TO COMPARE THE INFLATION HEDGING CAPABILITIES ACROSS THE JSE INDUSTRY STOCK RETURNS WHILE ACCOUNTING FOR INVESTOR SENTIMENT AND INTEREST RATES

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Abstract:
Rising energy and food prices, triggered by the Russian–Ukrainian conflict, alongside supply-chain disruptions from the COVID-19 pandemic, have driven global inflation to multi-decade highs, heightening uncertainty in financial markets. In this environment, understanding which assets offer effective inflation protection has become increasingly important. This study aims to evaluate the inflation-hedging capabilities of 10 sectoral stock indices and the JSE All Share Index in South Africa over the period 2007–2024. To achieve this, the research employs ARDL and NARDL models to capture both symmetric and asymmetric long-run relationships between stock returns, inflation, interest rates, and investor sentiment. The results from the Wald test show that all sectors exhibit asymmetric long-run relationships, indicating that the effects of inflation, interest rates, and sentiment vary depending on the direction of change. Consistent with the Fisher hypothesis and the tax-augmented theory, the Consumer Discretionary, Consumer Staples, Financials, Industrials, Retail, and Technology sectors, as well as the JSE All Share Index, act as effective hedges during periods of rising inflation. Conversely, the overall market and the Basic Materials sector perform better during deflationary periods, whereas the Healthcare sector responds negatively to both rising and falling inflation, rendering it an ineffective hedge. Additionally, Consumer Services and Telecommunications display no significant linkage to inflation. These findings contribute to the literature by demonstrating the need for a state-contingent, sector-specific investment strategy that recognises the asymmetric effects of inflation on equity returns in developing markets such as South Africa.

Keywords: Inflation Hedging, Investor Sentiment, ARDL/NARDL Models, Sectoral Stock Returns

INTRODUCTION

Emerging markets have attracted growing investor interest in recent years due to their stronger growth prospects, improved risk-return trade-offs, and portfolio diversification benefits (Chinmaya Narayany et al., 2025). Inflows into major emerging stock and bond markets reached approximately $17 billion in the first three weeks of 2021, following a $180 billion surge in Q4 of 2020 (Monk, 2021). However, such capital flows increase exposure to asset price volatility and macroeconomic policy shifts, which, in developing economies, are often accompanied by elevated inflation and rising interest rates (Hoque and Zaidi, 2020; Ali, Khokhar, and Sulehri, 2023). South Africa exemplifies this, facing persistent inflationary pressures and monetary tightening, making its financial markets more vulnerable to external shocks (Phiri, 2023). Inflation and interest rate dynamics also affect investor sentiment, an increasingly crucial behavioural component of asset pricing. Negative sentiment can amplify the adverse effects of inflation by reducing investment flows, weakening risk appetite, and increasing market volatility. Conversely, clearer policy direction and disinflation may restore confidence, thereby strengthening equities' role as inflation hedges (Kawawa, 2018). Significantly, sentiment varies across sectors. Defensive industries such as Consumer Staples may retain investor support during inflationary periods, whereas cyclical sectors such as Industrials and Consumer Discretionary are more susceptible to sentiment-driven declines. This divergence supports a disaggregated, sector-level analysis to evaluate the effectiveness of equities in hedging inflation.The most widely accepted empirical definition of inflation hedging states that “an asset is an inflation hedge if its real return is independent of the rate of inflation,” implying a positive correlation between nominal returns and inflation (Arnold and Auer, 2015). If this correlation equals one, the asset is considered a perfect hedge. This notion is rooted in the Fisher hypothesis, which posits that stock returns should rise proportionally with inflation, leaving real returns unaffected (Neifar and Hachicha, 2022). Fisher also argued that nominal interest rates equal the sum of the real interest rate and expected inflation, and that real and nominal factors in the economy function independently. Over time, this logic has been extended to suggest that equities, under efficient market conditions, should act as natural inflation hedges (Arnold and Auer, 2015). Given inflation’s erosion of purchasing power, evaluating the hedging potential of sector-specific stocks is crucial for long-term portfolio decisions. Inflation remains a key global concern for investors, influencing stock performance and investment policy (Chiang and Chen, 2023; Hoong et al., 2023). While existing research explores inflation’s effects on equities, studies often examine aggregate indices, overlooking sectoral variation (Al-Nassar and Bhatti, 2019; Chiang and Chen, 2023). This limits practical insights, particularly in emerging markets such as South Africa.Though the Fisher hypothesis has been widely tested in developed and emerging markets, findings remain mixed, often revealing a negative inflation–stock return relationship (Camba Jr and Camba, 2021; Neifar and Hachicha, 2022; Fehrle, 2023). African studies are minimal. In South Africa, most research focuses on macroeconomic determinants of stock returns rather than explicitly testing sector-specific inflation-hedging capacity (Alagidede, 2009; Phiri, 2023). Some studies offer conflicting results. Maratela (2023) argues equities are poor hedges, while Phiri (2023) finds supportive evidence. Moreover, behavioural drivers such as investor sentiment have been mainly neglected, despite their influence on equity market responses to inflation. Understanding inflation hedging at the sector level, while incorporating interest rate dynamics and sentiment, is particularly relevant in South Africa, where structurally high inflation and volatile rates persist (Phiri, 2023). Most prior studies assume symmetry in equity responses to macroeconomic shocks; yet investors may react differently to rising versus falling inflation or interest rates (Ben Nasr et al., 2018; Kawawa, 2018). This study addresses that gap by applying a nonlinear autoregressive distributed lag (NARDL) framework to capture potential short- and long-run asymmetries in sectoral stock responses to inflation, interest rates and investor sentiment (Moussa and Delhoumi, 2022). Furthermore, while past studies employing cointegration techniques increasingly support the Fisher hypothesis (Arnold and Auer, 2015), they rarely account for asymmetries or behavioural influences. Sectoral variation remains underexplored in African contexts, even though different industries display distinct inflation sensitivities. Inflation's impact may also vary depending on the inflation regime, moderate versus high inflation, affecting hedging capacity (Le Long et al., 2013; Maratela, 2023; Phiri, 2023). To address this, the present study evaluates whether South African sectoral equities on the JSE serve as inflation hedges, incorporating interest rates and sentiment, using the South African Fear and Greed Index. By explicitly accounting for asymmetric relationships, the analysis offers more realistic insights into inflation hedging in an emerging market context.

LITERATURE REVIEW

Theoretical review of the inflation hedging and return relationship.

Fisher's (1930) foundational work proposed a positive relationship between inflation and stock prices, arguing that nominal interest rates consist of a real rate plus expected inflation, and that real and monetary sectors of the economy operate independently (Nelson, 1976). Fama and Schwert (1977) extended this by distinguishing between expected and unexpected inflation. However, empirical results have challenged the universality of the Fisher hypothesis. In South Africa, findings are mixed: some studies report a positive inflation–stock return relationship (Phiri, 2023), while others show negative or insignificant correlations (Maratela, 2023; Trecy, et al., 2024). To explain the inverse relationship, Fama (1981) proposed the proxy hypothesis, linking unexpected inflation to declines in real economic activity, reduced savings, and lower demand for equities. Geske and Roll (1983) offered an alternative explanation, the inflation hypothesis, highlighting fiscal and monetary policy interactions that transmit inflation's negative effects to stock markets. Although these studies advanced understanding, they primarily focus on aggregate markets and often ignore sector-specific heterogeneity, particularly in developing economies like South Africa. Moreover, earlier models overlook behavioural and structural factors such as investor sentiment and asymmetric responses to interest rate shocks, which are increasingly relevant in modern financial markets. This study addresses these gaps by examining sectoral inflation hedging capacities on the JSE, explicitly accounting for investor sentiment and interest rate asymmetries to provide a more comprehensive understanding of the inflation–stock return relationship.

Empirical review of the inflation hedging and return relationship.

Understanding the inflation-hedging potential of sector-specific equity returns is of growing importance for both investors and policymakers seeking to manage risk and maintain real investment value amid rising inflation. While traditional research often focuses on aggregate stock market responses to inflation, increasing evidence shows that this approach masks significant heterogeneity across industries (Ang, et al., 2012). According to Fama (1981), inflation contains useful information about future real economic activity, making it a key variable in stock valuation.

Blanchard (1982) was among the first to examine sectoral differentiation, showing that the food and energy sectors exhibit greater inflation-related volatility than intermediate-goods sectors. Wei and Wong (1992), using NYSE data across 19 industries surrounding World War II, found a negative inflation–return relationship for natural resource industries, although not consistently across all sectors. Luintel and Paudyal (2006) employed a cointegration methodology and found that UK equities hedge inflation effectively over time, with consumer goods performing best, and mineral extraction performing the worst. Sadorsky (2001) and Ciner (2015) argued that natural resource stocks are not always reliable hedges and suggested that smaller or technology-oriented firms may better absorb inflation shocks due to their pricing flexibility.

Bampinas and Panagiotidis (2016) found that many individual equities in the energy, materials, and consumer goods sectors showed significant positive long-term correlations with inflation. These findings underscore the necessity of analysing disaggregated stock data by industry to evaluate the effectiveness of inflation hedging. In South Africa, Kawawa (2018) provided crucial evidence of sectoral heterogeneity on the JSE. All sector indices were positively correlated with the CPI, but Consumer Services, Consumer Goods, Health Care, Telecommunications, and Industrials outperformed the broader All-Share Index. In contrast, Technology, Financials, and Basic Materials underperformed, suggesting weaker inflation protection. Chiang and Chen (2023) support the monetary policy uncertainty premium theory, which posits that heightened uncertainty suppresses returns. Their findings, consistent with Husted, et al., (2020), showed that although some sectors hedge inflation effectively (energy, technology), the overall market does not. Bouri, et al., (2023) reported that most stock sectors had a positive link with inflation during major crises like the GFC, COVID-19, and the Russia-Ukraine war, though short-term performance, especially in energy and materials, sometimes contradicted long-run support for the Fisher hypothesis.

Recent studies highlight the nonlinear and asymmetric inflation–equity relationship, contrasting earlier linear assumptions. Stock responses differ across inflation regimes and market structures (Doho et al., 2023). Evidence from Thailand and Vietnam shows a weak negative correlation with limited hedging under moderate inflation (Le Long et al., 2013), while positive inflation–stock relationships dominate most countries except France, Italy, and South Africa (Ibn Boamah, 2017). Using an asymmetric kernel method, Doho et al. (2023) analysed the effects of inflation on West African sectoral indices between 2001 and 2020, identifying all sectors as inflation-sensitive, with utilities and agriculture being the most vulnerable. Their results suggest a nonlinear relationship shaped by inflation intensity. Chiang and Chen (2023) confirmed these findings: energy stocks exhibited positive responses to rising inflation, while others reacted more strongly to disinflationary news, paralleling results from Bouri et al. (2023).

Interest rates and investor sentiment further influence the inflation–equity relationship. Rising interest rates typically reduce consumption and investment, dampening equity prices and firm earnings (Setiawan, 2020). As borrowing costs rise, stocks become less appealing relative to bonds (Mega and Widayat, 2019). Most of the literature supports a negative link between returns and the rate of return, although Hajilee and Al Nasser (2017) found a positive long-run relationship, with equity returns gradually becoming less sensitive to interest rates. Eldomiaty, et al., (2020) noted significant differences between developed and developing economies in this regard. From a behavioural perspective, investor sentiment introduces additional complexity. Sentiment-driven trading, often irrational, can distort stock pricing. Fisher and Statman (2000) demonstrated that investor sentiment negatively predicts returns. Yu, et al., (2014) supported this contrarian view, showing sentiment holds significant predictive power over stock performance. Taken together, this literature highlights the need for sector-level analysis that integrates macroeconomic and behavioural variables. This study addresses this need by investigating the inflation-hedging effectiveness of JSE sectoral stocks, incorporating interest rate dynamics and investor sentiment, as measured by a South African version of the Fear and Greed Index.

DATA AND METHODOLOGY

Data

Sample

To examine the inflation hedging capabilities of sectoral stock returns in South Africa, accounting for investor sentiment and interest rates, this article examines a diverse range of sectoral stocks. The study sample comprises monthly data from June 2007 to June 2024, allowing for the inclusion of events such as the global financial crisis of 2008, the COVID-19 pandemic, and the sharp increase in interest rates in South Africa and globally after the pandemic. All sector stocks were obtained from the IRESS database. This included the overall South African stock Market index, the FTSE-JSE All Share Index, and 10 sectors: Basic Materials, Consumer Discretionary, Consumer Services, Consumer Staples, Financials, Healthcare, Industrial, Retailers, Technology, and Telecommunications. These sectors were selected from the JSE ICB classification and form part of the financial (FIN15), industrial (IND25), and resource (RES10) industries, which constitute the foundation of the JSE All Share index (SAShares, 2024).

Methodology

A linear and non-linear ARDL model is used to examine the short and long-run relationships between the model's variables based on the work of Sari, et al., (2013). In essence, separate models are estimated for each sector and for the JSE, with CPI, LINT, SINT, and INVS as independent variables. The ARDL model was established by Pesaran, et al., (2001) to identify the long- and short-term connections between the variables, regardless of whether the variables are integrated at order one I (1) or stationary at levels I (0). The ARDL model was established by Pesaran, et al., (2001) to identify the long- and short-term connections between variables, regardless of whether the variables are integrated at order one I (1) or stationary at levels I (0). This feature makes ARDL particularly useful when dealing with a mixture of I (0) and I (1) series in time series analysis. The variables' stationarity is checked to ensure they are I (0) and/or I (1) before the ARDL model is estimated. The stationarity of each variable is evaluated in this study using the Augmented Dickey-Fuller (ADF) and Zivot-Andrew unit root tests. Next, the ARDL model is estimated for South Africa's sectoral stock markets. This study employs the ARDL technique in a three-step protocol. In the first phase, the bounds-testing approach checks for cointegration among the variables. This aims to find any long-term correlations between the explanatory and dependent variables. For the bounds-testing process in step one, the following linear ARDL model is utilized:

$$\Delta lnSP_t = \alpha_0 + \beta_1 lnSP_{t-1} + \beta_2 lnCPI_{t-1} + \beta_3 lnLINT_{t-1} + \beta_4 lnSINT_{t-1} + \beta_{51} lnINVS_{t-1} + \sum_{i=1}^{p} \alpha_{1i} \Delta lnSP_{t-i} + \sum_{i=0}^{q} \alpha_{2i} \Delta lnCPI_{t-i} + \sum_{i=0}^{q} \alpha_{3i} \Delta lnLINT_{t-i} + \sum_{i=0}^{q} \alpha_{4i} \Delta lnSINT_{t-i} + \sum_{i=0}^{q} \alpha_{5i} \Delta lnINVS_{t-i} + e_t \quad \ldots (1)$$

Where ΔCPI, $\Delta LINT$, $\Delta SINT$, and $\Delta INVS$ stand for the changes in the natural logarithms of the inflation, long and short interest rate, and investor sentiment index, respectively, and ΔSP is the change in the natural logarithm of the sectoral stock market price. The short-run coefficients in the ARDL model above are denoted by $\alpha_{1i} - \alpha_{4i}$, and the long-run coefficients by $\beta_1 - \beta_4$. The constant and error terms are shown by α_0 and e_t , respectively. Several information criteria, such as the Schwarz Information Criterion (SIC), and the Akaike Information Criterion (AIC), are used to determine the ideal lag lengths for the bounds-testing process.

However, this study identifies the optimal lag lengths for the ARDL and NARDL models using the Schwarz Information Criterion (SIC). A key factor in macroeconomic time-series analysis is SIC's ability to select more parsimonious models, reducing the risk of overfitting and preserving degrees of freedom (Sun and Xu, 2010). It is noteworthy to note that $\beta_{11} = \beta_{21} = \beta_{31} = \beta_{41} = \beta_{51} = 0$ is implied by the null hypothesis of no cointegration. The ARDL (x, y, z, a, b) model is used in the second stage of the linear ARDL technique to estimate the long-run coefficients. The alphabets in parentheses indicate the ideal lag length for each variable, which is chosen by the bounds-testing process. Equation (1) is the source.

$$\Delta lnSP_t = \alpha_{01} + \beta_{11} lnSP_{t-1} + \beta_{21} lnCPI_{t-1} + \beta_{31} lnLINT_{t-1} + \beta_{41} lnSINT_{t-1} + \beta_{51} lnINVS_{t-1} + e_t \quad \ldots (2)$$

Where the previously specified terms and variables are used. If a long-run relationship exists, determining the short-run dynamics by estimating the error-correction model (ECM) associated with the long-run regression is the third and final stage of the linear ARDL technique. Equation (1) is the source of the ECM, which has the following specifications:

$$\Delta lnSP_t = \alpha_0 + + \sum_{i=1}^{p} \alpha_{1i} \Delta lnSP_{t-i} + \sum_{i=0}^{q} \alpha_{2i} \Delta lnCPI_{t-i} + \sum_{i=0}^{q} \alpha_{3i} \Delta lnLINT_{t-i} + \sum_{i=0}^{q} \alpha_{4i} \Delta lnSINT_{t-i} + \sum_{i=0}^{q} \alpha_{5i} \Delta lnINVS_{t-i} + \theta \mu_{t-1} + e_t \quad \ldots (3)$$

Where e_t indicates an error term and μ_{t-1} is the error-correction term that sheds light on the rate of adjustment in relation to the long-run equilibrium. The linear ARDL model does not account for nonlinearities in economic interactions, yet it remains a widely used tool for examining long- and short-run correlations among variables in the system. A non-linear ARDL (NARDL) model by Shin, et al., (2014) is estimated in accordance with Muzindutsi, et al., (2020) to augment the conclusions of the linear ARDL models, and the outcomes are compared. To account for asymmetries in the long- and short-term connections, the following NARDL model is estimated:

$$\Delta lnSP_t = \alpha_0 + \beta_1 lnSP_{t-1} + (\beta_{21}^{+} lnCPI_{t-1}^{+} + \beta_{22}^{-} lnCPI_{t-1}^{-}) + (\beta_{31}^{+} lnLINT_{t-1}^{+} + \beta_{32}^{-} lnLINT_{t-1}^{-}) + (\beta_{41}^{+} lnSINT_{t-1}^{+} + \beta_{42}^{-} lnSINT_{t-1}^{-}) + (\beta_{51}^{+} lnINVS_{t-1}^{+} + \beta_{52}^{-} lnINVS_{t-1}^{-}) + \sum_{i=1}^{p-1} \alpha_{1i} \Delta lnSP_{t-i} + \sum_{i=0}^{q-1} (\alpha_{2i}^{+} \Delta lnCPI_{t-i}^{+} + \alpha_{3i}^{-} \Delta lnCPI_{t-i}^{-}) + \sum_{i=0}^{q-1} (\alpha_{4i}^{+} \Delta lnLINT_{t-i}^{+} \alpha_{5i}^{-} \Delta lnLINT_{t-i}^{-}) + \sum_{i=0}^{q-1} (\alpha_{6i}^{+} \Delta lnSINT_{t-i}^{+} \alpha_{7i}^{-} \Delta lnSINT_{t-i}^{-}) + \sum_{i=0}^{q-1} (\alpha_{8i}^{+} \Delta lnINVS_{t-i}^{+} + \alpha_{9i}^{-} \Delta lnINVS_{t-i}^{-}) + e_t \ldots (4)$$

Where $INF^{+}$and INF^{-}represent increases and decreases in inflation, respectively. The same applies to interest rate and investor sentiment. In line with the linear ARDL model, Equation (4) suggests that $\beta_1 = \beta_{21}^{+} = \beta_{22}^{-} = \beta_{31}^{+} = \beta_{32}^{-} = \beta_{41}^{+} = \beta_{42}^{-} = \beta_{51}^{+} = \beta_{52}^{-} = 0$. under the null hypothesis of no cointegration. The following ECM, linked to the NARDL model, is estimated to look at the short-term relationships if cointegration is present:

$$\Delta lnSP_t = \alpha_0 + \sum_{i=1}^{p-1} \alpha_{1i} \Delta lnSP_{t-i} + \sum_{i=0}^{q-1} (\alpha_{2i}^{+} \Delta lnCPI_{t-i}^{+} + \alpha_{3i}^{-} \Delta lnCPI_{t-i}^{-}) + \sum_{i=0}^{q-1} (\alpha_{4i}^{+} \Delta lnLINT_{t-i}^{+} \alpha_{5i}^{-} \Delta lnLINT_{t-i}^{-}) + \sum_{i=0}^{q-1} (\alpha_{6i}^{+} \Delta lnSINT_{t-i}^{+} \alpha_{7i}^{-} \Delta lnSINT_{t-i}^{-}) + \sum_{i=0}^{q-1} (\alpha_{8i}^{+} \Delta lnINVS_{t-i}^{+} + \alpha_{9i}^{-} \Delta lnINVS_{t-i}^{-}) + \theta \mu_{t-1} + e_t \ldots (5)$$

Where the error-correction is $\theta \mu_{t-1}$ term and the error term are e_t. Using the following null hypotheses, $\beta_{21}^{+} = \beta_{22}^{-}$, $\beta_{31}^{+} = \beta_{32}^{-}$, $\beta_{41}^{+} = \beta_{42}^{-}$ and $\beta_{51}^{+} = \beta_{52}^{-}$ The asymmetry of the long-run impacts of positive and negative changes in the ratings is examined using the Wald test technique. Similarly, using the Wald test technique and the following null hypotheses, the asymmetry of the short-run impacts of positive and negative changes in the ratings is investigated: Therefore, $\sum_{i=0}^{q-1} \alpha_{2i}^{+} = \sum_{i=0}^{q-1} \alpha_{3i}^{+}$, $\sum_{i=0}^{q-1} \alpha_{4i}^{+} = \sum_{i=0}^{q-1} \alpha_{5i}^{+}$,$\sum_{i=0}^{q-1} \alpha_{6i}^{+} = \sum_{i=0}^{q-1} \alpha_{7i}^{+}$ and $\sum_{i=0}^{q-1} \alpha_{8i}^{+} = \sum_{i=0}^{q-1} \alpha_{9i}^{+}$. Moreover, all models were tested for stability using the CUSUM and CUSUM squared tests to guarantee that the estimated models do not deviate from the relevant econometric assumptions. Notably, a dummy variable will be introduced to account for the 2008–2009 financial crisis, which affected global financial markets, if the model fails the parameter stability tests.

Empirical Analysis

Unit Root testing

Table 1: ADF and Zivot-Andrews Unit Root Test Results

	ADF	ADF 1ST	ZA Lag Length	ZA Break date	ZA Model A	ZA Model B	ZA Model C
JSE	-0,69300	**-15,05385*** **	4	2012M07	-3.663991	-3.525338	-3.621570*
Bas	-1,70936	**-15,09345*** **	1	2014M08	-4.241257	-3.650279	-4.112961*
Con Dis	-0,50273	**-13,94149*** **	3	2018M07	-4.116517	-3.637946	-4.116517*
Con Ser	-0,96116	**-14,25755*** **	2	2011M10	-3.534185	-3.428657	-3.193608*
Con Sta	-1,57631	**-16,86805*** **	1	2017M11	-3.517224	-3.627508	-3.675859*
Fin	-1,03309	**-14,89600*** **	1	2019M07	-3.794919	-3.377486	-3.631386*
Hea	-1,17175	**-14,44809*** **	4	2014M10	-5.890574	-4.241257	-11.63797*
Indus	-0,95014	**-15,05134*** **	2	2018M07	-4.128238	-3.637946	-4.116517*
Ret	-1,42214	**-14,15241*** **	4	2011M10	-3.428543	-3.878217	-3.639276*
Tech	-1,42492	**-13,91927*** **	3	2017M05	-3.393364	-3.312265	-3.615126*
Tel	-1,70327	**-15,12272*** **	2	2015M07	-2.898614	-2.725621	-3.333578*
LNCPI	-1,86996	**-4,26590*** **	1	2020M03	-4.958877	-4.172743	-4.890777*
LNLINT	-1,13269	**-12,44611*** **	4	2012M06	-4.345965	-5.031497	-5.437189*
LNSINT	-2,32843	**-7,90810*** **	2	2011M10	-3.534185	-3.428657	-3.193608*
LNINVS	**-3,33084** **	**-14,57191*** **	4	2010M07	-3.675859	-3.393364	-6.063788*

*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 unit root test results, presented in Table 1, indicate that all variables are integrated of order I(1), except for investor sentiment, which is stationary at level, I (0), based on the ADF test at the 1%, 5%, and 10% significance levels. No variable is integrated at I (2), validating the use of the ARDL and NARDL model (Lee, et al., 2022). Furthermore, Model C results indicate the presence of a unit root with structural breaks in both the trend and intercept, as the null hypothesis cannot be rejected at the 5% level. Following Baum (2015), this confirms that Models A and B are not applicable. These findings support the progression to ARDL and NARDL cointegration analysis by confirming the necessary integration conditions.

The Linear Autoregressive Distributed Lag (ARDL) Model (Results)

As noted earlier, the Schwarz Information Criterion (SIC) is used in this work to select lags for the ARDL and NARDL models. In macroeconomic time-series analysis, the SIC is favoured because it yields more parsimonious models, reducing the risk of overfitting while maintaining degrees of freedom (Sun and Xu, 2010).

Table 2: ARDL Schwarz Criteria and Bounds Test

ARDL	Schwarz Criteria	Estimated F-statistic:	Significance level	Lower bound CV	Upper Bound CV
JSE	(2,0,1,0,1)	4,47	10%	2,20	3,09
Bas	(1,0,1,0,1)	4,52	5%	2,56	3,49
Con Dis	(1,0,1,0,0)	5,36	1%	3,29	4,37
Con Ser	(2,0,1,0,1)	4,98			
Con Sta	(2,1,0,0,1)	6,23			
Fin	(2,0,1,1,1)	5,53			
Hea	(1,0,0,0,0)	5,15			
Indus	(1,0,0,0,1)	5,64			
Ret	(2,0,1,0,1)	5,31			
Tech	(1,0,0,0,1)	5,11			
Tel	(1,0,2,0,0)	5,33			

Table 2 presents the ARDL bounds test results, showing that for all markets, the F-statistic exceeds the upper bound at the 1% significance level. This allows rejection of the null hypothesis of no cointegration, confirming the presence of significant cointegration across all models.

Table 3 presents the ARDL model's error correction and long-run results. The error-correction term indicates that all market variables adjust toward equilibrium at rates between 1% and 8% following a shock. The long-run estimates indicate that the JSE All Share Index (0.37), Consumer Discretionary (3.02), Consumer Staples (1.33), Financials (0.46), Industrials (1.97), and Technology (0.46) sectors exhibit statistically significant positive relationships with inflation (LNCPI), supporting the tax-augmented Fisher hypothesis. These findings suggest that these sectors serve as effective long-term inflation hedges, consistent with Kawawa (2018) and Alagidede and Panagiotidis (2010).

Table 3: ARDL Long-run Form and Error correction term

	Long-run Form					ECT
Variables	LNCPI	LNLINT	LNSINT	LNINVS	C	COINTEQ*
JSE	0,396 ***	0,940	-0,621***	0,488***	6,306***	-0,041***
Bas	-0,481	2,536***	-0,700***	0,086	7,783***	-0,089***

	Long-run Form					ECT
Variables	LNCPI	LNLINT	LNSINT	LNINVS	C	COINTEQ*
Con Dis	3,016***	-0,648	0,019	0,425***	-3,765***	-0,077***
Con Ser	-3,999	8,629	-2,446	1,827	4,516***	-0,019***
Con Sta	1,331*	-1,631	-0,657	0,420***	8,566***	-0,044***
Fin	0,458***	-0,318	-0,230	0,594***	7,230***	-0,057***
Hea	-4,902**	2,300	-1,021	0,738	24,367***	-0,046***
Indus	1,969***	-0,931	-0,210	0,326**	3,611***	-0,053***
Ret	-2,560	4,115	-1,699***	1,347	8,527***	-0,028***
Tech	0,464***	-0,555	-0,403	0,513***	8,376***	-0,038***
Tel	-0,852	-0,874	-0,905	0,232***	15,115***	-0,055***

Note: *, **, and * indicate a 1%, 5% and 10% level of significance respectively All figures are rounded off to 3 decimal places*

The study finds no significant relationship between inflation and the Basic Materials, Consumer Services, Retail, and Telecommunications sectors. In contrast to Kawawa (2018), Healthcare displays a significant negative long-run coefficient for inflation (–4.90). Basic Materials is the only sector showing a significant positive response (2.54) to long-term interest rates. Short-term interest rates, however, have significant negative effects on the JSE All Share Index (–0.62), Basic Materials (–0.70), and Retail (1.70). Additionally, the South African Fear and Greed Index exhibits significant positive relationships with the JSE All Share Index (0.48), Consumer Discretionary (0.43), Consumer Staples (0.42), Financials (0.59), Industrials (0.32), Technology (0.51), and Telecommunications (0.23), suggesting that rising sentiment (greed) is associated with higher sectoral returns.

The Nonlinear Autoregressive Distributed Lag (NARDL) Model (Results)

Table 4 below shows each market's chosen NARDL model using the Schwarz Criteria.

Table 4: NARDL Schwarz Criteria and Bounds Test

NARDL	Schwarz Criteria	Estimated F-statistic:	Significance level	Lower bound CV	Upper Bound CV
JSE	(2,0,0,2,0,0,0,1,1)	5,21	10%	1,85	2,85
Bas	(1,0,0,1,0,0,0,0,1)	4,34	5%	2,11	3,15
Con Dis	(1,0,0,0,0,0,0,0,0)	4,86	1%	2,62	3,77
Con Ser	(2,0,0,1,1,0,0,0,0)	5,28			
Con Sta	(2,1,0,0,0,0,0,0,1)	5,32			
Fin	(3,0,0,1,0,0,1,0,0)	5,87			
Hea	(1,0,0,0,0,0,0,0,1)	5,39			
Indus	(1,0,1,0,0,0,0,1,0)	5,20			
Ret	(2,0,0,1,1,0,0,0,0)	5,32			
Tech	(1,0,0,0,0,0,0,0,0)	4,93			
Tel	(1,0,0,2,0,0,0,0,0)	5,04			

Table 4 presents the NARDL bounds test results, showing that the F-statistics for all markets exceed the upper bound at the 1% significance level. This leads to the rejection of the null hypothesis of no level relationship, confirming significant cointegration across all models.

Table 5: Wald Test results for the NARDL

	Wald Test NARDL										
Test Statistic	**JSE**	**Bas**	**Con Dis**	**Con Ser**	**Con Sta**	**Fin**	**Hea**	**Indus**	**Ret**	**Tech**	**Tel**
T-Statistic	12,526***	7,386***	26,319***	15,022***	17,536***	18,034***	1,909***	19,479***	17,604***	10,157***	6,650***
F-Statistic	156,892***	54,560***	692,709***	225,652***	307,503***	325,215***	3,644***	379,443***	309,887***	103,164***	44,223***
Chi Square	156,892***	54,560***	692,709***	225,652***	307,503***	325,215***	3,644***	379,443***	309,887***	103,164***	44,223***
c (2)-c (3)	Null Hypothesis c (2) =c (3) Normalized restriction (=0)										
Value	1,836	1,825	5,234	4,109	4,452	3,276	1,463	3,753	4,450	3,840	1,909
Std. Error	0,147	0,247	0,199	0,274	0,254	0,182	0,766	0,193	0,253	0,378	0,287

Note: *, **, and * indicate a 1%, 5% and 10% level of significance respectively All figures are rounded off to 3 decimal places*

The Wald test results indicate an asymmetric long-run cointegration relationship among sectoral stock returns, inflation, interest rates, and investor sentiment, with substantial disparities between positive and negative adjustment coefficients. The Wald test confirms nonlinear and behavioural dynamics in South African markets by rejecting the null hypothesis of symmetric adjustment (Table 5), which is in line with Shin, et al, (2014). As a result, the NARDL model's capture of long-run asymmetric effects, which emphasise how stock returns react differentially to increases and declines in these variables, is the main topic of discussion. Table 6 presents the NARDL model's error-correction and long-run results, showing that short-run adjustments range from 1% to 10% toward equilibrium following shocks. The primary focus remains on the long-term coefficients.

Table 6: NARDL Long-run Form and Error correction term

	Long-run Form									ECT
Variables	**LNCPI +**	**LNCPI -**	**LNLINT +**	**LNLINT -**	**LNSINT +**	**LNSINT -**	**LNINVS +**	**LNINVS -**	**C**	**COINTEQ***
JSE	17,819***	-22,367***	2,273	-3,251	0,102***	0,269**	0,692*	0,493	11,289***	-0,038***
Bas	-18,305	-18,560***	4,699***	-1,678***	-0,188**	-0,028	0,106*	-0,023***	10,781***	-0,110***
Con Dis	5,160**	-0,944	1,631	0,746	-0,419**	0,541	0,017**	0,315	8,088***	-0,086***
Con Ser	13,391	18,318	-1,040**	1,072*	0,221	-2,645	0,180***	0,879	8,688***	-0,027***
Con Sta	2,719***	85,421	0,263	0,007	-0,507	-1,605	0,262***	0,058	10,208***	-0,029***
Fin	3,616**	23,612	0,770***	1,135	-0,039	-0,149	0,033	0,157	10,105***	-0,106***
Hea	-13,773***	14,972***	2,712	-4,406	-0,800	0,625***	0,296**	0,833	10,705***	-0,092***
Indus	7,001***	28,935	1,487	0,313	-0,420	0,232	0,094	0,152	9,826***	-0,049***
Ret	13,709*	28,299	-0,641	1,014	-0,650***	-1,748	0,037	0,616	8,452***	-0,041***
Tech	8,796***	19,110	1,547	-5,081	-1,030	2,620	0,540***	0,735	9,352***	-0,029***
Tel	2,069	4,767	1,931	1,134	-0,838	-0,276	-0,276	0,093	9,011***	-0,125***

Note: *, **, and * indicate a 1%, 5% and 10% level of significance respectively All figures are rounded off to 3 decimal place*

Inflation

The findings in Table 6 can be interpreted similarly to those for the typical ARDL in Table 3, with one significant difference: the division of the ß coefficients of LNCPI, LNLINT, LNSINT, and LNINVS into positive and negative partial sum decompositions, represented by the symbols β^{+} and β^{-}, respectively (Moores-Pitt, 2019). Starting with the JSE All Share Index, both the positive adjustment coefficient (β^{+}) and the negative adjustment coefficient (β^{-}) under LNCPI are statistically significant, at 17.82 and -22.37, respectively. This suggests that the JSE and inflation are positively correlated: stock prices rise 17.82% in response to increases in inflation (positive LNCPI adjustments), whereas decreases in inflation (negative LNCPI adjustments) lead to a larger positive effect of 22.37%. According to Moores-Pitt (2019), this imbalance implies that investors respond more favourably to reducing inflationary pressures, hence enhancing the JSE's function as an efficient inflation hedge. However, industries including Consumer Discretionary, Consumer Services, Finance, Retail, and Technology only exhibit notable positive reactions to inflation increases (β^{+}), whilst Basic Materials only exhibit positive reactions to inflation decreases (β^{-}). These results are also supported by Ang et al. (2012), who found that among S&P industry indices, only Basic Materials had a positive beta with inflation. The impact of inflation on stock returns varies across industries, reflecting sector-specific risk exposures and sensitivities, as this sector-specific divergence demonstrates. The Healthcare industry shows a strong negative response to both inflation increases (-13.73%) and decreases (14.97%), suggesting it does not act as an inflation hedge. Telecommunications and Consumer Services sectors show insignificant results, underscoring further heterogeneity. These results were supported by Luintel and Paudyal (2006) and Kawawa (2018).

Long Term Interest Rate

When examining the effects of long-term interest rates, the results reveal asymmetric impacts on sectoral stocks. The long-term interest rate had a positive adjustment coefficient for Basic Materials and Financials, and a negative adjustment coefficient for Basic Materials, indicating a favourable influence on these stocks. Higher demand for raw materials during periods of economic expansion and currency depreciation benefits Basic Materials by lowering export costs and increasing sales (PwC, 2016). Financials gain when banks lend at higher long-term rates while borrowing short-term, increasing profitability through wider net interest margins (Demirgüç-Kunt, et al., 2021). Additionally, investors are drawn to fixed-income instruments since rising long-term rates raise bond yields (Vayanos and Vila, 2021). Consumer Services, by contrast, exhibits significantly negative positive and significantly negative negative adjustment coefficients; it responds negatively to rising long-term rates. This suggests that higher rates lead to higher borrowing costs and mortgage payments, which, in turn, reduce consumer spending on discretionary goods and services (Majapa and Gossel, 2016).

Short Term Interest Rate

The impact of short-term interest rates on sectoral stock returns is asymmetrical. For the retail, Consumer Discretionary, and Basic Materials sectors, the positive adjustment coefficient was significantly negative, indicating that these industries are adversely affected by rising short-term rates. This is because many Retail and Consumer Discretionary purchases are made using credit, which raises the cost of borrowing for consumers. Retailers also have to pay higher costs for operations and inventory financing (Majapa and Gossel, 2016). Because of weaker economic development and stronger currencies, which lower commodity prices, rising short-term rates for Basic Materials raise producers' financing costs and reduce demand (Kilian and Zhou, 2022). However, the positive adjustment coefficient was significant and positive for the JSE. The negative adjustment coefficient was significant and positive for the JSE and healthcare sector. The JSE all-share index reflects rising corporate debt; businesses rely on credit for operations, recruitment, and growth. Short-term rate increases limit profit growth by increasing the cost of debt (Alam et al., 2021). Moreover, lower stock valuations and future earnings become less valuable as interest rates rise, thereby lowering stock values by increasing the discount rate used in valuation models.

Additionally, funds shift into bonds, making them more appealing as short-term rates rise, thereby deterring investors from buying equities and negatively affecting market performance. Short-term debt is used by many pharmaceutical businesses, biotech companies, and healthcare organizations to fund facility expansions, research, and the creation of new drugs. Additionally, profits are reduced as interest rates rise because loan repayments become more costly. Moreover, increasing short-term rates raises the interest rates on credit cards and medical loans, increasing the burden of paying for healthcare out of pocket (Alam et al., 2021).

Fear and Greed Investor Sentiment

The analysis of the fear and greed investor sentiment variable reveals an asymmetric long-run relationship with sectoral stock returns. There is an asymmetric long-term link between sectoral stock returns and the investor sentiment variable, which measures fear and greed. For the JSE All Share Index`, Consumer Discretionary, Consumer Staples, Consumer Services, Healthcare, and Technology sectors, the positive adjustment coefficient was statistically significant and positive. This indicates that increasing investor optimism supports equity prices in these markets. Asymmetry is further evident in the Basic Materials sector, which responds favorably to both positive and negative sentiment shifts. This suggests that, because Basic Materials play a vital role in the South African economy, investor excitement not only drives up Basic Materials stocks but also sentiment reversals (from greed to fear) may spark interest. Particularly in cyclical industries such as Consumer Discretionary and Basic Materials, which benefit from optimistic projections of future economic conditions, positive sentiment boosts equity demand and share prices. Furthermore, sentiment-driven confidence increases consumption, benefiting consumer-related industries such as Consumer Services, Staples, and Discretionary Services. Defensive industries such as Healthcare and Consumer Staples attract investors despite sentiment upswings because of their apparent steadiness. The broader JSE All Share Index, which includes a variety of sectors, benefits from capital inflows into stocks as sentiment improves. These findings are consistent with prior literature, which demonstrates that optimism reduces return uncertainty and promotes positive contemporaneous return dynamics (McGurk, et al., 2020; Al-Nasseri, et al., 2021; Abdul Karim et al., 2022).

According to the Wald test, the results support the existence of statistically significant asymmetric long-run relationships between the variables and sectoral stock returns (Table 6). The nonlinear and behavioural dynamics in South African financial markets are evident in the varying magnitudes and directions of the ß+ and ß- coefficients, which indicate how stock returns respond differently to positive and negative fluctuations in inflation, interest rates, and investor sentiment. Because the effectiveness of sectoral stocks varies with the direction of changes in variables such as inflation, interest rates, and investor sentiment, this asymmetry suggests that investors and portfolio managers should account for the direction of these changes when designing inflation-hedging strategies. Thus, the asymmetric behavioural dynamics in the South African equity market, influenced by investor variables, are well captured by the NARDL model's decomposition.

CUSUM and CUSUM of squares stability tests

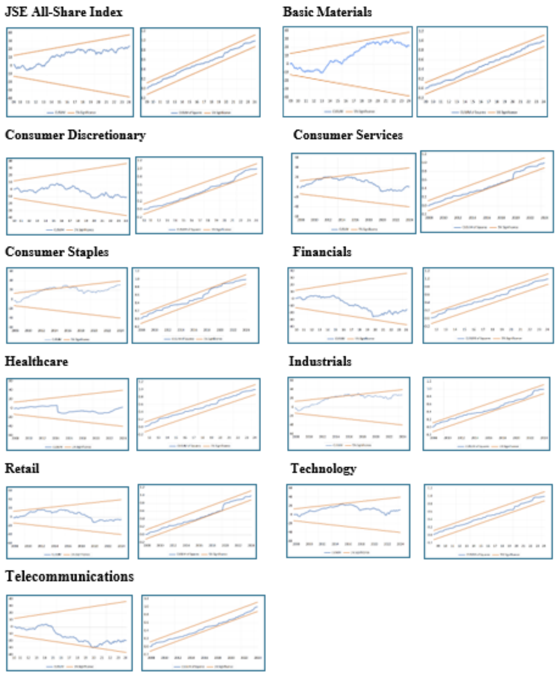
The CUSUM and CUSUM of squares stability tests, conducted at the 5% significance level, confirmed that the estimated relationships remained stable over the study period, as all deviations lay within the confidence bounds and both tests supported model stability. These findings are shown in the appendix below.

CONCLUSION

Using both linear (ARDL) and nonlinear (NARDL) models, this study investigated the long-term relationship between sectoral stock returns and important macro-financial variables on the Johannesburg Stock Exchange (JSE), including inflation, long- and short-term interest rates, and investor sentiment. The study's emphasis on the asymmetric nature of these relationships, which is often overlooked in conventional inflation-hedging literature, is one of its main contributions. The use of the NARDL framework was supported by Wald test results, which indicated substantial long-run asymmetries (Shin et al., 2014). This result challenges the notion of symmetric market behaviour by suggesting that sectoral stock returns in South Africa react differentially to increases and decreases in inflation and other macroeconomic factors and sentiment. The analysis shows that inflation does not consistently erode stock values across industries from an investment standpoint. While some industries, like Consumer Discretionary, Industrials, and Technology, provide inflation hedging benefits particularly during periods of rising inflation, others, like Basic Materials and the JSE All-Share Index, seem to gain more from dropping inflation. These findings both confirm and extend prior research by Alagidede and Panagiotidis (2010), Kawawa (2018), and Moores-Pitt (2019), demonstrating the impact of sentiment and interest rate directionality on results. The behavioural interpretation of these inequalities is further improved with the addition of the South African Fear and Greed Index. According to Sayim and Rahman (2015) and McGurk et al, (2020), who highlight the importance of optimism in influencing stock returns, investor sentiment, for instance, consistently demonstrated a significant and positive influence across the majority of sectors.

The policy implications are equally noteworthy. Market asymmetry implies that changes in sentiment, interest rate increases, or inflationary shocks do not have an equal impact on all industries. Standard monetary tools may have sector-specific effects that either mitigate or increase systemic risk, so policymakers should be mindful of this. According to Majapa and Gossel (2016) and Alam et al, (2021), higher interest rates, which are frequently employed to combat inflation, have a stronger negative impact on consumer-oriented and capital-intensive industries (like Retail and Healthcare), particularly in the short term. These results emphasise the necessity for investors to implement dynamic asset allocation methods that account for macroeconomic trends. In addition to sectoral exposure, portfolio diversification should account for macroeconomic shocks, such as whether inflation is rising or falling, interest rates are rising or falling, and sentiment is bullish or bearish. Suboptimal investment choices may result from ignoring these nonlinear effects, which are evident in symmetric models. All things considered, this analysis provides solid evidence that South African stocks' ability to hedge against inflation is asymmetric and sector-specific. By going beyond linear frameworks and broad index-level research, it fills a significant gap in the literature on emerging markets. In addition to making a substantial scholarly contribution, the study provides useful information for asset managers and policymakers negotiating inflationary uncertainty in dynamic, sentiment-driven markets. Future research could expand on this study by more thoroughly examining how global commodity cycles, ESG considerations, or high-frequency investor sentiment data shape these correlations.

Appendix



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