (-1.271), Consumer Staples (-2.607), and the JSE overall (-6.632), reflecting higher borrowing costs and reduced speculative activity.

Investor sentiment ($LnINVS$) also exerts a strong influence in bear markets. It significantly boosts liquidity in Consumer Staples (1.868), consistent with the defensive-sector "flight-to-safety" channel where investors cluster in essential goods during uncertainty (Assagaf & Kartikasari, 2019; Chasanah & Sucipto, 2019). However, sentiment reduces liquidity across the JSE (-1.834), Financials (-0.429), Consumer Services (-0.341), and Telecommunications (-1.636), echoing Zhang et al. (2021). This asymmetry between sectors highlights that sentiment not only affects the level of liquidity but also its distribution across the market, favouring defensive over cyclical sectors when conditions deteriorate. Furthermore, Ogunmuyiwa (2010), who argued that sentiment-driven liquidity shocks are unevenly distributed across sectors, amplifying systemic risk. By showing that bearish sentiment simultaneously supports sectoral safe havens while draining liquidity elsewhere, the results advance the behavioural finance literature by demonstrating that sentiment's effects are both regime-dependent and sector-specific. These bear-market patterns are strongly aligned with Prospect Theory, particularly loss aversion: investors react more intensely to negative shocks, rapidly exiting risk-sensitive sectors and reallocating capital toward defensive assets. This behavioural shift increases liquidity in safe-haven sectors while accelerating illiquidity in vulnerable industries, producing the regime-dependent asymmetries captured by the MSM model.

Overall, the findings connect closely with prior research. Inflation and interest rates often act as liquidity constraints (Zhang et al., 2019), though mixed evidence in other contexts (Gali & Gambetti, 2015; Helen, 2023) highlights the importance of regime-sensitive approaches. The decisive role of sentiment is consistent with Ogunmuyiwa (2010), Liu (2015), and Debata et al. (2017), who emphasise sentiment as a key driver of liquidity in emerging markets. By confirming these dynamics in South Africa, the study extends earlier work by Muller and Ward (2013), McKane (2017), and Malebana (2019), adding regime-based and sector-level insights. More broadly, the results align with Just and Echaust (2020) on nonlinear macro-financial dependencies and Yacouba and Altintas (2019) on regime-dependent liquidity, while the evidence of inefficiency in bearish regimes echoes Cifter (2017), who questioned normality assumptions in high-volatility states. Together, these comparisons show that the study both supports and extends existing literature by integrating sectoral and behavioural dimensions into a South African context.

The Jarque-Bera test confirms that the residuals of the Markov Switching model deviate from normality at the 1% level, allowing rejection of the null hypothesis. This aligns with the model's theoretical design, which permits discrete regimes with distinct means and variances. As a result, skewness and excess kurtosis emerge from the mixture of regime-specific distributions. Thus, the failure of normality is expected and reinforces the Markov Switching model's suitability for capturing structural breaks and nonlinear dynamics. This further supports the behavioural interpretation of liquidity, as regime-dependent shifts in investor psychology naturally generate non-normal return and liquidity distributions (Yacouba & Altintas, 2019). This methodological robustness echoes Yacouba and Altintas (2019), who emphasised the importance of nonlinear models in capturing regime-dependent liquidity dynamics.

5. Conclusion

This study applied a Markov Switching Model to examine how investor sentiment, interest rates, and inflation affect sector-level stock liquidity in the Johannesburg Stock Exchange (JSE) under bull and bear market conditions. The results show that regime-sensitive modelling is important in emerging markets. Liquidity responses are sector-specific, nonlinear, and shaped by macroeconomic shifts. From an investment perspective, the findings highlight the need for liquidity-aware sector rotation strategies. Defensive sectors such as Consumer Services, Retail, and Financials provide stability. They may serve as safer allocations during contractionary or inflationary periods. Cyclical and debt-reliant sectors like Technology, Telecommunications, and Consumer Discretionary are more vulnerable. They require cautious engagement, especially under tightening cycles. Investor sentiment also plays a decisive role. Speculative enthusiasm in bull markets can constrain liquidity in Consumer Services, Retail, and the JSE. In downturns, sentiment tends to sustain defensive sectors such as Consumer Staples. These behavioural asymmetries show the need for dynamic modelling frameworks that capture investor psychology. Taken together, the evidence shows that liquidity in the JSE is fundamentally asymmetric, shaped by shifts in confidence, risk perception, and sector-specific sensitivities that differ markedly across market regimes.

For policymakers and regulators, the findings suggest that transparent monetary policy communication and forward guidance are crucial. Interest rate dynamics and investor expectations strongly influence liquidity. Policymakers may need to provide targeted liquidity support or regulatory interventions for sentiment-driven sectors during stress periods. The study shows that South African liquidity patterns change with market regimes: efficiency strengthens in bullish phases, while inefficiency dominates downturns marked by uncertainty and risk aversion. More broadly, the evidence indicates that liquidity in emerging markets is not uniform. Structural features and behavioural drivers interact in complex ways and ignoring regime dependence underestimates systemic vulnerabilities. For investors, this calls for strategies that explicitly integrate asymmetric and nonlinear responses of liquidity to macroeconomic conditions. For policymakers, recognising that investor sentiment can amplify or dampen economic shocks is vital in designing stabilisation measures. These insights highlight the behavioural foundations of liquidity. Loss aversion, adaptive expectations, and changes in market participation shape the depth and resilience of trading activity.

In terms of contribution, this study contributes to the literature by jointly modelling the asymmetric impacts of inflation, sentiment, and interest rates on sectoral liquidity, providing one of the first regime-based analyses in the JSE context. However, its reliance on monthly data and a single-country focus limits generalisability. Future research should adopt broader approaches that apply across diverse markets and contexts. For example, studies could use higher-frequency data, extend analysis to multiple emerging and developed markets, and incorporate additional dimensions such as ESG factors, technological change, or global shock spillovers. The broader lesson is that liquidity in emerging markets reflects universal behavioural and macro-financial dynamics: regime dependence, sentiment-driven asymmetries, and sectoral heterogeneity are not unique to South Africa but are relevant to other volatile markets worldwide. Global readers can infer that ignoring regime shifts risks underestimating systemic vulnerabilities, while integrating behavioural factors into liquidity modelling offers a more robust framework for understanding financial stability across diverse economies. Such generalisable extensions can improve understanding of how macroeconomic and behavioural forces jointly shape liquidity in diverse and volatile environments. Overall, the study reinforces the central theme of this research. Market behaviour in emerging economies shows nonlinear, regime-dependent patterns and reflects investor psychology, setting the stage for further exploration of financial stability.

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Reference

Abdullahi, I. B., & Fakunmoju, S. K. (2019). Market liquidity and stock return in the Nigerian Stock Exchange market. *Binus Business Review, 10(2).* https://doi.org/10.21512/bbr.v10i2.5588

Al Oshaibat, S., & Majali, A. (2016). The relationship between stock returns and each of inflation, interest rates, share liquidity and remittances of workers in the Amman stock exchange. *Journal of Internet Banking and Commerce, 21(2), 1.*

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets, 5(1),* 31–56. https://doi.org/10.1016/s1386-4181(01)00024-6

Amihud, Y., Mendelson, H., & Pedersen, L. H. (2005). Liquidity and asset prices. *Foundations and Trends in Finance, 1(4),* 269–364.

Apergis, N., Artikis, P. G., & Kyriazis, D. (2015). Does stock market liquidity explain real economic activity? New evidence from two large European stock markets. *Journal of International Financial Markets, Institutions and Money, 38,* 42–64. https://doi.org/10.1016/j.intfin.2015.05.002

Asghari, E., Abbasian Fredoni, M. M., & Naslmosavi, S. (2020). The impact of investor sentiments on stock market liquidity. *Journal of Accounting Advances, 12(1),* 1-27.

Assagaf, A., & Kartikasari, D. (2019). Determinants of Stock Returns with Liquidity as Moderators: Empirical Study in Indonesia Stock Exchange. *In Proceedings of the 1st International Conference on Applied Economics and Social Science (ICAESS 2019)* (pp. 20-23). Atlantis Press. https://doi.org/10.2991/icaess-19.2019.64

Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets, 7(3),* 271–299. https://doi.org/10.1016/j.finmar.2003.11.005

Balli, F., Billah, M., Balli, H. O., & De Bruin, A. (2021). Spillovers to sectoral equity returns: do liquidity and financial positions matter? *Applied Economics, 53(27),* 3097-3130. https://doi.org/10.1080/00036846.2021.1875120

Brooks, C. (2019). *'Introductory Econometrics for Finance'*, Cambridge University Press, New York, https://doi.org/10.1017/9781108524872

Chasanah, N., & Sucipto, A. (2019). Liquidity ratio, profitability, and solvency on stock returns with capital structure as an intervening variable (study on food and beverage sub sector listed in Indonesia Stock Exchange (Idx) period 2013-2017). *Ekspektra: Jurnal Bisnis dan Manajemen, 3(1),* 52-68. https://doi.org/10.25139/ekt.v3i1.1476

Chen, S., & Qiu, J. (2021). Market sentiment and economic cycles: Insights from the adaptive market hypothesis. *Journal of Financial Markets, 24(3),* 178–195.

Cifter, A. (2017). Estimating the effect of inflation on stock returns using regime dependent impulse response analysis. *Aurum Sosyal Bilimler Dergisi, 2(2),* 1-16.

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance, 67(2),* 719–760. https://doi.org/10.1111/j.1540-6261.2012.01729.x

Debata, B., Dash, S.R., & Mahakud, J., (2017). Investor sentiment and emerging stock market liquidity. *Finance Research Letters 26,* 15–31. https://doi.org/10.1016/j.frl.2017.11.006

Eldomiaty, T. Saeed, Y.& Hammam, R. (2020). The associations between stock prices, inflation rates, interest rates are still persistent Empirical evidence from stock duration model. *Journal of Economics, Finance and Administrative Science, 25(*49) https://doi.org/10.1108/jefas-10-2018-0105

Eyshi Ravandi, M., Moeinaddin, M., Taftiyan, A., & Rostami Bashmani, M. (2024). Investigating the Impact of Investor Sentiment and Liquidity on Stock Returns of the Iranian Stock Exchange. *Dynamic Management and Business Analysis, 3(1),* 40-52. https://doi.org/10.61838

Fama, E.F. (1970) Efficient capital markets: A review of theory and empirical work. *The journal of Finance, 25(2),* 383-417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Fisher, I. (1930). *The Theory of. Interest.* New York: The McMillan Co.

Gabauer, D., & Gupta, R. (2018). On the transmission mechanism of country-specific and international economic uncertainty spillovers: Evidence from a TVP-VAR connectedness decomposition approach. *Economics Letters, 171,* 63-71. https://doi.org/10.1016/j.econlet.2018.07.007

Gali J., & Gambetti L. (2015) The effects of monetary policy on stock market bubbles: Some evidence. *American Economic Journal-Macroeconomics. 7(1),* 233–257 https://doi.org/10.1257/mac.20140003

Helen, I. U. (2023). Liquidity of Stock Market and Inflation in Nigeria. *Journal of Academic Research in Economics, 14(3).* 642-653.

Just, M., & Echaust, K. (2020). Stock market returns, volatility, correlation and liquidity during the COVID-19 crisis: Evidence from the Markov switching approach. *Finance Research Letters, 37,* 101775. https://doi.org/10.1016/j.frl.2020.101775

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *In Handbook of the fundamentals of financial decision making: Part I* (pp. 99-127).

Keynes, J. M. (1936). *The general theory of employment, interest and money.* London: Macmillan.

Khoza, F. (2025). The impact of liquidity and leverage on the financial performance of the Johannesburg stock exchange-listed consumer goods firms. *Journal of Risk and Financial Management, 18(9),* 510. https://doi.org/10.3390/jrfm18090510

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society,* 1315-1335. https://doi.org/10.2307/1913210

Lee, H., & Park, J. (2021). Participant investment behaviour and investment performance in defined contribution plans: Evidence from small firms in South Korea. *Global Business & Finance Review (GBFR), 26(2),* 34–48. https://doi.org/10.17549/gbfr.2021.26.2.31

Liu, S. (2015). Investor sentiment and stock market liquidity. *The Journal of Behavioural Finance, 16(1),* 51–67 https://doi.org/10.1080/15427560.2015.1000334

Lo, A.W. (2004) The adaptive markets hypothesis. *The Journal of Portfolio Management, 30(5),* 15-29. https://doi.org/10.3905/jpm.2004.442611

Lyu, X., & Hu, H. (2024). The dynamic impact of monetary policy on stock market liquidity. *Economic Analysis and Policy, 81,* 388-405. https://doi.org/10.1016/j.eap.2023.12.007

Malebana, M. B. (2019). The relationship between liquidity and stock market returns in South Africa. *University of Johannesburg (South Africa).*

Mckane, G. (2017). Liquidity and Size Effects on the JSE. *University of the Witwatersrand, Johannesburg (South Africa).*

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American economic review, 48(3),* 261-297.

Muller, C., & Ward, M. (2013). Style-based effects on the Johannesburg Stock Exchange: A graphical time-series approach. *Investment Analysts Journal, 42(77),* 1-16. https://doi.org/10.1080/10293523.2013.11082552

Naicker, P. (2017). *The effect of macroeconomic factors on the JSE All Share Index and Sectoral Returns.* (Doctoral Dissertation, University of Cape Town, South Africa).

Naik, P., & Reddy, Y. V. (2021). Stock market liquidity: A literature review. *Sage Open, 11(1),* 2158244020985529. https://doi.org/10.1177/2158244020985529
Naidoo, D., Moores-Pitt, P., & Muzindutsi, P. F. (2025). The South African Fear and Greed Index and Its Connectedness to the US Index. *Journal of Risk and Financial Management, 18(7),* 349. https://doi.org/10.3390/jrfm18070349
Nyika, P. H. (2018*). Monetary Policy and Stock Market Liquidity: Empirical Evidence from the Johannesburg Stock Exchange (JSE).* (University of the Witwatersrand, Johannesburg, South Africa).
Ogunmuyiwa, M.S., (2010). Investors sentiments, stock market liquidity and economic growth in Nigeria. *Journal of Social Science 23 (1)*, 63–67. https://doi.org/10.1080/09718923.2010.11892812
Olokoyo, F. O., Ibhagui, O. W., & Babajide, A. (2020). Macroeconomic indicators and capital market performance: Are the links sustainable? *Cogent Business & Management, 7(1),* 1792258. https://doi.org/10.1080/23311975.2020.1792258
Ondiba Ochenge, R., Ngugi, R., & Muriu, P. (2020). Foreign equity flows and stock market liquidity in Kenya. *Cogent Economics & Finance, 8(1),* 1781503. https://doi.org/10.1080/23322039.2020.1781503
Peress, J., & Schmidt, D. (2020). Glued to the TV: Distracted noise traders and stock market liquidity. *The Journal of Finance, 75(2),* 1083-1133. https://doi.org/10.1111/jofi.12863
Pérez, F. Z., & Lucas, R. I. P. (2025). Combined Assurance Models and Sustainability Assurance: Impacts on Market Liquidity and Analyst Forecast Accuracy in South Africa. *Innovar, 35(98),* e123101. https://doi.org/10.15446/innovar.v35n98.123101
Prodromou, T., & Demirer, R. (2022). Oil price shocks and cost of capital: Does market liquidity play a role? *Energy Economics, 115,* 106340. https://doi.org/10.1016/j.eneco.2022.106340
Rösch, D. (2021). The impact of arbitrage on market liquidity. *Journal of Financial Economics, 142(1),* 195-213. https://doi.org/10.1016/j.jfineco.2021.04.034
Ross, S. A. (1976) The arbitrage theory of capital asset pricing. *Journal of Economic Theory, 13(3),* 341-360 https://doi.org/10.1016/0022-0531(76)90046-6
SAShares. (2024). "JSE All-Share index". [online]. Available at: https://www.sashares. co.za/jse-all-share-index/#gs.7vstwq [Accessed on 12 April 2024].
Schwartz, R. A., & Peng, L. (2021). Market liquidity. *In Encyclopaedia of finance* (pp. 1–5). Springer International Publishing. https://doi.org/10.1007/978-3-030-73443-5_37-1
Sidharth, J. (2025*). Assessing Market Liquidity Amidst Crisis: Evidence from Indian Stock Market* (No. 2025-283).
Smimou K., & Khallouli W. (2015) Does the euro affect the dynamic relation between stock market liquidity and the business cycle? *Emerging Markets Review; 25*, 52–60. https://doi.org/10.1016/j.ememar.2015.07.001
Sun, Y., & Yuan, X. (2021). Nonlinear relationship between money market rate and stock market liquidity in China: A multifractal analysis. *Plos one, 16(4),* e0249852. https://doi.org/10.1371/journal.pone.0249852
Yacouba, K. & Altintas, H. (2019). "The Asymmetric Impact of Macroeconomic Shocks on Stock Returns in Turkey: A Nonlinear ARDL Approach". *Journal for Economic Forecasting, 6(2),* pp. 98-116.
Yousuf, Z., & Makina, D. (2022). The behavioural finance paradigm and the adaptive market hypothesis: evidence from the JSE. *International Journal of Finance & Banking Studies, 11(2).* https://doi.org/10.20525/ijfbs.v11i2.1761
Zhang, Z. (2021). Stock Returns and Inflation Redux: an explanation from monetary policy in advanced and emerging Markets. *International Monetary Fund WP/21/219* https://doi.org/10.5089/9781513586755.001
Zhang, Q., Choudhry, T., Kuo, J. M., & Liu, X. (2021). Does liquidity drive stock market returns? The role of investor risk aversion. *Review of Quantitative Finance and Accounting, 57(3),* 929-958. https://doi.org/10.1007/s11156-021-00966-5
Zhang H., Ye J., Wei F., Kashif R., & Cao C. (2019) Monetary policy adjustment, corporate investment, and stock liquidity—empirical evidence from Chinese stock market. *Emerging Markets Finance and Trade. 55(5),* 1–16 https://doi.org/10.1080/1540496x.2019.1612363