Investor sentiment, stock returns and idiosyncratic volatility on the Johannesburg Stock Exchange

PAVAN RAKESH HIRAMONEY

215063232

This thesis was submitted in fulfilment of the requirements for the degree of Master of Commerce in Finance by research

School of Accounting, Economics and Finance

College of Law and Management Studies

Pietermaritzburg

Supervisor: Dr Lorraine Muguto

Co-supervisor: Prof Paul Francois Muzindutsi

2025

DECLARATION

I, Pavan Rakesh Hiramoney, declare that:

i. The research reported in this dissertation, except where otherwise stated, is my original research;

ii. This thesis has not been submitted for any degree or examination at this university or any other university;

iii. This thesis does not contain other person's data, pictures, graphs or other information, unless specifically acknowledged;

iv. This thesis does not contain other person's writing, unless specifically acknowledged as being sourced from other researchers;

v. Where other written sources have been quoted, their words have been rewritten but the general information attributed to them has been referenced and where their exact words have been used, their writing has been placed inside quotation marks, and referenced;

vi. This thesis does not contain text, graphics or tables copied and pasted from the internet, unless specifically acknowledged and the source being detailed in the Bibliography section.

vii. Artificial Intelligence (AI) was used responsibly to aid in conducting estimations and sourcing relevant literature to support arguments and statements.

Signed ..[redacted]....... Date 27 June 2025

ACKNOWLEDGEMENTS

Firstly, I would like to express my sincere and profound gratitude to my parents (Rakesh and Nisha Hiramoney) and sister (Nikita Hiramoney) for all their love and support given to me during the period of my Master's degree. I would also like to express my heartfelt gratitude to my supervisor Dr. Lorraine Muguto and co-supervisor Prof. Paul Francois Muzindutsi. Their unwavering support, patience, motivation and immense knowledge played a pivotal role towards my submission. I would like to pay my special condolences to my first supervisor, Dr. Abdulkader Cassim Mahomedy, who I lost during the duration of my studies and whom I miss immensely. His contribution towards my academic journey will never be forgotten. Also, I would like to thank all my conference lectures, presenters and participants, all my friends, my extended family and colleagues for all the unwavering love and support throughout my journey. Finally, I would like to bow down to God for the ultimate guidance and wellbeing that was necessary to complete my degree.

"*This knowledge is the king of education, the most secret of all secrets. It is the purest knowledge and because it gives direct perception of the self by realisation, it is the perfection of religion. It is everlasting and it is joyfully performed*."

- Bhagavad Gita (9.2)

GLOSSARY OF ACRONYMS

ADF -	Augmented Dickey Fuller
AIC -	Akaike Information Criterion
ALSI -	All Share Index
AMH -	Adaptive Markets Hypothesis
APT -	Arbitrage Pricing Theory
ARCH -	Autoregressive Conditional Heteroskedasticity
ARDL -	Autoregressive Distributive Lag
ARMA-GARCH -	Autoregressive Moving Average -Generalized Autoregressive Conditional Heteroskedasticity
BAPT -	Behavioural Asset Pricing Theory
BPT -	Behavioural Portfolio Theory
CAPM -	Capital Asset Pricing Model
CCI -	Consumer Confidence Index
CLRM -	Classical Linear Regression Model
CRSP -	Crispr Therapeutics AG
CSI -	Chinese Securities Index
E-GARCH -	Exponential Generalized Autoregressive Conditional Heteroskedasticity
ECM -	Error Correction Model
EDA -	Exploratory Data Analysis
EMH -	Efficient Market Hypothesis
EMSI -	Emerging Markets Index

FDI -	Foreign Direct Investment
G7 -	Group of Seven
GARCH -	Generalized Autoregressive Conditional Heteroskedasticity
GCC -	Gulf Cooperation Countries
GDP -	Gross Domestic Product
GLS -	Generalized Least Squares
GMM -	Generalized Method of Moments
HML -	High Minus Low
JB -	Jarque-Bera
JSE -	Johannesburg Stock Exchange
KOSDAQ -	Korean Securities Dealers Automated Quotations
KOSPI -	Korea Composite Stock Price Index
KPSS -	Kwiatkowski-Phillips-Schmidt-Shin
KZN -	KwaZulu-Natal
LB -	Low Beta
LFM -	Linear Factor Models
LM -	Lagrange Multiplier
LV -	Low Volume
MENA -	Middle East and North Africa
MSM -	Markov-Switching Multi-Fractal
MLE -	Maximum Likelihood Estimation
MPT -	Modern Portfolio Theory
MSCI -	Morgan Stanley Capital International

NASDAQ -	National Association of Security Dealers Automated Quotations
NARDL -	Nonlinear Autoregressive Distributed Lag
NCD -	Negotiable Certificate of Deposit
NYSE -	New York Stock Exchange
OLS -	Ordinary Least Squares
PCA -	Principal Component Analysis
PP -	Phillips-Perron
REIT -	Real Estate Investment Trust
RSI -	Relative Strength Index
S&P -	Standard and Poor’s 500
SARB -	South African Reserve Bank
SMB -	Small Minus Big
SML -	Security Market Line
STAR -	Smooth Transition Autoregressive
STT -	Securities Transaction Tax
UK -	United Kingdom
USA -	United States of America
VAR -	Vector AutoRegression
VECM -	Vector Error Correction Model
VIX -	Volatility Index
ZAR -	South African Rand

ABSTRACT

The convergence of modern finance theory and empirical evidence is explored to identify the impact of idiosyncratic volatility on stock returns. Whilst traditional financial theory indicates that idiosyncratic volatility should not significantly affect stock returns, real-world data indicates that investors often struggle to diversify effectively, rendering idiosyncratic volatility a relevant risk factor. Traders frequently rely on sentiment to gauge short-term price movements driven by investor behaviour. Therefore, this study argues that investor sentiment, which is not usually grounded in fundamentals, plays an important role in explaining idiosyncratic volatility, thereby influencing stock returns. Consequently, the research investigates the intricate relationship between investor sentiment, stock returns and idiosyncratic volatility within the various sectors of the JSE from January 2003 to December 2022. The study used monthly closing stock prices and dividend yield data from sector indices. PCA was used to gauge investor sentiment, incorporating various proxy indicators, including the rand/dollar exchange rate, repo rate, trading volume, volatility index, net migration rate, price of oil and price of gold, collectively providing an estimate of an investor sentiment index. Idiosyncratic volatility was estimated using computed sector and market returns, size, value, profitability and investment factors. To calculate idiosyncratic volatility, the study applied both the CAPM and the Fama and French 3 & 5 Factor models, which collectively generated a comprehensive measure of idiosyncratic volatility for the analysis. The objectives of the study was to develop an idiosyncratic volatility series for each JSE sector index, to determine the relationship between investor sentiment and idiosyncratic volatility across JSE sectors, to examine the impact of idiosyncratic volatility on stock market returns within the JSE sectors and to analyse the relationship between investor sentiment and stock market returns across JSE sectors. Thereafter, the NARDL model was used as the analysis method to achieve the study's objectives. The study found a significant interplay among investor sentiment, stock returns and idiosyncratic volatility. These key findings highlight a dual relationship for all sectors: firstly, that investor sentiment substantially influences both stock returns and idiosyncratic volatility and secondly, that idiosyncratic volatility exerts a notable impact on stock returns. This underlines the important role of investor sentiment and idiosyncratic volatility as significant risk factors that offer valuable insights for investors seeking to apply valuation models to specific stocks listed on the JSE. Importantly, the

quality of financial information distributed by the market and individual firms plays a central role in shaping both investor sentiment and idiosyncratic volatility.

Key words: Investor sentiment, stock returns, idiosyncratic volatility, JSE, systematic risk, investors and portfolio diversification.

Contents

CHAPTER 1: INTRODUCTION

1.1. Background of the study

Investor sentiment and idiosyncratic volatility have become critical focus areas in modern financial research due to their influence on market efficiency, asset pricing and portfolio management (Seok, Cho and Ryu, 2024). Investor sentiment refers to investors' overall mood or attitude towards market conditions, which can often deviate from fundamental valuation principles (Baker and Wurgler, 2006). This deviation is particularly significant in emerging markets, where behavioural biases and informational asymmetries are more pronounced, distorting pricing mechanisms and contributing to inefficiencies (Barberis, Shleifer and Vishny, 1998). As a prominent emerging market, South Africa is especially susceptible to these inefficiencies as factors such as limited access to reliable financial information and reduced market maturity exacerbate behavioural and structural challenges. These inefficiencies, in turn, amplify idiosyncratic risk, volatility specific to individual firms or sectors rather than the broader market (Nyarikini, 2024).

Unlike systematic risk, which is market-wide and often addressed through macroeconomic policies, idiosyncratic risk can theoretically be mitigated through portfolio diversification (Ellis, Sharma and Brzeszczyński, 2022). However, in practice, achieving optimal diversification in emerging markets is constrained by several factors, including limited investment options, high transaction costs and weak regulatory environments (Meher and Mishra, 2024). Limited investment options are a key constraint in many emerging markets, where the availability of diverse asset classes and a large pool of publicly traded companies is often lacking (Chauhan and Banerjee, 2018). Sectoral concentration exacerbates this issue, as many emerging markets rely heavily on specific industries such as mining, energy or agriculture. For example, the Johannesburg Stock Exchange (JSE) is heavily skewed toward resource-based companies, with mining and resources accounting for approximately 25% of its market capitalisation (Johannesburg Stock Exchange, 2023). This overreliance on a single sector makes it challenging for investors to diversify effectively, leaving portfolios highly susceptible to commodity price fluctuations and external shocks.

Furthermore, the absence of well-developed markets for alternative investments, such as derivatives, Real Estate Investment Trusts (REITs) or venture capital funds, limits diversification opportunities even further (Moagi, 2021). In Nigeria, for instance, the stock market is dominated by financial services and energy companies, with little representation from sectors such as technology, healthcare or consumer discretionary industries (Nigerian Stock Exchange, 2023). Such structural limitations make it difficult for investors to spread their risk across a variety of asset classes and sectors.

High transaction costs are another significant barrier to diversification in emerging markets. These costs include brokerage fees, taxes and market impact costs, all of which are typically higher than those in developed markets (Frazzini, Israel and Moskowitz, 2018). For instance, brokerage fees in South Africa range from 0.5% to 1% of the transaction value, compared to less than 0.1% in the United States of America (USA) (Financial Times, 2024). Similarly, higher bid-ask spreads, driven by low market liquidity, further increase the cost of trading. This liquidity premium makes it more expensive for investors to enter and exit positions, discouraging frequent trading and portfolio rebalancing (Li, 2021). In India, transaction costs are compounded by the Securities Transaction Tax (STT) and stamp duty, which further deter investors from adjusting their portfolios (Meher and Mishra, 2024). These elevated costs not only reduce the efficiency of diversification but also dissuade investors from participating in markets with higher transaction burdens.

Weak regulatory environments further undermine the ability to achieve diversification in emerging markets. Many of these markets lack robust legal and institutional frameworks to protect investors, which fosters mistrust and discourages long-term investments. Corporate governance issues, such as fraud, insider trading and opaque financial disclosures, are prevalent in emerging markets and increase the perceived risk of investing in these regions (Aguilera and Haxhi, 2019). For example, the Steinhoff scandal in South Africa revealed significant gaps in regulatory oversight, eroding investor confidence in the JSE (Johannesburg Stock Exchange, 2015). Regulatory inefficiencies also contribute to market volatility, as seen in Argentina in 2019 when abrupt foreign exchange policy changes triggered massive sell-offs, destabilising the market (Zhao and Wei, 2024).

In many African markets, inconsistent regulatory enforcement and weak investor protections deter both domestic and foreign investors from diversifying into smaller or less liquid securities (Christelis, Georgarakos, Jappelli and Kenny, 2024). These issues limit the ability of investors to construct well-diversified portfolios, thereby increasing their exposure to idiosyncratic risk. As a result, investor sentiment plays a crucial role in shaping asset pricing dynamics, particularly in these African markets. Addressing these challenges requires structural reforms to expand market opportunities, lower transaction costs and strengthen regulatory frameworks. By doing so, these emerging markets can better support diversified portfolios, enhance investor confidence and reduce the impact of idiosyncratic risk.

The JSE, Africa's largest stock exchange and among the top 20 globally by market capitalisation, is integral to South Africa's economy (Johannesburg Stock Exchange, 2023). As of 2023, the JSE hosts over 300 listed companies with a combined market capitalisation exceeding R21 trillion, contributing significantly to regional and global markets (Johannesburg Stock Exchange, 2023). Despite its size and prominence, the JSE faces unique challenges associated with its emerging market status, including limited sectoral diversification, greater exposure to macroeconomic volatility and heightened sensitivity to investor sentiment (Buzuzi, 2023). Compared to developed markets such as the United States or the United Kingdom, where robust institutional frameworks and advanced infrastructure mitigate behavioural inefficiencies, the JSE operates under conditions that amplify the influence of sentiment-driven trading (Muguto, Muguto, Bhayat, Ncalane, Jack, Abdullah, Nkosi and Muzindutsi, 2022). These factors highlight the importance of studying behavioural drivers such as investor sentiment, particularly in their interaction with idiosyncratic volatility across JSE sectors.

Studies in mostly developed markets have shown that investor sentiment strongly correlates with stock returns, often amplifying idiosyncratic volatility (Chuang, Ouyang and Lo, 2010; Li, 2020). In these developed markets, robust institutional frameworks and access to timely financial information help mitigate these behavioural effects (Garad, Riyadh, Al-Ansi and Beshr, 2024). However, investor sentiment in emerging markets such as South Africa often magnifies market inefficiencies due to limited transparency, information asymmetry and underdeveloped regulatory environments (Shenjere, Ferreira-Schenk and Moodley, 2025). This poses significant challenges for investors, who must contend with greater susceptibility to sentiment-driven fluctuations, particularly in political or economic uncertainty periods. For example, during South Africa's Nenegate scandal in 2015, heightened pessimism caused the JSE ALSI to decline by 2.94% in a single day, showing the destabilising effect of sentiment-driven trading (Johannesburg Stock Exchange, 2015). In May 2024, following South Africa's national elections, the JSE experienced notable market movements. The FTSE JSE ALSI increased by approximately 4.1% during this period, reflecting investor optimism. This positive sentiment also led to a surge in the South African rand and strong performance of local assets (Hayward, Moshodi and Abdulla, 2024).

Efficient diversification, a cornerstone of Modern Portfolio Theory (MPT) developed by Markowitz (1991), posits that spreading investments across uncorrelated assets reduces overall portfolio risk. While this principle is widely accepted, practical application often falls short, especially in emerging markets where market imperfections abound (Lukomnik and Hawley, 2021). Imperfections such as information asymmetry, high taxation, wealth restrictions and unobservable market portfolios limit investors' ability to diversify adequately (deLlano-Paz, Calvo-Silvosa, Antelo and Soares, 2017). Studies indicate that South African investors frequently encounter these barriers, leading to suboptimal portfolio performance (Christelis et al., 2024). When diversification is hindered, investors will likely demand a premium to compensate for heightened idiosyncratic risk, significantly impacting asset pricing and overall market efficiency (Levy, 1978; Merton, 1987).

The rationale for efficiently diversifying a portfolio is that if one/few assets perform poorly, others may perform profitably, thereby balancing the portfolio's overall performance. Meher and Mishra (2024) emphasise the importance of efficient diversification, particularly for risk-averse investors. They argue that this strategy enables investors to maintain and pursue the highest expected return for any level of portfolio risk. This reduction of risk is known as the diversification strategy (Chao, 2019), which is a concept that draws its theoretical and practical foundation from MPT, as a diversified portfolio of uncorrelated assets can lead to lower overall risks than any individual assets within the portfolio.

While traditional asset pricing models, such as the Capital Asset Pricing Model (CAPM), assume that only systematic risk is relevant because idiosyncratic risk can be eliminated through diversification (Sharpe, 1964), the reality in emerging markets often deviates from this assumption, making idiosyncratic volatility a significant risk factor for investors (Rutkowska-Ziarko, Markowski, Pyke and Amin, 2022). Research indicates that idiosyncratic risk destabilises portfolio performance and disproportionately affects sectors with higher investor sentiment-driven volatility, such as technology and consumer discretionary industries (Candemir and Karahan, 2024).

The relationship between investor sentiment and idiosyncratic volatility is well-documented in the literature. Investor sentiment significantly influences asset prices by shaping individual investors' perceptions and decisions regarding specific stocks (Nikoo, Ebrahimi and Jalali, 2020). During periods of heightened optimism, demand for certain stocks rises, leading to price surges and increased susceptibility to sentiment-driven volatility (Zhang, Bissoondoyal-Bheenick and Zhong, 2023). Conversely, during periods of pessimism or uncertainty, negative sentiment often triggers sharp declines in stock prices, independent of fundamental factors (Dalika and Seetharam, 2015; Rupande, Muguto and Muzindutsi, 2019; Muguto et al., 2022). These dynamics are particularly pronounced in emerging markets where macroeconomic events such as currency fluctuations and policy announcements often sway investor behaviour.

Investor sentiment has consistently played a pivotal role in driving stock market behaviour, often causing significant deviations from fundamental valuations. Globally, the 2008 global financial crisis provides a notable example, where pessimistic sentiment amplified sell-offs and contributed to a sharp decline in stock prices, with the Standard and Poor's 500 (S&P) losing nearly 38% of its value in a single year (Standard & Poor's, 2008). Similarly, during the COVID-19 pandemic in 2020, optimistic sentiment following stimulus announcements led to a rapid recovery in equity markets, with the Morgan Stanley Capital International (MSCI) World Index increasing by 14% by the end of the year, despite ongoing economic uncertainties (MSCI, 2020).

In South Africa, investor sentiment significantly influences the JSE (Rupande et al., 2019; Muguto et al., 2022; Muzindutsi, Apau, Muguto and Muguto, 2023). For instance, during periods of political instability, such as the announcement of “Nenegate” in 2015, where South Africa’s finance minister was abruptly replaced, the JSE All Share Index (ALSI) fell by 2.94% in a single day, reflecting heightened uncertainty (Johannesburg Stock Exchange, 2015). Conversely, positive sentiment following the election of Cyril Ramaphosa in 2018 led to a “Ramaphoria” rally, during which the JSE ALSI rose by 4.9% in February alone (Financial Times, 2018). These examples highlight the profound impact of sentiment on market performance, with both global and local markets reacting swiftly to shifts in investor sentiment, often independent of underlying economic fundamentals. Therefore, understanding how investor sentiment interacts with idiosyncratic volatility is critical for assessing stock market performance and improving portfolio strategies.

1.2. Problem Statement

The global financial crisis of 2007-2008 exposed the vulnerabilities of financial markets, particularly during periods of price bubbles and heightened volatility, when insufficient liquidity significantly affected market participants and the broader economy (Thakor, 2015). Liquidity, which reflects the ease with which assets can be traded without substantial price disruptions, is critical for efficient markets (Trebbi and Xiao, 2019). Yet, its determinants remain complex and not fully understood, particularly in emerging economies. Extensive research has shown that behavioural factors, such as investor sentiment, play a pivotal role in liquidity dynamics. For example, Baker and Stein (2004) argue that increased noise trading during periods of heightened sentiment directly impacts liquidity, while overconfidence and excessive optimism indirectly influence market stability (Liu, 2015). Despite the clear implications of these findings, there is limited understanding of how investor sentiment interacts with other key financial factors, such as idiosyncratic volatility, particularly in emerging markets such as South Africa.

The COVID-19 pandemic further highlighted the critical role of investor sentiment in driving stock market behaviour, particularly in emerging markets such as South Africa. The unprecedented uncertainty during the early months of the pandemic led to heightened market volatility as investors reacted to rapidly evolving information. On the JSE, the pandemic-induced selloff in March 2020 saw the FTSE/JSE ALSI plummet by over 30% within weeks, reflecting widespread panic and pessimism among investors (Johannesburg Stock Exchange, 2020). This extreme volatility highlighted the influence of investor sentiment on market movements, with sentiment-driven trading exacerbating idiosyncratic risk across sectors such as travel, retail and financial services (Vengesai, 2022). Conversely, positive sentiment driven by global stimulus measures and vaccine rollouts in late 2020 contributed to a swift recovery, with the FTSE/JSE ALSI rebounding by 54% by the end of the year (MSCI, 2020). These developments emphasised the vulnerability of emerging markets to sentiment-induced fluctuations, which often amplify idiosyncratic volatility. Understanding the interplay between investor sentiment, stock returns and idiosyncratic risk during crises such as COVID-19 is crucial for developing resilient investment strategies and improving market efficiency in such volatile environments.

Despite the prominence of the JSE, it faces unique challenges that make it particularly vulnerable to the influence of investor sentiment. Political instability, fluctuating macroeconomic conditions and structural inefficiencies have resulted in periods of underperformance, as seen during the early 2020s when economic recovery lagged behind global trends (Nel, 2020). At the same time, idiosyncratic volatility has become a critical risk factor on the JSE, driven by sectoral dynamics, such as resource dependence and limited diversification across industries (Muguto et al., 2022). These challenges emphasise the need for a deeper understanding of how investor sentiment interacts with idiosyncratic volatility to influence stock returns, particularly in an emerging market context where traditional asset pricing models do not account for behavioural effects in financial markets (Sharpe, 1964; Wang, 2024).

As discussed earlier, emerging markets face additional complexities due to market imperfections, such as high transaction costs, inadequate liquidity and unobservable market portfolios. These imperfections often hinder optimal portfolio diversification, exposing investors to higher levels of idiosyncratic risk (deLlano-Paz et al., 2017). In South Africa, where structural inefficiencies exacerbate idiosyncratic risk, investors frequently encounter challenges in balancing risk and return. This is particularly evident in the technology and consumer discretionary sectors, where sentiment-driven trading tends to amplify price volatility (Candemir and Karahan, 2024). Understanding the relationship between investor sentiment and idiosyncratic volatility is critical for academics and practitioners seeking to enhance investment strategies, improve market efficiency and mitigate risks.

Despite the extensive literature on investor sentiment and its relationship with stock returns in developed markets such as Baker and Wurgler (2007); (Schmeling, 2009), significant gaps persist in the context of emerging markets such as South Africa. The existing research often overlooks the role of behavioural biases in shaping market outcomes in regions where economic instability and institutional weaknesses magnify these effects especially its impact on idiosyncratic volatility. This gap is particularly concerning for the JSE, given its systemic importance to South Africa's economy and its influence on regional financial stability. Understanding how investor sentiment drives stock returns and interacts with idiosyncratic volatility in this unique context is crucial for addressing market inefficiencies, developing more robust asset pricing models and informing both policy and investment decisions.

While investor sentiment has been widely studied in developed markets, its effects on stock returns and idiosyncratic volatility remain under-researched in emerging markets such as South Africa. The unique structure of the JSE, together with limited sector-specific studies and a lack of locally developed investor sentiment indices, highlights a significant gap in literature. This study seeks to address the lack of empirical evidence on how investor sentiment influences idiosyncratic volatility and stock returns across different sectors of the JSE, especially in the context of South Africa's evolving post-COVID-19 market environment.

1.3. Research Aim, Objectives and Questions

1.3.1. Research Aim

The research aims to investigate the relationships between investor sentiment, stock returns and idiosyncratic volatility on the Johannesburg Stock Exchange.

1.3.2. Research Objectives

To achieve the above aim, the study, therefore, seeks to:

i. Develop an idiosyncratic volatility series for each JSE sector index.

ii. Determine the relationship between investor sentiment and idiosyncratic volatility across JSE sectors.

iii. Examine the impact of idiosyncratic volatility on stock market returns within the JSE sectors; and,

iv. Analyse the relationship between investor sentiment and stock market returns across JSE sectors.

1.3.3. Research Questions

The above objectives are achieved by answering these questions:

i. What is the nature of idiosyncratic volatility across the JSE sectors?

ii. How does investor sentiment influence idiosyncratic volatility within the JSE sector-based indices?

iii. How does idiosyncratic volatility impact stock market returns across JSE sectors?

iv. How does investor sentiment affect stock market returns in the context of JSE sector indices?

1.4. Significance of the Study

This study holds significant importance as it seeks to address a critical gap in the literature by examining the relationship between investor sentiment, stock returns and idiosyncratic volatility within the context of an emerging market, South Africa. While an abundance of research exists on these topics, the majority focuses on developed markets with well-established regulatory frameworks, mature institutions and robust financial infrastructures (Baker and Wurgler, 2006; Li, 2020). Emerging markets, however, present unique challenges such as heightened information asymmetry, limited diversification opportunities and greater susceptibility to sentiment-driven trading (Meher and Mishra, 2024; Zhao and Wei, 2024). By focusing on the JSE, this study provides a comprehensive understanding of how behavioural factors, such as investor sentiment, interact with structural inefficiencies to shape market outcomes in a developing economy. The findings of this study are expected to contribute valuable empirical evidence to the field of behavioural finance, offering insights into how sentiment influences idiosyncratic volatility and stock returns in the JSE sectors (Candemir and Karahan, 2024).

Furthermore, these insights have practical implications for policymakers and regulators, who can use the results to design more effective market stabilisation measures and improve investor confidence (Chuang et al., 2010; Liu, 2015). For investors and portfolio managers, understanding these dynamics will aid in developing strategies to mitigate sentiment-driven volatility, optimise portfolio diversification and enhance long-term returns (deLlano-Paz et al., 2017). By bridging the gap between developed and emerging market studies, this research enriches the global discourse on behavioural finance and provides actionable knowledge tailored to the unique challenges and opportunities present in South Africa's financial markets.

1.5. Theoretical Framework and Scope of the Study

This study is grounded in several key theories that underpin its empirical framework, model selection and variable choices. These theories, including the CAPM, the Efficient Market Hypothesis (EMH), and Behavioural Finance Theory, provide a comprehensive foundation for examining the relationships between investor sentiment, idiosyncratic volatility and stock returns. While this section introduces these theories, their detailed discussions and applications are expanded in Chapter 2.

The CAPM is one of the most influential models in finance, describing the relationship between risk and expected return for financial assets such as stocks (Treynor, 1962; Sharpe, 1964; Lintner, 1965a; Mossin, 1966; Chen, 2022; Wang, 2024). CAPM provides a foundational framework for understanding the relationship between risk and return. It focuses on systematic risk, which is market-wide and cannot be diversified away while assuming that idiosyncratic or firm-specific risk can be mitigated through diversification (Dybvig and Ross, 1985). However, in emerging markets such as South Africa, structural constraints such as sectoral concentration, limited investment opportunities and weak institutional frameworks make idiosyncratic risk more prominent and difficult to eliminate. This challenges CAPM's core assumption of full diversification, making the study of idiosyncratic volatility particularly relevant on the JSE. Moreover, CAPM assumes that investors are rational and base their decisions solely on logic and available information (Muth, 1961). However, the influence of investor sentiment, which drives irrational decision-making, directly contradicts this assumption. Sentiment-driven trading caused by excessive optimism or pessimism can inflate or deflate asset prices, leading to deviations from the risk-return relationship predicted by CAPM (Baker and Wurgler, 2006). These behavioural influences are especially significant in markets prone to inefficiencies, such as South Africa's JSE.

CAPM also assumes market efficiency, where asset prices fully reflect all available information, yet sentiment-driven mispricing often leads to inefficiencies, especially in emerging markets (Malkiel, 2003). While CAPM provides a theoretical basis for estimating stock returns based on an asset's beta (a measure of systematic risk), it fails to account for behavioural factors such as investor sentiment, which independently drives stock returns and amplifies idiosyncratic volatility (Chuang et al., 2010). For example, sentiment-driven trading often causes stocks with high idiosyncratic risk to exhibit abnormal returns, creating anomalies that CAPM cannot explain. By exploring the effects of investor sentiment on idiosyncratic volatility and stock returns, this study addresses gaps in CAPM's ability to explain pricing dynamics in emerging markets fully. Furthermore, CAPM serves as a foundation for many empirical models, including the Fama-French 3 and 5 Factor models used in this study to estimate idiosyncratic volatility (Fama and French, 2015). This study provides practical implications for investors, portfolio managers and policymakers by acknowledging CAPM's limitations and incorporating behavioural insights. It highlights the importance of integrating behavioural factors into asset pricing models to improve market efficiency and resilience, particularly in emerging markets.

The EMH asserts that financial markets are informationally efficient, meaning that asset prices fully reflect all available information at any given time (Fama, 1970; Degutis and Novickytė, 2014). This implies that rational investors promptly adjust their portfolios in response to new information, making it nearly impossible to achieve excess returns through arbitrage consistently. According to Malkiel (2003), the EMH suggests that any opportunities for mispricing are quickly eliminated as information is incorporated into asset prices. However, the validity of the EMH is often challenged, particularly in the context of emerging markets such as South Africa. In these markets, structural inefficiencies such as limited transparency, information asymmetry and high transaction costs hinder the full integration of information into asset prices, allowing mispricing and inefficiencies to persist over time.

On the JSE, such inefficiencies are exacerbated by factors such as sectoral concentration, political instability and limited institutional investor participation, all of which reduce market efficiency and create opportunities for sentiment-driven price movements. For instance, during periods of heightened optimism or pessimism, investor sentiment can drive asset prices away from their fundamental values, contradicting the EMH's assumption of rational price adjustments. This dynamic is particularly relevant to the study of idiosyncratic volatility, as persistent inefficiencies amplify firm-specific risks that traditional models like the EMH fail to fully explain. Understanding the limitations of the EMH in the context of the JSE underscores the importance of behavioural factors, such as investor sentiment, in explaining stock returns and volatility in emerging markets.

Behavioural Finance Theory bridges the gap between traditional finance theories, such as the EMH & CAPM and the psychological factors influencing investor behaviour. This theory challenges the assumption of rationality in financial decision-making, instead focusing on how cognitive biases, emotions and heuristics drive investment choices (Prosad, Kapoor and Sengupta, 2015). Sewell (2010) emphasises that psychological biases such as overconfidence, herd behaviour and loss aversion are key contributors to market inefficiencies. These biases often result in deviations from the rational expectations predicted by traditional finance theories, leading to anomalies such as excessive price volatility and mispricing.

In the context of the JSE, behavioural finance provides a critical lens for examining the impact of investor sentiment on stock returns and idiosyncratic volatility. For example, overconfident investors may drive up stock prices during periods of strong optimism, increasing idiosyncratic risk as individual stocks become overvalued relative to their fundamentals. Conversely, during periods of pessimism, herd behaviour and loss aversion may lead to sharp declines in stock prices, further amplifying volatility. Shiller (1981); Thaler (1999) demonstrated that stock prices often exhibit greater volatility than can be justified by changes in intrinsic value, a phenomenon also observed on the JSE during events like South Africa’s Nenegate scandal and the COVID-19 pandemic. This study leverages behavioural finance to explore how investor sentiment influences market dynamics, highlighting the role of psychological biases in shaping asset prices and firm-specific risks on the JSE. By integrating insights from behavioural finance, the study aims to address gaps in traditional theories and provide a more comprehensive understanding of market behaviour in emerging economies.

This study employs a quantitative research methodology, utilising both descriptive and econometric approaches to examine these relationships. The Fama-French 3 and 5 Factor Models are applied to estimate idiosyncratic volatility, providing insights into firm-specific risks beyond the broader market factors. Additionally, Principal Component Analysis (PCA) is used to construct a comprehensive investor sentiment index, which captures the aggregate mood of the market based on multiple indicators. To assess the dynamic relationships among the variables, the study employs the Nonlinear Autoregressive Distributed Lag (NARDL) model with regressions estimated using the Ordinary Least Squares (OLS) method. Key statistical outputs, such as F-statistics, T-statistics and adjusted R-squared values, are used to evaluate the robustness of the models.

The findings of this study have significant implications for both theoretical and practical domains. Theoretically, the study enhances the understanding of behavioural biases in emerging markets and their impact on asset pricing models. Practically, it provides valuable insights for investors, regulators and policymakers. For instance, an updated monthly investor sentiment index could serve as a tool for regulators to monitor market irrationality and implement timely stabilisation measures. Moreover, the study highlights the challenges investors face in achieving optimal diversification due to idiosyncratic volatility, which is exacerbated by the limited industry representation on the JSE. Addressing this issue may require introducing policy measures, such as financial incentives for new industries, regulatory adjustments and mandatory public listings for firms exceeding specific sales thresholds. These steps could improve diversification opportunities and foster a more efficient and resilient financial market in South Africa.

1.6. Delimitations of the Study

This study investigates the relationships between investor sentiment, idiosyncratic volatility and stock returns, focusing specifically on sectors within the JSE. While the scope of the study is adequate to meet its stated objectives, certain delimitations should be acknowledged. By narrowing the analysis to JSE sectors, the findings may not fully capture the dynamics of other stock markets, particularly those in different emerging economies or developed markets. As a result, the ability to generalise the study's conclusions beyond the JSE is limited. However, the selected JSE sectors provide a robust and relevant sample for investigating the relationship between investor sentiment, stock returns and idiosyncratic volatility, making the study's findings highly applicable within the South African context. Given the JSE's importance as Africa's largest stock exchange and a representative benchmark for South African financial markets, this focus still provides meaningful insights into the behavioural and structural factors influencing asset pricing in emerging markets.

Another delimitation of the study relates to the frequency of the data used for empirical modelling and analysis. Monthly data was used to analyse long-term trends in investor sentiment and market dynamics. While this frequency helps reduce the noise and anomalies often present in high-frequency data such as daily or weekly series, it may overlook short-term fluctuations in investor sentiment and their immediate impact on idiosyncratic volatility. The rationale for using monthly data is that it offers a clearer perspective on broader market trends and is more suited to capturing the persistent relationships between investor sentiment, stock returns and idiosyncratic volatility. Moreover, high-frequency data often increases computational complexity and introduces greater sensitivity to transient market shocks, which may detract from the study's focus on long-term dynamics. Despite these limitations, the study employed various robustness checks and validation procedures to ensure the reliability and validity of its findings. These methodological precautions reinforce the credibility of the study's results and support its contribution to understanding the behavioural and structural drivers of stock market dynamics in South Africa.

1.7. The Structure of the Study

The structure of this thesis is organised as follows: Chapter 1 introduces the study, including the research topic, problem statement and objectives, while emphasising the significance of addressing the identified gaps in the literature. Chapter 2 provides a comprehensive review of the theoretical and empirical literature, establishing the conceptual framework and exploring existing studies on the key variables of interest. Chapter 3 outlines the research methodology and analytical techniques employed to achieve the study's objectives, including model specifications and data collection methods. Chapter 4 presents and discusses the empirical results, interpreting the findings within the context of the research objectives and the broader literature. Chapter 5 concludes with remarks on the study's contributions, practical implications, limitations and recommendations for future research.

1.8. Summary

Chapter 1 introduced the study by providing a comprehensive overview of its focus on the relationship between investor sentiment, idiosyncratic volatility and stock returns within the JSE context. The chapter outlined the research problem, highlighting the gaps in existing literature, particularly the limited focus on emerging markets such as South Africa, where behavioural biases and structural inefficiencies play a significant role in financial market dynamics. The study's objectives emphasise the need to understand how investor sentiment influences idiosyncratic volatility and stock returns across JSE sectors. The chapter also discussed the study's theoretical foundations, including the CAPM, the EMH and Behavioural Finance Theory and their relevance to the research topic. By addressing these gaps, the study aims to contribute to the growing field of behavioural finance while providing practical insights for investors, portfolio managers and policymakers to enhance market efficiency and optimise investment strategies in South Africa. The following chapter, Chapter 2, builds on this foundation by conducting a detailed review of existing theoretical and empirical literature, providing deeper insights into the key variables of interest, investor sentiment, stock returns and idiosyncratic volatility, and their interconnected dynamics in both developed and emerging market contexts.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

Chapter 1 outlined the logic and general context of the study. This chapter reviews the existing literature on the subject. Reviewing the existing literature is important to position the research study against the context of related studies. In addition, the literature review highlights this study's significance, justification and contribution to the body of knowledge. The chapter begins by exploring investor sentiment, stock returns, idiosyncratic volatility and key theories and concepts in this domain. Finally, the chapter reviews the study's theoretical and empirical framework, concluding with a summary. It is important to acknowledge that the existing literature has abundant research evidence on the subject. However, while there has been a significant number of research material on the subject, there is a lack of a general consensus on the nature of relationships as well as the behaviour of the variables when modelled under varying conditions, with different proxies and under different study contexts. Therefore, continuous research on this subject, in this discipline is warranted.

2.2. Theoretical Framework

This section of the study presents the theoretical frameworks that underpins the conceptual and empirical frameworks of this study. This discussion will be succeeded by empirical evidence on the subject.

2.2.1. Efficient Market Hypothesis

The EMH, proposed by Fama (1970), asserts that financial markets show informational efficiency. This implies that the asset prices are fully reflective of all information that is currently available in the market. The EMH contends that consistently achieving higher returns than the entire market by selecting stocks or timing the market is impossible. This is as a result of all new information being immediately and fully reflected in asset prices (Fama, 1970). The EMH is classified into three forms: weak, semi-strong and strong. Each of these forms represents different conditions of market efficiency.

In a weak-form efficient market, historical price fluctuations and sentiment indicators ought not to affect subsequent returns. Empirical research indicates that investor sentiment influences stock prices, especially in small-cap and speculative stocks (Baker and Wurgler, 2006). According to the semi-strong form of the EMH, all publicly accessible information, including sentiment indicators such as trading volume, surveys and media attention, should be immediately reflected in asset prices. Studies indicates that investor sentiment may result in mispricing, leading to foreseeable price reversals (Barberis et al., 1998).

In strong-form efficiency, prices incorporate even private information, negating chances for sentiment-driven trading advantages. Behavioural biases, including overconfidence and herding behaviour, indicate that investor attitude influences stock price formation, resulting in enduring inefficiencies (Daniel, Hirshleifer and Subrahmanyam, 1998). These anomalies challenge the strict assumptions of the EMH, especially in markets with lower liquidity.

Idiosyncratic volatility, indicative of firm-specific risk, is anticipated to be mitigated in an efficient market. Studies indicates that increased sentiment periods enhance implied volatility, especially in speculative stocks (Stambaugh, Yu and Yuan, 2012). During periods of high sentiment, investors tend to overreact to favourable news, resulting in increased volatility and stock-specific risk. In contrast, during times of lower sentiment, risk-averse conduct decreases trade volume and suppresses implied volatility, indicating that sentiment-driven trading behaviour opposes the predictions of the EMH (Brown and Cliff, 2005).

In highly efficient markets, implied volatility should not forecast excess returns, as prices adapt to new information without systematic mispricing. Empirical data shows that stocks with high implied volatility show return reversals, consequently challenging the EMH’s claim that stock prices adequately incorporate all risks (Ang, Hodrick, Xing and Zhang, 2006).

Despite the EMH arguing that active trading methods should not exceed the performance of passive indexing, data indicates that sentiment-driven distortions generate short-term mispricing opportunities. Portfolio managers and traders can capitalise on sentiment-induced inefficiencies by using opposing strategies in overpriced markets and momentum strategies in sentiment-driven uptrends (Huang, Jiang, Tu and Zhou, 2015). Moreover, alternative asset pricing models, such Behavioural Asset Pricing Theory (BAPT), use investor sentiment to clarify differences from fundamental prices (Shefrin and Statman, 2000).

Experimental studies seek to harmonise the EMH with anomalies caused by investor sentiments. Baker and Wurgler (2006) show that investor sentiment is a strong predictor of future stock returns, especially in speculative stocks, which undergo price corrections following times of high sentiment. Research on market anomalies, such as momentum and mean reversion effects, indicates that investor sentiment creates transient inefficiencies, challenging the stringent assumptions of the EMH (Da, Engelberg and Gao, 2015).

Regression models linking sentiment indicators to stock returns and volatility reveal that excessive trading activity and speculative behaviour aggravate inefficiencies, creating opportunity for counter tactics. Moreover, event studies such as Zhu, Niu and Zhao (2020) examining investor reactions to earnings announcements and macroeconomic information indicate that markets do not consistently respond immediately, allowing for sentiment-induced mispricing.

2.2.2. Markowitz Portfolio Selection Theory

Literature on the predictability of stock returns gained popularity with Markowitz (1967)'s Portfolio Selection study. The model is based on the notion that diversifying financial assets reduces risk instead of holding a single type. The model also suggests that an asset's risk and return should be measured in the context of its proportion to the overall portfolio's risk and return (Markowitz, 1967). Therefore, an investor willing to take on more risk is typically rewarded with higher returns, while a risk-averse investor will receive proportionately lower returns.

Investor sentiment significantly influences portfolio selection and asset pricing by influencing investor behaviour and market efficiency. During times of increased sentiment, investors show increased risk-taking patterns, resulting in increased demand for volatile assets and a deviation from rational portfolio management (Barberis et al., 1998). This undue optimism may amplify anticipated returns while also increasing portfolio variability, rendering conventional MPT assumptions less relevant. In contrast, during periods of low sentiment, investors show risk aversion, reallocating their resources to safe-haven assets, which subsequently diminishes stock market volatility and portfolio risk (Baker, Wurgler and Yuan, 2012).

Idiosyncratic volatility, indicating stock-specific risk unaccounted for by market forces, is especially responsive to sentiment-induced mispricing. During periods of increased sentiment, retail investors show herding behaviour, resulting in increased volatility in small-cap and growth companies (Tetlock, 2007). The increased implied volatility diminishes the diversification advantages of Markowitz's portfolio selection, as sentiment-driven stocks show correlated movements, consequently undermining the efficacy of risk minimisation measures (Stambaugh et al., 2012). Conversely, in sentiment-depressed environments, stock prices are more closely correlated with principles, resulting in less implied volatility and facilitating more effective portfolio diversification (Brown and Cliff, 2005).

Experimental studies have examined the influence of investor sentiment on portfolio efficiency and the risk-return trade-offs of stocks. Baker and Wurgler (2006) show that portfolios formed during periods of high sentiment typically underperform in later periods, as overvalued stocks undergo correction over time. Regression models correlating sentiment indices with portfolio returns indicate that excess volatility and sentiment-induced mispricing are substantial factors influencing stock performance (Da et al., 2015). Moreover, mean-variance analysis indicates that sentiment cycles affect the configuration of the efficient frontier, whereby elevated sentiment increases systematic risk exposure and reduces diversification benefits (Campbell and Vuolteenaho, 2004).

Further studies also indicates that integrating sentiment indicators into portfolio development can improve investment methods (Huang et al., 2015). By dynamically modifying portfolio weights according to sentiment indicators like the Volatility Index (VIX), trading volume and investor surveys, investors can alleviate sentiment-induced volatility and mispricing. Behavioural Portfolio Theory (BPT) has arisen as an alternative to MPT, addressing investor irrationality and sentiment-driven decision-making (Shefrin and Statman, 2000). Furthermore, sophisticated econometric models like the NARDL framework can be used to assess asymmetric investor responses to sentiment fluctuations, therefore offering a more precise risk assessment methodology (Zhu et al., 2020).

2.2.3. Capital Asset Pricing Model

Following Markowitz (1952), Treynor (1962); Sharpe (1964); Lintner (1965b); Mossin (1966) developed the CAPM in the 1960's. This model is used to price individual securities or portfolios, considering an asset's sensitivity to systematic risk, indicated by Beta (Connor and Korajczyk, 1995). For pricing individual assets, the model employs the Security Market Line (SML), which relates expected return to systematic risk, showing that the market prices assets according to their risk class. The security market line thus allows the calculation of the risk-to-reward ratio for a single asset in relation to the overall market (Connor and Korajczyk, 1995). These theories highlighted the crucial direct relationship between risk and returns.

The mean-variance efficient portfolio, for example, may be challenging to build in reality due to a variety of limitations, including cost, interest rate, currency and behavioural characteristics like rational investors. It also makes numerous assumptions that may not hold true in the real world. As a result, idiosyncratic risk should not be undervalued because it has significant ramifications for understanding asset-pricing models (Vidal-García, Vidal, Boubaker and Manita, 2019). In fact, it has been established throughout time that many unsystematic factors such as fund managers' skills and techniques, timing abilities and market inefficiencies can outweigh superior return performance (Ajadi, 2023).

A major limitation of CAPM in emerging markets is the absence of idiosyncratic risk. The model proposes that unsystematic risk can be mitigated through diversification; however, investors in emerging markets may not have completely diversified portfolios due to market constraints (Zaimovic, Omanovic and Arnaut-Berilo, 2021). The absence of diversity compels investors to seek a premium for incurring idiosyncratic risk. Rupande et al. (2019) showed evidence supporting this idea, showing that firm-specific factors significantly influence stock returns on the JSE. This finding undermines the CAPM assumption that only systematic risk is priced and indicates that idiosyncratic risk plays a more significant role in emerging markets.

van Rensburg and Robertson (2003) studied the effectiveness of CAPM on the JSE and determined that the model did not adequately address specific anomalies, including the size and value effects. They also noted that smaller firms and those with higher book-to-market ratios usually outperform, suggesting that risk factors beyond market beta may affect stock returns on the JSE. This coincides with the findings of Fama and French (1992), who recognised similar anomalies in United States markets, resulting in the formulation of the Fama-French 3 Factor Model.

The significance of CAPM in emerging markets, including South Africa’s JSE, have undergone rigorous investigation as seen by Segojane and Ndlovu (2022); Vidal-García and Vidal (2024). Emerging markets frequently display features that undermine the foundational assumptions of CAPM, such as market inefficiencies, increased transaction costs, information asymmetry and political instability. These factors may result in differences between the expected returns forecasted by CAPM and the actual returns experienced in these markets. Reddy and Thomson (2011) studied the empirical validity of the CAPM in the South African stock market by analysing quarterly total returns from ten sectoral indexes on the JSE from June 1995 to June 2009. Their findings showed that although CAPM may be rejected for specific intervals, its application for long-term actuarial modelling in the South African market is justifiably reasonable. This indicates that CAPM may possess limited applicability in the short term, although it may however provide usefulness in long-term financial planning.

Furthermore, the assumption of market efficiency inherent in CAPM is frequently violated in emerging markets. Information asymmetry, weak regulatory frameworks and limited investor knowledge could result in mispricing and anomalies that the CAPM cannot address (Tompo, 2023). Ananwude and Osakwe (2017) emphasised that political instability, liquidity constraints and economic shocks greatly influence asset pricing on the JSE, factors overlooked in the CAPM framework.

2.2.4. Arbitrage Pricing Theory

Developed by Ross (1976) in the 1970's, the Arbitrage Pricing Theory (APT) offers an alternative to the CAPM by explaining asset returns through multiple factors rather than a single market index. APT indicates that asset returns can be predicted using a linear relationship between the expected return and various macroeconomic factors, such as inflation, interest rates and industrial production (Ross, 1976). The theory allows for a more flexible and comprehensive approach to asset pricing by considering multiple sources of systematic risk. The APT is a one-period model, in which preclusion of arbitrage over static portfolios of these assets lead to a linear relation between the expected return and its covariance with the factors.

The empirical validation of the APT has been an important topic in financial studies, with several studies examining the model's relevance across diverse markets and time periods. Chen, Roll and Ross (1986) conducted a study that identified key economic variables influencing stock returns. The study emphasised that unexpected changes in inflation, industrial production, risk premiums and changes in the term structure are crucial factors influencing asset returns, thereby supporting the multifactorial essence of APT. Iqbal and Haider (2005) studied the APT model on returns from 24 actively traded stocks in the Karachi Stock Exchange, using monthly data from January 1997 to December 2003 within the context of emerging markets. The findings showed that both anticipated and unanticipated inflation, as well as market index and dividend yield, were major influences of stock returns, thereby offering empirical support for the APT in the Pakistani market.

Recent developments in econometric techniques allowed for more rigorous testing of the APT. Moriya and Noda (2023) analysed the time-varying framework of APT using Japanese sector indexes. The study used a rolling window approach to evaluate the impact of fluctuations in monetary policy and economic conditions on the validity of the APT over time. The results indicate that the applicability of APT is inconsistent, with its validity affected by external economic variables. The flexibility of APT allows it to be used in various financial contexts. Huberman (2005) studied the implications of APT in the evaluation of managed portfolios. They indicated that although the APT establishes a linear relationship between expected returns and factor loadings, it does not eliminate the possibility of arbitrage within dynamic portfolios, indicating constraints in its use for assessing the performance of actively managed funds.

Despite its advantages, APT encounters numerous challenges, especially in the identification and selection of adequate risk factors. In contrast to CAPM, which identifies the market portfolio as the single component, APT lacks clear direction for the factors to incorporate into the model (Wu, 2022). The absence of specificity may result in model ambiguity, as many studies may regard various factors as significant. Moreover, the sensitivity of asset returns to these factors, shown by factor loadings, may fluctuate over time, so complicating the estimate process and potentially weakening the model’s forecast accuracy (Cakici and Zaremba, 2024). Changes in macroeconomic conditions may impact the relationships between variables and asset returns, requiring ongoing monitoring and adjustment of the model. Furthermore, the presumption of linear correlations between variables and returns may also simplify the intricacies of financial markets, thus constraining the model’s relevance in specific circumstances (Ndlovu, Faisal, Resatoglu and Tursoy, 2018).

2.2.5. Behavioural Finance

Kahneman and Tversky (1979) developed the concept of Prospect Theory. The theory centres on the premise that profits and losses are assigned distinct values. Therefore, investors are expected to make investment decisions based on potential profits instead of potential losses. Loss aversion is the fundamental principle of Prospect Theory. This implies that when an investor is faced with two choices, one offering the possibility of gains and the other the possibility of losses, the investor will select the alternative that has the potential for profits (Kahneman and Tversky, 1979). Prospect theory, a component of behavioural economics, implies that investors make decisions based on anticipated gains due to the substantial emotional impact caused by losses (Barberis, 2013).

Investor sentiment significantly influences market price fluctuations and anomalies, as it fosters irrational optimism and pessimism. Behavioural Finance recognises two primary psychological biases influencing stock returns: heuristics and framing effects (Kahneman and Tversky, 1979). During times of increased investor sentiment, individuals frequently show overconfidence and herd behaviour, resulting in asset overvaluation and eventual declines in returns (Barberis et al., 1998). In contrast, during periods of low sentiment, risk aversion prevails, resulting in the undervaluation of stocks and slow price movements (Baker and Wurgler, 2006).

Conversely, when sentiment decreases, stock prices realign with fundamentals, resulting in reduced excess volatility. Institutional investors dominate trade, limiting speculative price fluctuations, which minimises idiosyncratic volatility and facilitates improved portfolio optimisation (Brown and Cliff, 2005).

Idiosyncratic volatility, indicative of firm-specific risk, is also affected by investor sentiment. Behavioural Finance argues that stocks showing higher susceptibility to sentiment demonstrate increased idiosyncratic volatility as a result of speculative trading and noise trader risk (De Long, Shleifer, Summers and Waldmann, 1990). In periods of increased sentiment, retail investors participate in speculative trading, leading to stock price volatility and increasing mispricing, especially in small-cap, growth and technology stocks. The advantages of diversification diminish as sentiment-driven assets exhibit greater correlation (Stambaugh et al., 2012).

In the past few years, Prospect Theory has been extensively used and examined across multiple scenarios. Barberis (2013) conducted an extensive study of its applications in economics, explaining how the theory accounts for phenomena such as the stock premium puzzle and the disposition effect in financial markets. The equity premium puzzle implies the empirical finding that stocks have continuously surpassed bonds by a greater extent than traditional financial theories can explain. Prospect Theory suggests that loss aversion leads investors to seek a greater premium for holding riskier stocks, therefore providing an adequate justification for this unpredictability.

Empirical studies shows that sentiment-induced mispricing results in return anomalies, exemplified by momentum and reversal effects, wherein overvalued stocks incur negative future returns and undervalued stocks earn higher future returns (Da et al., 2015). These findings challenge the EMH, illustrating how sentiment affects stock price movement and return predictability.

Behavioural finance challenges traditional financial theories by including investor psychology to analyse investor behaviour. This theory includes psychological components into financial theory. It suggests that investors frequently make decisions based on emotions rather than rationality, emphasising the effect of behavioural biases and emotional factors on investor behaviour (Almansour, Elkrghli and Almansour, 2023). Fundamental concepts in behavioural finance includes overreaction, wherein investors frequently show an exaggerated response to new information, leading to disproportionate movements in asset prices. Such responses could result in the formation of price bubbles or an excessive level of volatility (Hammond, 2015). The concepts highlighted in behavioural finance include overconfidence, loss aversion and herd behaviour, which can cause anomalies from hypotheses and the predictions of models such as the EMH and CAPM. Behavioural finance provides a nuanced understanding of market dynamics by recognising the impact of human behaviour on idiosyncratic volatility.

In financial markets, this behaviour is seen in the overreaction to recent losses and the underreaction to prospective future gains, affecting investor sentiment and trading patterns. Investors sometimes retain underperforming stocks longer than advisable (the disposition effect) while liquidating profitable stocks prematurely to realise gains (Shefrin and Statman, 1985). In emerging markets such as South Africa, characterised by significant retail investor involvement and potentially weak regulatory control, these behavioural biases increase market volatility and induce price inefficiencies (Moodley, Ferreira-Schenk and Matlhaku, 2024). Barberis, Huang and Santos (2001) argue that loss aversion induces momentum effects, since investors change their expectations at a slower pace than rational models anticipate. Page, McClelland and Auret (2020) found that trading influenced by investor sentiment on the JSE leads to price momentum and subsequent reversals, consequently underscoring the claim that investor sentiment considerably influences stock returns.

Prospect Theory impacts sentiment-driven trading through the framing effect, whereby investors evaluate profits relative to their previous expectations rather than in absolute terms. Studies shows that in emerging markets, significant investor responses to recent performance frequently result in mispricing, as investors excessively prioritise recent losses (Daniel et al., 1998). Chinzara (2011) showed that sentiment-induced mispricing results in excessive volatility on the JSE, especially affecting small-cap and low-liquidity companies, which are more susceptible to speculative trading. In addition, loss aversion induces asymmetrical market responses, wherein adverse news causes more pronounced price decreases than the increases observed following positive news. Naidoo, Moores-Pitt and Muzindutsi (2025) assert that investor pessimism stemming from political and economic instability results in excessive sell-offs, increasing short-term price decreases. This corresponds with Prospect Theory's assertion that investors tend to engage in excessive risk-taking to evade loss realisation, consequently fostering speculative trading and volatility in emerging markets.

2.2.6. Adaptive Markets Hypothesis

The Adaptive Markets Hypothesis (AMH), introduced by Lo (2004), reconciles the EMH with Behavioural Finance by positing that market efficiency develops over time as investors adjust to fluctuating market conditions. In contrast to the EMH, which posits that markets are perpetually efficient, the AMH proposes that efficiency is flexible, influenced by the learning behaviours of market players, prevailing economic conditions and cycles of sentiment. This approach offers an extensive framework for understanding the relationship between investor sentiment, stock returns and idiosyncratic volatility.

Within the framework of AMH, investor sentiment significantly influences stock return dynamics, as market players acquire knowledge from experience and change their investment strategy accordingly. In times of high sentiment, markets may show inefficiencies as investors become too optimistic, resulting in mispricing and speculative bubbles (Lo, 2005). In contrast, during times of lower sentiment, risk aversion dominates, leading to undervaluation and price adjustments (Daniel et al., 1998).

Contrary to the EMH, which argues that all accessible information is immediately incorporated into stock prices, the AMH proposes that market efficiency varies according to investor learning and adaptation. This illustrates the persistence of sentiment-driven anomalies, including momentum, reversals and speculative mispricing, in financial markets (Timmermann and Granger, 2004). Empirical data indicates that sentiment-sensitive stocks, such as small-cap and high-growth stocks, undergo more significant mispricing effects, thereby supporting the AMH (Baker and Wurgler, 2006). AMH indicates that idiosyncratic volatility embodies adaptive learning. As market participants accumulate knowledge, mispricing effects diminish over time, yet they never completely get eliminated (Lo, 2017).

2.3. Empirical Evidence

2.3.1. Relationship between Investor Sentiment and Idiosyncratic Volatility

Fink, Fink, Grullon and Weston (2010) discovered that the aggregate idiosyncratic volatility spiked nearly fivefold during the internet boom of the late 1990s, in the United States market showing a significant difference in size or scale a moderately increasing trend. While some researchers such as Brown and Kapadia (2007) argue that this rise in idiosyncratic risk was the result of changes in the characteristics of public firms, others such as Cao, Simin and Zhao (2008) argue that it was driven by the changing sentiment of irrational traders. However, the results showed that there was no evidence that investor sentiment was a contributor to idiosyncratic risk throughout the internet boom.

Nguyen and Bhatti (2015) studied the idiosyncratic volatility puzzle and whether investor sentiment influences the relationship between idiosyncratic volatility and stock returns on the Chinese stock market. The findings indicate the existence of a negative idiosyncratic volatility effect in this market. The study also revealed that the relationship between idiosyncratic volatility and stock returns significantly depends on investor sentiment. Thus, investor sentiment plays a very important role in reconciling the relationship between idiosyncratic volatility and stock returns in the Chinese stock market.

Nikoo et al. (2020) investigated the effect of investor sentiment and idiosyncratic risk on stock market mispricing in listed companies on the Tehran Stock Exchange based on Rhodes–Kropf, Robinson and Viswanathan (2005)’s model. The study used investor sentiment, idiosyncratic risk, the Dow Jones Sustainability Emerging Markets Index (EMSI) and the remaining standard deviation of the CAPM regression. To test the research hypotheses, the information of 106 companies listed on the Tehran Stock Exchange was studied for the period of 2008 to 2017. The results indicated that both variables, investor sentiment and idiosyncratic risk have a positive and significant effect on mispricing stock markets.

The recent literature of Chowdhury (2021) studied the relationship between idiosyncratic volatility, investor sentiment and stock market returns of the Gulf Cooperation Countries (GCC). The objectives of the study were to determine the presence of idiosyncratic volatility and sentiment in the GCC market. The study employed the Fama-French 3 Factor Model to examine idiosyncratic volatility in the market. As with this study, the PCA was used to construct a unified proxy to measure investor sentiment. The Ordinary Least Squares (OLS) regression model was used to investigate the relationships between the variables. The findings of the study showed that there is an effect of investor sentiment on stock market returns within the markets. In addition, the study revealed a weak relationship between idiosyncratic volatility and stock returns, one of the implications presented in the study was to encourage companies to go public to ensure that investors have enough information to diversify their portfolios.

This implication comes from the idea presented in the study of Zhong and Gray (2016) which first established a clear connection between idiosyncratic volatility and its ability to predict future returns in the stock market, particularly in emerging markets. On the bedrock of their findings, these scholars argued that in the absence of ‘complete’ quality information, investors cannot fully rely on the available information. This therefore increases the investor’s dependence on firm-specific risk, which trickles down to a situation where idiosyncratic volatility goes undetected, especially in contexts where portfolios are not well diversified.

A similar study by Liu and Gupta (2022) examined the relationship between the uncertainty levels of investors, measured by the conditional volatility of investment as well as stock market volatility. As with the forecited studies, this study sought to determine the impact these variables have on predicting stock market returns. In the study, the Markov-Switching Multi-Fractal (MSM) model was used to empirically investigate the relationship, six global stock indices including Crispr Therapeutics AG (CRSP), New York Stock Exchange (NYSE), National Association of Security Dealers

Automated Quotations (NASDAQ) and S&P 500 were selected and the period spanned between 1987 to 2019. The study revealed varying degrees of power in relationships observed according to different models specified. However, the overarching conclusion was that forecasting stock market volatility in combination with information associated with investors' uncertainty generated smaller errors. The authors presented the recommendation that investors could improve their allocations in their portfolios by accounting for the role of uncertainty in their volatility models. Liu and Gupta (2022) maintained the same stance with managing the risks of their portfolios.

The correlation between sentiment and implied volatility can be explained through numerous behavioural finance theories. The Noise Trader Theory (De Long et al., 1990) proposes that irrational investors affect stock prices by disproportionately responding to non-fundamental signals, resulting in increased volatility. Behavioural Finance Theory (Barberis et al., 1998) asserts that investors' biases, including overconfidence and representativeness, could increase idiosyncratic volatility. The Limits to Arbitrage Hypothesis (Shleifer and Vishny, 1997) argues that rational investors may be unable to correct sentiment-driven mispricing due to risk limits, consequently allowing sentiment to substantially influence intrinsic value. Empirical studies corroborates these theoretical assertions; for example, Baker and Wurgler (2007) discovered that increased investor sentiment results in increased speculative trading, therefore augmenting implied volatility. Moreover, Yu and Yuan (2011) found that sentiment significantly influences implied volatility in small-cap, high-growth stocks due to their increased vulnerability to speculative demand. Conversely, Jiang, Lee and Zhang (2005) claimed that during times of weakening sentiment, implied volatility tends to decrease as market players move towards value investing.

Emerging markets show an unusual financial environment characterised by significant information asymmetry, lower market efficiency and increased vulnerability to external shocks relative to developed economies (Chiang, Li and Yang, 2015). In these markets, the influence of investor sentiment on implied volatility can be more significant due to the low presence of institutional investors and the predominance of retail traders, who are more susceptible to behavioural biases (Mroua and Trabelsi, 2020). Studies conducted in countries such as China (Huang et al., 2015) and India (Chowdhury, 2021) indicates that sentiment-driven volatility has increased in these regions, especially within size based portfolios. Similarly, Smales (2017) found that in Australia, investor sentiment influenced by media coverage substantially affects idiosyncratic volatility, with more pronounced effects during financial crises. Nonetheless, a significant gap exists in the literature about the JSE, where factors such as foreign investor dominance, economic instability and regulatory changes could create unique sentiment-idiosyncratic volatility dynamics. A study conducted by Muguto et al. (2022) shows that South African stock market volatility is affected by investor sentiment; however, the impact of investor sentiment on idiosyncratic volatility remains inadequately explored.

Most studies on investor sentiment and implied volatility focuses overall market indices instead of sectoral indices, thereby overlooking significant cross-sector differences (Baker et al., 2012). Different industries respond to sentiment differently; for example, high-growth sectors like Consumer Discretionary and Technology stocks show greater sentiment-induced volatility, while defensive sectors such as Financials show a lower sensitivity (Kaplanski and Levy, 2010). On the JSE, investor sentiment responses particular to sectors may vary due to structural factors such as industry concentration, regulatory frameworks and vulnerability to global economic trends (van Rensburg and Robertson, 2003). Mining stocks may be more affected by commodity price changes than by overall market sentiment, but banking companies may respond to interest rate expectations and changes differently and in accordance with the change. Despite these differences, limited research has explored the sectoral influence of investor sentiment on idiosyncratic volatility within the JSE, indicating a significant research gap that requires attention.

2.3.2. Relationship between Idiosyncratic Volatility and Stock Market Returns

Jiang and Lee (2006) found that regressing excess returns on one-lagged volatility provides only a limited impact of the dynamic effect of idiosyncratic risk, which tends to be persistent over time. By correcting for the serial correlation in idiosyncratic volatility, the study found out that idiosyncratic volatility has a significant positive effect on stock returns. The findings were robust for various firm size portfolios, sample periods and measures of idiosyncratic risk.

Fu (2009) used the Exponential Generalized Autoregressive Conditional Heteroskedasticity (E-GARCH) model and found a significantly positive relationship between the estimated conditional idiosyncratic volatilities and expected stock returns. The results confirm that the findings of Ang et al. (2006) are largely explained by the return reversal of a selection of small stocks with high idiosyncratic volatilities.

Pukthuanthong-Le and Visaltanachoti (2009) employed a two-pass regression model to calculate the conditional idiosyncratic volatility of individual stock market returns in 36 countries from 1973 to 2007. The results found that when it comes to pricing idiosyncratic risk, there is a positive risk premium for stock returns in the Philippines and United States. The study additionally found a negative correlation between idiosyncratic risk and stock returns in Australia, Canada, Finland, France, Hong Kong, India, Japan, Mexico, Singapore and the United Kingdom (UK). The statistical findings were highly significant, providing strong support for the existing financial theories that suggest a positive relationship between idiosyncratic risk and predicted stock returns. This suggests that the belief that idiosyncratic volatility is significant is premature.

Khovansky and Zhylyevskyy (2013) proposed a new approach to estimating the idiosyncratic volatility premium. In contrast to the popular two-pass regression method, the study incorporated a novel Generalized Method of Moments (GMM) type estimation procedure that uses only a single cross-section of return observations to obtain consistent estimates. The study applied the approach to daily, weekly, monthly, quarterly and annual United States stock return data over the period 2000 to 2011. The results found that the idiosyncratic volatility premium tends to be positive on daily return data, but negative on monthly, quarterly and annual data.

Empirical studies on implied volatility and stock returns shows contrasting results. In developed markets, Ang et al. (2006); Ang, Hodrick, Xing and Zhang (2009) discovered that stocks showing significant implied volatility provide lower expected returns in the United States, challenging conventional asset pricing models. Bali and Cakici (2008) challenged this conclusion, asserting that the adverse association between investment volatility and returns disappears when accounting for company attributes such as size and liquidity. Conversely, Fu (2009) employed a conditional objective variable model and identified a positive correlation between key variables and expected stock returns, indicating that riskier stocks attract a premium. The discussion includes emerging markets, where results are similarly unpredictable. Chiang and Zheng (2010) identified a positive idiosyncratic volatility-return correlation in Asian markets, whereas Mroua and Trabelsi (2020) found a negative correlation in Middle East and North Africa (MENA) markets.

Chowdhury (2021)'s findings challenge previous findings by indicating that investors do not account for anticipated idiosyncratic volatility; rather, only the unexpected portion of idiosyncratic volatility affects stock returns. This suggests that the pricing of idiosyncratic volatility is influenced by market inefficiencies, speculative trading and fluctuations in investor sentiment, rather than solely by risk-based compensation mechanisms. Chowdhury (2021) correspond with prior behavioural finance studies (Baker and Wurgler, 2006; Baker and Wurgler, 2007; Yu and Yuan, 2011; Stambaugh et al., 2012; Da et al., 2015; Huang et al., 2015) indicating that the relationship between idiosyncratic volatility and stock returns are more pronounced in emerging markets due to increased information asymmetry and speculative trading. These results raise important questions regarding the applicability of similar dynamics to South Africa's JSE, where foreign capital flows, macroeconomic volatility and liquidity constraints can aggravate the correlation between idiosyncratic volatility and stock returns.

Although there has been major international research on idiosyncratic volatility, studies focusing on sectoral indices, especially regarding the JSE, are very limited. Different sectors show different levels of idiosyncratic volatility due to differences in laws and regulations, market concentration and responsiveness to macroeconomic factors (Bali, Cakici and Whitelaw, 2011). High-growth sectors, such as Consumer Discretionary and Technology, typically show higher idiosyncratic volatility due to innovation risk and changing consumer patterns, while Financials show reduced idiosyncratic volatility owing to predictable revenue streams (Chordia, Goyal and Saretto, 2018). In the South African market, van Rensburg and Robertson (2003) found that firm size and liquidity influence implied volatility patterns on the JSE. Nevertheless, studies investigating the impact of idiosyncratic volatility on sector-specific stock returns is rare. Considering South Africa's resource-intensive economy, it is important to analyse the impact of idiosyncratic volatility on stock returns in critical sectors such as Basic Materials and Financials, along with the moderating effects of macroeconomic factors on this relationship.

2.3.3. Relationship between Investor Sentiment and Stock Market Returns

Schmeling (2009) examined whether consumer confidence as a proxy for individual investor sentiment affects expected stock returns internationally in 18 industrialised countries. The study found that investor sentiment negatively forecasts aggregate stock returns on average across countries. When sentiment is high, future stock returns tend to be lower and vice versa. This relation also holds for returns of value stocks, growth stocks, small stocks and for different forecasting horizons. The study also used a cross-sectional analysis and found that the effect of investor sentiment on stock returns is higher for countries which have less market integrity, and which are culturally more prone to herd-like behaviour and overreaction.

Namouri, Jawadi, Ftiti and Hachicha (2018) investigated the relationship between investor sentiment and stock returns for the Group of Seven (G7) countries from June 1987 to February 2014. They proposed an empirical non-linear panel data specification based on the panel switching transition model to capture the investor sentiment-stock return relationship while enabling investor sentiment to act asymmetrically, non-linearly and time varyingly according to the market state and investor attitude towards risk. The findings were twofold. Firstly, the results showed that the hypotheses of efficiency, rationality and representative agent do not hold in reproducing stock market dynamics. Second, investor sentiment affects stock returns significantly and non-linearly, but its effects vary with the market conditions.

Wang, Su and Duxbury (2021) assessed the impact of investor sentiment on future stock returns in 50 global stock markets. Using the Consumer Confidence Index (CCI) as the investor sentiment proxy, the results found a negative relationship between investor sentiment and future stock returns at a global level. While the separation between developed and emerging markets did not disrupt the negative pattern, investor sentiment had more instant impact in emerging markets, but a more enduring impact in developed markets. Individual stock markets revealed heterogeneity in the sentiment-return relationship. The heterogeneity can be explained by cross-market differences in culture and institutions, along with intelligence and education, to varying degrees influenced by the extent of individual investor market participation.

Kim and Lee (2022) examined the relationship between investor sentiment and stock returns in two active but different Korean stock markets. Using daily Korea Composite Stock Price Index (KOSPI) and Korean Securities Dealers Automated Quotations (KOSDAQ) data, an investor sentiment index was constructed which included adjusted turnover rate, buy-sell imbalance and Relative Strength Index (RSI). The results found that investor sentiment significantly affects stock returns, more so in the KOSDAQ with high individual participation. Company specifications, including size and stock price affect the relationship between investor sentiment and stock returns.

A recent study on the subject by Guo (2023) examined the relationship using China's stock market. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was used to calculate the volatility of the return of the Chinese Securities Index (CSI) 300 Index. In addition, to the empirical model, the Granger causality was used to test the causal nature of the relationship between the variables. Guo (2023) revealed a positive correlation between investor sentiment and stock price volatility, this finding implied that the two variables, investor sentiment's volatility and China's stock market returns, move in the same direction. While a correlation was established and observed, in the study, it was observed that the fluctuation of investor sentiment and its impact on the stock market has a cross-nature period. Moreover, investor sentiment's impact on the stock market eventually decreases as the number of periods increases. A similar study by Raphael and Jacob (2018) revealed a negative correlation between investor sentiment and excess return rate stock market returns on the Indian Capital Market during the period 1995 to 2017.

On the same note, Lu and Lai (2012) have reported that investor sentiment has a one-way impact on the stock market. The study used China's newly opened stock trading accounts to proxy investor sentiment. The authors analysed the asymmetric impact of investor sentiment on the Shanghai and Shenzhen 300 Index yield. As with the study by Guo (2023), Lu and Lai (2012) examined the causal nature of the relationship, moreover, they employed the Autoregressive Moving Average - Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) model to empirically investigate the relationship. The findings of the study revealed that the change rate of investor sentiment has no significant granger causal relationship. In spite of the findings showing that the factor returns of the stock market is a significant factor to the change rate of investor sentiment. The results further showed that investors adjust their sentiment based on different characteristics of market performances. For instance, a rising period in the stock market means that investors are most likely to behave in a more optimistic spirit and vice versa.

Although investor sentiment has been thoroughly examined in developed countries, its significance on the JSE is still little investigated. Current research underscores notable sectoral disparities in sentiment sensitivity. However, a thorough investigation into sector-specific investor sentiment impacts on the JSE remains absent. The influence of global sentiment on JSE stock returns remains an unresolved research inquiry, considering South Africa's significant overseas investment exposure. Rectifying these deficiencies will yield significant information for investors, policymakers and market analysts aiming to comprehend the influence of sentiment on stock returns in emerging markets.

2.3.4. Fama-French vs Alternative Models

The Fama and French Five Factor model improves previous models by including profitability and investment factors, however, its explanatory power in emerging markets such as South Africa is still uncertain. Foye (2018), in a study covering several emerging markets, including the JSE, found that the size and value premiums, fundamental to Fama French models, are often unreliable or non-existent. Moreover, data quality constraints and an inefficient trading environment may limit the model's prediction efficacy.

The Carhart (1997) Four Factor model, which adds a momentum factor into the Fama French Three Factor model, has shown strong empirical validity in developed markets. However, its theoretical foundation is questioned. Momentum is often regarded as a behavioural anomaly rather than a risk premium (Traut, 2023). Chui, Titman and Wei (2010) indicated that momentum effects are less apparent or more volatile in emerging markets due to lower liquidity and more market shocks.

The APT provides theoretical flexibility by accommodating several unspecified risk factors. This generality, however, highlights its main weaknesses, as it offers no direction on which criteria to choose. This presents significant difficulties in empirical testing, particularly in data-limited contexts such as the JSE, where the likelihood of data mining and overfitting increases (Cooper, Ma, Maio and Philip, 2021).

Within the structure of the JSE, empirical studies have produced conflicting findings regarding the relationship between investor sentiment, idiosyncratic volatility and stock returns. For instance, while studies such as Ang et al. (2006) support a significant negative association between idiosyncratic volatility and future returns, Scrooby (2023) found that this relationship weakens or disappears once market conditions or sectoral differences are accounted for. Similarly, the influence of investor sentiment on returns remains inconsistently measured across sectors and timeframes, largely due to differences in model specifications and the exclusion of nonlinear and behavioural effects (Muguto et al., 2022). These inconsistencies highlight a methodological gap: conventional linear multifactor models such as CAPM and Fama-French models often fail to capture the asymmetric and sector-specific behavioural dynamics that are prominent in emerging markets such as South Africa. Consequently, adopting more flexible econometric frameworks, such as the NARDL model, offers a promising alternative. The NARDL model can explicitly account for asymmetry, short and long-run dynamics and mixed integration orders, making it well-suited to uncover the nuanced interplay between investor sentiment, stock returns and idiosyncratic volatility on the JSE.

2.4. Chapter Summary

The chapter looked at two of the most common theories that govern investor sentiment, stock returns and idiosyncratic volatility. These theories included CAPM, Markowitz Portfolio Selection Theory, Arbitrage Pricing Model, Behavioural Finance, EMH and Prospect Theory. Finally, it looked at the empirical evidence directly addressing the objectives of the study. Despite the global evidence, numerous research gaps remain. Sectoral differences in sentiment-driven stock returns have been thoroughly investigated in developed markets, however, no thorough investigation has been conducted on JSE sectoral indices. Addressing these shortcomings requires sector-specific analysis, nonlinear econometric models and alternate investor sentiment measures. Understanding the investor sentiment-return-volatility relationship in the JSE will provide important knowledge for investors, policymakers and financial regulators, allowing for improved risk management and investment decision making. The next chapter will expand on these findings by defining the empirical framework for investigating the impact of investor sentiment on stock returns and idiosyncratic volatility in South Africa, focusing sectoral dynamics.

CHAPTER THREE: METHODOLOGY

3.1. Introduction

Chapter 2 reviewed the existing literature, highlighting key theoretical and empirical insights that define the relationships between investor sentiment, stock returns and idiosyncratic volatility. The review identified research gaps and justified this study's relevance in the JSE context. This chapter builds upon that foundation by detailing the research methodology, data collection processes, empirical model specifications and econometric techniques employed to achieve the study's objectives. The primary focus is on assessing the effects of investor sentiment on sector-specific idiosyncratic volatility, sector-specific stock returns on idiosyncratic volatility and investor sentiment on sector-specific stock returns using the NARDL model.

This study adopts a quantitative research methodology appropriate for examining numerical data and testing hypotheses through rigorous statistical techniques. De Vaus (2001) states that quantitative research is essential for analysing variable relationships with measurable accuracy, making it particularly well-suited for financial and econometric studies. The methodology ensures objectivity and reliability in understanding the dynamics of investor sentiment, stock returns and idiosyncratic volatility. The study considers a sectoral analysis of the JSE, focusing on Basic Materials, Consumer Discretionary, Consumer Staples, Financials, Health Care, Industrials, Technology and Telecommunications. The rationale for sector-specific analysis stems from the varying influences of sentiment and volatility across industries, which requires a disaggregated approach.

The structure of the rest of this chapter is as follows: Section 3.2 outlines the data collection process, the type of data used, and the sources of the variables used in the study. This is followed by a discussion on the selection of proxies for investor sentiment, idiosyncratic volatility and stock returns, ensuring alignment with the study's research questions and objectives. Section 3.3 details the empirical model framework, mathematical formulation, and the econometric techniques used to estimate relationships among the variables. Finally, Section 3.4 presents concluding remarks, summarising the key methodological choices and setting the stage for the empirical findings in Chapter 4.

3.2. Data and Variable Description

As indicated in Section 3.1., this section describes the data sources and data variables used in the empirical modelling and analysis to aid in attaining the study's stated objectives. The study originally began with 10 sectors which consisted of all sectors on the JSE. The sectors eliminated were Energy and Real Estate. The Energy sector was eliminated due to the fact that it had missing data for 2016 and 2017. The Real Estate sector was eliminated due to the fact that it only had data for 2021 and 2022. The elimination of these sectors meant that the remaining 8 sectors, as mentioned in the chapter introduction above, all have consistent data for analysis and comparison. The study further did not omit any outliers in the study to ensure reporting accuracy between sectors for comparison. The sectors chosen broadly represents the JSE, as each sector capture different sectors of economic activity and provides an overall representation of the market structure in South Africa.

The Basic Materials sector includes chemical, mining and forestry. This sector is a dominant sector in the JSE due to South Africa being a resource-rich economy. Major companies in this sector comprise Anglo American, BHP, Sasol and Sibanye Stillwater (Johannesburg Stock Exchange, 2023). The Consumer Discretionary sector includes companies that sell non-essential goods and services. These include automotive, leisure and retail companies. This sector is sensitive to consumer confidence and economic cycles. Major companies in this sector comprise The Foschini Group, Motus and Mr Price (Johannesburg Stock Exchange, 2023). The Consumer Staples sector includes essential goods and services such as household products, food and beverages. This sector is usually conservative in nature, which provides stability to investors during economic downturns (Johannesburg Stock Exchange, 2023). The Financials sector includes asset management, banking and insurance. This sector is a major driver of capital markets in South Africa. Big companies in this sector comprise FirstRand Bank, Nedbank, Standard Bank and Old Mutual (Johannesburg Stock Exchange, 2023). The Health Care sector includes healthcare providers, hospitals and pharmaceutical companies. These companies are less dominant in the market but is still crucial to the economy. Major companies in this sector include Netcare, Mediclinic and Aspen Pharmacare (Johannesburg Stock Exchange, 2023). The Industrials sector is the working sector of the economy and includes construction companies, logistics companies and manufacturing companies. The sector is key for infrastructure development and trade. Major companies in this sector include Bidvest, Murray & Roberts and Barloworld (Johannesburg Stock Exchange, 2023). The Technology sector includes companies such as IT services, software and tech-related businesses. This sector is ever growing but still relatively small compared to the overall market. Major companies in this sector include EOH, Altron and Datatec (Johannesburg Stock Exchange, 2023). Finally, the Telecommunications sector comprises companies such as broadband services and mobile network providers. This sector is important for digital innovation and transformation in South Africa. Major companies in this sector include Vodacom, MTN and Telkom (Johannesburg Stock Exchange, 2023).

The sectors are important to the structure of the JSE as they show diversification in that they collectively outline the country's financial and commodity-based economy. The sectors show resource dependency due to the fact that sectors such as Basic Materials, is heavily weighted due to the country's wealth in natural resources. These sectors are the financial backbone of the economy. Sectors such as the Financials sector is important for investments and capital markets, in order to maintain economic stability. The sectors also outline a consumer-based economy in the form of sectors such as Consumer Discretionary and Consumer Staples. This encompasses that a country is made up of its people and outline their domestic consumption trends. The sectors also include those that are still growing, such as the Technology and Telecommunications sectors and those are necessary to aid the growth of the economy such as the Industrials and Health Care sectors. These sectors collectively provide an overall balance of the JSE, whereby it includes traditional resource alliance as well as upcoming consumer and digital trends.

The selection of variables was chosen by various finance theories that were discussed in Chapter 1. In this study, a monthly data set spanning the period between January 2003 to December 2022 was collected. The rationale for using monthly data is that it covers a near-accurate representation of short-term changes, particularly on the variable of investor sentiment and idiosyncratic volatility compared to data with lower frequency such as quarterly data. The justification of the period under investigation is that it accommodates the pre-post events and developments in South Africa.

During the period 2002-2008, the country experienced rising commodity prices such as coal, platinum and gold, which uplifted the country's economy. This period showed strong growth due to the Basic Materials and Financials sector. This period also saw a reduction in government debt, increased public sector infrastructure spending and improved public finances. In 2008, South Africa was affected by the Global Financial Crises. This caused not only a setback in South Africa, but a global recession, impacting financial markets and South Africa's exports. Many investors pulled out of the JSE, and this saw a depreciation in the Rand to R11/$. The South African Reserve Bank (SARB) reduced interest rates in response to the crises. During the period 2009-2015, South Africa saw an economic recovery where the economy improved with a rise in Gross Domestic Product (GDP) of 3%-4% per year. This period also saw an infrastructure increase in projects due to the FIFA World Cup held in South Africa. The period 2012 saw mining companies suffering huge production losses due to the Marikana Massacre and several mining sector strikes. The political risks and labour disputes led to the Rand depreciating further. During the period 2014-2015, Eskom began to experience financial struggles, and this led to rolling power cuts in the form of loadshedding. Business operations suffered as GDP slowed to below 2% for the period. The Basic Materials sector and Industrials sectors suffered most during this period (stats sa, 2016). The period 2016-2019 saw major political uncertainty and credit downgrades. Finance Minister Nhlanhla Nene was fired by President Jacob Zuma in 2016 leading to market panic and the rand depreciating from R14/$ to R16/$. South Africa's credit rating was also downgraded by Fitch and S&P. In 2017, corruption scandals in the form of state capture under the Gupta family caused South Africa's credit rating to be downgraded further to junk status. However, in late 2017, President Cyril Ramaphosa replaced President Jacob Zuma as president of South Africa, and this led to some restoration in market optimism. This boom was short-lived as in 2018-2019, Eskom's financial struggles continued, and GDP slowed to below 1% for the period. This also led to Foreign Direct Investment (FDI) declining due to political uncertainty (The Guardian, 2017). The final period of the study, 2020-2022, began with the COVID-19 pandemic. The JSE fell by over 30% in March 2019 as global markets collapsed. The rand depreciated further to R19/$ which was its weakest in history of the country. The pandemic led South Africa to enforce a strict lockdown, which caused GDP to fall by 7%. Although the South African government provided a stimulus, debt levels soared. In 2021, the economy improved with GDP rising by 4.9% in 2021. However, in July 2021, following former President Jacob Zuma's arrest, KwaZulu-Natal (KZN) and Gauteng provinces suffered looting and riots which caused approximately R50 billion in damages and led to reduced investor confidence. Unemployment during this period soared to 35%. In 2022, due to the Russia-Ukraine war, food and oil prices began to rise significantly, which led to an increase in the inflation rate. To respond to this, the SARB raised interest rates to tighten financial control. Eskom's financial struggles worsened and loadshedding increased which led to increased decline in economic growth and business operations (Muthu and Wesson, 2023). This will offer valuable insights into the market behaviours during and post-crisis period, therefore allowing for a comprehensive and robust statistical analysis (The World bank, 2015).

Data was collected from reputable secondary sources such as IRESS, the SARB, Bloomberg and Peresec (see Table 3.1. below), these sources allow for integrity and reliability in the collection and storage of data, therefore, the data is reliable for estimation purposes. During the process of data collection, however, there were challenges encountered which warranted some remedial measures to not only protect the validity of the model but also the integrity and reliability of the findings presented in this study. Some of the remedial measures included generating time series of objects for analysis.

3.2.1. Stock Market Returns

The study used daily annualised dividend yield data obtained from the Iress (2024) database as opposed to the dividend payment and date of payment. Soe (2013) examined the relationship between dividends and risk, contending that companies that distribute dividends prioritise sustaining an income stream, thereby offering protection for investors' portfolios during market downturns. In contrast to share returns, dividends cannot be negative; therefore, investors receive their dividends even during periods of low returns. Fuller and Goldstein (2011) show that the returns on non-dividend paying companies were 1% to 2% lower than those of dividend-paying companies during market downturns from 1970 to 2007. This confirms that dividends increase returns and therefore control risk. Given the presented information, it is evident that excluding dividends from return calculations distorts the actual value of the share (Brooks, 2019) and may yield an inaccurate assessment of risk. This study incorporated dividends to yield the highest accuracy, aligning with various other South African studies that have included this component of total returns, such as (van Rensburg and Robertson, 2003; Basiewicz and Auret, 2010; Ward and Muller, 2012).

The monthly annualised dividend yield data obtained from the Iress (2024) database was in contrast to the dividend payment and payment date needed for the study. In this context, the study assumed that the dividend was distributed equally throughout the year, in accordance with Strugnell, Gilbert and Kruger (2011). The monthly dividend was calculated by dividing the annualised dividend yield by the 12 trading months in the year and multiplying by the monthly price as shown below:

$$D_t = \left(\frac{1}{12}\right) \times P_t \times \frac{DY_t}{100} \tag{1}$$

Where, D_t is the monthly dividend payment, P_t is the monthly closing price and DY_t is the dividend yield. The equivalent monthly dividend payment was added to the price in the computation of the stock market returns.

The monthly indices stock market returns were calculated as follows:

$$r_t = \ln\left(\frac{P_t + D_t}{P_{t-1}}\right) \times 100 \tag{2}$$

Where, Ln is the natural logarithm operator and r_t is the return for month t.

3.2.2. Investor Sentiment

Investor sentiment can be described as the overall opinion of investors in the market, reflecting their behaviour of optimism or pessimism, sector specific stock returns can be described as financial gains or losses made from investing in stocks on the sectors of the JSE which were chosen for investigation in the study, sector specific CAPM can be described as financial gains or losses calculated for the sectors chosen in the study by using the CAPM, Fama-French 3 Factor Model (sector specific) can be described as financial gains or losses calculated for the sectors chosen in the study by using the Fama-French 3 Factor Model and Fama-French 5 Factor Model (sector specific) can be described as financial gains or losses calculated for the sectors chosen in the study by using the Fama-French 5 Factor Model.

In this study, investor sentiment was computed using a series of variables that were reduced to a single index using the PCA technique, the justification of the variables selected to compute the investor sentiment index is presented in Table 1. The selected sentiment variables have the common intention of capturing the market's behavioural bias and therefore, individual proxies may contain common information. This can increase the likelihood of correlation among the proxies of sentiment. Which, when modelled together in a regression could violate one of the assumptions of the classical linear regression model, causing the problem of multicollinearity. Also, some of the redundant common information can be disregarded. Consequently, researchers often use tools such as PCA to estimate a single (unified) sentiment measure.

The study used PCA in EViews 13 to create the investor sentiment index. Firstly, it was important to ensure that all variables were correlated and measured the same underlying concept. Afterwards, it was necessary to check if the data had any missing points that needed to be addressed. Once the data was ready for analysis, standardisation was important to remove the effects of different units of measurement using the following formula:

$$z = \frac{X - \bar{x}}{\sigma} \tag{3}$$

Where, X is the original variable, $\bar{X}$ is the variable mean and σ is the standard deviation.

The proc function was then used in EViews 13, to make Principal Components. Covariance matrix was chosen since the variables were standardised. A default eigenvalue > 1 was chosen as number of principal components. PCA is useful for reducing multicollinearity in regression models (Gwelo, 2019). Baker and Wurgler (2006) provide the procedure for using PCA to create a unified sentiment proxy as follows:

$$\begin{aligned} Sentiment_t = {} & \partial_1 Volume_{t-1} + \partial_2 Volume_t + \partial_3 Repo_{t-1} + \partial_4 Repo_t + \partial_5 Exch_{t-1} \\ & + \partial_6 Exch_t + \partial_7 VIX_{t-1} + \partial_8 VIX_t + \partial_9 Migration_{t-1} + \partial_{10} Migration_t \\ & + \partial_{11} Oil_{t-1} + \partial_{12} Oil_t + \partial_{13} Gold_{t-1} + \partial_{14} Gold_t \end{aligned} \tag{4}$$

$$\begin{aligned} InvSent_t = {} & \partial_1 Volume_{t-1/t} + \partial_2 Repo_{t-1/t} + \partial_3 Exch_{t-1/t} + \partial_4 VIX_{t-1/t} \\ & + \partial_5 Migration_{t-1/t} + \partial_6 Oil_{t-1/t} + \partial_7 Gold_{t-1/t} \end{aligned} \tag{5}$$

Where, ∂_i displays factor loadings on the proxies' first principal components that are lagged and contemporary. The relationship between sentiment and price volatility is contemporary, at the level of individual securities (Kumari and Mahakud, 2015).

The investor sentiment index used was followed by Rupande et al. (2019). Each of these factors represents distinct elements of market conditions and investor behaviours. When combined, they offer a comprehensive perspective on investor sentiment. It is crucial to acknowledge that the way they are understood can differ in various market situations and their choice should be backed by strong empirical data that shows their importance to investor sentiment.

Table 1: Proxies of investor sentiment used to create investor sentiment index

Variable	Justification
Trading volume	Increased trade volume is often linked to increased market activity and can indicate the intensity of investor sentiments. It can function as an indicator of investor sentiment, where abnormally high or low volumes frequently align with extreme sentiment (Karpoff, 1987). When trading volume increases, it frequently suggests higher investor activity, driven by optimism, speculation or momentum trading. Investors are more prone to trade aggressively in optimistic markets due to fear of missing out. Low trading volume may suggest uncertainty, anxiety or lack of confidence in the market. During bearish situations, risk-averse investors may avoid investing owing to fear of losses. Trading volume surges before price reversals, signalling speculative bubbles or panic-driven trading. High volume frequently correlates with overreaction, leading to momentum effects or contrarian strategies (Grinblatt and Keloharju, 2006).
Repo rate	The repo rate serves as an indicator of the central bank's monetary policy and the current state of short-term liquidity in the financial markets. The repo rate has the potential to impact investor sentiment because of its influence on borrowing costs and risk-taking behaviour (Acharya and Merrouche, 2013). When the reserve bank reduces the repo rate, borrowing becomes cheaper. Lower interest rates often contribute to greater stock market valuations as the cost of capital decreases. Investors become more hopeful, leading to higher risk appetite and increased market involvement. Stock market rallies and greater trading volume generally follow repo rate reduction. In emerging economies like South Africa, rate cuts frequently lead to optimistic market sentiment, while increase in rates dampen optimism. This relationship is particularly significant in the Consumer Discretionary and Financials sectors, which are sensitive to borrowing costs (South African Reserve Bank, 2024).
Exchange rate (Rand/dollar)	The exchange rate is an indication of how international investors perceive the strength of a country's economy and can be affected by the movement of investments across borders. The volatility in the exchange rate can reflect the willingness of global investors to take risks and therefore serve as an indicator of global investor sentiment (Bacchetta and Van Wincoop, 2006). When the local currency strengthens against major currencies, there are higher foreign investment inflows (capital moving into stocks, bonds and businesses). There are also increased confidence in macroeconomic stability and economic growth prospects and lower inflation expectations, improving consumer and investor sentiment. A rising exchange rate reflects risk-on behaviour, where investors are willing to take additional risks in emerging markets. When the currency declines, it signals capital withdrawals due to risk aversion, investor concerns over inflation, political instability or financial crises. This may result in higher import costs, which can undermine company and consumer confidence, potential interest rate hikes by the reserve bank, tightening financial conditions. A declining exchange rate generally correlates with market sell-offs, excessive volatility and economic uncertainty (Loewald, 2021).

Volatility index	The VIX, commonly known as the “fear index”, quantifies the market’s anticipation of volatility by analysing S&P 500 index options. It serves as a precise indicator of market sentiment, where larger levels signify increased uncertainty and fear among investors (Whaley, 2000). A high VIX rating shows that investors expect higher market volatility and are apprehensive about future price movements. During financial crises or big sell-offs, the VIX jumps, signalling panic selling. Investors prefer safe-haven assets such as cash, bonds and gold, when sentiment is poor. A low VIX value shows that investors are optimistic and predict stable markets. Low volatility is often linked with positive markets and higher risk-taking. Investors are willing to invest funds to risky assets such as cryptocurrencies and high-yield bonds (Venditti and Veronese, 2020).
Net migration rate	Although migration rates are not a direct financial indicator, they serve as an indirect indication of broader economic and social factors that have an impact on investor sentiment. The level of migration can be linked to either positive or negative economic outlook, depending on specific factors (Dustmann, Fasani, Frattini, Minale and Schönberg, 2017). If more individuals are coming into a country, it suggests economic optimism and strong labour market prospects, a stronger investment climate attracting qualified workers as well as businesses and political stability in which favourable business is present. Investors view good migration trends as an optimistic indication, driving money flows into shares and real estate. If more people are leaving the country, it frequently signals economic uncertainty such as periods of recession, high unemployment or low wage growth, diminishing investor confidence due to policy instability, criminality or corruption and capital flight, as rich individuals and firms relocate assets elsewhere. Investors regard high emigration rates as a warning indicator, lowering market confidence and resulting to lower stock prices, weaker currencies and fewer FDI (Naudé, Siegel and Marchand, 2017).
Price of oil (R)	The price of oil is of utmost importance for a diverse range of economic sectors and therefore serve as an indicator of the overall wellbeing of the global economy. Increasing oil prices may suggest increased demand and a favourable economic forecast, which might impact market sentiment (Hamilton, 2003). Higher oil prices lead to higher inflation in the form of increases costs for businesses and consumers, tighter monetary policy whereby the reserve bank raise interest rates to curb inflation, reducing liquidity, lower economic growth expectations which slows industrial production and corporate profits and increased geopolitical risks where oil price spikes due to supply shocks such as the Russia-Ukraine war and OPEC decisions. Investors react negatively to rising oil prices by reducing equities exposure and migrating to safer assets such as the dollar, bonds or gold. Lower oil prices often suggest lower inflation which eases pressure on the reserve bank to raise interest rates, greater economic growth which supports consumer spending and corporate earnings and stronger stock market performance particularly in oil-importing countries. Investors become more bullish and invest more cash to equities, especially in consumer discretionary and industrial sectors (Naudé et al., 2017).

Price of gold (R)	Gold is commonly regarded as a secure investment, with its demand rising during periods of market turmoil or ambiguity. Gold prices can serve as a contrary signal of market sentiment, increasing when sentiment is negative and decreasing when sentiment is positive (Baur and Lucey, 2010). When investors anticipate economic instability, inflation or market downturns, they allocate capital to gold, resulting in an increase in its price. Increased gold prices are frequently linked to stock market declines whereby investors flight to safety, significant inflation whereby gold is used as an inflation hedge, geopolitical uncertainties in the form of war and financial crises and falling currencies such as a weakening ZAR/USD, prompting investors to seek gold as a reliable store of value. When investor confidence is increased, capital is directed towards stocks, fixed-income securities and high-yield instruments, thereby diminishing the demand for gold. Decreasing gold prices frequently signify bullish stock markets, low inflation, strong economic growth, robust currency performance as investors chooses stocks over safe-haven assets and diminishing market volatility, resulting in less need for hedging products (Chang, 2024).

3.2.3. Idiosyncratic Volatility

The estimation of idiosyncratic volatility involved isolating the portion of a security's total volatility that is specific to that particular security and not related to the overall market movements. The approach used to estimate idiosyncratic volatility was the CAPM, Fama-French 3 Factor Model and Fama-French 5 Factor Model. The CAPM measures idiosyncratic volatility solely through market risk, but the Fama-French 3 Factor Model improves the estimation by including the size and value components. The Fama-French 5 Factor Model further improves idiosyncratic volatility calculations by including the profitability and investment factors. Each model offers distinct insights into the characteristics of idiosyncratic volatility, assisting scholars and investors in identifying whether observed stock movements result from systematic risk or firm-specific factors. In emerging markets such as the JSE, where market inefficiencies and foreign investor dominance may increase idiosyncratic volatility, employing multiple models facilitates a more accurate and comprehensive analysis of idiosyncratic volatility.

Market risk underpins the CAPM model and is included in the Fama-French 3 and Fama-French 5 Factor Models. Beta measures a stock's responsiveness to market fluctuation. A $\beta > 1$ indicates that the stock shows greater volatility than the market, whereas a $\beta < 1$ implies less systematic risk. The core assumption of CAPM is that any variations in stock returns can be explained by beta, indicating that idiosyncratic risk represents the residual variation not accounted for by movements in the market. However, empirical studies indicate that beta alone fails to comprehensively account for variation in stock returns (Fama and French, 1992). Studies has shown that high-beta stocks do not reliably produce higher returns, challenging the CAPM's assertion of a straight risk-return relationship. This led to the creation of multi-factor models that include additional factors of risk in addition to market exposure.

The size effect is included in the Fama-French 3-Factor Model, which addresses the empirical observation that small-cap companies generally outperform large-cap stocks on a risk-adjusted basis (Banz, 1981). The Small Minus Big (SMB) factor measures the effect by calculating the return differential between small and large companies. Small companies often have increased growth potential; however, they face increased uncertainty, liquidity limitations and information asymmetry, leading to increased idiosyncratic volatility. In contrast, large companies usually show greater stability, own diversified revenue streams and attract institutional investors, leading to less idiosyncratic volatility. Including SMB into the Fama-French 3 Factor Model enhances the accuracy of idiosyncratic volatility estimation, as it accounts for the additional volatility in small-cap stocks that CAPM does not address. Still, the size effect is diminished in specific developing economies (Hou, Xue and Zhang, 2015), indicating that its influence may differ in South Africa's less liquid, resource-dependent economy.

The HML (High Minus Low) component, also included in the Fama-French 3 Factor Model, represents the value premium, indicating that value stocks (high book-to-market ratios) generally outperform growth stocks (low book-to-market ratios) (Fama and French, 1993). Value stocks typically belong to established, stable companies with strong earnings, whereas growth stocks are frequently speculative, depending on anticipated expansion and innovation. Growth stocks, being more dependent on investor expectations and sentiment, show higher idiosyncratic volatility and value companies, supported by strong fundamentals, show lower idiosyncratic volatility. The HML component improves idiosyncratic volatility estimates by addressing this discrepancy as stocks with high HML loadings demonstrate lower idiosyncratic volatility, whereas those with lower HML loadings show greater sentiment-driven mispricing. In emerging markets such as South Africa, macroeconomic volatility may skew the value effect, requiring the investigation of whether HML considerably improves idiosyncratic volatility estimates on the JSE.

Linear Factor Models (LFM) are often used in finance to help investors understand the relationship between the expected return and its associated covariance with risk factors (Fletcher and Hillier, 2002). In essence, these models aid in clarifying the trade-off between risk and return. According to Meucci, Ardia and Colasante (2014), LFM's are considered as the foundation of factor investing, this is because they are primary quantitative tools that are used to create systematic factor strategies. This section of the study will present the methodology for constructing various factor model specifications according to a South African financial agency, Peresec (2023). The methodology used in constructing these factor models has considered quite a few factors that not only ensure that the models fit the South African perspective but also adheres to international standards. The Peresec (2023) database has six standard models, namely the Fama-French 3 Factor, Carhart 4 Factor, the Fama-French 5 Factor, the AQR 6 Factor, the Peresec Low Volume (LV) 7 Factor and finally, the Peresec Low Beta (LB) 7 Factor. This study employed the CAPM, Fama-French 3 Factor and Fama-French 5 Factor Models as the method of analysis to estimate idiosyncratic volatility. The Carhart 4 Factor Model was omitted due to the fact that the Fama-French 5 Factor Model already incorporates the missing factor that is not included in the Fama-French 3 Factor Model.

The CAPM (Treynor, 1962; Sharpe, 1964; Lintner, 1965a; Mossin, 1966) is represented as follows:

$$R_i = R_f + \beta_i \times (R_m - R_f) \tag{6}$$

Where, R_i is the expected return of each sectors stock returns i, R_f denotes the 91-day treasury bill rate, which is the risk-free rate, β_i is the systematic risk of asset i, R_m is the expected market return and $(R_m - R_f)$ represents the market risk premium.

The sector-specific excess returns were calculated using the following formula:

$$Excess\ Returns_{sector} = R_i - R_f \tag{7}$$

Regression analysis was used to estimate the systematic risk (β) of the security with respect to the chosen factors. The coefficients obtained from the regression represented how much the security's returns are influenced by each factor.

The residuals were then calculated from the regression which represent the portion of the security's returns not explained by the systematic factors. These residuals capture the idiosyncratic risk. The residuals for the CAPM were calculated using the following formula:

$$Residuals_{sector} = CAPM\ Return - Stock\ Return \tag{8}$$

The CAPM was then extended to estimate the expected return using the Fama-French 3 Factor Model (Fama and French, 1992) represented as follows:

$$R_i = R_f + \beta_1(Market) + \beta_2(Size) + \beta_3(Value) + \varepsilon_t \tag{9}$$

Where, In this equation, R_i denotes the expected return, R_f is the risk-free rate and β_i is the factors coefficient (sensitivity).The market risk premium is denoted with $Market$, while $Size$ represents the excess returns of small-cap companies over large-cap companies. $Value$ is the excess returns of value stocks over growth stocks and ε_t denotes the error term at time t.

The residuals for the Fama-French 3 Factor Model were calculated using the following formula:

$$Residuals = R_i - (\alpha + (\beta_1 \times Mkt) + (\beta_2 \times Size) + (\beta_3 \times Value)) \tag{10}$$

The Fama-French 3 Factor Model was then extended to estimate the expected return using the Fama-French 5 Factor Model (Fama and French, 2015) represented as follows:

$$R_i = R_f + \beta_1(Market) + \beta_2(Size) + \beta_3(Value) + \beta_4(Profitability) + \beta_5(Investment) + \varepsilon_t \tag{11}$$

Where, R_i is the expected return, R_f is the risk-free rate and β_i is the factors coefficient (sensitivity). $Market$ is the market risk premium, $Size$ is the excess returns of small-cap companies over large-cap companies, $Value$ denotes the excess returns of value stocks over growth stocks, $Profitability$ is the return of stocks with high operating profit minus the return of stocks with low operating profit, $Investment$ is the level of capital used to maintain and grow the business and ε_t is the error term at time t.

The residuals for the Fama-French 5 Factor Model were calculated using the following formula:

$$Residuals = R_i - (\alpha + (\beta_1 \times Mkt) + (\beta_2 \times Size) + (\beta_3 \times Value) + (\beta_4 \times Profitability) + (\beta_5 \times Investment)) \tag{12}$$

The idiosyncratic volatility for CAPM, Fama-French 3 Factor and Fama-French 5 Factor Models was estimated using a 6-month rolling standard deviation of the residuals to understand the volatility over time. This was done using the following formula:

$$\sigma_{rolling,6\ month} = \sqrt{\frac{1}{(N-1)}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

(13)

Where, $\sigma_{rolling,6\ month}$ is the 6-month rolling standard deviation, N is the number of observations in each rolling window (up to 6), x_i is each residual value in the window, $\bar{x}$ is the mean of the residuals within the window. For the initial values where a 6-month window cannot be formed, an expanding window was used starting from the first available data point. This expanding calculation includes all data up to the current point, providing a progressively comprehensive estimate of standard deviation from the start of the dataset.

This is represented as follows:

$$\sigma_{expanding} = \sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n}(x_i - \bar{x}_n)^2}$$

(14)

Where, n increases from 2 up to the size of the first 6-month window, $\bar{x}_n$ is the mean of residuals up to the n^{th} data point, for the first data point, the standard deviation value from the second position was duplicated as a pragmatic solution to ensure that no initial values were missing, the 6-month rolling standard deviation was then converted to a monthly scale by dividing by $\sqrt{6}$. This adjustment is based on the assumption that volatility scales within the square root of time.

$$\sigma_{monthly} = \frac{\sigma_{rolling,6\ month}}{\sqrt{6}}$$

(15)

3.3. Empirical Model Specification

This section of the study presents the methodology applied to fulfil the study's research objectives. Moreover, this section details the econometric techniques used to ensure that the model meets the assumptions of the Classical Linear Regression Model (CLRM). Thus, this section is divided into three sub-sections, namely pre-modelling analysis, empirical model, and post-model diagnostics.

The primary objective of this study was to examine the relationships between investor sentiment, stock returns and idiosyncratic volatility with the focus on JSE sectors. In this study, the empirical model is expressed where the dependent variable is expressed as a function of the independent variables. Theoretically, this research study draws its philosophy from various finance theories such as Markowitz (1991)'s MPT. These theories such as Levy (1978); Merton (1987); deLlano-Paz et al. (2017) have underpinned similar studies in literature. Drawing from the theoretical and empirical foundation, the mathematical function of this model is presented in a general equation below as follows:

$$Y_t = f(X_{t,}X_t, X_t) \tag{16}$$

Where, Y_t, is the dependent variable and X_t is the independent variables.

3.3.1. Pre-Modelling Analysis

The sub-section presents the pre-modelling techniques and approaches that were used before conducting the empirical model of the study. These approaches include, among others, stationarity tests, correlation analysis and descriptive statistics. According to Alem (2022), this form of data analysis, also known as Exploratory Data Analysis (EDA) is a crucial part of research that makes the results of the study more effective. This idea presented by Alem (2022) essentially implies that whatever the data is, it is the analysis (of the data) that forms the outcome of the research. This notion is also echoed by the early scholarly work of Patton (1990), who argued that data analysis is a process that allows researchers to discover useful information that could aid in decision-making, suggest possible hypotheses, and shape the nature of the outcome of the research. Kothari (2004) presents an argument that is also relevant to this study: EDA is a process that allows research to detect errors, omissions and other data artefacts and correct them when possible. This allows researchers to present findings that are reliable and valid (Muraina, Adesanya, Agoi and Onen, 2023).

3.3.3.1. Stationarity Tests

The concept of stationarity is an important concept in statistics, particularly in the context of time series modelling as applied across various disciplines. The idea of stationarity refers to a data series whose statistical properties become stable over time. These statistical properties include the mean and variance of the dataset. According to Asteriou and Hall (2021), a time series dataset is said to be stationary if it satisfies three conditions, (a) it exhibits a mean reversion that fluctuates around a constant long-run mean, (b) it has finite variance that is time-invariant, and (c) finally, has a correlogram that diminishes as the number of lags increase. Mathematically, these assumptions are expressed as follows, for simplicity:

(a) $E(Y_t)$ - is constant for all t (time series periods observed),
(b) $Var(Y_t)$ – is constant for all time t,
(c) $Cov(Y_t, Y_k)$ – is constant for all time t, where k is not equal to 0 or if its mean, variance, and covariance remain constant over time.

A violation of these principles constitutes non-stationarity. This is when the current value of a series (Y_t) is equal to its previous value (Y_{t-1}) plus an error term (ε_t) (Mohr and Selk, 2020). Mohr and Selk (2020) posits further that variables exhibiting this kind of behaviour are said to be of integrated order *I*(*d*) series, with (d) denoting the number of difference operators required to address the non-stationarity of the series, this notion is also echoed by Petrică, Stancu and Ghițulescu (2017). The process of transforming non-stationary data is done by differing the log (logarithm) of the series (Musbah, Aly and Little, 2023). Theoretically and in practice, usually one or two differencing operators should be enough to address the problem of a unit root in a series (Mills and Mills, 2015; Hossain, Rahman, Hossain and Karami, 2019). There are many reasons why a series must be free from the problem of unit root before modelling, especially in classical linear regression models. Out of all these reasons, arguably the most important one is that stationary data helps avoid spurious regression (Gujarati and Porter, 2009).

Many tests can be used to test for the unit root, including the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), Phillips-Perron (PP) test (Phillips and Perron, 1988), Dickey-Fuller GLS (Generalized Least Squares) test (Elliott, Rothenberg and Stock, 1992) and Kwiatowski, Phillips, Schmidt, and Shin (KPSS) test (Kwiatkowski, Phillips, Schmidt and Shin, 1992). In this study, the ADF and the KPSS unit root tests were used to examine the stationarity of the variables. The stationarity tests were performed in EViews 13. The rationale for choosing these tests over the others is solely because of the principle of robustness particularly because the two tests are built under two different null hypotheses. The ADF has a null hypothesis of non-stationarity, which means that it considers the data series to contain a unit root. The KPSS on the other hand has a null hypothesis of stationarity which means that it considers the data series to be free from the problem of unit root.

While these two hypotheses conflict with each other, they are useful in research because they contribute to the robustness of the findings. For instance, in a case where the ADF fails to reject its null hypothesis (suggesting non-stationarity), and the KPSS rejects its null hypothesis (also suggesting non-stationarity), then the conclusion of stationarity would be strongly supported. In addition to this, using these two tests helps to gauge more meaningful insights on the type of stationarity that may be present in the data series (trend stationary vs difference-stationary). In the preliminary data examination, it was discovered that the investor sentiment series appeared to show some degree of trend and not a zero mean. Therefore, the ADF test was estimated using a constant and trend.

The ADF test equation for investor sentiment is represented as follows (Dickey and Fuller, 1979):

$$\Delta y_t = \alpha + \beta_t + \gamma_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + \varepsilon_t \tag{17}$$

The stock returns and idiosyncratic volatility series appeared to show fluctuations from the mean without a clear upward or downward trend. Therefore, the ADF test was estimated using a constant only.

The ADF test equation for stock returns and idiosyncratic volatility series is represented as follows (Dickey and Fuller, 1979):

$$\Delta y_t = \alpha + \gamma_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + \varepsilon_t \tag{18}$$

Where, Δy_t is the first difference of the series Y_t, α is the constant term, γ_{t-1} is the coefficient on the lagged level of the series, $\sum_{i=1}^{p} \delta_i \Delta Y_{t-1}$ are the lagged differences of the series up to lag p and ε_t is the error term at time t.

The null hypothesis tested by the ADF is stated as follows:

$H_0: a = 0 \leftrightarrow y_t \sim I(1)$ which means that the data series is not stationary,

$H_1: a < 0 \leftrightarrow y_t \sim I(0)$ which means that the data series is stationary.

The null hypothesis will be tested out at the 5% significance level. The null hypothesis is rejected when the p-value associated with the ADF- statistic is less than 0.05 and vice versa.

The KPSS test equation is represented as follows (Kwiatkowski et al., 1992):

$$Y_t = \mu + \beta_t + r_t + \varepsilon_t \tag{19}$$

Where, Y_t is the observed time series, μ is the concept term, β_t is the deterministic time trend, r_t is a random walk term and ε_t is the error term at time t.

As with the ADF statistic, the null hypothesis will be tested on a 5% significance level. This test will be performed in accordance with the Lagrange Multiplier (LM) test statistic. The null hypothesis of the test is that the series is trend stationary, and the alternative hypothesis is that there is no unit process in the data series. The ADF decision rule also applies to the KPSS test.

3.3.3.2. Empirical Modelling and Econometric Techniques

3.3.3.2.1. Establishing the presence of a long-run relationship

In the study, prior to presenting the econometric model, the first step upon testing for stationarity of the variables was to examine for the presence of a long-run relationship between the variables. More so, cointegration is carried out to identify a connection between variables that are not stationary at the same level (Gujarati and Porter, 2009). According to Asteriou and Hall (2021), cointegration is a powerful tool to detect the presence of economic structures between two variables. The concept of cointegration in time series models stems from the idea that if two variables are non-stationary, the errors can be represented as cumulated error processes where ordinarily when combined, they should be able to produce another non-stationary process (Asteriou and Hall, 2021). The principle of Engle and Watson (1981) states that in a case where two variables (X and Y) are related, their error processes are expected to move together, therefore their stochastic trends would be similar. This allows for a process where it is possible to attain a linear combination that eliminates the non-stationarity (Engle and Watson, 1981; Engle and Granger, 1987).

In the literature, scholars argue that testing for cointegration is a requirement for any model using non-stationary data (McCoskey and Kao, 1998; Cubadda, 1999). The importance of cointegration is emphasised from the perspective that if there are no cointegrating vectors among the linear combination of variables, then a problem of spurious regression is likely (Asteriou and Hall, 2021). Similarly, Cubadda (1999) argues that cointegrated models are hyped up for their ability to tackle the problem of spurious regression, which in this context refers to the inability to obtain efficient estimates of (Beta 1 and 2), in a situation where X and Y are both of the first order of integration I(1). Differencing the data series is often one of the efficient ways to address this issue so that researchers can obtain correct parameter estimates (Musbah et al., 2023).

In an instance where stationary variables are cointegrated, using the Error Correction Model (ECM) is warranted and necessary (Muscatelli and Hurn, 1992; Uddin, 2009). The rationale for the ECM is that, very often there is a presence of a theoretical and sometimes a practical long-run equilibrium relationship when there is a long-run equilibrium relationship between two variables, however, in the short-run, it is often to observe a disequilibrium among the variables. In the case of a disequilibrium in the short-run, the error correction process is used as an instrument to correct short-run and long-run behaviour (Uddin, 2009). The error correction can be expressed in the following equation following Granger (1988):

$$\Delta X_t = \alpha + \sum_{i=1}^{m} \beta_i \, \Delta X_{t-i} + \sum_{j=1}^{n} \gamma_j \, \Delta Y_{t-j} + \delta ECM_{t-1} + \mu_t \tag{20}$$

$$\Delta Y_t = \alpha + \sum_{i=1}^{m} b_i \, \Delta Y_{t-i} + \sum_{j=1}^{n} c_j \, \Delta X_{t-j} + dECM_{t-1} + \nu_t \tag{21}$$

In these equations, the short-run dynamic coefficients of the error-correction process are denoted by β_i & b_i and γ_j & c_j. The long-run dynamic coefficients on the other hand are represented with δ, the residuals are denoted by μ_t & ν_t. The speed of adjustment of correcting the short-run disequilibria is captured by the absolute value of δ. In this study, the Pesaran, Shin and Smith (2001) cointegration test was employed to determine the long-term relationship between the variables. The hypothesis is presented as follows:

H_0: There is no cointegration
H_1: There is cointegration

Decision Rule: Do not reject H_0 if the probability value is greater than 5% and conclude that there is no cointegration at the 5% critical level.

The Pesaran et al. (2001) cointegration test equation is represented as follows:

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + \sum_{j=0}^{q} \beta_j \Delta X_{1,t-j} + \sum_{j=0}^{r} \gamma_j \Delta X_{2,t-j} + \cdots + \sum_{j=0}^{s} \delta_j \Delta X_{k,t-j} + \emptyset_1 Y_{t-1} + \emptyset_2 X_{1,t-1} + \emptyset_3 X_{2,t-1} + \cdots + \emptyset_{k+1} X_{k,t-1} + \varepsilon_t \tag{22}$$

Where, Δ is the difference operator, Y_t is the dependent variable at time t, $X_{i,t}$ denotes the independent variable at time t, α_0 is the intercept term and α_i are the coefficients for the lagged differences of the dependent variable. The coefficients for the lagged differences of the independent variables are denoted by β_j, γ_j, δ_j, …, $\emptyset_1$ is the coefficients for the lagged level of the dependent variable, while $\emptyset_2$, $\emptyset_3$, …, $\emptyset_{k+1}$ represents the coefficients for the lagged levels of the independent variables and ε_t denotes the error term at time t.

3.3.2. Empirical Model

Most econometric models are based on the assumption of linearity (Allen and McAleer, 2020; Hussein and Hmood, 2024), while these models have contributed immensely to advancing and understanding the interaction, behaviour and relationships between economic variables in economics and other disciplines, they are not always effective in capturing nonlinear and asymmetric relationships (Shin, Yu and Greenwood-Nimmo, 2014). Thus, a model capturing these dynamics was warranted. According to Shin et al. (2014), co-posit that before their NARDL framework, a model introduced to address the shortcomings of linear models, the field of applied econometrics was dominated by three models, the ECM developed by Engle and Granger (1987), the Markov-Switching ECM developed by Hamilton (1989) and the Smooth Transition Autoregressive (STAR) Model developed by Chan and Tong (1986). Shin et al. (2014) argue that the emergence of these models including theirs is a reflection that linear models may be restrictive in a wide range of situations, particularly when long-run relationships cannot be represented as symmetric linear combinations of non-stationary regressors.

Various studies have established a non-linear relationship among the variables in the short-run and long-run (Chang, Sharif, Aman, Suki, Salman and Khan, 2020; Jamshidi, Owjimehr and Etemadpur, 2023). These studies and others alike, have taken into consideration of asymmetric effects that one variable has on the other, their findings have captured complex dynamics between variables by modelling nonlinearities. Thereby, extracting more insights into the relationships of variables that linear models could not capture effectively. It is because of the aforementioned, that this study employed the NARDL model to investigate the long-run relationships established through the Pesaran et al. (2001) cointegration test. The NARDL model, an extension of the Autoregressive Distributive Lag (ARDL) model is a valuable econometric technique for analysing asymmetric relationships between variables. It allows for the identification of both the short-term and long-term asymmetries (Shin et al., 2014). Short-term asymmetries refer to how variables react differently to each other in the immediate or near future.

Long-term asymmetries on the other hand, capture discrepancies in how relationships evolve over time (Shin et al., 2014). One of the distinctive features of the NARDL model lies in its ability to decompose the independent variable into its positive and negative changes. This allows for a nuanced analysis of how changes in the independent variable impact the dependent variable. This distinction is crucial as real-world scenarios often exhibit asymmetric responses, where the effects of an increase in a variable may not mirror the effects of a decrease in the same variable.

3.3.2.1. NARDL Model Structure

The NARDL model by Shin et al. (2014) is represented as:

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_1 \Delta Y_{t-1} + \sum_{i=0}^{q} \alpha_2 \Delta X_{t-i}^{+} + \sum_{i=0}^{q} \alpha_3 \Delta X_{t-i}^{-} + \rho Y_{t-1} + \varphi_1^{+} X_{t-1}^{+} + \varphi_2^{-} X_{t-1}^{-} + \varepsilon_t \tag{23}$$

In the equation specified, ΔY_t denotes the first difference of the dependent variable (Y) observed at time t, $\sum_{i=1}^{p} \alpha_1 \Delta Y_{t-1}$ are some lags of 1st difference of Y; $\sum_{i=0}^{q} \alpha_2 \Delta X_{t-i}^{+}$ are the current plus some lags of 1st difference of X^{+}, $\sum_{i=0}^{q} \alpha_3 \Delta X_{t-i}^{-}$ are the current plus some lags of 1st difference of X^{-}, ρY_{t-1} is the first lag of Y, $\varphi_1^{+} X_{t-1}^{+}$ is the 1st lag of partial sum of positive change in X, $\varphi_2^{-} X_{t-1}^{-}$ is the 1st lag of partial sum of negative change in X, $\sum_{i=1}^{p} \alpha_1 \Delta Y_{t-1} + \sum_{i=0}^{q} \alpha_2 \Delta X_{t-i}^{+} + \sum_{i=0}^{q} \alpha_3 \Delta X_{t-i}^{-}$ are the short-run terms, $\rho Y_{t-1} + \varphi_1^{+} X_{t-1}^{+} + \varphi_2^{-} X_{t-1}^{-}$ are the long-run terms and ε_t is the error term at time t.

3.3.3. Post-Model Diagnostics

As indicated in earlier sections, this sub-section is dedicated to post-model diagnostic, which is a pivotal part of econometric modelling to ensure that the model meets all the assumptions of the CLRM. The diagnostic analysis includes selecting the best fit model, residual diagnostic (serial correlation and equal variance), and normality of residual distribution.

3.3.3.1. Model Selection Criteria

The appropriate lag length for the NARDL model is determined using Information Criteria. This study used the Akaike Information Criteria (AIC). The study used the AIC model over the other model selection criteria because AIC is often preferred in situations where predictive accuracy is more important than identifying the true model. The selection of the Adjusted R^2 value is exclusively applicable to linear regression models and is not applicable in other types of models. However, the AIC is suitable for a broad spectrum of statistical models since it provides a more adaptable and unified approach for selecting models. The model selection procedure was then estimated by using different lag lengths and selecting the model with the lowest AIC value.

The model selection criteria are represented as follows:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \sum_{i=1}^{lags}(\alpha_i X_{t-i} + \gamma_i X_{t+i}) + \varepsilon_t \tag{24}$$

Where, Y_t is the value of the dependent variable at time t, Y_{t-1} is the one-period lag of the dependent variable, X_{t-i} are the lagged values of the independent variable up to the optimal lag length, X_{t+i} are the future values of the independent variable up to the optimal lag length, β_0 is the intercept term, β_1 is the coefficient of the lagged dependent variable, α_i and γ_i are the coefficients for the lagged and future values of the independent variable and ε_t is the error term at time t.

3.3.3.2. Jarque-Bera Test for Normality

The study employed the Jarque-Bera (JB) test Jarque and Bera (1980) to assess the normality of the data used. The JB test evaluates the skewness and kurtosis of the data, comparing them to the expected values under a normal distribution. Under the null hypothesis of normality, the JB statistic asymptotically follows a Chi-squared distribution with two degrees of freedom. The null hypothesis is a joint hypothesis of the skewness being 0 and the excess kurtosis being 0. Samples from a normal distribution have an expected skewness of 0 and an expected kurtosis of 0, which is the same as a kurtosis of 3. A statistically significant JB statistic indicates that the data deviates significantly from a normal distribution. This is crucial as normality is critical for the validity of the NARDL model. Many of the statistical inference procedures used in the NARDL, such as t-tests and F-tests, rely on the assumption of normally distributed errors. Deviations from normality can lead to inaccurate p-values, inflated Type I error rates and unreliable parameter estimates (Ghasemi and Zahediasl, 2012). This can undermine the reliability of the model's results and conclusions.

Sample size is a critical component that dictates the power of the JB stat test, in this study, small sample size could potentially reduce the power of the JB test thereby increasing the risk of falsely accepting the null hypothesis of normality. According to Asteriou and Hall (2021), normality tests may lack sufficient statistical power to detect deviations from normality. This can lead to misleading conclusions about the distributions of the data, which could have significant implications for the reliability of the NARDL model results.

The JB test statistic is represented as follows (Jarque and Bera, 1980):

$$JB = \frac{n}{6}(S^2 + \frac{(K-3)^2}{4} \tag{25}$$

Where, n is the sample size, the sample's skewness is denoted by S is the sample skewness and K is the sample kurtosis.

3.3.4. Heteroskedasticity Test

The study employed rigorous diagnostic checks to ensure the validity of the model's results. One key assumption of the NARDL model is homoskedasticity which means constant variance of the error term. The violation of this assumption can lead to biased and inefficient parameter estimates (Gujarati and Porter, 2009) this can render the model's inferences (t-statistics and F-statistics) as unreliable. To assess the presence of heteroskedasticity, this study employed the Autoregressive Conditional Heteroskedasticity (ARCH) test by Engle (1982). The choice of this test was guided by the characteristics of the data and the suspected pattern of heteroskedasticity which was explored through preliminary data analysis.

The ARCH test equation is represented as follows (Engle, 1982):

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + B_k X_{kt} + \varepsilon_t \tag{26}$$

Where, Y_t is the dependent variable at time t, β_0 is the intercept term, β_1, β_2, …, B_k are the coefficients of the independent variables, X_{1t}, X_{2t}, …, X_{kt} are the independent variables ε_t is the error term at time t.

3.3.5. Lagrange Multiplier Test

The Lagrange Multiplier (LM) test, also known as the score test, is a statistical method used to test constraints in statistical models, particularly in the context of regression analysis and econometrics (Gujarati and Porter, 2009). Named after the French mathematician Joseph-Louis Lagrange, the test assesses whether a simpler model (the null hypothesis) provides an adequate fit compared to a more complex model (the alternative hypothesis). The LM test is particularly useful when dealing with models where the Maximum Likelihood Estimation (MLE) is complex or difficult to compute (Gujarati and Porter, 2009). This test has numerous advantages including computational simplicity as it only requires estimation of the restricted model unlike its counterparts such as the likelihood ratio tests that require the estimation of both the restricted and unrestricted model. In addition, the LM test is generally more robust to deviations from normality assumptions compared to likelihood ratio tests (Breusch and Pagan, 1979). In the context of this study, the LM test was employed not only to test for model misspessification but also to assess for the presence of asymmetric effects which were partially detected during the preliminary exploratory data analysis. Furthermore, the test was used to assess the presence of serial correlation in the data used. It assesses the presence of serial correlation that has not been included in a proposed model structure and which, if present, would mean that incorrect conclusions would be drawn from other tests or that sub-optimal estimates of model parameters would be obtained.

The LM test statistic is represented as follows (Breusch and Pagan, 1979):

$$LM = nR^2 \tag{27}$$

Where, n is the number of observations and R^2 is the coefficient of determination from an auxiliary regression.

3.3.6. NARDL vs Alternative Models

The choice of the NARDL model is driven by the nature of the data and the research objectives. In contrast to traditional time-series models, such as Vector Autoregression (VAR) or Vector Error Correction Model (VECM), the NARDL model is adept at handling regressors with varying orders of integration (I(0) and I(1)), thus avoiding the requirement that all series must share the same order of integration (Pesaran et al., 2001). This adaptability is important in emerging markets such as South Africa, where macroeconomic and sentiment-related factors frequently show different levels of stationarity due to structural volatility and data quality limitations (Naidoo et al., 2025).

The NARDL model allows the breakdown of explanatory variables into positive and negative partial sums, therefore allowing the estimate of both short and long-term asymmetric effects. This is a significant methodological advantage over linear models such as VAR and VECM, which assume symmetrical reactions to shocks. In financial markets, especially during uncertain periods such as post-crisis recoveries or policy changes, investor sentiment often shows nonlinearity and asymmetry. Negative investor sentiment shocks could have a more pronounced effect on idiosyncratic volatility than positive sentiment of equivalent magnitude, a characteristic that linear models may not adequately capture (Shin et al., 2014).

The limitations of the testing approach used in the NARDL model for examining cointegration relationships are somewhat mitigated by its resilience to certain forms of endogeneity, particularly when the dependent variable exhibits weak exogeneity (Mwiya, Simaundu, Nyau and Phiri, 2024). For example, if idiosyncratic volatility is specified as the dependent variable in a model assessing the impact of investor sentiment, the NARDL framework allows for valid inference even if investor sentiment itself is influenced by past values of idiosyncratic volatility, provided idiosyncratic volatility does not respond contemporaneously to changes in investor sentiment. This characteristic enables more reliable estimation in behavioural finance contexts where feedback effects are common but the strict exogeneity assumption of traditional models may be too restrictive. This feature is advantageous due to the potential for concurrent responses between investor sentiment and market volatility, which may violate exogeneity assumptions in traditional OLS estimates (Abdelmalek, 2022). While VAR and VECM models can address endogeneity, they necessitate that all variables be I(1) and cointegrated, a condition that may not be satisfied in this study. Moreover, VAR-based models typically require a more substantial sample size and degrees of freedom, consequently restricting their efficacy in studies with limited data length, which is common in emerging market conditions such as the JSE (Amunkete, 2023).

The NARDL model aligns with key theoretical foundations of behavioural finance, such as Prospect Theory and the concept of asymmetric investor reactions to profits and losses, by allowing for nonlinear and asymmetric dynamics in economic relationships (Rashid, Azam, Sarmidi and Radzi, 2024). Similarly, it complements idiosyncratic volatility modelling theories that recognise market overreactions and sentiment-driven mispricings, as reflected in models such as the AMH (Andleeb, 2024). From an econometric perspective, NARDL is particularly advantageous when dealing with small samples and variables integrated at different orders (I(0) or I(1)), which is often the case in sectoral studies on the JSE. Its ability to capture short- and long-run asymmetries makes it well-suited to explain the complex and behavioural-driven relationships between investor sentiment, stock returns and idiosyncratic volatility in the South African market context (Naidoo, 2021).

3.4. Conclusion

The chapter has provided a detailed account of the research methodology employed in the study. The steps from data collection, cleaning and preparation to the specification and estimation of the NARDL model have been thoroughly explained. The study employed diagnostic, asymmetry tests and cointegration tests to ensure the robustness of the model. The interpretation of the results section guides understanding of the statistical significance and practical implications of the findings. This comprehensive methodology framework ensures the reliability and validity of the research outcomes.

CHAPTER 4: EMPIRICAL RESULTS AND ANALYSIS

4.1. Introduction

The study investigates the relationships between investor sentiment, stock returns and idiosyncratic volatility across JSE sectors, as stated in Chapters 1 and 3. The study employed various mathematical, statistical, econometric and analytical techniques to fulfil the research objectives stated in Chapter 1. This chapter presents the empirical findings, analysis and estimation techniques utilised to satisfy the study's research objectives.

The CAPM, Fama-French 3-Factor Model and Fama-French 5-Factor Model are extensively used to explain stock returns. Upon analysing the correlation among investor sentiment, stock returns and idiosyncratic volatility, the Fama-French 5-Factor Model is superior as it offers a more thorough risk-adjusted elucidation of returns and more effectively addresses sentiment-induced mispricing and volatility impacts.

CAPM argues that market risk (β) is the sole systematic risk influencing stock returns. The effects of investor sentiment are overlooked, as sentiment-driven mispricing cannot be entirely accounted for by the market risk component. Idiosyncratic volatility is regarded as mere noise, rather than a possible indicator of sentiment-driven trading or price inefficiencies. CAPM is unable to differentiate between risk-based and sentiment-based return fluctuations, rendering it insufficient for examining sentiment-related effects (Baker and Wurgler, 2006).

Small-cap stocks generally surpass large-cap stocks, partly due to their increased responsiveness to sentiment-driven trading. Value stocks generally surpass growth companies in performance over time; but market sentiment can momentarily boost growth stock prices beyond their underlying values. Small-cap and growth stocks are more susceptible to fluctuations in sentiment due to their relative pricing challenges compared to large-cap and value stocks. HML reflects speculative overvaluation, which is occasionally influenced by sentiment. Small-cap and growth stocks usually show higher implied volatility, attributable to sentiment-induced mispricing and noisy trading. The Fama French 3 Factor Model more effectively accounts for extra volatility compared to CAPM. Fama French 3 Factor Model continues to overlook profitability and investment factors, which are associated with sentiment-driven expectations and stock misvaluation (Rompotis, 2018).

During periods of high sentiment, investors frequently misvalue companies showing poor profitability. Sentiment-driven investors could overvalue high-risk investment stocks, resulting in subsequent corrections. These reasons explain why stocks that were overvalued due to sentiment ultimately experience reversals. Companies showing low profitability and substantial investment typically experience increased idiosyncratic volatility as a result of speculative trading. The Fama French 5 Factor Model shows how sentiment-induced mispricing generates excess stock-specific volatility, an issue absent in Fama French 3 Factor Model and CAPM. The Fama French 5 Factor Model reduces unexplained alpha, indicating it offers a superior asset pricing structure that incorporates market anomalies influenced by sentiment. During periods of increased investor mood, stocks showing weak fundamentals are more susceptible to mispricing. The Fama French 5 Factor Model addresses this issue (PH and Rishad, 2020).

4.2. Preliminary Findings and Discussion

The purpose of this section is to provide preliminary findings. The crux of this is to provide a broad overview of the trends of the variables of interest in this study. This is important particularly because the period under investigation covers pre-post disastrous periods that have caused economic shocks such as the global financial crisis in 2008 as well as the global Covid-19 pandemic in 2020. These periods have had a significant impact on the JSE sectors under investigation and it is important to demonstrate how they were affected.

The study conducted three NARDL models using three model specifications, the CAPM, the Fama and French Three Factor Model and the Fama and French Five Factor Models. These models were all conducted based on their theoretical and practical significance in describing the relationships that this study was interested in. The preliminary findings of this study revealed that the average monthly exchange rate for the period under investigation was R10.51/$. Despite the findings showing a strong currency over the period, in reality, the South African rand (ZAR) has gone through significant fluctuations depicting an increasing trend. In periods, 2004 to the pre-global financial crisis, the country had a strong currency with the findings showing the currency was as strong as R5,90/$1. However, the global financial crisis resulted in a significant currency depreciation in South Africa and many parts of the world (Kaendera, Dixit and Ltaifa, 2009). Including exchange rate fluctuations into idiosyncratic volatility estimates, given these industry-specific dynamics, provides a more thorough examination of the interaction between macroeconomic drivers and firm-specific risk.

Figure 1: Source: Own Estimation (2024)

A similar trend was observed with the pre-Covid and post-Covid era, with the currency showing significant spike post-crisis period, averaging at R18.30/$1. The relationship between exchange rate and investor sentiment has been established and documented in the literature (Ghumro, Soomro and Abbas, 2024). Ghumro et al. (2024) co-posit that exchange rate have a strong influence on investor sentiment because it affects the risk appetite of investors, though the relationship between investor sentiment and exchange rate is more complex. Nonetheless, their relations are important because investor sentiment can trigger market fluctuations, as well as affect the stock market and exchange rate as shown in other studies (Dalika and Seetharam, 2014; Naidoo et al., 2025), with respect to the investor sentiment index and stock market returns. The findings revealed an upward trend in terms of investor sentiment over the years.

As expected, the results showed a line that is not smooth, which indicated significant fluctuations in investor sentiment. Scoping down on the findings, the results show a relatively low and volatile sentiment between 2003 and 2008. As noted in the exchange rate discussion the pre- and post-crisis period is a significant factor, this notion is echoed by Bandopadhyay (2012). An upward trend is observed post 2008 to 2015 - 2016 possibly signifying an improvement in investor confidence, positive economic conditions, such as an increase in economic activity and infrastructure development in the country could have influenced this. Heading to the year 2022, the findings continue to show an upward trend.

The findings on the relationships between investor sentiment and stock returns show that investor sentiment has varying impacts in terms of the relationship as well as the level of degree or magnitude of impact. Sectors such as Basic Materials, Consumer Discretionary, Technology and Telecommunications among others showed a negative relationship with investor sentiment. On the other hand, the Industrial sector has shown a positive relationship. A similar study by also found similar results in which investor sentiment has varying impact on stock market returns of various sectors. Also interesting to this study was the statistical significance of the coefficients. This might suggest that there is not much disparity in terms of types of investors between optimists and pessimists. A study by Curatola, Donadelli, Kizys and Riedel (2016) attributed the insignificant coefficients associated with the modelled sectors to a consequence of variation in investor and composition type. This notion is also echoed by Qadan and Aharon (2019).

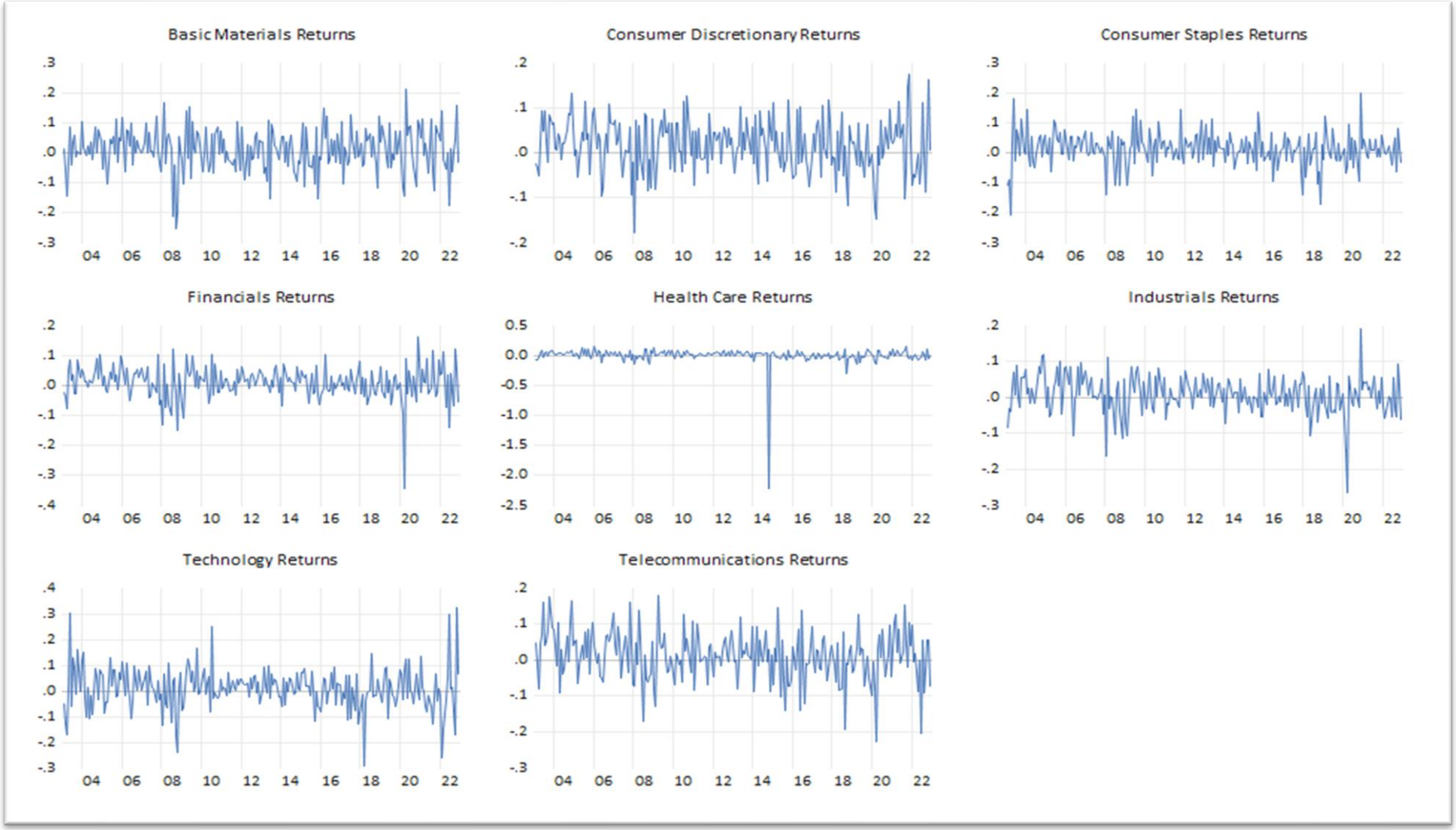

Figure 2: Average Sector Stock Returns 2003 – 2022 Source: Own Estimation (2024)

In terms of sectoral performance, the findings showed a significant variation in volatility, with some sectors showing a high degree of volatility such as Consumer Discretionary and others with low volatility such as the Health Care sector. Scoping down on the results, the findings show that Basic Materials is a relatively stable sector compared to others, despite having some periods of sharp spikes and drops over the period. The Consumer Discretionary sector showed substantial volatility with frequent upswings in returns for investors. These upswings in returns as well as volatility indicate a significant level of risk for investors investing in the sector. As for the Consumer Staples, the sector showed a considerable level of volatility accompanied by generally less extreme fluctuations that are observed in other sectors. A similar trend is observed in the Financials sector in terms of volatility, however, in terms of returns the sector showed both significant gains and losses.

The Health Care sector showed the lowest volatility compared with other sectors, however, there is a notable outlier in the year 2014, which at face value could indicate risk. The sharp decline in returns in the sector could be explained by the tough period between 2013 to 2015, which marked significant changes in the private sector such as regulatory frameworks (Competition Commission, 2018) that might have caused an upset in the stock market and contributed to market uncertainties and negative returns. This notion holds merit considering that post-2015, the sector reverted to its stable market returns accompanied by low volatility. The Technology sector, on the other hand, exhibited high volatility coupled with periods of sharp gains and losses. Despite the high level of volatility observed, the tech sector remains one of the most stable sectors to invest in, although there is still inherent risk. On a slightly different note, the Telecommunications sector showed moderate volatility with less extreme fluctuations as observed in other sectors. The same trend was observed in the Industrials sector.

4.3. Data Descriptive Statistics

This section presents the summary statistics of the data utilised in this study. The crux of this is to get a better understanding of the data series and draw meaningful insights before empirical modelling. The table below presents the summary statistics of the variables used to construct the investor sentiment variable, these variables are the Rand/Dollar exchange rate, price of gold, net migration rate, price of oil, the repo rate, the volatility index and trading volume. These variables are crucial in capturing the complex and diverse character of market sentiment and its possible nonlinear effect on stock market returns and idiosyncratic volatility. As mentioned in Chapter 3, the PCA technique was used to create a single index.

The findings show that the average exchange rate was 10.5144, with a standard deviation of 3.6152. This indicates a considerable fluctuation in currency values, which can affect international investment decisions and sentiment towards domestic markets. The positive skewness (0.4063) and relatively low kurtosis (1.7126) suggest that while extreme values are not common, they do exist and could represent periods of significant economic uncertainty or policy shifts. The price of gold, averaged at 13 208.9999 accompanied by a substantial standard deviation of 8 455.9377 and a positive skewness of 0.5605 underscores the variable's sensitivity to global economic and political events, influencing investor sentiment towards riskier assets. Net migration rate, an unconventional but insightful variable, shows a slight negative skewness (-0.8979), indicating that higher migration movements, potentially signifying stronger economic conditions or geopolitical stability, are less frequent but impactful on investor sentiment and market dynamics.

The price of oil shows a substantial mean accompanied by a large standard deviation, emphasising the crucial impact of oil on economic conditions and market sentiment. The occurrence of significant price spikes, generally related to geopolitical tensions or supply disruptions, is indicated by the positive skewness and high kurtosis. These spikes can quickly change market sentiment. The repo rate and its statistical characteristics suggest a relatively stable monetary policy environment over the period, with occasional policy shifts indicated by its positive skewness and kurtosis. Such shifts are vital for understanding the liquidity conditions in the market, affecting investor sentiment and risk-taking behaviour. The VIX demonstrates the market's perception of risk and uncertainty. Its high mean and standard deviation, coupled with significant positive skewness and kurtosis, indicate periods of extreme fear or complacency among investors, pivotal in sentiment analysis.

Trading volume, with its immense mean and median, reflects the overall market activity. The presence of positive skewness and high kurtosis indicates that specific events or time periods result in substantial trading activity, which is likely associated with changes in investor sentiment. The descriptive statistics indicate notable variability, skewness, and kurtosis among the variables, indicating that the distributions are not normal. The indication of the series being not normally distributed is important as it suggests the use of econometric models that address skewness, leptokurtosis and heteroscedasticity over traditional models (Bollerslev, 1986; Fama and French, 2015). The fluctuations in oil prices and exchange rates, together with the consistent repo rate and the large increases in gold prices and trading volumes, are expected according to the behavioural finance theory. The theory posits that market performance can be induced by investor sentiment, without fundamental values (Shleifer, 2000). The fluctuations highlight the behavioural patterns of the market, where issues such as geopolitical tensions, changes in economic policy and global economic indicators influence investor sentiment and, consequently, market performance.

	Exchange Rate	Price of Gold	Migration Rate	Price of Oil	Repo Rate	Volatility Index	Trading Volume
Mean	10.5144	13 208.9999	0.0088	698.4205	0.0198	209.3762	4 411 358 621.2000
Standard Deviation	3.6152	8 455.9377	0.0015	303.6422	0.0064	128.4232	1 441 094 111.1079
Skewness	0.4063	0.5605	-0.8979	0.8913	1.0308	1.9799	1.1577
Kurtosis	1.7126	2.4478	2.2381	4.3453	4.0475	8.3697	6.1249
Jarque-Bera (P-Value)	23.1775 (0.0000)	15.6151 (0.0004)	38.0541 (0.0000)	49.8764 (0.0000)	53.4708 (0.0000)	445.1402 (0.0000)	151.2649 (0.0000)
Observations	240	240	240	240	240	240	240

Table 2: Descriptive statistics for investor sentiment variables. Source: Own Estimation (2024)

Basic Materials: The average monthly return, as indicated by the mean of 0.0088, is moderate. The standard deviation of 0.0711 shows a medium level of volatility. The results show a negative skewness (-0.3812) and a high kurtosis (3.7241), alluding to the occurrence of infrequent negative returns. The distribution is leptokurtic, suggesting a greater probability of outlier events in comparison to a normal distribution. On Consumer Discretionary, the findings show a mean of 0.0170 and a standard deviation of 0.0574. The low standard deviation observed suggests less volatility. The skewness is recorded at -0.1927, while the kurtosis is at 3.1356, these values suggest a relatively normal distribution with a slight tendency towards negative outliers. Consumer Staples recorded an average of 0.0127, this implies a stable performance in the sector. The standard deviation of 0.0557 indicates low volatility, which is enticing for those who are risk averse. The presence of a negative skewness (-0.2327) and a high kurtosis (4.7968) alludes that the distribution is characterised by infrequent but significantly negative returns.

The Financial sector showed an average return of 0.0102, and the data of the sector showed a skewness of -1.3064 and a kurtosis value of 10.7305, implying the occurrence of major negative tail events and extreme outliers. This is further supported by the significant Jarque-Bera test statistic, which suggests that the data is not normally distributed and that there are severe negative returns. The Health Care sector exhibits an anomaly characterised by a negative mean of -0.0002 and a high standard deviation of 0.1553, suggesting a high level of risk and a negative performance throughout the period. The extreme skewness of -12.2570 and kurtosis of 175.3262, coupled with an astronomical JB statistic, suggest extreme negative returns far from a normal distribution. The performance of the Industrial sector is modest, with an average of 0.0085, a negative skewness of -0.7415 and a high kurtosis of 6.4681. These values indicate a distribution with negative tail events and a higher propensity for outliers, suggesting occasional significant downturns.

The Technology sector exhibits an average of 0.0091 accompanied by a high standard deviation of 0.0804, implying greater volatility. The slight positive skewness of 0.0883 and Kurtosis of 5.7832 indicate a relatively balanced distribution with a propensity for positive extreme returns, as highlighted by the maximum return of 0.3214. The Telecommunication sector showed a strong performance this is evident by the average of 0.0117, and a relatively low standard deviation, implying low volatility in the sector within the period under investigation. The distribution implies a modest tend towards negative outliers, as shown by a negative skewness of -0.3052. However, the overall balance of the distribution is evident from a kurtosis value of 3.7444.

The risk and return of the sectors provide a comprehensive analysis of market sentiment. The substantial disparity within sectors in terms of average returns, volatility and distribution characteristics underscores the importance of sector analysis in studies on investor sentiment. The Health Care sector exhibited a significant negative skewness and kurtosis, indicating the possibility of outliers that could have a substantial impact on investor mood and behaviour. In contrast, sectors such as Consumer Discretionary and Telecommunications demonstrate more stable and positive performance, indicating the existence of unique investor sentiment dynamics.

	Basic Materials	Consumer Discretionary	Consumer Staples	Financials	Health Care	Industrials	Technology	Telecommunications
Mean	0.0088	0.0170	0.0127	0.0102	-0.0002	0.0085	0.0091	0.0117
Median	0.0049	0.0204	0.0130	0.0131	0.0113	0.0085	0.0063	0.0127
Maximum	0.2099	0.1746	0.2000	0.1634	0.1461	0.1888	0.3214	0.1792
Minimum	-0.2527	-0.1762	-0.2088	-0.3449	-2.2189	-0.2640	-0.2945	-0.2267
Standard Deviation	0.0711	0.0574	0.0557	0.0533	0.1553	0.0515	0.0804	0.0675
Skewness	-0.3812	-0.1927	-0.2327	-1.3064	-12.2570	-0.7415	0.0883	-0.3052
Kurtosis	3.7241	3.1356	4.7968	10.7305	175.3262	6.4681	5.7832	3.7444
Jarque-Bera	11.0537	1.6684	34.4503	665.8783	302 972.5676	142.2654	77.7753	9.2680
Probability	0.0040	0.4342	0.0000	0.0000	0.0000	0.0000	0.0000	0.0097
Sum	2.1089	4.0799	3.0483	2.4495	-0.0551	2.0380	2.1734	2.8136
SumSq Deviation	1.2085	0.7883	0.7420	0.6800	5.7614	0.6336	1.5465	1.0892
Observations	240	240	240	240	240	240	240	240

Table 3: Descriptive statistics for stock market returns. Source: Own Estimation (2024)

4.4. Stationarity Tests

As mentioned in Chapter 3, conducting unit root tests was important in this study, as with any time series study. This was to ensure that the data series did not suffer from unit root problems and avoid the problem of spurious regression. To examine for the presence of unit root, the study employed the ADF and KPSS unit root tests. The results of these tests are presented in Table 5. The findings presented in Table 5 show the unit root test results of the JSE sectors that are investigated in this study. The results show a varying order of integration among the variables across all tests. This is evident of a variation in terms of stationarity, with some variables being stationary at level and others at first difference. The observed order of integration further validated the selected model choice as autoregressive distributive lag models often work under conditions of varying order of integration.

Variable Name	Test Type	Model Specification	Test	Test Statistic	Critical Value (5%)	p-value
Basic Materials	ADF	Intercept	Levels	-2.7227	-2.8738	0.0717*
Basic Materials	ADF	Intercept	1st difference	-8.7734	-2.8738	0.0000***
Basic Materials	KPSS	Intercept	Levels	0.1343	0.4630	
Consumer Discretionary	ADF	Intercept	Levels	-3.9152	-2.8738	0.0023***
Consumer Discretionary	KPSS	Intercept	Levels	0.3370	0.4630	
Consumer Staples	ADF	Intercept	Levels	-3.9187	-2.8738	0.0022***
Consumer Staples	KPSS	Intercept	Levels	0.0945	0.4630	
Financials	ADF	Intercept	Levels	-2.4904	-2.8738	0.1191
Financials	ADF	Intercept	1st difference	-10.6514	-2.8738	0.0000***
Financials	KPSS	Intercept	Levels	0.3181	0.4630	
Health Care	ADF	Intercept	Levels	-3.7071	-2.8738	0.0046***
Health Care	KPSS	Intercept	Levels	0.1552	0.4630	
Industrials	ADF	Intercept	Levels	-4.3093	-2.8738	0.0005***
Industrials	KPSS	Intercept	Levels	0.1721	0.4630	
Technology	ADF	Intercept	Levels	-1.9565	-2.8738	0.3060
Technology	ADF	Intercept	1st difference	8.9466	-2.8738	0.0000***
Technology	KPSS	Intercept	Levels	0.3351	0.4630	
Telecommunications	ADF	Intercept	Levels	-4.6595	-2.8738	0.0001***
Telecommunications	KPSS	Intercept	Levels	0.1474	0.4630	

****indicates significance at the 1%, 5% and 10% levels of significance respectively.*

Table 4: Stationarity tests JSE sectors. Source: Own Estimation (2024)

Table 5 below shows the results for stationarity testing using the ADF and KPSS stationarity test types applied to the investor sentiment variable. The tests were conducted on levels and first differences of the data, using a model specification that included both an intercept and a trend. On the ADF test, the findings show a p-value of 0.0000 which is lower than all critical levels, 1%, 5% and 10%. This indicates that the data series does not have a unit root problem, therefore the null hypothesis series contains unit root can be rejected at all levels of significance. The rejection of the null hypothesis means that the series is stationary at level. The findings of the KPSS tests revealed that the test statistic (0.2952) is greater than all benchmark critical values at all significance levels. This meant that the null hypothesis of no unit root can be rejected. The rejection of the null hypothesis implied that the test should be conducted at 1st difference. The findings showed that the series is stationary at 1st difference as the KPSS test statistic was lower than all benchmark critical levels, indicating that the series is stationary at first difference.

Variable Name	**Test Type**	**Model Specification**	**Test**	**Test Statistic**	**Critical Value (5%)**	**p-value**
Investor sentiment	ADF	Trend and intercept	Levels	-5.4244	-3.4287	0.0000***
Investor sentiment	KPSS	Trend and intercept	Levels	0.2952	0.1460	
Investor sentiment	KPSS	Trend and intercept	1st Difference	0.0224	0.1460	

****indicates significance at the 10%, 5% and 1% levels of significance respectively.*

Table 5: Stationarity tests for investor sentiment. Source: Own Estimation (2024)

4.5. Empirical Model Evidence

In this study, three models capturing different dynamics were used to investigate the underlying relationships between variables of interest. The NARDL analysis was conducted using the AIC as the information criteria, thus the selection of the best fit solely depended on the theoretical computational power variation and which model is comprehensive and covers many dynamics at once. This theoretical justification has been explored in other studies before. Thus, in this study, the Fama and French 5 Factor Model was selected as the best-fit model. The analysis and discussion of this study are built solely on the chosen model, all other models (CAPM and Fama and French 3 Factor Models) are presented in the Annexure for intra-comparison purposes. This section is divided into sub-sections, following the proposed structure: The first sub-section discusses the cointegration results.

4.5.1. Investigating the Relationship between Investor Sentiment and Idiosyncratic Volatility

This sub-section presents the sectoral analysis on the relationship between investor sentiment and idiosyncratic volatility coefficients using the Fama-French 5 Factor Model. The empirical results are presented in Table 6.

Basic Materials

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Basic Materials sector in the previous sector (Lagged Dependent Variable 1) is associated with a decrease of 0.1326 units in the current period's volatility. This change is statistically significant at the 1%, 5% and 10% levels of significance. Investor sentiment positive shows a positive change in investor sentiment is associated with a decrease of 0.0003 units in idiosyncratic volatility of the Basic Materials sector. Investor sentiment negative shows a negative change in investor sentiment is associated with an increase of 0.0012 units in idiosyncratic volatility of the Basic Materials sector.

The residual standard error is 0.0031. On average, the regression model's predictions differ from the actual observed values by 0.0031 units. Therefore, the estimates of idiosyncratic volatility for the Basic Materials sector differ from the actual observed values by 0.0031 units. The Adjusted R-Squared value of 5.16% indicates that the variability in idiosyncratic volatility of the Basic Materials sector is explained by investor sentiment and the lagged dependent variable. This shows that the model has a low prediction power. The F-statistic of 2.819 indicates that the model has statistical significance. This implies that there is enough evidence to reject the null hypothesis, suggesting that investor sentiment (together with any other predictors in the model) effectively accounts for the differences in idiosyncratic volatility in the Basic Materials sector.

Consumer Discretionary

The lagged dependent variables show that a one unit increase in idiosyncratic volatility of the Consumer Discretionary sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.0722 units in the current period's volatility. For Lagged Dependent Variable 2, it is associated with a decrease of 0.2093 units as well as an increase of 0.2592 units and a decrease of 0.1188 for Lagged Dependent Variables 3 and 4 respectively. Investor sentiment positive shows a positive change in investor sentiment is associated with an increase of 0.0005 units in idiosyncratic volatility of the Consumer Discretionary sector. Investor sentiment negative shows a negative change in investor sentiment is associated with an increase of 0.0006 units in idiosyncratic volatility of the Consumer Discretionary sector.

The residual standard error is 0.0032. On average, the regression model's predictions differ from the actual observed values by 0.0032 units. Therefore, the average difference between the calculated idiosyncratic volatility and the observed values of idiosyncratic volatility for the Consumer Discretionary sector is 0.0032 units. The F-statistic of 4.846 indicates that the model is statistically significant. Therefore, based on the data estimated, the null hypothesis is rejected. This implies that investor sentiment, along with other factors examined in the analysis, significantly contributes to the variations in idiosyncratic volatility within the Consumer Discretionary sector.

Consumer Staples

The lagged dependent variables show that a one unit increase in idiosyncratic volatility of the Consumer Staples sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.0988 units in the current period's volatility. For Lagged Dependent Variable 2, it is associated with an increase of 0.1094 units as well as a decrease of 0.0039 units and 0.0968 units for Lagged Dependent Variables 3 and 4 respectively. Investor sentiment positive shows that a positive change in investor sentiment is associated with an increase of 0.0009 units in idiosyncratic volatility of the Consumer Staples sector. Investor sentiment negative shows that a negative change in investor sentiment is associated with an increase of 0.0011 units in idiosyncratic volatility of the Consumer Staples sector. The residual standard error is 0.0035. This means that on average, the predictions made by the regression model deviate from the actual observed values by 0.0035 units. Thus, the idiosyncratic volatility estimates for the Consumer Staples sector are, on average, 0.003495 units away from the actual observed values of idiosyncratic volatility.

The Adjusted R-Squared value of 10.58% indicates the variability in idiosyncratic volatility of the Consumer Staples sector is explained by investor sentiment and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 5.634 indicates that the model has a statistically significant effect. This implies that there is enough evidence to reject the null hypothesis, suggesting that investor sentiment (together with any other variables used in the model) effectively accounts for the differences in idiosyncratic volatility in the Consumer Staples sector.

Financials

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Financials sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.0016 units in the current period's volatility. Investor sentiment positive shows that a positive change in investor sentiment is associated with an increase of 0.0025 units in idiosyncratic volatility of the Financials sector. Investor sentiment negative shows that a negative change in investor sentiment is associated with an increase of 0.0008 units in idiosyncratic volatility of the Financials sector. The residual standard error is 0.0034. This means that on average, the predictions made by the regression model deviates from the actual observed values by 0.0034 units. Thus, the idiosyncratic volatility estimates for the Financials sector are, on average, 0.0034 units away from the actual observed values of idiosyncratic volatility.

The Adjusted R-squared value of 13.45% indicates that the variability in idiosyncratic volatility of the Financials sector is explained by investor sentiment and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 5.566 indicates that the model has a statistically significant effect. This implies that there is enough evidence to reject the null hypothesis, suggesting that investor sentiment (together with any other variables considered in the model) effectively accounts for the differences in idiosyncratic volatility in the Financials sector.

Health Care

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Health Care sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.1770 units in the current period's volatility. Investor sentiment positive shows that a positive change in investor sentiment is associated with a decrease of 0.0010 units in idiosyncratic volatility of the Health Care sector. Investor sentiment negative shows that a negative change in investor sentiment is associated with a decrease of 0.0013 units in idiosyncratic volatility of the Health Care sector. The residual standard error is 0.0321. On average, the regression model's predictions had a deviation of 0.0321 units from the actual observed values. On average, the Health Care sector's idiosyncratic volatility estimates deviate by 0.0321 units from the actual observed values of idiosyncratic volatility.

The Adjusted R-squared value of 7.68% indicates that the variability in idiosyncratic volatility of the Health Care sector is explained by investor sentiment and the lagged dependent variable. This shows that the model has a low prediction power. The F-statistic of 7.600 indicates that the model has a statistically significant effect. This implies that there is enough evidence to reject the null hypothesis, suggesting that investor sentiment (together with any other predictors used in the model) effectively accounts for the differences in idiosyncratic volatility in the Health Care sector.

Industrials

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Industrials sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.2100 units in the current period's volatility. Investor sentiment positive shows that a positive change in investor sentiment is associated with an increase of 0.0014 units in idiosyncratic volatility of the Industrials sector.

Investor sentiment negative shows that a negative change in investor sentiment is associated with a decrease of 0.0000 units in idiosyncratic volatility of the Industrials sector. The residual standard error is 0.0027. This means that on average, the predictions made by the regression model deviates from the actual observed values by 0.0027 units. Thus, the idiosyncratic volatility estimates for the Industrials sector are, on average, 0.0027 units away from the actual observed values of idiosyncratic volatility.

The Adjusted R-Squared value of 12.43% indicates that the variability in idiosyncratic volatility of the Industrials sector is explained by investor sentiment and the lagged dependent variable. This shows that the model has a low prediction power. The F-statistic of 5.170 indicates that the model has a statistically significant effect. Consequently, there is enough proof to reject the null hypothesis, suggesting that investor sentiment, along with any other factors considered in the analysis, plays a substantial role in explaining the fluctuations in idiosyncratic volatility in the Industrials sector.

Technology

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Technology sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.1298 units in the current period's volatility. Investor sentiment positive shows that a positive change in investor sentiment is associated with an increase of 0.0003 units in idiosyncratic volatility of the Technology sector.

Investor sentiment negative shows that a negative change in investor sentiment is associated with an increase of 0.0021 units in idiosyncratic volatility of the Technology sector. The residual standard error is 0.0059. This means that on average, the predictions made by the regression model deviate from the actual observed values by 0.0059 units. Thus, the idiosyncratic volatility estimates for the Technology sector are, on average, 0.0059 units away from the actual observed values of idiosyncratic volatility. The Adjusted R-Squared value of 6.64% indicates that the variability in idiosyncratic volatility of the Technology sector is explained by investor sentiment and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 3.377 indicates that the model has statistical significance. Consequently, there is enough evidence to reject the null hypothesis, suggesting that investor sentiment (together with any other predictors considered in the model) effectively accounts for the fluctuations in idiosyncratic volatility in the Technology sector.

Telecommunications

The lagged dependent variable showed that a one unit increase in idiosyncratic volatility of the Telecommunications sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.1998 units in the current period's volatility. Investor sentiment positive shows that a positive change in investor sentiment is associated with an increase of 0.0010 units in idiosyncratic volatility of the Telecommunications sector. Investor sentiment negative shows that a negative change in investor sentiment is associated with an increase of 0.0012 units in idiosyncratic volatility of the Telecommunications sector.

The residual standard error is 0.0042. This means that on average, the predictions made by the regression model deviates from the actual observed values by 0.0042 units. Thus, the idiosyncratic volatility estimates for the Telecommunications sector are, on average, 0.0042 units away from the actual observed values of idiosyncratic volatility. The Adjusted R-squared value of 9.58% indicates that the variability in idiosyncratic volatility of the Telecommunications sector is explained by investor sentiment and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 9.383 indicates that the model has a statistically significant effect. This implies that there is enough evidence to reject the null hypothesis, suggesting that investor sentiment (together with any other variables used in the model) effectively accounts for the differences in idiosyncratic volatility in the Telecommunications sector.

The findings presented in Table 8 revealed a significant negative relationship between investor sentiment and idiosyncratic volatility for all the sectors. These findings mirror the findings of similar studies such as Corredor, Ferrer and Santamaria (2015) conducted on the USA market and Yang, Ryu and Ryu (2017) conducted from the Korean market perspective. The negative relationship between investor sentiment and idiosyncratic volatility could be attributed to various factors including information asymmetry, risk appetite and herding behaviour. For instance, high sentiment could be an indication that there is greater availability of information in the market at the time, resulting in reduced uncertainty and lower idiosyncratic risk. This idea is echoed in previous studies such as Lee and Ryu (2024), though their study disapproved of the use of news sentiment indices as investor sentiment. However, it still maintained that the disapproval of the proxy does not necessarily root out its association with investor sentiment.

As mentioned earlier, the negative relationships observed between idiosyncratic volatility and investor sentiment could be attributed to risk appetite, a study by Qadan and Aharon (2019) presented a similar notion. The rationale for ascribing the observed relationship to risk appetite comes from the idea that when investor sentiment is high, investors tend to be less risk-averse and willing to invest in riskier assets. Now this causes the demand for risk premiums to reduce, thereby lowering idiosyncratic volatility (Huber, Huber and Kirchler, 2021; Aragó, Barreda-Tarrazona, Breaban, Matallín and Salvador, 2022). On the matter of herding, it is believed that investors tend to follow the crowd, and evolving trends and invest in similar assets (Hari and Das, 2023). This logic of behaviour could be used to explain the negative association observed between idiosyncratic volatility and investor sentiment as herding often reduces idiosyncratic risk as individual stock returns become more correlated with the market.

	Dependent Variable	Independent Variable	Constant	Lagged Dependent Variable (1)	Lagged Dependent Variable (2)	Lagged Dependent Variable (3)	Lagged Dependent Variable (4)	Positive Change in Independent Variable	Negative Change in Independent Variable	Residual Standard Error	Adjusted R-Squared	F-Statistic	P-Value
Model 17	Basic Materials	Investor sentiment	0.0023	-0.2964	0.1490			0.0005	0.0011	0.0030	0.0960	5.175	0.0001***
Model 18	Consumer Discretionary	Investor sentiment	0.0018	-0.0693	-0.2039	0.1966	-0.0544	0.0005	0.0006	0.0030	0.0775	4.292	0.0004***
Model 19	Consumer Staples	Investor sentiment	0.0029	-0.1636				0.0005	0.0019	0.0034	0.1034	4.857	0.0000***
Model 20	Financials	Investor sentiment	0.0020	-0.1816				0.0016	0.0016	0.0035	0.0117	5.203	0.0000***
Model 21	Health Care	Investor sentiment	0.0043	-0.1778				-0.0008	-0.0010	0.0312	0.0773	7.648	0.0001***
Model 22	Industrials	Investor sentiment	0.0029	-0.2071				0.0018	0.0000	0.0026	0.1236	5.143	0.0000***
Model 23	Technology	Investor sentiment	0.0033	-0.1296				0.0004	0.0023	0.0057	0.0671	3.406	0.0018***
Model 24	Telecommunications	Investor sentiment	0.0036	-0.1753				0.0005	0.0006	0.0041	0.0779	7.704	0.0001***

****indicates significance at the 10%, 5% and 1% levels of significance respectively*

Table 6: Investigating the Relationship between Investor Sentiment and Idiosyncratic Volatility. Source: Own Estimation (2024)

4.5.2. Investigating the Relationship between Idiosyncratic Volatility and Stock Returns Coefficients

Basic Materials

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Basic Materials sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.3022 units in the current period's volatility. For Lagged Dependent Variable 2, it is associated with an increase of 0.1638 units. Basic Materials returns positive shows that a positive change in Basic Materials returns is associated with an increase of 0.0072 units in idiosyncratic volatility of the Basic Materials sector. Basic Materials returns negative shows that a negative change in Basic Materials returns is associated with a decrease of 0.0052 units in idiosyncratic volatility of the Basic Materials sector. The residual standard error is 0.0030. On average, the regression model's predictions had a deviation of 0.0030 units from the actual observed values. Therefore, the average deviation between the estimated idiosyncratic volatility for the Basic Materials sector and the actual observed values is 0.0030 units.

The Adjusted R-Squared value of 9.79% indicates that the variability in idiosyncratic volatility of the Basic Materials sector is explained by Basic Materials returns and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 4.660 indicates that the model has statistical significance. This indicates that there is enough evidence to reject the null hypothesis, indicating that the returns of Basic Materials, along with any other predictors in the model, effectively account for the variation in idiosyncratic volatility in the Basic Materials sector.

Consumer Discretionary

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Consumer Discretionary sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.0908 units in the current period's volatility. For Lagged Dependent Variable 2, it is associated with a decrease of 0.1848 units as well as an increase of 0.1468 units for Lagged Dependent Variable 3.

Consumer Discretionary returns positive shows that a positive change in Consumer Discretionary returns is associated with an increase of 0.0108 units in idiosyncratic volatility of the Consumer Discretionary sector.

Consumer Discretionary returns negative shows that a negative change in Consumer Discretionary returns is associated with a decrease of 0.0256 units in idiosyncratic volatility of the Consumer Discretionary sector. The residual standard error 0.0029. This means that on average, the predictions made by the regression model deviates from the actual observed values by 0.0029 units. Thus, the idiosyncratic volatility estimates are, on average, 0.0029 units away from the actual observed values of idiosyncratic volatility.

The Adjusted R-Squared value of 13.33% indicates that the variability in idiosyncratic volatility of the Consumer Discretionary sector is explained by Consumer Discretionary returns and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 4.615 indicates that the model has a statistically significant effect. This implies that there is enough evidence to reject the null hypothesis, suggesting that the returns of Consumer Discretionary (as well as any other variables in the model) effectively account for the changes in idiosyncratic volatility in the Consumer Discretionary sector.

Consumer Staples

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Consumer Staples sector in the previous period (Lagged Dependent Variable 1), is associated with a decrease of 0.2480 units in the current period’s volatility. Consumer Staples returns positive shows that a positive change in Consumer Staples returns is associated with an increase of 0.0221 units in idiosyncratic volatility of the Consumer Staples sector. Consumer Staples returns negative shows that a negative change in Consumer Staples returns is associated with a decrease of 0.0270 units in idiosyncratic volatility of the Consumer Staples sector. The residual standard error is 0.0031. This means that on average, the predictions made by the regression model deviates from the actual observed values by 0.0031 units. Thus, the idiosyncratic volatility estimates for the Consumer Staples returns are, on average, 0.0031 units away from the actual observed values of idiosyncratic volatility.

The Adjusted R-Squared value of 24.84% indicates that the variability in idiosyncratic volatility of the Consumer Staples sector is explained by Consumer Staples returns and the lagged dependent variable. This shows that the model has a low prediction power. The F-statistic of 12.090 shows that the model is highly significant. This indicates that there is enough evidence to reject the null hypothesis, indicating that the returns of Consumer Staples (as well as any other variables considered in the model) effectively account for idiosyncratic volatility variations in the Consumer Staples sector.

Financials

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Financials sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.1713 units in the current period’s volatility. For Lagged Dependent Variable 2, it is associated with an increase of 0.0703 units as well as a decrease of 0.1328 units for Lagged Dependent Variable 3.

Financials returns positive shows that a positive change in Financials returns is associated with an increase of 0.0245 units in idiosyncratic volatility of the Financials sector. Financials returns negative shows that a negative change in Financials returns is associated with a decrease of 0.0359 units in idiosyncratic volatility of the Financials sector. The residual standard error is 0.0033. On average, the regression model's predictions differ from the actual observed values by 0.0033 units. Thus, the estimates of idiosyncratic volatility for the Financials sector differ from the actual observed values by 0.0033 units. The Adjusted R-squared value of 21.89% indicates that the variability in idiosyncratic volatility of the Financials sector is explained by Financials returns and the lagged dependent variables. This shows that the model has a low prediction power.

The F-statistic of 6.962 indicates that the model has a statistically significant effect. This implies that there is enough evidence to reject the null hypothesis, suggesting that the Financials returns, together with any other predictors in the model, have a significant impact on the variation in idiosyncratic volatility in the Financials sector.

Health Care

The lagged dependent variable shows that a one-unit increase in idiosyncratic volatility of the Health Care sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.3210 units in the current period's volatility. Health Care returns positive shows that a positive change in Health Care returns is associated with an increase of 0.0461 units in idiosyncratic volatility of the Health Care sector. Health Care returns shows that a negative change in Health Care returns is associated with a decrease of 0.1496 units in idiosyncratic volatility of the Health Care sector. The residual standard error is 0.0200. This means that on average, the predictions made by the regression model deviate from the actual observed values by 0.0200 units. Thus, the idiosyncratic volatility estimates for the Health Care sector are, on average, 0.0200 units away from the actual observed values of idiosyncratic volatility.

The Adjusted R-squared value of 62.77% indicated that the variability in idiosyncratic volatility of the Health Care sector is explained by Health Care returns and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 50.310 shows that the model has a high level of statistical significance. This implies that there is enough evidence for rejecting the null hypothesis, suggesting that the returns of the Health Care sector (as well as any other variables considered in the model) effectively account for the fluctuations in idiosyncratic volatility within the Health Care industry.

Industrials

The lagged dependent variable shows that a one-unit increase in idiosyncratic volatility of the Industrials sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.1689 units in the current period's volatility. Industrials returns positive shows that a positive change in Industrials returns is associated with a decrease of 0.0036 units in idiosyncratic volatility of the Industrials sector. Industrials returns negative shows that a negative change in Industrials returns is associated with a decrease of 0.0120 units in idiosyncratic volatility of the Industrials sector.

The residual standard error is 0.0027. This means that on average, the predictions made by the regression model deviates from the actual observed values by 0.0027 units. Thus, the idiosyncratic volatility estimates for the Industrials sector are, on average, 0.0027 units away from the actual observed values of idiosyncratic volatility. The Adjusted R-Squared value of 7.55% indicates that the variability in idiosyncratic volatility of the Industrials sector is explained by Industrials returns and the lagged dependent variable. This shows that the model has a low prediction power. The F-statistic of 3.390 shows that the model has a statistically significant effect. This indicates that there is enough evidence to reject the null hypothesis, suggesting that Industrials (together with any other predictors in the model) adequately accounts for the variation in idiosyncratic volatility in the Industrials sector. The p-value associated with the F-statistic is 0.0000. Given that this value is below the conventional levels of significance, the null hypothesis is rejected. Hence, the regression model as a whole is statistically significant.

Technology

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Technology sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.1714 units in the current period’s volatility. Technology returns positive shows that a positive change in Technology returns is associated with an increase of 0.0358 units in idiosyncratic volatility of the Technology sector. Technology returns negative shows that a negative change in Technology returns is associated with a decrease of 0.0389 units in the idiosyncratic volatility of the Technology sector.

The residual standard error is 0.0052. This means that on average, the predictions made by the regression model deviates from the actual observed values by 0.0052 units. Thus, the idiosyncratic volatility estimates for the Technology sector are, on average, 0.0052 units away from the actual observed values of idiosyncratic volatility. The Adjusted R-Squared value of 22.94% indicates that the variability in idiosyncratic volatility of the Technology sector is explained by Technology returns and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 7.965 implies that the model has a statistically significant effect. This indicates that there is enough evidence to reject the null hypothesis, indicating that Technology returns (together with any other variables in the model) effectively account for the variation in idiosyncratic volatility in the Technology sector.

Telecommunications

The lagged dependent variable shows that a one unit increase in idiosyncratic volatility of the Telecommunications sector in the previous period (Lagged Dependent variable 1) is associated with a decrease of 0.3619 units in the current period's volatility. For Lagged Dependent Variable 2, it is associated with an increase of 0.0882 units. Telecommunications positive returns shows that a positive change in Telecommunications returns is associated with an increase of 0.0346 units in idiosyncratic volatility of the Telecommunications sector. Telecommunications negative returns shows that a negative change in Telecommunications returns is associated with a decrease of 0.0267 units in idiosyncratic volatility of the Telecommunications sector.

The residual standard error is 0.0037. On average, the regression model's predictions differ from the actual observed values by 0.0037 units. Thus, the idiosyncratic volatility estimates for the Telecommunications sector differ from the actual observed values of idiosyncratic volatility by 0.0037 units. The Adjusted R-Squared value of 28.08% indicates that the variability in idiosyncratic volatility of Telecommunications sector is explained by Telecommunications returns and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 8.613 indicates that the model has a statistically significant effect. This implies that there is enough evidence to reject the null hypothesis, suggesting that the returns of the Telecommunications industry, together with any other factors considered in the model, have a significant impact on the variation in idiosyncratic volatility in the Telecommunications sector.

Several studies have confirmed an inverse correlation between idiosyncratic volatility and stock returns, challenging traditional asset pricing theories that state that higher risk should yield higher returns. Ang et al. (2006) found that firms with high idiosyncratic volatility tend to earn lower future returns. Bhootra (2011) linked this phenomenon to Prospect Theory, showing that the negative idiosyncratic volatility-stock return relation is significant among stocks experiencing unrealised capital losses. Scrooby (2023) suggests this pattern remains relevant on the JSE, confirming that idiosyncratic volatility is negatively associated with stock returns, even after controlling for size and value effects.

While the NARDL models for all eight sectors show statistical significance at the 1% level, the analysis indicates that several individual coefficients, especially those relating to investor sentiment factors and lagged volatility terms, had no statistical significance in certain sectors. The adverse shift in investor sentiment was seen as minor in the Health Care sector, while both the positive and negative sentiment components had no significance in the Consumer Staples, Technology and Telecommunications sectors. The absence of significance indicates that investor sentiment does not consistently influence idiosyncratic volatility across all sectors.

From an economic and behavioural perspective, these findings may indicate the defensive and fundamentally driven nature of sectors such as Consumer Staples and Health Care, where prices show lower sensitivity to fluctuations in investor sentiment and speculative behaviour. The EMH Fama (1970) asserts that in more informationally efficient or established sectors, prices completely reflect available information, thereby lowering the probability that behavioural biases such as investor sentiment can substantially affect volatility. The AMH Lo (2004) offers a dynamic perspective: markets adjust to changing conditions and the influence of investor sentiment may fluctuate over time and across sectors based on investor learning, institutional frameworks and historical experience.

	Dependent Variable	Independent Variable	Constant	Lagged Dependent Variable (1)	Lagged Dependent Variable (2)	Lagged Dependent Variable (3)	Lagged Dependent Variable (4)	Positive Change in Independent Variable	Negative Change in Independent Variable	Residual Standard Error	Adjusted R-Squared	F-Statistic	P-Value
Model 33	Basic Materials	Basic Materials stock returns	0.0013	-0.3022	0.1638			0.0072	-0.0052	0.0030	0.0979	4.660	0.0001***
Model 34	Consumer Discretionary	Consumer Discretionary stock returns	0.0010	-0.0908	-0.1848	0.1468		0.0108	-0.0256	0.0029	0.1333	4.615	0.0000***
Model 35	Consumer Staples	Consumer Staples stock returns	0.0041	-0.2480				0.0221	-0.0270	0.0031	0.2484	12.090	0.0000***
Model 36	Financials	Financials stock returns	0.0005	-0.1713	0.0703	-0.1328		0.0245	-0.0359	0.0033	0.2189	6.962	0.0000***
Model 37	Health Care	Health Care stock returns	-0.0033	-0.3210				0.0461	-0.1496	0.0200	0.6277	50.310	0.0000***
Model 38	Industrials	Industrials stock returns	0.0030	-0.1689				-0.0036	-0.0120	0.0027	0.0755	3.390	0.0011***
Model 39	Technology	Technology stock returns	0.0015	-0.1714				0.0358	-0.0389	0.0052	0.2294	7.965	0.0000***
Model 40	Telecommunications	Telecommunications stock returns	0.0015	-0.3619	0.0882			0.0346	-0.0267	0.0037	0.2808	8.613	0.0000***

****indicates significance at the 10%, 5% and 1% levels of significance respectively*

Table 8: Investigating the Relationship between Idiosyncratic Volatility and Stock Returns Coefficients. Source: Own Estimation (2024)

4.5.3. Investigating the Relationship between Investor Sentiment and Stock Returns

Basic Materials

The lagged dependent variable shows that a one unit increase in investor sentiment in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.2823 units in the current period's investor sentiment. For Lagged Dependent Variable 2, it is associated with a decrease of 0.0150 units as well as an increase of 0.1657 units for Lagged Dependent Variable 3. Basic Materials returns positive shows that a positive change in Basic Materials returns is associated with a decrease of 1.5944 units in investor sentiment of the Basic Materials sector. Basic Materials returns negative shows that a negative change in Basic Materials returns is associated with a decrease of 0.8251 units in idiosyncratic volatility of the Basic Materials sector. The residual standard error is 0.3728. Therefore, the regression model's predictions differ from the actual observed values by 0.3728 units. Thus, the average deviation between the estimated investor sentiment and the actual observed values of investor sentiment for the Basic Materials sector is 0.3728 units.

The Adjusted R-Squared value of 16.94% indicates that the variability in investor sentiment of the Basic Materials sector is explained by Basic Materials returns and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 6.327 indicates that the model has statistical significance. This implies that there is enough evidence to reject the null hypothesis, suggesting that the returns of Basic Materials, together with any other variables in the model, significantly account for the change in investor sentiment in the Basic Materials sector.

Consumer Discretionary

The lagged dependent variable shows that a one unit increase in investor sentiment of the Consumer Discretionary sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.3499 units in the current period's investor sentiment. For Lagged Dependent Variable 2, it is associated with a decrease of 0.0091 units as well as an increase of 0.1393 units and 0.0822 units for Lagged

Dependent Variables 3 and 4 respectively. Consumer Discretionary returns positive shows that a positive change in Consumer Discretionary returns is associated with a decrease of 1.8021 units in investor sentiment of the Consumer Discretionary sector.

Consumer Discretionary returns negative shows that a negative change in Consumer Discretionary returns is associated with a decrease of 2.7260 units in investor sentiment of the Consumer Discretionary sector. The residual standard error 0.3593. This means that on average, the predictions made by the regression model deviates from the actual observed values by 0.3593 units. Thus, the investor sentiment estimates are, on average, 0.3593 units away from the actual observed values of investor sentiment.

The Adjusted R-Squared value of 22.82% indicates that the variability in investor sentiment of the Consumer Discretionary sector is explained by Consumer Discretionary returns and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 10.930 shows that the model has a high level of statistical significance. This indicates that there is enough evidence to reject the null hypothesis, suggesting that the returns of Consumer Discretionary (as well as any other variables in the model) adequately account for the changes in investor sentiment in the Consumer Discretionary sector.

Consumer Staples

The lagged dependent variable shows that a one unit increase in investor sentiment of the Consumer Staples sector in the previous period (Lagged Dependent Variable 1), is associated with a decrease of 0.2995 units in the current period's volatility. For Lagged Dependent Variable 2, it is associated with a decrease of 0.0262 units as well as an increase of 0.1543 units for Lagged Dependent Variable 3. Consumer Staples returns positive shows that a positive change in Consumer Staples returns is associated with a decrease of 0.2242 units in investor sentiment of the Consumer Staples sector. Consumer Staples returns negative shows that a negative change in Consumer Staples returns is associated with a decrease of 2.3936 units in investor sentiment of the Consumer Staples sector.

The residual standard error is 0.3761. On average, the regression model's predictions differ from the actual observed values by 0.3761 units. Thus, the investor sentiment estimations for the returns of Consumer Staples are 0.3761 units different from the actual observed values of investor sentiment. The Adjusted R-squared value of 15.58% indicates that Consumer Staples explains the variability in investor sentiment of the Consumer Staples sector returns and the lagged dependent variable. This shows that the model has a low prediction power. The F-statistic of 5.320 indicates that the model is highly significant. This implies that there is enough evidence to reject the null hypothesis, suggesting that the returns of Consumer Staples (as well as any other variables considered in the model) effectively account for the fluctuations in investor mood within the Consumer Staples sector.

Financials

The lagged dependent variable shows that a one unit increase in investor sentiment of the Financials sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.2897 units in the current period's investor sentiment. For Lagged Dependent Variable 2, it is associated with a decrease of 0.0333 units as well as an increase of 0.1345 units and 0.0591 units for Lagged Dependent Variables 3 and 4 respectively. Financials returns positive shows that a positive change in Financials returns is associated with a decrease of 3.5666 units in investor sentiment of the Financials sector.

Financials returns negative shows that a negative change in Financials returns is associated with a decrease of 3.5907 units in investor sentiment of the Financials sector. The residual standard error is 0.3337. This indicates that the regression model's predictions differ from the actual observed values by 0.3337 units. Thus, the investor sentiment estimates for the Financials sector deviate by 0.3337 units from the actual observed levels of investor sentiment. The Adjusted R-Squared value of 33.45% indicates that the variability in investor sentiment of the Financials sector is explained by Financials returns and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 17.870 indicates that the model has a high level of statistical significance. This indicates that there is enough evidence to reject the null hypothesis, implying that the variation in investor sentiment in the Financials sector is strongly explained by Financials returns and other indicators included in the model.

Health Care

The lagged dependent variable shows that a one unit increase in investor sentiment of the Health Care sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.3058 units in the current period's investor sentiment. For Lagged Dependent Variable 2, it is associated with a decrease of 0.0242 units as well as an increase of 0.1982 units for Lagged Dependent Variable 3. Health Care returns positive shows that a positive change in Health Care returns is associated with a decrease of 1.9416 units in investor sentiment of the Health Care sector. Health Care returns negative shows that a negative change in Health Care returns is associated with a decrease of 0.1113 units in investor sentiment of the Health Care sector. The residual standard error is 0.3757. This means that on average, the predictions made by the regression model deviates from the actual observed values by 0.3757 units. Thus, the investor sentiment estimates for the Health Care sector are, on average, 0.3757 units away from the actual observed values of investor sentiment.

The Adjusted R-squared value of 15.93% indicated that the variability in investor sentiment of the Health Care sector is explained by Health Care returns and the lagged dependent variables. This shows that the model has a low prediction power. The F-statistic of 6.592 indicates that the model has a statistically significant relationship. This indicates that there is enough evidence to reject the null hypothesis, suggesting that the returns of the Health Care sector, together with any other predictors in the model, significantly account for the variation in investor sentiment in the Health Care sector.

Industrials

The lagged dependent variable shows that a one unit increase in investor sentiment of the Industrials sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.3622 units in the current period's investor sentiment. For Lagged Dependent Variable 2, it is associated with an increase of 0.6668 units as well as an increase of 0.1154 units and 0.0881 units for Lagged Dependent Variables 3 and 4 respectively. Industrials returns positive shows that a positive change in Industrials returns is associated with a decrease of 3.6672 units in investor sentiment of the Industrials sector. Industrials returns negative shows that a negative change in Industrials returns is associated with a decrease of 3.8359 units in investor sentiment of the Industrials sector. The residual standard error is 0.3318. This indicates that the regression model's predictions differ from the actual observed values by 0.3318 units. Thus, the investor sentiment estimates for the Industrials sector deviate by 0.3318 units from the actual observed levels of investor sentiment. The Adjusted R-Squared value of 34.19% indicates that the variability in investor sentiment of the Industrials sector is explained by Industrials returns and the lagged dependent variable. This shows that the model has a low prediction power.

The F-statistic of 16.260 indicates that the model has a statistically significant effect. This implies that there is enough evidence to reject the null hypothesis, suggesting that Industrials (together with any other predictors used in the model) effectively accounts for the variability in investor sentiment in the Industrials sector.

Technology

The lagged dependent variable shows that a one unit increase in investor sentiment of the Technology sector in the previous period (Lagged Dependent Variable 1) is associated with a decrease of 0.2873 units in the current period's investor sentiment. For Lagged Dependent Variable 2, it is associated with a decrease of 0.0638 units as well as an increase of 0.1879 units for Lagged Dependent Variable 3. Technology returns positive shows that a positive change in Technology returns is associated with a decrease of 0.5169 units in investor sentiment of the Technology sector.

Technology returns negative shows that a negative change in Technology returns is associated with a decrease of 0.4780 units in the idiosyncratic volatility of the Technology sector. The residual standard error is 0.3816. This indicates that, on average, the regression model's predictions differ from the actual observed values by

0.3816 units. Thus, the investor sentiment estimates for the Technology sector deviate by 0.3816 units from the actual observed levels of investor sentiment. The Adjusted R-Squared value of 16.44% indicates that Technology returns and the lagged dependent variables explain the variability in investor sentiment of the Technology sector. This shows that the model has a low prediction power. The F-statistic of 4.917 indicates that the model has statistical significance. This implies that there is enough evidence to reject the null hypothesis, suggesting that Technology returns (together with any other variables in the model) effectively account for the variation in investor sentiment in the Technology sector.

Telecommunications

The lagged dependent variable shows that a one unit increase in investor sentiment of the Telecommunications sector in the previous period (Lagged Dependent variable 1) is associated with a decrease of 0.2970 units in the current period's investor sentiment. For Lagged Dependent Variable 2, it is associated with a decrease of 0.0353 units as well as an increase of 0.1237 units and 0.0641 units for Lagged Dependent Variables 3 and 4 respectively.

Telecommunications returns positive shows that a positive change in Telecommunications returns is associated with a decrease of 1.8170 units in investor sentiment of the Telecommunications sector. Telecommunications returns negative shows that a negative change in Telecommunications returns is associated with a decrease of 1.3663 units in investor sentiment of the Telecommunications sector. The residual standard error is 0.3665. This indicates that the regression model's predictions differ from the actual observed values by 0.3665 units. Thus, the investor sentiment estimates for the Telecommunications sector deviate by 0.3665 units from the actual observed levels of investor sentiment.

The Adjusted R-squared value of 19.71% indicates that Telecommunications returns and the lagged dependent variables explain the variability in investor sentiment of Telecommunications sector. This shows that the model has a low prediction power. The F-statistic of 9.243 indicates that the model has a high level of statistical significance. This implies that there is enough evidence to reject the null hypothesis, suggesting that the variance in investor sentiment in the Telecommunications sector can be significantly explained by Telecommunications returns and other indicators included in the model.

	Dependent Variable	Independent Variable	Constant	Lagged Dependent Variable (1)	Lagged Dependent Variable (2)	Lagged Dependent Variable (3)	Lagged Dependent Variable (4)	Positive Change in Independent Variable	Negative Change in Independent Variable	Residual Standard Error	Adjusted R-Squared	F-Statistic	P-Value
Model 41	Investor sentiment	Basic Materials stock returns	-0.4053	-0.2823	-0.0150	0.1657		-1.5944	-0.8251	0.3728	0.1694	6.327	0.0000***
Model 42	Investor sentiment	Consumer Discretionary stock returns	-0.3144	-0.3499	-0.0091	0.1393	0.0822	-1.8021	-2.7260	0.3593	0.2282	10.930	0.0000***
Model 43	Investor sentiment	Consumer Staples stock returns	-0.5233	-0.2995	-0.0262	0.1543		-0.2242	-2.3936	0.3761	0.1558	5.320	0.0000***
Model 44	Investor sentiment	Financials stock returns	-0.2578	-0.2897	-0.0333	0.1345	0.0591	-3.5666	-3.5907	0.3337	0.3345	17.870	0.0000***
Model 45	Investor sentiment	Health Care stock returns	-0.1426	-0.3058	-0.0242	0.1982		-1.9416	-0.1113	0.3757	0.1593	6.592	0.0000***
Model 46	Investor sentiment	Industrials stock returns	0.2001	-0.3622	0.0668	0.1154	0.0881	-3.6672	-3.8359	0.3318	0.3419	16.260	0.0000***
Model 47	Investor sentiment	Technology stock returns	-0.6565	-0.2873	-0.0638	0.1879		-0.5169	-0.4780	0.3816	0.1644	4.917	0.0000***
Model 48	Investor sentiment	Telecommunications stock returns	-0.4958	-0.2970	-0.0353	0.1237	0.0641	-1.8170	-1.3663	0.3665	0.1971	9.243	0.0000***

****indicates significance at the 10%, 5% and 1% levels of significance respectively*

Table 9: Investigating the Relationship between Investor Sentiment and Stock Returns. Source: Own Estimation (2024)

Although the NARDL models show overall statistical significance, the short-run findings indicate that investor sentiment lacks a statistically meaningful effect on stock returns across various JSE sectors. Both positive and negative movements are minor in the Consumer Staples, Technology and Telecommunications sectors. Furthermore, at least one sentiment component is insignificant in the Basic Materials, Consumer Discretionary and Health Care sectors. The data indicate that, in the short term, sentiment-driven changes do not consistently affect price movements across all market categories.

A possible explanation is that these sectors could show less responsiveness to temporary behavioural shifts, particularly if they are primarily influenced by long-term institutional investors or have more stable fundamentals. The EMH (Fama, 1970) asserts that prices quickly assimilate all accessible information, thereby providing little opportunity for momentary investor sentiment fluctuations to affect stock returns. The AMH (Lo, 2004) argues that markets change and react variably to information based on context. In certain sectors, investor sentiment may be less pertinent to valuation or may only become evident over long timeframes.

In addition, methodological factors could account for these non-significant results. The investor sentiment metric may inadequately reflect investor sentiment at a sectoral level, or temporary volatility may hide the correlation between investor sentiment and stock returns. These findings strengthen the perspective that investor sentiment effects are not consistently evident or instantaneous and that short-term market reactions are influenced by a combination of behavioural inertia, sector composition and informational efficiency.

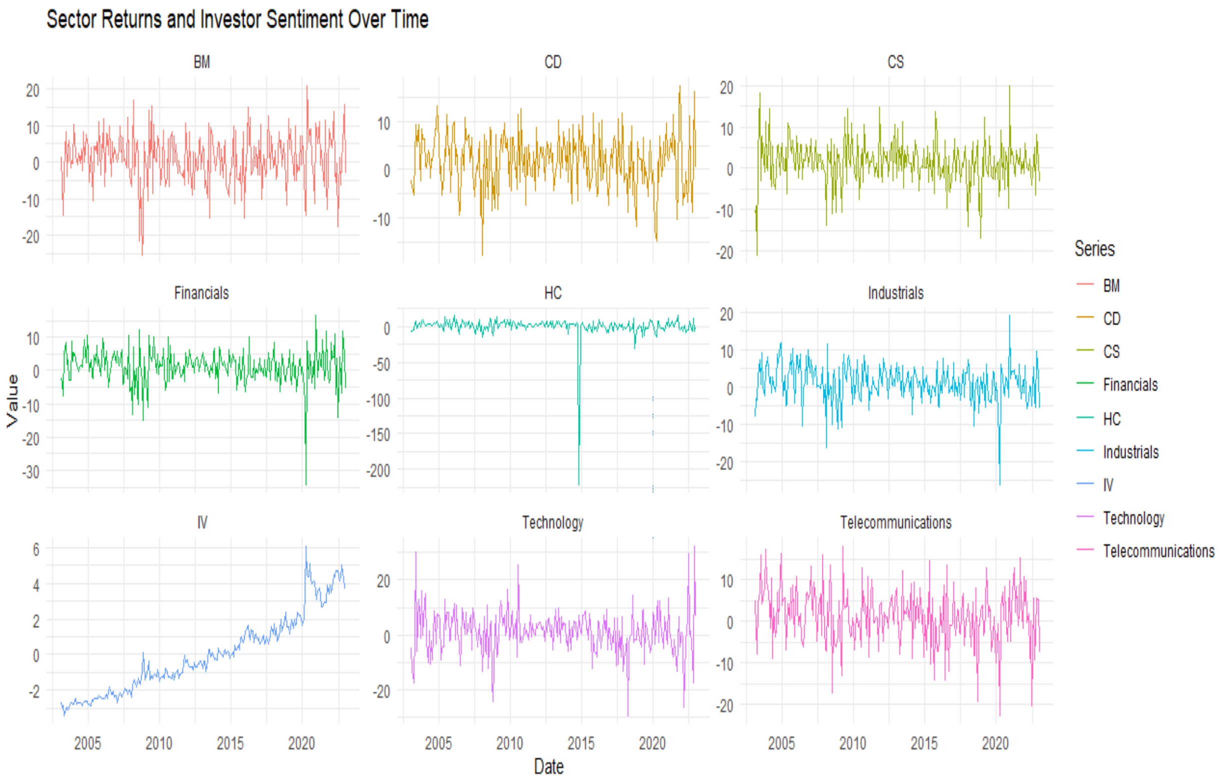

Figure 2: The Relationship between Investor Sentiment and Sector Stock Returns 2002 – 2022. Source: Own Estimation (2024)

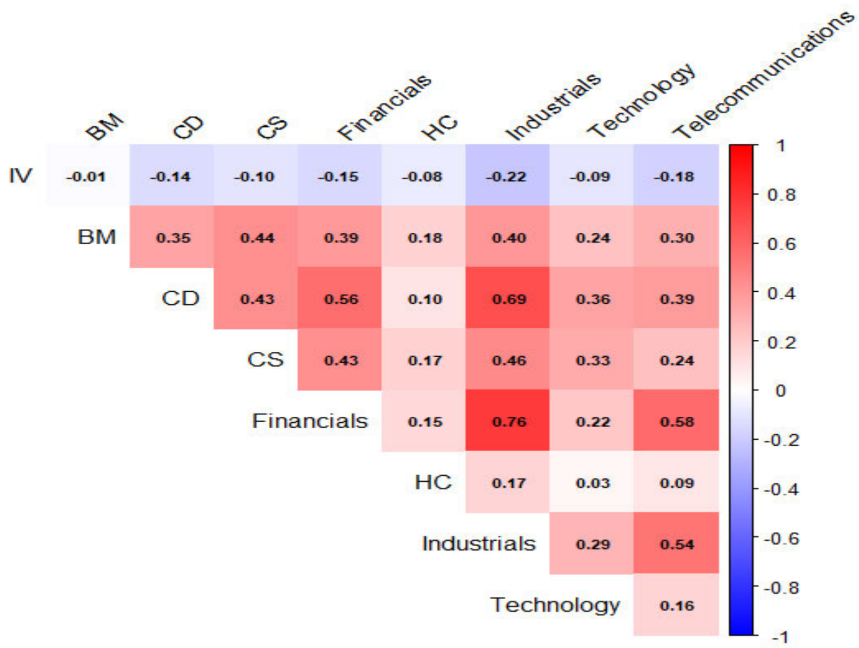

Figure 3: Correlation Investor Sentiment and JSE sector returns (EViews 13, 2024)

4.6. Cointegration Test

As indicated in Chapter 3, the methodology section, the cointegration test was used to establish the presence of a long-run relationship among the variables. The test was conducted under the null hypothesis of No Cointegration, which means that the variables have no cointegrating vectors. In layman's terms, it means the variables have no long-run relationship. The findings of the cointegration are presented in Table 7 below. The findings reveal that there is at least one cointegrating vector among the variables, which means that there is at least one long-run relationship among the variables. This is because the computed F-statistic is greater than the I(0) critical value at all levels of significance. The implication of this finding is that an Error Correction Model (ECM) was required to better understand the short-run and long-run dynamics of the variables under investigation.

Number of Regressors (k): 2 Case: 3		
<------------	I(0) ------------	I(1) ----->
10% critical value	3.17	4.14
5% critical value	3.79	4.85
1% critical value	5.15	6.36
F-statistic = 5.17517338888811		

Table 9: Cointegration test. Source: Own Estimation (2024)

4.7. Post Diagnostics Results

This section presents the post-model diagnostics results. As indicated in Section 4.1. and in Chapter 3, these diagnostic test results are important to ensure that the model conforms with the assumptions of the classical linear regression results. The model diagnostic is tested on the residuals of the model. Therefore, the findings presented are serial correlation, normality of data distribution and heteroskedasticity. The findings are presented in Table 11 below:

Fama-French 5 Factor Model				
		JB test	**LM test**	**ARCH test**
Basic Materials	Statistic	0.9472	0.5099	1.3956
Basic Materials	p-value	0.0000	0.7036	0.4977
Consumer Discretionary	Statistic	0.9583	6.9315	5.4812
Consumer Discretionary	p-value	0.0000	0.2766	0.2414
Consumer Staples	Statistic	0.7902	2.4404	0.0359
Consumer Staples	p-value	0.0000	0.3625	0.8498
Financials	Statistic	0.8949	0.6753	0.4834
Financials	p-value	0.0000	0.5621	0.4869
Health Care	Statistic	0.2258	2.3480	0.1566
Health Care	p-value	0.0000	0.3681	0.6923
Industrials	Statistic	0.9099	0.1509	0.0003
Industrials	p-value	0.0000	0.7641	0.9861
Technology	Statistic	0.9009	0.1139	0.2161
Technology	p-value	0.0000	0.7928	0.6420
Telecommunications	Statistic	0.9768	0.0320	2.0228
Telecommunications	p-value	0.0006	0.8873	0.1550

Table 10: Post model results for the model: Investor sentiment and idiosyncratic volatility. Source: Own Estimation (2024)

The findings from the post-model diagnostic show that the model violates one assumption of the classical linear regression model, which is that the residuals are normally distributed. This is evident from the p-value associated with the JB stat, which is less than the 0.05 benchmark at the 5% significance level. However, on the flipside, the findings show that the model does not suffer from serial correlation and heteroskedasticity. This is evident of the p-value associated with the LM test and the ARCH test. Therefore, in this study, the hypotheses of these tests could not be rejected.

Fama-French 5 Factor Model				
		JB test	LM test	ARCH test
Basic Materials	Statistic	0.9493	0.8219	2.3318
Basic Materials	p-value	0.0000	0.6150	0.3116
Consumer Discretionary	Statistic	0.9709	4.9944	1.7130
Consumer Discretionary	p-value	0.0001	0.3151	0.6341
Consumer Staples	Statistic	0.9253	0.1579	0.0065
Consumer Staples	p-value	0.0000	0.7592	0.9355
Financials	Statistic	0.8577	3.2384	6.8919
Financials	p-value	0.0000	0.3828	0.0754
Health Care	Statistic	0.3982	7.5992	14.2855
Health Care	p-value	0.0000	0.2215	0.0002
Industrials	Statistic	0.8968	0.0567	0.0423
Industrials	p-value	0.0000	0.8512	0.8371
Technology	Statistic	0.9408	0.2187	0.6183
Technology	p-value	0.0000	0.7215	0.4317
Telecommunications	Statistic	0.9918	13.4182	1.0491
Telecommunications	p-value	0.2146	0.1895	0.5918

Table 11: Post-model diagnostic: Investigating investor sentiment and stock returns. Source: Own Estimation (2024)

The findings from the post-model diagnostic show that the model violates one assumption of the classical linear regression model, which is that the residuals are normally distributed. This is evident from the p-value associated with the JB stat, which is less than the 0.05 benchmark at the 5% significance level. However, on the flipside, the findings show that the model does not suffer from serial correlation and heteroskedasticity. This is evident of the p-value associated with the LM test and the ARCH test. Therefore, in this study, the hypotheses of these tests could not be rejected.

CHAPTER 5: CONCLUDING REMARKS AND RECOMMENDATIONS FOR FUTURE RESEARCH

The thesis investigated the triple relationship between investor sentiment, stock returns and idiosyncratic volatility. This study focused on selected JSE sectors with the time series spanning the period between January 2003 to November 2022. The objectives of this study were to: firstly, develop an idiosyncratic volatility series for each of the JSE sector index, secondly, to determine the relationship between investor sentiment and idiosyncratic volatility across all sampled JSE sectors. Examining the impact of idiosyncratic volatility on the stock market returns and analysing the relationship between investor sentiment and stock market returns across the JSE sectors were the fourth and fifth objectives of this study. These objectives were fulfilled in Chapter 4 of this study respectively.

In the quest to fulfil the stated objectives, this study uncovered various relationships and dynamics relating to the variables of interest, among the findings include the negative relationship between idiosyncratic volatility and investor sentiments which was attributed to various factors including herding, risk aversion, and information asymmetry in the market. Another interesting finding includes the variation and significant disparities in terms of the average stock market returns as well as volatility in these sectors, with the Health Care sector showing the greatest stability among all sectors and the Technology sector showing high volatility and stable returns over the years.

Though this study managed to fulfil its stated research objectives, there were, however, several delimitations that could be improved upon, particularly to inform future studies. One of the recommendations is to investigate investor sentiment in more depth, by distinguishing between different types of investor sentiments (i.e. pessimistic versus optimistic). In addition to this, another recommendation would be to cross-reference these findings with other emerging markets to be able to draw insights and a broader understanding of the emerging market region. Another recommendation would be to explore this model under different model conditions to ensure that the results hold merit under different model conditions.

	Dependent Variable	Independent Variable	Constant	Lagged Dependent Variable (1)	Lagged Dependent Variable (2)	Lagged Dependent Variable (3)	Lagged Dependent Variable (4)	Positive Change in Independent Variable	Negative Change in Independent Variable	Residual Standard Error	Adjusted R-Squared	F-Statistic	P-Value
Model 1	Basic Materials	Investor sentiment	0.0021	-0.1318				0.0005	0.0006	0.0030	0.0608	6.134	0.00050***
Model 2	Consumer Discretionary	Investor sentiment	0.0024	-0.0763	-0.2070	0.2554	-0.1164	0.0005	0.0006	0.0032	0.0904	4.891	0.0001***
Model 3	Consumer Staples	Investor sentiment	0.0034	-0.1124	0.0096	-0.0389	-0.0909	0.0008	0.0010	0.0035	0.1208	6.384	0.0000***
Model 4	Financials	Investor sentiment	0.0018	-0.2388				0.0043	-0.0006	0.0040	0.1822	7.543	0.0000***
Model 5	Health Care	Investor sentiment	0.0038	-0.1772				0.0011	-0.0014	0.0323	0.0770	7.619	0.0001***
Model 6	Industrials	Investor sentiment	0.0027	-0.1979				0.0030	-0.0015	0.0028	0.1479	9.227	0.0000***
Model 7	Technology	Investor sentiment	0.0030	-0.1320				0.0020	0.0012	0.0061	0.0742	3.345	0.0012***
Model 8	Telecommunications	Investor sentiment	0.0048	-0.1172	0.0306	-0.1300		0.0013	0.0016	0.0044	0.1047	6.522	0.0000***

****indicates significance at the 1%, 5% and 10% levels of significance respectively.*

Table 12: Using CAPM as an estimate of idiosyncratic volatility in investigating the relationship between investor sentiment and idiosyncratic volatility coefficients. Source: Own Estimation (2024)

	Dependent Variable	Independent Variable	Constant	Lagged Dependent Variable (1)	Lagged Dependent Variable (2)	Lagged Dependent Variable (3)	Lagged Dependent Variable (4)	Positive Change in Independent Variable	Negative Change in Independent Variable	Residual Standard Error	Adjusted R-Squared	F-Statistic	P-Value
Model 9	Basic Materials	Investor sentiment	0.0026	-0.1326				-0.0003	0.0012	0.0031	0.0516	2.819	0.0078***
Model 10	Consumer Discretionary	Investor sentiment	0.0023	-0.0722	-0.2093	0.2592	-0.1188	0.0005	0.0006	0.0032	0.0894	4.846	0.0001***
Model 11	Consumer Staples	Investor sentiment	0.0030	-0.0988	-0.0109	0.0039	-0.0968	0.0009	0.0011	0.0035	0.1058	5.634	0.0000***
Model 12	Financials	Investor sentiment	0.0016	-0.1968				0.0025	0.0008	0.0034	0.1345	5.566	0.0000***
Model 13	Health Care	Investor sentiment	0.0038	-0.1770				-0.0010	-0.0013	0.0321	0.0768	7.600	0.0001***
Model 14	Industrials	Investor sentiment	0.0033	-0.2100				0.0014	0.0000	0.0027	0.1243	5.170	0.0000***
Model 15	Technology	Investor sentiment	0.0032	-0.1298				0.0003	0.0021	0.0059	0.0664	3.377	0.0019***
Model 16	Telecommunications	Investor sentiment	0.0043	-0.1998				0.0010	0.0012	0.0042	0.0956	9.383	0.0000***

****indicates significance at the 10%, 5% and 1% levels of significance respectively.*

Table 13: Using Fama French 3 Factor Model as an estimate of idiosyncratic volatility in investigating the relationship between investor sentiment and idiosyncratic volatility coefficients. Source: Own Estimation (2024)

	Dependent Variable	Independent Variable	Constant	Lagged Dependent Variable (1)	Lagged Dependent Variable (2)	Lagged Dependent Variable (3)	Lagged Dependent Variable (4)	Positive Change in Independent Variable	Negative Change in Independent Variable	Residual Standard Error	Adjusted R-Squared	F-Statistic	P-Value
Model 25	Basic Materials	Basic Materials stock returns	0.0014	-0.1354				0.0066	-0.0081	0.0030	0.0702	4.577	0.0005***
Model 26	Consumer Discretionary	Consumer Discretionary stock returns	0.0015	-0.0936	-0.1874	0.2305	-0.1014	0.0147	-0.0278	0.0030	0.1719	5.048	0.0000***
Model 27	Consumer Staples	Consumer Staples stock returns	-0.0003	-0.2727				0.0112	-0.0198	0.0033	0.2087	9.814	0.0000***
Model 28	Financials	Financials stock returns	0.0006	-0.2573	0.1282	-0.1478		0.0299	-0.0479	0.0039	0.2521	8.169	0.0000***
Model 29	Health Care	Health Care stock returns	-0.0038	-0.3211				0.0358	-0.1558	0.0205	0.6345	51.770	0.0000***
Model 30	Industrials	Industrials stock returns	0.0025	-0.1747				0.0087	-0.0294	0.0028	0.1432	8.924	0.0000***
Model 31	Technology	Technology stock returns	0.0008	-0.2486				0.0432	-0.0426	0.0054	0.2881	9.609	0.0000***
Model 32	Telecommunications	Telecommunications stock returns	0.0015	-0.3050				0.0307	-0.0329	0.0039	0.3141	10.740	0.0000***

****indicates significance at the 10%, 5% and 1% levels of significance respectively*

Table 14: Using CAPM as an estimate of idiosyncratic volatility in investigating the relationship between idiosyncratic volatility and stock market returns coefficients. Source: Own Estimation (2024)

	Dependent Variable	Independent Variable	Constant	Lagged Dependent Variable (1)	Lagged Dependent Variable (2)	Lagged Dependent Variable (3)	Lagged Dependent Variable (4)	Positive Change in Independent Variable	Negative Change in Independent Variable	Residual Standard Error	Adjusted R-Squared	F-Statistic	P-Value
Model 33	Basic Materials	Basic Materials stock returns	0.0015	-0.1862	0.1553	-0.1015		0.0066	-0.0071	0.0030	0.0722	3.624	0.0010***
Model 34	Consumer Discretionary	Consumer Discretionary stock returns	0.0014	-0.0931	-0.1905	0.2340	-0.1019	0.0147	-0.0271	0.0030	0.1686	4.953	0.0000***
Model 35	Consumer Staples	Consumer Staples stock returns	0.0040	-0.2446				0.0221	-0.0290	0.0032	0.2443	11.850	0.0000***
Model 36	Financials	Financials stock returns	0.0009	-0.1817	0.0804	-0.1437		0.0273	-0.0347	0.0032	0.2439	7.863	0.0000***
Model 37	Health Care	Health Care stock returns	-0.0039	-0.3212				0.0372	-0.1546	0.0205	0.6316	51.140	0.0000***
Model 38	Industrials	Industrials stock returns	0.0028	-0.1538				-0.0066	-0.0065	0.0028	0.0738	5.720	0.0002***
Model 39	Technology	Technology stock returns	0.0015	-0.1854				0.0377	-0.0396	0.0054	0.2284	7.926	0.0000***
Model 40	Telecommunications	Telecommunications stock returns	0.0022	-0.3238				0.0347	-0.0272	0.0037	0.3076	10.450	0.0000***

****indicates significance at the 10%, 5% and 1% levels of significance respectively*

Table 15: Using Fama-French 3 Factor Model as an estimate of idiosyncratic volatility in investigating the relationship between idiosyncratic volatility and stock returns coefficients. Source: Own Estimation (2024)

ANNEXURE E

		CAPM			Fama-French 3 Factor Model			
		JB test	**LM test**	**ARCH test**	**JB test**	**LM test**	**ARCH test**	**JB test**
Basic Materials	Statistic	0.9671	0.8973	0.0441	0.9658	0.4839	0.3858	0.9472
Basic Materials	p-value	0.0000	0.5172	0.8337	0.0000	0.6131	0.5345	0.0000
Consumer Discretionary	Statistic	0.9438	12.5353	1.3550	0.9467	12.7758	1.6153	0.9583
Consumer Discretionary	p-value	0.0000	0.2084	0.8520	0.0000	0.2065	0.8060	0.0000
Consumer Staples	Statistic	0.9374	12.2133	4.7023	0.9214	12.6981	1.5538	0.7902
Consumer Staples	p-value	0.0000	0.2110	0.3192	0.0000	0.2071	0.8171	0.0000
Financials	Statistic	0.8215	0.0199	0.3504	0.8134	0.6072	0.0788	0.8949
Financials	p-value	0.0000	0.9108	0.5539	0.0000	0.5786	0.7789	0.0000
Health Care	Statistic	0.2121	2.4527	0.1358	0.2147	2.4339	0.1507	0.2258
Health Care	p-value	0.0000	0.3618	0.7124	0.0000	0.3629	0.6978	0.0000
Industrials	Statistic	0.9469	0.1122	0.0064	0.9153	0.3161	0.0300	0.9099
Industrials	p-value	0.0000	0.7942	0.9360	0.0000	0.6739	0.8625	0.0000
Technology	Statistic	0.9153	0.3161	0.0300	0.8928	0.6532	0.1222	0.9009
Technology	p-value	0.9729	1.0327	2.4161	0.0000	0.5673	0.7266	0.0000
Telecommunications	Statistic	0.9658	0.4839	0.3858	0.9729	1.0327	2.4161	0.9768
Telecommunications	p-value	0.0000	0.5786	0.7789	0.0002	0.4949	0.1201	0.0006

Table 16: Determine the relationship between investor sentiment and idiosyncratic volatility. Source: Own Estimation (2024)

ANNEXURE F

	CAPM		Fama-French 3 Factor Model		Fama-French 5 Factor Model	
	W-stat	**p-value**	**W-stat**	**p-value**	**W-stat**	**p-value**
Basic Materials	1.3727	0.5034	2.0122	0.3656	0.3523	0.8385
Consumer Discretionary	1.3198	0.5169	1.3003	0.5220	1.2245	0.5421
Consumer Staples	2.4832	0.2889	3.2943	0.1926	0.0035	0.9982
Financials	4.3348	0.1145	0.7786	0.6775	1.5071	0.4707
Health Care	0.1112	0.9459	0.1003	0.9511	0.0714	0.9649
Industrials	8.7606	0.0125	0.8136	0.6658	1.5624	0.4579
Technology	0.0497	0.9755	0.7735	0.6793	0.9542	0.6206
Telecommunications	0.1242	0.1242	2.5032	0.2860	0.7446	0.6891

Table 17: Short-run asymmetry test. Source: Own Estimation (2024)

ANNEXURE G

	CAPM		Fama-French 3 Factor Model		Fama-French 5 Factor Model	
	W-stat	p-value	W-stat	p-value	W-stat	p-value
Basic Materials	79.0100	0.0000	114.4847	0.0000	4.0106	0.1346
Consumer Discretionary	226.6944	0.0000	249.1515	0.0000	254.9055	0.0000
Consumer Staples	196.4256	0.0000	337.6444	0.0000	0.1069	0.9479
Financials	76.0151	0.0000	20.1089	0.0000	56.3288	0.0000
Health Care	3.5445	0.1699	3.2018	0.2017	2.2596	0.3231
Industrials	223.7564	0.0000	18.4421	0.0000	36.4302	0.0000
Technology	2.8522	0.2402	45.9277	0.0000	56.7816	0.0000
Telecommunications	303.8802	0.0000	62.6961	0.0000	24.2181	0.0000

Table 18: Long-run asymmetry test. Source: Own Estimation (2024)

		CAPM			Fama-French 3 Factor Model			
		JB test	LM test	ARCH test	JB test	LM test	ARCH test	JB test
Basic Materials	Statistic	0.9698	1.5801	0.0039	0.9731	4.1349	1.1477	0.9493
Basic Materials	p-value	0.0001	0.4278	0.9500	0.0002	0.3434	0.7656	0.0000
Consumer Discretionary	Statistic	0.9569	13.6549	1.0684	0.9579	14.4498	1.4604	0.9709
Consumer Discretionary	p-value	0.0000	0.2000	0.9000	0.0000	0.1945	0.8336	0.0001
Consumer Staples	Statistic	0.9521	2.4659	0.0312	0.9428	0.0460	0.1009	0.9253
Consumer Staples	p-value	0.0000	0.3610	0.8598	0.0000	0.8655	0.7507	0.0000
Financials	Statistic	0.8582	5.7104	2.3236	0.8840	4.3104	4.6738	0.8577
Financials	p-value	0.0000	0.2962	0.5080	0.0000	0.3370	0.1972	0.0000
Health Care	Statistic	0.3756	7.3576	13.6421	0.3767	7.0617	13.8322	0.3982
Health Care	p-value	0.0000	0.2249	0.0002	0.0000	0.2291	0.0002	0.0000
Industrials	Statistic	0.9458	0.3435	0.2484	0.9137	0.2465	0.0575	0.8968
Industrials	p-value	0.0000	0.6625	0.6182	0.0000	0.7066	0.8106	0.0000
Technology	Statistic	0.9316	0.0005	0.0623	0.9267	0.0455	0.3194	0.9408
Technology	p-value	0.0000	0.9857	0.8029	0.0000	0.8663	0.5720	0.0000
Telecommunications	Statistic	0.9918	4.1010	0.9518	0.9934	2.8673	0.5641	0.9918
Telecommunications	p-value	0.2156	0.2920	0.3293	0.1210	0.3396	0.4526	0.2146

Table 19: Determine the relationship between idiosyncratic volatility and stock returns. Source: Own Estimation (2024)

ANNEXURE I

	CAPM		Fama-French 3 Factor Model		Fama-French 5 Factor Model	
	W-stat	**p-value**	**W-stat**	**p-value**	**W-stat**	**p-value**
Basic Materials	5.4792	0.0646	4.6759	0.0965	3.4782	0.1757
Consumer Discretionary	20.5841	0.0000	20.0403	0.0000	14.4557	0.0002
Consumer Staples	20.9275	0.0000	33.3401	0.0000	33.3125	0.0000
Financials	41.2680	0.0000	37.3350	0.0000	33.5085	0.0000
Health Care	30.1407	0.0000	30.2744	0.0000	32.9849	0.0000
Industrials	18.1974	0.0001	0.0001	0.1000	0.8881	0.6414
Technology	61.0601	0.0000	50.4912	0.0000	51.2679	0.0000
Telecommunications	45.3337	0.0000	46.81300	0.0000	46.9051	0.0000

Table 20: Short-run asymmetry test. Source: Own Estimation (2024)

ANNEXURE J

	CAPM		Fama-French 3 Factor Model		Fama-French 5 Factor Model	
	W-stat	**p-value**	**W-stat**	**p-value**	**W-stat**	**p-value**
Basic Materials	299.0384	0.0000	134.8113	0.0000	38.0854	0.0000
Consumer Discretionary	2351.0110	0.0000	2312.2340	0.0000	2116.2150	0.0000
Consumer Staples	281.4193	0.0000	557.1289	0.0000	541.7257	0.0000
Financials	623.5275	0.0000	1131.1260	0.0000	1141.4230	0.0000
Health Care	292.3381	0.0000	293.3722	0.0000	320.1376	0.0000
Industrials	596.3267	0.0000	0.0066	0.9967	31.1466	0.0000
Technology	988.1178	0.0000	1468.2380	0.0000	1744.2940	0.0000
Telecommunications	487.2033	0.0000	446.4107	0.0000	358.0836	0.0000

Table 21: Long-run asymmetry test. Source: Own Estimation (2024)

		JB test	LM test	ARCH test
Basic Materials	Statistic	0.9101	2.3879	6.8257
Basic Materials	p-value	0.0000	0.4364	0.0777
Consumer Discretionary	Statistic	0.8886	4.3960	7.8009
Consumer Discretionary	p-value	0.0000	0.3417	0.0992
Consumer Staples	Statistic	0.8739	3.3721	7.8871
Consumer Staples	p-value	0.0000	0.3761	0.0484
Financials	Statistic	0.9629	8.9974	28.1647
Financials	p-value	0.0000	0.2444	0.0000
Health Care	Statistic	0.8961	10.6719	8.4450
Health Care	p-value	0.0000	0.2205	0.0377
Industrials	Statistic	0.9558	7.0503	11.9064
Industrials	p-value	0.0000	0.2744	0.0181
Technology	Statistic	0.8738	3.1583	9.6665
Technology	p-value	0.0000	0.3870	0.0216
Telecommunications	Statistic	0.9027	0.6019	13.1260
Telecommunications	p-value	0.0000	0.7331	0.0107

Table 22: Determine the relationship between idiosyncratic volatility and stock returns. Source: Own Estimation (2024)

	W-stat	p-value
Basic Materials	1.3727	0.5034
Consumer Discretionary	1.3198	0.5169
Consumer Staples	2.4832	0.2889
Financials	4.3348	0.1145
Health Care	0.1112	0.9459
Industrials	8.7606	0.0125
Technology	0.0497	0.9755
Telecommunications	4.1716	0.1242

Table 23: Short-run asymmetry test. Source: Own Estimation (2024)

	W-stat	p-value
Basic Materials	11.2924	0.0035
Consumer Discretionary	16.5991	0.0002
Consumer Staples	47.7124	0.0000
Financials	0.0120	0.9940
Health Care	93.9807	0.0000
Industrials	0.1964	0.9065
Technology	0.0665	0.9673
Telecommunications	6.8548	0.0325

Table 24: Long-run asymmetry test. Source: Own Estimation (2024)

ANNEXURE N

Variable Name	Test Type	Model Specification	Test	Test Statistic	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)	p-value	Conclusion
Basic Materials	ADF	Intercept	Levels	-16.2451	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Basic Materials	KPSS	Intercept	Levels	0.0816	0.7390	0.4630	0.3470		Stationary
Consumer Discretionary	ADF	Intercept	Levels	-14.3121	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Consumer Discretionary	KPSS	Intercept	Levels	0.2291	0.7390	0.4630	0.3470		Stationary
Consumer Staples	ADF	Intercept	Levels	-17.0253	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Consumer Staples	KPSS	Intercept	Levels	0.3056	0.7390	0.4630	0.3470		Stationary
Financials	ADF	Intercept	Levels	-15.4847	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Financials	KPSS	Intercept	Levels	0.2429	0.7390	0.4630	0.3470		Stationary
Health Care	ADF	Intercept	Levels	-15.5815	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Health Care	KPSS	Intercept	Levels	0.2709	0.7390	0.4630	0.3470		Stationary
Industrials	ADF	Intercept	Levels	-13.5627	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Industrials	KPSS	Intercept	Levels	0.4968	0.7390	0.4630	0.3470		Stationary
Industrials	KPSS	Intercept	1st difference	0.4066	0.7390	0.4630	0.3470		Stationary
Industrials	KPSS	Intercept	2nd difference	0.1247	0.7390	0.4630	0.3470		Stationary
Technology	ADF	Intercept	Levels	-14.6789	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Technology	KPSS	Intercept	Levels	0.3076	0.7390	0.4630	0.3470		Stationary
Telecommunications	ADF	Intercept	Levels	-14.8151	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Telecommunications	KPSS	Intercept	Levels	0.5390	0.7390	0.4630	0.3470		Stationary
Telecommunications	KPSS	Intercept	1st difference	0.2271	0.7390	0.4630	0.3470		Stationary

****indicates significance at the 1%, 5% and 10% levels of significance respectively.*

Table 25: Stationarity tests – stock returns. Source: Own Estimation (2024)

ANNEXURE O

Table 26: Stationarity tests – idiosyncratic volatility: CAPM. Source: Own Estimation (2024)

Variable Name	Test Type	Model Specification	Test	Test Statistic	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)	p-value	Conclusion
Basic Materials	ADF	Intercept	Levels	-4.0744	-2.8734	-2.5732	-2.5732	0.0013***	Stationary
Basic Materials	KPSS	Intercept	Levels	0.1416	0.4630	0.4630	0.3470		Stationary
Consumer Discretionary	ADF	Intercept	Levels	-4.1334	-2.8734	-2.8734	-2.5732	0.0010***	Stationary
Consumer Discretionary	KPSS	Intercept	Levels	0.2039	0.4630	0.4630	0.3470		Stationary
Consumer Staples	ADF	Intercept	Levels	-3.6746	-2.8738	-2.8738	-2.5734	0.0051***	Stationary
Consumer Staples	KPSS	Intercept	Levels	0.1543	0.4630	0.4630	0.3470		Stationary
Financials	ADF	Intercept	Levels	-2.4147	-2.8738	-2.8738	-2.5734	0.1388	Not Stationary
Financials	ADF	Intercept	1st difference	-10.8732	-2.8738	-2.8738	-2.5734	0.0000***	Stationary
Financials	KPSS	Intercept	Levels	0.4726	0.4630	0.4630	0.3470		Not Stationary
Financials	KPSS	Intercept	1st difference	0.0308	0.4630	0.4630	0.3470		Stationary
Health Care	ADF	Intercept	Levels	-3.7761	-2.8738	2.8738	-2.5734	0.0036***	Stationary
Health Care	KPSS	Intercept	Levels	0.1341	0.4630	0.4630	0.3470		Stationary
Industrials	ADF	Intercept	Levels	-4.1567	-2.8738	-2.8738	-2.5734	0.0010***	Stationary
Industrials	KPSS	Intercept	Levels	0.1318	0.4630	0.4630	0.3470		Stationary
Technology	ADF	Intercept	Levels	-1.6382	-2.8738	-2.8738	-2.5734	0.4614	Not Stationary
Technology	ADF	Intercept	1st difference	-9.4721	-2.8738	-2.8738	-2.5734	0.0000***	Stationary
Technology	KPSS	Intercept	Levels	0.3761	0.4630	0.4630	0.3470		Stationary
Technology	KPSS	Intercept	1st difference	0.0557	0.4630	0.4630	0.3470		Stationary
Telecommunications	ADF	Intercept	Levels	-3.4409	-2.8738	-2.8738	-2.5734	0.0105**	Stationary
Telecommunications	ADF	Intercept	1st difference	-10.1745	-2.8738	-2.8738	-2.5734	0.0000***	Stationary
Telecommunications	KPSS	Intercept	Levels	0.2550	0.4630	0.4630	0.3470		Stationary

****indicates significance at the 1%, 5% and 10% levels of significance respectively.*

Variable Name	Test Type	Model Specification	Test	Test Statistic	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)	p-value	Conclusion
Basic Materials	ADF	Intercept	Levels	-3.9422	-3.4576	-2.8734	-2.5732	0.0021***	Stationary
Basic Materials	KPSS	Intercept	Levels	0.1052	0.7390	0.4630	0.3470		Stationary
Consumer Discretionary	ADF	Intercept	Levels	-4.0663	-3.4576	-2.8734	-2.5732	0.0013***	Stationary
Consumer Discretionary	KPSS	Intercept	Levels	0.2082	0.7390	0.4630	0.3470		Stationary
Consumer Staples	ADF	Intercept	Levels	-3.6339	-3.4576	-2.8734	-2.5732	0.0058***	Stationary
Consumer Staples	KPSS	Intercept	Levels	0.1087	0.7390	0.4630	0.3470		Stationary
Financials	ADF	Intercept	Levels	-2.5962	-3.4576	-2.8734	-2.5732	0.0952*	Stationary
Financials	ADF	Intercept	1st difference	-10.4910	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Financials	KPSS	Intercept	Levels	0.3154	0.7390	0.4630	0.3470		Stationary
Health Care	ADF	Intercept	Levels	-3.7415	-3.4576	-2.8734	-2.5732	0.0041***	Stationary
Health Care	KPSS	Intercept	Levels	0.1299	0.7390	0.4630	0.3470		Stationary
Industrials	ADF	Intercept	Levels	-4.4103	-3.4576	-2.8734	-2.5732	0.0004***	Stationary
Industrials	KPSS	Intercept	Levels	0.1443	0.7390	0.4630	0.3470		Stationary
Technology	ADF	Intercept	Levels	-1.6036	-3.4576	-2.8734	-2.5732	0.4791	Not Stationary
Technology	ADF	Intercept	1st difference	-9.3254	-3.4576	-2.8734	-2.5732	0.0000***	Stationary
Technology	KPSS	Intercept	Levels	0.3646	0.7390	0.4630	0.3470		Stationary
Technology	KPSS	Intercept	1st difference	0.0433	0.7390	0.4630	0.3470		Stationary
Telecommunications	ADF	Intercept	Levels	-3.6478	-3.4576	-2.8734	-2.5732	0.0055***	Stationary
Telecommunications	KPSS	Intercept	Levels	0.2260	0.7390	0.4630	0.3470		Stationary

****indicates significance at the 10%, 5% and 1% levels of significance respectively.*

Table 27: Stationarity tests – idiosyncratic volatility: Fama-French 3 Factor Model. Source: Own Estimation (2024)

ANNEXURE Q

Mean	0.0000
Median	-0.3442
Maximum	6.0519
Minimum	-3.4257
Standard Deviation	2.1745
Skewness	0.6005
Kurtosis	2.5339
Jarque-Bera	16.5945
Probability	0.0002
Sum	0.0000
SumSq Deviation	1 130.0966
Observations	240

Table 28: Descriptive statistics for investor sentiment. Source: Own Estimation (2024)

ANNEXURE R

	Basic Materials	Consumer Discretionary	Consumer Staples	Financials	Health Care	Industrials	Technology	Telecommunications
Mean	0.0161	0.0162	0.0153	0.0136	0.0269	0.0138	0.0223	0.0255
Median	0.0157	0.0151	0.0138	0.0115	0.0161	0.0131	0.0213	0.0241
Maximum	0.0380	0.0389	0.0352	0.0441	0.3771	0.0333	0.0479	0.0878
Minimum	0.0020	0.0038	0.0027	0.0016	0.0007	0.0027	0.0055	0.0052
Standard Deviation	0.0063	0.0067	0.0067	0.0083	0.0566	0.0058	0.0082	0.0131
Skewness	0.3596	0.8993	0.7203	1.6742	5.8567	0.6624	0.6573	1.8715
Kurtosis	3.3561	4.1453	2.8989	5.9009	36.1890	3.1871	3.4659	8.7122
Jarque-Bera	6.4399	45.4690	20.8583	196.2661	12 387.0964	17.9027	19.4521	466.3870
Probability	0.0400	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0000
Sum	3.8672	3.8822	3.6638	3.2715	6.4642	3.3125	5.3565	6.1157
SumSq Deviation	0.0093	0.0106	0.0107	0.0165	0.7661	0.0081	0.0161	0.0411
Observations	240	240	240	240	240	240	240	240

Table 29: Descriptive statistics for idiosyncratic volatility – CAPM. Source: Own Estimation (2024)

ANNEXURE S

	Basic Materials	Consumer Discretionary	Consumer Staples	Financials	Health Care	Industrials	Technology	Telecommunications
Mean	0.0159	0.0162	0.0149	0.0129	0.0271	0.0129	0.0251	0.0220
Median	0.0151	0.0151	0.0134	0.0110	0.0174	0.0123	0.0236	0.0214
Maximum	0.0371	0.0393	0.0327	0.0401	0.3753	0.0343	0.0845	0.0409
Minimum	0.0019	0.0044	0.0048	0.0017	0.0021	0.0038	0.0035	0.0062
Standard Deviation	0.0064	0.0067	0.0068	0.0071	0.0563	0.0054	0.0126	0.0074
Skewness	0.4012	0.9290	0.7741	1.6211	5.8699	0.9284	1.8292	0.2803
Kurtosis	3.2713	4.1541	2.8299	5.7748	36.2973	4.4813	8.5528	2.5447
Jarque-Bera	7.1738	47.8396	24.2563	182.1115	12 465.3169	56.4225	442.1675	5.2163
Probability	0.0277	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0737
Sum	3.8169	3.8890	3.5729	3.0959	6.5002	3.0887	6.0224	5.2689
SumSq Deviation	0.0098	0.0107	0.0111	0.0120	0.7576	0.0070	0.0381	0.0131
Observations	240	240	240	240	240	240	240	240

Table 30: Descriptive Statistics of Idiosyncratic Volatility – Fama-French 3 Factor Model. Source: Own Estimation (2024)

	Basic Materials	Consumer Discretionary	Consumer Staples	Financials	Health Care	Industrials	Technology	Telecommunications
Mean	0.0148	0.0154	0.0147	0.0124	0.0296	0.0122	0.0251	0.0213
Median	0.0142	0.0141	0.0134	0.0095	0.0198	0.0111	0.0242	0.0210
Maximum	0.0309	0.0385	0.0331	0.0377	0.3656	0.0326	0.0825	0.0401
Minimum	0.0027	0.0043	0.0051	0.0024	0.0033	0.0029	0.0046	0.0062
Standard Deviation	0.0057	0.0064	0.0064	0.0073	0.0546	0.0052	0.0122	0.0074
Skewness	0.4570	0.9212	0.8407	1.6575	5.7893	1.1681	1.7552	0.2002
Kurtosis	2.6725	3.9817	3.0550	5.2361	35.6481	5.0872	8.2202	2.3971
Jarque-Bera	9.4260	43.5847	28.2991	159.8984	11 999.5863	98.1371	395.7430	5.2376
Probability	0.0090	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0729
Sum	3.5533	3.6906	3.5340	2.9675	7.0966	2.9281	6.0169	5.1094
SumSq Deviation	0.0078	0.0098	0.0099	0.0128	0.7134	0.0064	0.0357	0.0131
Observations	240	240	240	240	240	240	240	240

Table 31: Descriptive statistics for idiosyncratic volatility – Fama-French 5 Factor Model. Source: Own Estimation (2024)

Basic Materials

	CAPM	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Mean	0.0161	0.0159	0.0148
Median	0.0157	0.0151	0.0142
Maximum	0.0380	0.0371	0.0309
Minimum	0.0020	0.0019	0.0027
Standard Deviation	0.0063	0.0064	0.0057
Skewness	0.3596	0.4012	0.4570
Kurtosis	3.3561	3.2713	2.6725
Jarque-Bera	6.4399	7.1738	9.4260
Probability	0.0400	0.0277	0.0090
Sum	3.8672	3.8169	3.5533
SumSq Deviation	0.0093	0.0098	0.0078
Observations	240	240	240

Table 32: Descriptive statistics for idiosyncratic volatility – sector model analysis. Source: Own Estimation (2024)

Consumer Discretionary

	CAPM	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Mean	0.0162	0.0162	0.0154
Median	0.0151	0.0151	0.0141
Maximum	0.0389	0.0393	0.0385
Minimum	0.0038	0.0044	0.0043
Standard Deviation	0.0067	0.0067	0.0064
Skewness	0.8993	0.9290	0.9212
Kurtosis	4.1453	4.1541	3.9817
Jarque-Bera	45.4690	47.8396	43.5847
Probability	0.0000	0.0000	0.0000
Sum	3.8822	3.8890	3.6906
SumSq Deviation	0.0106	0.0107	0.0098
Observations	240	240	240

Table 33: Descriptive statistics for idiosyncratic volatility – sector model analysis. Source: Own Estimation (2024)

Consumer Staples

	CAPM	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Mean	0.0153	0.0149	0.0147
Median	0.0138	0.0134	0.0134
Maximum	0.0352	0.0327	0.0331
Minimum	0.0027	0.0048	0.0051
Standard Deviation	0.0067	0.0068	0.0064
Skewness	0.7203	0.7741	0.8407
Kurtosis	2.8989	2.8299	3.0550
Jarque-Bera	20.8583	24.2563	28.2991
Probability	0.0000	0.0000	0.0000
Sum	3.6638	3.5729	3.5340
SumSq Deviation	0.0107	0.0111	0.0099
Observations	240	240	240

Table 34: Descriptive statistics for idiosyncratic volatility – sector model analysis. Source: Own Estimation (2024)

Financials

	CAPM	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Mean	0.0136	0.0129	0.0124
Median	0.0115	0.0110	0.0095
Maximum	0.0441	0.0401	0.0377
Minimum	0.0016	0.0017	0.0024
Standard Deviation	0.0083	0.0071	0.0073
Skewness	1.6742	1.6211	1.6575
Kurtosis	5.9009	5.7748	5.2361
Jarque-Bera	196.2661	182.1115	159.8984
Probability	0.0000	0.0000	0.0000
Sum	3.2715	3.0959	2.9675
SumSq Deviation	0.0165	0.0120	0.0128
Observations	240	240	240

Table 35: Descriptive statistics for idiosyncratic volatility – sector model analysis. Source: Own Estimation (2024)

Health Care

	CAPM	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Mean	0.0269	0.0271	0.0296
Median	0.0161	0.0174	0.0198
Maximum	0.3771	0.3753	0.3656
Minimum	0.0007	0.0021	0.0033
Standard Deviation	0.0566	0.0563	0.0546
Skewness	5.8567	5.8699	5.7893
Kurtosis	36.1890	36.2973	35.6481
Jarque-Bera	12 387.0964	12 465.3169	11 999.5863
Probability	0.0000	0.0000	0.0000
Sum	6.4642	6.5002	7.0966
SumSq Deviation	0.7661	0.7576	0.7134
Observations	240	240	240

Table 36: Descriptive statistics for idiosyncratic volatility – sector model analysis. Source: Own Estimation (2024)

Industrials

	CAPM	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Mean	0.0138	0.0129	0.0122
Median	0.0131	0.0123	0.0111
Maximum	0.0333	0.0343	0.0326
Minimum	0.0027	0.0038	0.0029
Standard Deviation	0.0058	0.0054	0.0052
Skewness	0.6624	0.9284	1.1681
Kurtosis	3.1871	4.4813	5.0872
Jarque-Bera	17.9027	56.4225	98.1371
Probability	0.0001	0.0000	0.0000
Sum	3.3125	3.0887	2.9281
SumSq Deviation	0.0081	0.0070	0.0064
Observations	240	240	240

Table 37: Descriptive statistics for idiosyncratic volatility – sector model analysis. Source: Own Estimation (2024)

Technology

	CAPM	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Mean	0.0255	0.0251	0.0251
Median	0.0241	0.0236	0.0242
Maximum	0.0878	0.0845	0.0825
Minimum	0.0052	0.0035	0.0046
Standard Deviation	0.0131	0.0126	0.0122
Skewness	1.8715	1.8292	1.7552
Kurtosis	8.7122	8.5528	8.2202
Jarque-Bera	466.3870	442.1675	395.7430
Probability	0.0000	0.0000	0.0000
Sum	6.1157	6.0224	6.0169
SumSq Deviation	0.0411	0.0381	0.0357
Observations	240	240	240

Table 38: Descriptive statistics for idiosyncratic volatility – sector model analysis. Source: Own Estimation (2024)

Telecommunications

	CAPM	Fama-French 3 Factor Model	Fama-French 5 Factor Model
Mean	0.0223	0.0220	0.0213
Median	0.0213	0.0214	0.0210
Maximum	0.0479	0.0409	0.0401
Minimum	0.0055	0.0062	0.0062
Standard Deviation	0.0082	0.0074	0.0074
Skewness	0.6573	0.2803	0.2002
Kurtosis	3.4659	2.5447	2.3971
Jarque-Bera	19.4521	5.2163	5.2376
Probability	0.0001	0.0737	0.0729
Sum	5.3565	5.2689	5.1094
SumSq Deviation	0.0161	0.0131	0.0131
Observations	240	240	240

Table 39: Descriptive statistics for idiosyncratic volatility – sector model analysis. Source: Own Estimation (2024)

REFERENCES

Acharya, V. V. and Merrouche, O. (2013). Precautionary hoarding of liquidity and interbank markets: Evidence from the subprime crisis. *Review of finance, 17*, 107-160.

Aguilera, R. V. and Haxhi, I. (2019). Comparative corporate governance in emerging markets. *The Oxford handbook of management in emerging markets*, 185-218.

Alem, N. (2022). Factors influencing salesperson performance of real estate companies in Addis Ababa. St. Mary's University.

Allen, D. E. and Mcaleer, M. (2020). A Nonlinear Autoregressive Distributed Lag (NARDL) analysis of west texas intermediate oil prices and the Dow Jones Index. *Energies, 13*, 4011.

Almansour, B. Y., Elkrghli, S. and Almansour, A. Y. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. *Cogent Economics and Finance, 11*, 2239032.

Ananwude, A. C. and Osakwe, C. I. (2017). Stock market development and economic growth: A comparative evidence from two emerging economies in Africa: Nigeria and South Africa. *Archives of current research international, 11*, 1-15.

Ang, A., Hodrick, R. J., Xing, Y. and Zhang, X. (2006). The cross-section of volatility and expected returns. *The journal of finance, 61*, 259-299.

Ang, A., Hodrick, R. J., Xing, Y. and Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further US evidence. *Journal of Financial Economics, 91*, 1-23.

Aragó, V., Barreda-Tarrazona, I., Breaban, A., Matallín, J. and Salvador, E. (2022). Market risk aversion under volatility shifts: An experimental study. *International Review of Economics & Finance, 80*, 552-568.

Asness, C. S., Frazzini, A., Israel, R. and Moskowitz, T. J. (2015). Fact, fiction and value investing. *Journal of Portfolio Management, 42*.

Asteriou, D. and Hall, S. G. (2021). Applied econometrics. Bloomsbury Publishing.

Bacchetta, P. and Van Wincoop, E. (2006). Can information heterogeneity explain the exchange rate determination puzzle? *American Economic Review, 96*, 552-576.

Baker, M. and Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of financial Markets, 7*, 271-299.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance, 61*, 1645-1680.

Baker, M., Wurgler, J. and Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of financial economics, 104*, 272-287.

Bali, T. G., Cakici, N. and Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of financial economics, 99*, 427-446.

Bandopadhyay, K. (2012). Capital structure of growth companies with reference to Indian Software Industry. *Indian Journal of Accounting, 45*, 63-70.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of financial economics, 9*, 3-18.

Barberis, N., Huang, M. and Santos, T. (2001). Prospect theory and asset prices. *The quarterly journal of economics, 116*, 1-53.

Barberis, N., Shleifer, A. and Vishny, R. (1998). A model of investor sentiment. *Journal of financial economics, 49*, 307-343.

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *Journal of economic perspectives, 27*, 173-196.

Basiewicz, P. and Auret, C. (2010). Feasibility of the Fama and French three factor model in explaining returns on the JSE. *Investment Analysts Journal, 39*, 13-25.

Baur, D. G. and Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial review, 45*, 217-229.

Bhootra, A. 92011). Are momentum profits driven by the cross-sectional dispersion in expected stock returns? *Journal of Financial Markets, 14*, 494-513.

Blitz, D. and Van Vliet, P. (2007). The volatility effect: Lower risk without lower return. *Journal of portfolio management*, 102-113.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of econometrics, 31*, 307-327.

Breusch, T. S. and Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. Econometrica: *Journal of the econometric society*, 1287-1294.

Brooks, C. (2019). Introductory Econometrics for Finance, Cambridge, United Kingdom: Cambridge University Press.

Brown, G. and Kapadia, N. (2007). Firm-specific risk and equity market development. *Journal of financial economics, 84*, 358-388.

Brown, G. W. and Cliff, M. T. (2005). Investor sentiment and asset valuation. *The Journal of Business, 78*, 405-440.

Buzuzi, M. (2023). Macroeconomic drivers of the Johannesburg Stock Exchange, 2003-2021. University of Johannesburg.

Cakici, N. and Zaremba, A. (2024). What drives stock returns across countries? Insights from machine learning models. *International Review of Financial Analysis, 96*, 103569.

Campbell, J. Y. and Vuolteenaho, T. (2004). Inflation illusion and stock prices. *American Economic Review, 94*, 19-23.

Candemir, I. and Karahan, C. C. (2024). Testing asset pricing models with individual stocks: An instrumental variables approach. *Borsa Istanbul Review*.

Cao, C., Simin, T. and Zhao, J. (2008). Can growth options explain the trend in idiosyncratic risk? *The Review of Financial Studies, 21*, 2599-2633.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance, 52*, 57-82.

Chan, K. S. and Tong, H. (1986). On estimating thresholds in autoregressive models. *Journal of time series analysis, 7*, 179-190.

Chang, B. H., Sharif, A., Aman, A., Suki, N. M., Salman, A. and Khan, S. A. R. (2020). The asymmetric effects of oil price on sectoral Islamic stocks: New evidence from quantile-on-quantile regression approach. *Resources Policy, 65*, 101571.

Chang, X. (2024). Gold price inflation and its implications for financial markets: Strategies for mitigation. *Advances in Economics, Management and Political Sciences, 119*, 189-194.

Chao, H. P. (2019). Incentives for efficient pricing mechanism in markets with non-convexities. *Journal of Regulatory Economics, 56*, 33-58.

Chauhan, G. S. and Banerjee, P. (2018). Financial constraints and optimal working capital. Evidence from an emerging market. *International Journal of Managerial Finance, 14*, 37-53.

Chen, N. F., Roll, R. and Ross, S. A. (1986). Economic forces and the stock market. *Journal of business*, 383-403.

Chen, Z. (2022). The applicability of classic Capital Asset Pricing Model in Chinese stock market. 7th International Conference on Financial Innovation and Economic Development (ICFIED), 2022. *Atlantis Press*, 1213-1218.

Chiang, T. C., Li, J. and Yang, S.-Y. (2015). Dynamic stock–bond return correlations and financial market uncertainty. *Review of Quantitative Finance and Accounting, 45*, 59-88.

Chiang, T. C. and Zheng, D. (2010). An empirical analysis of herd behaviour in global stock markets. *Journal of Banking & Finance, 34*, 1911-1921.

Chinzara, Z. (2011). Macroeconomic uncertainty and conditional stock market volatility in South Africa. *South African Journal of Economics, 79*, 27-49.

Chordia, T., Goyal, A. and Saretto, A. (2018). Anomalies and multiple hypothesis testing: Evidence from two million trading strategies. Working paper, Emory University, University of Lausanne, and The University.

Chowdhury, S. S. H. (2021). Idiosyncratic volatility, investor sentiment and returns of the GCC stock markets. Investment Management and Financial Innovations, 18.

Christelis, D., Georgarakos, D., Jappelli, T. and Kenny, G. (2024). Wealth shocks and portfolio choice. *Journal of Monetary Economics*, 103632.

Chuang, W. J., Ouyang, L. Y. and Lo, W. C. (2010). The impact of investor sentiment on excess returns: A Taiwan stock market case. *International Journal of Information and Management Sciences, 21*, 13-28.

Connor, G. and Korajczyk, R. A. (1995). The arbitrage pricing theory and multifactor models of asset returns. *Handbooks in operations research and management science, 9*, 87-144.

Corredor, P., Ferrer, E. and Santamaria, R. (2015). The impact of investor sentiment on stock returns in emerging markets: The case of Central European Markets. Eastern European Economics, 53, 328-355.

Cubadda, G. (1999). Common cycles in seasonal non-stationary time series. *Journal of Applied Econometrics, 14*, 273-291.

Curatola, G., Donadelli, M., Kizys, R. and Riedel, M. (2016). Investor Sentiment and Sectoral Stock Returns: Evidence from World Cup Games. Finance Research Letters, 17, 267-274.

Da, Z., Engelberg, J. and Gao, P. (2015). The sum of all fears - investor sentiment and asset prices. *The Review of Financial Studies, 28*, 1-32.

Dalika, N. K. and Seetharam, Y. (2014). Sentiment and returns: Analysis of investor sentiment in the South African market. University of the Witwatersrand, Faculty of Commerce, Law and Management.

Dalika, N. K. and Seetharam, Y. (2015). Sentiment and returns: Analysis of investor sentiment in the South African market. University of the Witwatersrand, Faculty of Commerce, Law and Management.

Daniel, K., Hirshleifer, D. and Subrahmanyam, A. (1998). Investor psychology and security market under and overreactions. *The Journal of Finance, 53*, 1839-1885.

De Long, J. B., Shleifer, A., Summers, L. H. and Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of political Economy, 98*, 703-738.

De Vaus, D. (2001). Research design in social research.

Degutis, A. and Novickytė, L. (2014). The Efficient Market Hypothesis: A critical review of literature and methodology. *Ekonomika, 93*, 7-23.

deLlano-Paz, F., Calvo-Silvosa, A., Antelo, S. I. and Soares, I. (2017). Energy planning and modern portfolio theory: A review. *Renewable and Sustainable Energy Reviews, 77*, 636-651.

Dickey, D. A. and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association, 74*, 427-431.

Dustmann, C., Fasani, F., Frattini, T., Minale, L. and Schönberg, U. (2017). On the economics and politics of refugee migration. *Economic policy, 32*, 497-550.

Dybvig, P. H. and Ross, S. A. (1985). Differential information and performance measurement using a security market line. *The Journal of finance, 40*, 383-399.

Elliott, G., Rothenberg, T. J. and Stock, J. H. (1992). Efficient tests for an autoregressive unit root. National Bureau of Economic Research Cambridge, Massachusetts, USA.

Ellis, S., Sharma, S. and Brzeszczyński, J. (2022). Systemic risk measures and regulatory challenges. *Journal of Financial Stability, 61*, 100960.

Engle, R. and Watson, M. (1981). A one-factor multivariate time series model of metropolitan wage rates. *Journal of the American Statistical Association, 76*, 774-781.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the econometric society*, 987-1007.

Engle, R. F. and Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: Journal of the Econometric Society*, 251-276.

Eviews 13 (2024). Student Version.

Fama, E. F. (1970). Efficient capital markets. *Journal of finance, 25*, 383-417.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*, 427-465.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics, 33*, 3-56.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics, 116*, 1-22.

Financial Times. (2018). Financial Times [Online]. Available: https://www.ft.com/ [Accessed 16 December 2024].

Financial Times. (2024). Financial Times [Online]. Available: https://www.ft.com/ [Accessed 21 December 2024].

Fink, J., Fink, K. E., Grullon, G. and Weston, J. P. (2010). What drove the increase in idiosyncratic volatility during the internet boom? *Journal of Financial and Quantitative Analysis, 45*, 1253-1278.

Fletcher, J. and Hillier, J. (2002). On the usefulness of linear factor models in predicting expected returns in mean-variance analysis. *International Review of Financial Analysis, 11*, 449-466.

Frazzini, A., Israel, R. and Moskowitz, T. J. (2018). Trading costs. SSRN 3229719.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of financial Economics, 91*, 24-37.

Fuller, K. P. and Goldstein, M. A. (2011). Do dividends matter more in declining markets? *Journal of Corporate Finance, 17*.

Garad, A., Riyadh, H. A., Al-Ansi, A. M. and Beshr, B. A. H. (2024). Unlocking financial innovation through strategic investments in information management: A systematic review. *Discover Sustainability, 5*, 1-20.

Ghasemi, A. and Zahediasl, S. (2012). Normality tests for statistical analysis: A guide for non-statisticians. *International journal of endocrinology and metabolism, 10*, 486.

Ghumro, N. H., Soomro, I. A. and Abbas, G. (2024). Asymmetric effect of exchange rate and investors' sentiments on stock market performance. *Journal of Economic and Administrative Sciences, 40*, 1192-1204.

Granger, C. W. (1988). Some recent development in a concept of causality. *Journal of econometrics, 39*, 199-211.

Grinblatt, M. and Keloharju, M. (2006). Sensation Seeking, Overconfidence and Trading Activity. *The Journal of Finance, 64*.

Gujarati, D. N. and Porter, D. C. (2009). Basic econometrics. McGraw-Hill.

Guo, Q. (2023). The relationship between investor sentiment and stock market price. *Frontiers in Business, Economics and Management, 9*, 124-129.

Gwelo, A. (2019). Principal components to overcome multicollinearity problem. *Oradea Journal of Business and Economics, 4*, 79-91.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the econometric society*, 357-384.

Hamilton, J. D.(2003). What is an oil shock? *Journal of econometrics, 113*, 363-398.

Hammond, R. C. (2015). Behavioral finance: Its history and its future.

Hari, G. and Das, V. (2023). Examining the Herd Behavior of Different Asset Classes. SSRN 4515807.

Hayward, A., Moshodi, K. and Abdulla, M. (2024). Surge in South African Markets Amid Historic Election and New Government of Unity. South African Market Commentary: June 2024.

Hossain, Z., Rahman, A., Hossain, M. and Karami, J. H. (2019). Over-differencing and forecasting with non-stationary time series data. *Dhaka University Journal of Science, 67*, 21-26.

Hou, K., Xue, C. and Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies, 28*, 650-705.

Huang, D., Jiang, F., Tu, J. and Zhou, G. (2015). Investor sentiment aligned: A powerful predictor of stock returns. *The Review of Financial Studies, 28*, 791-837.

Huber, C., Huber, J. and Kirchler, M. (2021). Market shocks and professionals' investment behavior. Evidence from the COVID-19 crash. *Journal of Banking and Finance, 133*, 106247.

Huberman, G. (2005). Arbitrage pricing theory. Staff Report.

Hussein, M. A. and Hmood, M. Y. (2024). Nonstationary time series models using ARDL and NARDL estimation. *Journal of Economics and Administrative Sciences, 30*, 439-456.

Iqbal, J. and Haider, A. (2005). Arbitrage pricing theory: Evidence from an emerging stock market.

Iress. (2024). Iress Research Domain [Online]. Available: http://research.mcgregorbfa.com.ukzn.idm.oclc.org/Default.aspx [Accessed 19 June 2019].

Jamshidi, N., Owjimehr, S. and Etemadpur, R. (2023). Financial innovation and environmental quality: Fresh empirical evidence from the EU Countries. *Environmental Science and Pollution Research, 30*, 73372-73392.

Jarque, C. M. and Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics letters, 6*, 255-259.

Jiang, G., Lee, C. M. and Zhang, Y. (2005). Information uncertainty and expected returns*. Review of Accounting Studies, 10*, 185-221.

Jiang, X. and Lee, B. S. (2006). The dynamic relation between returns and idiosyncratic volatility. *Financial Management, 35*, 43-65.

Johannesburg Stock Exchange. (2015). Johannesburg Stock Exchange Website [Online]. Available: https://www.jse.co.za/ [Accessed 15 November 2023].

Johannesburg Stock Exchange. (2020). Johannesburg Stock Exchange Website [Online]. Available: https://www.jse.co.za/ [Accessed 17 November 2023].

Johannesburg Stock Exchange. (2023). Johannesburg Stock Exchange Website [Online]. Available: https://www.jse.co.za/ [Accessed 21 November 2023].

Kaendera, S., Dixit, S. and Ltaifa, N. B. (2009). Impact of the global financial crisis on exchange rates and policies in sub-Saharan Africa. International Monetary Fund.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Handbook of the fundamentals of financial decision making: Part I. World Scientific.

Kaplanski, G. and Levy, H. (2010). Sentiment and stock prices: The case of aviation disasters. *Journal of financial economics, 95*, 174-201.

Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and quantitative Analysis, 22*, 109-126.

Khovansky, S. and Zhylyevskyy, O. (2013). Impact of idiosyncratic volatility on stock returns: A cross-sectional study. *Journal of Banking & Finance, 37*, 3064-3075.

Kim, Y. and Lee, K. Y. (2022). Impact of investor sentiment on stock returns. *Asia-Pacific Journal of Financial Studies, 51*, 132-162.

Kothari, C. R. (2004). Research methodology. New Age International.

Kumari, J. and Mahakud, J. (2015). Does investor sentiment predict the asset volatility? Evidence from emerging stock market India. *Journal of Behavioral and Experimental Finance, 8*, 25-39.

Kwiatkowski, D., Phillips, P. C., Schmidt, P. and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of econometrics, 54*, 159-178.

Lee, G. and Ryu, D. (2024). Investor sentiment or information content? A simple test for investor sentiment proxies. *The North American Journal of Economics and Finance, 74*, 102222.

Levy, H. (1978). Equilibrium in an imperfect market: A constraint on the number of securities in the portfolio. *The American Economic Review, 68*, 643-658.

Lo, A. (2017). Adaptive markets: Financial evolution at the speed of thought, Princeton University Press.

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management, Forthcoming*.

Lo, A. W. (2005). Reconciling efficient markets with behavioral finance: the adaptive markets hypothesis. *Journal of investment consulting, 7*, 21-44.

Li, G. (2020). Investor sentiment and size effect. *Open Journal of Social Sciences, 8*, 252-266.

Li, S. (2021). Should passive investors actively manage their trades? SSRN 3967799.

Lintner, J. (1965a). Security prices, risk and maximal gains from diversification. *The journal of finance, 20*, 587-615.

Lintner, J. (1965b). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. Stochastic optimisation models in finance. Elsevier.

Liu, R. and Gupta, R. (2022). Investors' uncertainty and forecasting stock market volatility. *Journal of Behavioral Finance, 23*, 327-337.

Liu, S. (2015). Investor sentiment and stock market liquidity. *Journal of Behavioral Finance, 16*, 51-67.

Loewald, C. (2021). Macro works: applying integrated policy frameworks to South Africa. *South African Reserve Bank Working Paper Series, 21*.

Lu, X. F. and Lai, K. K. (2012). Relationship between stock indices and investors' sentiment index in Chinese financial market. *Xitong Gongcheng Lilun Yu Shijian / System Engineering Theory and Practice, 32*, 621-629.

Lukomnik, J. and Hawley, J. P. (2021). Moving beyond modern portfolio theory: Investing that matters. Routledge.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of economic perspectives, 17*, 59-82.

Markowitz, H. (1952). The utility of wealth. *Journal of political Economy, 60*, 151-158.

Markowitz, H. M. (1967). Portfolio selection: efficient diversification of investments, J. Wiley.

Markowitz, H. M. (1991). Foundations of portfolio theory. *The journal of finance, 46*, 469-477.

Mccoskey, S. and Kao, C. (1998). A residual-based test of the null of cointegration in panel data. *Econometric reviews, 17*, 57-84.

Meher, P. and Mishra, R. K. (2024). Risk-Adjusted Portfolio Optimization: Monte Carlo Simulation and Rebalancing. *Australasian Accounting, Business and Finance Journal, 18*, 85-101.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information.

Meucci, A., Ardia, D. and Colasante, M. (2014). Portfolio construction and systematic trading with factor entropy pooling. *Risk Magazine, 27*, 56-61.

Mills, T. C. and Mills, T. C. (2015). Modelling stationary time series: The ARMA approach. *Time Series Econometrics: A Concise Introduction*, 5-40.

Moagi, O. (2021). Developed practices in the African Real Estate Investment Trusts as a conduit for improving capital investment in the African Real Estate Market. The 20th Annual Afres Conference, 2021. 38.

Moodley, F., Ferreira-Schenk, S. and Matlhaku, K. (2024). Effect of Market-Wide Investor Sentiment on South African Government Bond Indices of Varying Maturities under Changing Market Conditions. Economies, 12, 265.

Mohr, M. and Selk, L. (2020). Estimating change points in nonparametric time series regression models. *Statistical Papers, 61*, 1437-1463.

Moriya, K. and Noda, A. (2023). On the time varying structure of the Arbitrage Pricing Theory using the Japanese sector indices.

Mossin, J. (1966). Equilibrium in a capital asset market. Econometrica: *Journal of the econometric society*, 768-783.

MSCI. (2020). MSCI World Index [Online]. Available: https://www.msci.com/indexes/index/990100 [Accessed 7 December 2024].

Mroua, M. and Trabelsi, L. (2020). Causality and dynamic relationships between exchange rate and stock market indices in BRICS countries: Panel/GMM and ARDL analyses. Journal of Economics, *Finance and Administrative Science, 25*, 395-412.

Muguto, H. T., Muguto, L., Bhayat, A., Ncalane, H., Jack, K. J., Abdullah, S., Nkosi, T. S. and Muzindutsi, P. F. (2022). The impact of investor sentiment on sectoral returns and volatility: Evidence from the Johannesburg stock exchange. *Cogent Economics and Finance, 10*, 2158007.

Muraina, I. O., Adesanya, O. M., Agoi, M. A. and Onen, S. (2023). The necessity of exploratory data analysis: How are preprocessing activities beneficial to data analysts and professional researchers in academia? *Internal Journal of Science and Research in Computer Science and Engineering, 11*.

Musbah, H., Aly, H. H. and Little, T. A. (2023). A proposed novel adaptive DC technique for non-stationary data removal. *Heliyon, 9*, e13903.

Muscatelli, V. A. and Hurn, S. (1992). Cointegration and dynamic time series models. *Journal of Economic Surveys, 6*, 1-43.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: Journal of the Econometric Society*, 315-335.

Muthu, K. and Wesson, N. (2023). The impact of COVID-19 on company performance per industry sector: Evidence from South Africa. *Journal of Economic and Financial Sciences, 16*, 801.

Muzindutsi, P. F., Apau, R., Muguto, L. and Muguto, H. T. (2023). The impact of investor sentiment on housing prices and the property stock index volatility in South Africa. Real Estate Management and Valuation, 31, 1-17.

Naidoo, T., Moores-Pitt, P. and Muzindutsi, P. F. (2025). The effect of investor sentiment on stock market liquidity under changing market conditions: Evidence from South Africa. *Cogent Economics and Finance, 13*, 2444395.

Namouri, H., Jawadi, F., Ftiti, Z. and Hachicha, N. (2018). Threshold effect in the relationship between investor sentiment and stock market returns: A PSTR specification. *Applied Economics, 50*, 559-573.

Naudé, W., Siegel, M. and Marchand, K. (2017). Migration, entrepreneurship and development: Critical questions. *IZA Journal of Migration, 6*, 5.

Ndlovu, B., Faisal, F., Resatoglu, N. and Tursoy, T. (2018). The impact macroeconomic variables on stock returns: A case of the Johannesburg Stock Exchange. *Revista De Statistica*, 2018.

Nel, H. (2020). The financial stability focus is a compilation of South African Reserve Bank topical briefings. South African Reserve Bank.

Nguyen, C. and Bhatti, M. I. (2015). Investor sentiment and idiosyncratic volatility puzzle: Evidence from the Chinese Stock Market.

Nigerian Stock Exchange. (2023). Nigerian Stock Exchange Website [Online]. Available: https://ngxgroup.com/ [Accessed 23 October 2023].

Nikoo, H., Ebrahimi, S. K. and Jalali, F. (2020). The relationship between investor sentiment and idiosyncratic risk with stock mispricing: Evidence from Tehran Stock Exchange. *Journal of Financial Management Strategy, 8*.

Nyarikini, C. O. (2024). Effect of idiosyncratic risks and earnings quality on volatility of stock returns amongst firms quoted at the Nairobi securites exchange. Maseno university.

Page, D., Mcclelland, D. and Auret, C. (2020). Idiosyncratic momentum on the JSE. *Investment Analysts Journal, 49*, 180-198.

Patton, M. Q. (1990). Qualitative evaluation and research methods. Sage.

Peresec. (2023). South African Factor Data Library [Online]. Available: https://www.peresec.com/insights/south-african-factor-data-library/ [Accessed 7 December 2023].

Pesaran, M. H., Shin, Y. and Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics, 16*, 289-326.

Petrică, A. C., Stancu, S. and Ghițulescu, V. (2017). Stationarity - The central concept in time series analysis. *International Journal of Emerging Research in Management, 6*, 6-16.

Ph, H. and Rishad, A. (2020). An empirical examination of investor sentiment and stock market volatility: Evidence from India. *Financial Innovation, 6*, 34.

Phillips, P. C. B. and Perron, P. (1988). Testing for a unit root in time series regression. biometrika.

Prosad, J. M., Kapoor, S. and Sengupta, J. (2015). Behavioral biases of Indian investors: A survey of Delhi-NCR region. *Qualitative research in financial markets, 7*, 230-263.

Pukthuanthong-Le, K. and Visaltanachoti, N. (2009). Idiosyncratic volatility and stock returns: A cross country analysis. *Applied Financial Economics, 19*, 1269-1281.

Qadan, M. and Aharon, D. Y. (2019). Can investor sentiment predict the size premium? *International Review of Financial Analysis, 63*, 10-26.

R Studio (2024). Computer Statistical Software.

Raphael, R. and Jacob, T. (2018). Foreign institutional investment behaviour and Indian capital market: A causality analysis. *International Journal of Management, Technology and Engineering, 8*, 412-420.

Reddy, T. L. and Thomson, R. (2011). The capital asset pricing model: The case of South Africa. Refereed paper. *South African Actuarial Journal, 11*, 43-84.

Rhodes–Kropf, M., Robinson, D. T. and Viswanathan, S. (2005). Valuation waves and merger activity: The empirical evidence. *Journal of financial Economics, 77*, 561-603.

Rompotis, G. (2018). Large-cap vs small-cap portfolio performance: New empirical evidence from ETFs. *Review of Accounting and Finance, 18*.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory, 13*, 341-360.

Rupande, L., Muguto, H. T. and Muzindutsi, P. F. (2019). Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange. *Cogent Economics and Finance*.

Rutkowska-Ziarko, A., Markowski, L., Pyke, C. and Amin, S. (2022). Conventional and downside CAPM: The case of London stock exchange. *Global Finance Journal, 54*, 100759.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of empirical finance, 16*, 394-408.

Seok, S., Cho, H. and Ryu, D. (2024). Dual effects of investor sentiment and uncertainty in financial markets. *The quarterly review of Economics and Finance, 95*, 300-315.

Sewell, M. (2010). Behavioural Finance. University of Cambridge.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance, 19*, 425-442.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance, 40*, 777-790.

Shefrin, H. and Statman, M. (2000). Behavioral portfolio theory. *Journal of financial and quantitative analysis, 35*, 127-151.

Shenjere, P. A., Ferreira-Schenk, S. and Moodley, F. (2025). Does investor sentiment influence South African ETF flows during different market conditions? *Economies, 13*, 10.

Shiller, R. J. (1981). Do stock prices move too much to be justified by subsequent changes in dividends?

Shin, Y., Yu, B. and Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. Festschrift in honor of Peter Schmidt: Econometric methods and applications, 281-314.

Shleifer, A. (2000). Inefficient markets: An introduction to behavioural finance, Oup Oxford.

Shleifer, A. and Vishny, R. W. (1997). The limits of arbitrage. *The Journal of finance, 52*, 35-55.

Smales, L. A. (2017). The importance of fear: investor sentiment and stock market returns. *Applied Economics, 49*, 3395-3421.

Soe, A. M. (2013). Dividend Investing and a look Inside the S&P Dow Jones Dividend Indices, United States of America: McGraw Hill Financial.

South African Reserve Bank. (2024). Monetary Policy [Online]. Available: https://www.resbank.co.za/en/home/what-we-do/monetary-policy [Accessed 3 December 2024].

Stambaugh, R. F., Yu, J. and Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics, 104*, 288-302.

Standard & Poor's. 2008. Standard & Poor's Website [Online]. Available: https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview [Accessed 5 November 2024].

Stats Sa. (2016). The economy: winners and losers of 2015 [Online]. Available: https://www.statssa.gov.za/?p=6233 [Accessed 1 December 2024].

Strugnell, D., Gilbert, E. and Kruger, R. (2011). Beta, size and value effects on the JSE, 1994–2007. *Investment Analysts Journal, 40*, 1-17.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of finance, 62*, 1139-1168.

Thakor, A. V. (2015). The financial crisis of 2007–2009: Why did it happen and what did we learn? *The Review of Corporate Finance Studies, 4*, 155-205.

Thaler, R. H. (1999). The end of behavioral finance. *Financial Analysts Journal, 55*, 12-17.

The Guardian. (2017). Jacob Zuma urged to quit after South Africa credit rating downgrade [Online]. Available: https://www.theguardian.com/world/2017/apr/04/south-africa-credit-rating-junk-status-sends-rand-tumbling/ [Accessed 3 August 2024].

The World Bank. (2015). South Africa Economic Update.

Timmermann, A. and Granger, C. W. (2004). Efficient market hypothesis and forecasting. *International Journal of forecasting, 20*, 15-27.

Trebbi, F. and Xiao, K. (2019). Regulation and market liquidity. *Management Science, 65*, 1949-1968.

Treynor, J. L. (1962). Toward a theory of market value of risky assets.

Uddin, J. (2009). Time series behavior of imports and exports of Bangladesh: Evidence from cointegration analysis and error correction model. *International Journal of Economics and Finance, 1*, 156-162.

Van Rensburg, P. and Robertson, M. (2003). Explaining the cross-section of returns in South Africa: Attributes or factor loadings? *Journal of Asset Management, 4*, 334-347.

Venditti, F. and Veronese, G. (2020). Global financial markets and oil price shocks in real time. European Central Bank, 2472.

Vengesai, E. (2022). COVID-19 shock and sectorial index response in South Africa: a cross-sector analysis. *International Journal of Economics and Financial Issues, 12*, 123-136.

Vidal-García, J., Vidal, M., Boubaker, S. and Manita, R. (2019). Idiosyncratic risk and mutual fund performance. *Annals of Operations Research, 281*, 349-372.

Wang, W. (2024). Investor sentiment and stock market returns: a story of night and day. *The European Journal of Finance, 30*, 1437-1469.

Wang, W., Su, C. and Duxbury, D. (2021). Investor sentiment and stock returns: Global evidence. *Journal of Empirical Finance, 63*, 365-391.

Ward, M. and Muller, C. (2012). Empirical testing of the CAPM on the JSE. *Investment Analysts Journal, 41*, 1-12.

Whaley, R. E. (2000). The investor fear gauge. *Journal of portfolio management, 26*, 12.

Wu, R. (2022). Model comparison between CAPM and APT: With focus on application of Factor Models. *BCP Business & Management, 30*, 583-587.

Yang, H., Ryu, D. and Ryu, D. (2017). Investor sentiment, asset returns and firm characteristics: Evidence from the Korean Stock Market. *Investment Analysts Journal, 46*, 132-147.

Zhang, X., Bissoondoyal-Bheenick, E. and Zhong, A. (2023). Investor sentiment and stock market anomalies in Australia. *International Review of Economics and Finance, 86*, 284-303.

Zhao, Q. and Wei, Q. (2024). The impact of investor sentiment on stock returns in developing countries. *Cuadernos de Economía, 47*, 103-108.

Zhong, A. and Gray, P. (2016). The MAX effect: An exploration of risk and mispricing explanations. *Journal of Banking and Finance, 65*, 76-90.

Zhu, B., Niu, F. and Zhao, Y. (2020). The Non linear impact of investor sentiment on stock returns: Evidence from China. *International Review of Economics and Finance, 69*, 424-438.