



Strathmore
UNIVERSITY

SU+ @ Strathmore
University Library

Electronic Theses and Dissertations

2025

An Empirical investigation of the relationship between investor sentiment and volatility of the equities market in Kenya between 2013 and 2023.

Kiaritha, Eva Njeri
Strathmore Business School
Strathmore University

Recommended Citation

Kiaritha, E. N. (2025). *An Empirical investigation of the relationship between investor sentiment and volatility of the equities market in Kenya between 2013 and 2023* [Strathmore University].

<http://hdl.handle.net/11071/16013>

Follow this and additional works at: <http://hdl.handle.net/11071/16013>

**An Empirical Investigation of the Relationship Between Investor Sentiment and
Volatility of the Equities Market in Kenya Between 2013 And 2023**

Kiaritha Eva Njeri

094086

**Submitted in partial fulfilment of the requirements for the Degree of Master of
Commerce at Strathmore University**



Strathmore University Business School

Strathmore University

Nairobi, Kenya

June, 2025

DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the dissertation contains no material previously published or written by another person except where due reference is made in the dissertation itself.

© No part of this dissertation may be reproduced without the permission of the author and Strathmore University

Eva Njeri Kiaritha

Approval

The dissertation of Eva Njeri Kiaritha was approved by the following:

Name of Supervisor: Dr. Freshia Mugo - Waweru

School/Institute/Faculty: Strathmore University Business School

Dr. Caesar Mwangi

Executive Dean

Strathmore University Business School.

Prof. Bernard Shibwabo

Director, Office of Graduate Studies



ABSTRACT

Volatility is a key component of financial markets. It has direct bearing on market uncertainty and influences investment decisions. Higher stock market return volatility can enhance liquidity, but excessive volatility may precipitate crashes. Stock market volatility in Kenya has exhibited an upward trend which raises concerns on heightened market risk. This underscores the need for a comprehensive understanding of the factors driving volatility in the Kenyan market, including investor sentiment, which can cause price swings that are not always explained by fundamentals. This research therefore sought to examine the relationship between investor sentiment and volatility in the Kenyan stock market, guided by the efficient market hypothesis, market microstructure theory, and the noise trader theory. The study period spanned from 2013 to 2023 capturing significant events such as the 2013, 2017 and 2022 elections, the Covid-19 pandemic, currency depreciation and other socio-political-economic shifts which could impact the sentiment-volatility relationship. The study aimed at capturing and quantifying the prevailing market wide sentiment at various time intervals and on further analysis of the sentiment-volatility relationship. The asymmetric effect of sentiment on volatility and the variation in the relationship between high and low volatility regimes was also assessed. Investor sentiment was measured using a monthly sentiment index created using principal component analysis from market-based indicators, while controlling for macroeconomic variables and company fundamentals. The study leveraged on the Generalised Autoregressive Conditional Heteroscedasticity models and quantile regression to capture fluctuations in volatility over time and the impact of investor sentiment. The findings indicated that the sentiment index has significant impact on the return volatility in the Kenyan stock market, with positive sentiment increasing and negative sentiment decreasing volatility. This relationship varies across volatility regimes, being negative during low-volatility periods and positive during average and high-volatility periods. These findings offer practical implications for integrating sentiment analysis into investment and risk management strategies. Limitations include reliance on proxy-based sentiment measures and focus on a single market, suggesting avenues for future research using psychological sentiment indices and multi-market comparisons.



Table of Contents

DECLARATION	1
ABSTRACT.....	ii
LIST OF FIGURES	vi
LIST OF TABLES	vii
LIST OF ABBREVIATIONS.....	viii
DEFINITION OF TERMS	ix
ACKNOWLEDGEMENTS	x
CHAPTER ONE	1
INTRODUCTION	1
1.1 Background to the study.....	1
1.1.1 Investor sentiment.....	2
1.1.2 Stock market volatility.....	3
1.1.3 Market wide sentiment, stock returns and volatility.....	4
1.1.4 Equities Market in Kenya.....	6
1.2 Problem definition.....	7
1.3 Research objectives	8
1.3.1 General objective.....	8
1.3.2 Specific objectives.....	8
1.4 Research questions	8
1.5 Scope of the study	8
1.6 Significance of the study	9
1.6.1 Investors.....	9
1.6.2 Policymakers	9
1.6.3 Listing companies.....	9
1.7 Chapter Summary.....	9
CHAPTER TWO	10
LITERATURE REVIEW	10
2.1 Introduction	10

2.2 Theoretical review	10
2.2.1 Efficient Market Hypothesis	10
2.2.2 Market Microstructure Theory	13
2.3 Empirical review	15
2.3.1 Investor sentiment and stock market volatility	15
2.3.2 The sentiment-volatility relationship across different market conditions	18
2.3.3 Asymmetric effects of investor sentiment on stock market volatility	20
2.4 Research Gap	22
2.5 Conceptual framework	24
2.6 Operationalization of Study Variables	25
2.6.1 Investor Sentiment Proxies	25
2.6.2 Volatility	28
2.7 Chapter Summary	28
RESEARCH METHODOLOGY	29
3.1 Introduction	29
3.2 Research Philosophy	29
3.3 Research Design	29
3.4 Population and Sampling	30
3.5 Data Collection	30
3.6 Data Analysis	31
3.7 Ethical Considerations	33
CHAPTER FOUR	34
PRESENTATION OF RESEARCH FINDINGS	34
4.1 Introduction	34
4.2 General Information	34
4.3 Descriptive Statistics	34
4.4 Principal Component Analysis	35
4.5 Diagnostic Tests	37
4.5.1 Stationarity	37
4.5.2 Normality	38
4.5.3 Heteroscedasticity	38

4.6 GARCH Analysis	39
4.7 Quantile Regression	41
4.8 E-GARCH Analysis	42
4.9 Summary of the chapter	43
CHAPTER FIVE	44
DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS	44
5.1 Introduction	44
5.2 Discussions.....	44
5.2.1 Relationship Between Investor Sentiment and Volatility.....	44
5.2.2 Sentiment–Volatility Relationship Across Market Regimes.....	45
5.2.3 Asymmetric Effects of Investor Sentiment on Stock Market Volatility, Distinguishing Between Positive and Negative Sentiment	45
5.3 Conclusions	46
5.3.1 Relationship Between Investor Sentiment and Volatility.....	46
5.3.2 Sentiment–Volatility Relationship Across Market Regimes.....	46
5.3.3 Asymmetric Effects of Investor Sentiment on Stock Market Volatility, Distinguishing Between Positive and Negative Sentiment	46
5.4 Recommendations	47
5.4.1 Recommendations for theory.....	47
5.4.2 Recommendations for policy	47
5.4.3 Recommendations for practice	47
5.5 Research Areas for Further Studies.....	48
5.6 Limitations of the Study	48
REFERENCES	49
APPENDICES	59
Appendix I: NSE Listed Companies 2023	59
Appendix II: Secondary Data Collection Sheet	61
Appendix III: Ethical Clearance.....	62

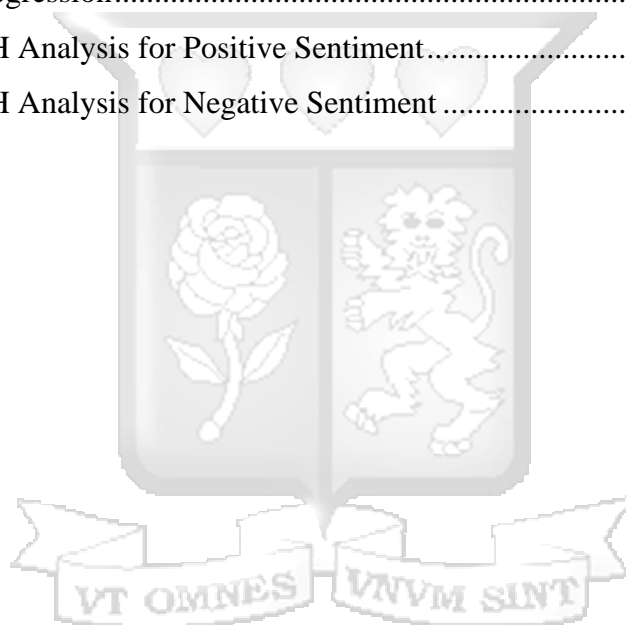
LIST OF FIGURES

Figure 1.1: NSE 20-Share Index Trend – (March 2014 to March 2023).....	6
Figure 2.1: Conceptual framework of investor sentiment and stock market volatility.....	25
Figure 4.1: Scree plot.....	36



LIST OF TABLES

Table 2.1 Research gap matrix.....	23
Table 4.1: Descriptive Statistics	34
Table 4.2: Principal Component Analysis	35
Table 4.3: Unit Root Test for Returns	37
Table 4.4: Unit roots for Sentiment Index	37
Table 4.5: Normality Test Results	38
Table 4.6: Breusch Pagan test for Heteroskedasticity	38
Table 4.7: ARCH-LM Test for Conditional Heteroskedasticity.....	39
Table 4.8: GARCH Results.....	39
Table 4.9: Quantile Regression.....	41
Table 4.10: E-GARCH Analysis for Positive Sentiment.....	42
Table 4.11: E-GARCH Analysis for Negative Sentiment.....	42



LIST OF ABBREVIATIONS

CBK- Central Bank of Kenya

CMA- Capital Markets Authority

NSE- Nairobi Securities Exchange

PCA- Principal Component Analysis

GARCH - Generalized Autoregressive Conditional Heteroskedastic



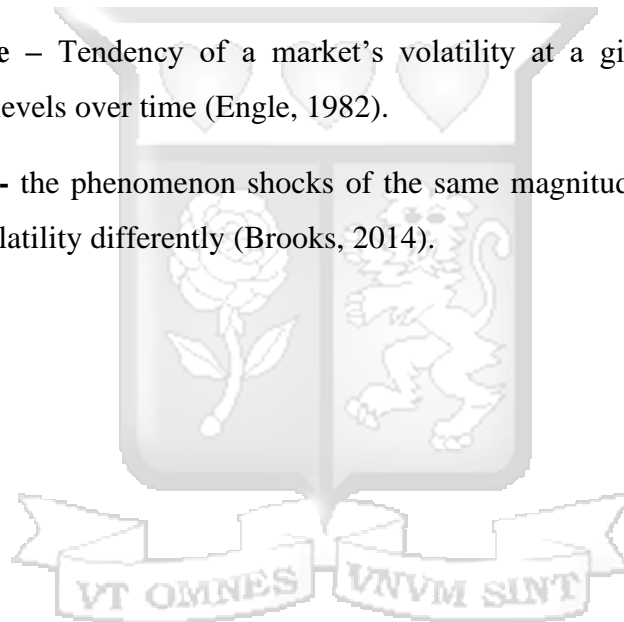
DEFINITION OF TERMS

Investor Sentiment – Unjustified convictions regarding projected cash flows and investment risks that do not align with current information (Baker & Wurgler, 2007). It is the general investor attitude towards financial markets i.e., optimism or pessimism of investors at a given point in time. These are the reactions, attitude and prejudices that surface during an investment decision (Corporate Finance Institute).

Stock market volatility – a statistical measure of an index or security's return dispersion. It is also defined as the fluctuation rate in asset prices, that is, degree of the decrease or increase in a security price at a certain time (Silva et al., 2017).

Volatility persistence – Tendency of a market's volatility at a given time, to continue influencing volatility levels over time (Engle, 1982).

Asymmetric Effects - the phenomenon shocks of the same magnitude, whether positive or negative, influence volatility differently (Brooks, 2014).



ACKNOWLEDGEMENTS

First and foremost, I would like to thank God for His grace and strength that guided me throughout this endeavour. I extend my deepest gratitude to my sister, Eirene, and my parents Mr. & Mrs. Kiaritha for their unwavering love, support, endless encouragement and belief in me. I would also like to express my sincere appreciation to my supervisor Dr. Freshia Waweru, for her invaluable guidance, insightful feedback and support throughout this research. Finally, I wish to acknowledge the support of my extended family, classmates, friends and colleagues, whose understanding and encouragement made this possible.



CHAPTER ONE

INTRODUCTION

1.1 Background to the study

Volatility is a significant aspect of the financial markets. It directly relates to market uncertainty and influences investment behaviour (Bhowmik & Wang, 2020). The COVID-19 pandemic, Russia-Ukraine war, and financial crisis resulted in notable spikes in equity market volatility sparking renewed interest in analysing equity market volatility to determine the main forces (Aawaar, 2023). The Nairobi Securities Exchange has experienced instances of high volatility which suggests that there may be underlying inefficiencies that have an effect on shareholder value (Cherono, 2020). While stock market return volatility may promote liquidity in the market, excess volatility may lead to crashes (Ndei et al., 2019). Investor sentiment which influences market behaviour, has been considered to be a contributing factor to volatility in emerging markets (Haritha & Rishad, 2020).

The modern finance theory suggests that investors consistently make rational investment decisions, but behavioural finance was developed as a response to this. Behavioural finance suggests that due to susceptibility to a variety of behavioral biases and beliefs, investors do not always take rational actions. The implication of this is that projected returns are not shaped by fundamental risks only, as suggested by the traditional asset pricing models and mean-variance portfolio theory but are also influenced by investor biases (Kapoor & Prosad, 2017). Market prices are therefore a combination of fundamental values and investor sentiment and therefore understanding investor behaviour is key to understanding the market as a whole (Reilly et al., 2019).

Behavioral finance seeks to explain the decision-making processes in real-life financial scenarios, exploring why choices made by decision-makers may not consistently exhibit rationality and, as a result, lead to unforeseeable outcomes. The theories establish that investors could develop inaccurate stochastic convictions either with extreme optimism or pessimism leading to incorrect evaluation of asset values which causes deviation in an asset's price from its intrinsic worth (De Long et al., 1990). Some behavioural decision-making attributes include the multifaceted nature of investor preferences and their possibility of changing, adaptability of decision-makers depending on the nature of the decision and their environment as well as the tendency to seek satisfactory as opposed to optimal solutions. These are likely to have systematic effects on the behaviour of financial markets (Olsen, 1998).

The foundation of behavioural finance is two premises. First, is the presumption that investors are exposed to sentiment (De Long, et al., 1990), and secondly, it is expensive and risky to bet against sentiment-driven investors as proposed by Shleifer and Vishny (1997). Smart money investors or those with more knowledge about financial markets may counteract noise that arises from irrational trading through arbitrage, however, limits to arbitrage exist. Mispricing therefore happens when irrational traders experience a shift in sentiment, and rational traders face constraints on arbitrage. With the limit in arbitrage, the larger divergence in opinion among investors leads to greater price volatility as well as higher equilibrium market prices (Baker & Wurgler, 2007; Olsen, 1998) and hence the need to study investor sentiment.

1.1.1 Investor sentiment

The concept of investor sentiment encompasses all the behavioural factors that could provide an explanation on how investors develop the beliefs on which they base their decisions. De Long et al (1990) described investor sentiment to be the convictions regarding risks associated with investments and cashflows in the future, that are not supported by present facts. It can also be understood as an inclination to react on the basis of noise signals instead of substantive information. Baker and Wurgler (2006), defined sentiment as the pessimism and optimism among investors and it is sometimes also described as the propensity to speculate.

Investors that are too optimistic or pessimistic push prices beyond or below fundamental values, and these pricing distortions typically correct over a period of years (Ayinola & Adetiloye, 2023). Sentiment has a connotation with emotions; it is described as investors' aversion to risk (Brad & Terrance, 2013). The sentiment includes common errors in judgement made by numerous investors, rather than being only uncorrelated random errors (Sheifler, 2000). These beliefs may result from individuals incorporating accurate information wrongly or utilizing wrong information correctly. Brown and Cliff (2004) suggest that it is the representation of what market participants anticipate in relation to a benchmark. Bullish investors anticipate gains that are above average, while those who are negative anticipate below-average returns.

Factors such as information signals published in the market, information on specific companies, economic indicators, and liquidity measures in the financial market contribute to sentiment (Raissi & Missaoui, 2016). Bennet et al. (2012) stated that the attitude of investors is impacted by intuition, rumours, media coverage of the stocks and investor herd mentality. Zhang (2008) highlighted that the discrepancy between an objectively accurate forecast based

solely on relevant information and an individual's subjective evaluation considering all available information plus potentially skewed private information, is a good way to conceptualize investor sentiment. The stock market is therefore susceptible to the influence of sentiment highlighting the need to understand the psychological factors underlying human behaviours (Chang et al., 2002). Sentiment can be categorized into positive, negative and neutral.

Various approaches have been developed for the measurement of sentiment. The bottom-up approach uses biases exhibited by retail investors such as representativeness, loss aversion, overconfidence, belief perseverance, herding, anchoring, conservatism, availability bias and mental accounting, to describe the response of investors to past returns or fundamental information. The approach provides micro-foundations for the diversity in investor sentiment but suffers from the inability to capture the complexity of investors and markets in a limited number of biases and trade frictions. On the other hand, the top-down model concentrates on gauging the aggregate sentiment and monitoring how it affects market returns. Among the market-based sentiment proxies adopted in previous studies are the number of newly opened stock accounts, dividend premium, market turnover rates, initial public offerings and their first day returns, closed-end fund discounts, mutual fund flows, share value, put-call ratio, trading volume, market capitalization, stock price momentum, market breadth, equity shares in new issues and turnover ratio. The top-down model has the capacity to encompass bubbles, crashes, and stock prices trends in an insightful, straightforward and comprehensive way (Baker & Wurgler, 2007). This paper will utilize the top-down investor sentiment approach which utilizes market-based proxies providing a market wide perspective.

1.1.2 Stock market volatility

Sentiment has been observed to be an important component in the explanation of excess returns that may arise from high volatility. Volatility refers to the changes in a variable over time. The more the variable fluctuates, the higher the volatility. Volatility is often associated with fear and other investor attitudes. It is the digression of market returns from the predicted value and could either be conditional meaning that the variability measure changes over time and is randomly distributed, or unconditional where the measure of dispersion is time-invariant (Daly, 2008; Osimbo, 2020). Volatility is associated with uncertainty, investment risk, and unpredictability (Daly, 2007). As a result, high volatility is perceived as an indication of market interference depicting unfairly priced securities and presence of anomalies in the capital market (Schwert, 1990).

Volatility has numerous applications in finance ranging from its pivotal role in asset allocation using the mean-variance framework to its uses in the derivatives market. A solid understanding of volatility and how to estimate it is important for predicting the expected returns of risky assets. Volatility is quantified by percentage variations in prices or returns (Schwert, 1990).

There are several commonly employed measures of volatility in financial research. Historical volatility refers to the standard deviation of asset returns over a specified time window and serves as a backward-looking estimate of risk (Hull, 2015). In contrast, GARCH models capture time-varying volatility by modeling the current conditional variance as a function of past squared returns and past variances, allowing for volatility clustering observed in financial time series (Engle, 1982; Bollerslev, 1986). Another widely used measure is implied volatility, which represents future volatility as perceived by the market and is extracted from option prices, serving as a forward-looking indicator (Whaley, 2000).

1.1.3 Market wide sentiment, stock returns and volatility

Baker and Wurgler (2006) found a strong association between sentiment and the differences in stock returns across various companies in America. They concluded that investor sentiment leads to short-term pricing distortions, but these are eventually corrected in the long run. Chen et al. (2020) established investor sentiment leads to stock market volatility during severe market fluctuations and also established that sentiment indeed predicts realized volatility in the Chinese market. Haritha and Rishad (2020) similarly determined that irrational sentiment plays a major part in causing excessive fluctuations in the Indian market. Further research on the influence of investor sentiment on the cross-section of returns and volatility has been done in other markets like New Zealand, Australia, European countries (Schmeling, 2008), Pakistan (Muhammad, 2021) and have confirmed that a connection exists between sentiment and the stock market but with varying conclusions. Zheng (2020) provides that the variance in findings on the relationship between sentiment and stock returns is attributable to variations in measurements, techniques, study periods, and locales.

The area of research has also been explored in Africa. Rupande, et al. (2019) conducting the study in South Africa, concluded that investor sentiment significantly influences stock return volatility on the Johannesburg Stock Exchange. The study found that noise trader activity driven by sentiment increases market volatility, and this effect persists for extended periods because of the large number of sentiment-driven noise traders and various limits to arbitrage. In Nigeria, Nnoje et al. (2021), went further and categorized sentiment into positive and

negative. It was found that the sentiment index is negatively and significantly associated with stock return volatility, with positive sentiment having a stronger asymmetrical impact on volatility than negative sentiment.

The relationship between sentiment and stock returns has been found to be inconsistent with conventional finance theory, which maintains that stock prices reflect the discounted value of anticipated cash flows and that arbitrage neutralizes irrational market activity. However, behavioral finance proposes that the outlook of investors, whether positive or negative, affects asset prices. According to Baker and Wurgler (2006), sentiment-driven mispricing occurs due to uninformed demand from certain investors, known as noise traders, and the constraints faced by arbitrageurs.

Kenya presents a compelling context for investigating the influence of investor sentiment on stock market volatility, in view of the unique market characteristics such as the high percentage of retail investors which stands at 46.112% (Capital Markets Authority [CMA], 2023). This is a stark contrast to major financial markets like the UK, Europe, USA and Japan with retail participation of around 20% and India at 2% (Pandey & Sehgal, 2019). The notion held is that sentiment waves mainly affect retail investors who lead to a divergence between market prices and fundamental values as institutional investors tend to demonstrate greater informational rationality in their trading behaviors (Pandey & Sehgal, 2019). This suggests that sentiment effects may be more pronounced in Kenya than in more institutionally dominated markets.

Previous studies done in Kenya either used behavioral biases (Cherono et al., 2019), single variables (Mohamed, 2013; Musembi, 2020) or combination of weighted ratios (Nabosu et al., 2022) as sentiment indicators. The studies established a significant relationship between sentiment and stock market performance. This study therefore seeks further the research by constructing a sentiment index, examining the relationship between sentiment and volatility, the presence of the asymmetric effect and the relationship during different regimes, which are less explored in the Kenyan market. This research also includes the pre-pandemic, pandemic and post-pandemic period which is significant as market sentiment is dynamic and changes rapidly in response to new information, events or other shifts in the market. According to Gao et al. (2022), market volatility is more vulnerable to investor sentiment after the COVID-19 pandemic and hence the need to include the study period.

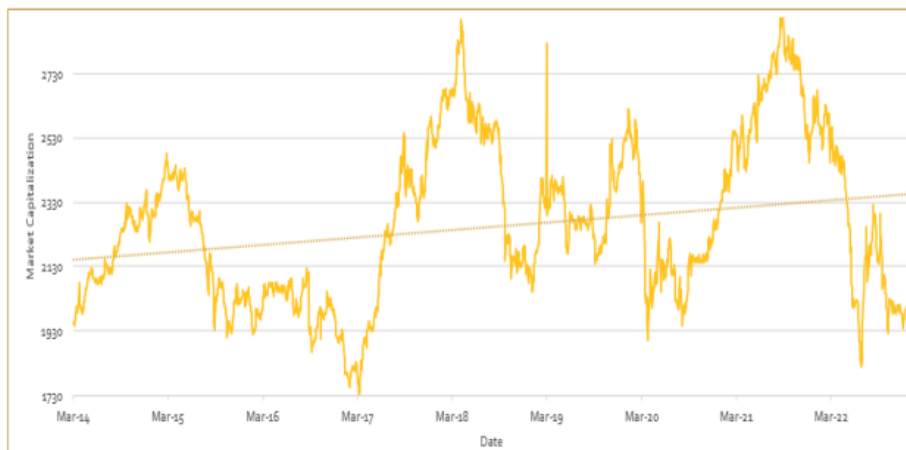
1.1.4 Equities Market in Kenya

The Nairobi Securities Exchange serves as Kenya's principal bourse, providing an automated listing and trading platform for different securities. There were 66 listed companies on the exchange as at December 2023 (CMA, 2023) under 11 sectors. The NSE market has three indices. The NSE 20-Share index mirrors the geometric average prices of the leading 20 listed companies, while the NSE 25-Share Index is crafted to depict the performance of listed Kenyan firms. Additionally, the NSE All Share Index encompasses all companies listed on the NSE, serving as a comprehensive gauge of market performance (Makau, 2016).

The performance of the listed securities remained subdued in 2022 in line with the sharp price volatility observed in global asset prices. The market experienced capital outflows and reallocation of funds to fixed income assets with the equity market turnover decreasing by 31% to KES 94.2 billion from KES 137.4 billion in 2021 (Nairobi Securities Exchange [NSE], 2023). Moreover, the market capitalization decreased by 27.59% from KES 2,425 billion in Q1 2022 to KES 1756 billion in Q1 2023 (CMA, 2023). The trend has been fluctuating over the years as demonstrated in Figure 1. Coffie and Chukwulobelu (2013), attributed high volatility, thin trading, illiquidity, asset mispricing and abnormally distributed equity returns to the market.

Volatility reduces investors' confidence thus disrupting smooth functioning of the securities market (Ndwiga & Muriu, 2016) which negatively affects the economy as well. Fluctuation in share prices presents a challenge in making investment decisions. Consequently, sufficient knowledge of volatility is vital for investors and other participants as asymmetric volatility increases market risk.

Figure 1.1: NSE 20-Share Index Trend – (March 2014 to March 2023)



Source: NSE/CMA

1.2 Problem definition

Stock market volatility in Kenya has exhibited an upward trend over the past decade, rising from 10.12% in 2015 to 17.09% in 2021, based on World Bank development metrics, measured by the 360-day mean volatility of the national stock market index. The June 2023 Morgan Stanley Capital International Index further revealed that Kenya's volatility surpasses that of frontier markets and global indices, with a 10-year annualized standard deviation of 21.23%, compared to 14% and 14.5% for the respective benchmarks. Such heightened volatility increases market risk, creates uncertainty, and undermines investor confidence, ultimately impacting financial market liquidity and returns (Bhowmik & Wang, 2020; Muguto & Muzindutsi, 2022). Understanding the nature of this volatility is therefore crucial for developing strategies that enhance market stability.

Amidst global economic disruptions, the external environment has become more challenging (CMA, 2022), which could contribute to the higher volatility in the stock market. Between November 2019 and November 2022, foreign holdings of listed equities declined by 4.3 billion units, with the exit of foreign investors leaving a more volatile bourse and lower share prices (Muiruri, 2023). Existing literature suggests that traditional fundamental and technical analysis alone cannot fully explain stock market volatility without incorporating investor sentiment (Rehman, 2013). Studies across different markets, including India (Haritha & Rishad, 2020) and South Africa (Rupande et al., 2019), indicate a strong association between sentiment and volatility, with negative sentiment exerting a more dominant effect (Paramanik & Singhal, 2020). However, Xiao and Aumeboonsuke (2022) argue that sentiment and volatility are not correlated over the long run, underscoring the need for market-specific investigations. Investor attitudes tend to fluctuate periodically and vary across countries due to country-specific factors, influencing how market-wide sentiment affects stock returns (Anusakumar et al., 2017). This makes it essential to explore sentiment and its relationship with volatility in the Kenyan market.

In Kenya, investor sentiment has been associated with market performance. Musembi (2020) found that trading volume, as a sentiment proxy, significantly influences market capitalization, while Mohamed (2013) identified both short- and long-run relationships between sentiment, trading volume, and market capitalization. Cheroni et al. (2019) emphasized the role of behavioural biases such as overconfidence and loss aversion. However, limited research has examined how sentiment relates to stock return volatility, which captures the aspect of market risk. This study addressed that gap this study explored the sentiment–volatility dynamics in the

Kenyan market, examining the presence of asymmetry and the nature of the relationship across different market regimes. This study also sought to enhance the robustness of measuring sentiment and to reduce measurement error compared to single proxies, by constructing a sentiment index. The findings offer insights for investors and policymakers seeking to manage sentiment-driven volatility and strengthen market resilience.

1.3 Research objectives

1.3.1 General objective

To investigate the relationship between investor sentiment and volatility in the Kenyan equities market.

1.3.2 Specific objectives

- i. To examine the baseline relationship between investor sentiment and volatility in the Kenyan stock market.
- ii. To investigate the heterogenous impact of investor sentiment on stock market volatility across different volatility regimes.
- iii. To analyze the asymmetric effects of investor sentiment on stock market volatility, distinguishing between positive and negative sentiment.

1.4 Research questions

- i. What is the relationship between investor sentiment and stock market volatility in Kenya?
- ii. How does the impact of investor sentiment on stock market volatility differ across various volatility regimes?
- iii. Do positive and negative investor sentiment shocks have asymmetric effects on stock market volatility?

1.5 Scope of the study

The study aimed to determine the relationship between investor sentiment and volatility with the scope limited to the equities market in Kenya. The dataset used in the study covers the period from January 2013 to December 2023. The period captured the lowest and highest points in stock market volatility in Kenya over the last eleven years. This included major events such as the 2013, 2017 and 2022 elections, the Covid-19 pandemic, currency depreciation and other

social, political, and economic changes which could have influenced the stock market volatility.

1.6 Significance of the study

The study would benefit retail and institutional investors, policymakers, and other researchers.

1.6.1 Investors

Enhanced understanding on the impact of investor sentiment on volatility may enable investors and fund managers to make better investment decisions and enhance the performance of their portfolios hence maximizing their profits (Haritha & Rishad, 2020). It sheds light on the inclusion of sentiment factors when measuring total risk (Rupande et al., 2019) and consideration of the factor alongside established fundamental drivers of volatility. It also provides information that would help investors and trade participants decide and advise on entry and exit points appropriately. The study is also beneficial to foreign investors investing in Kenya as it provides insights into the influence of sentiment on stocks within the country.

1.6.2 Policymakers

The results may also be useful in the development of policies to stabilize the volatility of the stock market, protect the wealth of investors along with attracting new participants into the market (Rupande, Muguto, & Muzindutsi, 2019). The finding may also aid in the formulation of regulations that mitigate against noise trading and market manipulation that lead to extreme investor sentiment (Nnoje et al., 2021).

1.6.3 Listing companies

Companies that are seeking a listing on the NSE can utilize the study's results to comprehend how investor actions affect share values, enabling the setting of realistic prices that will draw the targeted investors without causing market distortions (Cherono et al., 2019).

1.7 Chapter Summary

The chapter outlines the research background, problem statement, objectives, scope and significance of the study. The chapter highlights the influence of investor sentiment on stock market behavior and the need to understand its impact on volatility.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the theories that inform the research namely, Efficient Market Hypothesis, Market Microstructure Theory and Noise Trader Theory. It also includes a review of prior studies on the investor sentiment and stock markets relationship as done by previous researchers and identifies the research gap. The conceptual framework is also presented.

2.2 Theoretical review

This study was anchored on the Efficient Market Hypothesis, Market Microstructure Theory and Noise Trade Theory.

2.2.1 Efficient Market Hypothesis

Fama (1970) proposed the Efficient Market Hypothesis (EMH). It contends that in an efficient market, security prices accurately represent all information that is accessible at any moment. Prices record past data in their weak form, and they effectively adapt to other publicly accessible information in their semi-strong form. The strong form implies that prices already account for all information, private and public, such that individuals or groups with monopolistic access to information are not at an advantage. Goudarzi & Ramanarayanan (2011) supports this providing that fluctuations in security prices indicate market efficiency in stock markets where prices account for all available data.

Under the semi-strong and strong forms, EMH dictates that investor sentiment should not influence stock prices or volatility as prices already reflect all information efficiently. However, empirical evidence indicates deviations from the theory, with abnormal phenomena in financial markets explained through the lens of investor psychology and behaviour from a sociological perspective (Hu et al., 2021). This suggests that if sentiment significantly influences volatility, there are inefficiencies in the market.

Fama (1970) acknowledges that while the theory assumes rationality, there are instances where psychological factors can lead to market anomalies which create temporary mispricing and profit opportunities. The researcher indicates that differing interpretations of specific information among investors does not imply market inefficiency, unless there exist investors who can reliably make more accurate evaluations of available information than what is reflected in market prices. Based on the theory, markets may not be perfectly efficient owing

to factors like as transaction costs and limited investor rationality, but the markets remain efficient in the processing of available information (Fama, 1970; Malkiel 2003).

EMH suggests that security prices are unpredictable based on historical data as price movements should follow a random walk and that investors do not have an opportunity to earn abnormal profits. Malkiel (2003) explains that irregularities in pricing and predictable trends in stock returns can emerge and persist for short durations. However, such patterns discovered from historical experience, are unlikely to persist and to lead to consistent extraordinary returns. Similarly, Timmermann and Granger (2004), argued that in an efficient market, asset returns can be predicted although for a short time, after taking time-varying risk and transaction costs into consideration. Once the predictable patterns are discovered by a wide group of investors, their information may be incorporated into the prices thus the models cease to be effective.

The theory holds that markets are efficient, with information quickly incorporated into prices which makes it challenging to forecast market movements. It further implies that investor sentiment should not cause asymmetry or time-varying effects in volatility. This study sought to investigate this relationship. The hypothesis implies that shifts in the asset prices is caused by the arrival of new information. Market sentiment is however interpretation of existing information by market participants, and hence this study aimed to investigate whether it plays a role in volatility. EMH suggests that asset prices adjust rapidly in response to updated information, potentially leading to sudden and significant price movements that contribute to market volatility (Beechey et al., 2000) which was the focus of this study. Recent findings however show that market efficiency may weaken during periods of extreme uncertainty. For instance, Gu (2023) found that during the COVID-19 pandemic, markets did not always efficiently incorporate new information, leading to observable mispricing and volatility distortions which challenging the core assumptions of EMH in certain market conditions.

Despite its strengths, EMH does not fully account for behavioural biases (Fama, 1991), that influence investor decisions and adequately explain anomalies and volatility clustering in financial markets (Barberis & Thaler, 2003). This research therefore studies the competing views between EMH and behavioural finance by examining the presence of sentiment-induced volatility which would contradict the hypothesis of market efficiency. Asymmetric volatility responses to investor sentiment and the nature of the relationship across different volatility regimes were also examined. Significant asymmetry or varying effects between different

market conditions could imply violation of the semi-strong form of EMH, suggesting market inefficiencies (Verma & Soydemir, 2006).

2.2.2 Noise Trader Theory

The Noise Trader Theory posits that a significant portion of investors, termed "noise traders," base their trading decisions on non-fundamental information such as sentiment, rumours, or misinterpretations, rather than on rational analysis of intrinsic asset values (De Long et al., 1990). These traders act under the mistaken belief that they possess superior insights into future market movements (Shleifer & Summers, 1990). As a result, asset prices are influenced not only by the actions of rational, informed investors but also by noise-driven trades (Black, 1986; De Long et al., 1990).

Although rational arbitrageurs (often termed smart money) are expected to exploit and correct these mispricings, their capacity to fully neutralize the impact of noise traders is constrained. This is largely due to noise trader risk—the uncertainty stemming from the irrational and unpredictable nature of noise trader sentiment (DeLong et al., 1990; Chen et al., 2022). Such risk is particularly pronounced for investors with short-term horizons, as sentiment can deviate further from fundamentals before reverting, rendering arbitrage both risky and potentially unprofitable.

The persistence of noise traders and the inherent limitations to arbitrage suggest that shifts in investor sentiment can become key drivers of asset price dynamics (Shleifer & Summers, 1990). When noise traders constitute a significant proportion of market participants, their sentiment-driven trades can substantially amplify market volatility and lead to price distortions (De Long et al., 1990). This theoretical lens helps explain phenomena such as excess volatility and asset mispricing, where price fluctuations are not fully justified by changes in fundamental information (Black, 1986).

Some investors may even pursue anticipatory strategies, attempting to predict future changes in noise trader sentiment based on market signals such as trading volume or price trends, and positioning themselves accordingly (De Long et al., 1990). Empirical studies support the prevalence and impact of noise traders across different markets, including those influenced by online search behavior and peer-to-peer lending platforms (Hervé et al., 2019; Lin et al., 2018; Hartmann et al., 2018). Additionally, investor sentiment has been linked to capital flows into equity mutual funds and new equity issuances (Chiu & Kini, 2014). The Noise Trader Theory

therefore offers a robust conceptual framework for understanding how investor sentiment, particularly when driven by non-fundamental factors can significantly influence stock market volatility (Ramiah et al., 2015).

2.2.2 Market Microstructure Theory

O'Hara (1995) described market microstructure as the analysis of procedures and results of trading assets within defined trading rules. The theory endeavours to establish how prices are discovered in financial markets (Nevmyvaka, 2005) in the presence of risks, costs and asymmetric information (Stoll, 2002). It studies the actual transaction process between buyers and sellers and how it affects price formation and trading volumes in the market (Aigbovo & Isibor, 2017). The discovery of prices is a dynamic process by which markets find the balance between buyers and sellers, continuously incorporating new information and reflecting the collective belief of many market participants (Christiansen, 2009). According to Madhavan (2000), this field of study in Finance looks at how investors' latent demand is eventually converted into transactions. Market microstructure is therefore shaped by trading mechanisms and rules and it presents a challenge to the traditional notion of efficient markets, which overlooked the processes involved in the formation of securities prices (Asmar & Ahmad, 2011).

According to Biais et al., 2005, the study of market microstructure examines the short-term convergence and deviation of transaction prices from long-term equilibrium values. Similarly, Madhavan (2000) proposes that asset prices may deviate from their full-information expectations because of frictions in the market like asymmetry in information, transaction costs, and market inefficiencies (O'Hara, 1995). This is in line with behavioural finance which holds that prices do not always reflect their intrinsic value. The frictions may lead to market failures under certain protocols or may result in large deviations between fundamental value and stock prices (Madhavan, 2000) which may increase volatility while reducing liquidity and increasing counterparty risk (Biais et al., 2005, as cited in Okumu, 2013). Stoll (2002) also links market frictions to differences between bid and ask prices resulting in short term price volatility.

The theory enables measurement of the degree to which participants in a market conform to equilibrium behaviours, the relationship between their actions and the market's structure, and the impact of psychological factors on behaviour, all of which are crucial in understanding market dynamics and decision-making processes (Biais et al., 2005). It covers the trading rules

and mechanism that a market uses to translate investors' future expectations and trading tactics into the current trading prices and volumes (Asmar & Ahmad, 2011). This made this theory fundamental in the study of the impact of investor sentiment on the equities market.

The literature on microstructure also contends that long-term market equilibrium prices are impacted by information risk resulting from asymmetric information as well as variations in liquidity over time and amongst companies (Christiansen, 2009; Aigbovo & Isibor, 2017). Aigbovo and Isibor (2017) acknowledged that accurate information regarding a company's fundamentals may not be spread evenly across market participants and that their interpretations may differ. Therefore, even in the unlikely event that all players are acting rationally, prices cannot be expected to instantly reflect information. A fundamental aspect of market microstructure is therefore the method by which prices adapt in response to new information. Market participants continuously receive information, assess the significance and implication of that information on the asset value and adjust their expectations and trading decisions. As trading occurs, prices then adjust to reflect the new information (Madhavan, 2000). Buy and sell orders act as a signal about future value and induce adjustment of beliefs (Madhavan, 2002). This infers that stock prices are not purely determined by fundamentals which is the basis of this study.

Microstructure studies propose theoretical frameworks that outline the behaviour of different market participants, including informed traders, liquidity traders, and market makers (Nevymyvaka, 2005). Uninformed traders favour trading in liquid and deep markets to reduce transaction expenses, consequently enhancing market depth and liquidity, which in effect draws more trading participation. Informed traders on the other hand, employ trading tactics to mask their identity and information, resulting in greater disclosure of information and amplified price volatility (Calamia, 1999). This interaction between traders is likely to result in time-varying effects on volatility, where sentiment-driven price movements fluctuate across different market conditions. Madhavan (2002) also attributes excess volatility in financial markets to inventory and information effects. Inventory adjustments by market participants and reactions to a broad range of news or sentiment can lead to price movements that appear to exceed changes in fundamental factors.

In order to study market activity, market microstructure theory first formulates the behaviour of a single trader at the micro level, and then it aggregates the behaviour of multiple traders (Calamia, 1999). Muranaga (1999) argues that the actions of the individual traders when

combined shape the overall functioning and efficiency of financial markets. This provides a platform for the top down approach of measuring sentiment which centres on analysing aggregate sentiment indicators and tracing their effects on stock prices and market returns (Baker & Wurgler, 2007). A key factor in how actual markets function is the relationship between a market's organisational characteristics and the actions of heterogeneous traders, as this influences vital elements such as volatility (Calamia, 1999). While the theory acknowledges the influence of investor behaviour on price formation, it does not provide a direct framework for quantifying sentiment.

The literature has demonstrated that trades affect prices in both temporary and permanent ways. The permanent component is presumed to be related to information and influenced by the level of information asymmetry, whereas the transitory component is attributed to trade-related disruptions brought about by market frictions thus pushing the current and subsequent prices away from the efficient prices (Biais et al., 2005; Calamia, 1999). During periods of heightened uncertainty, sentiment-driven trading causes stronger deviations from fundamental values, whereas in more stable conditions, sentiment has a weaker and more temporary impact on volatility. However, the theory primarily analyses short-term dynamics and may not fully capture persistent structural inefficiencies in the market.

Developments in market microstructure have focused on integrating insights from behavioural finance and attempt to incorporate traders' psychology into the models to explain phenomena like overconfidence of informed traders and hoarding behaviour of informed and liquidity traders, which cause excess volatility and bubbles (Madhavan, 2000). Market Microstructure Theory therefore provides a framework for understanding how sentiment-driven trading affects price dynamics, bid-ask spreads, and volatility.

2.3 Empirical review

This section presents a review of existing literature on investor sentiment and the relationship between investor sentiment and market returns, stock market volatility.

2.3.1 Investor sentiment and stock market volatility

Hu et al. (2021) discusses two methods of gauging investor sentiment. Firstly, is the direct approach which involves the collection of investors' opinions about potential market developments through surveys. Conversely, the indirect method entails construction of an investor sentiment index from selected market data pertaining to investor sentiment. The market-based measures depend on observable market statistics, for which latent investor

sentiment is presumed to be an underlying factor. Since this data reflects actual market activity, it captures sentiment that investors have acted upon, unlike survey-based measures, which lack the element of respondents having a tangible stake in their responses (Ung et al., 2023). However, relying on individual market-based variables as proxies for overall investor sentiment is likely to be ineffective, as they tend to contain inherent idiosyncratic noise or random fluctuations that can obscure the true sentiment component within each variable. To remedy this, Baker and Wurgler (2007) proposed the construction of a composite sentiment index combining several single market-based proxies. They employed principal component analysis (PCA) to create an investor sentiment composite index by combining six individual sentiment indicators in the U.S. stock market. The core concept of PCA is to decrease the dimensionality of a dataset with many interconnected variables while preserving as much of the original variation as possible. Hu et al. (2021) employed a similar approach based on Chinese stock market data, Haritha and Rishad (2020) in India, Andleeb and Hassan (2023) in selected developing markets including South Africa, Indonesia, Brazil, India, Russia, China, and Pakistan and Ayinuola and Adetilote (2023) in Nigeria.

Various research papers have endeavoured to explain the connection between investor sentiment and the volatility of stock markets. In developed markets, sentiment's influence exists but findings have emphasized structural constraints and long-term correction mechanisms. For example, Baker and Wurgler (2006) observed that U.S. sentiment affects small, volatile, high-growth stocks, with low sentiment leading to high subsequent returns, while high sentiment depresses them. Brown (1999) found that abnormally high sentiment among U.S. individual investors increases closed-end fund volatility, but only during active trading hours. However, Sibley et al. (2016) challenged this, asserting that economic fundamentals, not sentiment per se, predict stock returns.

In Europe, Schneller et al. (2017) and Yang and Copeland (2014) showed that sentiment affects volatility and excess returns in Germany and the UK, with bullish sentiment boosting returns. Raissi and Missaoui (2016) identified that investor psychology has a notable effect on French small-cap stocks, but not on large-caps. Temporal dynamics further differentiate developed markets. In the U.S., Marczak and Beissinger (2016) found that sentiment impacts short-term returns, but the relationship weakens in the long run as overvaluation is corrected. Lao et al. (2018) similarly noted a two-way relationship over time, and Niu et al. (2021) confirmed a

short-term bi-directional causality between sentiment and sectoral returns, turning one-way in the long term.

In contrast, in emerging markets, several studies emphasize the dominant and more persistent role of investor sentiment in driving stock market volatility and returns. In India, Haritha and Rishad (2020) used a GARCH model and found that irrational sentiment significantly amplifies market volatility, with asymmetries suggesting inefficiencies. Pillada and Rangasamy (2023) further confirmed a long-term impact of sentiment on returns. In China, Li et al. (2020) linked investor cognitive and emotional deviations to pricing distortions and inefficiencies, while Rehman (2013) in Pakistan identified a clear connection between sentiment and returns, even in weakly efficient markets. Muhammad (2021) also noted that sentiment affects firm performance, cash flows, and discount rates, with market-based measures showing stronger predictive power than media sentiment.

In Nigeria, Alajekwu et al. (2017) and Nnoje et al. (2021) found that high sentiment corresponds to higher returns, often more influential than macroeconomic fundamentals, and linked to non-diversifiable risk. Dalika and Seetharam (2015) echoed these results for South African markets, emphasizing the impact of sentiment on small, volatile, and growth-oriented stocks. Country-specific effects are also notable. Anusakumar et al. (2017) found varying sentiment-return relationships across Asian markets, with mixed signs even under a shared panel framework, suggesting that results in one country may not generalize to others. Corredor, Ferrer, and Santamaria (n.d.) drew similar conclusions from Czech Republic, Hungary, and Poland, where sentiment had a greater influence than in developed European markets despite shared market characteristics.

Several studies have similarly explored the relationship between investor sentiment and the stock market in Kenya. Mohamed (2013) used share volume and value as sentiment proxies and market capitalization as a measure of equity market performance. The study analyzed quarterly time series data from 1996 to 2013 using the augmented Engle and Granger co-integration test along with the Error Correction Model. The results revealed both positive long- and short-term relationships between investor sentiment and market performance. Similarly, Musembi et al. (2020) investigated monthly data from 2008 to 2018 and found a significant positive association between investor sentiment and equity market performance. Sentiment was measured through trading volume, and the research employed Cointegration, ARDL, and NARDL models.

Additionally, stock market volatility has also been linked to macroeconomic factors. Kinuthia and Jagongo (2021) concluded that systematic risk caused by inflation, GDP, exchange rate and treasury bills increases the Kenyan stock market volatility with frequent fluctuations in share prices and returns. Consequently, this study controlled for macroeconomic variables in examining how investor sentiment influences stock market volatility. This aligns line with Khan and Ahmad (2019) who eliminated the non-sentiment component, by orthogonalizing the sentiment index to the major macroeconomic variables, so as to isolate sentiment's impact on returns. Firm characteristics were also controlled for to ensure that the relationship between sentiment and stock market volatility, is not solely driven by variations in the financial performance of companies.

2.3.2 The sentiment-volatility relationship across different market conditions

Growing evidence suggests that the sentiment-volatility relationship is not static but evolves over time in response to changing market conditions, sentiment dynamics, and economic factors. Smales (2012) demonstrated that news sentiment exerts a substantial and dynamic influence on implied volatility and stock returns, highlighting the need to account for regime-varying effects in such analyses.

Hu et al. (2021) explored the evolving relationship between market volatility, returns, and investor sentiment using the MS-VAR model. The number of newly opened A-share accounts, market turnover rates, monthly initial public offerings and their first-day returns and closed-end fund discounts in the development of a Chinese sentiment index. The study also considered two regimes, a bear market to represent a downturn and bull market to represent an upsurge of the stock market. The paper found inverse correlation between investor sentiment and stock market returns in the bear market and a positive correlation between the two in the bull market state. Sentiment and stock market volatility have a positive correlation during a bear market and a negative correlation during a bull market. Moreover, in the short run, optimistic sentiment may cause stock market returns to decrease instantly in the case of a bear market state, while in a bull market, it may cause returns to immediately rise. However, over the long term, returns exhibit the same reaction to the impact of sentiment regardless of bullish or bearish state. Using TVP-VAR model, Zhang et al. 2022 further established that investor sentiment influences Chinese stock market volatility indicators more strongly in bear markets than in bull ones, and the strength of the effects progressively decreases following several adjustments throughout the last five days.

In order to investigate how investor sentiment affects stock returns and how this influence differs between bull and bear regimes, Wang et al. (2022) studied 40 different worldwide stock markets. The study used GARCH-type models and the turnover ratio as an investor sentiment proxy. The study established a more pronounced positive effect of sentiment on stock performance in bear compared to bull regimes. It was concluded that optimistic swings in investor sentiment boost stock returns whereas pessimistic shifts decrease the yields in bull regimes. In bear regimes on the other hand, optimistic shifts decrease stock returns and vice versa in line with Hu et al. (2021). The study thus confirmed that a constant sentiment-return link across the sample period is not maintained when a conditional context is applied highlighting the necessity of differentiating the sentiment impact across different market situations.

Kremer (2018), applied a model to estimate weekly returns for the S&P 500 price index that allowed for sudden transitions between low, medium and high-volatility regimes from January 1928 to May 2018 in the US market. The model revealed that volatility tends to cluster within these regimes, with low and medium-volatility periods being more persistent and high-volatility regimes less frequent, except during significant historical events. The study also highlighted that the stock market turbulence in early 2018, triggered by policy uncertainties, did not cause a shift to a high-volatility regime but rather a transition from low to medium volatility, suggesting a potential normalization rather than a move towards extreme volatility. Adrangi et al. (2023) concluded that link between realized volatility and sentiment differs across high- and low-volatility regimes, as evidenced by the GARCH-MIDAS model, regime-switching Markov Chain, and quantile regression analyses, with investors' sensitivity to market uncertainties influencing this association. This was consistent with Ho et al. (2013) in their study of the dynamic relationship between company-level return volatility and public news sentiment, who employing Markov Regime- Switching GARCH found that news sentiment contributes more significantly to volatility persistence in the high-volatility regime compared to the low-volatility regime.

Abdelmalek (2022) also explored the asymmetric relationship between investor sentiment and realized volatility employing quantile regression. He concluded that the sentiment-volatility interaction is not uniform across the distribution; specifically, sentiment had a more pronounced effect during extreme market conditions, that is both high and low volatility regimes.

These findings suggest that developed markets tend to exhibit more persistent and stable volatility regimes, where sentiment influences volatility primarily under extreme conditions. In contrast, emerging markets demonstrate heightened sensitivity to investor sentiment across regimes, with more pronounced and regime-dependent effects on both volatility and returns. This divergence likely stems from structural differences in market maturity, investor composition, and the depth of institutional participation.

The results imply that the intricacy of the sentiment-volatility relationship may not be sufficiently captured by conventional linear models. They highlight the importance of incorporating models that capture the dynamic interactions between sentiment and volatility, ensuring a more comprehensive understanding of market behaviour.

2.3.3 Asymmetric effects of investor sentiment on stock market volatility

Chen and Haga (2021) analysed the influence of sentiment on stock returns during periods leading up to market crashes and employing the E-GARCH model. It was established that both optimistic and pessimistic sentiment had a significant effect on the Chinese stock returns, implying that fluctuating sentiment is among the influences of stock price patterns. However, Huang et al. (2014) established that pessimistic investor attitude did not notably affect returns, but optimistic sentiment positively impacted stock returns across most industries.

These results were comparable to those of Haritha and Rishad (2020), who created a sentiment index and assessed its impact on volatility by modelling it using the GARCH and Granger causality framework. Following the separation of the sentiment index into negative and positive components, the analysis revealed an asymmetric relationship in the Indian stock market. Positive sentiment was found to have a strong positive impact on excess market returns, while the effect of negative sentiment on negative returns was comparatively weaker. These findings implied that heightened investor optimism about the market's ability to generate excess returns drives more speculative behaviour, encouraging investors to increase their investments. Paramanik and Singhal (2020) alternatively utilized news-based sentiment analysis of the market and found that there is noise-based trading in the Indian stock market and that negative market sentiment has a more dominant influence than a positive one. Kumari and Mahakud (2016) found negative shocks to persist longer than positive shocks.

Hu et al. (2021) concluded that the influence of investor sentiment on the stock market in China is asymmetric. The orthogonal cumulative impulse response analysis results indicated that

investor sentiment shocks exert a notable influence on returns, with the effect being substantially stronger in bullish markets compared to bearish markets.

Smales (2012) found evidence of asymmetry in which the magnitude of changes in the implied volatility index was greater during periods of negative news on the US market. However, that asymmetry seemed to reverse when there was an excessive amount of bad news, probably because the market had already factored in the negative information and had become more responsive to positive news. The researcher suggested that the alternative was that option traders are more cautious when there is high volatility but respond more aggressively to bad news during times of low volatility, sharply increasing implied volatility.

Liston and Huerta (2012) estimated an augmented GARCH-in-mean model to investigate the influence of investor sentiment on excess returns and conditional volatility of the emerging Mexican stock market. The findings revealed that shifts in sentiment positively and significantly impacted the market portfolio suggesting that the higher risk created by uninformed traders due to market misperceptions and noise trading, led to higher returns. The study also revealed that although insignificant, positive shifts in sentiment were linked to lower volatility in the subsequent period. Conversely, bearish swings in sentiment led to higher volatility.

In 2021, Ferreira et al. examined the asymmetric relationship between investor sentiment on stock market volatility in Brazil. The results of the investigation showed a substantial and negative association between volatility and investor sentiment, indicating that the volatility of the Brazilian market is explained in part by investor sentiment. Additionally, this relationship displayed an asymmetric pattern, with pessimistic sentiment exhibiting a stronger explanatory power for volatility. These findings were similar to those of developed markets suggesting that similar mechanisms underlie the uneven impact of investor sentiment regardless of the distinct risk perceptions in developed and emerging markets, and the view that the latter are more vulnerable.

In a study of eighteen industrialized countries, Schmeling (2009) found mixed evidence of asymmetry with some markets showing strong asymmetric effects, while others do not. This variation highlights the need to examine the phenomenon in the Kenyan stock market with its unique characteristics. Similarly, the findings of Mashamba and Magweva (2019) employing the EGARCH model, found mixed results among Southern African countries. The study revealed leverage effects in the Namibian and South African markets, demonstrating that

unfavorable shocks tend to impact future return volatility more strongly than equivalent positive shocks. The researchers emphasized that investors in these markets should consider leverage effects when estimating value at risk and enhance their strategies by accounting for skewness, excess kurtosis, and leverage effects. Additionally, firms raising capital should anticipate paying a risk premium due to high uncertainty for capital providers. Conversely, in Zimbabwe, Zambia, and Malawi, the absence of asymmetric volatility implies that future return volatility is affected equally by negative and positive shocks to stock market returns.

Rupande et al. (2019) confirmed the significance of investor sentiment in explaining returns in the Johannesburg Stock Exchange. The findings also demonstrated substantial proof of a positive risk-return relationship suggesting that volatility is factored into prices in the market, as well as the existence of leverage effects and volatility persistence. A constructed daily sentiment composite index was used and GARCH models employed using data from July 2002 to June 2018. In Nigeria, Ayinuola and Adetiloye (2023), found that positive sentiment has a stronger asymmetrical effect on stock return volatility compared to negative sentiment.

These insights highlight the importance of considering asymmetric dynamics when analysing the sentiment-volatility relationship in the Kenyan stock market.

2.4 Research Gap

Most of the empirical studies revealed a link between investor sentiment and its impact on equity markets. The studies cut across developed and emerging economies as well as different periods. The scope of the existing studies includes; whether investor sentiment affects stock returns, whether sentiment affects stocks with different characteristics differently, the direction of causal effect between sentiment and returns and the relationship between sentiment and stock market volatility. Majority of the works in Kenya focused on the relationship between investor sentiment and the performance of the equities market. This study therefore furthered the research by examining the nature of the relationship between investor sentiment and stock market volatility across high and low volatility regimes. Moreover, the study will investigate the presence of asymmetric effects, particularly how positive and negative sentiment differentially influence market volatility across varying market conditions. The study will employ multiple market-based indicators as proxies for sentiment because a single variable as used in some cases might not be adequate in explaining market sentiments (Haritha & Rishad, 2020). Studies such as Sibley et al. (2016) concluded that stock returns are not predicted by investor sentiment but by economic fundamental variables and thus the motivation to study the

relationship between sentiment and stock market volatility after accounting for the company's fundamentals and macro-economic factors in the Kenyan market.

The table below summarizes previous studies, results, research gaps and how the study sought to address these gaps.

Table 2.1 Research gap matrix

Study	Findings	Research gap and proposed solution
Musembi et al., (2020)	Investor sentiment and equity market performance have a significant positive relationship	Investor sentiment was measured using a single variable, that is, trading volume. This study will employ multiple market-based indicators to provide a more comprehensive representation of sentiment.
Rupande et al., (2019)	Established a strong association between investor sentiment and the volatility of stock returns in South Africa	The gap is on the resemblance of the South African evidence in Kenya. This study therefore attempts to investigate the sentiment-volatility relationship in the Kenyan market.
Nabosu et al., (2022)	Investor sentiment exerts a positive and significant impact on stock market returns within non-financial firms.	The study focused on returns of non-financial firms only. This study will consider a wider scope of the stock market and will go further to examine volatility of the returns.
Cherono et al., (2019)	In Kenya, the stock market's reaction was significantly influenced by loss aversion, mental accounting, and overconfidence, whereas	The study was conducted at a different time. This study seeks to bridge the gap by evaluating the influence of sentiment on stock market volatility for a period

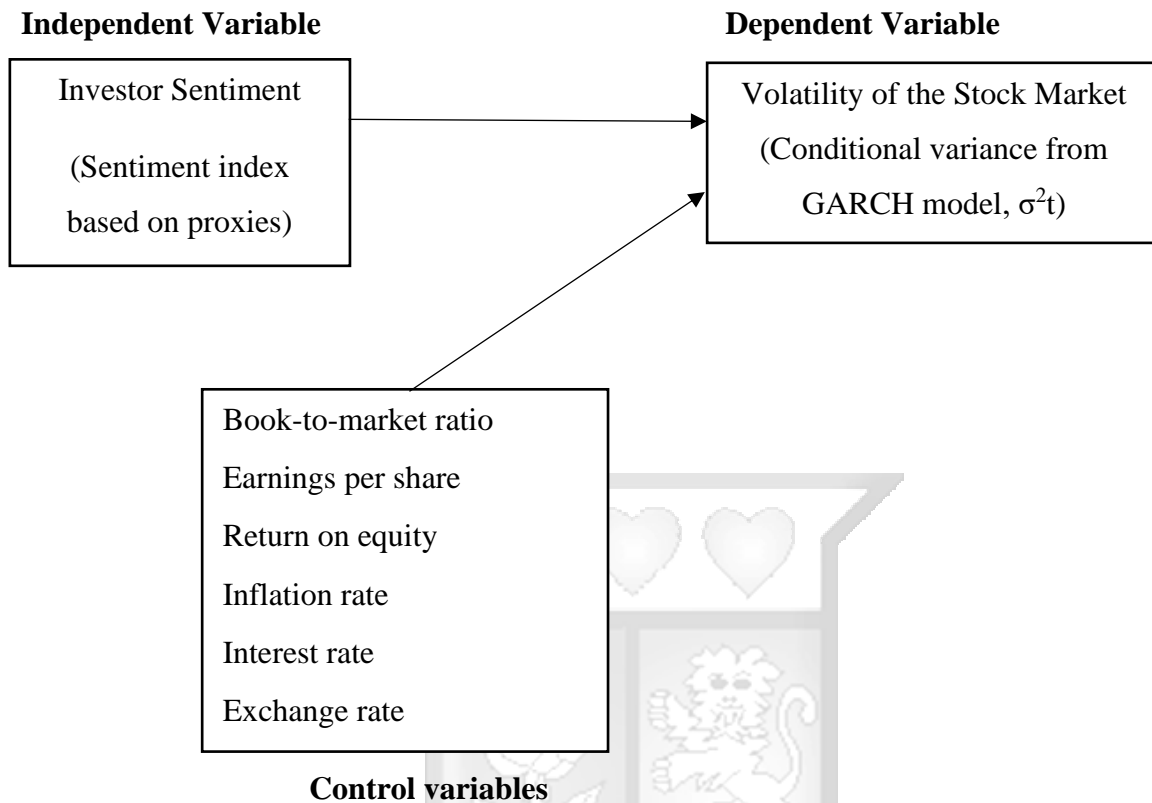
	herd behavior had little effect for the period 2004 to 2016.	including the pandemic and post-pandemic era.
Chen and Haga (2021)	Changes in investor sentiment have a differential impact on the rate of return ahead of and following stock market crash	The influence of sentiment on market behavior was explored during periods of instability. This study covers a wider scope by considering high and low volatility regimes.
Hu et al., (2021)	Asymmetric impact of investor sentiment on the stock market depending on the stock market regime.	The gap is on the similarity of the findings at NSE.

2.5 Conceptual framework

This section conceptualizes the study of the relationship between investor sentiment and stock market volatility. Investor sentiment, derived from a sentiment index constructed using market-based proxies (trade volume, advance-decline ratio, relative strength index, and market turnover), serves as the independent variable. The study examines its effect on stock market volatility, measured as the conditional variance (σ^2_t) derived from a GARCH model.

Additionally, the framework incorporates control variables including book-to-market ratio, earnings per share, return on equity, inflation rate, interest rate, and exchange rate, to capture fundamental and macroeconomic influences on market volatility. These control variables are incorporated during the construction of the investor sentiment index. The market-based sentiment proxies are regressed on these variables and the residual component extracted, to ensure that sentiment effects on stock market volatility are isolated from macroeconomic influences. These controls do not therefore reappear in subsequent models.

Figure 2.1: Conceptual framework of investor sentiment and stock market volatility



2.6 Operationalization of Study Variables

This section explains how the variables for the research were measured.

2.6.1 Investor Sentiment Proxies

Investor sentiment is described as convictions regarding future cash flows and risk levels which are not supported by fundamentals (Baker and Wurgler, 2007). It primarily relates to an overstated belief or simply a viewpoint that is being expressed (Zhou, 2018). Given that it is difficult to measure sentiment and there is no undisputed and universally accepted sentiment measure (Beer and Zouaoui, 2013), some previous studies have employed direct methods of sentiment measurement whereas others have employed indirect approaches.

Zhou (2018) identified three categories of measures of investor sentiment depending on the data used. Firstly, is the market-based approach where sentiment is measured from market data observations for instance, prices and trading activities. The second type of measurement is the survey-based, which entails polling market participants to determine their opinion as demonstrated by Brown and Cliff (2004) and Schmeling (2009). Survey data offers a unique

viewpoint on how investors create their beliefs (Zhou, 2018) but is faced with the challenge of a difference between the statements of the investors surveyed and their actual actions and limited representativeness of the population (Amdouni, 2021). Thirdly, is the textual analysis and media-based category, where opinions are extracted from publications, texts and other online content.

Baker and Wurgler (2007), employing the market-based method, developed a top-down approach to assess investor sentiment indirectly and gauge its outcomes. This method is distinct from the bottom-up method, which uses psychological biases in individual investors to explain the overreaction or underreaction of investors to historical returns or fundamentals. The authors argue that the complexity of real investors and markets makes it difficult to condense them into a small number of selected biases and trading frictions and hence the introduction of the new approach. The top-down approach is centred on quantifying aggregate sentiment in a reduced-form manner and links its impacts to both market returns and individual stocks. This approach is considered advantageous due to its ability to capture bubbles, crashes, and everyday trends in stock prices simply, intuitively, and comprehensively.

To measure sentiment using the top-down approach, Baker and Wurgler (2007) developed an index from market-based proxies using principal component analysis. This was founded on the premise that an external shock to investor sentiment has the potential to set off a series of events, and the shock itself might theoretically be detected at any point along the chain. Investor beliefs may then result to observable patterns in transactions. The approach considers the source of investor sentiment to be exogenous with the focus directed to its observable impacts. Consequently, the emphasis of the study is on studying the observable outcomes of investor sentiment rather than on the factors that lead to changes in investor sentiment. Hirathi and Rishad (2020) argued that given the variety of factors that influence single variable proxies, relying solely on one variable to explain market sentiments may not be adequate and hence the use of an aggregate index.

Baker and Wurgler's composite sentiment index was developed using six market-based proxies: the discount on closed-end funds, trading activity represented by NYSE share turnover, the count and average first-day performance of initial public offerings, the proportion of equity in total new issuances, and the premium on dividend-paying stocks. Each proxy was regressed on specific macroeconomic factors, and the regressions' residuals were used as sentiment proxies in order to lessen the likelihood that these proxies reflect economic

fundamentals. After obtaining the common sentiment component from the proxies, they were averaged into an index to iron out the remaining idiosyncrasies.

Similarly, examining the Indian stock market, Haritha and Rishad (2020) formulated an investor sentiment index based on several trading activity indicators. These included measures such as overall trading volume, the proportion of put to call options, the ratio of advancing to declining stocks, market and share turnover rates, as well as the frequency of initial public offerings. They employed principal component analysis, focusing on the first principal component and incorporating lagged values to account for delayed sentiment reflections in certain variables. A similar methodology was adopted by Rupande et al. (2019), who constructed their sentiment index using daily observations from South Africa. Their inputs included Rand–US Dollar exchange rate fluctuations, key interest rates, market activity metrics, changes in volume-weighted average prices on the All Share Index, and the South African Volatility Index (SAVI). The authors emphasized the importance of the PCA technique in determination of the common component among the proxies, which is considered to be sentiment.

Within the context of Baker and Wurgler (2006, 2007), different market-determined sentiment proxies, based on data availability, their application in literature and relevance with the Kenyan context, were used to construct an aggregate sentiment index. The proxies used for this study included trading volume, market turnover, advance-decline ratio and relative strength index (Haritha & Rishad, 2020; Shin & Choi, 2022; Ayinuola & Adetiloye, 2023).

2.6.1.1 Trading Volume

Trading volume is a gauge of liquidity in the market and has been used by researchers such as Baker and Wurgler (2006), He et al. (2017), Mohammed (2013) among others to proxy sentiment.

2.6.1.2 Advance- Decline Ratio

This is a market-breadth indicator which examines the ratio of advancing to declining shares. Decreasing trends in the ratio signal a downward trend in the market while increasing trends confirm an upward trend. The ratio can be used as a measure of market performance (Brown & Cliff, 2004).

2.6.1.3 Market Turnover

Market turnover is a reflection of active participation of investors. It is determined by dividing the total share value traded by the average market capitalization for a certain period (Haritha & Rishad, 2020). Market turnover is expected to be low when the market is bearish and high when the market is bullish. Overly optimistic investors are likely to accelerate the turnover and hence this is a suitable gauge for investor sentiment (Baker & Stein, 2004).

2.6.1.4 Relative Strength Index

Relative Strength Index (RSI) is a market indicator for investor sentiment. It displays the momentum and strength of price movements. RSI values above 80 are generally considered to be a sign that shares are overbought implying a significant upward price movement and over optimism. Conversely, RSI values below 20 usually suggest an oversold asset and a likelihood that investors are excessive pessimistic (Seok et al., 2019; Shin & Choi, 2022). RSI is calculated as follows:

$$RSI_{i,t} = 100 \times \frac{\sum_{i=1}^{14} (P_{t-i} - P_{t-i-1})}{\sum_{i=1}^{14} |P_{t-i} - P_{t-i-1}|}$$

Where P_t denotes the closing price of firm i shares in month t .

2.6.2 Volatility

The individual monthly average closing prices were used to compute the volatility of the market. Returns were computed as shown below, after which the volatility was modelled as the conditional variance (σ^2_t) of stock returns.

$$Return_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where $Return_t$ is the return at time t , P_t is the stock price at time t , and P_{t-1} is the stock price at time $t-1$

2.7 Chapter Summary

This chapter begins with a discussion of the relevant theories that ground the research including Efficient Market Hypothesis, Market Microstructure Theory and Noise Trader Theory. The chapter also includes an empirical review of the topic across regions and the research gap that this study intends to address. It is concluded by presenting the conceptual framework and operationalization of variables.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter describes the approach the study employed to address the research objectives. It covers the research philosophy, research design, population and sampling, data collection, operationalization of variables and ethical considerations.

3.2 Research Philosophy

Saunders et al. (2019) define research philosophy as the underlying framework of assumptions and convictions regarding the advancement of knowledge in a given discipline. It encompasses the source, nature and advance of knowledge and is deductive. This study adopted positivism. Positivism entails engaging with observable social realities to generate law-like generalisations and advocates for the utilization of scientific methods (Saunders et al., 2019). It holds that reality is real, external, independent, and steady and is observable and explainable through an objective lens (Levin, 1988). Researchers such as Musembi et al. (2020), Cherono et al. (2019) and Mugenda et al. (2022) utilized this approach in the study of investor sentiment and stock markets.

The positivist approach is suitable for this study because it uses secondary data and quantitative analysis and aims at investigating the existence phenomena and possible relationships that exist between the predictor and dependent variable. In line with this philosophy, the research sought to establish the causal relationships between sentiment and volatility.

3.3 Research Design

The research design specifies a framework for data collection and analysis and thus determines the research method (Walliman, 2011). It represents the conceptual structure that guides the conduct of research (Kothari, 2013). This study employed a quantitative longitudinal research design, which is appropriate for analysing variables observed over time. Quantitative research tests objective theories through the study of variable interactions, which is the purpose of this study. These variables are usually gauged using instruments, enabling the analysis of numerical data through statistical methods (Creswell, 2009). The basis of this method is the assumption that the world is reasonably uniform, stable and coherent and is measurable, understandable and generable, suggesting that scientific research can be conducted to understand the world and its governing laws (Gay et al., 2012). A longitudinal design was adopted to investigate the

dynamic relationship between investor sentiment and stock market volatility over time, using monthly aggregated market-level data from 2013 to 2023. A longitudinal design involves repeated observations of the same variables over a prolonged period and is particularly useful for identifying patterns, trends, and time-dependent relationships (Menard, 2002; Brooks, 2008). A longitudinal design implemented through a time-series framework enabled the researcher to explore patterns in the data, possible asymmetries and time-varying effects within different volatility regimes (Woolridge, 2010).

3.4 Population and Sampling

Population denotes the total set of observable characteristics to which the research findings will be generalized (Kothari, 2013). The population of this study consisted of the listed firms on the Nairobi Securities Exchange. As at the fourth quarter of 2023, 66 companies were listed on the bourse (CMA, 2023).

A sample of individual stocks was selected using purposive sampling, which involves selection of the stocks based on specific criteria (Saunders et al., 2019). The study followed the 80% threshold in line with the Cronbach' alpha criterion as used by Ogega and Waweru (2016). A sample of 19 companies comprised in the NSE 20 Share Index which had been actively and consistently traded on the NSE for a minimum of 80% of the study period were selected. The study period spanned from January 2013 to December 2023.

3.5 Data Collection

The study relied on secondary data sourced from NSE registered data vendors and the Central Bank of Kenya for the three objectives. The data collected included trading volume, shares traded, value of shares traded, and market capitalization which were obtained for the determination of investor sentiment. For determination of volatility, monthly individual stock prices were collected. Macroeconomic indicators including interest, inflation and exchange rates and company fundamentals consisting of net income and shareholders' equity were collected as control variables. This is because each indicator is made up of an irrational part which represents sentiment and a rational component linked to fundamentals or the economic cycle. Controlling for the macroeconomic and fundamental factors therefore aided in neutralizing them to isolate the sentiment component.

The study relied on data collected over an eleven-year timeframe from January 2013 to December 2023. The period captures the lowest and highest points in stock market volatility in Kenya over the last eleven years. This includes major events such as the 2013, 2017 and 2022

elections, the Covid-19 pandemic, currency depreciation and other social, political and economic changes which could have influenced the stock market volatility.

3.6 Data Analysis

Data analysis is the processing of raw data into useful information (Saunders et al., 2019). After data was collected and checked for completeness descriptive and inferential statistics were done using STATA.

The investor sentiment proxies were analysed using Principal Component Analysis to distil the most pertinent information from the dataset by simplifying its complexity and condensing its size, through linear transformations. This eliminated multicollinearity in the data and increased interpretability without loss of information (Baker & Wurgler, 2007; Rupande et al., 2019). Each indicator contains an irrational component linked to sentiment and a rational part linked to fundamentals or the economic cycle. To neutralize the effects linked to economic fundamentals, each sentiment indicator was regressed against a group of macroeconomic factors consistent with Qiu and Welch (2006), Baker and Wurgler (2007) and Huang et al. (2015). The residues were retained as the irrational part of the indicator (Amdouni, 2021). The study also controlled for company fundamentals including the return on equity, book to market ratio and earnings per share to enhance the robustness of the analysis, by accounting for the effects of financial performance on the relationship between sentiment and returns (Anusakumar et al., 2017; Gao et al., 2022).

The beginning-of-period sentiment was used in the study line with Baker and Wurgler (2006). The prevailing sentiment at the beginning of each month was considered consistent with the ex-ante nature of investor sentiment.

To achieve the first objective, GARCH model was used as adopted by Haritha and Rishad (2020) to analyse the baseline relationship between investor sentiment and stock market volatility. Diagnostic tests including stationarity, normality and heteroscedasticity were performed to understand the return series' characteristics, as a prerequisite for the GARCH model. To test for stationarity, the Levin-Lin-Chu (LLC) unit root test was employed. Stationarity is a necessary condition for GARCH modelling, as the model assumes a constant unconditional mean and variance over time (Wooldridge, 2010). Second, the Jarque-Bera (JB) test was applied to examine the normality of the return series. The JB test evaluates whether the series the distribution of the data departs significantly from a normal distribution, which could affect model estimation and inference. To test for heteroskedasticity, the study applied

the Pagan/Cook-Weisberg test, which tests for homoscedasticity under the null hypothesis. Rejection of the null suggests the presence of heteroskedasticity, a condition that supports the use of GARCH that is designed to handle conditional variance (Engle, 1982). ARCH-LM test was also conducted to check whether past residuals predict variance which is a necessary condition for GARCH.

GARCH model is used to analyze and model volatility in time series data and is therefore suitable for effectively capturing the dynamics of stock market volatility and its relationship with investor sentiment. The model is represented as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i r_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \gamma \cdot \text{Sentiment}_t$$

Where σ_t^2 is the conditional variance, ω is a constant, α_i measures the impact of past shocks on future volatility, r_{t-i} are the squared returns of the asset at lagged time periods i , β_j measures the persistence of past volatility in the current period, $\beta_{\text{sentiment}}$ indicates the sensitivity of volatility to changes in sentiment and p and q are the orders of the autoregressive and moving average terms, respectively.

Secondly, the study investigated whether the relationship between investor sentiment and stock market volatility varies across different market conditions, including low, median and high volatility regimes. Quantile regression first proposed by Koenker and Bassett (1978) was employed. This is because the model allows for the examination of heterogeneity in relationships (Koenker, 2017). Abdelmalek (2022), Yadav and Naik (2023) and Guo and Shi (2024) adopted a similar approach.

$$Q_\tau(\log(\text{Volatility}_i)) = \beta_{0,\tau} + \beta_{1,\tau} \log(\text{Sentiment}_i)$$

Where: Q_τ is the conditional quantile of volatility given the sentiment index, $\beta_{0,\tau}$ is the intercept for quantile τ , $\beta_{1,\tau}$ is the effect of log sentiment on log volatility at quantile τ

The study also sought to examine whether investor sentiment has asymmetric effects on stock market volatility, distinguishing between positive and negative shocks. The Exponential GARCH model introduced by Nelson (1991) was employed as it allows for the capture of the asymmetric property of conditional volatility (Kumari and Mahakud, 2016). E-GARCH offers the advantage of modelling volatility in logarithmic form, which eliminates the need for parameter restrictions during estimation. This was adopted in previous studies such as Chen

and Haga (2021), Mashamba and Magweva (2019) and Muguto et al. (2022). The general form of the EGARCH (1,1) model is:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^q \beta_i \ln(\sigma_{t-i}^2) + \sum_{j=1}^p \alpha_j \left(\frac{|\epsilon_{t-j}|}{\sigma_{t-j}} - E \left[\frac{|\epsilon_{t-j}|}{\sigma_{t-j}} \right] \right) + \sum_{j=1}^p \gamma_j \frac{\epsilon_{t-j}}{\sigma_{t-j}}$$

Where:

σ_t^2 = Model's estimate of variance at time t

ω = Constant term

β_i = Persistence parameter

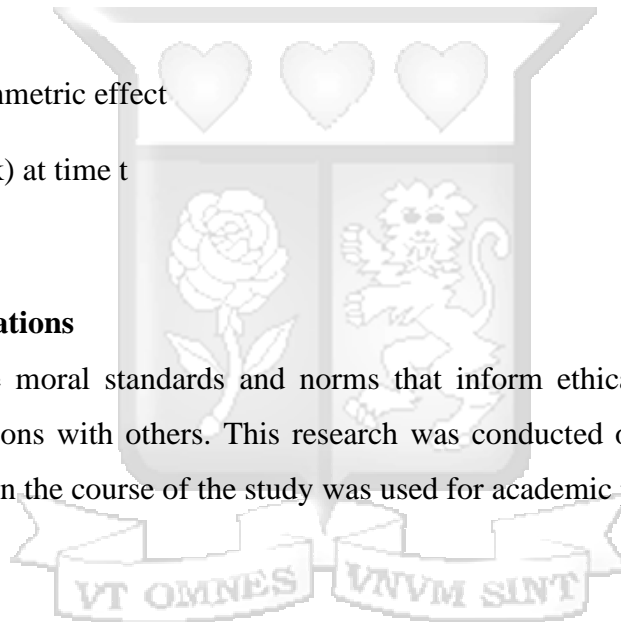
α = Magnitude effect

γ_j = Captures the asymmetric effect

ϵ_t = Innovation (shock) at time t

3.7 Ethical Considerations

Ethics encompass the moral standards and norms that inform ethical decisions about our behavior and interactions with others. This research was conducted objectively, and all the information obtained in the course of the study was used for academic purposes only.



CHAPTER FOUR

PRESENTATION OF RESEARCH FINDINGS

4.1 Introduction

The general objective of this study was to investigate the relationship between investor sentiment and volatility in the Kenyan equities market. This chapter consists of the results of the study and the interpretations. Section 4.2 presents the general information while Section 4.3 captures the descriptive statistics. Section 4.4 presents the principal component analysis which was used to derive the independent variable. Section 4.5 provides the diagnostic tests. Section 4.6 discusses the first objective which examines the relationship between investor sentiment and volatility in the Kenyan stock market. Section 4.7 discuss the second objective: To investigate the nature of the relationship between investor sentiment and stock market volatility across different market regimes. Section 4.8 presents the results for the third objective that is to analyze the asymmetric effects of investor sentiment on stock market volatility, distinguishing between positive and negative sentiment, and the chapter concludes with a summary in Section 4.9.

4.2 General Information

The data collected for the study was trading volumes, shares traded, value of shares traded, market capitalization, monthly stock prices, net income and shareholders' equity for 19 companies comprised in the NSE 20 Share Index that had been actively and consistently traded on the NSE for a minimum of 80% of the study period and interest, inflation and exchange rates from 2013 to 2023.

4.3 Descriptive Statistics

Table 4.1 presents the descriptive statistics of the variables in the study which includes the independent variables, dependent variables and the control variables.

Table 4.1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Closing price	2508	88.117	147.183	1.3	950
Return (%)	2503	-0.1	8.9	-74	47.9
TradingVolume2	2507	20365643	49741171	7600	471708300
Advance Decline Ratio	2470	1.519	2.1	0	18
Market Turnover (%)	2508	0.6	0.2	0.2	1.3
Relative Strength Index	2256	44.77	18.371	1.878	98.22
Earnings per Share	2479	8.579	11.958	-6.32	68.92
Return on Equity (%)	2479	45.5	218.4	-1257.3	1748.5
Annual Average Inflation (%)	2508	6.367	1.136	4.44	8.78
Exchange Rates	2508	104.931	14.396	84.15	154.09

Interest rates (%)	2508	14.157	2.092	11.75	18.3
--------------------	------	--------	-------	-------	------

The findings in Table 4.1 show that the closing prices in the stock market during the 11 years period averaged at 88.117 with a standard deviation of 147.183. The minimum price was 1.3 and the maximum was 950. The results also showed that the Return had a negative mean of -0.1% with a standard deviation of 8.9% and the minimum was -74% and maximum 47.9%. Further, it was evident that the average trading volume in the stock market during the 11 years' period was 20,365,643. The trading volume ranged between 7,600 to 471,708,300. Furthermore, the advance decline ratio in the period had a mean of 1.519 and a standard deviation of 2.1 and the minimum value was 0 and maximum was 18. Market turnover further had a mean of 0.6%, a standard deviation of 0.2% and minimum and maximum values of 0.2% and 1.3% respectively. Additionally, relative strength index averaged 44.77 with a standard deviation of 18.371, a minimum value of 1.878 and a maximum value of 98.22. The mean of earning per share was 8.579, the standard deviation 11.958, the minimum value was -6.32 and maximum was 68.92. Further still, the mean of return on equity was 45.5% and standard deviation was 218.4% which was a high deviation from the mean, minimum value was -1257.3% and the maximum was 1748.5%. The mean for annual average inflation was 6.367%, standard deviation was 1.1.36% and ranged between 4.44 and 8.78%. The average exchange rate was 104.931, standard deviation was 14.396 and ranged between 84.15 and 154.09. Finally, interest rates during the period averaged 14.157 with a standard deviation of 2.092 and ranged between 11.75 and 18.3.

4.4 Principal Component Analysis

Principal component analysis was implemented to reduce the number of proxies for the variable investor sentiment. It also helped in simplifying its complexity and condensing its size, through linear transformations. A sentiment index was also built using this method. The results for this analysis were as presented in Table 4.2.

Table 4.2: Principal Component Analysis

Principal components/correlation	Number of obs	=	2,219
	Number of comp.	=	4
	Trace	=	4
Rotation: (unrotated = principal)	Rho	=	1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.358	0.381	0.340	0.340
Comp2	0.977	0.015	0.244	0.584
Comp3	0.962	0.259	0.240	0.824
Comp4	0.703	.	0.176	1.000

Principal components (eigenvectors)					
Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
Trading Volume	0.544	-0.574	0.224	0.570	0
Advance Decline Ratio	0.426	0.551	-0.605	0.385	0
Market Turnover	0.289	0.590	0.754	0.022	0
Relative Strength Index	0.663	-0.141	-0.123	-0.725	0

Based on Kaiser's Rule of One, there was a one component solution. This means that the proxies of the independent variable investor sentiment could be reduced to one proxy which had an eigenvalue of 1.358 and a proportion of 34%. Further according to the results, trading volume was explained by 54.4% in component 1, advance decline ratio explained 42.6%, market turnover explained 28.9% and relative strength index 66.3%.

Figure 4.1 shows a scree plot for the number of components that can be extracted.

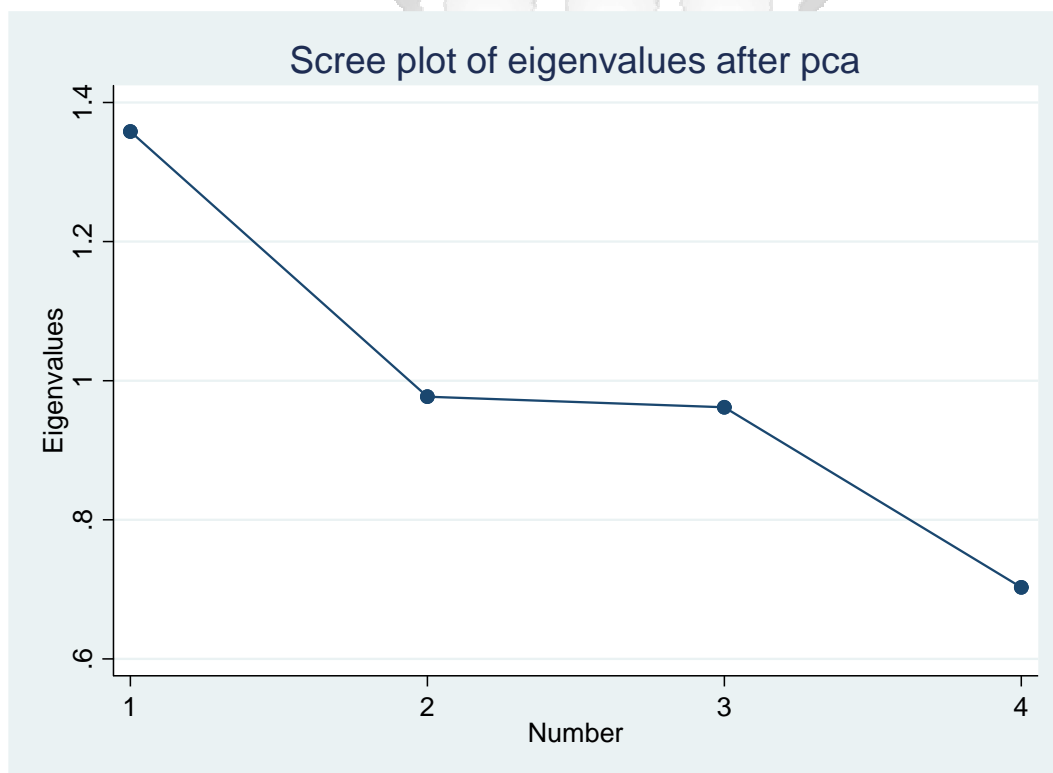


Figure 4.1: Scree plot

The results of the scree plot confirm the results in Table 4.2 where only one component can be extracted which has an eigenvalue above 1.

To neutralize the effects linked to economic fundamentals, the sentiment indicator was regressed against a set of macroeconomic factors including inflation, exchange rates and interest rates and microeconomic factors which included return equity, book to market ratio

and earnings per share. The residues were retained as the irrational part of the indicator and this formed the indicator for the independent variable investor sentiment.

4.5 Diagnostic Tests

Diagnostic tests including tests for stationarity, normality and heteroskedasticity were performed before applying the GARCH model to capture volatility persistence.

4.5.1 Stationarity

To test for unit roots, the Levin Lin Chu test was adopted. Table 4.3 shows the unit root tests results for the variable return and Table 4.4 shows the unit root test results for sentiment index.

Table 4.3: Unit Root Test for Returns

Ho: Panels contain unit roots		Number of panels = 19
Ha: Panels are stationary		Number of periods = 3987
AR parameter: Common		Asymptotics: N/T -> 0
Panel means: Included		
Time trend: Not included		
ADF regressions: 1 lag		
LR variance: Bartlett kernel, 50.00 lags average (chosen by LLC)		
	Statistic	P value
Unadjusted t	-45.7115	
Adjusted t*	-30.2013	0.0000

The Levin-Lin-Chu test evaluates the null hypothesis that the data contain unit roots, against the alternative that the panels are stationary. The results presented in Table 4.3 shows that the P value was $0.00 < 0.05$. Hence, the null hypothesis of presence of unit roots was rejected and the alternative hypothesis that all panels are stationary kept. This implied that the panels for the variable returns were stationary.

Table 4.4: Unit roots for Sentiment Index

Ho: Panels contain unit roots		Number of panels = 19
Ha: Panels are stationary		Number of periods = 3987
AR parameter: Common		Asymptotics: N/T -> 0
Panel means: Included		
Time trend: Not included		
ADF regressions: 1 lag		
LR variance: Bartlett kernel, 50.00 lags average (chosen by LLC)		

	Statistic	P value
Unadjusted t	-30.4959	
Adjusted t*	-18.9624	0.0000

The LLC test evaluates the null hypothesis that the panels contain unit roots against the alternative hypothesis that the panels are stationary. As shown in Table 4.6, the P-value was 0.00, which is less than 0.05. Therefore, the null hypothesis of the presence of unit roots was rejected. This indicates that the panels for the sentiment index variable were stationary.

4.5.2 Normality

To test for normality, the Jarque-Bera (JB) test was used. The results were as presented in Table 4.5.

Table 4.5: Normality Test Results

Jarque-Bera normality test		
3133 Chi(2)	p value	0.000

The rule of thumb for the JB is that a chi p value less than 0.05 means the data is not normally distributed. The results showed that the P value was 0.000 indicating non normality. To address the problem of non-normality, bootstrapping was used where 1000 bootstraps were replicated.

4.5.3 Heteroscedasticity

To test for general forms of heteroskedasticity, the Breusch-Pagan test was conducted. To assess the presence of time-varying volatility, the ARCH-LM test was also performed. The results were as in Table 4.6 and Table 4.7.

Table 4.6: Breusch Pagan test for Heteroskedasticity

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity	
Ho: Constant variance	
Variables: fitted values of Return	
chi2(1)	= 1.23
Prob > chi2	= 0.02667

The null hypothesis for this test was constant variance. The results obtained showed a P value of $0.02667 < 0.05$. This means that the null hypothesis was rejected hence the data was heteroscedastic.

Table 4.7: ARCH-LM Test for Conditional Heteroskedasticity

LM test for ARCH disturbances

Chi-squared (1) = 24.35

Prob > chi2 = 0.0000

To confirm the presence of conditional heteroskedasticity, an ARCH-LM test was conducted using the ARCH(1) specification. The test yielded a p-value less than 0.05, indicating significant ARCH effects in the return series. This confirmed the suitability of using GARCH models.

4.6 GARCH Analysis

The first objective examined the baseline relationship between investor sentiment and volatility in the Kenyan stock market. This was addressed by using the GARCH analysis. The results were as tabulated in Table 4.8.

Table 4.8: GARCH Results

Return	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
ARCH family regression						
Sample: Jan-13 - Dec-23, but with gaps			Number of obs =		75,753	
Distribution: Gaussian			Wald chi2(1) =		1.27e+06	
Log likelihood = 204561.2			Prob > chi2 =		0.0000	
Return						
SentimentIndex	.0270509	.000024	1127.77	0.000	.0270039	.0270979
_cons	.0021167	.0000171	123.44	0.000	.002083	.0021503
ARCH						
arch L1.	.9517922	.0239488	39.74	0.000	.9048535	.998731
garch L1.	.0639102	.0030777	20.77	0.000	.0578781	.0699423
_cons	1.00e-06	5.22e-08	19.20	0.000	9.00e-07	1.10e-06

From the results obtained and presented in Table 4.8, the coefficient for sentiment index was positive ($\beta=0.027009$) and also significant ($p = 0.00$), indicating that investor sentiment has a positive and significant impact on stock returns volatility in the Kenyan stock market. Further, these results reveal that with inclusion of sentiment index, the volatility in stock market increases.

The results of the second model show that the coefficient on the lagged squared error term, the ARCH term is positive and statistically significant ($\beta = 0.9517922$, $p = 0.000$). This suggests that past shocks play a substantial role in influencing current stock market volatility. The high coefficient indicates a strong degree of volatility clustering, implying that periods of high volatility are likely to be followed by similar periods. In essence, the return series is highly sensitive to past disturbances, highlighting the persistence of volatility over time. Moreover, the coefficient on the lagged squared error term (GARCH term) was positive ($\beta=0.0639102$) and significant ($p=0.000$). This indicated that the past shocks have a longer-lasting impact on the series. This further implied that previous days of volatility of stock prices can influence the current volatility of stock prices.

The estimated GARCH(1,1) model yielded a log-likelihood value of 204561.2. This value reflects the likelihood of observing the actual stock return data given the estimated model parameters and the assumption of a Gaussian distribution for the conditional returns. A higher log-likelihood generally indicates a better fit of the model to the data statistically. The constant term in the variance equation, estimated at $1.00e-06$ and statistically significant, represents the unconditional or long-term average level of return volatility when the effects of past shocks and past volatility are absent. This suggests that even when investor sentiment and recent market dynamics have no immediate influence, a minimal level of volatility remains, likely driven by underlying structural or fundamental factors not captured by short-term sentiment-driven fluctuations.

The study therefore established that investor sentiment has a positive and statistically significant relationship with volatility of the Kenyan stock market. These findings support the conclusion that investor sentiment plays a statistically significant role in predicting and explaining the volatility of the Kenyan stock market, with evidence of persistent and clustered volatility patterns as captured by the GARCH(1,1) model.

4.7 Quantile Regression

The second objective aimed at investigating the varying nature of the relationship between investor sentiment and stock market volatility across different market regimes. To examine whether the relationship between investor sentiment and stock market volatility varies across different volatility levels, this study employed quantile regression at three key points of the volatility distribution: the 10th percentile (low-volatility regime), 50th percentile (typical market conditions), and 90th percentile (high-volatility regime). The results of the test were as shown in Table 4.9.

Table 4.9: Quantile Regression

.1 Quantile regression						Number of obs =	1361
Raw sum of deviations 584.0897 (about -8.4442215)							
Min sum of deviations 579.42						Pseudo R2	= 0.0080
log_Volatility	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]		
Log_SentimentIndex	-.1287043	.0561737	-2.29	0.022	-.2389009	-.0185077	
_cons	-8.977708	.2356912	-38.09	0.000	-9.440066	-8.51535	

Median regression						Number of obs =	1361
Raw sum of deviations 1175.768 (about -6.6649737)							
Min sum of deviations 1160.29						Pseudo R2	= 0.0132
log_Volatility	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]		
Log_SentimentIndex	.143616	.0331538	4.33	0.000	.0785779	.208654	
_cons	-6.190354	.139105	-44.50	0.000	-6.463238	-5.91747	

.9 Quantile regression						Number of obs =	1361
Raw sum of deviations 422.107 (about -5.771605)							
Min sum of deviations 418.4911						Pseudo R2	= 0.0086
log_Volatility	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]		
Log_SentimentIndex	.1057019	.036519	2.89	0.004	.0340621	.1773416	
_cons	-5.293509	.1532248	-34.55	0.000	-5.594091	-4.992926	

From the results obtained and presented in Table 4.8, at the 10th percentile, sentiment has a significant negative effect on volatility suggesting that in calm periods, more optimistic sentiment lowers volatility. On the contrary, sentiment shows a positive and highly significant effect during average conditions. This suggests that sentiment can drive mild volatility during

these periods. Similarly, at the 90th percentile, sentiment was discovered to exhibit a statistically significant positive effect. This means that investor sentiment amplifies volatility further in high volatility regimes. This indicates that the sentiment index has significant and varying effects on market volatility across different regimes.

4.8 E-GARCH Analysis

The third objective sought to analyse the asymmetric effects of investor sentiment on stock market volatility, distinguishing between positive and negative sentiment. To do this, E-GARCH Analysis was used. First, the variable sentiment index was categorized into positive sentiment and negative sentiment. Table 4.10 and 4.11 show the results.

Table 4.10: E-GARCH Analysis for Positive Sentiment

Return	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
positivesentiment	.047	.004	13.27	0.000	.04	.054	***
Constant	-.024	.003	-9.34	0.000	-.029	-.019	***
E-garch	-.12	.003	-40.11	0.000	-.126	-.114	***
arch	81.133	
Constant	-6.101	
Mean dependent var		-0.001	SD dependent var				0.089
Number of obs		2503	Chi-square				176.048
Prob > chi2		0.000	Akaike crit. (AIC)				-5198.875
*** $p < .01$, ** $p < .05$, * $p < .1$							

The results showed that the coefficient for positive sentiment was positive (0.047) and the P value was $0.000 < 0.05$. This implied that the effect of positive investor sentiment on stock market volatility is positive and statistically significant. Therefore, when investors exhibit positive sentiment, stock market volatility increases.

Table 4.11: E-GARCH Analysis for Negative Sentiment

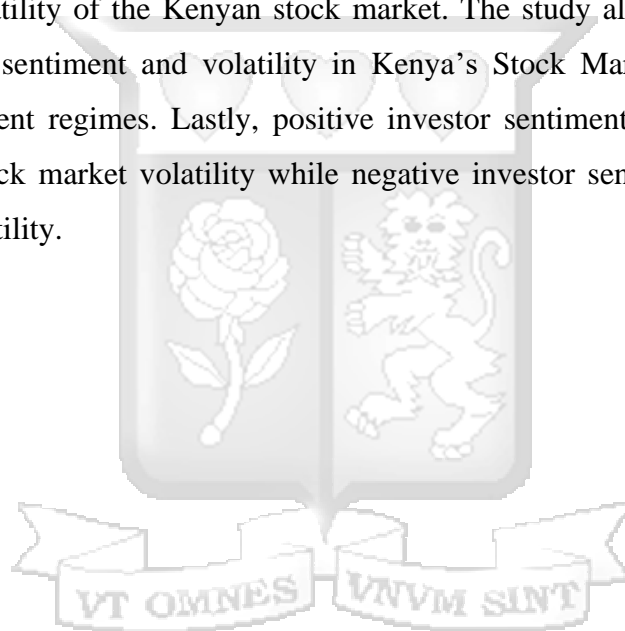
Return	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
negativesentiment	-.047	.004	-13.27	0.000	-.054	-.04	***
Constant	.023	.002	9.65	0.000	.018	.027	***
e-garch	-.118	.003	-39.52	0.000	-.124	-.112	***
arch	81.745	
Constant	-6.097	
Mean dependent var		-0.001	SD dependent var				0.089
Number of obs		2503	Chi-square				176.047
Prob > chi2		0.000	Akaike crit. (AIC)				-5198.875
*** $p < .01$, ** $p < .05$, * $p < .1$							

Contrary to the results of positive sentiment, the study showed that negative sentiment has a negative coefficient (-0.047) and a p value that is less than 0.05 ($p=0.000$). This means that

negative investor sentiment has a negative and statistically significant effect on stock market volatility. Therefore, if more of investors portray a negative investor sentiment, then stock market volatility reduces.

4.9 Summary of the chapter

The chapter presented the results of the analysis aimed at addressing the three objectives: To examine the relationship between investor sentiment and volatility in the Kenyan stock market; To investigate the nature of the relationship between investor sentiment and stock market volatility across different market regimes; To analyze the asymmetric effects of investor sentiment on stock market volatility, distinguishing between positive and negative sentiment. The study concluded that investor sentiment has a positive and statistically significant relationship with volatility of the Kenyan stock market. The study also established that the relationship between sentiment and volatility in Kenya's Stock Market is significant and changes across different regimes. Lastly, positive investor sentiment was found to have a positive effect on stock market volatility while negative investor sentiment had an inverse relationship with volatility.



CHAPTER FIVE

DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

The chapter consists of the discussions of the study findings, the conclusions made based on the study findings, the recommendations for practice and policy and also for further research. The chapter lastly presents the limitations of the study.

5.2 Discussions

5.2.1 Relationship Between Investor Sentiment and Volatility

The first objective of the study was to examine the relationship between investor sentiment and volatility in the Kenyan stock market. Utilizing a GARCH model to capture the conditional variance in returns, the outcome revealed a statistically significant and positive relationship between the sentiment index and stock market volatility. In particular, an increase in investor sentiment was associated with a rise in volatility, implying that periods of elevated optimism or pessimism among investors tend to coincide with greater fluctuations in market returns.

A number of findings agree with this study's results. For instance, Haritha and Rishad (2020) found that excessive market volatility is largely caused by irrational sentiment. The findings further agreed with Liston and Huerta (2012) who showed that shifts in sentiment positively and significantly impacted the market portfolio suggesting that the higher risk created by uninformed traders due to market misperceptions and noise trading, led to higher returns. Schneller et al. (2017) furthermore highlighted that the sentiment of investors in Germany and around Europe has significant effects on volatility of returns in local stock markets. Raissi and Missaoui (2016), also established that investor psychology considerably affects small capitalization returns in France such that positive investor sentiment affects returns positively. By using the VAR model, it was observed that there is a reciprocal relationship between investor sentiment and stock returns supporting the current study findings. Brown (1999) found strong evidence that higher volatility of closed-end investment funds is linked to abnormally high levels of sentiment among individual investors.

These findings however contrasted with those of Baker and Wurgler (2006) who observed that high sentiment resulted in relatively low returns. Further, they differed from Sibley et al. (2016) who argued that cross-sectional stock returns are not necessarily predicted by investor sentiment or irrational behaviour.

5.2.2 Sentiment–Volatility Relationship Across Market Regimes

The second objective of the study was to investigate the nature of the sentiment-volatility relationship across different market regimes. Using quantile regressions, the analysis revealed that the market volatility is significantly impacted by the sentiment index across different regimes.

This was in line with Smales (2012) who demonstrated that news sentiment exerts a significant and dynamic influence on implied volatility and stock returns, highlighting the need to account for heterogenous effects in such analyses. Similarly, Adrangi et al. (2023) reported that the relationship between realized volatility and sentiment varies across high- and low-volatility regimes. This was also consistent with Ho et al. (2013) in their study of the dynamic relationship between company-level return volatility and public news sentiment, who employing Markov Regime- Switching GARCH found that news sentiment contributes more significantly to volatility persistence in the high-volatility regime compared to the low-volatility regime.

In this study, a significant negative relationship was established between investor sentiment and stock market volatility in periods of low volatility whereas in average conditions and high volatility regimes, a positive and statistically significant relationship was found.

5.2.3 Asymmetric Effects of Investor Sentiment on Stock Market Volatility, Distinguishing Between Positive and Negative Sentiment

The third objective sought to examine the asymmetric effects of investor sentiment on stock market volatility, distinguishing between positive and negative sentiment. The analysis revealed that positive investor sentiment has a positive effect on stock market volatility while the relationship between negative investor sentiment and stock market volatility is inverse. This implies that positive sentiment increases volatility, while negative sentiment tends to reduce it.

This was in line with Chen and Haga (2021) who analysed the role of investor sentiment in shaping stock returns around market crashes and employing the E-GARCH model. It was established that both optimistic and pessimistic sentiment affected Chinese stock market returns significantly, implying that fluctuating sentiment is among the influences of stock price patterns. Similarly, Haritha and Rishad (2020), who developed a sentiment index revealed an asymmetric relationship when the sentiment index was decomposed into positive and negative sentiment in the Indian stock market. The positive sentiment index was found to positively influence excess market returns, while the intensity of negative sentiment was less pronounced

on negative returns. Further, Liston and Huerta (2012) revealed that although insignificant, positive shifts in sentiment were linked to lower volatility in the subsequent period.

5.3 Conclusions

5.3.1 Relationship Between Investor Sentiment and Volatility

The findings showed a significant influence of sentiment index on volatility which leads to the conclusion that investor sentiment has a relationship with volatility. The influence was also shown to be positive. Therefore, the study concludes that high levels of investor sentiments lead to increased changes in the stock returns. Periods of high investor sentiment translate to volatility in the stock market for at most one month.

5.3.2 Sentiment–Volatility Relationship Across Market Regimes

Quantile regression analysis revealed a nuanced sentiment-volatility relationship across different distribution quantiles. A significant positive association was established in median and high volatility periods indicating that heightened investor sentiment is linked to increased market volatility during these phases. This suggests that when market volatility is moderate to high, sentiment can further amplify volatility. Conversely, during periods of low volatility, a significant negative relationship was observed implying that during calmer market phases, increased sentiment tends to be associated with reduced volatility. These findings conclude that the impact of investor sentiment on volatility varies substantially depending on the prevailing level of market volatility.

5.3.3 Asymmetric Effects of Investor Sentiment on Stock Market Volatility, Distinguishing Between Positive and Negative Sentiment

Based on the study's findings, stock market volatility rises when investors are feeling confident. This could imply that stock values may fluctuate more during periods of high investor confidence, either as a result of speculation or the quick movement of investments. On the other hand, stock market volatility decreases when investors are apprehensive or pessimistic. This may indicate that the market becomes more stable during times of low confidence, perhaps as a result of investors refraining from making bold moves or a decrease in speculative activity.

5.4 Recommendations

5.4.1 Recommendations for theory

The research emphasized on the influence of sentiment on trading behavior and volatility, which advances the idea of market microstructure and the noise trader theory. This contradicts the Efficient Market Hypothesis, which assumes that pricing is efficient based only on fundamentals, by showing that sentiment and other non-rational factors can have a substantial impact on stock prices and volatility. These results add to the knowledge of how market dynamics are influenced by the emotions of market participants and reinforce the expanding corpus of Behavioral finance research. The underlying psychological processes that cause negative sentiment to decrease volatility and positive sentiment to increase volatility should be incorporated in theories. To explain these consequences, more intricate models may need to be created that incorporate behavioral finance and macroeconomic variables. In order to better capture sentiments in investor behavior, future research could focus on improving mood indexes.

5.4.2 Recommendations for policy

The study recommends implementation of investor education initiatives to inform investors on how emotion affects the stock market. By doing this, unjustified volatility will be lessened and market and listed company information will be transparent. To counteract unduly positive views, regulations can include stricter margin trading guidelines or limitations on short-term trading. In order to provide a stabilizing effect during times of strong sentiment, mechanisms such as circuit breakers or automated trading halts could also be enhanced to reduce excessive volatility driven by sentiment-induced oscillations.

5.4.3 Recommendations for practice

The study encourages financial analysts, fund managers, and investors to consider investor sentiment as a relevant factor influencing stock market volatility. Given the observed link between sentiment and volatility, particularly under different market regimes, it is advisable to implement risk management strategies such as portfolio diversification and hedging during periods of heightened sentiment-driven volatility. Furthermore, while sentiment indicators can provide useful signals, reliance solely on sentiment is discouraged. Instead, investors should complement sentiment analysis with robust information and volatility measures. Financial products such as swaps, options, and volatility indices could be introduced to help mitigate the risks associated with excessive sentiment-driven volatility.

5.5 Research Areas for Further Studies

The scope of this study was limited to the relationship between investor sentiment and volatility in the Kenyan equities market. Further studies may adopt other variables that may affect the volatility and study them. Further, future researchers may conduct a similar study on individual companies to provide more precise insights enabling investors to identify the companies that are more sensitive to sentiment shifts, manage risk more effectively and capitalize on potential opportunities.

Additionally, future studies could consider incorporating a psychological sentiment index derived from survey-based or behavioral data to complement market-based sentiment measures. This would provide a more comprehensive understanding of investor behavior by capturing emotional and cognitive aspects of sentiment that may not be fully reflected in market variables.

5.6 Limitations of the Study

The study faced the limitation of missing values since secondary data was used. To address this limitation, the missing values were interpolated so as to ensure that the findings were reliable. Additionally, data was obtained from credible sources to guarantee reliability. Monthly data was used to reduce noise and highlight longer-term relationships between sentiment and volatility. Future research may however explore the use of high-frequency data to examine immediate market reactions to sentiment shifts. While the investor sentiment index constructed from market-based proxies offers the advantage of capturing observable trading behavior, it remains an indirect representation of the complex psychological dimensions of investor sentiment. Future research could enhance the robustness of these findings by exploring alternative or composite sentiment measures that incorporate a broader range of indicators. Lastly, this study was limited to the Kenyan stock market hence the findings may not be generalizable to other emerging markets. Further research across different market is necessary to determine if similar patterns hold.

REFERENCES

- Abbas, R., Ijaz, M. B., & Javeed, A. (2024). Impact of Bullish and Bearish Trends on Investor Sentiment in Stock Market: A study from Pakistan. *Contemporary Journal of Social Science Review*, *II*(4).
- Abdelmalek, W. (2022). Investor sentiment, realized volatility and stock returns. *Review of Behavioral Finance*, *14*(5), 668-700. doi:10.1108/RBF-12-2020-0301
- Adrangi, B., Chatrath, A., & Raffiee, K. (2023). S&P 500 volatility, volatility regimes, and economic uncertainty. *Bulletin of Economic Research*, *75*(4), 1362-1387. doi:https://doi.org/10.1111/boer.12406
- Alajekwu, B. U., Okoro, C. O., Obialor, M. C., & Ibenta, N. (2017). Effect of Investor Sentiment on Future Returns in the Nigerian Stock Market. *International Journal of Trend in Scientific Research and Development*, *1*(5).
- Amdouni, A. (2021). Investor Sentiment Measurement Techniques: A Review of Literature. *Arabian Journal of Business and Management Review*.
- Anusakumar, S. V., Ali, R., & Wooi, H. C. (2017). The effect of investor sentiment on stock returns: Insight from emerging Asian markets. *Asian Academy of Management Journal of Accounting and Finance*, *13*(1), 159-178.
- Ayinuola, T. F., & Adetiloye, K. A. (2023). Investigating the Nexus Between Investor Sentiment and Stock Return Volatility in Nigeria. *International Journal of Multidisciplinary and Current Research*, *5*(3), 160-173.
- Baariu, J. M., & Jagongo, A. (2022). Macroeconomic Variables, Sectoral Index Volatility, and Investro Sentiment among Listed Firms at Nairobi Securities Exchange, Kenya. *International Journal of Finance and Accounting*, *VII*(1), 61-75.
- Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets*, *7*(3), 271-299. doi:doi:10.1016/j.finmar.2003.11.005
- Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, 1645-1680.
- Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, 129-151.
- Ballinari, D., & Behrendt, S. (2020). *How to gauge investor behavior? A comparison of online investor sentiment measures*. University of Basel, Zeppelin University.
- Barberis, N., & Thaler, R. (2003). A Survey of Behavioral Finance. *Handbook of the Economics of Finance*, 1052-1090.
- Beechey, M., Gruen, D., & Vickery, J. (2000). The Efficient Market Hypothesis: A Survey. *Economic Research Development*.
- Beer, F., & Zouaoui, M. (2013). Measuring Stock Market Investor Sentiment. *The Journal of Applied Business Research*, *29*(1), 51-68.

- Bennet, E., Selvam, M., Vivek, N., & Shalin, E. E. (2012). The impact of investors' sentiment on the equity market: Evidence from Indian stock market. *African Journal of Business Management*, 6(32), 9317-9325. doi:10.5897/AJBM11.588
- BenSaïda, A. (2017, November). Herding effect on idiosyncratic volatility in U.S. industries. *Finance Research Letters*, XXIII, 121-232. doi:https://doi.org/10.1016/j.frl.2017.03.001
- Bill, C. (2021). China's Stock Market. Impact of Investor's Sentiment on Returns of Stocks.
- Black, F. (1986). Noise. *The Journal of Finance*, 41(3), 528-543.
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics*, 307-327.
- Bollerslev, T., Engle, R., & Wooldridge, J. (1988). A Capital Asset Pricing Model with Time Varying Covariances. *Journal of Political Economy*, 96(1), 116-131. doi:http://dx.doi.org/10.1086/261527
- Brooks, C. (2014). *Introductory Econometrics for Finance* (3rd ed.). Cambridge University Press.
- Brown, G. W. (1999). Volatility, Sentiment, and Noise Traders. *Financial Analysts Journal*, 55(2), 82-90. doi:10.2469/faj.v55.n2.2263
- Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, 1-27. doi:10.1016/j.jempfin.2004.04.001
- Byrne, A., & Brooks, M. (2008). Behavioral Finance: Theories and Evidence. *The Research Foundation of CFA Institute Literature Review*. doi:https://doi.org/10.2470/rflr.v3.n1.1
- Cabarcos, A. L., Pico, P. A., Rodriguez, P. V., & Perez, L. L. (2019). Investor sentiment in the theoretical field of behavioural finance. *Economic Research-Ekonomska Istraživanja*. doi:10.1080/1331677X.2018.1559748
- Cagli, E. C., Ergun, Z. C., & Durukan, M. B. (2020). The causa linkages between investor sentiment and excess returns on Borsa Instabul. *Borsa Instabul Review*, 20(3), 214-223.
- Capital Markets Authority. (2023). *Quarterly Statistical Bulletin Quarter ended March 2023*. Nairobi: Capital Markets Authority. Retrieved from <https://cma.or.ke/wp-content/uploads/2023/06/Capital-Markets-Authority-CMA-Quarterly-Statistical-Bulletin-Q1-2023.pdf>
- Caporale, G. M., Gil-Alana, L. A., & Tripathy, T. (2020). Volatility persistence in the Russian stock market. *Finance Research Letters*, 32. doi:https://doi.org/10.1016/j.frl.2019.06.014
- CFI Team. (n.d.). *Market sentiment*. Retrieved from Corporate Finance Institute: https://corporatefinanceinstitute.com/resources/career-map/sell-side/capital-markets/market-sentiment/?utm_source

- Chang, A. C.-C., Yu, S. C., Reinstein, A., & Churyk, N. T. (2002). An Overview of Investor Sentiment in Stock Market. *Oxford University Press*.
- Chege, A. K., & Otieno, C. O. (2020, May). Research Philosophy Design and Methodologies: A Systematic Review of Research Paradigms in Information Technology. *Global Scientific Journals, VIII(5)*.
- Chen, C., Hu, C., & Yao, H. (2022). Noise Trader Risk and Wealth Effect: A Theoretical Framework. *Mathematics, 10(20)*.
- Chen, S. T., & Haga, K. Y. (2021). Using E-GARCH to Analyze the Impact of Investor Sentiment on Stock Returns Near Stock Market Crashes. *Frontiers in Psychology, 12*. doi:<https://doi.org/10.3389/fpsyg.2021.664849>
- Chen, Y., Zhao, H., Li, Z., & Lu, J. (2020). A Dynamic Analysis of the Relationship between Investor Sentiment and Stock Market Realized Volatility: Evidence from China. *PLoS ONE*.
- Cherono, I., Olweny, T., & Nasieku, T. (2019). Investor Behavior Biases and Stock Market Reactions in Kenya. *Journal of Applied Finance & Banking, 9(1)*, 147-180.
- Chiu, C.-W. (., Harris, R. D., Stoja, E., & Chin, M. (2016, August). Financial market volatility, macroeconomic fundamentals and investor sentiment. *Staff Working Paper No. 608*. doi:<https://doi.org/10.2139/ssrn.2827569>
- Chiu, H.-H., & Kini, O. (2014). Equity Issuances, Equity Mutual Fund Flows, and Noise Trader Sentiment. *Review of Finance, 18(2)*, 749-802.
- Chu, X., Wu, C., & Qiu, J. (2015). A nonlinear Granger causality test between stock returns and investor sentiment for Chinese stock market: a wavelet-based approach. *Applied Economics, 1915-1924*. doi:10.1080/00036846.2015.1109048
- Coffie, W., & Chukwulobelu, O. (2013, July). Cost of Equity Capital in Emerging Market - The Case of Kenya. *GSTF Journal of Business Review, II(4)*. Retrieved from <http://dl6.globalstf.org/index.php/gbr/article/view/198>
- Dalika, N., & Seetharam, Y. (2015). Sentiment and returns: an analysis of investor sentiment in the South African market. *Investment Management and Financial Innovations, 12(1-2)*, 267-276.
- De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy, 98(4)*, 703-738.
- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50(4)*, 987-1007.
- Enow, S. T. (2023). Forecasting Volatility Persistence: Evidence from International Stock Markets. *Dinasti International Journal of Economics, Finance and Accounting, IV(3)*, 383-389. doi:<https://doi.org/10.38035/dijefa.v4i2>
- Fama, E. F. (1970, May). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance, 25(2)*, 383-417.

- Fama, E. F. (1991). Efficient Capital Markets II. *The Journal of Finance*, 46(5), 1575-1617. doi:<https://doi.org/10.1111/j.1540-6261.1991.tb04636.x>
- Ferreira, T. S., Machado, M. A., & Silva, P. Z. (2021). Asymmetric Impaact of Investor Sentiment on Brazilian Market Volatility. *Revista de Administração Mackenzie*, 22(4), 1-28. doi:10.1590/1678-6971/eRAMF210208
- Gao, Y., Zhao, C., Sun, B., & Zhao, W. (2022). Effects of investor sentiment on stock volatility: new evidences from multi-source data in China's green stock markets. *Financial Innovation*. doi:<https://doi.org/10.1186/s40854-022-00381-2>
- Granger, C. (1980). Testing for causality: A personal viewpoint. *Journal of Economic Dynamics and Control*, 329-352.
- Gu, Y. (2023). Efficient Market Hypothesis during COVID-19 Pandemic. *Advances in Economics, Management and Political Sciences*, 2(6), 301-307.
- Guo, P., & Shi, J. (2024, May). Geopolitical risks, investor sentiment and industry stock market volatility in China: Evidence from a quantile regression approach. *The North American Journal of Economics and Finance*, 72. doi:<https://doi.org/10.1016/j.najef.2024.102139>
- Haritha, P. H., & Rishad, A. (2020). An empirical examination of investor sentiment and stock market volatility: Evidence from India. *Financial Innovation*.
- Haritha, P. H., & Uchil, R. (2020). Influence of investor sentiment and its antecedent on investment decision-making using partial least square technique. *Management Research Review*, 43(11), 1441-1459. doi:<https://doi.org/10.1108/MRR-06-2019-0254>
- Hartmann, C., Burghof, H. P., & Mehlhorn, M. (2018). An Action – Identifying Noise Traders Entering the Market with Google and Twitter. *SSRN Electronic Journal*.
- He, G., Zhu, S., Gu, H., & McMillan, D. (2017). On the construction of Chinese stock market investor sentiment index. *Cogent Economics & Finance*, 5(1). doi:10.1080/23322039.2017.1412230
- Hervé, F., Zouaoui, M., & Belvaux, B. (2019). Noise traders and smart money: Evidence from online searches. *Economic Modelling*, 141-149.
- Ho, K.-Y., Shi, Y., & Zhang, Z. (2013). How does news sentiment impact asset volatility? Evidence from long memory and regime-switching approaches. 26, 436-456. doi:<https://doi.org/10.1016/j.najef.2013.02.015>
- Hu, J., Sui, Y., & Ma, F. (2021). The Measurement Method of Investor Sentiment and Its Relationship with Stock Market. *Computational Intelligence and Neuroscience*. doi:<https://doi.org/10.1155/2021/6672677>
- Huang, C., Yang, X., Yang, X., & Sheng, H. (2014, April 17). An Empirical Study of the Effect of Investor Sentiment on Returns of Different Industries. (F. Wen, Ed.) *Mathematical Problems in Engineering*. doi:<https://doi.org/10.1155/2014/545723>
- Hull, J. C. (2015). *Options, Futures and Other Derivatives*. Pearson Education.

- Kamoune, A., & Ibenrissoul, N. (2022). Traditional versus Behavioral Finance Theory. *International Journal of Accounting, Finance, Auditing, Management and Economics*, 3(2-1), 284-294.
- Khan, M. A., & Ahmad, E. (2019). Measurement of Investor Sentiment and Its Bi-Directional Contemporaneous and Lead-Lag Relationship with Returns: Evidence from Pakistan. *Sustainability*, 11(1). doi:<https://doi.org/10.3390/su11010094>
- Kinuthia, D. N., & Jagongo, A. (2021). Systematic Risks and Stock Market Volatility in Kenya. *International Research Journal of Business and Strategic Management*, 3(3).
- Koenker, R. (2017). Quantile Regression: 40 Years On. *Annual Review of Economics*, 9:155-176. doi:<https://doi.org/10.1146/annurev-economics-063016-103651>
- Koenker, R., & Bassett, G. J. (1978). Regression Quantiles. *Econometrica*, 46(1), 33-50. doi:<https://doi.org/10.2307/1913643>
- Kothari, C. R. (2013). *Research Methodology: Methods and Techniques*. New Age International Pvt Limited Publishers.
- Kremer, M. (2018, May). Regime shifts in stock market volatility: a historical perspective on the US market. *Financial Stability Review May 2018 – Financial markets and valuations*.
- Kumari, J., & Mahakud, J. (2016). Investor Sentiment and Stock Market Volatility: Evidence from India. *Journal of Asia-Pacific Business*, 17(2), 173-202. doi:10.1080/10599231.2016.1166024
- Lao, J., Nie, H., & Jiang, Y. (2018). Revisiting the investor sentiment-stock returns relationship: A multi-scale perspective using wavelets. *Statistical Mechanics and its Applications*, 499, 420-427. doi:10.1016/j.physa.2018.02.043
- Li, X., Lin, C., & Xu, X. (2020). Influence of psychological bias of financial investors on the investment returns. *Revista Argentina de Clínica Psicológica*, 29(1), 249-254.
- Lin, M., Sias, R. W., & Zaiyan, W. (2018). The Survival of Noise Traders: Evidence From Peer-to-Peer Lending. *SSRN Electronic Journal*.
- Malkiel, B. G. (2003). The Efficient Market Hypothesis and Its Critics. *Journal of Economic Perspectives*, 17(1), 59-82.
- Marczak, M., & Beissinger, T. (2016). Bidirectional Relationship between Investor Sentiment and Excess Returns: New Evidence from the Wavelet Perspective. 23(18), 1305-1311. doi:10.1080/13504851.2016.1153782
- Mashamba, T., & Magweva, R. (2019). Dynamic volatility behaviour of stock markets in Southern Africa. *Journal of Economic and Financial Services*, 12(1). doi:<https://doi.org/10.4102/jef.v12i1.396>
- Menard, S. (2002). *Longitudinal Research* (2nd ed.). Sage Publications.
- Mohamed, H. A. (2013). *Investor Sentiment and Equity Markets: Evidence From Kenya*. Master's Thesis, University of Nairobi.

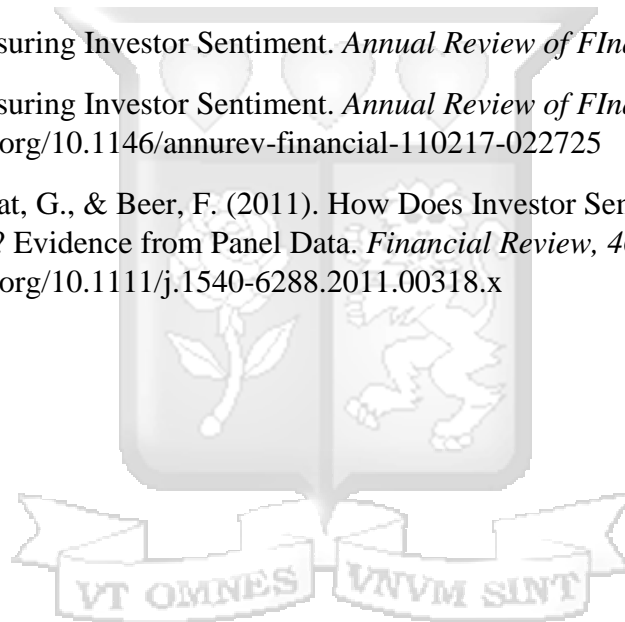
- MSCI Kenya Index (USD)*. (2023, June 30). Retrieved from <https://www.msci.com/>
- Mugenda, N. G., Olweny, T., & Wepukhulu, J. M. (2022). The role of investor sentiment on pricing effect of profitability risk factor in Kenya. *International Journal of Accounting & Finance Review*, *X*(1). doi:10.46281/ijafr.v10i1.1569
- Muguto, H. T., Muguto, L., Bhayat, A., Nicalane, H., Jack, K. J., Abdullah, S., Muzindutsi, P.-F. (2022). The impact of investor sentiment on sectoral returns and volatility: Evidence from the Johannesburg stock exchange. *Cogent Economics & Finance*, *10*(1). doi:doi=10.1080/23322039.2022.2158007
- Muguto, L., & Muzindutsi, P. F. (2022). A Comparative Analysis of the Nature of Stock Return Volatility in BRICS and G7 Markets. *Journal of Risk and Financial Management*, *15*(2). doi:10.3390/jrfm15020085
- Muhammad, A. u. (2021). The impact of investor sentiment on returns, cash flows, discount rates, and performance. *Borsa Istanbul Review*. doi:<http://dx.doi.org/10.1016/j.bir.2021.06.005>
- Muiruri, K. (2023, March 20). *Foreign investors dump over four billion NSE shares*. Retrieved from Business Daily: <https://www.businessdailyafrica.com/bd/markets/capital-markets/foreign-investors-dump-over-four-billion-nse-shares--4165110>
- Mungiria, J. B., & Jagongo, A. (2022). Macroeconomic Variables, Sectoral Index Volatility and Investor Sentiment among Listed Firms at Nairobi Security Exchange, Kenya. *International Journal of Finance and Accounting*, *VII*(4), 61-75.
- Musembi, M. M., Simiyu, E., & Njoka, C. (2020). Symmetric and Asymmetric effect of Investor Sentiment on Performance of Equity Market in Nairobi Securities Exchange, Kenya. *International Journal of Management and Commerce Innovations*, *8*(1), 438-447.
- Muzinda, E. T. (2016). *The impact of good news and bad news on South Africa's sectoral stock return volatility: An asymmetric GARCH Analysis*. Master's thesis, Rhodes University. Retrieved from <http://hdl.handle.net/10962/6425>
- Nabosu, S. S., M'ithiria, E. N., & Wepukhulu, J. M. (2022, August). Investor Sentiment and Stock Market Return of Non-Financial Firms Listed on the Nairobi Securities Exchange. *Journal of Finance and Accounting*, *6*(3), 65-81. doi:<https://doi.org/10.53819/81018102t2081>
- Naik, P. K., & Padhi, P. (2016, July). Investor sentiment, stock market returns and volatility: evidence from National Stock Exchange of India. *International Journal of Management Practice*, 213-237. doi:10.1504/IJMP.2016.077816
- Nairobi Securities Exchange. (2023). *Integrated Report & Financial Statements 2022*. Nairobi. Retrieved from <https://www.nse.co.ke/wp-content/uploads/NSE-Annual-Report-2022-Integrated-Report.pdf>

- Ndwiga, D., & Muriu, P. (2016, February). Stock Returns and Volatility in An Emerging Equity Market. Evidence From Kenya. *European Scientific Journal*, 12(4), 79-98. doi:<http://dx.doi.org/10.19044/esj.2016.v12n4p79>
- Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59, 347-370. doi:<https://doi.org/10.2307/2938260>
- Neves, M. E., Gonçalves, L. M., Ribiero, M. J., Feiteira, P. J., & Viseu, C. M. (2016). The unidirectional relationship between consumer confidence and PSI-20 returns - The influence of the economic cycle. *USP, São Paulo*, 27(72), 363-377. doi:10.1590/1808-057x201602280
- Niu, H., Lu, Y., & Wang, W. (2021). Does investor sentiment differently affect stocks in different sectors? Evidence from China. *International Journal of Emerging Markets*. doi:<https://doi.org/10.1108/IJOEM-11-2020-1298>
- Nnoje, A. I., Okonkwo, J. J., & Anachedo, K. C. (2021). Investors' Sentiments, Market Dynamics and Stock Market Returns in Nigeria. *Journal of Contemporary Issues in Accounting*, 1(1), 56-73.
- Ogega, H. O., & Waweru, F. M. (2016). Analysis of asymmetric and persistence in stock return volatility in the Nairobi Securities Exchange market phases. *Journal of Finance and Economics*, 4(3), 63-73. doi:10.12691/jfe-4-3-1
- Olsen, R. A. (1998). Behavioral Finance and Its Implications for Stock-Price Volatility. *Financial Analysts Journal*, 54, 10-18. doi:<https://doi.org/10.2469/faj.v54.n2.2161>
- Paramanik, R., & Singhai, V. (2020). Sentiment Analysis of Indian Stock Market Volatility. *Procedia Computer Science*, 330-338. doi:10.1016/j.procs.2020.08.035
- Pillada, N., & Rangasamy, S. (2023). An empirical investigation of investor sentiment and volatility of realty sector market in India: an application of the DCC-GARCH model. *SN Bus Econ*, III(55). doi:<https://doi.org/10.1007/s43546-023-00434-3>
- Prasad, M., Bakry, W., & Varua, M. E. (2020). Examination of information release on return volatility: A market and sectoral analysis. *Heliyon*. doi:<https://doi.org/10.1016/j.heliyon.2020.e03885>
- Qiu, L. X., & Welch, I. (2006, July 28). Investor Sentiment Measures. doi:<https://dx.doi.org/10.2139/ssrn.589641>
- Raissi, N., & Missaoui, S. (2016). Role of investor sentiment in financial markets: An explanation by behavioural finance approach. *International Journal of Accounting and Finance*.
- Ramiah, V., Xu, X., & Moosa, I. A. (2015). Neoclassical finance, behavioral finance and noise traders: A review and assessment of the literature. *International Review of Financial Analysis*, 89–100.
- Rehman, M. U. (2013). Investor's sentiments and stock market volatility: An empirical evidence from emerging stock market. *Pakistan Journal of Commerce and Social Sciences*, 7(1), 80-90.

- Reilly, F. K., Brown, K. C., & Leeds, S. J. (2019). *Investment Analysis & Portfolio Management*. Boston: Cengage Learning.
- Ricciardi, V., & Simon, H. K. (2000). What is Behavioral Finance? *Business, Education & Technology Journal*, 2(2), 1-9.
- Rugut, D. C. (2021). Stock market volatility forecasting at the Nairobi Securities Exchange: A comparison between asymmetric GARCH models and neural networks. *Master's Thesis, Strathmore University*.
- Rupande, L., Muguto, H. T., & Muzindutsi, P. F. (2019). Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange. *Cogent Economics & Finance*.
- Saleem, A., Bárczi, J., & Sági, J. (2021). COVID-19 and Islamic Stock Index: Evidence of Market Behavior and Volatility Persistence. *Journal of Risk and Financial Management*. doi:<https://doi.org/10.3390/jrfm14080389>
- Saunders, M. N., Lewis, P., & Thornhill, A. (2019). *Research Methods for Business Students* (8th ed.). Harlow, United Kingdom: Pearson Education Limited.
- Schmeling, M. (2008). Investor sentiment and stock returns: some international evidence. *Diskussionsbeitrag*(407).
- Schneller, D., Heiden, S., Heiden, M., & Hamid, A. (2017). Home is Where You Know Your Volatility - Local Investor Sentiment and Stock Market Volatility. *German Economic Review*, 19(2), 209-236. doi:<https://doi.org/10.1111/geer.12125>
- Seok, S. I., Cho, H., & Ryu, D. (2019). Firm-specific investor sentiment and daily stock returns. *The North American Journal of Economics and Finance*, 50. doi:<https://doi.org/10.1016/j.najef.2018.10.005>
- Shin, H., & Choi, S.-Y. (2022). Firm-specific investor sentiment and stock price crash risk: The role of foreign investors in Korea's stock market. *Investment Management and Financial Innovations*, 19(4), 309-326. doi:[10.21511/imfi.19\(4\).2022.25](https://doi.org/10.21511/imfi.19(4).2022.25)
- Shleifer, A., & Summers, L. H. (1990). The Noise Trader Approach to Finance. *Journal of Economic Perspectives*, 4(2), 19-33.
- Sibley, S. E., Wang, Y., Xing, Y., & Zhang, X. (2016). The information content of the sentiment index. *Journal of Banking & Finance*, 62(C), 164-179. doi:<https://doi.org/10.1016/j.jbankfin.2015.10.001>
- Silva, H. D., McMurrin, G. M., & Miller, M. N. (2017). Diversification and the Volatility Risk Premium. In E. Jurczenko, *Factor Investing* (pp. 365-387). Elsevier. doi:<https://doi.org/10.1016/B978-1-78548-201-4.50014-3>
- Simiyu, E., Korir, J., & Laiboni, G. (2020). Dynamic Linkages of Stock Market Sectors: Evidence from the Kenyan Stock Market. *Journal of Finance and Economics*, 8(1), 33-39. doi:[10.12691/jfe-8-1-5](https://doi.org/10.12691/jfe-8-1-5)
- Smales, L. A. (2012). Time-varying relationship of news sentiment, implied volatility and stock returns. *SSRN Electronic Journal*. doi:[10.2139/ssrn.2186267](https://doi.org/10.2139/ssrn.2186267)

- Son-Turan, S. (2016). The impact of Investor Sentiment on the "Leverage Effect". *International Econometric Review*, 8(1), 4-18.
- Srivastava, K. (2020). Factors Affecting Investors Sentiments: A Review of the Literature. *International Journal of Emerging Technologies*, XI(2), 154-159.
- Timmermann, A., & Granger, C. W. (2004). Efficient market hypothesis and forecasting. *International Journal of Forecasting*, 15-27.
- Tversky, A., & Kahneman, D. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty*, 297-323.
- Ung, S. N., Gebka, B., & Anderson, D. (2023). An enhanced investor sentiment index. *The European Journal of Finance*, 30(8), 827-864. doi:10.1080/1351847X.2023.2247440
- Uygur, U., & Tas, O. (2014). The impacts of investor sentiment on different economic sectors: Evidence from Instabul Stock Exchange. *Borsa Instabul Review*, XIV(4), 236-241. Retrieved from <http://www.elsevier.com/journals/borsa-istanbul-review/2214-8450>
- Verma, R., & Soydemir, G. (2006). The Impact of U.S. Individual and Institutional Investor Sentiment on Foreign Stock Markets. *Journal of Behavioral Finance*, 7(3), 128-144. doi:https://doi.org/10.1207/s15427579jpfm0703_2
- Walliman, N. (2011). *Research Methods The Basics*. New York, USA: Routledge.
- Wang, W. (2018). Investor sentiment and the mean-variance relationship: European evidence. *Research in International Business and Finance*, 227-239. doi:<https://doi.org/10.1016/j.ribaf.2018.02.006>
- Wang, W., Su, C., & Duxbury, D. (2022). The conditional impact of investor sentiment in global stock markets: A two channel examination. *Journal of Banking and Finance*, 138. doi:<https://doi.org/10.1016/j.jbankfin.2022.106458>
- Wang, Y.-h., Keswani, A., & Taylor, S. J. (2006). The Relationships between Sentiment, Returns and Volatility. *International Journal of Forecasting*, 22(1), 109-123. doi:<https://doi.org/10.1016/j.ijforecast.2005.04.019>
- Whaley, R. E. (2000). The investor gauge. *Journal of Portfolio Management*, 26(3), 12-17.
- Woolridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). MIT Press.
- World Bank Group. (2020). Kenya Economic Update.
- Yadav, A., Chakraborty, A., & Vijaya. (2022). Modeling a bi-directional sentiment-return relationship: Evidence from the Indian market. *Investment Management and Financial Innovations*, 19(4), 83-98. doi:10.21511/imfi.19(4).2022.07
- Yadav, Y., & Naik, P. K. (2023). Investors' Irrational Sentiment and Stock Market Returns: A Quantile Regression Approach Using Indian Data. *Business Perspectives and Research*, 12(1). doi:<https://doi.org/10.1177/22785337231165870>

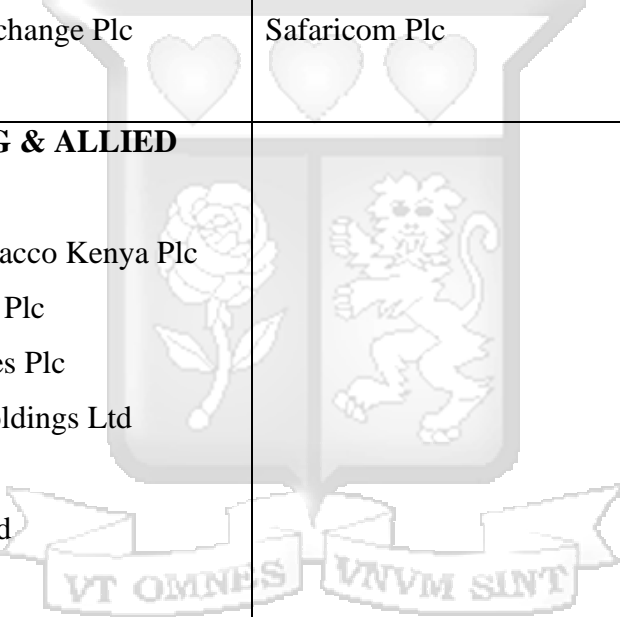
- Yang, Y., & Copeland, L. (2014). The Effects of Sentiment on Market Return and Volatility and The Cross-Sectional Risk Premium of Sentiment-affected Volatility. *Cardiff Economics Working Papers*.
- Yuan, Y. (2015). Market-wide attention, trading, and stock returns. *Journal of Financial Economics*, 116(3), 548-564. doi:<https://doi.org/10.1016/j.jfineco.2015.03.006>
- Zhang, C. (2008, April). *Defining, Modeling, and Measuring Investor Sentiment*. University of California, Department of Economics, Berkeley.
- Zhang, C., Wu, X., Deng, H., & Zhang, H. (2022). A Time-Varying Study of Chinese Investor Sentiment, Stock Market Liquidity and Volatility: Based on Deep Learning BERT Model and TVP-VAR model. *arXiv preprint*. doi: arXiv:2205.05719
- Zheng, Y., Osmer, E., & Zhang, R. (2018, March). Sentiment hedging: How hedge funds adjust their exposure to market sentiment. *Journal of Banking & Finance*, 88, 147-160. doi:<https://doi.org/10.1016/j.jbankfin.2017.11.016>
- Zhou, G. (2017). Measuring Investor Sentiment. *Annual Review of Financial Economics*.
- Zhou, G. (2018). Measuring Investor Sentiment. *Annual Review of Financial Economics*. doi:<https://doi.org/10.1146/annurev-financial-110217-022725>
- Zouaoui, M., Nouyrigat, G., & Beer, F. (2011). How Does Investor Sentiment Affect Stock Market Crises? Evidence from Panel Data. *Financial Review*, 46(4), 723-747. doi:<https://doi.org/10.1111/j.1540-6288.2011.00318.x>



APPENDICES

Appendix I: NSE Listed Companies 2023

<p>AGRICULTURAL</p> <p>Eagads Limited</p> <p>Kakuzi Plc</p> <p>Kapchorua Tea Kenya</p> <p>The Limuru Tea Co. Plc</p> <p>Sasini Plc</p> <p>Williamson Tea Kenya Plc</p>	<p>AUTOMOBILES & ACCESSORIES</p> <p>Car & General (K) Ltd</p>
<p>BANKING</p> <p>ABSA Bank Kenya Plc</p> <p>BK Group Plc</p> <p>Diamond Trust Bank Kenya Ltd</p> <p>Equity Group Holdings Plc</p> <p>HF Group Plc</p> <p>I&M Group Plc</p> <p>KCB Group Plc</p> <p>NCBA Group Plc</p> <p>Stanbic Holdings Plc</p> <p>Standard Chartered Bank Kenya Ltd</p> <p>The Co-operative Bank of Kenya Ltd</p>	<p>COMMERCIAL AND SERVICES</p> <p>Deacons (East Africa) Plc</p> <p>Eveready East Africa Ltd</p> <p>Express Kenya Plc</p> <p>Homeboyz Entertainment Plc</p> <p>Kenya Airways Ltd</p> <p>Longhorn Publishers Plc</p> <p>Nairobi Business Ventures Ltd</p> <p>Nation Media Group Ltd</p> <p>Sameer Africa Plc</p> <p>Standard Group Plc</p> <p>TPS Eastern Africa Ltd</p> <p>Uchumi Supermarket</p> <p>WPP Scangroup</p>
<p>CONSTRUCTION & ALLIED</p> <p>ARM Cement Plc</p> <p>Bamburi Cement Ltd</p> <p>Crown Paints Kenya Plc</p> <p>E.A. Cables Ltd</p> <p>E.A. Portland Cement Co. Ltd</p>	<p>ENERGY & PETROLEUM</p> <p>KenGen Co. Plc</p> <p>Kenya Power & Lighting Co Ltd</p> <p>Total Energies Marketing Kenya Plc</p> <p>Umeme Ltd</p>

<p>INSURANCE</p> <p>Britam Holdings Plc CIC Insurance Group Ltd Jubilee Holdings Ltd Kenya Re Insurance Corporation Ltd Liberty Kenya Holdings Ltd Sanlam Kenya Plc</p>	<p>INVESTMENT</p> <p>Centum Investment Co Plc Home Afrika Ltd Kurwitu Ventures Ltd Olympia Capital Holdings Trans-Century Plc</p>
<p>INVESTMENT SERVICES</p> <p>Nairobi Securities Exchange Plc</p>	<p>TELECOMMUNICATION & TECHNOLOGY</p> <p>Safaricom Plc</p>
<p>MANUFACTURING & ALLIED</p> <p>B.O.C Kenya Plc British American Tobacco Kenya Plc Carbacid Investments Plc East African Breweries Plc Flame Tree Group Holdings Ltd Kenya Orchids Ltd Mumias Sugar Co. Ltd Unga Group Ltd</p>	

Appendix II: Secondary Data Collection Sheet

Year	Trading volume	Market Capitalization	Number of shares listed	Monthly average closing prices	Inflation rate	Interest rate	Exchange rate
Source	NSE	CMA/NSE	NSE	NSE	CBK	CBK	CBK

Year	Shareholders' Equity	Net Income	Weighted average number of outstanding shares
Source	Company financials	Company financials	Company financials

Appendix III: Ethical Clearance



22nd April 2024

Ms Kiaritha Eva,
evakiaritha@gmail.com

Dear Ms Kiaritha,

RE: An Empirical Investigation of the Relationship between Investor Sentiment and Volatility of the Equities Market in Kenya

This is to inform you that SU-ISERC has reviewed and approved your above SU-masters research proposal. Your application reference number is SU-ISERC2223/24. The approval period is from 22nd April 2024 to 21st April 2025.

This approval is subject to compliance with the following requirements:

- i. Only approved documents including (informed consents, study instruments, MTA) will be used.
- ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
- iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
- iv. Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
- v. Clearance for the export of biological specimens must be obtained from relevant institutions.
- vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
- vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) <https://research-portal.nacosti.go.ke/> and obtain other clearances needed.

Yours sincerely,

A handwritten signature in blue ink, appearing to read "Ambrose Rachier".

Mr Ambrose Rachier,
Chairperson; SU-ISERC