Investor Sentiment in the South African Stock Market

Master of Commerce (50% Research) in Finance

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This study examines the relationship between investor sentiment and individual stock returns on the Johannesburg Stock Exchange (JSE) over the period 2000 to 2024. Using a sentiment index constructed from local market-based proxies, the analysis explores whether investor sentiment predicts future returns beyond the explanatory power of the Fama-French three-factor model. Two key hypotheses are tested: first, that investor sentiment has a statistically significant negative relationship with future stock returns; and second, that this effect is more pronounced for stocks that are difficult to value or arbitrage. The empirical methodology includes time-series and cross-sectional regressions, with robustness checks. The results provide evidence supporting both hypotheses, highlighting the relevance of behavioural factors in asset pricing on the JSE. This research contributes to the emerging market behavioural finance literature and offers insights for investors and portfolio managers seeking to better understand sentiment-driven mispricing and improve risk-adjusted returns.

Declaration

I, Mphulane Thato Hlapisi, declare that this research paper is my own work and that I have correctly acknowledged the work of others. It is submitted to fulfil the requirements for the degree of Master of Commerce in Finance at the University of the Witwatersrand, Johannesburg. I declare that this research paper has not been submitted for any other degree or examination in this or any other institution.

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Table of Contents

List of figures

List of tables

Definition of abbreviations and terms

Behavioural Finance – A field of finance that examines how psychological influences and biases affect financial decision-making and market outcomes.

CCI – Consumer Confidence Index

CSI 300 – China Stock Index 300

Disposition Effect – The tendency of investors to sell winning stocks too early and hold onto losing stocks too long.

Efficient Market Hypothesis (EMH) – The theory that asset prices fully reflect all available information at any given time.

FEARS – Financial and Economic Attitudes Revealed by Search

FTSE/JSE – Financial Times Stock Exchange/Johannesburg Stock Exchange

GARCH – Generalised Autoregressive Conditional Heteroskedasticity

GCN – Graph Convolutional Networks

GDP – Gross Domestic Product

GRU – Gated Recurrent Unit

Herd Mentality – A behavioural finance phenomenon where investors follow the actions of others rather than making independent decisions.

Investor Sentiment – The overall attitude of investors toward a particular market or asset, often reflected in trading activity and stock prices.

IPOs – Initial Public Offerings

JALSH – Johannesburg All Share Index

KMO – Kaiser-Meyer-Olkin Measure of Sampling Adequacy

LDA – Latent Dirichlet Allocation

LSTM – Long Short-Term Memory (Neural Network)

MAE – Mean Absolute Error

Market Liquidity – The ability to buy or sell assets in the market quickly and at stable prices without causing significant price changes.

ML – Machine Learning

Momentum Investing – A strategy that involves buying stocks that have performed well in the past and selling those that have performed poorly.

MSE – Mean Squared Error

Neural Network – A machine learning model designed to mimic the way the human brain processes data, often used for pattern recognition in financial markets.

OLS – Ordinary Least Squares

PCA – Principal Component Analysis

PECS – Private Equity Confidence Survey

PVAR – Panel Vector Autoregression

Quantile Regression – A statistical technique that estimates the relationship between variables across different quantiles of the dependent variable's distribution.

RNN – Recurrent Neural Network

Sentiment Index – A composite measure derived from multiple investor sentiment proxies (such as IPO activity, market turnover, and volatility premium).

SHAP – SHapley Additive exPlanations

Stock Market Volatility – A statistical measure of the dispersion of stock returns, often linked to investor sentiment.

SVM – Support Vector Machine

Value-at-Risk (VaR) – A risk management tool used to estimate potential losses in an investment portfolio over a given time period

VIX – CBOE Volatility Index (also called the "Fear Index")

VPREM – Volatility Premium

1 Introduction

1.1 Background and overview

Yang, Ryu and Ryu (2017) note that changes in economic fundamentals and systematic risks drive asset values in rational asset pricing frameworks, in line with traditional theories and models in the fields of finance and investing. The demands of rational arbitrageurs counterbalance those of irrational and/or noisy investors, and the transactions made by the latter have no impact on the underlying dynamics of asset prices (Yang et al., 2017). Tuyon, Ahmad and Matahir (2016) raise that according to behavioural finance, behavioural risks distort investors' full rational decision making, which posits that investors make decisions purely based on logical reasoning and available information, causing deviations on assets' fundamental valuation and inducing market inefficiency. Baker and Wurgler (2007) note that there have been a few instances of stock market bubbles and crashes, which are defined as significant fluctuations in stock prices that appear to defy traditional finance explanations, and these provide evidence of market inefficiency. The alternative school of thought, behavioural finance, seeks to augment the standard efficient markets model with an alternative one built on the assumptions of; 1) investors' subjectivity to sentiment and 2) the costliness and riskiness of betting against sentimental investors (Baker and Wurgler, 2007). It follows that investor sentiment, which affects stock prices, trading volumes, and market volatility, is crucial to the functioning of financial markets.

1.2 Motivation of the study

Aggarwal (2019) posits that the key issue in asset pricing theory is comprehending the elements that need to be factored into the asset pricing theories. Decision-making mistakes arise from the limited human capacity of information processing while taking the behavioural and market factors into account. Hirshleifer (2001) notes that it is mostly investigated within the heuristics, biases, and sentiments branches of behavioural finance research. The incorporation of these enables the development of more realistic theories. Baker and Wurgler (2006) point out that the cross-section of stock returns is significantly impacted by investor sentiment. They contended that investors tended to speculate on prices instead of making decisions based on asset fundamentals when market sentiment leads them to be either optimistic or pessimistic. Naturally, one would ask how to measure sentiment and incorporate it into prices. Baker and Wurgler (2007) criticise the "bottom up" approach which uses biases in individual investor psychology for explaining why individual investors overreact or underreact to fundamentals or historical returns. They argue for their "top down" and macroeconomic investor sentiment approach. To identify which stocks are most likely to be impacted by sentiment, it focuses on measuring reduced-form, aggregate sentiment and links its impacts to market returns and individual stocks. This motivates this study's use of the aggregate sentiment approach in the South African context.

1.3 Knowledge gap and research objective

The study by Dalika and Seetharam (2015) provided profound insights into the nature of sentiment-based mispricing in the South African context. Brown and Cliff (2005) provided evidence of a negative correlation between sentiment and stock returns. Based on this, they hypothesised that: 1) Investor sentiment has a strong negative predictive power for future aggregate market returns, and this link holds true even after correcting for asset fundamentals, and 2) For equities that are difficult to value or arbitrage, the impact of sentiment on returns is larger. They find that young stocks, small company stocks, extremely volatile stocks, and rapid growth have lower future returns than other securities when investor sentiment is relatively strong. The evolution of the financial landscape over the past almost decade warrants a re-examination of the Dalika and Seetharam (2015) findings. This study seeks to build upon and extend their work by updating their findings by addressing the following motivations:

1) Incorporating New Data: This research analyses investor sentiment over a comprehensive period from 2000 to 2024, which includes the COVID-19 pandemic as a key sub-period. While not limited to the pandemic, the study captures the onset, duration, and aftermath of the COVID period, defined as the time between the declaration and lifting of the National State of Disaster. This allows for an exploration of both long-term sentiment trends and the impact of extreme market disruptions such as the pandemic.
2) Validation and Robustness: Replicating and extending their study will contribute to literature and validate their original findings to ensure their applicability in today's market context. Further tests on the non-linear nature of the relationship between proxies and the sentiment index improve robustness of the findings.
3) Investigating Return Distribution: This study investigates how investor sentiment relates to different quantiles of stock returns, providing insight into whether sentiment has varying

effects across the return distribution, such as during periods of extremely low, median, or high returns.

1.4 Problem statement

While investor sentiment has been studied in the South African market, human emotions and market conditions continually evolve, warranting a re-assessment to determine if the prevailing findings still hold true, especially in light of the COVID period. A thorough analysis of sentiment during this era enhances the generalisability of findings to other black swan events, offering deeper insights into how markets and investors react under various conditions. The current study will therefore investigate whether investor sentiment can help explain stock returns on the Johannesburg Stock Exchange (JSE) by extending the traditional Fama-French three-factor model.

1.5 Potential benefits of the study

Historical events that led to speculative bubbles make it crucial to question the assumption and definition of rationality in finance literature (Aggarwal, 2019). Making wise investing decisions requires an understanding of the illogical sentiments held by market players (Haritha & Rishad, 2020). Therefore, understanding investor sentiment is crucial for several stakeholders. For investors, it provides insights into potential market movements that are not captured by fundamental analysis alone, helping fund managers and investors decide when to enter and exit the market (Haritha & Rishad, 2020). For policymakers and regulators, it aids in formulating strategies that improve their efforts to stabilise stock market volatility and uncertainty in order to protect investors' wealth and attract more investors (Haritha & Rishad, 2020). For academics, it contributes to the broader field of behavioural finance by providing empirical evidence from various market contexts.

By focusing on investor sentiment in the South African market, this research aims to enhance market predictions and investment strategies. It will also contribute to the existing body of literature on behavioural finance, offering new perspectives and empirical evidence on sentiment's role and influence in market dynamics.

1.6 Structure of the research report

The rest of the paper is structured as follows: Section 2 presents a comprehensive literature review, outlining the theoretical framework and previous research on investor sentiment. Section 3 outlines the methodology details, the research design, data collection methods, and analysis techniques employed. Section 4 outlines the results of the analysis and section 5 concludes.

2 Literature review

2.1 Definition of investor sentiment

The definition of sentiment is ill-defined in finance literature and is in a state of flux with no single uncontested definition (Peterson, 2016). There is no one, accepted definition of sentiment, and the concept is constantly changing in the financial literature (Peterson, 2016). Sentiment is defined as a view, opinion, or concept based on a feeling about a circumstance or a manner of thinking about something by the Cambridge Dictionary (2017). Thus, investor sentiment describes the collective viewpoint and stance of investors about a specific financial asset or market (Hao, 2017). Some other definitions are, De Long, Shleifer, Summers, and Waldmann (1990) who defines investor sentiment as market participants' expectations about investment risk and cash flows (returns) that lie in the future. Shleifer and Summers (1990) defined it as the general investor attitude toward financial markets. As mentioned in Hao, (2017), Baker and Wurgler (2007) perceive sentiment as a conviction about investment risks and expected cash flows that is not factually justifiable by available data, and mention another view of investor sentiment as widespread optimism or pessimism about stocks. Due to this paper's intent to investigate how sentiment influences stock market performance in South Africa, it leans towards the Baker and Wurgler (2007) definition.

While these definitions provide a wide view definition of what investor sentiment is, Zhang (2008) notes that they lack a set of necessary and sufficient conditions that makes clear exactly what we mean when we refer to investor sentiment. Zhang (2008) defines it as market participants' beliefs about future cash flows relative to some objective norm, namely the true fundamental value of the underlying asset. It is clear that some incorrect beliefs are incorporated in decision making. Zhang (2008) notes two possibilities: the correct use of wrong information, or the wrong use of correct information. Sentiment would therefore be what market participants expect asset returns to be beyond what Bayesian updating and fundamental values would suggest. An investor could be overconfident in a certain stock and act on the particular stock differently from a Bayesian trader who trades on fundamental values alone. Zhang (2008) then proposes a simplified way of thinking about investor sentiment as the discrepancy between two forecasts: (i) an individual's subjective assessment based on all available information in addition to potentially biased private information, and (ii) the objectively correct forecast based only on relevant information alone. In the event that an investor is rational and their beliefs are correct and reflect the true fundamental value, such a discrepancy would not exist and sentiment would effectively be zero. Such a scenario is classified as a necessary but not sufficient condition to infer that beliefs are formed according to standard probability axioms and only reflect relevant pricing information (Zhang, 2008). At an aggregate level, investor sentiment matters at least when these conditions hold:

1. Sentimental investors make up a "big enough" proportion of all traders. Or alternatively, sentimental investors disproportionately hold certain assets.
2. Beliefs are correlated across investors in a way that cannot be perfectly forecasted by rational arbitrageurs.
3. Investor beliefs are not independently distributed so that the aggregate effect of sentiment does not cancel out in equilibrium (Zhang, 2008). This simply means that aggregate sentiment amplifies market movements in the same direction and rational arbitrageurs are unable to forecast changes.

In the presence of a discrepancy between the two forecasts mentioned above, investor sentiment can be categorised into the two broad types, bullish and bearish. Bullish (bearish) sentiment is when an investor expects returns to be above (below) average, whatever "average" may be. A general unrealistically optimistic (pessimistic) feeling is indicated by bullish (bearish) mood, which is frequently accompanied with upward (downward) price movement. This attitude is derived from both technical and fundamental factors, such as economic events, market trends, business reports and price development (Hao, 2017).

2.2 Significance of investor sentiment

Investor sentiment plays a crucial role in financial markets by influencing asset prices, trading behaviour, and market dynamics in ways that deviate from traditional rational models. Sentiment, reflecting the collective optimism or pessimism of investors, can lead to price movements that are disconnected from fundamental values. This can result in phenomena such as speculative bubbles, overreaction to news, and momentum in stock prices.

The role of sentiment becomes especially significant in the presence of limited arbitrage, where rational traders are unable to fully counteract the mispricing caused by sentiment-driven investors. Retail investors, often more prone to sentiment, contribute to market inefficiencies by acting on biased or incomplete information, while arbitrageurs may exploit these behaviours rather than correcting them. For example, sentiment has been linked to puzzles like Initial Price Offering (IPO) underpricing, closed-end fund discounts, and the predictability of stock returns based on past trends (Ibrahim & Benli, 2022).

Furthermore, sentiment can amplify market volatility during periods of extreme optimism or fear, affecting trading volumes and liquidity. Positive sentiment often correlates with increased trading activity and rising prices, while negative sentiment can exacerbate downturns, as seen in periods of financial crises (Haritha & Rishad, 2020). By serving as both a driver of short-term market trends and a potential explanation for long-term anomalies, investor sentiment remains a critical factor in understanding and modelling financial markets.

The impact of investor sentiment on financial markets is multifaceted, influencing a range of market behaviours and outcomes. From shaping price dynamics and trading activity to exposing underlying behavioural biases, sentiment plays a critical role in both short-term volatility and long-term market anomalies. This section explores the various dimensions of sentiment's role, starting with its influence on market movements, followed by its effect on trading volume and volatility. The discussion then delves into how behavioural biases amplify sentiment-driven patterns, its predictive power for future market trends, and the broader policy implications for managing sentiment's effects on market stability.

2.2.1 Market movements

Investor sentiment plays a critical role in driving market movements, often resulting in significant deviations from fundamental asset values. Haritha and Rishad (2020) argue that investors actively participate in the market with the hope of earning larger profits when sentiment is positive. On the other hand, investors withdraw from the market when pessimism is prevalent due to their low expectations for market returns. Bank and Brustbauer (2014) highlight that these waves of optimism or pessimism among investors can lead to speculative bubbles during periods of excessive enthusiasm or crashes during widespread fear. For example, investor optimism during IPO "hot issue" markets often inflates prices well beyond intrinsic values, creating long-term underperformance as prices eventually correct. Similarly, the closed-end fund puzzle demonstrates how changes in retail investor sentiment can lead to persistent mispricing of fund shares relative to their net asset value, reflecting the influence of sentiment on asset valuations. Shleifer and Summers (1990) argue that sentiment-driven deviations from fundamentals challenge the assumption of efficient markets, as these movements cannot be entirely explained by rational behaviour. The cyclical nature of sentiment, shifting between overvaluation and undervaluation, suggests that investor beliefs are not randomly distributed but instead follow collective patterns that shape broader market trends.

Da, Engelberg, and Gao (2014) measure investor sentiment by the FEARS index and argue that it plays a critical role in driving market movements, often leading to significant deviations from fundamental asset values. They demonstrate that spikes in fear, captured through internet search behaviours related to terms like “recession” or “bankruptcy,” result in immediate market mispricing. Specifically, heightened fear correlates with low market returns on the same day, followed by return reversals over the next two days. This pattern underscores the temporary nature of sentiment-induced mispricing, as markets correct themselves when sentiment subsides. These effects are particularly pronounced in high-beta and high-volatility stocks, which tend to attract noise traders and are harder for arbitrageurs to stabilise due to institutional and capital constraints. Such dynamics illustrate how collective sentiment can disrupt market equilibrium, creating price anomalies in the short term. These findings align with behavioural finance theories that emphasise the influence of non-rational factors, such as fear and optimism, on asset prices.

2.2.2 Trading volume and volatility

Bank and Brustbauer (2014) highlight how sentiment influences both trading volume and market volatility. Positive sentiment, often associated with bullish market conditions, leads to increased trading volumes as optimistic investors actively buy into the market. Conversely, during periods of pessimism, trading activity declines as fear and uncertainty discourage participation. Haritha and Rishad (2020) argue that market players will leave the market if they do not get a market risk premium for their anticipated volatility, which will further increase market volatility. Baker and Stein (2004) observe that retail investors tend to trade more during optimistic periods, while Griffin, Nardari, and Stulz (2006) document a positive correlation between trading volume and past market returns across 46 countries, particularly in markets with higher retail investor participation. Furthermore, Bank and Brustbauer (2014) note that sentiment-driven markets exhibit heightened volatility, especially during bear markets when negative sentiment leads to sharper declines and more extreme price swings. This asymmetric relationship between sentiment and volatility underscores the role of investor behaviour in exacerbating market instability during periods of fear, as reflected in the CBOE Volatility Index (VIX index) often referred to as the "fear gauge."

Da et al. (2014) establishes a strong link between investor sentiment and market volatility, showing how spikes in fear coincide with heightened trading volume and increased market uncertainty. Using both realised volatility and the VIX index as measures, the study finds that fear-induced sentiment drives temporary spikes in market volatility, as noise traders amplify price movements by reacting emotionally to perceived risks. This sentiment-driven volatility often dissipates over time, reflecting the transient nature of fear's impact on financial markets. Additionally, the FEARS index highlights how heightened fear impacts mutual fund flows, with significant outflows from equity funds and inflows into bond funds during periods of pessimism. This flight-to-safety behaviour exacerbates volatility in equity markets while simultaneously increasing demand for safer asset classes, such as treasury securities. These findings provide empirical support for theories that link sentiment-driven trading to market instability and highlight the need to better understand the interplay between sentiment, trading activity, and volatility.

2.2.3 Behavioural biases

Investor sentiment is deeply intertwined with behavioural biases, which amplify its impact on market outcomes. Bank and Brustbauer (2014) emphasise that biases such as overconfidence, herding, and heuristics play a central role in shaping sentiment-driven behaviours. Overconfidence, for instance, leads investors to overestimate their ability to interpret market signals, resulting in excessive trading and momentum in stock prices (Daniel, Hirshleifer, & Subrahmanyam, 1998). Herding behaviour further magnifies sentiment-driven trends as investors collectively follow market movements, often disregarding fundamental analysis (Lee & Swaminathan, 2000). Additionally, heuristics like representativeness and availability distort investor decision-making by causing them to rely on simplified mental shortcuts rather than rational evaluations of market conditions. Almansour, Elkrghli, and Almansour (2023) show that herding, disposition effect, and blue-chip bias have a significant positive impact on risk perception, which heavily influences sentiment. Phenomena such as the disposition effect, where investors sell winning stocks prematurely and hold on to losing positions for too long reflect their emotional attachment to past decisions, underscoring how psychological factors exacerbate market inefficiencies.

The role of behavioural biases in shaping investor sentiment is indirectly addressed in Almansour, Elkrghli, and Almansour (2023), as it links fear-driven trading to irrational behaviours. Noise traders, often guided by emotional responses rather than fundamental analysis, exhibit tendencies such as loss aversion and the flight-to-safety bias during periods of heightened fear. This is evidenced by the flow of funds out of equity markets and into bond markets following spikes in the FEARS index. Such behaviour reflects common psychological biases, including overreaction to negative signals and an aversion to perceived risk, even when fundamentals do not justify such actions. These patterns align with theories of noise trading, where uninformed investors amplify market inefficiencies through herding and emotional decision-making.

2.2.4 Predictive power

Investor sentiment can serve as a predictive indicator of future market movements. Sentiment analysis, which involves measuring and interpreting sentiment from various sources (e.g., surveys, social media and news articles), can provide valuable insights regarding market trends. Bank and Brustbauer (2014) highlight that sentiment indices, such as those developed by Baker and Wurgler (2006), effectively predict future stock returns, particularly for small-cap, high-volatility, and growth-oriented stocks. Sentiment-driven markets often display patterns of underreaction in the short term and overreaction in the long term. For instance, Hong and Stein (1999) show how bounded rationality among investors leads to gradual incorporation of news, resulting in momentum effects in stock prices. Additionally, sentiment predicts anomalies such as IPO underpricing, where overly optimistic retail investors inflate first-day returns, and the timing of equity issuance, where firms capitalise on high sentiment to issue stock at favourable valuations. Despite its predictive potential, Bank and Brustbauer (2014) acknowledge that sentiment is not infallible and can occasionally fail to account for unexpected market shifts, highlighting the need for complementary tools in forecasting. Guo, Sun, and Qian (2017) further demonstrate that the sentiment data from their studied social networks was not always predictive of the stock price and that the stock price should only be predicted by sentiment when the firm is receiving a lot of attention from investors. Additionally, they point out that while investor mood isn't always a reliable indicator of the stock market, it is a useful tool for analysing present performance of the market most of the time.

The FEARS index in Da et al. (2014) demonstrates significant predictive power in financial markets, particularly in forecasting short-term market movements. Da et al. (2014) shows that spikes in the FEARS index predict return reversals in the subsequent two trading days, with high levels of fear leading to low returns today but higher returns over the next two days. This pattern is especially evident in high-beta and high-volatility stocks, which are more sensitive to sentiment-driven trading. The predictive power of the FEARS index extends beyond equity markets, as it also forecasts fund flow movements, with investors reallocating their portfolios from equities to bonds during periods of heightened fear. These findings suggest that sentiment measures, such as the FEARS index, can be valuable tools for predicting short-term price dynamics and identifying periods of temporary market inefficiency. The ability of such indices to provide high-frequency insights into market sentiment makes them particularly useful for practitioners and researchers seeking to understand and forecast market behaviour.

2.2.5 Policy implications

For policymakers and regulators, monitoring investor sentiment is crucial for maintaining market stability. Extreme levels of sentiment can signal the need for regulatory interventions to prevent market bubbles or crashes. Sentiment analysis can also help policymakers gauge the effectiveness of their measures and understand the market's response to policy changes. Understanding these biases is essential for explaining market anomalies. Investors, advisors and policymakers need to consider behavioural biases in order to develop strategies to mitigate their impact (Almansour et al., 2023).

Bank and Brustbauer (2014) underscore the policy implications of investor sentiment, particularly its role in creating market inefficiencies and volatility. Limited arbitrage, where rational traders are unable to fully correct sentiment-driven mispricing, presents a significant challenge for regulators. Shleifer and Summers (1990) argue that the persistence of mispricing due to sentiment necessitates regulatory intervention to maintain market stability. Bank and Brustbauer (2014) suggests that policies should focus on reducing the susceptibility of retail investors to sentiment-driven errors through improved financial education and greater transparency in financial markets. Regulatory tools such as circuit breakers and short-selling restrictions are also highlighted as mechanisms to mitigate the extreme effects of sentiment during market downturns. Furthermore, they point out the importance of global and cultural considerations in policy design, as sentiment impacts markets differently across regions. By addressing the behavioural underpinnings of sentiment, policymakers can work toward creating more resilient financial systems that are less prone to the destabilising effects of collective investor behaviour.

Investor sentiment also poses implications for financial policy, particularly in mitigating the destabilising effects of sentiment-driven market reactions. Kurov (2009) highlights how monetary policy decisions influence investor sentiment, with the impact varying across different market regimes. In bear markets, monetary shocks, especially unexpected changes in interest rates, significantly affect investor sentiment. These effects underscore the role of monetary policy not only in shaping economic fundamentals but also in influencing psychological factors that drive market behaviour. For example, the study finds that a 100 basis point cut in the federal funds rate during a bear market can increase sentiment measures by multiple standard deviations, reflecting a strong belief in the central bank's ability to stabilise markets in periods of stress.

This sentiment-driven response creates challenges for policymakers, as exaggerated market reactions can lead to short-term volatility and mispricing. Kurov (2009) shows that stocks more sensitive to sentiment changes, such as high-volatility and low-liquidity stocks react more strongly to monetary news. These dynamics suggest that policymakers must consider sentiment as a key factor when designing interventions, particularly during periods of economic stress. By targeting sentiment-sensitive segments of the market, policymakers can better address the uneven distribution of monetary policy effects.

Kurov (2009) also highlights the importance of transparency and predictability in monetary policy to mitigate excessive sentiment-driven reactions. Clear communication of policy intentions can reduce uncertainty and prevent investor overreaction to timing surprises. Additionally, the need for macroprudential tools such as liquidity facilities to stabilise markets during periods of extreme sentiment swings is highlighted. These measures can help prevent panic-driven sell-offs and reinforce investor confidence in the resilience of financial systems. Overall, incorporating sentiment analysis into policy frameworks can improve the effectiveness of monetary interventions and contribute to greater financial stability.

2.3 Behavioural finance theories

Although it is anticipated that expected emotions are taken into account when making rational decisions, the theoretical foundation for doing so has not yet been completely developed. They are somewhat studied in the framework of heuristics and biases in behavioural finance theories (Aggarwal, 2019). These theories provide a framework for understanding how psychological factors and cognitive biases influence investor behaviour and, consequently, market outcomes. This section explores key behavioural finance theories and concepts that are pertinent to investor sentiment.

2.3.1 Prospect theory

Prospect theory, introduced by Kahneman and Tversky (1979), is a foundational concept in behavioural finance and economics that explains how individuals make decisions under conditions of uncertainty. Unlike traditional utility theory, which assumes rational decision-making based on objective probabilities, prospect theory argues that investors' decisions are influenced by psychological factors known as behavioural biases, which cause them to stray from rational behaviour (Zahera & Bansal, 2018). It highlights that decision-making is influenced by perceived gains or losses relative to a reference point, rather than by the absolute outcome of the decision. Investors are risk-averse whenever it comes to profits and risk-seeking whenever it comes to losses. Even when the projected value of both is the same, investors place a higher value on the one that is certain. Investors also try to avoid losing money, even if it means taking on more risk (Gautam & Kumar, 2021).

Key principles of the theory include reference dependence, where decisions are influenced by a benchmark such as the status quo or expectations, and loss aversion, which highlights that the emotional impact of losses is significantly greater than the satisfaction derived from equivalent gains. The theory also incorporates diminishing sensitivity, reflected in a concave value function for gains and a convex one for losses, meaning the perceived value of changes diminishes as their magnitude increases. Lastly, prospect theory introduces probability weighting, wherein individuals overweight small probabilities and underweight moderate to high probabilities, leading to a distortion in decision-making that deviates from rational probability models (Wan, 2018). Together, these principles explain common behavioural tendencies and deviations from traditional utility-based economic models, making prospect theory a cornerstone of behavioural finance.

2.3.2 Overconfidence

According to Zahera and Bansal (2018), overconfidence is the state in which individuals have a great deal of optimism over the outcomes of trade and believe that the information at their disposal is sufficient for them to make wise investing decisions. Simply, investors have excessive belief in their knowledge, abilities, and judgment. Kahneman and Riepe (1998) argue that overconfidence arises from people’s misjudgement of evidence, where the perceived strength of evidence outweighs its actual predictive validity. This cognitive error leads individuals to place undue weight on their own opinions or interpretations of data. They undervalue risks associated with their decisions, often resulting in suboptimal outcomes. This bias is particularly detrimental in periods of heightened market uncertainty, where overconfident behaviour exacerbates market inefficiencies and contributes to financial instability.

In the context of financial markets, overconfidence manifests as frequent trading activity. Odean (1999) found that overconfident investors engage in excessive trading due to their belief that they possess superior information. This behaviour often results in higher transaction costs and diminished net returns. Furthermore, overconfidence fosters a false sense of control over market outcomes, causing individuals to misjudge the likelihood of favourable results. As a consequence, investors may underestimate the uncertainties and complexities of financial markets, leading to an overreaction to new information.

The phenomenon is not limited to individual investors but extends to institutional settings. For instance, overconfident managers are more likely to undertake aggressive acquisition strategies, frequently overestimating synergies and underestimating associated risks. Doukas and Petmezas (2007) observed that overconfidence in higher-order acquisitions often results in lower long-term returns, highlighting the detrimental impact of this bias on corporate decision-making. Additionally, overconfidence is observed in IPO bidding, where investors tend to overestimate the future performance of firms, leading to aggressive bidding and poor returns.

By overreacting to new information, overconfident investors are more likely to move prices away from their intrinsic values, which leads to increased trading volumes and heightened market volatility. According to Madaan and Singh (2019), overconfident investors often react disproportionately to new information, creating an environment where market trends are driven more by psychological factors than fundamental valuations. Lovric, Kaymak, and Spronk (2010) validate this view and discover that compared to the unbiased efficient market believers, more optimistic investors cause more noticeable market booms and crashes. During bullish periods, overconfident investors contribute to heightened optimism, as they interpret favourable news as validation of their predictive skills. This feedback loop can lead to speculative bubbles, where asset prices are driven far above their intrinsic values. Conversely, in bearish markets, overconfidence can exacerbate pessimism as investors fail to accurately assess risks or adapt to changing market conditions.

The influence of overconfidence on investor sentiment is also evident in the persistence of market anomalies. Overconfident investors are more likely to disregard warning signals, such as overvaluation, and continue trading based on their inflated self-belief. This behaviour reinforces collective sentiment swings, magnifying both the peaks and troughs of market cycles. As suggested by Madaan and Singh (2019), overconfidence also affects how investors process and share information, contributing to herding behaviour. Overconfident individuals often act as opinion leaders, influencing others through their perceived authority or expertise. This dynamic amplifies group sentiment, as others align their expectations with those of overconfident investors. The resulting herd behaviour further drives sentiment-driven mispricing and volatility, creating a cycle that is difficult to break.

Despite its negative implications, some studies suggest that overconfidence may occasionally lead to positive outcomes, such as fostering market liquidity and generating momentum in stock prices during bullish phases (Abdin, Farooq, Sultana, & Farooq, 2017). However, on balance, overconfidence is a major factor in the creation of speculative bubbles, as overly optimistic investors drive prices far above their intrinsic values.

2.3.3 Herd mentality

Herd mentality, or herding, is a common tendency of human nature to refer, observe, and imitate other's behaviour during the irregular condition in financial markets (Yu, Dan, Ma, & Jin, 2018). In its presence, investors follow the actions of others rather than relying on their independent analysis. This behaviour will then often result in correlated trading patterns that drive asset prices away from their fundamental values.

Dang and Lin (2016) find that it is particularly prevalent in markets with asymmetric information. In such environments, less informed investors often suppress their private insights to conform to the actions of others, resulting in information cascades. These cascades occur when individuals believe that the observed behaviour of others reflects superior information, leading to group-wide conformity. This is especially pronounced in emerging markets, where limited access to reliable firm-specific data compels investors to rely on observable actions or macroeconomic signals.

Dang and Lin (2016) also distinguishes between fundamental-driven herding and intentional herding. Fundamental-driven herding arises when investors respond similarly to common external signals, such as macroeconomic changes. Intentional herding, on the other hand, involves deliberate mimicry of other investors' actions, often driven by behavioural factors such as a preference for conformity or reputation concerns. For instance, noise traders, who lack sophisticated analysis, often herd based on pseudo-signals, while arbitrageurs may mimic others to align with market trends and reduce reputational risks.

Dang and Lin (2016) highlight the asymmetry in herding behaviour between rising and falling markets. Herding is more pronounced in up markets, as optimism and speculative momentum draw investors toward shared decisions. In down markets, herding tends to diminish as fear and individual risk aversion lead to more scattered behaviour. Their study also reveals that herding intensity decreases following financial crises, as participants become more cautious and markets stabilise. This indicates a learning effect, where investors adapt to past market shocks by developing more rational trading strategies.

Another critical aspect of herding is its impact on volatility and market stability. By clustering trades around consensus, herding suppresses price discovery and accelerates the formation of bubbles or crashes. Additionally, herding behaviour complicates diversification, as correlated actions reduce the benefits of holding varied assets. Dang and Lin (2016) employ measures such as cross-sectional absolute deviation (CSAD) to quantify herding and demonstrate its effects on market dynamics. They find that herding remains a significant behavioural phenomenon in financial markets, shaped by information asymmetry, behavioural preferences, and market conditions.

Hudson, Yan, and Zhang (2020) found evidence of fund managers herding on market portfolio, size, and value factors, both open-end funds and closed-end funds in the United Kingdom. Zahera and Bansal (2018) argue that it can cause deviations of prices from their fundamental values and pose a risk of reduced returns to investors. These price deviations can lead to the formation of bubbles and crashes.

Herding has a profound impact on investor sentiment by amplifying collective emotional states such as fear, optimism, and uncertainty within financial markets. When investors conform to the actions of others instead of relying on independent analysis, the resulting group behaviour creates feedback loops that magnify prevailing market sentiments. Dang and Lin (2016) highlight how herding behaviour drives exaggerated market trends, reinforcing optimism during bull markets and deepening pessimism during downturns. For example, during a rising market, the collective optimism generated by herding can push prices far above their fundamental values, creating speculative bubbles. Conversely, in a declining market, herding can intensify fear, triggering sharp sell-offs and exacerbating market crashes. This cyclical impact on sentiment disrupts the natural flow of information, leading to overreactions in both directions.

The asymmetry of herding's impact on sentiment in bull and bear markets is another notable finding. Dang and Lin (2016) observed that herding is more pronounced in rising markets, as speculative momentum fuels positive sentiment. During falling markets, however, investors exhibit greater caution and individuality, leading to fragmented actions and less collective pessimism. This divergence suggests that herding primarily strengthens positive sentiment but plays a less cohesive role in propagating negative sentiment.

Herding also undermines confidence in price stability and market efficiency, as correlated actions suppress price discovery and lead to volatility spikes. The clustering of trades around consensus positions reduces the reliability of market signals, fostering uncertainty and fluctuating sentiment among market participants. This is particularly evident in emerging markets, where limited access to firm-specific information exacerbates reliance on group behaviour, making sentiment more vulnerable to external shocks.

2.3.4 Disposition Effect

The disposition effect, first formally introduced by Shefrin and Statman (1985), refers to the tendency of investors to sell assets that have gained value too early (winners) and to hold onto assets that have lost value for too long (losers). This behaviour is rooted in cognitive biases, particularly those explained by prospect theory, such as loss aversion and reference dependence. Loss aversion suggests that investors feel the pain of realising a loss more acutely than the pleasure of realising an equivalent gain, while reference dependence leads them to evaluate outcomes relative to their initial purchase price as the benchmark.

This tendency is primarily driven by risk preferences in different return domain. When they experience a gain relative to their reference point, they exhibit risk-averse behaviour, opting to secure the certain profit by selling the winning investment. Conversely, when faced with a loss, they demonstrate risk-seeking behaviour, holding onto the losing investment in the hope of a recovery that would restore their original value. This reluctance to realise losses stems from the psychological discomfort of admitting a mistake, which investors often avoid by delaying the sale of underperforming assets (Weber & Camerer, 1998). For example, if an investor buys a stock for R100 and its value drops to R80, the investor is likely to hold onto it, betting on its recovery rather than accepting the R20 loss.

Additionally, Weber and Camerer (1998) note that regret aversion and self-control play critical roles in the disposition effect. Regret aversion drives investors to avoid actions that might lead to future regret, such as selling a losing investment only for it to recover later. Self-control issues further exacerbate the effect, as investors struggle to act rationally when emotional factors such as hope, fear, and overconfidence cloud their judgment. This interplay of cognitive and emotional biases creates persistent patterns in trading behaviour, making the disposition effect a widely observed phenomenon in securities markets.

The disposition effect has been extensively studied through both empirical data and experimental analyses. Weber and Camerer (1998) conducted controlled experiments in which participants traded assets in a simulated market. The study confirmed that participants sold winning assets at a significantly higher rate than losing ones, despite no rational basis for such behaviour. This pattern persisted even when participants were aware of the irrationality of their actions, underscoring the strength of the psychological drivers behind the effect. Furthermore, the study found that automated systems that enforced rules for selling or rebalancing portfolios reduced the prevalence of the disposition effect, highlighting the role of deliberate decision-making in amplifying the bias.

Field studies have also confirmed the disposition effect in real-world markets. Data from retail investors' trading behaviour shows that losing stocks are held onto longer than winners, regardless of fundamental analysis or market conditions. This behaviour negatively impacts portfolio performance, as losing investments often continue to underperform while winners tend to exhibit momentum in returns. The persistence of the disposition effect across different market environments and investor profiles demonstrates its universality, making it a critical area of focus in behavioural finance research (Weber & Camerer, 1998).

The disposition effect has profound implications for individual and market-level outcomes. At the individual level, it reduces portfolio performance by delaying the realisation of losses, thereby locking up capital that could otherwise be reallocated to better-performing investments. By clinging to underperforming assets, investors forgo opportunities to optimise their portfolios and improve their risk-adjusted returns. At the market level, the disposition effect contributes to inefficiencies in price discovery, as it slows the adjustment of prices to reflect fundamental values. For instance, when a large proportion of investors hold onto losing stocks, the downward adjustment in price is delayed, leading to a distortion in market signals and increased volatility (Weber & Camerer, 1998).

Efforts to mitigate the disposition effect have focused on increasing investor awareness and implementing systematic trading strategies. Automated trading systems, such as those incorporating pre-determined stop-loss orders, can help investors overcome their emotional biases by enforcing rational decision-making rules. Financial education programs that emphasise the long-term consequences of the disposition effect may also reduce its prevalence by encouraging investors to focus on fundamental analysis rather than emotional reactions to short-term price movements.

The disposition effect reinforces irrational decision-making patterns, amplifying market-wide emotional responses. While behavioural biases like the disposition effect are often viewed as drivers of investor sentiment, recent evidence suggests a more dynamic relationship. Yang and Yang (2024) demonstrate that the disposition effect's intensity varies with market conditions and sentiment, but crucially, sentiment itself can moderate the bias. In bull markets, heightened sentiment exacerbates the disposition effect, as optimism encourages investors to lock in gains by selling winners prematurely. Conversely, in bear markets, elevated sentiment reduces the bias, as optimistic investors hold losers longer, expecting recoveries. This reveals a bidirectional relationship: sentiment not only emerges from behavioural biases but also shapes their expression. Such interactions complicate traditional "bottom-up" models of sentiment formation, highlighting the need to account for recursive effects between psychological biases and aggregate market mood.

This dynamic interplay creates feedback loops that amplify market trends. In bullish periods, the disposition effect drives a speculative rush as investors lock in profits, bolstering sentiment and encouraging further optimism. During bearish conditions, pessimistic sentiment exacerbates losses as investors irrationally hold onto underperforming assets, deepening market declines. These behaviours are underpinned by psychological factors such as overconfidence, loss aversion, and belief updates. Investors with high sentiment are particularly prone to overconfidence, which intensifies their disposition effect tendencies, while those with lower sentiment are more cautious, leading to reduced disposition effects and greater rationality in decision-making (Yang & Yang, 2024) .

Moreover, Yang and Yang (2024) found that the disposition effect manifests differently in developed and developing markets due to varying levels of investor sophistication. For example, in China's stock market, where individual investors dominate and speculative tendencies are high, the disposition effect is more pronounced. The study underscores that sentiment-driven irrational behaviours significantly distort asset pricing and market efficiency, as large-scale investor actions based on the disposition effect lead to mispricing and momentum effects.

2.4 Measurement Techniques for Investor Sentiment

Zhou (2018) discusses several measures of investor sentiment, which can be grouped into three main categories based on the data they utilise:

2.4.1 Market-Based Measures

These measures are considered indirect methods of quantifying investor sentiment because they do not capture sentiment explicitly through direct interaction with investors. Instead, they infer sentiment by analysing observable market activities and financial data. For example, proxies like trading volumes, IPO activity, and the closed-end fund discount reflect collective investor behaviour in response to market conditions but do not provide direct insights into the psychological state of individual investors (Zhang, 2008). As such, these measures are driven by the assumption that certain market trends or anomalies are the result of sentiment-driven behaviours rather than fundamental economic factors.

Zhang (2008) posits that these approaches leverage the idea that sentiment impacts asset prices and trading volumes, leading to deviations from fundamental values. By focusing on market data, researchers interpret patterns that may suggest optimism or pessimism without directly measuring emotional or cognitive states of investors. Zhang (2008) cautions that this method, while practical and widely used, relies heavily on the correlation between sentiment and the chosen financial indicators, making it a less direct but effective way to assess aggregate sentiment.

The benefits of using market-based approaches to measure investor sentiment are substantial. The nature of data they use offers objective and continuous measures of sentiment. Unlike surveys, market-based measures reflect real-time investor behaviour and eliminate biases associated with self-reporting, such as prestige bias. Moreover, they provide a consistent framework for analysing sentiment across different time horizons and market conditions, enabling researchers to study its influence on asset pricing and market dynamics. By focusing on actual market activities, these proxies can capture sentiment indirectly but effectively, even when sophisticated financial theories are unavailable to validate them.

However, market-based measures also have limitations. As cautioned by Zhang (2008), many of these proxies, such as IPO activity and trading volume, can be influenced by factors beyond investor sentiment, including macroeconomic shifts, liquidity conditions, and regulatory changes. This overlap makes it imperative, however challenging it may be, to isolate sentiment as the sole driver of observed patterns. Additionally, market-based measures often fail to capture the heterogeneity of sentiment across different investor groups, such as retail versus institutional investors, as they aggregate data without distinguishing between these segments. Another drawback is that these measures are retrospective; they rely on past market activity, which may not fully represent current sentiment. Finally, while market-based measures are effective for high-frequency analysis, they may lack the psychological depth of survey-based methods, which directly account for optimism, pessimism, and neutrality. These limitations underscore the importance of using market-based approaches alongside complementary methods, such as surveys, to provide a more holistic and accurate understanding of investor sentiment.

Several financial proxies have been identified in the literature as effective tools for indirectly measuring investor sentiment, each offering unique insights into market dynamics and behavioural patterns. Some of the proxies are:

Closed-End Fund Discount: This is the average difference between the net asset values (NAV) of closed-end stock fund shares and their market prices, with prior studies suggesting that CEFD is inversely related to sentiment (Baker & Wurgler, 2006). A smaller discount or a premium would indicate higher investor optimism. The converse of this statement holds.

Number of IPOs (NIPO): This is the logarithm of the total number of initial public offerings (IPOs) in a given year. IPO volume activity is often considered a reflection of market sentiment. During periods of high optimism, more companies are likely to go public, whereas, in times of pessimism, IPO activity tends to decrease. Thus, NIPO serves as a proxy for market confidence and investor sentiment.

Initial Returns on IPOs (RIPO): This is the mean initial return of IPOs in a given year. High initial returns on IPOs often signify strong investor demand and optimism. Investors' willingness to bid up the prices of new issues reflects their overall market sentiment. By tracking these initial returns, we can gauge the level of investor enthusiasm and sentiment in the market.

Equity Share in New Issues: This proxy represents the proportion of equity (as opposed to debt) in new security issues. Zhang (2008) notes it as a broader measure of equity financing that quantifies all equity offerings, not just IPOs. According to Baker and Wurgler (2000), high values of the equity share predict low market returns. This proxy captures the sentiment-driven preference for equity financing, which tends to rise in bullish markets.

Trading volume: It is defined as the natural logarithm of the turnover ratio of trading volume to the number of shares listed on the stock exchange, detrended by the 5-year moving average (Zhou, 2018). In markets with short-selling constraints, optimistic retail investors are more inclined to actively trade, contributing to higher trading volumes. Consequently, market liquidity tends to rise during periods of optimism, when traders are betting on stock prices increasing, rather than during periods of pessimism, when traders are betting on price declines (Zhang, 2008).

Dividend Premium: The dividend premium is the log difference of the average market-to-book ratios of payers and nonpayers. Fama and French (2001) notes that payers are generally larger, more profitable firms with weaker growth opportunities. They also note that when they are at a premium, firms are more likely to pay them, and less likely to do so when they are valued at a discount. A higher premium might indicate risk aversion or pessimism since it indicates that investors are favouring safer, income-producing stocks. Conversely, a smaller or negative premium can suggest more optimism and a desire for growth and riskier investments

The above proxies form the Baker and Wurgler (2006) sentiment index. The actual sentiment index is constructed using Principal Component Analysis (PCA), a method that isolates the first principal component of the six sentiment proxies listed above, extracting their common features into a unified index. This approach ensures a cleaner and more representative measure of sentiment by focusing on shared components across the proxies. To further refine the measure and remove the influence of economic fundamentals, each proxy is regressed on key macroeconomic indicators. The residuals from these regressions, which exclude the effects of fundamentals such as industrial production growth, real growth in durable and non-durable consumption, services consumption growth, employment growth, and an NBER recession indicator, are used as the sentiment variable (Zhang, 2008).

Zhang (2008) cautions that constructing a sentiment index based on return expectations or market reactions poses challenges due to issues like omitted variables and confounding factors, meaning that even averaging multiple proxies into a single measure does not fully resolve the problem. Nonetheless, this method of isolating a sentiment component from proxies linked to fundamentals is a strong start to approaching the problem.

2.4.2 Survey-Based Measures

Survey-based measures are considered direct methods of quantifying investor sentiment because they explicitly capture the immediate psychological and emotional states of investors when making a decision (Aggarwal, 2019). Zhang (2008) notes that these measures rely on standardised surveys and questionnaires to gather responses directly from individuals or groups, allowing researchers to assess optimism, pessimism, or neutrality in a systematic manner. Surveys such as the University of Michigan Consumer Sentiment Index and the UBS/Gallup Investor Optimism Index provide structured insights into investor outlook on financial markets and economic conditions, risk tolerance, and confidence levels. Since they provide a snapshot of collective investor beliefs and expectations, which are often used as proxies for market sentiment, Zhou (2018) notes the importance of such data because it allows for an examination of whether certain sentiment measures based on market data are consistent with investors' beliefs.

Unlike market-based measures, survey-based approaches focus on subjective investor perspectives, offering a clearer view of sentiment at a personal level. By directly asking respondents about their outlook on economic conditions or market trends, surveys capture sentiment in its raw psychological form. This approach provides a unique advantage in understanding investor psychology and its potential influence on market dynamics, although it may be influenced by biases such as response and timing effects (Zhang, 2008).

According to Zhang (2008), since the survey-based approach to measuring investor sentiment involves collecting individual responses to questions designed to assess confidence in the broader economy or the stock market specifically, it operates on the premise that investor confidence and investor sentiment are closely related concepts, allowing the former to serve as a proxy for the latter. By this reasoning, investor sentiment can be interpreted as the degree of optimism or pessimism held by individuals, aligning with their definition of the concept.

Aggarwal (2019) argues that surveys enabled researchers to separately examine the sentiments of small vs large investors which was not able to examine through direct market measures. This differentiation between retail and institutional sentiments thus enabled the examination of the different impact of each on market. The different types of surveys used to measure sentiment can be broadly classified into the following categories:

Consumer Confidence Surveys: These surveys, like the FNB/BER Consumer Confidence Index (CCI) and the University of Michigan Consumer Sentiment Index (Lansing & Tubbs, 2018) and the gauge consumer perceptions of the economy. The FNB/BER Consumer Confidence Index (CCI) is South Africa's primary measure of consumer sentiment, designed to capture the public's expectations regarding economic conditions, household finances, and spending patterns (Martin, 2010). Conducted quarterly by the Bureau for Economic Research in collaboration with First National Bank, the CCI is based on responses to three key questions, each carrying a specific weight. Solanki & Seetharam (2014) note these questions as:

1. How do you expect the general economic position in South Africa to develop during the next 12 months? Will it improve considerably, improve slightly, deteriorate slightly, deteriorate considerably or don't know?

2. How do you expect the financial position in your household to develop in the next 12 months? Will it improve considerably, improve slightly, deteriorate slightly, deteriorate considerably or don't know?

3. What is your opinion of the suitability of the present time for the purchase of domestic appliances such as furniture, washing machines, refrigerators etc.? Do you think that for people in general it is the right time, neither a good nor a bad time or the wrong time?

The responses to these questions are weighted as follows: for questions 1 and 2, "improve considerably" is scored at +10, "improve slightly" at +5, "deteriorate slightly" at -5, and "deteriorate considerably" at -10. For question 3, responses of "right time to buy" are scored at +10 and "wrong time to buy" at -10. The final CCI score is a weighted average of these results, expressed as a net balance, calculated as the difference between the percentage of positive and negative responses (Solanki & Seetharam, 2014).

The CCI is particularly valuable because it provides a quantitative measure of sentiment that can help identify trends in consumer spending behaviour and their potential impact on the economy. However, it is not without limitations. The index relies on subjective responses, which may be influenced by temporary factors or biases. Furthermore, it focuses on broad consumer behaviour, which may not fully align with the more specific sentiment-driven behaviours of investors. Despite these challenges, the CCI remains a critical tool for understanding the dynamics of consumer sentiment and its broader implications for South Africa’s economy.

The RMB/BER Business Confidence Index (BCI) is one of South Africa’s key indicators for assessing business sentiment and economic performance. Conducted quarterly, the BER’s surveys draw data from various sectors, including manufacturing, building, retail, wholesale, and motor trade, to measure the prevailing confidence levels of business executives (Kershoff, 2000).

The BER employs a robust methodology similar to international standards established by the Ifo Institute in Germany and INSEE in France. The process involves distributing qualitative surveys to senior executives, who provide their assessments of business conditions. The survey sample consists of approximately 3,800 firms, divided across sectors, with responses weighted according to company turnover and workforce size. This ensures the index reflects the economic significance of each participant. Each quarter, the survey asks respondents to evaluate whether prevailing business conditions are "satisfactory" or "unsatisfactory." The index is then derived from the percentage of respondents indicating satisfaction. The BCI is expressed on a scale of 0 to 100, where 50 represents neutrality, values above 50 indicate optimism, and values below 50 signify pessimism (Kershoff, 2000).

The RMB/BER BCI survey maintains a consistent panel of respondents, enabling longitudinal analysis. Firms are carefully selected to provide broad sectoral representation, with participation validated every few years to ensure accurate classifications and reflect changes in company performance. Each respondent completes a standardised questionnaire during the final month of every quarter, which includes qualitative questions about current and expected business conditions, sales, orders, and employment (Kershoff, 2000).

The structured approach ensures reliable and timely data, providing early insights into economic conditions before official statistics are available. Business confidence scores, in particular, are an important barometer for private investment and economic growth. For instance, higher scores often precede increased inventory and fixed investment, while declining confidence can signal economic slowdowns. This makes the RMB/BER BCI a valuable tool for policymakers, economists, and investors, helping them anticipate economic cycles and adjust strategies accordingly.

While not directly focused on investor sentiment, these surveys can offer correlated insights, as consumer confidence often influences investment decisions. For instance, positive consumer sentiment can spill over into increased optimism about the stock market.

Investor Surveys: These surveys specifically target investors, inquiring about their outlook on market returns, risk tolerance, and investment intentions. Examples include surveys conducted by the Bureau for Economic Research (BER), American Association of Individual Investors (Zhou, 2018), Investors Intelligence, and various financial institutions.

Surveys of Experts: Some surveys focus on the opinions of financial professionals, such as fund managers and analysts. These surveys can offer valuable insights from experienced market participants, but they may also be influenced by the respondents' own investment positions and biases. In South Africa, the Deloitte Africa Private Equity Confidence Survey (PECS) provides insights into how private equity (PE) practitioners view the African PE landscape, specifically their future expectations over the next 12 months, as well as regional macroeconomic perspectives across East, North, Southern, and West Africa.

2.4.3 Text and Media-Based Measures

Textual sentiment analysis involves extracting and quantifying the sentiment—positive, negative, or neutral—embedded in various forms of written communication, including corporate disclosures, media articles, and internet postings. It utilises computational methods to quantify the sentiment embedded in textual data. Sentiment scores are assigned to textual inputs using natural language processing (NLP) techniques. These scores are aggregated to create indices that can track market sentiment over time. Unlike traditional numerical data, textual sentiment provides qualitative insights into market participants' emotions and expectations, offering a richer context for understanding financial behaviours and market dynamics (Kearney & Liu, 2014). According to Nyakurukwa and Seetharam (2024), traditional news sentiment is derived from sources such as newspapers and online financial news, while social media sentiment is typically based on user-generated content from platforms like X, formerly Twitter, and forums such as Seeking Alpha.

Kearney and Liu (2014) note one common approach to textual sentiment analysis; the dictionary-based method. It relies on pre-defined word lists to classify text. Words are categorised as positive, negative, or neutral, and their frequencies are calculated to generate a sentiment score. While dictionary-based techniques are simple and efficient, their effectiveness depends on the relevance of the dictionary to the financial context. For example, general-purpose dictionaries may misclassify words with domain-specific meanings, such as "tax" or "liability" (Kearney & Liu, 2014).

Kearney and Liu (2014) also note another advanced method, machine learning, where algorithms are trained on labelled datasets to classify sentiment. These techniques can capture nuanced sentiment patterns and achieve higher accuracy than dictionary-based approaches. Machine learning models, such as Naive Bayes or neural networks, learn the sentiment characteristics of text and apply this knowledge to analyse large corpora (Kearney & Liu, 2014). This approach is particularly useful for analysing internet postings or social media, which often include informal language and diverse sentiment expressions.

Nyakurukwa and Seetharam (2024) caution that one limitation of using textual sentiment as a proxy is the potential for confounding variables. Sentiment extracted from one source (e.g., social media) may influence or be influenced by another source (e.g., traditional news). Failing to account for this interdependence can lead to misleading conclusions. Advanced methods, such as partial wavelet coherence, help isolate the independent effects of each sentiment source on stock returns, ensuring a more robust analysis (Nyakurukwa & Seetharam, 2024).

2.4.3.1 Sources of Textual Data

News Articles: Financial news articles from major publications and news wires can provide insights into prevailing market sentiment. Adams et al. (2023) analyses news articles to measure financial market sentiment. Zhou (2018) also mentions the work of Tetlock (2007), who demonstrated that news media content can predict stock market movements. Kearney and Liu (2014) emphasises the significant role of news articles in sentiment analysis, as they provide structured, formal, and often reliable information about financial markets, corporate announcements, and broader economic trends. News articles typically serve as a reflection of expert opinions and professional journalism, which can influence investor sentiment over both the short and long term. The sentiment extracted from news articles often involves analysing the tone and language used in financial reporting, such as the frequency of positive or negative words or the emphasis on uncertainty. The paper highlights that news sentiment, while impactful, may have a slower effect on market dynamics compared to social media due to its formal and edited nature. Advanced natural language processing (NLP) techniques, such as named entity recognition (NER) and topic modelling, are often applied to extract and quantify sentiment from large corpora of news articles.

Social Media Posts: Platforms like X, StockTwits, and Reddit offer a wealth of real-time data on investor sentiment. McGurk et al. (2019) examines the relationship between investor sentiment and stock returns using textual analysis of social media posts. Adams et al. (2023) focuses on X chatter and its impact on financial market sentiment. Lee et al. (2023) introduces StockEmotions, a dataset designed for financial sentiment analysis using social media data. Kearney and Liu (2014) underscores the importance of these platforms in capturing real-time and crowd-sourced investor sentiment. Social media posts are characterised by their immediacy, unfiltered opinions, and high volume, making them a valuable source for understanding market reactions to breaking news or significant events. Sentiment derived from social media is often short-term and highly reactive, reflecting the collective emotions and perceptions of retail investors and other market participants. However, analysing social media sentiment poses unique challenges due to informal language, abbreviations, emojis, and the presence of sarcasm or irony. Advanced machine learning models and NLP tools, including sentiment lexicons and deep learning techniques like transformers (e.g., BERT), are employed to process and interpret these data sources effectively.

Company Disclosures: Corporate disclosures represent another important sentiment source. These include official documents such as annual reports, earnings press releases, and conference call transcripts. Kearney and Liu (2014) points out that these documents provide formal and structured information about a company's financial performance and strategic direction, which investors often use to form expectations about future prospects. Their paper argues that they are particularly valuable because they originate from insiders with deep knowledge of the firm and the sentiment extracted from disclosures tends to have a longer-term influence compared to social media or internet forums. Studies such as those by Li (2006) and Feldman, Govindaraj, Livnat, and Segal (2008) emphasise that the tone, language, and frequency of positive or negative words in these disclosures can provide additional information about expected firm performance, complementing the quantitative data provided in financial statements. The downside to using corporate disclosures as sentiment sources is their infrequency, as they are usually released quarterly or annually. This limits their use for high-frequency time-series analyses but makes them suitable for event studies or cross-sectional analyses focusing on firm-specific sentiment.

Internet Forums and Blogs: Online forums and blogs dedicated to financial discussions can provide valuable insights into the views and opinions of individual investors. Kearney and Liu (2014) highlights the increasing role of internet forums and blogs as key sources of textual sentiment in finance. These platforms, including financial message boards, forums like Yahoo! Finance and Raging Bull, and blogs like Seeking Alpha, provide a rich repository of individual investor opinions and discussions about stocks and market trends. These discussions often encompass valuable insights, such as market sentiment, reactions to news, and even manipulative behaviour. Kearney and Liu (2014) also points out that sentiment derived from these sources is often short-term in nature, capturing immediate reactions to market events or corporate announcements. Studies such as Antweiler and Frank (2004) and Das and Chen (2007) demonstrate that the sentiment derived from these internet platforms can have significant effects on financial markets.

Internet-expressed sentiment, while valuable, is considered "noisier" compared to sentiment from corporate disclosures or media articles. This is because the content often reflects the views of individual traders, many of whom may be less informed or overly emotional in their investment decisions. However, this "noise" can provide unique insights into small investor sentiment, capturing a broader behavioural dynamic within the market (Kearney & Liu, 2014).

2.4.4 Combining Measures

While individual measures offer valuable insights, combining multiple measures can provide a more comprehensive and robust understanding of investor sentiment (Zhou, 2018). This can involve creating composite indices or using statistical models to integrate different data sources. Zhou (2018) notes that some researchers have combined market-based measures with survey data to create more accurate sentiment indicators. It advises that further research is needed to develop efficient methods for pooling information across various measures.

It's important to note that measuring investor sentiment is an ongoing area of research, and no single measure is perfect. Each approach has its limitations, and the interpretation of sentiment data can be subjective. However, by combining different methods and carefully analysing the available data, investors and researchers can gain valuable insights into the psychological factors driving market behaviour.

2.5 Advanced computational approaches

The development of advanced computational approaches has significantly enhanced the accuracy and efficiency of financial sentiment analysis (FSA), particularly in addressing the complexities of financial textual data. These methods encompass machine learning, deep learning, hybrid models, and optimisation frameworks, each targeting specific challenges in sentiment classification and financial forecasting.

2.5.1 Machine Learning Techniques

Machine learning (ML) techniques have emerged as indispensable tools in financial sentiment analysis (FSA), enabling the processing and interpretation of large-scale textual data. These approaches are particularly effective in extracting meaningful patterns and classifying financial markets' sentiment by utilising statistical and algorithmic methods to derive insights from vast volumes of financial text. Feature engineering is central to these approaches, involving the construction of linguistic features (e.g., n-grams, named entities), domain-specific keywords, and sentiment lexicon-based features. Modern word embeddings, such as Word2Vec, GloVe, and FastText, further enhance these models by capturing semantic relationships between words in continuous vector spaces (Du, Xing, Mao, & Cambria, 2024).

These techniques encompass a wide variety of algorithms, which can be broadly categorised into supervised, unsupervised, and hybrid methods. Supervised methods like SVM and Random Forests are widely recognised for their high accuracy and scalability, but they often require extensive labelled data for training. Unsupervised approaches, while less resource-intensive, may lack precision in distinguishing fine-grained sentiment categories. Hybrid models offer a balance, leveraging the strengths of both paradigms to improve robustness and adaptability in dynamic financial domains (Ahmad, Aftab, Muhammad, & Awan, 2017).

Renault (2019) offers a rigorous evaluation of various machine learning techniques applied to financial sentiment analysis, providing valuable insights into their effectiveness and limitations. The study utilized over one million labelled messages from the StockTwits platform to assess the performance of several machine learning algorithms. The dataset's large scale enabled robust

supervised learning without the need for manual annotation, a significant advantage for researchers working with financial social media data.
It found that simpler algorithms, such as Naive Bayes, Maximum Entropy (MaxEnt), and Support Vector Machines (SVMs), delivered performance that was comparable to or better than more complex methods like Random Forests and Multilayer Perceptrons (MLPs). Specifically, MaxEnt and SVMs slightly outperformed Naive Bayes in terms of classification accuracy, but at a substantially higher computational cost. Notably, Random Forests and MLPs did not yield significant improvements in accuracy despite their complexity and longer training times.

A key takeaway is that preprocessing techniques, including the use of bigrams, emojis, and punctuation, played a more substantial role in improving sentiment classification accuracy than the choice of algorithm. For instance, incorporating bigrams and emojis improved accuracy by over 2 percentage points. In contrast, methods such as stemming, stopword removal using generic corpora, and part-of-speech tagging reduced accuracy, especially when applied to the short, informal text common on social media. The study further highlighted that dataset size is a critical factor in model performance. Accuracy improved markedly with more training data, plateauing around 500,000 messages (Renault, 2019). This finding underscores the importance of using large, high-quality datasets.

For applications in the South African stock market, these findings suggest that leveraging simpler, interpretable machine learning models, combined with domain-specific preprocessing, may offer a more efficient and transparent approach to deriving investor sentiment indicators. This is particularly valuable in environments with limited computational resources or where interpretability is essential for regulatory or practical purposes.

2.5.2 Deep Learning Techniques

Sohangir, Wang, Pomeranets, and Khoshgoftaar (2018) note that Deep Learning has emerged as a powerful tool for sentiment analysis, particularly in the context of Big Data, due to its ability to automatically learn hierarchical representations from raw data. Unlike traditional data mining approaches, which rely heavily on manual feature engineering, Deep Learning models extract complex features through multiple layers of non-linear transformations, making them highly effective for tasks like financial sentiment analysis.

Their study highlights several Deep Learning techniques applied to sentiment analysis in financial social media, such as StockTwits. Among these, Convolutional Neural Networks (CNNs) stand out as the most effective model. CNNs leverage convolution layers to capture local patterns in text data, such as n-grams, and pooling layers to reduce dimensionality while retaining critical information. This architecture allows CNNs to account for word order and proximity, addressing a key limitation of the bag-of-words model. The study demonstrates that CNNs achieve an accuracy of 90.93% after 10,000 training steps, significantly outperforming logistic regression (70.88%) and other Deep Learning models like doc2vec (67.23%) and Long Short-Term Memory (LSTM) networks (69.23%).

LSTM networks, a variant of Recurrent Neural Networks (RNNs), are also explored for their ability to model sequential dependencies in text. However, their performance in this study was suboptimal compared to CNNs, likely due to the shorter length of StockTwits messages, where long-term dependencies are less critical. Doc2vec, another technique examined, extends word2vec by embedding entire paragraphs or documents into vector spaces. While it captures semantic relationships, its accuracy (67.23%) lags behind CNNs, suggesting that local text structure is more important for sentiment analysis in this domain (Sohangir et al., 2018).

Within these techniques, there exists hybrid approaches which integrate symbolic methods (e.g., lexicon-based techniques) with deep learning models to achieve superior accuracy and generalisability. By combining domain-specific sentiment dictionaries with neural network-based feature learning, these methods are particularly effective for tasks such as market prediction and volatility analysis. Optimisation techniques, including Bayesian optimisation, are increasingly used to fine-tune hyperparameters, ensuring that models achieve optimal predictive accuracy with minimal computational cost. These frameworks are crucial for maximising the performance of both machine learning and deep learning models (Du et al., 2024).

2.5.3 Quantile Regression

Quantile regression, introduced by Koenker and Bassett (1978), is a robust statistical technique that extends the traditional linear regression framework by estimating the conditional quantiles of the dependent variable. Unlike ordinary least squares (OLS) regression, which focuses on the mean of the dependent variable, quantile regression allows researchers to examine the relationship between independent variables and the dependent variable across different points in the conditional distribution. This approach is particularly useful in financial research, where the impact of explanatory variables may vary significantly across different market conditions, such as periods of high volatility versus periods of stability.

In the context of investor sentiment and stock markets, quantile regression offers several advantages. First, it provides a more nuanced understanding of how sentiment influences stock returns across different market conditions. For instance, during periods of market stress, investor sentiment may have a more pronounced impact on stock returns compared to periods of market stability (higher quantiles). This is particularly relevant during extraordinary events such as the COVID-19 pandemic, where market conditions were highly volatile, and investor sentiment played a critical role in shaping market outcomes.

Several studies have employed quantile regression to explore the asymmetric effects of investor sentiment on financial markets. For example, Cevik et al. (2022) argue that the relationship between investor sentiment and equity markets may vary across different return and volatility conditions, making quantile regression an ideal tool for capturing these dynamics. Similarly, Sing and Singh (2023) highlight the presence of asymmetric effects in investor sentiment, where negative sentiment tends to have a stronger impact on stock returns during periods of market downturns. These findings underscore the importance of using quantile regression to capture the full spectrum of market conditions and investor behaviours.

Moreover, quantile regression is particularly useful in sentiment research because it allows for the examination of non-linear relationships between sentiment proxies and market returns. Traditional linear models may fail to capture the complex dynamics of investor sentiment, especially during periods of extreme market stress or euphoria. By estimating the relationship between sentiment and returns at different quantiles, researchers can identify whether the impact of sentiment is consistent across the distribution or varies significantly at the tails. This is crucial for understanding how sentiment drives market behaviour during both normal and extreme market conditions.

In the context of the COVID-19 pandemic, quantile regression has been widely used to analyse the impact of investor sentiment on equity markets. For instance, Gherghina, Mehdian, and Stoica (2023) employ quantile regression to investigate the relationship between Google Search Volume (GSV) and equity market indices during the pandemic. Their findings reveal that GSV negatively influenced equity indices at lower quantiles, suggesting that heightened investor anxiety during the early stages of the pandemic had a more pronounced impact on market returns. Similarly, when using X-based Market Uncertainty (TMU) as a sentiment proxy, the study finds that TMU negatively impacted equity returns at lower quantiles, further highlighting the asymmetric effects of sentiment during periods of market stress.

Quantile regression provides a powerful framework for analysing the impact of investor sentiment on equity markets, particularly during periods of high uncertainty such as the COVID-19 pandemic. By capturing the conditional distribution of market returns, quantile regression allows researchers to uncover the nuanced and often asymmetric effects of sentiment across different market conditions. This approach not only enhances our understanding of the relationship between sentiment and market outcomes but also provides valuable insights for investors and policymakers seeking to navigate volatile market environments.

2.5.4 Applications of Advanced Approaches

The advanced computational approaches discussed in the paper have enabled significant progress in financial sentiment analysis, including:

- **Sentiment Classification**: Extracting and classifying investor sentiment from large-scale financial news, earnings calls, and social media feeds.
- **Market Forecasting**: Leveraging deep learning models like transformers to identify sentiment-driven trends and predict stock market movements.
- **Feature Learning for Volatility Analysis**: Combining sentiment indices with volatility measures to improve the accuracy of market turbulence predictions.

These advanced techniques represent a major leap forward in financial sentiment analysis, offering robust and scalable solutions for understanding the nuanced relationship between textual sentiment and financial market behaviour.

2.6 Evidence on Investor Sentiment in Global and Emerging Markets

2.6.1 Studies on investor sentiment in global markets

Baker and Wurgler (2007) explores how investor sentiment affects stock returns, focusing on its impact on different types of stocks and the mechanisms through which sentiment-driven mispricing occurs. They adopt a top-down approach to measuring investor sentiment, constructing a sentiment index based on multiple market-based proxies mentioned earlier. Each sentiment proxy is adjusted for macroeconomic fundamentals through regression analysis, ensuring that the index captures sentiment effects rather than fundamental economic changes. PCA is used to extract the common sentiment component from these proxies. They then use cross-sectional regression models to analyse how sentiment affects stock returns, with a particular focus on small, young, high-volatility, unprofitable, and non-dividend-paying stock.

Baker and Wurgler (2007) find that investor sentiment does affect stock prices, with speculative and difficult-to-value stocks being the most impacted. Specifically, sentiment-driven mispricing is more pronounced in small-cap, high-growth, and distressed stocks, which are harder to arbitrage due to higher transaction costs and short-selling restrictions. These stocks tend to be overvalued during periods of high sentiment and subsequently underperform when sentiment declines. Conversely, large, stable, dividend-paying stocks are less influenced by sentiment, as their valuations are anchored in stronger fundamentals.

Another key finding is the negative relationship between sentiment and future returns. The study shows that stocks benefiting from high sentiment tend to experience lower subsequent returns, supporting the idea that investor exuberance leads to temporary price distortions followed by corrections. This effect is strongest in stocks with high idiosyncratic volatility, where speculative demand drives excessive price swings.

Furthermore, Baker and Wurgler (2007) identifies a sentiment-based “seesaw” effect, where high sentiment boosts speculative stocks while safer, bond-like stocks see limited or negative effects. This suggests that sentiment-induced mispricing is not uniform across the market but also depends on stock characteristics and investor behaviour.

Corredor, Ferrer, and Santamaria (2013) examine the impact of sentiment on stock market performance across four major European markets—France, Germany, Spain, and the United Kingdom—and investigates whether sentiment effects are primarily driven by stock characteristics or country-specific factors. A PCA is used to construct sentiment indices for each country, incorporating proxies such as trading volume, volatility premiums, and consumer confidence indices**.** To examine the long-term impact of sentiment, the study applies long-short portfolio sorting, where stocks are grouped into quintiles based on characteristics such as size, book-to-market ratio, and dividend yield. Additionally, multilevel regression models are used to distinguish between the impact of stock characteristics and country-specific factors. To further ensure robustness, Granger-causality tests are employed to determine feedback effects between sentiment and stock returns over different time horizons.

The study finds that sentiment-driven mispricing is more pronounced in certain types of stocks, namely, small-cap stocks, high-volatility stocks, and non-dividend-paying stocks, which are more difficult to value and riskier to arbitrage. The results indicate a negative relationship between high sentiment and future returns, meaning that stocks tend to become overvalued during periods of optimism, followed by corrections as sentiment declines. Additionally, while sentiment significantly influences stock prices across all four markets, the strength of this effect varies based on institutional factors. For example, France and Spain exhibit stronger sentiment effects than Germany and the UK, which the authors attribute to differences in legal systems, investor protections, and market structures. Corredor et al. (2013) also finds that in countries with stronger corporate governance and information transparency, sentiment effects are somewhat mitigated due to better access to reliable financial information.

Tetlock (2007) investigates the role of media in shaping investor sentiment and its impact on stock returns in the U.S. stock market, using sentiment extracted from daily content in The Wall Street Journal's "Abreast of the Market" column over a 16-year period (1984–1999). He employs quantitative content analysis using General Inquirer (GI), a widely used sentiment analysis tool, to assess the tone of financial news articles. The GI program categorises words into predetermined sentiment classes (e.g., "negative," "weak," "fall," "fail") to construct a pessimism index based on daily news coverage. PCA is applied to extract a media sentiment factor, summarising the main variations in textual sentiment over time. To examine the predictive power of sentiment, vector autoregression (VAR) models are employed, estimating the intertemporal relationship between media pessimism, stock returns, and trading volume.

The study identifies a significant link between media sentiment and stock returns, demonstrating that high media pessimism leads to short-term negative returns, followed by a correction as prices revert to fundamental values. This supports behavioural finance theories suggesting that investor overreaction to negative news temporarily distorts stock prices. Additionally, the study finds that sentiment impacts market trading behaviour, as unusually high or low pessimism levels are associated with increased trading volumes, suggesting heightened investor uncertainty and speculative activity. Another key finding is that negative sentiment is often a reaction to past market performance rather than an independent driver of price movements. The study also shows that poor stock market returns tend to increase media pessimism, reflecting a feedback loop between investor sentiment and market behaviour. However, sentiment effects are short-lived, as stock prices tend to adjust within a few days, reinforcing the view that developed markets are more resilient to sentiment-driven distortions due to the presence of institutional investors and arbitrage opportunities.

2.6.2 Studies on investor sentiment in emerging markets

Investor sentiment plays a crucial role in shaping stock returns in emerging markets, where market inefficiencies, regulatory differences, and investor behaviour may contribute to heightened sensitivity to sentiment-driven fluctuations.

Corredor, Ferrer, and Santamaria (2015) examines the impact of sentiment on stock prices in three Central European emerging markets, the Czech Republic, Hungary, and Poland. They employ consumer confidence indices (CCI) as sentiment proxies then use PCA to extract sentiment indicators and apply regression models to assess their predictive power on stock returns. Their findings show that investor sentiment significantly influences stock returns in these economies, often more so than in developed markets. This is largely due to the greater difficulty in valuing firms and the limitations on arbitrage that characterise these economies. The study also finds that sentiment-driven mispricing is more pronounced for stocks that are small, young, highly volatile, and difficult to arbitrage, which aligns with existing behavioural finance findings (Baker & Wurgler, 2007). Additionally, the effect of sentiment is not uniform across all emerging markets, with Poland and the Czech Republic showing a stronger sentiment impact than Hungary. This variation is attributed to country-specific factors such as stock market structures, privatisation trends, and foreign stock penetration.

Another key finding is the twofold nature of sentiment, global and local. While local sentiment influences market dynamics, global sentiment plays a significantly larger role, particularly due to the dependence of these markets on foreign investment flows (Corredor et al., 2015). This suggests that investor sentiment does not spread primarily through capital movements but rather through behavioural contagion mechanisms such as herding, media influence, and psychological biases.

Dalika and Seetharam (2015) examine the relationship between stock returns in the South African market and investor sentiment over the period 1999 - 2009. They employ PCA to construct an aggregate sentiment index based on financial proxies, including market turnover, initial public offering (IPO) volume, IPO first-day returns, and volatility premiums, and examine its influence on market performance. To refine the sentiment measure, each proxy is orthogonalised against macroeconomic variables, such as inflation, employment growth, and industrial production growth, ensuring that the sentiment index captures only behavioural factors rather than fundamental economic influences.

Their results indicate a negative relationship between sentiment and future stock returns, meaning that periods of high sentiment lead to overvaluation and subsequent price corrections. This suggests that investor sentiment has a substantial and predictable impact on stock returns in South Africa**.** The study further confirms that sentiment disproportionately affects small-cap stocks, high-volatility stocks, non-dividend-paying stocks, and high-growth firms, which are more susceptible to speculative trading. During low sentiment periods, these stocks tend to outperform as investors demand higher risk premiums, while in high sentiment environments, their future returns are significantly lower (Dalika & Seetharam, 2015).

2.7 Investor Sentiment During The COVID-19 Pandemic

Investor sentiment during the COVID-19 pandemic emerged as a critical factor influencing stock market performance worldwide. Cevik, Altinkeski, Cevik, and Dibooglu (2022) conducted an in-depth examination of the relationship between positive and negative investor sentiment and stock market returns and volatility across G20 countries, which account for the majority of global economic activity. The study utilised the Google Search Volume Index (GSVI) as a proxy for investor sentiment. Negative sentiment was captured using search terms related to COVID-19 (e.g., “COVID-19,” “Coronavirus,” “Pandemic”), while positive sentiment was proxied through searches for COVID-19 vaccine-related terms (e.g., “Pfiser,” “Moderna,” “AstraZeneca”). Using weekly data from March 2020 to May 2021, the authors employed advanced econometric models, including fixed-effects panel regressions, panel quantile regressions, and panel vector autoregression (PVAR), to explore the dynamic nature of these relationships. It found that negative investor sentiment significantly decreased stock market returns, particularly at the lower quantiles of the return distribution, indicating a stronger impact during periods of poor market performance. Simultaneously, negative sentiment led to heightened volatility across the board, reflecting the uncertainty and fear dominating investor behaviour during the pandemic (Cevik et al., 2022). This aligns with behavioural finance theories, such as the mood sensitivity hypothesis, which suggest that investors’ emotional responses to crises amplify market reactions.

In contrast, positive investor sentiment, driven by optimism surrounding vaccine developments, exerted a positive influence on stock returns and had a calming effect on market volatility. The effect was consistent across quantiles, highlighting that positive sentiment not only supported higher returns but also reduced market turbulence. Importantly, the results showed an asymmetry in investor sentiment's impact: while negative sentiment exacerbated market losses and volatility, positive sentiment had a moderating effect but did not completely offset the damage caused by fear and uncertainty.

The panel vector autoregression (PVAR) model further reinforced these findings, showing that investor sentiment plays a predictive role in stock market behaviour. Granger causality tests revealed unidirectional causality from negative sentiment to stock market returns and volatility, indicating that negative sentiment is a key driver rather than a response to market changes. Positive investor sentiment, on the other hand, exhibited a bidirectional causal relationship with stock market volatility, suggesting a dynamic interplay between optimistic market outlooks and market stability (Cevik et al., 2022).

The authors also conducted country-specific regressions to identify heterogeneity in sentiment's impact across individual G20 markets. Results indicated that negative investor sentiment universally decreased returns and increased volatility across most countries, though the magnitude varied. Positive sentiment, while generally associated with reduced volatility, showed mixed effects on returns, which may reflect differences in economic resilience, government responses, and investor behaviour across regions.

Jiang, Zhu, Zhang, Yan, and Shen (2021) employed the Baidu Index as a proxy for investor sentiment in China, using search volume data for keywords such as "N95 masks" and "COVID-19." This approach provided a real-time reflection of investor attention toward epidemic-related stocks. The study found that heightened search activity corresponded to increased trading volume and price volatility in the stock market, particularly during periods of high uncertainty.

Empirical analysis demonstrated that incorporating the Baidu Index into the extended GARCH model stock returns promptly reflect investor sentiment. This finding suggests that real-time sentiment data from search engines can capture the immediacy of investor reactions, outperforming traditional models that rely on lagging economic indicators. Moreover, the model including the Baidu index can significantly improve forecasts (Jiang et al., 2021).

Sun and Shi (2022) leverages the outbreak to investigate sentiment dynamics during a natural black swan within the Chinese stock market. Using daily individual return rate, daily trading volume, and the corresponding daily returns of the Chinese Stock Index (CSI) 300 data, they apply the Event Study Methodology (ESM). Their research identified the Wuhan lockdown on January 23, 2020, as the event date, marking the onset of significant investor behaviour shifts. The study measured abnormal returns (AR), cumulative abnormal returns (CAR), and excessive trading volume (ETV) within the event window. It found that both AR and CAR dropped substantially immediately after the event. On the first trading day post-lockdown, the CSI 300 Index fell by 7.88%, the largest single-day decline since 2015, underscoring the immediate market panic.

Excessive trading volume (ETV) surged following the event, reflecting heightened investor activity driven by increased uncertainty and pessimism. The ETV for companies in Hubei Province, a region heavily affected by the pandemic, was significantly higher than for firms in other regions. This indicates a local bias in investor behaviour, as proximity to the epicentre amplified perceptions of risk.

Employing a Difference-in-Differences (DID) model to explore the impact of geographic location on stock market reactions, Sun and Shi (2022) also find that while ETV exhibited significant regional variation, CAR did not show a corresponding pattern, suggesting that investor pessimism was widespread, transcending regional boundaries. This highlights the dual influence of localised and national-level factors on sentiment during crises, particularly in big markets like China.

Mili, Amoodi, and Bawazir (2023) investigated the asymmetric effects of pandemic-related announcements on investor sentiment, focusing on the Kingdom of Bahrain. The study employed a Non-Linear Autoregressive Distributed Lag (NARDL) model, which allowed for the examination of both short- and long-term effects of positive and negative news on investor behaviour. Investor sentiment was measured using five indicators: daily trading volume, market turnover, the high-low market price index, the Psychological Line Index (PSY), and the Relative Strength Index (RSI).

The study found that increases in new COVID-19 cases and deaths had a stronger impact on investor sentiment than decreases in these indicators, demonstrating an asymmetric relationship where negative news disproportionately influenced market behaviour. In both the short and the long-run, the PSY and RSI indices demonstrated heightened sensitivity to negative shocks, with investor pessimism dominating market reactions during periods of rising case counts. Conversely, positive shocks, such as declines in new cases or deaths, led to modest recoveries in sentiment. The daily trading volume and turnover indicators reflected similar patterns, with negative news prompting a surge in trading activity driven by fear and uncertainty (Mili et al., 2023). This aligns with behavioural finance theories which suggest that investors tend to overreact to adverse information during periods of uncertainty.

The COVID-19 pandemic underscored the profound influence of investor sentiment on financial markets. Negative sentiment, fuelled by pandemic-related fears, had a disproportionate impact on stock market returns and volatility, particularly during periods of heightened uncertainty. Positive sentiment, driven by optimism surrounding vaccines, provided a stabilising force but remained asymmetrically weaker compared to negative sentiment. These findings underscore the growing importance of incorporating investor sentiment analysis into financial market models, particularly during global crises, as it serves as both a predictor and a driver of market outcomes (Cevik et al., 2022).

2.8 Summary of literature review

The literature on investor sentiment highlights its critical and multifaceted role in influencing financial markets. Despite the lack of a universally accepted definition, consensus generally centres on investor sentiment as beliefs or feelings about future asset values that may not be justified by fundamental information. Definitions by Baker and Wurgler (2007), Zhang (2008), and others frame sentiment as a discrepancy between subjective expectations and objective valuations, driven by psychological biases and collective mood.

Empirical research demonstrates that sentiment significantly affects asset prices, trading volumes, and market volatility. Sentiment-driven deviations from fundamentals challenge the assumptions of market efficiency, especially in the presence of limited arbitrage. Studies such as Shleifer and Summers (1990) and Da et al. (2014) show that positive sentiment can fuel bubbles while negative sentiment can exacerbate downturns, with fear-based indices like the FEARS Index offering predictive insights into short-term price movements and reversals.

Investor sentiment is also deeply intertwined with behavioural biases such as overconfidence, herding, heuristics, and the disposition effect. These biases distort decision-making and contribute to market inefficiencies. Overconfident investors overtrade and amplify volatility; herding causes correlated actions that suppress price discovery; the disposition effect causes irrational holding of losing assets and premature selling of winners, impacting both portfolio performance and market stability.

Moreover, sentiment exhibits predictive power for future returns, particularly for small-cap, high-volatility, and growth stocks. Indices like those developed by Baker and Wurgler (2006) and Da et al. (2014) have demonstrated that sentiment can forecast short-term anomalies and market corrections. However, the effectiveness of sentiment as a forecasting tool is contingent on market attention and may vary across market regimes.

From a policy standpoint, investor sentiment has implications for regulatory interventions, especially during periods of extreme optimism or fear. Policymakers are urged to integrate sentiment analysis into decision-making frameworks to enhance market resilience, with tools like financial education, circuit breakers, and transparent monetary policy serving as buffers against sentiment-driven instability (Kurov, 2009; Bank & Brustbauer, 2014).

Behavioural finance theories such as prospect theory, overconfidence, herding, and the disposition effect provide foundational insights into how psychological biases shape investor sentiment. These theories explain deviations from rational behaviour and support empirical observations of sentiment's impact on market dynamics.

The literature also details various sentiment measurement techniques. Market-based proxies (e.g., IPO activity, trading volume, CEFD), survey-based indices (e.g., CCI, BCI), and text/media-based methods (e.g., NLP on news or social media) each offer unique advantages and limitations. Increasingly, advanced computational methods, machine learning, deep learning (e.g., FinBERT, CNN-RNN hybrids), and ensemble models, are employed to extract and analyse sentiment from financial texts with greater accuracy and predictive utility.

Quantile regression has emerged as a robust analytical tool for capturing the asymmetric effects of sentiment across different market conditions. It is particularly relevant in periods of heightened uncertainty, such as the COVID-19 pandemic, where studies show that negative sentiment significantly reduced returns and increased volatility, while positive sentiment offered limited relief.

Finally, empirical studies underscore sentiment's variable impact across different markets. In developed markets, sentiment effects are typically short-lived due to arbitrage, whereas in emerging markets, including South Africa, sentiment plays a stronger and more persistent role due to structural inefficiencies, retail investor dominance, and limited institutional mitigation.

Investor sentiment is a vital behavioural force that influences financial markets through price distortions, volatility, and trading patterns. Its effects are amplified by behavioural biases, observable across market regimes, and measurable using increasingly sophisticated tools. Understanding and modelling sentiment is therefore essential for academics, practitioners, and policymakers aiming to interpret or intervene in financial markets effectively.

3 Description of data and research methodology

3.1 Detailed hypotheses and framework

This study investigates the role of investor sentiment in explaining stock returns on the Johannesburg Stock Exchange (JSE), extending the traditional Fama-French three-factor model. Specifically, it tests whether sentiment, measured using a PCA based sentiment index adds explanatory power beyond the established market risk (MKT), size (SMB), and value (HML) factors. The first hypothesis is that investor sentiment is negatively associated with future returns, even after controlling for these three fundamental risk factors:

H1: Investor sentiment has a statistically significant negative relationship with future stock returns on the JSE, beyond what is explained by the Fama-French three-factor model.

In line with behavioural finance theory and limits-to-arbitrage, the second hypothesis explores cross-sectional variation in the effect of sentiment. It posits that sentiment has a stronger influence on stocks that are harder to value or arbitrage, typically small-cap, high-volatility, or low-liquidity stocks:

H2: The effect of investor sentiment on stock returns is more pronounced for stocks that are difficult to value or arbitrage.

Using a database of all stocks listed on the FTSE/JSE All Share Index (JALSH), this study constructs a sentiment index using PCA applied to a set of well-established investor sentiment proxies from the literature, outlined in the following subsection. PCA identifies the dominant component of variation across these proxies, isolating the most influential common sentiment factor.

The sentiment index is constructed by extracting the first principal component from the matrix of standardised sentiment proxies. This process is mathematically represented as:

$$\boldsymbol{Z} = \boldsymbol{XW} \tag{1}$$

Where:

$\boldsymbol{X}$ is the $n \times p$ matrix of standardised sentiment proxies (with n observations and p variables)

$\boldsymbol{W}$ is the matrix of eigenvectors (loading weights), and

$\boldsymbol{Z}$ is the matrix of principal components.

The first column of $\boldsymbol{Z}$, denoted Z_1, is retained and used as the investor sentiment index.

To examine the effect of investor sentiment on stock performance, the sentiment index is included in a time-series and cross-sectional regression where the dependent variable is the return on individual stocks. This approach tests whether aggregate investor sentiment improves the ability to explain future market returns, beyond what is accounted for by the traditional Fama-French three-factor model, where portfolios are constructed to estimate the factor returns.

The empirical model is specified as:

$$R_{i,t} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \gamma SENT_t + \varepsilon_t \tag{2}$$

Where:

$R_{i,t}$ is the return on stock *i* at time *t*,

MKT_t, SMB_t, HML_t are the standard Fama-French three factors,

$SENT_t$ is the investor sentiment derived from PCA, and

γ measures the marginal impact of sentiment on market returns.

Principal Component Analysis

Investor sentiment is inherently unobservable and is often proxied using multiple indicators that capture different aspects of investor behaviour. Since the four proxies used in this study are likely to be interrelated, this study utilises PCA to construct an aggregate investor sentiment indicator from the chosen sentiment proxies. PCA is a multivariate technique that analyses a data table in which observations are described by several intercorrelated quantitative dependent variables. The goal of PCA is to extract the important information from the table and to express this information as a set of new orthogonal variables called principal components (Dalika & Seetharam, 2015). However, the principal component approach inherently assumes linearity, capturing sentiment effects as linear combinations of underlying proxies. This assumption leaves room for non-linear relationships. Consequently, PCA may overlook intricate, non-linear interactions that are critical in fully understanding investor sentiment.

Neural Network Implementation

This inherent limitation of PCA underscores the motivation to employ neural networks (NNs). Neural networks build upon the foundational approach of PCA by modelling non-linear relationships among investor sentiment proxies and market returns. Unlike PCA, NNs can dynamically adapt to changing market conditions, capturing complex, non-linear dependencies and temporal patterns that reflect the prevailing sentiment more accurately. Thus, this approach offers a robust methodological advancement. To determine whether there exists non-linearity between the sentiment proxies and expected market returns, equation (2) will be run via a neural network model. A Feed Forward Neural Network is chosen because it can capture complex, non-linear relationships between sentiment proxies and market returns, which may not be adequately captured by linear models. Further analysis is conducted using a Long Short-Term Memory (LSTM) network to capture temporal dependencies more effectively. While the Feed Forward Neural Network captures non-linear relationships at a static point in time, the LSTM is specifically designed to process sequential data, making it well-suited for financial time series where past sentiment and return dynamics may influence future outcomes. The LSTM's memory architecture enables the model to retain and leverage long-term dependencies, offering deeper insight into how evolving sentiment patterns affect stock returns over time. This sequential modelling approach adds an important temporal dimension to the analysis, complementing the findings obtained from the FNN.

Quantile Regression Analysis

To determine if the association between sentiment proxies and market returns is constant across the distribution or differs noticeably at different quantiles, quantile regression models on equation (2) will be estimated for a range of quantiles. According to Nyakurukwa and Seetharam (2022), the quantile regression estimator allows the explanatory variable's influence to vary across the dependent variable's quantiles. This approach captures possible variability in the way sentiment affects returns under various market situations, offering a more thorough understanding of the impact of investor mood. This study attempts to identify both linear and non-linear influences of sentiment throughout the whole range of market returns by combining quantile regression with neural network analysis.

3.2 Data

The study examines the impact of investor sentiment on returns in the South African market. It follows the market data approach where market data is used to construct a sentiment index, then applies advanced computational methods to analyse the relationships between the proxies and the expected returns. This is done using monthly data for all (active and delisted) JALSH constituent firms for the period 1 January 2000 to 31 November 2024. A particular focus is put on data from 1 January 2020 to 30 June 2022 to analyse the impact of sentiment during the Covid-19 period. This period is longer than the Covid-19 national state of disaster period at the tails. The national state of disaster was declared by President Cyril Ramaphosa on 15 March 2020 and was lifted at midnight on 5 April 2022. This is done to capture investor sentiment in anticipation and “post Covid-19 anxiety” of market dynamics. All data is collected from Bloomberg.

This study measures investor sentiment through various proxies, each capturing distinct facets of market behaviour and sentiment-driven activities. These proxies were selected based on data availability and their combined ability to provide a comprehensive and multifaceted view of investor sentiment. Specifically, the proxies used in this analysis include:

3.2.1 Number of IPOs

The number of initial public offerings (IPOs) reflects the willingness of firms to go public and the market’s capacity to absorb new equity. High IPO activity typically coincides with periods of heightened optimism, as firms capitalise on favourable valuations driven by positive sentiment (Baker & Wurgler, 2000). It is calculated as the logarithm of the total number of initial public offerings (IPOs) in a given year and serves as a proxy for market confidence and investor sentiment.

During periods of high optimism, more companies are likely to go public, whereas, in times of pessimism, IPO activity tends to decrease. It follows that firms are more likely to conduct IPOs during these "hot markets," characterised by overvaluation and investor enthusiasm. Ritter (1991) and Loughran and Ritter (1997) provide evidence that IPO activity peaks during such periods, often followed by subpar long-term performance. This cyclical pattern underscores the role of sentiment in driving IPO timing.

Dalika and Seetharam (2015) found that the number of IPOs positively correlates with sentiment in the South African market. A surge in IPO activity often precedes periods of market correction, as the optimism that fuels IPOs subsides. The study highlights the number of IPOs as a robust indicator of speculative waves in emerging markets.

3.2.2 The initial return on IPOs

This is the mean initial return of IPOs in a given year. High initial returns on IPOs often signify strong investor demand and optimism. Investors' willingness to bid up the prices of new issues reflects their overall market sentiment. By tracking these initial returns, we can gauge the level of investor enthusiasm and sentiment in the market.

Dalika and Seetharam (2015) documented that high initial IPO returns align with periods of high sentiment in the South African market. During optimistic periods, investors exhibit overconfidence, driving up demand and initial returns for IPOs. This behaviour is consistent with global trends identified by Loughran and Ritter (1997), where high first-day IPO returns often precede disappointing long-term performance.

The return on IPOs reflects sentiment-driven pricing inefficiencies. In high-sentiment environments, irrational exuberance inflates IPO prices, while low-sentiment periods are marked by cautious valuations and more measured first-day returns.

3.2.3 Market Turnover

Market turnover is measured by the ratio of total trading volume to market capitalisation. High turnover indicates elevated market activity, often driven by speculative trading. As Baker and Stein (2004) argue, in markets with short-selling constraints, a surge in trading activity often reflects investor overconfidence rather than rational decision-making. This overconfidence inflates prices, leading to lower subsequent returns.

Dalika and Seetharam (2015) identified a positive relationship between market turnover and sentiment in the South African stock market. When sentiment is high, market turnover increases as unsophisticated investors actively trade, anticipating future price gains. However, this heightened activity is typically followed by price corrections, resulting in abnormally low returns. Conversely, low turnover suggests pessimistic sentiment and undervaluation, often preceding higher future returns.

Market turnover serves as a barometer for the speculative appetite of market participants. High turnover, indicative of optimistic sentiment, often coincides with periods of mispricing, particularly in small-cap and illiquid stocks. This makes it a valuable tool for understanding the sentiment-driven divergence from fundamental values.

3.2.4 Volatility Premium

The concept of the volatility premium serves as a critical proxy for understanding investor sentiment, particularly in the context of emerging markets such as South Africa. It reflects periods when the valuation of high-volatility stocks diverges significantly from that of low-volatility stocks, signalling variations in market sentiment. The volatility premium is calculated as the logarithmic ratio of the value-weighted average market-to-book ratio of high-volatility stocks to low-volatility stocks (Dalika & Seetharam, 2015).

High-volatility stocks are inherently riskier, attracting speculative behaviour and reducing their appeal to rational arbitrageurs. According to Wurgler and Zhuravskaya (2002), this dynamic makes high-volatility stocks more susceptible to noise-trader sentiment. Noise traders, driven by irrational optimism or pessimism, exacerbate mispricing, making volatility a potent indicator of sentiment-driven anomalies.

Dalika and Seetharam's (2015) study on the South African market provides compelling evidence of the utility of the volatility premium as a sentiment proxy. They argue that volatile stocks, often difficult to value and arbitrage, are disproportionately influenced by sentiment waves. The study’s findings align with Baker and Wurgler (2006), who noted that during periods of high sentiment, speculative stocks (e.g., high-volatility, growth-oriented firms) tend to experience lower subsequent returns. Conversely, these stocks yield higher returns when sentiment is low.

The volatility premium acts as a diagnostic tool for sentiment-driven market behaviours, especially in conditions where short-selling is constrained, as in the Johannesburg Stock Exchange. High volatility premium values often correlate with speculative bubbles, while low values indicate market pessimism or undervaluation opportunities. This relationship underscores its relevance in behavioural finance and its predictive power for market correction

4 Results

This section presents the empirical findings on investor sentiment in the South African stock market. The analysis begins with descriptive statistics of the sentiment proxies, providing an initial understanding of their distribution, central tendencies, and correlations. This is followed by diagnostic tests, including the Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity, to assess the suitability of the data for PCA. The results of PCA are then discussed, followed by an examination of the sentiment index over time. Finally, to explore the relationship between investor sentiment and market returns, various modelling approaches are employed, including predictive models such as neural networks and linear regression, as well as quantile regression to capture relationships across different points of the return distribution.

4.1 Descriptive Statistics

Table 1 below presents the descriptive statistics for the sentiment proxies on a monthly basis. The mean values provide insight into the central tendency of each proxy, while the standard deviation captures the variability in the data. Over the 299 monthly observations, the Number of IPOs (NIPO) totalled 183, with a mean of 0.61, indicating that, on average, IPO activity is relatively low per month. Between 2000 and 2013, NIPO remained relatively low and stable, with the highest number recorded at 10 in 2007, and the lowest point occurring in 2008, when no IPOs were listed. However, a notable shift emerged in 2014, when the NIPO more than doubled from 7 in the previous year to 16. This upward trend continued, reaching a peak of 23 IPOs in 2017 before declining to 13 in 2018. Notably, the highest NIPO in a single month was observed in October 2017, during which 5 companies were listed, a monthly record within the period under review. Offer to First-Day Performance (%) (RIPO) shows a mean of 2.56%, suggesting a moderate average first-day return on IPOs. Market turnover (TURN) has a very low mean of 0.0007, reflecting minimal changes in trading activity. In contrast, the Volatility Premium (VPREM) has a significantly higher mean of 43.88, indicating periods of high market uncertainty.

The median values reveal that most of these proxies frequently take on low or zero values. The median for NIPO, RIPO, and TURN is 0, suggesting that in many months, IPO activity was absent or minimal. The median VPREM is 15.64, which is significantly lower than its mean, indicating that extreme volatility events are skewing the average upward. Examining the dispersion measures, the standard deviations show that RIPO and VPREM are highly volatile, with values of 19.38 and 98.41, respectively. This suggests significant fluctuations in first-day IPO returns and volatility risk in the market. TURN, on the other hand, has an extremely small standard deviation of 0.001, reinforcing the observation that trading volume remains stable and does not exhibit large fluctuations. NIPO (3.10) and RIPO (113.84) show high positive skewness, meaning occasional months of extreme IPO activity or first-day returns drive the averages upward. TURN (1.184) is slightly right-skewed, while the VPREM (27.24) is heavily skewed, showing rare but extreme spikes in market volatility. Kurtosis values further confirm these insights. RIPO (9.87) and VPREM (5.02) exhibit excess kurtosis, suggesting that these variables frequently experience extreme values. This is typical of financial markets where rare but significant shocks occur. NIPO has moderate kurtosis (1.76), while TURN (0.739) depicts a moderate departure from normality. The minimum and maximum values further highlight these extremes. RIPO (%) ranges from 0% to 260.11%, reinforcing the presence of outliers in IPO performance. Similarly, the VPREM varies between 0.34 and 751.28, confirming high market stress periods.

Unsurprisingly, the most extreme volatility premium values were observed between August 2007 and March 2008, in alignment with the Global Financial Crisis. The Covid period had relatively normal values for the proxies, with the exception of May 2020 where the offer to first day performance of 260,11% was recorded.

Table 1: Descriptive statistics for the sentiment proxies

Proxy	Statistic							
	Mean	Med	SD	Min	Max	Skew	Kurt	Obs
NIPO	0.61	0	0..94	0	5	3.10	1.76	299
RIPO	2.56	0	19.38	0	260.11	113.84	9.87	299
TURN	0.0007	0.001	0.001	0.0002	0.021	1.184	0.739	299
VPREM	43.88	15.64	98.41	0.34	751.28	27.24	5.02	299

Note(s): SD shows the standard deviation of the variables, Obs the number of observations, while Med, Min and Max, Skew, Kurt represent the median, minimum, maximum, skewness and kurtosis values of the variables respectively.

Correlation Analysis

Table 2 presents the correlation matrix for the proxies examined in this study. It is worth noting that none of the correlations were statistically significant. The correlation between NIPO and RIPO is

0.220, indicating a positive but moderate relationship. This suggests that during periods of increased IPO activity, the relative first-day performance of IPOs tends to be higher. This could be attributed to heightened investor enthusiasm and demand during such periods, leading to greater underpricing.

The correlation between NIPO and TURN is -0.151, suggesting a weak negative relationship. This implies that a higher number of IPOs does not necessarily lead to an increase in overall market turnover. This could reflect the possibility that IPO activity diverts liquidity from existing stocks rather than increasing overall market trading volume.

A weak negative correlation (-0.022) is observed between NIPO and VPREM, indicating that the number of IPOs is largely uncorrelated with the volatility premium. This suggests that fluctuations in IPO activity do not have a significant impact on market volatility pricing.

The relationship between RIPO and TURN is slightly negative (-0.066), suggesting that higher first-day IPO returns are not necessarily associated with higher market turnover. This may indicate that extreme IPO underpricing does not drive increased trading activity across the broader market.

Similarly, RIPO and VPREM exhibit a weak negative correlation of -0.051, suggesting that the volatility premium does not meaningfully change in response to variations in IPO first-day performance. This result implies that investors do not systematically adjust their risk expectations in response to IPO performance.

Lastly, TURN and VPREM have a small positive correlation (0.116), indicating that higher market turnover is weakly associated with an increased volatility premium. While not a strong relationship, this suggests that periods of higher trading activity may coincide with a slight increase in market risk perception.

The correlation results suggest that while IPO activity and first-day returns have a moderate positive relationship, their interactions with market liquidity and volatility are relatively weak. These findings indicate that IPO-related market dynamics may be influenced by factors beyond simple liquidity movements and volatility pricing.

Table 2: Pearson's correlation matrix

Variables	NIPO	RIPO	TURN	VPREM
NIPO	1			
RIPO	0.220	1		
TURN	-0.151	-0.066	1	
VPREM	-0.022	-0.051	0.116	1

4.2 Preliminary tests

4.2.1 Kaiser-Meyer-Olkin measure of sampling adequacy

The Kaiser-Meyer-Olkin (KMO) test is used to assess the suitability of the dataset for factor analysis or PCA by measuring the proportion of variance in the variables that might be caused by underlying factors. The KMO statistic ranges between 0 and 1, where values closer to 1 indicate that PCA is appropriate, and values below 0.5 suggest that the dataset may not be well-suited for factor analysis (Kaiser, 1974).

Table 3 presents the KMO values for the sentiment proxies. The overall KMO measure is 0.5338, which is just above the threshold of 0.5, indicating marginal adequacy for factor analysis. Among the individual proxies, turnover (0.5510) has the highest sampling adequacy, suggesting that this variable has stronger partial correlations with the other sentiment proxies. VPREM (0.5301) and RIPO (0.5350) also meet the minimum adequacy requirement, further supporting PCA feasibility. NIPO (0.5245) is slightly above the 0.5 threshold, indicating moderate factorability.

While the overall KMO value suggests that factor analysis can proceed, the relatively low KMO values indicate that some variables may not be highly correlated, potentially affecting the robustness of PCA results. Additionally, the Bartlett's Test of Sphericity is employed to confirm the suitability of the dataset for factor extraction.

Table 3: Kaiser-Meyer-Olkin test

NIPO	0.5245
RIPO	0.5350
TURN	0.5510
VPREM	0.5301

4.2.2 Bartlett's Sphericity Test

Table 4 presents the results of Bartlett's test of sphericity, which assesses whether the correlation matrix differs significantly from an identity matrix (where all diagonal elements are 1 and all off-diagonal elements are 0). The test evaluates the hypothesis that the variables are uncorrelated, which would indicate that factor analysis is not appropriate.

The observed chi-square value is 26.4801, which is significantly higher than the critical chi-square value of 12.5916 at 6 degrees of freedom. The p-value (0.0002) is well below the significance level (alpha = 0.05), leading us to reject the null hypothesis that the correlation matrix is an identity matrix. This indicates that at least some of the correlations between the variables are significantly different from zero. Since the correlation matrix is statistically different from an identity matrix, factor analysis is deemed appropriate for the dataset. This confirms that the sentiment proxies have sufficient interrelationships to justify the application of PCA, strengthening the construction of an investor sentiment index.

Table 4: Bartlett's Sphericity Test values

Chi-square (Observed Value)	26.4801
Chi-square (Critical Value)	12.5916
Degrees of Freedom (DF)	6.0
P-Value	0.0002
Alpha Level	0.05

4.3 Principal Component Analysis (PCA)

After applying PCA to the four sentiment proxies, four principal components were extracted. Each principal component represents a linear combination of the original variables, with loadings indicating the relative weighting of each variable in defining the component.

The proportion of variance explained by each principal component is as follows:

- PC1 (First Principal Component): 33.28%
- PC2 (Second Principal Component): 25.46%
- PC3 (Third Principal Component): 22.37%
- PC4 (Fourth Principal Component): 18.76%

The first principal component (PC1) alone captures 33.28% of the total variance, suggesting that a single dominant factor explains a significant portion of the variation in investor sentiment proxies. The first two components together account for 58.74% of the total variance, while the first three components explain over 80%, indicating that the dataset can be effectively summarised using these components. The loadings for each proxy on PC1 lead to the following index:

$$SENT = 0.608NIPO + 0.549RIPO - 0.491TURN - 0.297VPREM \tag{3}$$

Important insights can be drawn from these results:

1. IPO activity and IPO returns as positive drivers

The positive loadings for NIPO and RIPO indicate that an increase in IPO activity and higher first-day IPO returns both contribute positively to PC1. This suggests that PC1 captures periods of heightened optimism and risk-taking behaviour, where investors are eager to participate in IPOs. Dalika and Seetharam (2015) find a similar relation.

2. Market turnover and volatility premium as negative contributors:

The negative loading on TURN suggests that higher trading volume (relative to market capitalisation) is associated with lower values of PC1. This could imply that during periods of heightened trading activity, sentiment may be driven by short-term speculation rather than sustained optimism. Similarly, the negative loading on the volatility premium suggests that higher uncertainty or risk aversion (indicated by a larger VPREM) corresponds with lower sentiment values. This is contrary to the findings of Dalika and Seetharam (2015), who report positive loadings for both variables. However, they note that they expected a negative loading for VPREM, consistent with what this research report notes.

Thus, PC1 can be interpreted as a broad measure of investor sentiment, where higher values reflect optimism (increased IPO activity and stronger IPO returns), and lower values suggest a shift toward risk aversion (higher turnover and volatility premium). It will be utilised as the primary sentiment measure in the subsequent empirical analysis, while acknowledging the presence of additional dimensions that may require further exploration.

Potential Limitations and Future Considerations

The relatively low KMO statistic suggests that additional sentiment proxies (e.g., textual sentiment from news reports, surveys, or Google search trends) could be incorporated to enhance the robustness of the sentiment measure. While PC1 captures the largest portion of the variance, PC2 and PC3 together contribute significantly, indicating that sentiment in the South African market may have multiple dimensions beyond what PC1 captures. Further analysis of PC2 and PC3 may provide additional insights.

The interpretation of PC1 assumes that higher IPO activity and returns correspond to positive sentiment. However, extreme speculative bubbles could lead to a scenario where rising IPOs and turnover indicate excessive risk-taking rather than sustained optimism which one could also argue that the excessive risk taking is a result of sustained optimism. The results of the PCA confirm that a common sentiment factor can be extracted from IPO activity, IPO returns, market turnover, and volatility premium. PC1 emerges as a strong candidate for a sentiment measure, as it captures a meaningful share of variance and aligns well with theoretical expectations of sentiment-driven market behaviour. However, the influence of turnover and volatility premium suggests that investor sentiment in the South African market may be more nuanced than a single-factor model implies. This is further validated by the positive values of 0.4024 and 0.7550 they load in PC2, respectively.

4.4 Sentiment Index Over Time

Figure 1 presents the sentiment index over time, capturing fluctuations in investor sentiment within the South African stock market. The sentiment index exhibits noticeable variability, reflecting periods of optimism and pessimism among investors.

Between 2000 and 2008, the sentiment index shows a gradual increase, peaking sharply during the 2008 Global Financial Crisis. This period is characterised by extreme fluctuations, highlighting heightened investor uncertainty and volatility in the market. Following this crisis, sentiment declines significantly but remains volatile, with intermittent spikes corresponding to market events. From 2012 to 2018, the sentiment index stabilises somewhat, with fewer extreme movements. However, the trend remains cyclical, suggesting that investor sentiment reacts dynamically to macroeconomic conditions and market developments.

A notable spike occurs again around 2020, coinciding with the onset of the COVID-19 pandemic. This surge indicates a period of extreme investor sentiment, likely driven by market reactions to the uncertainty and economic disruptions caused by the pandemic. Similarly, a major spike is observed in 2008 during the Global Financial Crisis. Although the sentiment index includes negative loadings on TURN and VPREM, the spikes in both 2008 and 2020 were primarily driven by unusually high values of NIPO and RIPO. In both instances, there were four IPOs recorded in a single month, an anomaly given that many months during the sample period had zero IPOs. These IPOs were accompanied by exceptionally high returns, amplifying the sentiment index due to the relatively strong positive loadings of these two proxies. In contrast, periods such as 2017 also saw an increase in IPO activity, but without corresponding spikes in the index. This is because the returns on those IPOs were relatively low, and thus their contribution to sentiment remained limited.

TURN values during these periods did not display extraordinary changes and therefore did not significantly influence the spikes. While some extreme values were observed in VPREM, its lower absolute coefficient in the index formula meant that its impact was dampened when aggregated with the other components. This supports the interpretation that the spikes in sentiment reflect complacent investor optimism associated with heightened IPO activity and performance rather than being a result of reduced volatility or turnover alone.

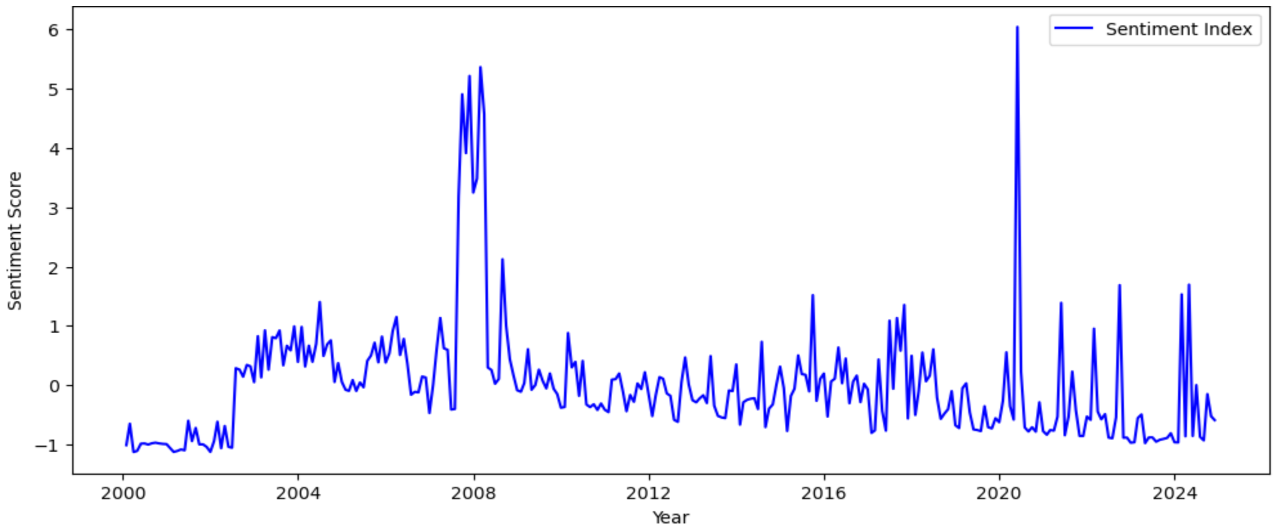

Figure 1: Sentiment Index Over Time

4.5 Regression analysis

The OLS regression results presented examine the relationship between individual stock returns and a set of explanatory variables including the Fama-French three factors, market risk premium (MKT), size (SMB), and value (HML), along with an investor sentiment variable. The model is estimated using heteroskedasticity-robust standard errors (HC3), based on a large sample of 36,952 observations. The R-squared value of 0.103 indicates that approximately 10.3% of the variation in individual stock returns is explained by the model. While modest, this level of explanatory power is not uncommon in cross-sectional stock return models.

All explanatory variables are statistically significant at the 1% level, with p-values less than 0.01, indicating strong evidence against the null hypothesis of no effect. The market factor (MKT) carries a coefficient of -0.4273, suggesting that, holding other factors constant, a 1-unit increase in the market return is associated with a 0.4273 unit decrease in the individual stock return. This counterintuitive negative sign might imply that the model is capturing a specific market segment or that the excess return calculation or data alignment warrants a second look.

The SMB factor (Small Minus Big), with a coefficient of 0.3084, shows a strong positive relationship with stock returns, indicating that smaller firms tend to outperform larger ones in the sample, consistent with the size effect documented in the asset pricing literature. Similarly, the HML factor (High Minus Low), which captures the value effect, has a negative coefficient of -0.2366, suggesting that growth stocks (low book-to-market) tend to outperform value stocks in this context, which could reflect market conditions or sample-specific effects.

Importantly, the investor sentiment variable enters the regression with a coefficient of -0.0014 and is statistically significant ($p = 0.012$). This negative relationship suggests that higher investor sentiment is associated with lower subsequent stock returns, consistent with the hypothesis that sentiment-driven mispricing corrects over time. Although the magnitude of the coefficient is small, its significance indicates that investor sentiment, as constructed via PCA, contains information relevant to market return dynamics that is not fully captured by the traditional risk factors. This finding supports the idea that sentiment may have a destabilising effect on pricing, leading to temporary overvaluation that subsequently reverses.

The diagnostic statistics show some issues with normality (e.g., high skewness and kurtosis, Jarque-Bera p-value = 0.00), suggesting that the distribution of residuals is not normal, perhaps due to outliers or non-linearities in the data. Figure 2 plots the distribution of residuals. However, the use of robust standard errors mitigates concerns about inference validity. The Durbin-Watson statistic of 1.972 is close to 2, indicating no significant autocorrelation in the residuals.

The regression results provide statistically significant evidence that investor sentiment negatively predicts future stock returns on the JSE, even after controlling for the Fama-French three factors. These findings offer empirical support for the first hypothesis in the study and contribute to the growing literature on behavioural influences in asset pricing.

This study further explores neural networks and quantile regression to better understand the potential influence of investor sentiment on market returns.

Table 5: Regression results

	Coef	Std err	t	P > | t |	[0.025	0.975]
Intercept	-0.036	0.001	-36.634	0.000	-0.038	-0.034
MKT	-0.427	0.011	-39.236	0.000	-0.449	-0.406
SMB	0.308	0.024	12.742	0.000	0.261	0.356
HML	-0.237	0.038	-6.289	0.000	-0.310	-0.163
SENT	-0.002	0.001	-2.502	0.012	-0.003	-0.000

Table 6: OLS model summary

Observations	36952
R-squared	0.103
Adjusted R-squared	0.103
F statistic	43.80
Durbin-Watson	0.169
Jarque-Bera	11.528
Kurtosis	38.705
Skewness	4.645

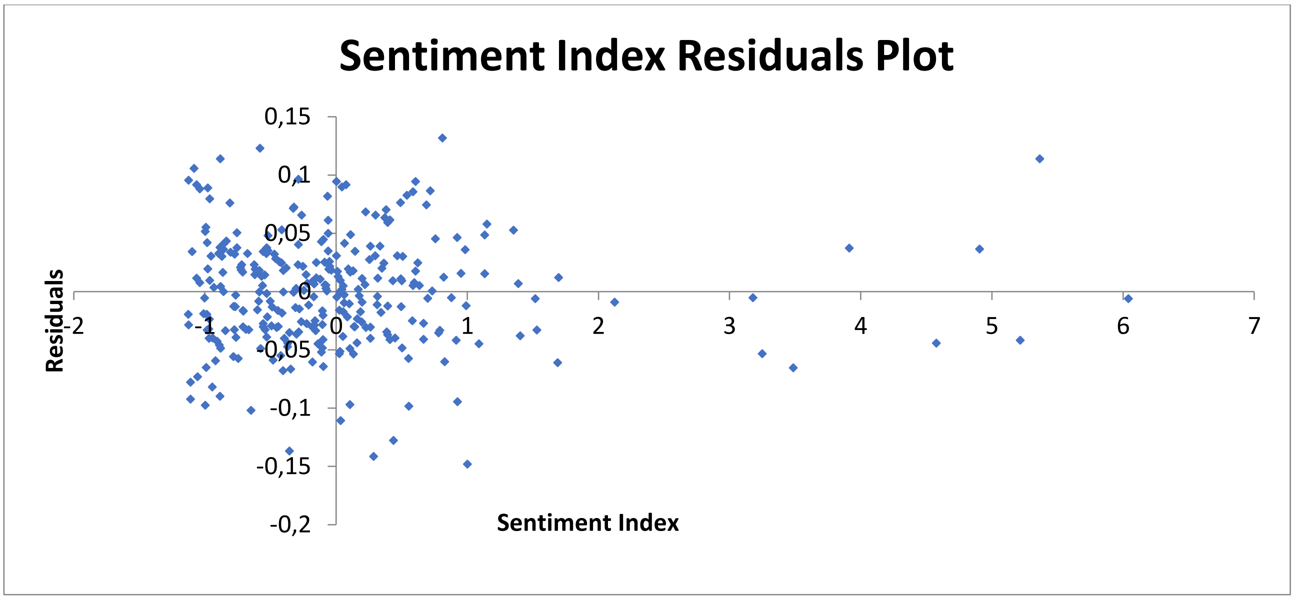

Figure 2: Sentiment regression residuals

4.6 Neural Network

A feedforward neural network (FNN) was trained to model individual stock returns using macroeconomic and behavioural predictors, namely the market risk premium, SMB, HML, and investor sentiment. The model achieved a mean squared error (MSE) of 0.0067 and a mean absolute error (MAE) of 0.0520 on the test set. The R^2 value of 0.1261 indicates that the model explains approximately 12.6% of the variation in stock returns, a modest but acceptable result given the well-known difficulty of predicting financial returns.

To assess the contribution of each input variable to the model's predictions, SHapley Additive Explanations (SHAP) values were computed. The SHAP summary plot reveals that the market risk premium was the most influential factor, with both high and low values showing strong directional impact on predicted returns. This aligns with traditional financial theory, where the market premium is expected to be a primary driver of stock-level performance. In contrast, SMB and HML exhibited moderate explanatory power, while sentiment had the weakest influence. The SHAP values for sentiment are tightly clustered around zero, suggesting that investor sentiment contributed little to the model's predictive decisions. However, high sentiment values predominantly reduced predicted returns and low sentiment values enhanced them. This finding strongly supports behavioural finance theories about investor sentiment driving market mispricing. It suggests that when allowing for non-linear and complex patterns, sentiment, in its modest effect size, influences the neural network's predictions in a manner that aligns with the negative relationship hypothesised in H1.

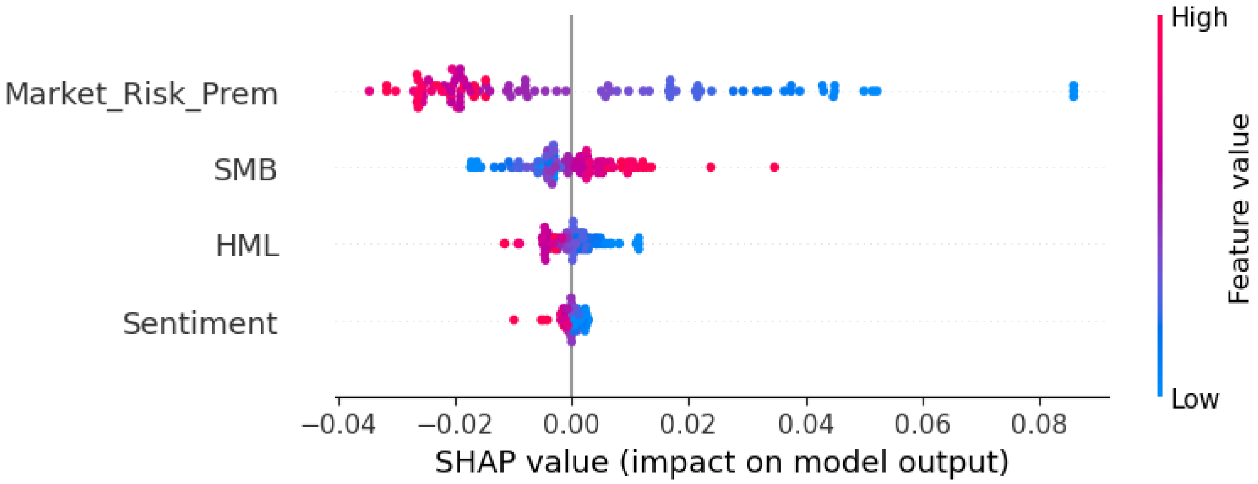

Figure 3: FNN SHAP summary plot

Building on the feedforward neural network (FNN) model, which allowed for non-linear interactions but treated each stock-month observation independently, a Long Short-Term Memory (LSTM) model was introduced to capture the temporal structure in stock returns. Unlike the FNN, the LSTM leverages sequential information by learning from rolling windows of past sentiment and market factors, allowing it to detect persistent patterns or lagged effects that evolve over time. The model was trained using 1-month input sequences. It achieved an MSE of 0.0071, an MAE of 0.0528, and an R^2 of 0.1363, slightly outperforming the FNN and suggesting that some time-dependent relationships may exist between inputs and returns. The LSTM SHAP plot reveals that the market risk premium is still the most influential predictor, with the widest spread along the x axis, with higher values strongly associated with increased forecasted returns. The SMB factor also contributes positively, albeit to a lesser extent, indicating that small-cap stocks are associated with higher expected returns. In contrast, the HML factor exhibits minimal impact, with SHAP values clustered around zero, suggesting that value-based effects offer limited explanatory power in this context.

Importantly, the sentiment variable demonstrates a consistent and more spread influence on the model's output. While the overall impact appears positive in raw SHAP values, a closer inspection reveals that lower sentiment scores are associated with higher predicted returns, and higher sentiment scores tend to reduce expected returns, consistent with a negative relationship. This pattern again supports the first hypothesis (H1), which posits that investor sentiment is negatively associated with future stock returns, beyond what is explained by Fama-French factors. In other words, elevated investor sentiment may reflect over-optimism, leading to lower subsequent returns, whereas low sentiment may signal undervaluation or risk aversion, often preceding higher returns.

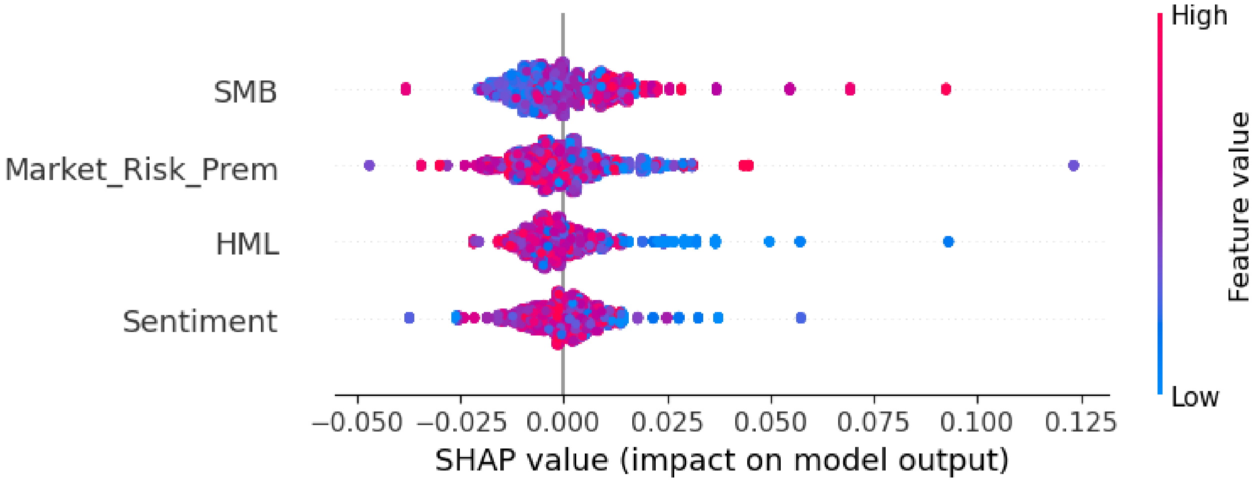

Figure 4: LSTM SHAP summary plot

4.7 Quantile Regression

In the quantile regression framework, the distribution of stock returns was divided into five quantiles, τ = 0.1, 0.25, 0.5, 0.75, and 0.9, allowing for an examination of how the effects of explanatory variables vary across the return distribution. This method captures the impact of predictors not just at the mean (as in OLS) but also at different points (quantiles) of the return distribution, particularly the extremes. Across all quantiles, MKT was found to be a statistically significant determinant of returns, with negative coefficients that increase in magnitude toward the tails of the return distribution. The MKT coefficient is -0.6248*** at τ = 0.1, narrows to -0.0805*** at τ = 0.5, and steepens again to -0.7464*** at τ = 0.9. This non-monotonic pattern indicates that market-wide shocks have a disproportionate effect on both the worst and best performing stocks, suggesting asymmetry in how systemic risk translates into firm-level returns. These results align with Nyakurukwa and Seetharam (2022), who also highlight stronger sensitivity of extreme returns to macroeconomic risk factors.

The SMB factor was positively and significantly associated with returns across all quantiles, with its strength increasing from 0.2955 in the lower tail to 0.4116 in the upper tail. This suggests that small-cap stocks outperform more consistently in the upper quantiles of the return distribution. This could indicate greater upside potential for smaller firms, especially in favourable market conditions.

The HML factor also exhibits a quantile-varying effect. It is positive and significant at the lower quantiles (e.g., 0.1448*** at $\tau = 0.1$ and 0.0938*** at $\tau = 0.25$), but becomes negative and significant at the upper quantiles, reaching -0.1251*** at $\tau = 0.9$. This reversal implies that value stocks are more defensive, offering better returns during downturns, while growth stocks dominate during high-return episodes.

Most importantly, sentiment (SENT) showed a statistically significant positive relationship with returns at the lower quantiles ($\tau = 0.1$, 0.25, and 0.5), but this relationship weakened and became statistically insignificant at $\tau = 0.75$ and even turned negative at $\tau = 0.9$. This pattern suggests that investor sentiment is most relevant in low to mid-return stocks (often associated with fear or uncertainty), but loses its explanatory power during more bullish or euphoric periods in stock returns. These findings align with prior empirical evidence (Ma, Xiao, & Ma, 2018), who argue that investor behaviour, and sentiment's impact, is most pronounced during times of anxiety rather than prosperity.

The quantile regression results reject the notion of a monotonic relationship between sentiment and returns. The coefficient path plots in Figure 5 further reinforce this non-linearity, showing clearly diverging trajectories across quantiles. As in Nyakurukwa and Seetharam (2022), our findings underscore the importance of accounting for asymmetric sentiment effects when modelling stock returns, particularly in emerging markets like South Africa where market dynamics are shaped by both institutional dominance and noise trading under stress.

Table 7: Quantile regression results

Dependent variable: Stock returns					
	τ = 0.1	τ = 0.25	τ = 0.5	τ = 0.75	τ = 0.9
Intercept	-0.0837*** (0.001)	-0.0389***(0.001)	-0.0016***(0.000)	0.0244***(0.000)	0.0740***(0.001)
MKT	-0.6248***(0.017)	-0.4767***(0.012)	-0.0805***(0.002)	-0.4135***(0.010)	-0.7464***(0.022)
SMB	0.2955***(0.029)	0.2641***(0.019)	0.0568***(0.004)	0.3055***(0.016)	0.4116***(0.035)
HML	0.1448***(0.020)	0.0938***(0.013)	-0.0110***(0.003)	-0.0440***(0.012)	-0.1251***(0.035)
SENT	0.0026***(0.001)	0.0013***(0.000)	0.0008***(0.000)	0.0002(0.000)	-0.007(0.001)
Pseudo R^2	0.0528	0.0546	0.0011	0.0504	0.092
Observations	37076	37076	37076	37076	37076

Note(s): The table reports the quantile regression coefficients for each variable; standard errors are in (brackets); * Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level

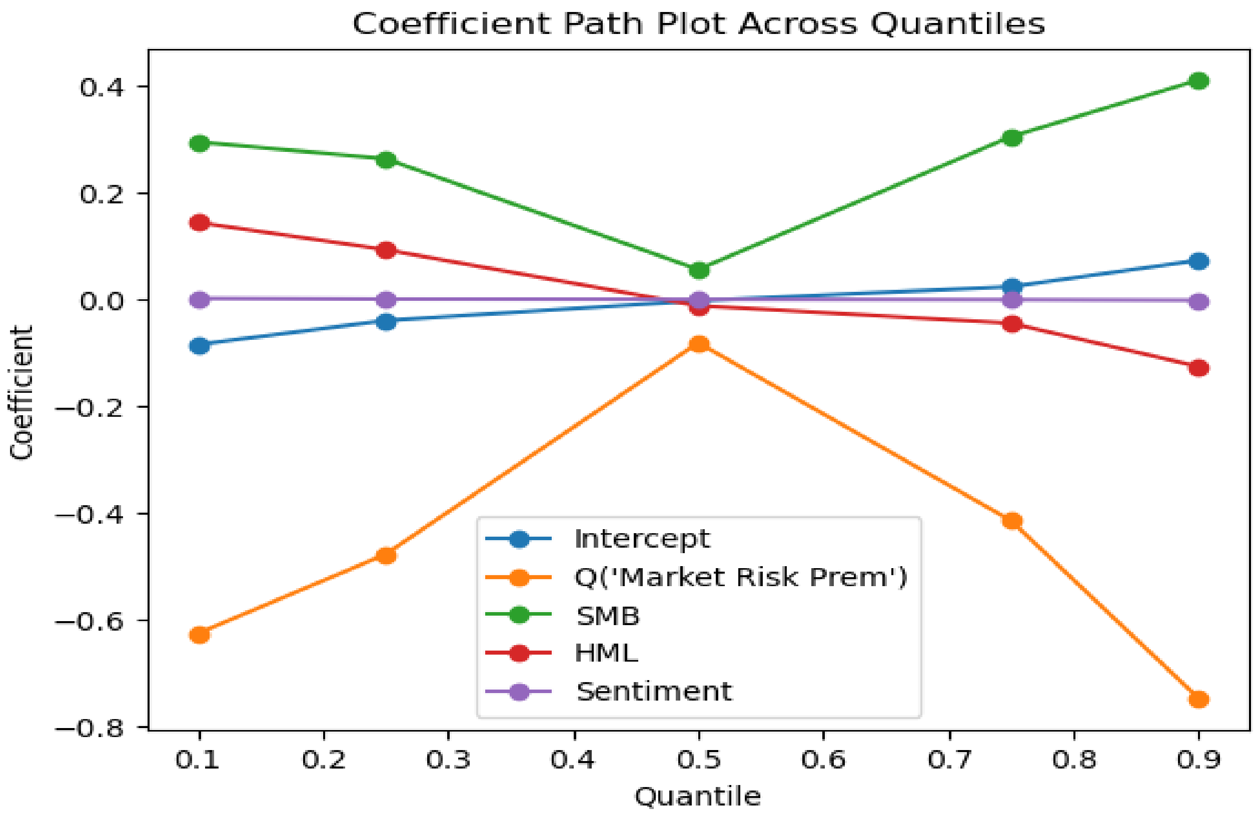

Figure 5: Quantile regression coefficients path plots

4.8 Portfolio Sorts

For portfolio sorting, the turnover variable (TURN) was selected as the sentiment proxy alongside the composite sentiment index. Among the available individual proxies, NIPO, RIPO, TURN, and VPREM, TURN was chosen simply as a representative variable. While there was no theoretical preference for TURN over the others, its inclusion allowed for a practical comparison between the composite sentiment index and one of its underlying components.

Table 8 reports the results of the two-way portfolio sorts examining the conditional effects of firm characteristics, specifically size (ME), Age, volatility, and the book-to-market ratio (BE/ME), conditioned on TURN. Stocks are placed monthly into bins according to their characteristic ranks at the beginning of the month and turnover sentiment from the end of the previous year. Portfolio 1 includes the bottom three deciles (lowest ranks), Portfolio 3 includes the top three deciles (highest ranks), and Portfolio 2 contains intermediate ranks. We report average monthly returns for each portfolio as well as differences between portfolios to assess the strength and direction of effects.

The first rows illustrate the conditional cross-sectional effect of size (ME) on returns, given the level of TURN. Under positive turnover conditions, there is an increase in returns moving from smaller firms (Portfolio 1: 0.10%) to larger firms (Portfolio 3: 0.23%). This indicates a modest preference for larger-cap stocks during periods of heightened turnover. Under negative turnover conditions, Portfolio 1 has a lower return (-0.30%) compared to Portfolio 3 (-0.14%). This suggests that across both turnover conditions, investors prefer larger stocks more.

Examining the conditional cross-sectional effects of Age, we observe a clearer pattern. Under positive turnover conditions, older firms (Portfolio 3) outperform younger firms (Portfolio 1), yielding returns of 0.20% and 0.03%, respectively. This suggests that during periods of high investor turnover and market liquidity, investors prefer older, possibly more established firms. Under negative turnover conditions, younger firms experience lower returns (-1.12%) compared to older firms (-1.07%), though the difference is less pronounced. The overall positive differences (1.15% to 1.27%) between younger and older firms highlight a consistent age-based effect, indicating older firms generally outperform younger ones irrespective of turnover sentiment. This result is consistent with the expectation that investors exhibit a stronger preference for older firms during times of uncertainty, perhaps due to perceived stability or lower valuation uncertainty associated with mature firms. This contrasts the findings of Dalika and Seetharam (2015), who report that younger firms that are traded more tend to generate higher portfolio returns when TURN is positive.

Turning to Volatility, under positive turnover conditions, there is a clear negative relation between volatility and returns, with Portfolio 1 (low volatility) earning 0.42% compared to just 0.05% for high-volatility stocks (Portfolio 3). The negative difference (-0.37%) indicates that higher volatility stocks are negatively impacted when trading activity is elevated. However, under negative turnover conditions, the relationship reverses; Portfolio 3 (high-volatility) yields higher returns (-0.22%) compared to Portfolio 1 (-0.86%). This reversal suggests that high-volatility stocks may correct previously driven sentiment mispricing during calmer market conditions, supporting behavioural finance theories that suggest volatility increases susceptibility to investor sentiment.

Lastly, the interaction between BE/ME ratios and turnover reveals a more pronounced effect. Under positive turnover conditions, higher BE/ME (value) stocks (Portfolio 3) outperform lower BE/ME (growth) stocks, with returns of -0.17% and -0.59%, respectively. This suggests investor preference for stocks perceived as undervalued during periods of active trading. Under negative turnover conditions, this relationship is amplified: Portfolio 3 significantly outperforms Portfolio 1 (-0.26%

versus -1.92%). Thus, across sentiment regimes, value stocks consistently outperform growth stocks, reinforcing the notion that growth stocks may suffer more from sentiment-driven mispricing that unwinds during low market liquidity periods.

The findings presented clearly support Hypothesis 2, which states that the harder it is to value or arbitrage a stock, the stronger the impact of sentiment on its returns. Specifically, the volatility and BE/ME portfolio sorts demonstrate distinct return patterns conditional on investor turnover sentiment. During periods of positive turnover sentiment, investors prefer low-volatility and high BE/ME (value) stocks, which are generally easier to value, thus resulting in superior returns compared to their high-volatility or growth-oriented counterparts. Conversely, high-volatility and growth stocks, typically harder to value and arbitrage, experience significant return reversals in negative sentiment periods, indicating that their pricing is more susceptible to sentiment-driven distortions. This conditional variability underscores that stocks characterised by greater valuation uncertainty (higher volatility, growth-oriented firms) experience stronger and more pronounced effects of investor sentiment.

Table 8: Two-way sorts: TURN and firm characteristics

Turnover		Portfolio			Overall			
		1	2	3	3-1	3-2	2-1	T-Stat
ME	Positive	0.10%	0.15%	0.23%	0.13%	0.08%	0.05%	0.04*
	Negative	-0.30%	-0.18%	-0.14%	0.16%	0.04%	0.02%	
	Difference	0.40%	0.33%	0.37%	-0.03%	0.04%	0.03%	
Age	Positive	0,03%	-0,25%	0,20%	0,17%	0,45%	-0,25%	0.01*
	Negative	-1,12%	-1,39%	-1,07%	0,06%	0,32%	-0,27%	
	Difference	1,15%	1,14%	1,27%	0,11%	0,13%	0,02%	
Volatility	Positive	0,42%	-0,30%	0,05%	-0,37%	0,35%	-0,72%	0.06
	Negative	-0,86%	-1,22%	-0,22%	0,64%	1,00%	-0,36%	
	Difference	1,28%	0,92%	0,27%	-1,01%	-0,65%	-0,36%	
BE/ME	Positive	-0,59%	0,27%	-0,17%	0,42%	-0,44%	0,86%	0.03*
	Negative	-1,92%	-1,11%	-0,26%	1,65%	0,84%	0,81%	
	Difference	1,32%	1,37%	0,09%	-1,23%	-1,28%	0,05%	

Note: *Denotes p-values that are statistically significant at the 5% level of significance.

Table 9 presents a two-way sort analysis similar to Table 8, with the difference that it focuses on the relationship between investor sentiment (SENTIMENT) and the aforementioned firm characteristics. Below is an analysis of the results:

Under positive sentiment conditions, larger firms (ME Portfolio 3) exhibit higher returns (-0.16%) compared to smaller firms (Portfolio 1: -0.36%), suggesting a marginal preference or lesser sensitivity among investors towards larger firms during optimistic market conditions. This relationship persists even under negative sentiment conditions, with smaller firms exhibiting slightly worse returns (-0.17%) than larger firms (-0.20%).

Examining Age, the conditional relationship is clearer. Under positive sentiment conditions, older firms (Portfolio 3: -0.40%) clearly outperform younger firms (Portfolio 1: -0.43%), suggesting investors favour established firms during optimistic market periods, possibly due to perceived stability. During negative sentiment periods, younger firms perform notably worse (-0.70%) compared to older firms (-0.43%), with a wider spread, further underscoring the relative vulnerability of younger firms to sentiment-driven mispricing.

The volatility characteristic displays clear sentiment-driven effects. Under positive sentiment conditions, lower-volatility stocks (Portfolio 1: -0.26%) underperform high-volatility stocks (Portfolio 3: 0.06%). This suggests that during periods of heightened market optimism, investors are more likely to trade high volatility stocks to realise higher portfolio returns. However, the differences are much less pronounced during negative sentiment periods, with low-volatility stocks (-0.17%) marginally outperforming high-volatility stocks (-0.20%). These patterns reinforce the hypothesis that sentiment disproportionately impacts stocks with higher valuation uncertainty.

Examining BE/ME ratios, under positive sentiment conditions, low BE/ME (growth) stocks (Portfolio 1: -1.17%) underperform high BE/ME (value) stocks (Portfolio 3: -0.25%). Under negative sentiment, this difference is slightly more pronounced, with value stocks performing considerably better (-0.32%) compared to growth stocks (-1.19%), suggesting growth stocks are more susceptible to sentiment-driven price distortions.

Overall, these findings strongly support Hypothesis 2, confirming that stocks difficult to value or arbitrage, characterised by high volatility, younger age, or lower BE/ME ratios, indeed experience stronger sentiment-related fluctuations in returns.

The analysis reveals that investor sentiment has a significant impact on the cross-sectional returns of firms with different characteristics. High sentiment tends to benefit larger, older, and low volatility firms, while low sentiment conditions favor smaller, younger, and high volatility firms. Additionally, value firms (high BE/ME) tend to underperform growth firms (low BE/ME) in both high and low sentiment conditions, though the effect is more pronounced in high sentiment scenarios. These findings align with the theoretical predictions that sentiment-driven trading disproportionately affects stocks that are harder to value and arbitrage, particularly in emerging markets like South Africa.

Table 9: Two-way sorts: Sentiment and firm characteristics

Sentiment		Portfolio			Overall			
		1	2	3	3-1	3-2	2-1	T-Stat
ME	Positive	-0.36%	-0.42%	-0.16%	0.20%	0.26%	-0.06%	0.07
	Negative	-0.53%	-0.25%	-0.32%	0.21%	-0.07%	0.28%	
	Difference	0.17%	-0.17%	0.16%	-0.01%	0.33%	-0.34%	
Age	Positive	-0,43%	-0,82%	-0,40%	0,03%	0,42%	-0,39%	0.00*
	Negative	-0,70%	-0,74%	-0,43%	0,27%	0,31%	-0,04%	
	Difference	0,28%	-0,08%	0,04%	-0,24%	0,12%	-0,36%	
Volatility	Positive	-0,26%	-0,77%	0,06%	0,32%	0,82%	-0,51%	
	Negative	-0,17%	-0,68%	-0,20%	-0,04%	0,47%	-0,51%	0.03*
	Difference	-0,09%	-0,09%	0,26%	0,35%	0,35%	0,00%	
BE/ME	Positive	-1,17%	-0,39%	-0,25%	0,92%	0,14%	0,78%	0.02*
	Negative	-1,19%	-0,31%	-0,32%	0,86%	-0,02%	0,88%	
	Difference	0,02%	-0,08%	0,07%	0,06%	0,15%	-0,09%	

Note: *Denotes p-values that are statistically significant at the 5% level of significance.

Both the sentiment and turnover results provide evidence, though nuanced that Hypothesis 2 is accepted. In both cases, stocks that are harder to value or arbitrage (smaller, younger, high volatility, and value stocks) show greater sensitivity to changes in sentiment and turnover.

The empirical findings presented in this report support both research hypotheses regarding the relationship between investor sentiment and stock returns in the South African market. Starting with

Hypothesis 1, which posits that investor sentiment has a statistically significant negative relationship with future stock returns on the JSE beyond what is explained by the Fama-French three-factor model, the results from multiple analytical approaches consistently support this assertion. The Ordinary Least Squares (OLS) regression reveals a statistically significant negative coefficient for the sentiment index (-0.0014, $p = 0.012$), indicating that higher investor sentiment is associated with lower future returns. This aligns with the behavioural finance framework proposed by Baker and Wurgler (2007), who argue that elevated sentiment leads to overpricing of speculative assets, which subsequently revert, producing lower returns. Similarly, findings from neural network and LSTM models reinforce this pattern, showing that while sentiment is not the most influential variable, its effect on returns is directionally consistent with the hypothesis: high sentiment tends to reduce predicted returns, while low sentiment is associated with higher expected returns. These results suggest that sentiment-driven mispricing exists in the JSE and can persist despite the influence of traditional risk factors.

Further confirmation of Hypothesis 1 is found in the quantile regression results, which show a non-linear relationship between sentiment and returns. Specifically, the sentiment variable is positively associated with returns at lower quantiles ($\tau = 0.1$, 0.25, and 0.5) but becomes statistically insignificant or negative at the higher quantiles ($\tau = 0.75$ and 0.9). This pattern supports the notion that investor sentiment plays a more substantial role during periods of fear or uncertainty than in bullish markets. These findings echo those of Ma, Xiao, and Ma (2018), who similarly observe stronger sentiment effects in the lower quantiles of return distributions. In the South African context, Nyakurukwa and Seetharam (2022) also highlight that social media-based sentiment indicators, such as tweet features, show stronger explanatory power for stock returns during volatile or extreme market states, particularly in the weekly and monthly data.

Hypothesis 2, which suggests that the impact of investor sentiment is more pronounced for stocks that are difficult to value or arbitrage, also finds strong empirical support. The portfolio sorts conducted in the study reveal that stocks with characteristics associated with greater pricing difficulty, such as high volatility, low book-to-market (growth stocks), and younger age, exhibit more substantial return differences across sentiment regimes. Specifically, during periods of high investor turnover (used as a proxy for sentiment), low-volatility and value stocks perform better, indicating investor preference for safer, more easily valued firms. In contrast, high-volatility and growth stocks underperform in high-sentiment periods and recover during low-sentiment periods, suggesting that sentiment-driven mispricing is particularly evident in speculative equities. These findings are consistent with the literature by Baker and Wurgler (2006, 2007), who document stronger sentiment effects in stocks that are difficult to arbitrage due to high idiosyncratic risk or limited institutional ownership. Corredor et al. (2013) also highlight that such effects are robust across European markets, reinforcing the argument that certain stock characteristics mediate the influence of sentiment on returns.

The portfolio sort results reveal a nuanced relationship between sentiment, turnover, and firm characteristics, which, upon closer examination, still align with Hypothesis 2. While large, older, and value firms generally outperform across sentiment regimes, suggesting a persistent preference for stability, the key support for Hypothesis 2 lies in the magnitude of underperformance by speculative stocks (small, young, high-volatility, and growth firms) during low-sentiment periods. For instance, growth stocks exhibit significantly worse returns (-1.92% vs. -0.26%) under negative turnover conditions (Table 8), and high-volatility stocks rebound during low sentiment (Table 9), consistent with sentiment-driven mispricing unwinding. The quantile regression results complement this by showing small-cap (SMB) and growth (HML) effects are asymmetric across return distributions, with SMB's upside potential in favourable conditions ($\tau = 0.9$) and HML's defensive role in downturns ($\tau = 0.1$). This asymmetry suggests that sentiment's impact is contingent on market states: speculative stocks are disproportionately penalized during stress, even if they do not uniformly outperform in high-sentiment periods. Thus, while the results are nuanced, the heightened sensitivity of hard-to-value firms to sentiment reversals, particularly in adverse conditions, supports Hypothesis 2, albeit with a more complex interplay of investor preferences than initially hypothesized.

In the South African literature, the results resonate with Dalika and Seetharam (2015), who argue that smaller, younger, and more volatile firms are more sensitive to investor sentiment. The present findings not only confirm these observations but further demonstrate that sentiment effects are conditional on turnover and market liquidity, with stronger mispricing emerging under negative sentiment regimes. The evidence from both traditional and machine learning-based models converges on the conclusion that investor sentiment modestly impacts stock returns on the JSE, with greater magnitudes in stocks that are speculative or hard to value. Thus, both Hypotheses 1 and 2 are supported, offering compelling empirical evidence of behavioural influences in the South African equity market.

5 Conclusion

This study investigated the relationship between investor sentiment and stock market returns in the South African context. Using sentiment analysis techniques applied to firm and market data, the analysis provided empirical evidence on how investor emotions influenced stock performance. The findings support the first hypothesis: investor sentiment holds a statistically significant negative relationship with future stock returns on the JSE, even after controlling for traditional risk factors such as those captured in the Fama-French three-factor model. Moreover, consistent with the second hypothesis, the impact of sentiment was more pronounced for stocks that are difficult to value or arbitrage, typically smaller, more volatile, or less liquid stocks. These results underscore the nuanced but powerful role of sentiment in driving market behaviour and highlight that psychological factors can amplify or dampen asset pricing mechanisms beyond traditional fundamentals. While sentiment demonstrated notable predictive power, its influence was neither uniform nor constant; instead, it varied across different sectors and periods, suggesting a dynamic interplay with broader market and economic conditions.

5.1 Limitations

While this research provides valuable insights, certain limitations must be acknowledged. First, the measurement of investor sentiment relies on market-based proxies, which may not fully capture the psychological and emotional aspects of investor behaviour. Second, the study's methodology, particularly the econometric models used, assumes linear relationships that may not fully account for the complexity of sentiment-driven market dynamics. Additionally, external macroeconomic factors, such as policy changes, global financial crises, and unforeseen shocks (e.g., the COVID-19 pandemic), may have influenced market behaviour in ways that were not entirely controlled for in the analysis. Finally, data limitations, particularly related to sentiment measures, may have constrained the study's ability to capture nuanced investor sentiment shifts over time.

5.2 Areas for future research

Given these limitations, future research can build upon this study in several ways. First, incorporating alternative sentiment measures, such as social media analytics and machine learning-based sentiment classifiers, could provide a more comprehensive understanding of investor behaviour. Second, applying non-linear modelling techniques may better capture the complexity of sentiment-driven market dynamics. Third, future research could explore sector-specific sentiment impacts to determine if certain industries are more influenced by investor mood shifts than others. Lastly, extending the study to a comparative analysis of multiple emerging markets could help contextualise South Africa's investor sentiment trends within a broader global framework.

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