Dynamic connectedness, hedging effectiveness and investor sentiment among South African sector indices

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DEDICATION

To my parents – Khawulani Petros Nkosi and Nelisiwe Nesi Nkosi.

ABSTRACT

Over the past two decades, the interconnectedness of markets has surged, intensifying the imperative to understand risk transmission in cross-market portfolios. Similar trends have been seen across different sectors within the same markets. Amidst a myriad of catalysts, investor sentiment has emerged as the most influential force in propelling this connectedness. This study assessed South African sector connectedness, hedging effectiveness, and susceptibility to investor sentiment using a proxy-based composite sentiment index from July 2009 to December 2022. The ADCC-GARCH model, the Diebold and Yilmaz (2015) spillover index and the t-copulas extension were used to gauge dynamic connectedness and hedging effectiveness among sector indices, contingent on prevailing market-wide investor sentiment.

The findings show that dynamic connectedness varies among sector indices in the South African market. During financial turbulence, the interconnectedness intensifies due to heightened volatility, resulting in significant spillovers. The financial and industrial sectors were net transmitters, whereas the rest were the net recipients of risk. The consumer services sector had the highest hedging effectiveness when paired with other sector indices. The inclusion of sentiment improved the measurement of dynamic connectedness and hedging effectiveness, as sentiment-augmented models were statistically more robust. This indicates that sentiment significantly influences the dynamic connectedness and hedging effectiveness among indices in the South African market.

This study's novelty lies in creating a composite sentiment index specifically designed for the South African market. Further, this study focused on individual sectors rather than broad markets, offering a more granular analysis. Its findings provide valuable insights to investors, portfolio managers, and policymakers, enhancing their understanding of the sectors' intricate dependencies and vulnerability to sentiment. This enables the implementation of optimum diversification, risk management and portfolio optimisation strategies. Through the creation of an investor sentiment measure, an examination of sector-level interconnections, and consideration of the distinctive attributes of the South African market, this study delivers significant insights for both market participants and researchers.

The findings have implications for investors, firms and policymakers. They reveal that sectoral return volatility often persists due to irrational trading behaviours, emphasising the need for policymakers to implement regulatory measures to manage volatility shocks effectively.

Investors and firms can use these insights to optimise portfolio strategies and improve risk management. Increased volatility connections during economic downturns highlight the importance of understanding how different sector indices react to external shocks for assessing portfolio risks. For policymakers, the findings offer insights into financial risk distribution, information efficiency, and market stability, aiding in the preventing of sector contagion and stabilising financial systems. Firms should consider how capital dynamics are influenced by volatility and factor in sentiment when making investment decisions.

Keywords: Connectedness; Hedging; Sentiment; DCC-GARCH; T-copulas; South Africa

JEL classification: G10; G15; G17; G40; G41

LIST OF COMMON ACRONYMS

ADCC	- Asymmetric Dynamic Conditional Correlation
ADF	- Augmented Dickey-Fuller
AIC	- Akaike Information Criterion
ALSI	- All Share Index
ARCH	- Autoregressive Conditionally Heteroskedastic
ARCH-LM	- Autoregressive Conditionally Heteroskedastic – Lagrange Multiplier
ARMA	- Autoregressive Moving Average
BGARCH	- Bivariate GARCH
CAPM	- Capital Asset Pricing Model
DCC	- Dynamic Conditional Correlation
DY	- Diebold and Yilmaz (2009, 2012, 2014, 2015)
E-GARCH	- Exponential GARCH
EMH	- Efficient Market Hypothesis
GARCH	- Generalised Autoregressive Conditional Heteroskedasticity
GDP	- Gross Domestic Product
GED	- Generalised Error Distribution
GJR	- Glosten, Jagannathan and Runkle

HQIC - Hannan and Quinn Information Criterion

IMH - Inefficient Market Hypothesis

JB - Jarque-Bera

JSE - Johannesburg Stock Exchange

KPSS - Kwiatkowski–Phillips–Schmidt–Shin

LB - Ljung-Box

LL - Log-Likelihood

M-GARCH - Multivariate Generalized Autoregressive Conditional Heteroskedasticity

PCA - Principal Component Analysis

SARB - South African Reserve Bank

SBIC - Schwarz Bayesian Criterion

VaR - Value-at-risk

VAR - Vector Autoregression

VIX - Volatility Index

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CHAPTER 1: INTRODUCTION

1.1 Background

Global financial crises often indicate increasing market interconnectedness, driven by financial market liberalisation and technological advances (Attarzadeh and Balcilar, 2022). These crises demonstrate rapid shock propagation with heightened connectedness, leading to contagion and instability, impacting portfolio and risk management practices. This aligns with modern portfolio theory, stating that diversification benefits decrease with significant connectedness among markets. Understanding the underlying mechanism of connectedness and its dynamics during economic periods is crucial for developing optimal portfolio strategies (Yousaf and Yarovaya, 2022). Consequently, market connectedness has become a focal point in portfolio theory discussions, emphasising the need to navigate its implications in the ever-evolving financial landscape.

Quantifying and modelling market connectedness enables informed decision-making, adequate portfolio diversification, and the design of risk mitigation measures. Analysing connectedness patterns allows investors to adapt strategies, enhancing resilience against systemic risks and contributing to global market stability. However, measuring dynamic connectedness faces challenges due to contagion issues, such as the rapid spread of panic-driven trading decisions and the tendency for market participants to imitate each other without independent analysis (Diebold and Yilmaz, 2012). These factors can amplify volatility spillover effects, leading to pervasive financial instability during crises. Global market interconnectedness and complex cross-border financial linkages further complicate assessing contagion risks and the potential for widespread disruptions (Muguto, 2021).

Yet, understanding risk transmission channels remains essential in cross-market portfolio management. Deltuvaite (2015) defines a risk transmission channel as the fundamental economic relationship among economies that allows for contagion to occur across those economies. Thus, examining the economic and financial variables that act as connections across different economies makes it possible to predict the risk of volatility transmission across those markets (Dias et al., 2019). Identifying transmission channels of risks from one market to another and the changing nature thereof have increasingly become essential considerations in cross-market portfolio management aspects (Gabauer, 2019; Ji et al., 2019). This is particularly so when developing hedging strategies for which hedging effectiveness is a subject of utmost importance.

This concept, hedging effectiveness, is the extent to which changes in the hedging item's fair value or cash flow are offset by opposite changes in the hedging instrument's fair value or cash flow (Bunea-Bontas, 2012). Hedging strategies generally allow investors to occupy similar positions in two markets, so risk transmission across those markets is an important consideration (Parekh, 2018). Understanding risk transmission channels helps investors and portfolio managers identify particular assets, called hedging assets, that can induce systemic risk mitigation and diversification in portfolios (Bhatia et al., 2020). However, examining risk transmission channels is complex because they exist in a complex and interconnected financial system. The same applies to measuring the hedging effectiveness of assets, a highly variable phenomenon due to its susceptibility to various financial or economic events (Chkili, 2016).

Market connectedness is not limited to stock markets but also occurs within other markets, such as commodities, cryptocurrencies, and foreign exchange markets (Maghyereh et al., 2016; Yousuf and Zhai, 2021). Previous research has also shown a significant connectedness between stock markets and these parallel markets. This may be due to having similar investors or similar subjectivity to economic shocks (Demirer et al., 2020). Behavioural biases that investors exhibit wherein they trade based on their emotions and fear of uncertainty have been the significant drivers of this market interrelationship (Svetlova and Thielmann, 2020; Suresh, 2024). In volatile periods characterised by considerable uncertainty and proneness to herding, the connectedness within and across markets has increased (Kang and Yoon, 2019; Zhang and Broadstock, 2020).

The examination of connectedness can extend to sector-level analysis within and across different markets. Such an analysis focusing on sectors within one market may result from home bias, where investors are likely to invest within their home countries due to information asymmetry that encourages an aversion to risky, unknown foreign markets. This may come at the expense of giving up international diversification benefits (Frydman and Carmerer, 2021). Thus, sectors' connectedness will be more attractive to them than broad market connectedness (Chatziantoniou et al., 2022; Costa et al., 2022). The interest in examinations of connectedness among similar sectors across different markets may be a result of certain groups of investors that specialise in specific industries across different markets when constructing their portfolios, despite the market itself (Mandaci and Cagli, 2021; Youssef et al., 2021).

Sector indices focus on specific industries like technology, finance, or basic materials, providing detailed insights into the performance and interconnectedness among those sectors.

This specialisation helps investors fine-tune their portfolios and understand sector-specific prospects. To manage concentration risk, hedging capabilities and diversification across multiple sectors are crucial, as they mitigate potential losses from sector-specific downturns (Gupta and Basu, 2009). Sector analysis, which includes evaluating qualitative and quantitative metrics), helps identify high-potential sectors and guide strategic investment decisions (Remesh, 2024). This analysis also involves understanding the competitive landscape within sectors, forecasting demand and supply, and ensuring portfolio exposure to diverse sectors to reduce volatility and capitalise on growth opportunities (Anon, 2023).

Of note, any examination of phenomena in financial markets is often rooted in the tenets of efficient market theory. This theory assumes that markets are efficient and stock prices reflect available fundamental information due to rational investor decision-making (Fama, 1970). Any temporary mispricing is swiftly arbitraged away by rational arbitrageurs, restoring equilibrium to stock values (Dalika and Seetharam, 2015). However, the limitations of this perspective come to the fore when confronted with a multitude of pricing anomalies and its failure to provide cogent explanations for phenomena such as bubble formation, bubble crashes, and heightened volatility. The intricate interplay between behavioural biases such as herding behaviour and investor sentiment with these phenomena has further highlighted the inadequacies of traditional financial theory in its applicability (Muguto et al., 2022).

Unsurprisingly, the limitations of traditional finance theory have given rise to behavioural finance theory. In this school of thought, the role of irrational investors making decisions based on non-fundamental information is recognised (Kapoor and Prosad, 2017). This perspective highlights how psychological aspects and biases influence investors' choices, potentially leading to inefficiencies in price discovery in financial markets (Rupande et al., 2019). Consequently, this approach is increasingly acknowledged as a more robust foundation for analysing various market phenomena, including the connectedness of stock market returns and return volatility across diverse assets and markets. Its growing popularity stems from its ability to provide more comprehensive explanations for numerous phenomena in financial markets.

Such phenomena include dynamic connectedness among markets, which indicates inefficiency, irrationality, and a disregard for fundamental information by investors (Kapoor and Prosad, 2017). This is because the traditional efficient market framework struggles to explain the intricate linkages observed across markets, particularly in extreme market conditions. On the other hand, behavioural finance theory offers a more nuanced lens to understand the contagion-like spread of investor sentiment that can lead to cross-market linkages (Agyei and Bossman, 2023). Considering the psychological and emotional factors underpinning market participants' decisions, this perspective unveils a richer understanding of the dynamic interplay of sentiment-driven behaviours and their impact on interconnected financial markets (Liu et al., 2020; Filip and Pochea, 2023).

According to Rupande et al. (2019), investor sentiment is an amalgamation of behavioural biases influencing investors' decision-making processes. It represents an outlook on future cash flows and risks that is not justified by the fundamental information present in the market but rather stems from investors' cognitive psychology, emotional reactions, and social psychology (Baker and Wurgler, 2007). Investor sentiment explains several irregular pricing patterns, such as speculative bubbles and subsequent bubble collapses on stock markets (Kapoor and Prosad, 2017). This sentiment materialises within the market through trading activities, wherein bullish sentiment mirrors optimistic shifts that lead to heightened trading volume and notable market volatility, indicative of increased trading frequency among irrational traders (Rupande et al., 2019; Muguto et al., 2022).

Bullish sentiment is often associated with the underpricing of risk, overvaluation of financial assets and a lack of arbitrage activity from rational traders, resulting in pricing bubbles. The subsequent mean-reversion of sentiment causes the bubbles to burst, leading to increased market volatility as investors scramble to liquidate their portfolios (Taffler et al., 2017). Rational arbitrageurs may fail to take full advantage of mispricing opportunities as there may be significant constraints to arbitrage activities. However, traditional finance theory overlooks the role of sentiment in asset pricing despite its well-documented impact on market dynamics. Notably, it disregards the sentiment-driven noise trading that increases volatility and risk in financial securities, surpassing the limits suggested by traditional asset pricing models (Rupande et al., 2019; Muguto et al., 2022).

Investor sentiment has been found to influence market connectedness, with bearish periods associated with increased volatility and interconnectedness. This is because investors become pessimistic and risk-averse during bearish and uncertain periods, making them more prone to biases (Bouri et al., 2022). As the dynamic connectedness increases, so do volatility spillovers, resulting in increased shock transmission (Chatzivgeri et al., 2023). The changes in sentiment impact market correlations and are likely to negatively impact diversification benefits. Thus, the link between investor sentiment, market volatility and market interconnectedness shows that some market dynamics are sentiment-driven. The same may apply at a sector level as distinct sectors mirror distinct markets but may become increasingly interconnected in volatile periods. This affects the hedging effectiveness across sectors (Costa et al., 2022).

However, multiple authors who subscribe to traditional finance theory have tried to shift the blame for the visible presence of anomalous pricing patterns to the inadequacy of asset pricing models instead of admitting that financial market participants sometimes make decisions that are marred by behavioural biases, some more than other (Muguto et al., 2022). For instance, according to Avramov and Chordia (2006), the beta component from the capital asset pricing model (CAPM) cannot capture all the systematic asset risk. Therefore, the abnormal returns seen are simply compensation for this risk. Based on this statement, replacement models such as the Intertemporal CAPM (Merton, 1973), the Arbitrage Pricing Theory (Ross, 1976), and the Consumption CAPM (Lucas, 1978) were developed. However, the models have been unable to replace the original CAPM formulation or explain away the anomalous patterns.

Their failure is argued to stem from their omission of behavioural factors or components in their formulation, even as mounting evidence and growing recognition highlight the influence of psychological aspects on market behaviour. Instead, these models dismiss financial market anomalies as mere indications of model inadequacy, particularly in measuring systematic risk (Rupande et al., 2019). However, Kapoor and Prosad (2017) assert that these significant and widespread anomalous pricing patterns cannot be casually brushed aside as outcomes of model shortcomings. Instead, they are propelled by behavioural biases, encompassing investor sentiment. Consequently, they should not be easily disregarded; instead, they should be treated as evidence challenging the fundamental premise of market efficiency upon which these models are built (Muguto et al., 2022).

Accordingly, this study investigates the connectedness and hedging effectiveness among South African sector indices, focusing on the influence of investor sentiment on both phenomena. Its findings can provide valuable insights for investors and portfolio managers to identify indices with effective hedging abilities and understand the dynamic interconnectedness among sector indices during different periods. Policymakers can utilise this knowledge to make informed decisions and manage risks effectively. The study emphasises the importance of monitoring changes in volatility spillover and investor sentiment, especially during turbulent periods. Overall, the research contributes to a deeper understanding of the interplay between connectedness, hedging effectiveness, and investor sentiment, enabling better risk mitigation, diversification, and improvement of portfolio performance.

1.2 Problem statement

The escalating complexity of stock market interconnectedness, coupled with its profound effects on portfolio hedging strategies, poses a significant challenge in the financial landscape. This issue is particularly pronounced during periods of market turbulence and uncertainty, where heightened volatility and increased interdependencies are prevalent (Bouri et al., 2022; Antonakakis et al., 2023; Chirilă, 2022). These conditions amplify the role of investor sentiment, which intertwines with decision-making processes, leading to cognitive biases that compromise accurate risk assessments (Apergis et al., 2022). As a result, risk transmission channels become more pervasive, further destabilizing markets and undermining traditional hedging strategies. The inability to effectively manage these interconnected risks has severe consequences for portfolio performance and financial stability.

Given these dynamics, the question arises as to whether market-wide sentiment-driven effects extend beyond broad market indices to influence individual stock market sectors. This inquiry is critical in advancing the ongoing debate about the necessity of incorporating behavioural components, especially investor sentiment, into established financial asset pricing models (Kapoor and Prosad, 2017; Muguto et al., 2022). The integration of these behavioural factors is essential for achieving accurate asset valuation and enhancing market efficiency (Rupande et al., 2019). Ignoring these elements may lead to flawed models and a failure to account for key drivers of market behaviour. Further, failure to address these behavioural influences risks perpetuating inefficiencies and inaccuracies in financial modelling, leading to suboptimal investment decisions.

This study, therefore, focused on the South African stock market sectors, with the goal of evaluating the impact of investor sentiment on the dynamic interconnectedness and the effectiveness of hedging strategies within these sectors. By addressing this gap, the research sought to contribute valuable insights into the interplay between sentiment, market connectedness, and hedging effectiveness, offering a more comprehensive understanding of these phenomena and their implications for portfolio management. The findings may provide critical guidance for investors and policymakers alike in developing more robust strategies for managing interconnected risks and optimizing portfolio outcomes. Ultimately, this research aimed to bridge the knowledge gap in how sentiment-driven market dynamics influence sector-specific hedging strategies, particularly in a highly interconnected financial environment.

1.3 Research aim and objectives

Given the significance of dynamic connectedness and its impact on hedging effectiveness, this study aimed to examine the dynamic connectedness and hedging effectiveness among South African stock market sector indices and their subjectivity to prevailing market-wide investor sentiment.

To achieve this, the study sought to answer the following questions:

1. What is the magnitude of dynamic connectedness among the major sector indices in the South African market?

2. How does the dynamic connectedness among the major sector indices in the South African market affect their hedging effectiveness?

3. What is the impact of prevailing investor sentiment on the dynamic connectedness and the hedging effectiveness among the major sector indices in South Africa?

To answer the questions, the study:

- determined the level of dynamic connectedness among the major sector indices in the South African market;

- assessed the impact of dynamic connectedness among the major sector indices in the South African market on their hedging effectiveness and;

- examined the influence of prevailing investor sentiment on the dynamic connectedness and hedging effectiveness among the major sector indices in South Africa.

In essence, this study examined the dynamic connectedness and hedging effectiveness among South African stock market sector indices, assessing the impact of prevailing investor sentiment on these relationships. The goal was to quantify the magnitude of dynamic connectedness, its influence on hedging strategies, and how investor sentiment modulates these effects within the South African market context.

1.5 Significance and importance of study

Understanding dynamic connectedness and its relation to portfolio performance is crucial for investors seeking to optimise their investment strategies. It allows investors to understand how the impact of economic changes contributes to how the correlation between assets differs and financial market dynamics (Antonakakis et al., 2023; Benlagha and Omar, 2022; Yadav et al., 2022). Investors utilise this knowledge by analysing how assets react to financial crises to identify and include diversifier assets for optimal portfolio performance (Chen et al., 2014). Neglection of the concept results in the implementation of inefficient investment strategies. Therefore, investors and portfolio managers must incorporate the influence of dynamic connectedness in the financial market during their decision-making process to mitigate risk transmission and enhance portfolio performance efficiently.

Understanding the role of market interdependencies and risk transmission channels is also essential for policymakers implementing effective market regulations and risk mitigation strategies. Analysing their influence allows policymakers to obtain early warning signs and enforce policies that guarantee efficient market regulations, risk management strategies and financial stability across the markets (Youssef et al., 2021). Further, by analysing the changes in investor sentiment influence dynamic connectedness and hedging effectiveness, policymakers can develop targeted intervention efforts to monitor market stability and prevent excessive volatility (Dahir et al., 2020). Therefore, by acknowledging these factors, policymakers can alter economic and political strategies to enhance their monitoring and regulatory frameworks and address challenges to ensure a robust and resilient financial system.

Understanding the effects of dynamic connectedness and investor sentiment on sector indices' performance can guide companies in timing their market entry or exit. If sentiment-induced shifts are anticipated, companies can plan capital-raising activities more astutely to optimise their fundraising efforts and costs (Diebold and Yilmaz, 2014). Investor sentiment also impacts the connectedness among indices in the market; therefore, based on the intensity of dynamic connectedness in the market, companies can estimate the availability and cost of capital from this (Muguto, 2021). When companies attempt to source capital, they need to be guided by sector indices that are primarily net transmitters and less prone to spillovers rather than indices that are net recipients. Further, companies need to be aware that the availability and cost of capital depend on volatility spillover and not only volatility shocks.

Incorporating sentiment and dynamic connectedness in risk practices contributes to advancing theoretical frameworks and academic literature in finance and economics (Agyei and Bossman, 2023). This offers insights into dynamic connectedness in South African stock sectors, enhancing the understanding of local market dynamics. Scholars can examine the impact of investor sentiment on dynamic connectedness, contributing to behavioural finance discourse. Further, the study contributes to and guides effective resource allocation decisions through sector-specific dynamics. It offers practical guidance for accessing capital markets in alignment with sentiment-induced shifts. In addition, the study provides sector-specific implications for hedging and adds depth to risk management literature. This enhances risk mitigation strategies by considering sector-specific dynamic and behavioural influences.

The novelty of this study is its development of a comprehensive measure of investor sentiment tailored explicitly for the South African market. Furthermore, unlike most studies focusing on broad markets, this study focuses on sectors, providing a more granular analysis. According to Chkili (2016), the correlation between sectors and the ability to hedge effectively depends on the financial market's development. Thus, it is crucial to comprehend the intricate relationships and interdependencies within the South African market. By doing so, practical strategies for diversification, risk mitigation, and portfolio optimisation can be implemented. By combining the development of a new investor sentiment measure, analysing sector-level interconnectedness, and considering the unique characteristics of the South African market, this study provides valuable insights for market participants and researchers alike.

Overall, this chapter highlighted the importance of understanding market interconnectedness and its implications for portfolio management, particularly during financial turbulence. The increasing complexity of financial markets, driven by globalization and technological advancements, has amplified interconnectedness among asset classes and sectors, making it essential for investors and policymakers to grasp the dynamics of risk transmission and volatility spillovers. Traditional financial theories, while foundational, have struggled to fully account for these complexities, especially when confronted with investor sentiment and behavioural biases that drive market anomalies. As financial markets evolve, the need for more robust models that incorporate these behavioural factors becomes evident. By focusing on interconnectedness among South African sector indices and the influence of investor sentiment, this study aims to enhance risk management strategies, improve portfolio diversification, and deepen understanding of market dynamics amid growing global financial interconnectedness.

CHAPTER 2: CONCEPTS, THEORIES AND EMPIRICAL LITERATURE

2.1 Introduction

In examining the influence of investor sentiment on dynamic connectedness and hedging effectiveness across sectors, the first chapter highlighted the importance of such an examination. In this chapter, the study reviews existing literature on dynamic connectedness, hedging effectiveness, and investor sentiment in financial markets. This review aims to achieve three objectives: determining dynamic connectedness levels among major sector indices in the South African market, assessing its impact on hedging effectiveness, and examining the influence of investor sentiment. The review follows a structured approach, including a conceptual framework, theoretical foundation, and empirical exploration. Through this analysis, the study seeks deeper insights into how these factors interact, contributing to a better understanding of financial market dynamics.

2.2 Conceptual framework

Connectedness in financial markets encapsulates the extent of interconnection and correlation among diverse market entities or assets (Antonakakis et al., 2018, 2020). It embodies the notion that fluctuations in one market aspect can substantially influence others (Youssef et al., 2021). This concept portrays the complex network of relationships among different financial instruments, illustrating how shocks or occurrences in one sector can propagate across markets, potentially resulting in contagion effects (Attarzadeh and Balcilar, 2022). This interconnectedness highlights the importance of understanding not only individual market components but also their collective interactions and systemic implications. These collective interactions can amplify market volatility, magnify the impact of financial shocks, and contribute to systemic risks, emphasising the need for a holistic approach to risk management and market analysis (Ji et al., 2019).

The measurement of connectedness within financial markets typically employs a variety of statistical methodologies to capture the intricate relationships among market entities or assets. These methodologies range from conventional techniques such as correlation coefficients and co-integration analysis to more sophisticated approaches (Akhtaruzzaman et al., 2021; So et al., 2021). Among the advanced techniques utilised are dynamic conditional correlation models, which account for time-varying correlations between assets, and the methodology proposed by Diebold and Yilmaz (2012, 2014), which provides insights into the direction and strength of spillover effects across markets. Furthermore, researchers often employ the generalised vector autoregressive (VAR) framework to analyse the dynamic interactions among multiple time series variables, allowing for examining interconnectedness over time (Shahzad et al., 2018).

Another notable approach often used is the time-varying parameter vector autoregression (TVP-VAR) developed by Koop and Korobilis (2014), which allows for the estimation of parameters that vary over time, enabling a more nuanced understanding of how connectedness evolves in response to changing market conditions (Bossman et al., 2022; Antonakakis et al., 2023). This is important because financial markets are inherently dynamic and subject to constant fluctuations and evolving conditions. Traditional static models may overlook the time-varying nature of parameters, leading to inaccurate assessments of connectedness and potentially misleading conclusions (Yadav, 2022). These diverse methodologies offer researchers a comprehensive toolkit to assess connectedness within financial markets, providing insights into the degree and dynamics of interdependence among market components (Mandaci and Cagli, 2022).

Hedging effectiveness refers to the ability of a hedging strategy to offset the risks from market fluctuations, thereby safeguarding investors' portfolios from potential losses (Bhatia et al., 2020). Particularly during volatile periods, when market uncertainties are heightened, investors commonly turn to hedging techniques to shield their assets from adverse movements in asset prices (Awang et al., 2014). Measuring hedging effectiveness involves evaluating the degree to which a specific hedging instrument or strategy aligns with the movements in the underlying asset being protected (Parekh, 2018). This assessment allows investors to gauge the efficacy of their hedging strategies in managing risk and preserving portfolio value amidst turbulent market conditions. This is more important during volatile periods where market fluctuations are amplified, as effective hedging becomes crucial for mitigating potential losses and maintaining portfolio stability (Buyukkara et al., 2022).

Commonly used metrics for measuring hedging effectiveness encompass a range of quantitative tools designed to assess the alignment between hedging strategies and underlying asset movements. These metrics include delta and beta, which provide insights into the sensitivity of an option or portfolio to changes in the price of the underlying asset (Hull and White, 2017; Shankar et al., 2021). Additionally, various risk-adjusted performance indicators, such as the Sharpe and Treynor ratios, offer assessments of the risk-return trade-off associated with hedging strategies (Van Dyk et al., 2014). More advanced statistical techniques, including the DCC-GARCH t-Copulas method, are also often employed. Pioneered by Antonakakis et al. (2018), it allows for modelling dynamic correlations and tail dependencies between assets, providing a comprehensive assessment of the effectiveness of hedging strategies in capturing market dynamics.

Similarly, the VAR-GARCH model introduced by Ling and McAleer (2003) enables the estimation of time-varying volatility and correlation, enhancing the accuracy of hedging effectiveness measurements on financial markets. Furthermore, researchers utilise hedge ratios, as Kroner and Sultan (1993) proposed in their early study, to determine the optimal allocation of hedging instruments in an investment portfolio, maximising overall risk reduction while minimising the costs of setting up that risk-minimal portfolio. Similarly, the optimal weights approach introduced by Kroner and Ng (1998) offers a method for determining the most efficient allocation of assets in a hedged portfolio, considering factors such as expected returns and risk levels. By employing these diverse metrics and methodologies, researchers can understand the effectiveness of hedging strategies in managing risk and preserving portfolio value in dynamic market conditions.

Notably, dynamic connectedness and hedging effectiveness are fundamentally linked, forming an intrinsic relationship that highlights the interconnected nature of financial markets (Singh et al., 2019). As dynamic connectedness measures the extent of interdependence among different entities or assets, it directly impacts the efficacy of hedging strategies in mitigating risks from market fluctuations (Lin et al., 2014; Hung et al., 2022). That is, the degree of dynamic connectedness dictates how effectively a hedging strategy can shield a portfolio from adverse market movements, with higher levels of connectedness potentially complicating the effectiveness of hedging techniques (Mezghani et al., 2021). A thorough understanding of the dynamic connectedness among market components is essential for accurately assessing hedging techniques' effectiveness, as interconnectedness changes can influence the transmission of risks and the performance of hedged portfolios.

Conversely, effective hedging strategies can also affect the level of dynamic connectedness by altering the relationships between market entities over time (Rabbani et al., 2023). When successfully implemented, hedging strategies can dampen the transmission of shocks or disturbances across markets, thereby influencing the degree of interconnectedness (Mensi et al., 2021). Effective hedging can contribute to a lower level of dynamic connectedness by reducing the correlation or dependence between assets, thus mitigating the spread of risks and enhancing market stability (Elsayed et al., 2020). Consequently, understanding the reciprocal relationship between hedging strategies and dynamic connectedness is imperative for investors seeking to navigate financial markets effectively and manage systemic risks (Harrathi et al., 2016). This recognition highlights the importance of adopting holistic approaches to risk management that consider this reciprocal relationship.

Dynamic connectedness and hedging effectiveness are also linked through their mutual subjectivity to other factors, such as market liquidity and macroeconomic conditions. Market liquidity, for instance, can influence both the degree of dynamic connectedness among assets and the effectiveness of hedging strategies (Kang et al., 2021). In liquid markets, assets are more readily traded, potentially facilitating the transmission of shocks and increasing dynamic connectedness (Liew et al., 2022). Similarly, the availability of liquid hedging instruments can enhance the effectiveness of hedging strategies by enabling investors to adjust their positions in response to market movements swiftly (Li et al., 2024). Macroeconomic conditions can also impact both dynamic connectedness and hedging effectiveness. Changes in macroeconomic variables may alter market dynamics, affecting the correlations between assets and the efficacy of hedging techniques (Barunik and Krehlik, 2016).

Another factor, perhaps more pertinent than market liquidity and fundamental macroeconomic factors owing to its ubiquitous impact on markets, is investor sentiment. Positive or negative sentiment can drive market movements, affecting the relationships between assets and the success of hedging strategies in managing risks (Mezghani et al., 2020). When investor sentiment is positive, markets tend to exhibit higher levels of interconnectedness as optimism fuels trading activity and increases correlations between assets (Bouri et al., 2022). Conversely, during periods of negative sentiment, correlations may weaken as investors seek to diversify their portfolios and mitigate risks through hedging strategies (Liu and Hamori, 2021). Therefore, understanding and gauging investor sentiment is essential for anticipating market movements, assessing dynamic connectedness, and optimising hedging strategies to manage risks in volatile market conditions effectively.

Investor sentiment encapsulates market participants' collective moods, opinions, and emotions, which can significantly impact financial decisions and market dynamics (Rupande et al., 2019). It represents the psychological aspects influencing buying or selling behaviours in financial markets, often leading to deviations from rational, fundamental analysis (Muguto et al., 2019, 2022). Various factors, including economic indicators, news events, and social media trends, can influence investor sentiment. During periods of optimism, investor sentiment tends to be positive, leading to increased risk-taking behaviour among sentiment-prone investors and higher asset prices. Conversely, investor sentiment may turn negative during pessimism, resulting in a flight to safety and lower asset prices (Yu and Zhao, 2017). The fluctuations in investor sentiment can profoundly affect market volatility, asset correlations, and the efficacy of hedging strategies.

The Venn diagram below in Figure 2.1 depicts the association between these three concepts in financial markets. The dynamic connectedness circle represents the extent of interconnection and correlation among different market entities or assets. It embodies the idea that changes in one market component can significantly influence others. On the other hand, the hedging effectiveness circle denotes the ability of hedging strategies to mitigate or offset risks associated with market fluctuations. It involves assessing how well a specific hedging instrument or strategy aligns with movements in the underlying asset being protected. The third circle, the investor sentiment circle, encompasses market participants' collective moods, opinions, and emotions. It influences buying or selling behaviours in financial markets, often deviating from rational, fundamental analysis.

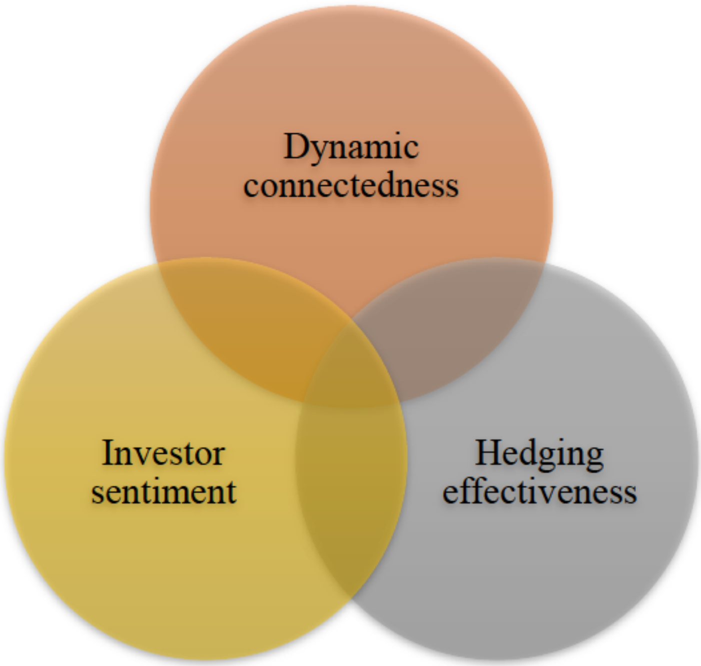

Figure 2. 1 Sentiment, connectedness, and hedging effectiveness

Source: Own depiction (2024)

The Venn diagram's overlapping areas signify the interconnected aspects between these concepts. For example, the overlap between dynamic connectedness and hedging effectiveness circles shows how the market interdependencies affect the hedging efficacy of assets from those markets. Likewise, the intersection of hedging effectiveness and investor sentiment illustrates how investor sentiment influences hedging during optimistic or pessimistic market periods. The dynamic connectedness and investor sentiment overlap demonstrates how shifts in sentiment affect market interconnections. Lastly, the overlap of all three represents instances where changes in connectedness affect hedging, influenced by sentiment. This overlap highlights the intricate relationship between market interconnections, risk management strategies, and investor behaviour.

Overall, this conceptual framework highlights the intricate dynamics of financial markets, emphasising the interconnectedness between dynamic connectedness, hedging effectiveness, and investor sentiment. Dynamic connectedness, representing the extent of interconnection among market entities, highlights the importance of understanding collective interactions (Singh et al., 2019). Hedging effectiveness, crucial during volatile periods, safeguards portfolios from market fluctuations (Bhatia et al., 2020). Influenced by numerous factors, investor sentiment significantly impacts market dynamics and the success of hedging strategies. The reciprocal relationship between dynamic connectedness and hedging effectiveness, influenced by factors like investor sentiment, highlights the need for understanding these relationships as it is essential for navigating financial markets effectively and managing risks amidst volatile conditions (Mezghani et al., 2020).

2.3 Theoretical framework

The cornerstone assumption of traditional finance theory hinges on the notion that within an efficient market, investors operate rationally, meticulously integrating all relevant fundamental information into their investment decisions. This premise finds its roots in the efficient market hypothesis, as Fama (1970) postulated. According to his theory, the prices of all securities consistently and accurately reflect the entirety of relevant information available to market participants. This hypothesis highlights the idea that asset prices promptly adjust to incorporate new information in such markets, leaving little room for investors to consistently outperform the market through superior information or analysis (Dalika and Seetharam, 2015). Based on this theory, investors must adopt approaches acknowledging the efficient market's capacity to incorporate information, thereby rapidly shaping their investment decisions.

A theory closely related to the efficient market hypothesis in terms of its impact on investment strategy and risk management is Markowitz's (1952) modern portfolio theory. While the efficient market hypothesis focuses on the efficiency of asset prices, modern portfolio theory complements this by providing a systematic framework for constructing portfolios that aim to optimise returns for a given level of risk or minimise risk for a desired level of return. By choosing securities with optimal risk-return opportunities, investors can induce portfolio diversification and improve hedging effectiveness in the portfolio (Prosad et al., 2015). Thus, both theories aim to enhance investment decision-making, with modern portfolio theory emphasising the importance of diversification and the efficient allocation of assets to achieve optimal portfolio performance (Khambholiya, 2017).

In theory, markets and financial assets operating according to the efficient market hypothesis should not experience volatility spillovers because the theory posits that asset prices fully reflect all available information (Fassas and Siriopoulos, 2019). This means that market participants, being rational and efficient, swiftly incorporate new information into asset prices, leaving little room for unexpected shocks or discrepancies between prices and their underlying fundamentals. With such efficient pricing, any potential volatility stemming from unanticipated events or changes in market conditions would be quickly absorbed and reflected in asset prices (Ying et al., 2019). Consequently, without information asymmetries or irrational behaviour, the likelihood of significant volatility spillovers from one market to another or between different groups of assets would be minimised (AlOmari, 2015).

Further, in the modern portfolio theory framework, assets are evaluated based on their interactions within a portfolio. By constructing diversified portfolios that combine assets with low or negative correlations, modern portfolio theory aims to reduce overall portfolio risk without sacrificing returns (Auounsdottir, 2011). If all investors strictly adhere to these principles, portfolios would be efficiently diversified, and any volatility in individual assets or markets would be offset by the diversification benefits across the entire portfolio (Lukomnik and Hawley, 2021). Volatility spillovers between markets or assets would be mitigated by the diversification effects achieved through portfolio construction, which considers correlations and risk-return trade-offs (Su, 2020). In essence, this theory provides a structured approach to portfolio management that seeks to optimise risk-adjusted returns by balancing the inherent risks associated with individual assets.

Regarding hedging effectiveness, in markets operating under the principles of these two theories, it would likely be influenced by the degree of market efficiency and the effectiveness of portfolio diversification strategies (Beyhaghi and Hawley, 2012). Since the efficient market hypothesis suggests that asset prices fully reflect all available information, including future expectations and risk assessments, the opportunities for profitable hedging strategies based on undervalued or overvalued assets may be limited (Malkiel, 2011). However, while individual assets may be efficiently priced, modern portfolio theory emphasises diversification across assets with different risk-return profiles to reduce portfolio risk. In this context, hedging effectiveness would primarily rely on constructing well-diversified portfolios that offset the risk of adverse price movements in specific assets or markets (Akkaya, 2021).

While initially celebrated as the founding mainstays of modern financial theory, both theories have since fallen short of their initial popularity owing to the discovery of pricing anomalies that are incongruent with their predictions (Iqbal et al., 2013). Financial market anomalies present themselves in three distinct forms: calendar, fundamental, and technical. Pricing irregularities within specific time frames characterise calendar anomalies. Examples include the January and day-of-the-week effects (Latif et al., 2011). Fundamental anomalies arise when investors' fundamental analyses impact stock trading patterns, leading to mispricing. Examples encompass value and growth anomalies (Elena-Dana and Ioana, 2013). Lastly, technical anomalies occur when investors utilise historical pricing data to predict future stock price movements, driving subsequent investment behaviour. Among these, widespread technical anomalies include the momentum and the reversal effects (Ching et al., 2014).

Volatility spillovers, indicative of market interconnectedness, have also challenged the principles of both theories. Their presence highlights the complex dynamics within financial markets, undermining the assumption of market efficiency inherent in the EMH (Fassas and Siriopoulos, 2019). Similarly, while MPT advocates for diversification to mitigate risk, volatility spillovers suggest that correlations between assets may increase during periods of market stress, potentially undermining the effectiveness of traditional diversification strategies (Chkili, 2016). Consequently, the presence of volatility spillovers has sparked debates and criticisms regarding the applicability and effectiveness of both EMH and MPT in navigating modern financial markets (Elyasiani and Mansur, 2017; Muguto, 2021). As a result, researchers and practitioners continue to explore alternative theories and approaches to capture better and manage the complexities of market interconnectedness and volatility dynamics.

One such is behavioural finance theory, a burgeoning branch of finance which challenges the foundational assumption of efficiency and rationality in traditional finance theory (Uygur and Tas, 2013). It integrates behavioural and cognitive psychology insights to illustrate that investors often exhibit irrational tendencies, leading to suboptimal financial decisions and potential market inefficiencies (Kamoune and Ibenrissoul, 2022). These biases, driven by heuristics and framing effects, significantly impact market dynamics. Heuristics such as availability, anchoring, and representativeness contribute to market underreactions and overreactions, while biases like optimism and overconfidence may fuel speculative bubbles and increased trading activity. Frame-dependent biases, including loss aversion and narrow framing, further influence investor behaviour, affecting trading volume and market efficiency (Prosad et al., 2015).

Ultimately, prejudices, emotions, and cognitive biases—an amalgam of which can be equated to investor sentiment—impede investors' ability to analyse information effectively, leading to decisions that deviate from rationality assumptions (Baddeley, 2010). Consequently, financial pricing anomalies occur as a result of these behavioural biases. For instance, investor sentiment can lead to herding behaviour, where individuals follow the crowd rather than conducting an independent analysis, causing prices to diverge from underlying fundamentals (Hudson et al., 2020). Moreover, biases such as overconfidence can lead to excessive trading and misallocation of resources, further distorting asset prices (Daniel and Hirshleifer, 2015). Furthermore, framing effects, where individuals perceive information differently based on its presentation, can lead to suboptimal decision-making and pricing anomalies (Suresh, 2024).

Behavioural finance offers researchers a more practical perspective, leading to the introduction of concepts such as prospect theory, behavioural portfolio theory, and noise trader theory. The prospect theory, developed by Kahneman and Tversky (1979), examines decision-making under risk, focusing on how individuals perceive gains and losses. The theory is an alternative to the expected utility theory, which states that individuals make decisions under risk by evaluating and comparing the expected utility values of different options (Prosad et al., 2015). Prospect theory reveals that people experience losses more intensely than gains of the same magnitude, a phenomenon known as loss aversion. The theory highlights that individuals are not consistently risk-averse; they tend to be risk-averse when dealing with potential gains but risk-seeking when facing potential losses. Additionally, it introduces the certainty effect, where individuals give greater weight to specific outcomes than those that are merely probable (Akkaya, 2021).

Behavioural portfolio theory, introduced by Shefrin and Statman (2000), offers a descriptive alternative to Markowitz's mean-variance portfolio theory by incorporating principles from mental accounting. Unlike the traditional model, where investors aim for an optimal risk-return trade-off with a single, consistent risk attitude, the theory acknowledges that investors are only partially rational. It views portfolios as collections of sub-portfolios or mental accounts, each tailored to different investment goals and risk profiles (Pavani, 2023; Kasemsap, 2015). The behavioural portfolio theory includes two versions: single mental accounting, where the entire portfolio is integrated into one mental account, and multiple mental accounting, which segregates assets into various mental accounts based on different objectives (Akkaya, 2021).

Noise Trader Theory, introduced by Black (1986), highlights how financial markets are impacted by traders who make decisions based on misinformation or irrational behaviour rather than fundamental data. Behavioural finance models show that noise traders significantly affect market returns and volatility, as their actions increase mispricing and return volatility (Rupande et al., 2019). These traders, influenced by emotions and cognitive biases, treat noise as fundamental information, intending to achieve abnormal returns (Muguto et al., 2022). While traditional finance argues that rational investors eliminate noise traders from the markets through arbitrage, noise traders can still impact markets. Further, during periods of high investor sentiment, noise traders tend to misinterpret optimism as fundamental information rather than noise (Shen et al., 2017).

Volatility spillovers can also be explained by behavioural biases in several ways. Firstly, during periods of market stress, investors may exhibit herd behaviour driven by fear or panic. This can lead to correlated selling across multiple asset classes, causing volatility spillovers (Kang and Yoon, 2019). Secondly, cognitive biases such as loss aversion and recency can exacerbate volatility spillovers. Loss aversion leads investors to disproportionately weigh potential losses over gains, prompting them to sell assets quickly during market downturns. Similarly, recency bias leads to increased volatility spillovers as investors extrapolate short-term trends into the future (Kapoor and Prosad, 2017; Ma et al., 2024). Additionally, behavioural biases such as anchoring and confirmation bias can lead investors to overlook diversification benefits during periods of market stress, exacerbating volatility spillovers as investors rush to exit positions without considering the broader portfolio implications (Wang, 2023).

Behavioural biases can contribute to increased market interconnectedness and reduced hedging effectiveness. Accordingly, this study employed an investor sentiment index to determine whether prevailing investor sentiment influences the dynamic connectedness and hedging effectiveness among major sector indices in South Africa. This approach is fitting because investor sentiment can significantly impact market dynamics and the effectiveness of diversification strategies. By incorporating the index, the study could capture the influence of behavioural biases on market interconnectedness and hedging effectiveness. Moreover, focusing on sector indices in South Africa allowed for a nuanced analysis of how investor sentiment affects different segments of the market and their interconnectedness, offering practical implications for investors and policymakers operating in dynamic market environments.

2.4 Empirical literature review

This section provides an empirical literature review of the changes in connectedness, hedging effectiveness, and investor sentiment across sector indices in developed and developing stock markets. Special attention was given to the factors, such as changes in economic events that influenced these changes and how different markets reacted to turbulent periods. This was because the type of market investigated impacted the attitude of investors, volatility spillover, and hedging capability across indices. Therefore, numerous studies were examined in this chapter to determine the nature of volatility spillover, hedging effectiveness, and investor sentiment in developed and developing markets. The differences and similarities in the findings in this chapter and these studies were considered in the discussion of results and concluding remarks sections.

2.4.1 Connectedness and risk transmission among sectors

Several studies have examined connectedness among sectors globally, revealing dominant sectors in volatility transmission and those that act as receivers. For instance, Wu et al. (2019) found that the industrial sector dominated volatility transmission from January 2000 to May 2018 in the Chinese stock market. The industrial sector's critical role in producing goods and China's status as the most prominent global exporter made it highly sensitive to economic changes. This sensitivity likely stems from the sector's integral position in global supply chains and its direct impact on export performance. The study suggests that any economic fluctuations or policy changes impacting the industrial sector could have widespread ramifications on the overall market volatility, highlighting the sector's significant influence on the Chinese economy.

Chatziantoniou et al. (2021) observed spillovers from cyclical to non-cyclical sectors in the Indian market, with sectoral connectedness evolving over time. Cyclical sectors, more aligned with economic trends, exhibited greater volatility than non-cyclical sectors. This suggests that sectors closely tied to economic cycles are more responsive to economic shifts, highlighting the importance of economic conditions in shaping sectoral volatility. It could also mean that cyclical sectors are a leading indicator of broader economic changes, as their volatility precedes shifts in the overall market. The dynamic nature of sectoral connectedness implies that investors and policymakers need to monitor economic indicators closely to effectively anticipate and manage potential volatility spillovers. This can aid in developing tailored risk management strategies and portfolios for diverse market conditions.

Ekinci and Gençyürek (2021) studied the Borsa Istanbul market, identifying the industrial and financial sectors as net transmitters, while technology, transportation, tourism, food, and retail trade sectors were net receivers. However, during the pandemic, the food sector transitioned to a volatility transmitter due to heightened uncertainty and market challenges. This shift highlights the pandemic's impact on essential sectors, making them more sensitive to economic changes and volatility. As a result, investors and policymakers need to recognize that the volatility transmission dynamics between sectors can be fluid and dependent on prevailing circumstances. In essence, the findings suggest that external shocks, such as global health crises, can reconfigure traditional volatility transmission roles among sectors, necessitating adaptive risk management strategies.

In the U.S. market, Ngene (2021) found that defensive sectors, immune to macroeconomic risks, were net recipients of shocks, while aggressive sectors were net transmitters. The direction and intensity of volatility spillovers varied with economic changes. This indicates that macroeconomic and financial market uncertainties substantially impact volatility, with cyclical sectors dominating defensive sectors due to the non-linear, asymmetric, and dynamic effects of these uncertainties. This emphasises the need for a nuanced understanding of sectoral behaviour under different economic conditions to devise robust investment strategies that can withstand varying levels of market volatility. Without that nuanced understanding, investors may misjudge the risk profile of different sectors, leading to suboptimal portfolio allocations and increased vulnerability to unexpected market shifts.

Shen et al. (2021) discovered that sectors like mechanical equipment, utilities, and electrical equipment were net transmitters in the Chinese stock markets, while bank, non-bank finance, and national defence sectors were net recipients. Sectors with service links were more likely to receive risk, and connectedness intensified during extreme risk events. High interwoven economic connections in financial networks significantly contributed to systemic risk and enhanced economic stability during turbulent periods. These findings highlight the critical role of financial sectors in stabilizing the economy during crises and the potential for increased systemic risk when these sectors are under stress. They also show how the nature and direction of volatility spillovers can be influenced by the specific characteristics of each sector and how these patterns can evolve during periods of heightened market stress.

Chirilă (2022) found that in the Polish stock market, banks, basic materials, construction, and oil and gas sectors were net transmitters before the pandemic. Only banks, basic materials, and construction remained net transmitters during the pandemic, while oil and gas became net recipients. The banking sector was the most significant shock transmitter, reflecting maximum vulnerability to economic changes. This aligns with Shen et al.'s (2021) findings on the banking sector's volatility spillover and increased sectoral connectedness during crises. The study suggests that financial stability measures should prioritize the banking sector to mitigate its outsized impact on overall market volatility during economic downturns. Furthermore, the shift of the oil and gas sector from net transmitter to net recipient during the pandemic shows that external shocks can significantly alter a sector's role in volatility transmission.

Costa et al. (2022) observed minimal structural changes in the U.S. stock market relationships across 11 sectors. However, during the pandemic, the I.T. and healthcare sectors shifted from net transmitters to net recipients, indicating lower sensitivity to shocks and reduced volatility. This shift can be attributed to the significant reliance on these sectors during the pandemic as people adapted to remote work, telehealth services, and digital solutions. The findings suggest that the benefits of sectoral diversification decrease during turbulent periods due to intensified connectedness among sectoral indices. This implies that traditional diversification strategies may be less effective in mitigating risk during periods of widespread economic stress, highlighting the need for adaptive and flexible investment approaches that account for evolving market dynamics.

In the Pakistan stock market, Khan et al. (2022) identified the financial sector as a consistent net transmitter throughout financial crises, with spillover increasing significantly during crises.

Dynamic connectedness intensified during periods of extreme negative and positive changes driven by uncertainty, pessimism, and optimism. This demonstrates that the financial sector's role in volatility transmission is amplified during periods of heightened market stress, impacting other sectors and potentially contributing to systemic risk. The financial sector's vulnerability to crises highlights its sensitivity to external shocks. This susceptibility can increase market volatility and disruptions in the broader economy. Thus, the sector requires robust regulatory frameworks and risk management practices to cushion against extreme volatility and ensure market stability.

The reviewed studies highlight varying degrees of sectoral connectedness and volatility transmission across different global markets and economic conditions. Key findings include the dominance of certain sectors in transmitting volatility, while others may shift roles during crises. The studies also reveal that external shocks can significantly alter sectoral dynamics and connectedness due to the fluid nature of market relationships. These insights emphasize the importance of understanding sectoral behaviour to develop effective risk management and investment strategies. However, gaps in the literature remain, particularly regarding the impact of dynamic connectedness on hedging effectiveness in specific regional contexts, such as South Africa. Additionally, the influence of investor sentiment on sectoral connectedness and hedging effectiveness has not been extensively studied, all of which this study sought to explore.

2.4.2 Hedging effectiveness

Numerous studies have assessed hedging effectiveness across diverse portfolios. Yet, within this literature, there is a notable absence of focus on hedging effectiveness across sectors in the same stock market but between stock markets and other markets. The focus has been mainly on identifying effective hedging instruments and evaluating the efficacy of assets like gold during turbulent periods. For instance, Awang et al. (2014) identified futures contracts of different indices as highly effective in the Malaysia and Singapore stock markets for managing price risks without altering portfolio composition. Buyukkara et al. (2021) found Borsa Istanbul 30 equity futures effective for spot equity portfolios, but COVID-19 negatively impacted currency futures' hedging capability. Hamma et al. (2021) noted the EURO STOXX 50 Volatility Index as the most efficient hedging asset for conventional and Islamic stock markets.

Raheem (2021) highlighted that conventional bonds and stocks had high hedging effectiveness on green markets during the pandemic, sensitive to economic events. Syriopoulos et al. (2015) observed dynamic volatility transmission between the US and BRICS stock markets, limiting diversification during crashes. These findings suggest that the effectiveness of traditional hedging tools can vary depending on the market environment and the nature of the assets involved. Herskovic et al. (2019) showed that hedging standard risk factors, like value and momentum, mitigated business cycle risk and yielded significant alphas. Opie and Riddiough (2020) demonstrated a superior dynamic hedging strategy for foreign exchange exposure in international portfolios. These studies show the importance of tailoring hedging strategies to specific risk factors and market conditions to achieve optimal returns and risk reduction.

Gold has been widely recognized for its hedging capabilities. Studies by Kumar (2014) and Arouri et al. (2015) affirmed gold's status as a safe haven, enhancing risk-adjusted returns in portfolios, particularly during times of economic uncertainty and market volatility. Chkili (2016) and Iqbal (2017) supported gold's role as a hedge in BRICS countries and against exchange rate risk in Pakistan and India, respectively, highlighting its versatility across different markets and risk factors. Robiyanto et al. (2017) confirmed gold's effectiveness in hedging against market volatility in the Indonesian and Kuala Lumpur stock exchanges, further solidifying its reputation as a valuable tool for risk mitigation in diverse financial landscapes. However, Shrydeh et al. (2019) noted decreased effectiveness post-2007 financial crisis, and Thampanya et al. (2022) observed gold's limited haven status in the Thai market.

Mensi et al. (2017) found volatility spillover between precious metals and stock markets, with Japan showing no spillover and more significant diversification benefits. This could mean that Japan's stock market is relatively insulated from fluctuations in precious metal prices, offering investors a potential haven during periods of market volatility. It could also suggest that precious metals might not be as effective a hedging tool in the Japanese market as other regions. Bhatia et al. (2020) identified silver as the most effective among precious metals, with palladium and BRICS stocks significantly reducing risk. This implies that silver might offer superior hedging benefits to other precious metals on financial markets due to its unique properties and various industrial applications, making it a valuable asset for diversification in financial portfolios.

Majumder (2021) found that crude oil and natural gas had the highest hedging effectiveness against the Indian stock market, while gold's effectiveness was lower. This suggests that the choice of hedging instrument can significantly impact its effectiveness in different markets, with energy commodities potentially playing a more prominent role in certain regions. Ozdemir and Ozedmir (2021) noted Bitcoin's high hedging effectiveness in the G7 financial market during the COVID-19 pandemic, highlighting the emergence of cryptocurrencies as potential hedging tools. This could indicate a shift in investor preferences towards digital assets to diversify risk. Wang et al. (2021) highlighted gold's short-term and the US dollar's medium- to long-term hedging effectiveness against global stock indices, demonstrating the importance of considering different time horizons when selecting hedging instruments.

Khalfaoui et al. (2015) showed oil's significant role in risk mitigation compared to stock indices of the G-7 countries, reinforcing its importance as a global hedging asset in stock markets. Sarwar et al. (2019) identified oil as the most efficient hedging instrument among the Shanghai, Nikkei, and Bombay stock exchanges, highlighting its effectiveness across diverse markets. Batten et al. (2021) found that hedging stocks with oil improved portfolio diversification considerably, with effectiveness depending on market conditions, suggesting that oil's hedging potential can vary based on prevailing economic and financial market factors. Shahzad et al. (2022) noted oil's high interdependence with BRIC stock markets, enhancing portfolio diversification and indicating its utility in emerging markets as a tool for managing risk exposure in these markets.

Lin et al. (2019) suggested a higher proportion of stocks than natural gas to minimize portfolio risk in the Chinese market, noting natural gas's ineffectiveness as a hedging asset. This emphasizes the need to carefully consider sector-specific characteristics and market conditions when selecting hedging instruments. The decision can also be market-specific. Boroumand et al. (2015) found optimal intra-day portfolios outperformed longer-term portfolios in electricity markets, highlighting dynamic risk management's importance and the potential for enhanced returns through frequent adjustments to hedging positions. This finding shows the value of actively adjusting hedging strategies to changing market conditions to maximize risk mitigation and potential returns, especially in volatile sectors like electricity, without which portfolios would be suboptimal.

The studies reviewed highlight the diverse effectiveness of hedging strategies across global financial markets and economic conditions. However, significant gaps persist in understanding dynamic connectedness and hedging effectiveness among sector indices within single stock markets, such as South Africa's. Existing research predominantly focuses on traditional hedging instruments applied broadly, overlooking sector-specific dynamics and the influence of investor sentiment. Addressing these gaps through a focused study could illuminate the extent of dynamic connectedness among South African sector indices, assess its implications for hedging effectiveness, and explore how investor sentiment shapes these dynamics. Such research would offer crucial insights for refining sector-specific risk management strategies and enhancing decision-making in volatile market environments.

Nevertheless, the reviewed literature suggests that the effectiveness of hedging strategies across sector indices within South Africa's market may be intricately influenced by sector-specific risk profiles and market interdependencies. Each sector's vulnerability to external shocks, such as economic cycles and regulatory changes, may also dictate its efficacy as a hedging instrument. The effectiveness of these sector indices as hedging instruments for other sectors may also be contingent on their correlation dynamics and the degree of market integration. These insights highlight the importance of adaptive hedging approaches that blend sector-specific risk assessment, appropriate instrument selection, and an understanding of market dynamics to optimize risk management and investment outcomes in South Africa's diverse market environment.

2.4.3 Investor sentiment, market connectedness and hedging effectiveness

Very few studies, possibly due to the complexity of quantifying and measuring sentiment, have explored the intricate relationship between investor sentiment, market connectedness, and hedging effectiveness. However, among the few that have studied these links, Bouri et al. (2021) and Huynh et al. (2021) revealed how negative news and heightened uncertainty amplified market volatility and interconnectedness, indicating a potential feedback loop where sentiment-driven volatility fostered further interconnectedness. This suggests that during periods of market stress, negative sentiment can create a self-reinforcing cycle of volatility and interconnectedness, making it difficult for investors to diversify risk effectively, causing amplified losses and potential market crashes.

Liu and Hamori (2021) added another layer to this complexity by highlighting increased connectedness during financial turmoil, suggesting that sentiment was crucial in exacerbating market vulnerabilities during crises. This finding implies that during times of financial stress and turbulence, investor sentiment can act as a catalyst for contagion, where shocks in one market quickly spread to others, amplifying the overall impact of the crisis. That is, sentiment can act as a transmission mechanism for financial shocks, making global markets more susceptible to systemic risk, particularly the less robust markets. Therefore, understanding and managing investor sentiment is crucial for maintaining financial stability and preventing the spread of crises.

Meanwhile, Mezghani et al. (2021) shed light on the bidirectional causality between sentiment and market performance, particularly during economic downturns, emphasizing that investor sentiment not only reacts to market events but also actively influences them, creating a complex feedback loop with implications for market stability and predictability. Apergis et al. (2022) further demonstrated the predictive power of COVID-19 news sentiment on volatility spillover shocks, with negative news disproportionately causing more spillovers than any positive news. This finding showed the need for effective sentiment analysis tools to anticipate and manage market volatility during crises, as timely identification of negative sentiment shifts could enable proactive risk mitigation strategies.

Investor sentiment also plays a significant role in hedging effectiveness, as evidenced by Corredor et al. (2015), who observed decreased hedging effectiveness during heightened sentiment in Central European markets. This suggests that during periods of extreme optimism or pessimism, traditional hedging strategies may become less effective as market behaviour becomes more unpredictable. Li and Liu (2020) and Cong and Wang (2022) both found a positive correlation between sentiment and hedging effectiveness in the Chinese futures and stock markets, respectively, highlighting the importance of sentiment-styled indices in trading decisions. That is, incorporating sentiment indicators into trading strategies can enhance hedging effectiveness, especially in markets where investor sentiment plays a significant role.

Su et al. (2020) noted that both pessimistic and optimistic sentiments can negatively affect hedging effectiveness due to increased market sensitivity and information asymmetry. This means that extreme positive or negative sentiment can lead to distorted market signals and increased volatility, making it difficult to assess accurately and hedge risk. As a result, investors need to adopt more dynamic and adaptive hedging strategies that consider the evolving nature of investor sentiment to effectively manage risk in volatile market conditions. Such strategies may include continuously monitoring market sentiment indicators, employing advanced analytical tools to predict sentiment shifts, and adjusting hedging positions in real-time to align with the current market sentiment landscape.

In times of crises, such as the COVID-19 pandemic, Trichilli et al. (2022) found that sentiment significantly influenced hedging effectiveness in the US market, with heightened uncertainty and rapid sentiment changes increasing market volatility and complicating hedging efforts. Similarly, Soltani et al. (2023) observed a bidirectional relationship between sentiment and hedging effectiveness in the Tunisian market, exacerbated by political instability, indicating that sentiment impacts hedging strategies and vice versa. These studies highlight the critical role of investor sentiment in hedging across different markets, emphasizing the need for investors to integrate sentiment analysis into their risk management practices and develop adaptive strategies to manage risks associated with fluctuating market sentiment.

Overall, these studies highlight the complex and dynamic relationship between investor sentiment, market connectedness, and hedging effectiveness. Given the significance of dynamic connectedness and its impact on hedging effectiveness, this study examined the dynamic connectedness and hedging effectiveness among South African stock market sector indices and their susceptibility to prevailing market-wide investor sentiment. It sought to answer critical questions about the magnitude of dynamic connectedness among major sector indices, its effect on hedging effectiveness, and the impact of prevailing investor sentiment. The study determined the level of dynamic connectedness, assessed its effect on hedging effectiveness, and examined how prevailing investor sentiment influences both dynamic connectedness and hedging effectiveness among South African sector indices.

2.5 Conclusion

This chapter examined the intricate relationship between investor sentiment, market connectedness, and hedging effectiveness, highlighting the shortcomings of traditional finance theories in explaining market anomalies and volatility spillovers. It explored how behavioural finance theory, incorporating investor sentiment, offers a more nuanced understanding of market dynamics. The empirical literature review revealed that while some studies have examined connectedness and hedging effectiveness across various markets, there remains a gap in understanding these dynamics within specific regional contexts, such as South Africa, and the influence of investor sentiment on these relationships. This study aimed to address this gap. The following chapter details the methodology employed to achieve this objective.

3. DATA AND METHODOLOGY

3.1 Introduction

In an empirical study, selecting an appropriate approach is paramount for achieving defined objectives. This chapter meticulously outlines the study methodology, commencing with a comprehensive description of the variables - stock market indices and investor sentiment proxies. It explores their nature, justification for use, data frequency, source, and sample period. Subsequent sections elucidate preliminary analyses and the analytical methods chosen, providing insights into the rationale behind their selection. This includes the ADCC-GARCH model and the Diebold and Yilmaz volatility spillover index employed for the first objective, the DCC-GARCH *t*-copulas employed to achieve the second objective and how the same models were re-estimated but with the inclusion of a sentiment index, the construction of which is described below, to attain the third objective.

3.2 Data

For this study, a sample period extending from July 2009 to December 2022 was utilised. The choice of utilising a period after 1995 as the starting date aligns with Muguto's (2015) recommendation, attributing its appropriateness to the abandonment of apartheid in 1994. Fuchs-Schundeln (2001) identifies this as the ideal commencement date after the undemocratic political climate in South Africa, in which foreign capital could not enter the local market. Opting for a more extended sample period benefits asset pricing tests, offering a more comprehensive perspective on sentiment and its impact on the South African stock market. This duration captures systematic risk and facilitates analysis of changes significantly impacting volatility and volatility spillovers, such as market integration, financial liberalisation, and technological advancements (Kurov, 2010; Muguto, 2021).

The study timeline included significant economic events that impacted the South African financial market, such as the 2008-2009 financial crisis, the 2010 World Cup, the 2015 Chinese stock market bubble, the 2018 US Stock market slide, the COVID-19 pandemic, and the recovery period. It was important for the sample period to span over these events to understand the changes in sentiment during irregular economic shocks and extreme regime changes better. A daily frequency was employed to ensure that crucial sentiment movements were not averaged out and sufficient observations were used (Muguto et al., 2022). This followed the studies of

Rupande et al. (2019), Mezghani, Boujelbene, and Elbayar (2021), and Muguto et al. (2022), who used daily data to evaluate the influence of investor sentiment among sector indices.

3.2.1 Sector indices

The daily closing prices and dividend yields on Telecommunications (J560), Consumer Services (J550), Technology (J590), Industrials (J520), Financials (J580), Basic Materials (J510), Travel and leisure (J575) sector indices and the All-share index were employed. This followed their use in the study by Muguto et al. (2022) in examining sentiment effects on the same market. The official classification categorises the sectors based on the industry classification benchmark, a commonly used standard for comparing and classifying companies (Johannesburg Stock Exchange, 2022). It is, therefore, not surprising that this classification has been utilised in multiple studies conducted on the South African market (Chipunza et al., 2020a, 2020b; Muzindutsi et al., 2020; Mokoena and Nomlala, 2022; Muguto et al., 2022;). The IRESS database was used to collect the data.

In financial literature, sectors are typically classified based on their sensitivity to macroeconomic conditions, industry-specific dynamics, and regulatory influences. Common classifications include defensive sectors, such as consumer services, which provide stability and consistent returns even during economic downturns, and cyclical sectors, like basic materials, financials, and travel and leisure, which tend to outperform during periods of economic growth but suffer in recessions (Chatziantoniou et al., 2021; Ngene, 2021). Additionally, sectors such as telecommunications, industrials, and technology are considered moderately sensitive, with some industries, like semiconductors, behaving defensively, while others, like consumer electronics, are more cyclical (Dang et al., 2023). The goal of this classification is to mitigate risks and enhance portfolio resilience through diversification.

The interaction between defensive and cyclical sectors, particularly in their response to economic conditions and investor sentiment, underscores their importance in portfolio management. Defensive sectors, known for their stability and steady demand, serve as a hedge during economic downturns, providing protection against market volatility. On the other hand, cyclical sectors, which benefit from economic expansion, are more prone to risk transmission and volatility (Shahzad et al., 2021). As the economy strengthens, investors often shift towards cyclical stocks for higher returns, whereas, during periods of uncertainty, they may rotate back into defensive stocks for stability, causing these sectors to outperform cyclical ones. This sector rotation is heavily influenced by investor sentiment, which is driven by economic expectations and prevailing market conditions (Bouri et al., 2021; Trichilli et al., 2022).

The sector classification used in this study aligns with the Johannesburg Stock Exchange (JSE) sector categorization, which groups listed companies into Resources, Financials, and Industrials based on their revenue streams. This classification is rooted in the Industry Classification Benchmark, ensuring consistency and comparability across markets. The Resources sector includes companies involved in Basic Materials and Energy, the Financials sector covers Financials and Real Estate, and the Industrials sector comprises all other companies. This structured approach not only provides a comprehensive overview of the South African market but also enables a focused analysis of sector-specific dynamics, which is crucial for understanding the unique behaviour of each sector within the broader economic context.

Multiple studies such as Muzindutsi et al. (2020) and Muguto and Muzindutsi (2022) do not consider including dividends when calculating returns because estimating the dividends for each stock component in indices is tedious. However, dividends have become essential to investors, particularly in bear market periods typified by meagre capital gains (Muguto, 2015; Rupande et al., 2019; Muguto et al., 2022). Dividend-paying stocks have a more foreseeable stream of income, which investors recognise as a notable trait for safety (Baker and Wurgler 2006). Firms are more likely to pay dividends at a premium and less likely to do so when they are at a discount. When firms decide to pay dividends on the margin, they will consider the current sentiment for or against "safety". Huxley (2007) states that stocks with a higher and more sustainable dividend yield are more resilient to economic shocks.

Therefore, investors find companies with high dividend yield patterns more attractive as they are perceived to have a healthier financial position (Bae and Elhusseiny, 2017). Brooks (2019) and Rupande et al. (2019) have argued that excluding dividends may distort the actual value of shares. Accordingly, the daily return on the sector indices, R_t, was calculated as follows:

$$R_{i,t} = \ln\{[P_t + (DY_t * P_t/100)]/P_{t-1}\} * 100 \quad (1)$$

Where: i refers to an index, P_t is the daily closing price on day t, and P_{t-1} is the previous day's closing price. DY_t, the dividend yield on day t, was multiplied by the closing price on the same day to estimate the dividend. Most studies that employed indices and included dividends in their analyses follow this approach (Rupande et al., 2019; Muguto et al., 2022).

3.2.2 Investor sentiment index

There is no universally accepted measure of investor sentiment (Baker and Wurgler, 2007). This complexity arises from the intricate interplay of diverse psychological, behavioural, and economic factors, making it challenging to distil into a single metric. Investor sentiment is multifaceted, encompassing emotions such as fear, greed, and optimism, further complicating comprehensive capture (Raissi and Missaoui, 2015; Rupande et al., 2019; Muguto et al., 2022). The presence of diverse market participants, the dynamic nature of sentiment influenced by ever-changing market conditions, and cultural disparities complicate the creation of a standardised sentiment measure (Smales, 2017; Zhou, 2018). Moreover, the contrarian nature of markets, investor heterogeneity, and the continuous evolution of financial markets and strategies add to the complexity of formulating a universally applicable sentiment indicator.

Nevertheless, measuring sentiment has necessitated using proxies, lexicons, and surveys. Surveys employing standardised questions independent of sophisticated financial theories effectively capture the psychological aspect of participants (Hengelbrock et al., 2013). Examples include investor surveys, online surveys, paper surveys, in-person surveys, and telephone surveys. Several authors, including Brown and Cliff (2004), Schemling (2007), Lux (2011), and Finter et al. (2012), have integrated sentiment surveys into their studies. This is primarily due to surveys' ability to forecast and capture investors' sentiments over the intermediate and long term. The ongoing publication of surveys generates new information, enabling researchers to observe changes in investor attitudes (Hengelbrock et al., 2013).

Nonetheless, economists approach surveys with suspicion due to the potential gap between investors' behaviour and their responses (Baker and Wurgler, 2007). Additionally, surveys, as outlined by Beer and Zouaoui (2013), are subject to variables influencing supposed cause and effect, prestige bias, and the failure to differentiate between diverse sentiment levels, leading to their exclusion in this study. Alternatively, lexicons could have been used to measure sentiment. These involve evaluating articles' orientation or written text and analysing words to conclude investors' general sentiment (Smales, 2017). Examples of this measure include the General Inquirer, Hu & Liu Opinion Lexicon, MPQA Subjectivity Lexicon, NRC Word-Sentiment Association Lexicon, and SO-CAL lexicon (Khoo and Johnkan, 2016).

The lexicon-based approach offers several advantages in measuring market-wide investor sentiment. For instance, it utilises easily accessible, valence-based, and human-curated data without requiring training (Bonta, Kumaresh, and Janardhan, 2019). However, its dependency on a sentiment dictionary to discern the positive or negative orientation of the articles poses a limitation for their usage. Lexicons are also subjective, showing significant variance in polarity classification across domains, unable to distinguish between conflicting opinions, and often missing context-specific words (Khoo and Johnkan, 2016; Dhaoui et al., 2017). Muguto (2021) also noted that implementing the lexicon approach requires financial journals with a substantial following, such as the Wall Street Journal, limiting its applicability to certain countries and precluding its use in this study.

The third, arguably the most widely adopted alternative, revolves around investor sentiment proxies. These factors indirectly convey the prevailing investor sentiment based on straightforward market data (Pandey and Sehgal, 2019). Such proxies encompass the Bloomberg commodity index, closed-end fund discounts, dividend premiums, the equity issue ratio, the Gold spot price, interest rates term structures, initial public offerings, MSCI emerging market index, S&P 500 index, and the US Dollar index (Baker and Wurgler, 2006; Uygur and Tas, 2014; Han and Li, 2017; Muguto et al., 2019; Rupande et al., 2019; Muguto, 2021). Numerous authors have found proxies effective in gauging investor sentiment in stock markets. They are also easily accessible, provide real-time observability, and reflect investors' strength in bullish and bearish periods (Rupande et al., 2019; Muguto et al., 2022).

However, proxies have their shortcomings. For instance, they depend on controversial theoretical explanations to link them to sentiment (Muguto, 2015). Moreover, proxies contain sentiment and idiosyncratic, non-sentiment-related components. This is because most proxies are endogenous to the financial market and economic events; therefore, they do not entirely measure sentiment. The proxies indicate economic expectations and investor sentiment; further adjustments are required to isolate the sentiment element. The significant number of sentiment proxies employed reflected no clear conception of sentiment. Therefore, combining the proxies into one composite index was more suitable for capturing sentiment from various angles to filter out the idiosyncratic noise and exclusively measure sentiment (Baker and Wurgler, 2007; Muguto, 2021).

Several authors propose that sentiment indices, constructed from various proxies, offer a more accurate measure of sentiment, overcoming the drawback of idiosyncratic components in individual proxies (Baker and Wurgler, 2006; Beer and Zouaoui, 2013; Rupande et al., 2019; Muguto et al., 2022). Principal Component Analysis (PCA) is typically employed for this purpose and is recognised for its versatility and widespread use. PCA integrates multivariate methods, such as linear discriminant and canonical variate analyses. Beyond versatility, PCA reduces data dimensionality, eliminates unrelated data qualities, and enhances dataset accuracy by capturing maximum variance through the first principal component. This approach ensures an improved measure of sentiment by linearly combining proxies (Abdi and Williams, 2010; Deeney et al., 2015; Jolliffe and Cadima, 2016; Zainnudin, 2018).

Accordingly, six proxies described below were used herein to construct a sentiment index:

1. The price of oil (Oil) represents the current spot price of a barrel of benchmark crude oil, making it a suitable sentiment proxy due to the similar impact of economic activities on both oil and stock prices (Olayeni et al., 2020). The proxy exhibits a time-varying relationship with sentiment, intensifying during turbulent periods (He et al., 2020). Investor sentiment is also significantly affected by unexpected shocks to oil prices (Qadan and Nama, 2018), and the financialisation of futures markets enables speculation among retail investors, becoming a substantial factor in the spot price of oil (Fattouh et al., 2013; Du and Zhao, 2017). Thus, numerous authors, including Rupande et al. (2019), He et al. (2020), Ye et al. (2020), Muguto (2021), and Muguto et al. (2022), consider the price of oil a suitable sentiment measure. The data on this series was sourced from Bloomberg.
2. The price of Gold (Gld) serves as a reliable proxy because gold is considered a safe-haven asset (Bouri et al., 2020) and a secure investment during economic uncertainty (Pandey and Sehgal, 2019). Investors incorporate gold as a recovery tool in their portfolios after turbulent periods to shield against potential losses. This proxy demonstrates a significant capability to predict how the behaviour of irrational investors can influence stock returns (Reis and Pinho, 2020). According to Hossenidoust et al. (2013), there is always a simultaneous movement between the gold and financial stock markets as they are substantially based on the same information set. Authors like Padungsaksawadi (2019), Rupande et al. (2019), Muguto (2021), and Muguto et al. (2022), who employed gold as a proxy, confirm its suitability. The data for this series was sourced from Bloomberg.
3. The Repo rate (Rpr), representing the percentage at which a country's central bank funds commercial banks, stands as a fitting proxy due to its direct impact on returns and discounting factors (Chen et al., 2014). The data must be aligned since the repo rate is updated less frequently, six times a year, while the other proxies are daily. The alignment is done by carrying forward the repo rate values to match the daily frequency of the other proxies. The latest repo rate is applied to all days until the next update. This ensures that the repo rate data is available for each day, though it may not capture immediate changes in monetary policy. Monetary policy changes, reflected in the repo rate, also directly affect

the economy and expected dividends (Davidsson, 2022). Muguto et al. (2022) noted that fluctuations in the repo rate directly influence investors' expectations and sentiment. Higher rates attract foreign investors seeking enhanced returns, boosting demand for the local currency. However, they also elevate borrowing costs, negatively affecting company profitability and resulting in poor stock performance. Rupande et al. (2019) and Muguto et al. (2022) confirm the repo rate's suitability as a measure of investor sentiment. The data for this series was sourced from the SARB.

4. Trading volume (Tdv) is a technical indicator reflecting investors' perceptions of expected returns and risk (Baker and Wurgler, 2007). Investors with optimism and high-risk tolerance tend to trade more, generating a high turnover (Hoffmann et al., 2015). According to Baker and Stein (2004), a high trading volume signifies overvaluation, often due to investors overreacting to new information. Optimistic investors are more likely to participate in markets with short-sale constraints, betting on rising stocks, compared to pessimistic investors anticipating falling stocks (Philipps et al., 2011). Using the entire market's trading volume provides a broader context and better insights than index-specific volume, helping understand sector performance relative to the overall market. It also aids in identifying trends and anomalies affecting multiple sectors. Therefore, Baker and Wurgler (2007), Zhang (2008), Philipps et al. (2011), Rupande et al. (2019), and Muguto et al. (2021) assert that trading volume is a reliable sentiment proxy. The data for this series was sourced from IRESS.
5. The Volatility Index (Vix) gauges volatility expectations in the S&P 500 index (CBOE, 2019). As a suitable proxy, the index reveals the market's fear level, capturing investors' forward-looking volatility expectations (Lee, 2019). Widely employed as a sentiment and expectation barometer in global markets (Smales, 2017; Mbanga et al., 2019), the VIX enables capitalisation on volatility through VIX-linked futures and options. Prices of these instruments serve as a reliable indicator, reflecting sentiment changes. When market events unfold, traders and investors are inclined to purchase them, increasing prices (Muguto, 2021). The VIX’s broad market coverage, global recognition, and long track record make it a more influential and widely accepted measure of market volatility compared to the South African Volatility Index (SAVI). Smales (2017), Lee (2019), Mbanga et al. (2019), Rupande et al. (2019), Muguto (2021), and Muguto et al. (2022) affirm the VIX as a suitable proxy for measuring investor sentiment. The series data was sourced from Bloomberg.
6. The Rand/Dollar exchange rate (Exr) reflects the price at which the Rand is traded for the US Dollar. It is highly influenced by investors' expectations and the demand for assets in

South Africa (Mahapatra and Bhaduri, 2019). An appreciating Rand attracts investors, signalling a more robust economy (Muzindutsi and Niyimbanira, 2012; Muguto et al., 2019). Financial market liberalisation and cross-border investments impact exchange rates (Baloch et al., 2018; Gupta, 2020; Roy and Shijin, 2020). Consequently, changes in the exchange rate are likely to be a concern for investors and influence their sentiment. Muzindutsi and Niyimbanira (2021), Rupande et al. (2019), Muguto et al. (2022), and Nyakurukwa and Seetharam (2022) assert that the Rand/Dollar exchange rate is a suitable proxy for measuring investor sentiment. The data was collected from the SARB.

The proxies were standardised to eliminate the impact of varying measurement units, which the PCA can be sensitive to (Jaadi, 2021). After that, following Baker and Wurgler (2006), they were orthogonalised against four macroeconomic variables, namely, gross domestic product (Gdp), gross exports (Exp), population (Pop) and inflation (Inf), allowing their explanatory power to be purely behavioural and not concomitant of fundamental factors. This created variables that measure a common component better than non-orthogonalised variables as:

$$Proxy_t = \alpha_t + \beta_1 Gdp_1 + \beta_2 Exp_1 + \beta_3 Pop_t + \beta_4 Inf_1 + \varepsilon_t \quad (2)$$

The intercept, α_t, and the residuals, ε_t were used to represent the sentiment components. A sentiment index was then developed using the first principal components of the current and one-period lagged values of the orthogonal variables as:

$$Sent_t = \theta_1 Oil_{t-1} + \theta_2 Oil_t + \theta_1 Gld_{t-1} + \theta_2 Gld_t + \theta_1 Rpr_{t-1} + \theta_2 Rpr_t + \theta_1 Tdv_{t-1}$$
$$+ \theta_2 Tdv_t + \theta_1 Vix_{t-1} + \theta_2 Vix_t + \theta_1 Exr_{t-1} + \theta_2 Exr_t \quad (3)$$

The correlation between the first stage index and the current and lagged values of the respective proxies was evaluated, and the sentiment index was described as the first principal component of the factors' correlation matrix, depending on the stronger correlation in the first stage. This procedure did not significantly change the predictive power of the sentiment index. A composite index, $ComSent_t$, was then defined as the first principal component of correlation of each corresponding proxy’s current and previous values, depending on which had a stronger correlation with the first-stage index as:

$$ComSent_t = \theta_1 Oil_{t-1/t} + \theta_2 Gld_{t-1/t} + \theta_3 Rpr_{t-1/t} + \theta_4 Tdv_{t-1/t} + \theta_5 Vix_{t-1/t} + \theta_6 Exr_{t-1/t} \quad (4)$$

3.3 Method of analysis

This section describes the methods used to analyse the nature of volatility, dynamic connectedness, hedging effectiveness and the impact of investor sentiment among the seven sector indices mentioned above. These methods were selected based on their suitability to determine the analyses discussed above. The section first mentions the preliminary test conducted on the data used to examine the nature of volatility and return volatility. This is followed by an explanation of the components of the generalised autoregressive conditional heteroscedasticity (GARCH) models, including the mean and variance equations. Thereafter, the descriptions of the asymmetric dynamic conditional correlation (ADCC) and Diebold and Yilmaz volatility spillover follow to determine dynamic connectedness. The DCC-GARCH t-Copulas is introduced to examine hedging effectiveness. A description of the nature of investor sentiment on volatility spillover and hedging effectiveness volatility concludes this section.

3.3.1 Preliminary tests

In any analysis, preliminary tests are conducted on the data to understand the characteristics of the return series and the implications for volatility modelling before investigating the nature of volatility. These include stationarity, normality, serial correlation, autocorrelation, and heteroscedasticity tests. The presence of the ARCH effects justified using the GARCH modelling in this study. Without preliminary tests, there is a risk of not selecting the best models to interpret the results of the nature of volatility and return volatility.

3.3.1.1 Unit roots and stationarity tests

Before any estimations were conducted, the Augmented Dickey-Fuller (ADF, 1984) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS,1992) tests were utilised to evaluate the stationarity of the variables and their response to shocks. There was a need to test for stationarity as some of the methods employed subsequently in this study can only handle a certain level of variable integration. Accordingly, the ADF test for unit roots was defined as:

$$\Delta y_t = \psi y_{t-1} + \sum\nolimits_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t \qquad (5)$$

Where: y_t is the time series data, ψ is white noise, y_{t-1} the lagged level of the series, α_i the coefficient on the lagged changes, Δy_{t-1} the lagged changes and u_t is not correlated as per assumption. However, the ADF test has a low statistical power in distinguishing between a stationarity and a non-stationarity process when the unit root is close to zero. Therefore, the KPSS test was applied for a confirmatory determination of stationarity as:

$$x_t = r_t + \beta_t + \varepsilon_1 \qquad (6)$$

Where: β_t is the deterministic trend, r_t the random walk, and ε_1 the stationary error. In the case where the results from the ADF and KPSS tests were consistent with each other, the determination of stationarity was considered robust. However, in any instance of a discrepancy in the results, the KPSS test results were preferred over the ADF test results because the ADF test is likely to be biased toward rejecting the null hypothesis rather than failing to reject it (Brooks, 2014). Further, a test for stationarity is a more robust test than a test for unit roots.

3.3.1.2 Serial correlation tests

The Ljung-Box test (1978) was also employed to determine whether there was a significant serial correlation in the sectoral returns. The test used the past and current periods to determine serial correlation. Therefore, it was essential to state the number of lags applied in the study clearly; this helped examine the autocorrelation patterns amongst the sectoral returns (Brooks, 2019). McQuarrie and Tsai (1998) stated that no number of lags have been agreed upon universally for time-series data. As this study used daily data, there is a probability that the returns may be correlated over numerous periods. To achieve the test, the Q-statistic was calculated with T as the number of observations, m as the number of lags, and τ_k^2 as the square of sample autocorrelation for k lags. The LB test was calculated as follows:

$$Q^* = T(T+2)\sum_{k=1}^{m}\frac{\tau_k^2}{T-k} \sim \chi_m^2 \ (7)$$

Where: Q is χ^2distributed with j degrees of freedom and τ_j is the k^{th} order autocorrelation. In cases where $Q > \chi_m^2$, then the null hypothesis of no serial correlation was rejected in favour of the alternative and vice versa for a lower statistic.

The Autoregressive Conditional Heteroscedasticity (ARCH) test was applied to test for the presence of ARCH effects. The ARCH test is a non-linear financial model that examines volatility's time dynamics, such as volatility clustering. Volatility clustering refers to how large (small) changes in the volatility of stock prices follow large (small) changes in volatility (Su and Huang, 2010). Further, the test was also employed to determine the suitability of the GARCH models. According to Brooks (2014), when testing for ARCH effects, autocorrelation found within volatility was modelled by allowing the conditional variance of the error term (σ_t^2) to be dependent on the immediate previous value of the squared error as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \ (8)$$

The null and alternative hypotheses are H₀: $\gamma_1 = 0$ and $\gamma_2 = 0$ and $\gamma_3 = 0$ and ... and $\gamma_q = 0$.

H₁: $\gamma_1 \neq 0$ or $\gamma_2 \neq 0$ or $\gamma_3 \neq 0$ or ... or $\gamma_q \neq 0$. The null hypothesis is rejected in cases where the critical value found in the χ^2 distribution is lower than the test statistic. Therefore, the null hypothesis was rejected when the ARCH effects were found in the data, indicating heteroscedasticity, and the GARCH model was employed. All these preliminary tests ensured that the returns and volatility were modelled correctly.

3.3.2 Constant conditional correlations

According to Alqahtani et al. (2019), multivariate GARCH (MGARCH) models are highly efficient in finance applications. For the MGARCH model, an alternative to reduce the number of parameters requires the correlation between the disturbances, ϵ_t , (or equivalently between the observed variables, y_t) to be fixed throughout the period. While the conditional covariances are not fixed, they are linked to the variance proposed in the constant conditional correlation (CCC) model introduced by Bollerslev (1990). Among the different specifications of the MGARCH models, the most common is usually considered to be the CCC model. The set of univariate GARCH specifications was identical to the conditional variances in the fixed correlation model, although they were estimated together (Brooks, 2019)

$$h_{ii,t} = \omega + \alpha_i \epsilon_{i,t-i}^2 + \beta_i h_{ii,t-1}, \quad i = 1, \ . \ . \ ., N \ (9)$$

The off-diagonal elements of H_t, $h_{ii,t}$ $(i \neq j)$, are indirectly defined via the correlations as:

$$h_{ij,t} = \rho_{ij} h_{ii,t}^{1/2} h_{jj,t,}^{1/2} \quad i,j = 1, \ . \ . \ . \ , N, i < j \ (10)$$

The process $\{a_{it}\}$ is modelled as a univariate GARCH; therefore, the conditional variance could be written in the form of a vector:

$$h_t = c + \sum_{j=1}^{q} A_j a_{t-j}^{(2)} + \sum_{j=1}^{p} B_j h_{t-j} \quad (11)$$

Where c is $n \times 1$ vector, A_j and B_j are diagonal $n \times n$ matrices and $a_{t-j}^{(2)} = a_{t-j} \odot a_{t-j}$ is the element-wise product. As R is a positive definite, when the elements c and A_j and B_j are positive then H_t is an ensured positive definite. The models' estimations in this particular class are favourable because the correlation matrix is constant. In other instances, the CCC-GARCH model may be too restrictive; the model can then be generalised assuming that the correlation matrix is time-varying. This introduces the extension of the CCC-GARCH model, where A_j and B_j do not have to be diagonal.

3.3.3 Dynamic conditional correlation model

The disadvantage of the extended GARCH models is that they do not consider the correlation among the data of the sector indices. Therefore, the CCC-GARCH model was introduced to account for the correlation in the dataset. However, the CCC-GARCH cannot parameterise conditional correlation between two or more variables as it follows the univariate GARCH process, hence the need for the dynamic conditional correlation GARCH (DCC-GARCH) model proposed by Engel (2002). The two-step DCC-GARCH (1.1) model was thus employed to examine the sector indices' time-varying conditional volatilities as:

$$y_t = \mu_t + \epsilon_t \quad \epsilon_t | F_{t-1} \sim N(0, H_t) \ (12)$$

$$\epsilon = H^{\frac{1}{2}} u_t \quad u_t \sim N(0, I) \ (13)$$

$$H_t = D_t R_t D_t \ (14)$$

where F_{t-1} represents the available information for the period of $t-1$. y_t is the time series, μ_t is the conditional mean, ϵ_t is the error term, and u_t *is* the standardised error term, the parameters mentioned above are all $N \times 1$-dimensional vectors. H_t, D_t, and R_t are $N \times N$-dimensional matrices representing the dynamic variance-covariance matrix, diagonal conditional standard deviation matrix, and the time-varying conditional correlation matrix. The estimation procedure of the DCC-GARCH model consists of two stages. The estimated series of conditional variances is modelled as a univariate GARCH in the first stage. This is defined by estimating the constant conditional correlation (CCC) model by Bollerslev (1990), assuming that there is one shock and persistent parameter as per equation 9. At stage two, the dynamic conditional correlation between the parameters was estimated as follows:

$$R_t = diag\{Q_t^*\}^\wedge - 1 Q_t diag\{Q_t^*\}^\wedge - 1 \ (15)$$

$$Q_t = (1 - A - B)\bar{Q} + Au_{t-1}u'_{t-1} + BQ_{t-1} \quad (16)$$

Where $diag(\cdot)$ is a matrix that includes the main diagonal elements, Q^* is the matrix that takes the square root of every element in Q. Q_t and $\bar{Q}$ are the respective $N \times N - dimensional$ positive-definite matrices of the standardized conditional and unconditional matrices. If the sum of $A(\alpha)$, the positive shock and B(β), the persistency parameter is less than one, $A + B < 1$ $(\alpha + \beta \leq 1)$ then Q_t and R_t is time-varying, which indicates that there is a dynamic conditional correlation (Brooks, 2019).

3.3.4 Asymmetric dynamic conditional correlation model

The ADCC-GARCH model developed by Cappiello et al. (2006) was subsequently used to measure time-varying correlations in the volatilities among major sector indices. Compared to the multivariate GARCH models, the ADCC-GARCH allows for different responses of variances and covariances to positive and negative innovations of the same magnitude. At the same time, its number of parameters increases linearly rather than exponentially. The number of parameters estimated in the correlation procedures is independent of the number of series that need to be estimated; this results in an advantage when estimating large covariance matrices (Andersson-Säll and Lindskog, 2019). The model approach addresses several issues in the M-GARCH models, like forecasting multiple parameters at the same period and the positive definiteness of the covariance matrix (Antonakakis et al., 2018). Further, it is a valuable tool for analysing dynamic volatilities, covariances and correlations.

The ADCC-GARCH is an extension of the Dynamic Conditional Correlation GARCH (DCC-GARCH) of Engle (2002) in that it allows for the leverage effects in the underlying correlation structure. In turn, the DCC-GARCH model is an extension of the Constant Conditional Correlation GARCH (CCC-GARCH) in that the conditional correlation matrix is assumed to be time-varying. The model is a non-linear combination of univariate GARCH models that separate the covariance matrix into individual conditional variances and dynamic conditional correlation using the two-step procedure (Brooks, 2014). The extended DCC univariate GARCH models are employed to show that both emerging and developed financial markets are significantly impacted by herding behaviour amongst investors during economic downturn periods (Katzke, 2013). Constructing the DCC model includes finding the most appropriate univariate GARCH specifications for every series that best describes the return behaviour.

Firstly, univariate GARCH models are estimated using the continuously compounded returns from Equation 1 to extract the residuals. Based on the three main univariate GARCH models, which include the GARCH, TGARCH, and EGARCH, the most suitable univariate specification was chosen based on the information criteria. Considering this study's large sample size, the best model was selected based on Schwarz's Bayesian Criterion (SBIC). The SBIC is more consistent when dealing with a large sample than the Akaike Information Criterion (AIC). It was found that among all the various DCC models, the GARCH (1,1) was the optimal model as it minimised the information criterion. When evaluating the performance of the models using the error measurement approaches, the GARCH model was the most effective as it captured volatility more accurately during various crisis periods.

Equation 17 below shows the mean equations – common among the GARCH (1.1), E-GARCH (1.1), and GJR-GARCH (1.1) model specifications. This was defined as follows:

$$y_t = \mu + \alpha y_{t-1} + \nu\varepsilon_{t-1} + \theta\sigma^2_{t-1} + \varepsilon_t \quad (17)$$

Conditional variance equations for the GARCH (1.1), E-GARCH (1.1), and GJR-GARCH (1.1), distinct among the three formulations, were defined as:

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \quad (18)$$

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \gamma\varepsilon^2_{t-1} d_{t-1} \quad (19)$$

$$\ln(\sigma^2_t) = \omega + \beta\ln\left(\sigma^2_{t-1}\right) + \lambda\, \varepsilon_{t-1} \Big/ \sqrt{\sigma^2_{t-1}} + \delta\left[|\varepsilon_{t-1}| \Big/ \sqrt{\sigma^2_{t-1}} - \sqrt{2/\pi}\right] \quad (20)$$

Subsequently, the conditional correlations were assessed by applying these residuals estimated in the previous step. Brooks (2019) suggested constructing an autoregressive element into the return equation to address possible serial correlations as follows:

$$r_t = \mu + \alpha r_{t-1} + \varepsilon_t \quad (21)$$

Where: r_t indicates the current sector indices returns, μ represents the forecasted value of the conditional return, α indicates the autoregressive return coefficients, ε_t is the error term. The covariance matrix in the Engle (2002) DCC-GARCH was defined as:

$$H_t=D_tR_tD_t \text{ with } D_t=\begin{bmatrix} \left(h_{i,t}^2\right)^{1/2} & 0 \\ 0 & \left(h_{i,t}^2\right)^{1/2} \end{bmatrix} \quad (22)$$

Both symmetric and asymmetric univariate GARCH models were used in the equation. Assuming a symmetric univariate GARCH (p, q) model, h_t was expressed as:

$$h_t=w+\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2+\sum_{j=1}^{p}\beta_j h_{t-i} \quad (23)$$

$$R_t=\text{diag}\left(q_{1,t}^{-1/2},\ldots q_{n,t}^{-1/2},\ldots\right)Q_t\,\text{diag}\left(q_{1,t}^{-1/2},\ldots q_{n,t}^{-1/2}\right) \quad (24)$$

$$Q_t=(1-\theta_1-\theta_2)Q^*+\theta_1 z_{t-1}Z'_{t-1}+\theta_2\,Q_{t-1} \quad (25)$$

Where: H_t is a matrix of the covariance, D_t represents the conditional correlation. R_t represents a dynamic correlation matrix of the sector indices, the conditional correlation, Q_t represents a diagonal correlation matrix, Q^* is the unconditional correlation matrix of the residuals that follow a GARCH process. The scalar parameters θ_1 and θ_2 are non-negative and must satisfy the stability condition $\theta_1 + \theta_2<1$ for the model to be acceptable. Each index's correlations are dynamic if the two parameters are significant and greater than zero but less than 1. The conditional correlation coefficient between sector indices was specified as:

$$\rho_{i,j,t}=q_{i,j,t}/\sqrt{q_{i,i,t}q_{j,j,t}} \quad (26)$$

The sign, magnitude and significance of $\rho_{i,j,t}$ will be determined for each index. The standardised residuals determine the correlation between the sector indices. If the residuals move in the same direction, the correlation will increase and eventually return to the mean as all information is collected. As per Cappiello et al. (2006), by extending Equation 24, the ADCC-GARCH was written as follows:

$$h_{i,t}=\omega_i+\alpha_i\varepsilon_{i,t-n}^2+\beta_i h_{i,t-n}+d_i\varepsilon_{i,t-n}^2 I\left(\varepsilon_{i,t-n}\right) \quad (27)$$

If $\varepsilon_{i,t-n} < 0$, the indicator function I ($\varepsilon_{i,t-n}$) = 1. In this model, positive d indicates that negative shocks increase variance more than positive shocks of equal magnitude (Basher and Sadorsky, 2016). Incorporating the asymmetric effect and asset-specific news, Cappiello et al. (2006) expressed the news impact (dynamics on Q) as follows:

$$Q_t = \left(\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{Q^*}G\right) + A'z_{t-1}z'_{t-1}A + B'Q_{t-1}B + G'z_t^- z_t'^- G \quad (28)$$

Where: A, B and G are parameter matrices, $\overline{Q}$ and $\overline{Q^*}$ are unconditional matrices, z_t and z_t^- are zero-threshold standardised errors (Yarovaya and Lau, 2016). The asymmetry term must be significant if negative news significantly influences conditional correlations more than positive ones. For robustness, different distribution functions were assumed in the analysis.

Different starting values should be used when estimating to combat the issue of a flat likelihood function when using multivariate data in an analysis. Literature has shown that the financial time series often follows a non-normal distribution, such as the student t-distribution, due to fat-tailed distributions (Kayaba et al., 2018; Takahashi et al., 2019; Brooks, 2019). Bollerslev (1986) and Hsieh (1989) found evidence that returns are not normally distributed. Therefore, error distribution assumptions that allow for fat tails must be used. Malek (2018) found that student-t distribution is better at capturing kurtosis. This chapter employed both distribution assumptions to cater for the possibility of excess kurtosis and fat tails in the returns. After that, model adequacy tests were conducted to ensure the models were correctly specified, focusing mainly on the residuals.

3.3.5 Diebold and Yilmaz volatility spillover

To achieve the first objective of determining the level of dynamic connectedness among the sector indices in South Africa, the generalised spillover index from Diebold and Yilmaz (2015) was employed. This index is based on the variance decompositions from vector autoregressions (Sims, 1980). It computes the share of cross-market error variance relative to the total error variance of the markets examined. It aggregates it into a single value, which shows the degree of spillovers among the indices. This version overcomes the problems of order-dependent results caused by Cholesky factor orthogonalisation in Diebold and Yilmaz (2009). The dynamic changes in the influence of spillovers were illustrated using spillover plots generated from rolling-window estimations (Antonakakis et al., 2018). Following Diebold and Yilmaz (2015), the analysis first constructed a VAR with N variables and following the K^{th} order as:

$$y_t = \sum_{k=1}^{K} \Theta_k \, y_{t-k} + \varepsilon_t \quad (29)$$

where $y_t = (y_{1t}, y_{2t}, \ldots, y_{Nt})$ is a vector of endogenous variables, comprising n = 1,…, N(6) observations on the volatility of the sector indices at day t; Θ_k, k = 1, …; K, are N x N parameter matrices; and $\varepsilon_t \sim (0, \Sigma)$ is a vector of disturbances assumed to be independently distributed over time. The essential factor of the system was the moving average representation as:

$$y_t = \sum_{p=0}^{\infty} A_p \varepsilon_{t-p} \quad (30)$$

where the N x N coefficient matrices of A_p were recursively defined as follows:

$$A_p = \Theta_1 A_{p-1} + \Theta_2 A_{p-2} + \ldots + \Theta_p A_{p-1} \quad (31)$$

where A_0 is the N x N identity matrix and $A_p = 0$ for $p < 0$. The generalised VAR framework of Koop et al. (1996) and Pesaran and Shin (1998) helped evaluate the system's dynamics. The framework allows for the production of variance decompositions resistant to variable ordering. This can be particularly useful when looking at a VAR model with six variables and a sample of major financial crises. To take advantage of this, Diebold and Yilmaz (2012, 2014, 2015) employed the variant of the spillover index based on the generalised VAR to ensure that the forecast error variance remains invariant to the ordering of the variables. In the generalised VAR framework, the H-step-ahead forecast error variance decomposition was:

$$\emptyset_{ij}(H) = \sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma_{ej})^2 / \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right) \quad (32)$$

Where: Σ is the variance matrix of the error vector ε, σ_{jj} is the standard deviation of the error term for the volatility of index j, and e_i is a selection vector with 1 as the i^{th} element and zeros otherwise. The main diagonal elements include the own contributions of volatility shocks to index i to its forecast error variance. The off-diagonal elements represent cross-market volatility spillovers, which in this case are defined as contributions of other index j to the forecast error variance of index i. As own and cross-index variance contribution shares do not equate to 1 under the generalised decomposition, i.e., $\Sigma_{j=1}^{N} \phi_{ij}(H) \neq 1$, its row sum normalises every entry of the variance decomposition matrix such that

$$\tilde{\phi}ij(H) = \phi_{ij}(H) / \sum_{j=1}^{N} \phi_{ij}(H) \quad (33)$$

with $\sum_{j=1}^{N} \tilde{\phi}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H) = N$ by construction. From this expression, the total spillover index was constructed as follows:

$$T(S)H = \sum_{i,\ j=1,\ i\neq j}^{N} \tilde{\phi}_{ij}(H) / \sum_{i,\ j=1,}^{N} \tilde{\phi}_{ij}(H) \times 100 = \sum_{i,\ j=1,\ i\neq j}^{N} \tilde{\phi}_{ij}(H) / N \times 100 \quad (34)$$

Equation 35 was used to measure the contribution of volatility spillover shocks throughout all the indices to the total forecast error variance. This approach was used to examine directional volatility spillovers. Thus, the directional volatility spillovers that index i received from all other indices j and when index i transmitted to other indices j were defined respectively as:

$$DS_{i\leftarrow j}=\sum_{j=1,\, j\neq i}^{N}\tilde{\phi}_{ij}(H)/\sum_{i,\ j=1,}^{N}\tilde{\phi}_{ij}(H)\ \times 100=\sum_{j=1,\, j\neq i}^{N}\tilde{\phi}_{ij}(H)/N\ \times 100\ (35)$$

$$DS_{i\rightarrow j}=\sum_{j=1,\, j\neq i}^{N}\tilde{\phi}_{ji}(H)/\sum_{i,\ j=1,}^{N}\tilde{\phi}_{ji}(H)\ \times 100=\sum_{j=1,\, j\neq i}^{N}\tilde{\phi}_{ji}(H)/N\ \times 100\ (36)$$

This approach broke down the overall volatility spillovers into those that originate from a specific index or are directed towards it. By subtracting Equation 35 from Equation 36, the net volatility spillovers from index i to other indices j were obtained as:

$$NS_i(H)=DS_{i\rightarrow j}(H)\text{-}DS_{i\leftarrow j}(H)\ \ (37)$$

Equation 38 was used to determine the amount of volatility that each index contributes to the volatility of other indices, taking into account both the positive and negative volatility exchanges. The net pairwise volatility spillovers were calculated as follows:

$$NPS_{ij}(H)=\left(\frac{\tilde{\phi}_{ji}(H)}{\sum_{i,m=1,}^{N}\tilde{\phi}_{im}(H)}-\frac{\tilde{\phi}_{ij}(H)}{\sum_{j,m=1,}^{N}\tilde{\phi}_{jm}(H)}\right)\times 100=\frac{\tilde{\phi}_{ji}(H)-\tilde{\phi}_{ij}(H)}{N}\ \times 100\ (38)$$

The net pairwise volatility spillovers between indices i and j is the difference between the gross volatility shocks transmitted from index i and j and those transmitted from index j to index i. The Diebold and Yilmaz (2012, 2014, 2015) spillover index provides a way to examine the interrelationships between various indices simultaneously. It generates four distinct types of spillovers: total, directional, net, and pairwise.

3.3.6 DCC-GARCH t-Copulas

To achieve the second objective of assessing the impact of dynamic connectedness among the major sector indices in the South African market on their hedging effectiveness, the Student-*t* copulas DCC-GARCH, an extension of the DCC model, was employed. The copulas-based framework, an extension of the GARCH model, was applied as its time-varying strategies can outperform the DCC-GARCH model; this showed that the skewness and leptokurtosis significantly reflected the economic changes (Wu et al., 2012). The Student-*t* copulas, part of the elliptical copula functions, is symmetric, can specify various correlations between the marginals, and applies symmetric dependence in the extreme tails. According to Kim and Jung (2016), a copula efficiently identifies and constructs correlated multivariate random variables. The multivariate distribution function was defined as its marginal distribution function as:

$$F(x_1,...,x_n) = C(F_1(x_1),..., F_n(x_n) \quad (39)$$

Where x_i is a random variable, F_i is the marginal distribution function, and C is an n-dimensional copula determined in [0,1]^n for F-distribution defined as:

$$C(u_1,..., u_n) = F\, F_1^{-1}(u_1)..., F_n^{-1}(u_n)) \text{ for } \forall u_i \in [0,1],\ i= 1,...,n \quad (40)$$

After that, the density functions of *F* and *C* were written as

$$f(x_1, \ . \ . \ . \ ,x_n)= c(F_1(x_1), \ . \ . \ . \ , F_n(x_n)) \prod_{i=n}^{n} f_i(x_i) \quad (41)$$

$$c(u_1, \ . \ . \ . \ ,u_n)= \frac{f(F_1^{-1}(u_1), \ . \ . \ . \ ,F_n^{-1}(u_n))}{\prod_{i=1}^{n} f_i(F_1^{-1}(u_i))} \quad (42)$$

where f_i is the marginal density and F_i^{-1} is the margins' quantile functions. The density of the Student-*t* copula was defined by

$$C(u;R,\omega) = \frac{\Gamma(\frac{\omega+n}{2})(\Gamma(\frac{\omega}{2}))^\wedge n(1+\omega^{-1}u'R^{-1}u)^\wedge\text{-}\frac{(\omega+n)}{2}}{|R|^\wedge 1/2(\Gamma(\frac{\omega+n}{2}))^\wedge n\Gamma\left(\frac{\omega}{2}\right) \prod_{i=1}^{n} (1+\frac{u_i^2}{\omega})^\wedge\text{-}\frac{(\omega+1)}{2}} \quad (43)$$

Where R is the correlation matrix affected by the covariance matrix, ω is the shape parameter, $u_i = t_\omega^{-1}(F(x_i; \omega))$, and t_ω^{-1} is the quantile function. The extension of the Student-*t* copula was constructed using conditional correlation and, therefore, had a conditional density. The DCC-GARCH Student-*t* copula was defined as follows:

$$c_t(u_{it},..,u_{nt}|R_t,\omega) = f_t(F_i^{-1}(u_{it}|\omega), ...\ F_i^{-1}(u_{nt}|\omega)|R_t,\omega)/\prod_{i=1}^{n} f_i(F_i^{-1}(u_{it}|\omega)\,|\omega) \quad (44)$$

Where$u_{it} = F_{it}(r_{it}|h_{ii,t},\omega_i)$ is the likelihood transformed values by F_{it} estimated using the GARCH process and $F_i^{-1}(u_{it}|\omega)$ is the quantile transformation.

3.3.7 Investor sentiment impact on volatility spillovers and hedging effectiveness

To achieve the third objective of examining the influence of prevailing investor sentiment on the dynamic connectedness and hedging effectiveness among the major sector indices in South Africa, the modification of the GARCH models was utilised to generate the residuals used in the techniques above. The same models generated the residuals used to study volatility spillovers with the Diebold and Yilmaz (2015) spillover index. Equation 45 below showed how the mean equations – common among the GARCH (1.1), E-GARCH (1.1), and GJR-GARCH (1.1) model specifications – were augmented with the investor sentiment index, ComSent:

$$y_t = \mu + \alpha y_{t-1} + \nu\varepsilon_{t-1} + \theta\sigma^2_{t-1} + \varphi ComSent_t + \varepsilon_t \quad (45)$$

Where: φ captures investor sentiments' impact. A significant coefficient reveals the effect of investor sentiment on returns. The changes in other coefficients in the equation relative to the unaugmented model coefficients are examined, and the changes are attributed to the inclusion of sentiment. Similarly, the conditional variance for the GARCH (1.1), E-GARCH (1.1), and GJR-GARCH (1.1) was extended by adding the same investor sentiment index as:

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \varphi ComSent_t \quad (46)$$

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} + \gamma\varepsilon^2_{t-1}d_{t-1} + \varphi ComSent_t \quad (47)$$

$$\ln(\sigma^2_t) = \omega + \beta\ln\left(\sigma^2_{t-1}\right) + \lambda\, \varepsilon_{t-1}\Big/\sqrt{\sigma^2_{t-1}} + \delta\left[\left|\varepsilon_{t-1}\right|\Big/\sqrt{\sigma^2_{t-1}} - \sqrt{2/\pi}\right] + \varphi ComSent_t \quad (48)$$

The mean and variance equations were used to determine if sentiment impacts volatility. The $ComSent_t$ coefficient from the variance equation was analysed, as well as the coefficients from the sentiment-augmented and unaugmented variance equations. The conditions of stationarity and non-negativity for the respective models were also considered. The residuals extracted from the above models were then used in the ADCC-GARCH and DCC-GARCH t-Copulas models to examine the impact of the sentiment of investors on the connectedness and hedging effectiveness among the sector indices in South Africa.

3.4 Summary of the chapter

This chapter introduced an analysis of suitable methods to investigate the impact of dynamic connectedness, hedging effectiveness among stock market sector indices and their subjectivity to prevailing market-wide investor sentiment. A description of the preliminary tests was provided to examine the nature of volatility and return volatility among sector indices. The ADCC-GARCH model was introduced to determine the volatility spillover. After that, Diebold and Yilmaz's (2015) volatility spillover index was employed to determine dynamic connectedness and how the various indices reacted to the external shocks - if they maintained a net transmitter or net recipient position. To determine the hedging effectiveness among the indices, the DCC-GARCH t-Copulas was analysed. The chapter concluded by describing the nature of investor sentiment on volatility spillover and hedging effectiveness to provide a holistic view by including sentiment in the equations.

CHAPTER 4: DATA ANALYSIS AND PRESENTATION OF RESULTS

4.1 Introduction

A wide array of stakeholders must understand the nature of return volatility among sector indices, volatility spillovers, and sentiment impact for effective decision-making. As alluded to in Chapter 1, this study aimed to examine the dynamic connectedness and hedging effectiveness among South African stock market sector indices and their subjectivity to prevailing market-wide investor sentiment. This chapter presents the results of the tests conducted. First, the descriptive statistics, principal component analysis, serial correlation, and heteroscedasticity test results are presented. The model selection results on symmetric and asymmetric GARCH model specifications under the different error distribution assumptions then follow. Finally, the results from the GARCH, the ADCC-GARCH, and Diebold and Yilmaz volatility spillover estimations are reported and discussed.

4.2 Preliminary analysis

Before examining the nature of volatility, preliminary tests were conducted on the return series to understand the implications of data characteristics on volatility modelling. These tests included the determination of descriptive statistics and assessments for stationarity, normality, autocorrelation, and heteroscedasticity. Descriptive statistics provided a summary of the return distributions' central tendency, dispersion, and shape, and stationarity tests ensured that the return series did not exhibit trends over time, indicating a stable mean and variance. Normality tests assessed whether the return distributions conformed to a normal distribution, while autocorrelation tests checked for patterns in the volatility over time, identifying whether past volatility influenced future volatility. Heteroscedasticity tests - the Ljung-Box statistics and ARCH-LM tests - were used to detect the presence of ARCH effects (Brooks, 2019).

4.2.1 Sectoral returns

Figure 4.1 below shows the sectoral returns of seven sector indices and the broad market index. The stock return plots show that the variance varied over time and followed an autoregressive pattern, resulting in volatility clustering in all the sector indices. During turbulent periods, the sectors experienced high volatility, which indicated riskier periods. These riskier periods refer to the 2007-2008 Global Financial crisis, the COVID-19 pandemic, and the Russia-Ukraine war. The heightened volatility during these times highlights the significant impact that global economic events with origins elsewhere have on local market sectoral returns. The return plots showed a similar pattern to the aforementioned economic events that similarly impacted all the sector indices. Further, all the plots show constant means over the sample period, which confirms the series' stationarity.

From 2009 to 2015, the plots showed an increase in return and appeared less volatile; this was due to the recovery of the financial market from the 2008 Global Financial crisis. An additional contribution to the performance of the market was the 2010 Soccer World Cup hosted in South Africa. This significantly contributed to sectoral returns, and according to Prinsloo (2010), it resulted in an investment of R93 billion in the domestic economy. Therefore, investors identified this period as less risky as there was more certainty regarding the performance of the South African market. From 2009 onwards, the graphs display an upward trend with dips and peaks because of the historical economic events. However, towards the end of 2019, all the sectoral indices experienced high volatility and riskier periods. This was due to the onset of the COVID-19 pandemic, which halted global economic activities (Muguto et al., 2022).

Although the pandemic impacted all sectors, it is essential to note that the sensitivity of the sector indices differed depending on whether they were part of cyclical or non-cyclical industries. From the end of 2020 onwards, the industries began to experience a steady return increase as the restrictions placed during the pandemic were lifted and industries began to operate at full capacity again. However, at the beginning of 2022, some sector indices experienced a sharp return decrease. This was due to Russia’s invasion of Ukraine, which triggered uncertainty regarding the recovery from the global economy post the pandemic. As Russia is one of the world’s largest producers of raw materials such as oil, gas, and steel, the Ukraine-Russia war aggravated supply chain bottlenecks and inflationary pressures, resulting in an expeditious tightening of the monetary policy.

This description of sector returns illustrates that sectoral returns exhibit volatility clustering and autoregressive patterns, particularly during turbulent periods. These periods of heightened volatility suggest the interconnectedness of global and local markets, emphasizing the need for effective hedging strategies to mitigate risk. The period from 2009 to 2015, marked by increased returns and lower volatility due to market recovery and the 2010 Soccer World Cup, indicates phases where investor sentiment was more positive and markets were perceived as less risky. The sensitivity of sector indices to economic events, varying between cyclical and non-cyclical industries, highlights the importance of dynamic hedging approaches tailored to different sectors. The observed trends and volatility patterns suggest that understanding investor sentiment and its influence on market dynamics is crucial.

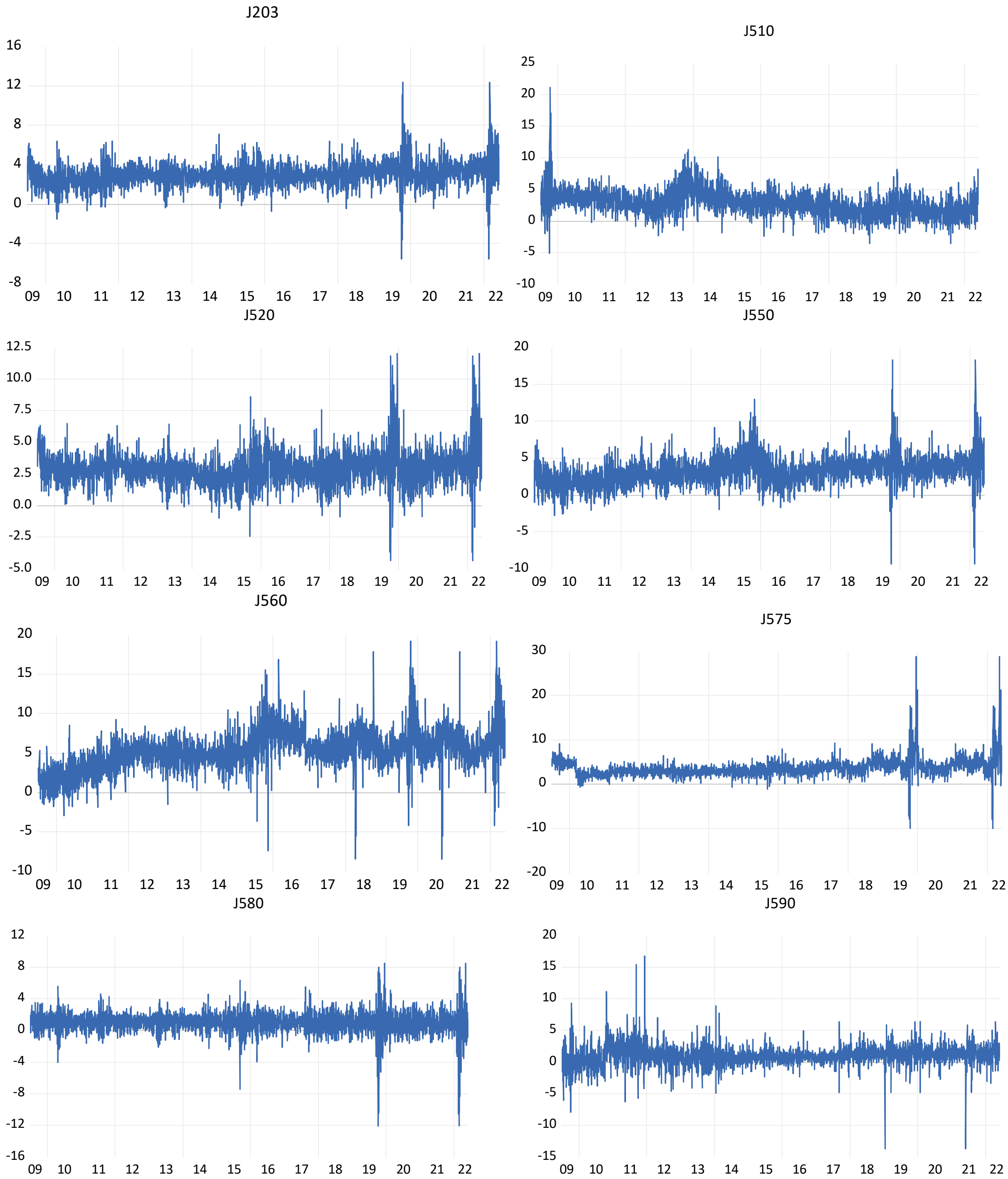

Figure 4. 1 The indices return graphs
Source: Own depiction (2024)

The sectoral returns of the seven sector indices and the broad market index reveal distinct differences in volatility timing and magnitude, driven by global economic events. Figure 4.1 shows volatility clustering across all sectors, particularly during the 2007-2008 Global Financial Crisis, the COVID-19 pandemic, and the Russia-Ukraine war. However, the timing of these spikes varies: cyclical sectors like basic materials and financials exhibit earlier and more intense volatility, while defensive sectors, such as consumer services, show delayed or muted responses. The 2009-2015 recovery, marked by increased returns and reduced volatility, also differed across sectors, with defensive sectors stabilizing faster. These variations in volatility timing highlight the importance of sector-specific analysis for investors, emphasizing the need for tailored hedging strategies to manage different risk exposures effectively.

4.2.2 Descriptive statistics

Table 4.1 reports the descriptive statistics for the index returns. All the mean daily returns were positive, suggesting a generally bullish sample period. Telecommunications had the highest average return of 5.28%, whereas the financial sector had the lowest average return of 0.99% over the sample period. This could be due to the increased reliance on connectivity for digital services, which has resulted in Telecommunications being one of the fastest-growing and essential sectors. The lower returns on the financial sector correspond with the sector's significant sensitivity to numerous global events, such as the 2009 global financial crisis, the 2015 Chinese stock market bubble and the COVID-19 pandemic. This sector underperformed the broad market index, earning 3.00% over the period. Overall, sectors performed differently, which indicates differences in sensitivity to various factors.

However, among the sectors, Telecommunications had the highest standard deviation (2.52%), while Industrials had the lowest (1.35%). The former is more aligned with the theory that high risk is supposed to be compensated for by high returns and vice versa (Ishfaq et al., 2020). Also, Telecommunications is characterized by rapid technological advancements and fierce competition, contributing to its higher volatility. With Industrials, the lower standard deviation could result from its stable demand compared to other sectors sensitive to consumer sentiment. It often engages in long-term contracts that reduce short-term volatility (Arouri et al., 2012). The sector serves essential needs such as infrastructure and manufacturing sourced from various industrial companies across diverse markets and products, allowing it to mitigate the impact of sector-specific shocks (Golmohamadi, 2022).

However, the broad market index had the lowest standard deviation (1.2110) over the sample period. This result was expected as the ALSI includes companies from all sectors and is, therefore, more diversified than the sector indices (Rupande et al., 2019). Thus, the ALSI is less susceptible to sector-specific volatilities and can balance out the fluctuations seen in individual sectors, providing a more stable overall performance. This diversification effect explains why the ALSI exhibits the lowest standard deviation, indicating lower overall volatility than the individual sector indices (Muguto et al., 2022). As such, investors seeking more stable returns might prefer the broad market index because it can mitigate risks associated with specific sectors. The lower volatility of the ALSI makes it a more attractive option for conservative investors looking for steady growth, reducing significant swings in its value.

All the indices, including the ALSI, were leptokurtic with kurtosis values greater than three, indicating a higher probability of generating extreme returns and thus resulting in a higher risk. Furthermore, all the indices, except the financial sector, were positively skewed. This indicates that the sectors experienced few large gains and frequent small losses. The negative skewness in the financial sector suggests that the sector experienced numerous small gains and minimal large losses (Wen et al., 2013; Theodossiou and Savva, 2016). This finding aligns with the inherent nature of the financial sector, which often benefits from incremental gains due to its diversified investment portfolios and risk management strategies. The results corresponded with the above findings that suggested investor sentiment significantly impacted sectoral returns and showed a proportional relationship between skewness and volatility.

The Jarque-Bera statistic was significant for all the indices. This meant that the null hypothesis of normality was rejected for all the indices in favour of the non-normality alternative hypothesis. This implies a significant impact on risk assessment and portfolio management due to the non-normality in the return distribution. When the distribution exhibits fat tails, traditional risk measures such as standard deviation may underestimate actual risk, resulting in underestimating downside risk and increased vulnerability to extreme events (Costa and Iezzi, 2006). Therefore, investors may need to adjust their strategies from those that rely on normality assumptions, such as mean-variance optimization, to those that require modification with alternative risk measures and portfolio construction that accounts for non-normality behaviour (Kharka et al., 2012).

This non-normality in return distributions provided an expectation regarding the likely error distribution assumptions in the model specification in the GARCH estimations below. This is because the departure from normality suggests that traditional statistical techniques assuming a normal distribution may not be appropriate for analyzing or modelling the index returns (Borowski, 2018). The pictorial evidence from the graphs in Figure 4.1 above confirmed the non-normality in the return distributions. These graphs illustrate the frequency and magnitude of extreme returns, reinforcing the need for advanced modelling techniques to capture the true risk dynamics. This visual confirmation further justified using GARCH models, which are better suited to handle the non-normal characteristics observed in the return data, thus providing more accurate and reliable risk assessments.

Table 4. 1 Descriptive statistics

Statistic	Mean (%)	Median (%)	Std dev. (%)	Skewness	Kurtosis	JB
J203	3.0005	2.9854	1.2110	0.4605	9.9794	6961.24***
J510	2.8001	2.7611	1.9030	0.8639	8.0329	3977.19***
J520	2.9235	2.8603	1.3553	0.8933	9.0785	5638.09***
J550	3.2243	3.2072	1.9317	0.5985	8.5616	4545.87***
J560	5.2772	5.2272	2.5263	0.2621	5.7615	1109.74***
J575	3.6058	3.3319	2.0330	2.7440	29.8881	105777.6***
J580	0.9907	1.0297	1.3639	-1.2539	18.2474	33537.61***
J590	1.0371	1.0306	1.5808	0.1164	15.0165	20289.14***

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

Source: Own estimations (2024)

4.2.3 Principal component analysis

As noted in section 3.3.2, orthogonalized proxies were used to execute the principal component analysis to construct a sentiment index, which offers a more accurate measure of sentiment as it overcomes the drawback of idiosyncratic components in individual proxies. Table 4.2 reports the results. The first principal component accounts for 47.36% of the total variance. This is slightly lower than the 53% Baker and Wurgler (2006) reported on the US market. However, the figure is robust. The variables that show a significant correlation with the first principal component, PC1, are Gld (0.5052). Exr (0.4647), Tdv (0.4145), Rpr (0.4131), and Vix (0.4128). However, its correlation with Oil (0.1263) is exceptionally low. Based on these values, $ComSent_t$ was defined as:

$$ComSent_t = 0.1263Oil_t + 0.5052Gld_t - 0.4131Rpr_t - 0.4145Tdv_t + 0.4128Vix_t + 0.4647Exr_t \quad (32)$$

Where: Oil is the global price of oil, Gld is the global price of gold, Rpr is the repo rate, Tdv is the trading volume on the South African market, Vix is the volatility index, and Exr is the Rand/Dollar exchange rate.

Table 4. 2 Principal component analysis

Eigenvalues: (Sum = 6, Average = 1)						
Number	Value	Difference	Proportion	Cum Value	Cum Prop	
1	2.841575	1.752282	0.4736	2.841575	0.4736	
2	1.089293	0.363680	0.1815	3.930868	0.6551	
3	0.725613	0.135411	0.1209	4.656482	0.7761	
4	0.590203	0.087430	0.0984	5.246684	0.8744	
5	0.502772	0.252229	0.0838	5.749456	0.9582	
6	0.250544	---	0.0418	6.000000	1.0000	
Eigenvectors (loadings):						
Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Oil	0.126343	0.848378	0.373009	0.293364	0.189742	-0.055615
Gld	0.505199	0.224205	-0.190474	-0.283811	-0.074527	-0.756388
Rpr	-0.413114	-0.204955	0.481219	0.504730	-0.547069	-0.041492
Tdv	-0.414529	-0.250866	0.506394	-0.171692	0.688620	0.071560
Vix	0.412777	0.047903	-0.577215	0.597658	0.323844	0.179090
Exr	0.464682	0.350360	-0.058315	-0.438135	-0.282995	0.621183
Ordinary correlations:						
	Oil	Gld	Rpr	Tdv	Vix	Exr
Oil	1.000000					
Gld	-0.071442	1.000000				
Rpr	-0.171692	0.420302	1.000000			
Tdv	-0.208626	0.453220	0.478147	1.000000		
Vix	-0.128273	0.537858	0.359414	0.315799	1.000000	
Exr	0.029656	0.726981	0.387769	0.387743	0.414997	1.000000

Source: Own estimations (2024)

The first principal component is positively correlated with four of these variables and negatively correlated with the other two. Therefore, increasing values of oil prices, gold prices, the volatility index, and the exchange rate will increase the value of the first principal component. Conversely, the increasing values of the repo rate and trading volume indices will decrease the value of the first principal component. The first two components explain 66% of the variation in the data. These two components lie on the steeper slope of the eigenvalue scree plot in Figure 4.2 below. Including the following two principal components accounts for 87%, making the slope less steep. The first two would have been an acceptable explanation level if the principal component analysis was for descriptive purposes only. However, all six proxies were used to analyse sentiment, even those with marginal explanatory power.

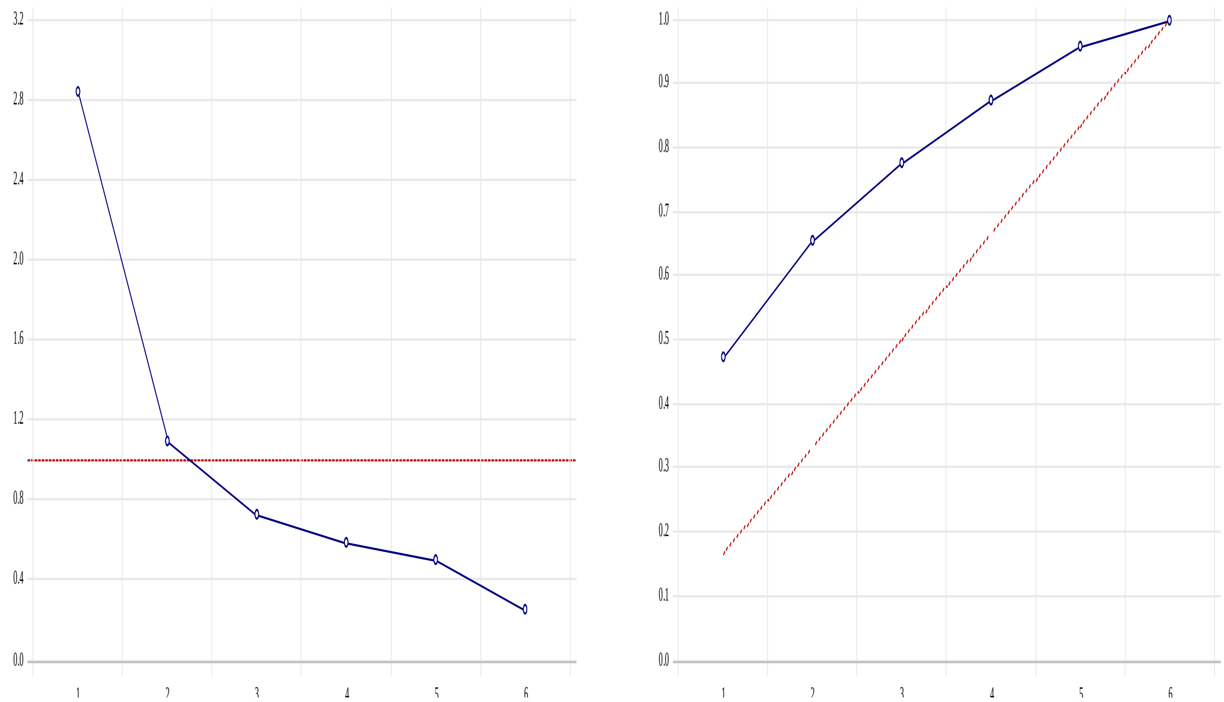

Figure 4. 2 Scree plot and eigenvalue cumulative proportion

Source: Own depiction (2024)

Figure 4.3 of the resulting index, ComSent, shows abrupt shifts in investor sentiment. Investor sentiment remained negative from 2009 to 2015, likely due to the aftermath of the 2007-2008 subprime crisis (Rupande et al., 2019). However, sentiment improved post-2010, with the market's recovery driven by the excitement surrounding the 2010 South African World Cup. Subsequently, following the 2015-2016 Chinese market turbulence (Han, 2019), sentiment shifted from negative to positive. A decline in South Africa's economic growth between 2017 and 2018, influenced by the 2016 Brexit and the 2018 US market slide, led to a slight dip in investor sentiment. From 2019 to 2020, investor sentiment was sharply downturn due to the COVID-19 pandemic (Cevik et al., 2022; Muguto et al., 2019). However, as the economy commenced its recovery post-pandemic, there was a steady increase in investor sentiment. The return data for sector indices shown in Figure 4.1 displays several patterns of volatility clustering and visually differs from the investor sentiment graph presented in Figure 4.3.

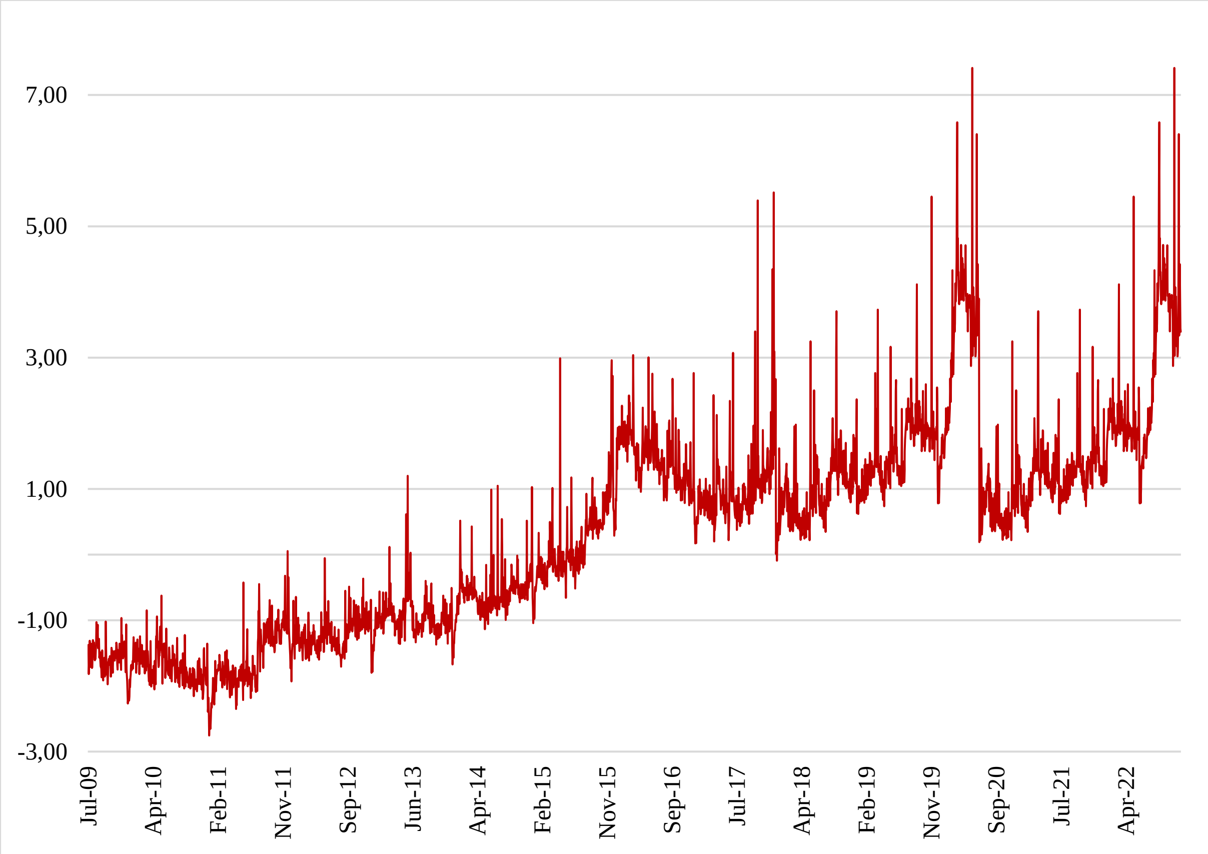

Figure 4. 3 Investor sentiment

Source: Own depiction (2024)

4.2.4 Unit root and stationarity tests

Table 4.3 below presents the outcomes of stationarity and unit root tests, corroborating the visual evidence and distribution statistics by affirming that all variables are integrated of order 0. The results from the ADF test indicate rejection of the null hypothesis of unit roots in favour of stationarity for all variables, including ComSent. Notably, all critical values exceeded the test statistic value in absolute terms. Similarly, the KPSS test yielded consistent findings, with all test statistics falling below the critical values, even at the 10% significance level. Consequently, the null hypothesis of stationarity in levels could not be dismissed in favour of the alternative hypothesis of unit roots. All subsequent analyses, thus, employed the series in levels as this confirmation of stationarity ensures that the data is suitable for further econometric modelling without the need for differencing.

Table 4. 3 Unit root and stationarity tests

Test	ADF	KPSS	Order of integration
	I(0)	I(0)	
J203	-16.5240***	0.1665	I(0)
J510	-7.0090***	0.3129	I(0)
J520	-7.5437***	0.5136	I(0)
J550	-7.9301***	0.3491	I(0)
J560	-5.9924***	0.7548	I(0)
J575	-9.8112***	0.3489	I(0)
J580	-20.6462***	0.3891	I(0)
J590	-10.6773***	0.3576	I(0)
ComSent	-4.9847***	0.2834	I(0)

***, ** and * denote significance at the 1%, 5% and 10% levels respectively. Critical values for ADF and KPSS tests were obtained from MacKinnon (1996) and Kwiatkowski et al. (1992).

Source: Own estimations (2024)

4.2.5 Serial correlation and heteroscedasticity tests

In addition to the descriptive statistics, Table 4.4 presents the results of the ARCH effects and autocorrelation tests on the sector indices. The LB statistics were significant for all the sector indices. This suggests temporal dependencies in the first moment of return distribution among the sector indices (Brooks, 2019). A Breusch-Godfrey serial correlation LM test was also conducted to verify the results. The test statistics were significant for all the sector indices, confirming serial correlation in returns. This contradicts the information efficiency in the EMH, as, in this case, past prices have some explanatory power over current prices. That is, the presence of serial correlation and ARCH effects implies that past returns and their volatility can predict future returns, indicating potential inefficiencies in the market.

The LB statistic for the squared returns was statistically significant for all the sector indices and higher than the LB statistic for the returns in the same table. According to Antoniou et al. (2005) and Muguto (2021), this indicates that higher-order temporal dependencies are more notable, an empirical pattern that has been widely documented in financial time series with high frequency. This supported the leptokurtic distributions seen in the return series in the descriptive statistics section. The evidence of serial correlation in the squared returns shows that the second moments of the series are dynamic, implying that there is heteroscedasticity. Specifically, the variability in returns is not constant over time but instead changes in response to past shocks, confirming the presence of ARCH effects. As a result, GARCH models could be used as they capture conditional volatility that is time-varying and autoregressive.

Table 4. 4 Serial correlation and heteroscedasticity tests on returns

	LB statistic	LB^2 statistic	Breusch-Godfrey LM statistic	Engle ARCH LM statistic
J203	52.502**	1871.000***	59.734**	1152.339***
J510	92.492***	1453.233***	98.007***	890.486***
J520	65.505***	675.667***	76.708***	462.800***
J550	78.854***	838.333***	91.267***	424.552***
J560	56.702**	2221.633***	64.696**	995.346***
J575	139.008***	2405.200***	161.884***	1130.333***
J580	61.635***	1282.667***	70.955***	665.608***
J590	43.362**	1172.367***	50.109**	644.260***

***, ** and * denote significance at the 1%, 5% and 10% levels respectively. LB and LB^2 denote the Ljung-Box statistics for the returns and squared returns, respectively. All four tests were conducted using 36 lags.

Source: Own estimations (2024)

4.3 Volatility analysis

The results from Table 4.4 in section 4.2.5 confirmed the presence of ARCH effects, which warranted using GARCH models, the results of which - unaugmented and augmented with sentiment - are analysed below. The best model selection was based on the SBIC, given the large sample size (Brooks, 2019). The analysis examined various aspects of the risk-return relationship, volatility persistence, leverage effects, and mean reversion among the sector indices. By incorporating sentiment as an augmenting factor, the study sought to explore how market sentiment influences volatility dynamics and whether it enhances the predictive power of the models. This comprehensive approach allowed for a nuanced understanding of how different factors interact to shape volatility in sectoral returns, providing insights crucial for effective risk management and investment decision-making in financial markets.

4.3.1 Model selection

In Table 4.5, the SBICs for the GARCH-M (1,1), GJR-GARCH-M (1,1) and E-GARCH-M (1,1) with three different distribution assumptions – normal, Student's t, and GED – are displayed. The highlighted values indicate the chosen model specifications that minimised the information criteria. Consistent with rejecting the null hypothesis of normality based on the Jarque-Bera statistic in the descriptive statistics, none of the selected models follow the normal distribution. This reflects the empirical evidence of non-normality in the return distributions. For both the sentiment unaugmented and augmented models, the GARCH-M (1,1) with a student's t-distribution and the GJR-GARCH-M (1,1) with a student's t-distribution were chosen for four and three sectors, respectively. The selection of the t-distribution extension was expected on daily returns in practice as the study used daily data.

The implications of selecting the student's t-distribution are significant for risk management. According to Sopov and Buzkova (2015), the GARCH-M (1,1) and GJR-GARCH-M (1,1) models with student-t distributions accurately capture volatility clustering and fat tail shape of the return distribution and do not result in systematic undervaluation of risk. The results show that only the financial and technology sectors differed in the models chosen between the sentiment unaugmented and augmented models. The financial sector with augmented sentiment chose the GJR-GARCH-M (1,1) with a GED distribution as the most efficient model. The GED distribution allowed for more general distributions of returns and a thick tail to capture the leptokurtic pattern evidence, volatility, and better forecast performance (Gregory et al., 2013).

When all the SBICs were compared from both the unaugmented and the sentiment-augmented models, the latter were mostly chosen except for the ALSI, basic materials, consumer services, and technology sector, signalling the significance of sentiment on the South African market. The ALSI consists of various sectors that are both sensitive and insensitive to sentiment; the results show that the sentiment-insensitive sectors dominated in this instance; hence, it had a lower SBIC where sentiment was unaugmented. The sectors that preferred sentiment omitted were those identified as essential as they produce goods and services with constant demand and low volatility regardless of the economic challenges faced. These sectors include utilities, healthcare, and certain industrials, which typically exhibit stable performance due to their essential nature and lower sensitivity to market sentiment fluctuations.

All the other sectors had lower SBICs when their models were augmented with sentiment, suggesting the significance of investor sentiment in explaining returns and volatility in the South African market. This indicates that market sentiment plays a crucial role in shaping sectoral performance, influencing both the direction and magnitude of returns and highlighting its importance in financial modelling and decision-making processes among investors. However, the differences suggest the presence of arbitrage based on prevailing sentiment. According to Muguto et al. (2022), the differences implied that an increase in sentiment resulted in overpricing rather than reduced uncertainty and volatility. This is due to the difference in the composition and types of investors, which is aligned with financial market anomalies linked to sentiment (Mahlophe and Muzindutsi, 2017).

Transforming the GARCH model mean equations into ARMA (1,1) models showed that historical returns and shocks in those historical returns could explain current returns. This transformation revealed that past returns and their volatility dynamics, encapsulated by the GARCH framework, provide significant explanatory power for current return movements. Further, the sentiment coefficients of some sectors and ALSI were significant. This implies that investor sentiment, as captured by the sentiment coefficients in the augmented models, has a statistically significant impact on current returns beyond the effects captured by past returns alone. That is, investor sentiment influences current returns independently of historical volatility, suggesting that market sentiment plays a crucial role in shaping short-term market dynamics and could potentially impact investment decisions and risk management strategies.

Muguto et al. (2022) found that the most efficient model for the South African market was the E-GARCH. However, this study found the GARCH-M and GJR-GARCH to be the most efficient models. The contrasts in the results can be explained by the different sample periods of each study and the specific characteristics of the datasets used, such as different market conditions and volatility patterns over time. Nevertheless, the study conducted by Rupande et al. (2019) and Rathilal (2021) concluded that the GJR-GARCH and GARCH-M were the most efficient models, respectively, supporting the findings of this study. These models excel in capturing the time-varying volatility dynamics and leverage effects observed in sectoral returns, providing robust frameworks for risk assessment and management in the South African market context.

Table 4. 5 Model selection

SBIC		GARCH-M (1.1)			GJR-GARCH-M (1.1)			E-GARCH-M (1.1)		
		Normal	T	GED	Normal	T	GED	Normal	T	GED
J203	-Sentiment	2.7932	2.7721	2.7748	2.7744	**2.7616***	2.7632	2.7811	2.7663	2.7682
	+Sentiment	2.7954	2.7747	2.7775	2.7745	**2.7629***	2.7643	2.7766	2.7643	2.7658
J510	-Sentiment	3.6370	**3.6315***	3.6330	3.7603	3.6338	3.6352	3.6388	3.6334	3.6348
	+Sentiment	3.6396	**3.6346***	3.6359	3.6419	3.7360	3.6381	3.7409	3.7233	3.6381
J520	-Sentiment	2.9860	2.9812	2.9823	2.9856	**2.9810***	2.9821	2.9888	2.9839	2.9851
	+Sentiment	2.9851	2.9808	2.9818	2.9845	**2.9806***	2.9816	2.9823	2.9787	2.9797
J550	-Sentiment	3.6283	3.6116	3.6161	3.62705	**3.6113***	3.6156	3.6398	3.6200	3.6252
	+Sentiment	3.6335	3.6162	3.6209	3.6319	**3.6157***	3.6203	3.6421	3.6232	3.6283
J560	-Sentiment	3.9486	**3.8581***	3.8819	3.9507	3.8602	3.8839	3.9483	3.8622	3.8856
	+Sentiment	3.9485	**3.8622***	3.8848	3.9499	3.8643	3.8865	4.0014	3.8649	3.8861
J575	-Sentiment	3.1004	**3.0543***	3.0631	3.1028	3.0565	3.0654	3.1140	3.0633	3.0736
	+Sentiment	3.0852	**3.0478***	3.0552	3.0874	3.0502	3.0576	3.0903	3.0543	3.0603
J580	-Sentiment	2.9995	2.9800	2.9823	2.9799	**2.9658***	2.9687	2.9904	2.9751	2.9748
	+Sentiment	2.9941	2.9746	2.9766	2.9796	2.9665	**2.9638***	2.9817	2.9678	2.9702
J590	-Sentiment	3.5008	**3.2673***	3.2967	3.5013	3.2682	3.2979	3.4924	**3.2566#**	3.2878
	+Sentiment	3.5050	**3.2698***	3.2998	3.5054	3.2711	3.3012	3.4958	3.6521	3.2909

* Denotes the selected model chosen using the SBIC information criteria

# Denotes that the chosen model using the SBIC information criteria was explosive.

Source: Own estimations (2024)

4.3.2 Discussion of the results on the nature of volatility among sector indices

Following the analyses on descriptive statistics, serial correlation, and heteroscedasticity tests, and the selection of appropriate GARCH models, this section presents results from selected sentiment-unaugmented and augmented models. The study examined the results from the mean equations associated with average returns, focusing on parameters such as risk premium, serial correlation, and the effects of past shocks. Additionally, the variance equations were scrutinized to understand the nature of volatility in terms of volatility persistence, asymmetry, and mean reversion. The inclusion of the sentiment component in both equations provided insights into how sentiment influences sector indices. Sentiment coefficients quantified the influence of market sentiment on current returns and volatility dynamics, including whether market shocks exhibited persistence and asymmetry in their responses.

4.3.2.1 The average returns

The mean equation intercept, μ, in Tables 4.6 and 4.7 showed the return when total risk, the effects of shocks, and past period return were zero. The parameter was statistically significant for all the sector indices for both the sentiment-unaugmented and augmented results. The parameter's significance showed that the indices' average return is determinable when total risk, the effects of shocks, and past period return are zero (Muguto, 2021). The sentiment-unaugmented and augmented results showed that the risk premium parameter, θ, in the mean equation was positive and statistically significant for all the sector indices except for the travel and leisure and financial sectors. This means there was a positive compensation for bearing risk as the risk measured by conditional variance increased with the mean daily return. The travel and leisure sector coefficients were statistically insignificant for both tables.

This contradicts the EMH and CAPM predictions that risk should correspond with returns. Therefore, the conditional mean equation received no feedback from conditional variance (Brooks, 2019). In comparison, the financial sector was negative and significant at 5% for the sentiment-unaugmented table and negative and insignificant for the sentiment-augmented table. This showed that a positive risk premium was not a standard feature across all sectors. The serial correlation parameter, α, was positive and significant for all the sector indices for both the sentiment-unaugmented and augmented results. This suggested a positive serial correlation in returns, implying that positive returns could explain future returns. The positive correlation contradicts the weak form of efficiency, as abnormal returns can be earned using technical trading strategies (Bodie et al., 2019; Muguto, 2021).

The coefficient that captures the effect of past shocks on returns, ν, was negative and statistically significant for all the indices in both the sentiment-unaugmented and augmented results. This indicated that future returns could be explained by past negative shocks, reflecting a persistent impact of adverse market events on subsequent performance. This finding notes the challenge for investors to counteract noise trading effectively, suggesting market inefficiencies persist despite efforts to mitigate their effects. That is, market participants continue to struggle to price assets efficiently in the face of past negative shocks, potentially leading to suboptimal investment decisions and heightened market volatility. Understanding and managing the implications of historical shocks on future returns remain critical for effective risk management and investment strategy formulation.

4.3.2.2 The nature of volatility among sector indices

The conditional variance equation showed that the leverage effect parameter, δ, was significant and positive for all the sector indices for both sentiment-unaugmented and augmented equation results. This confirmed the presence of the leverage effect because negative shocks increased volatility more than positive shocks of an equal magnitude. The leverage effect is explained by the financial leverage hypotheses of Black (1976) and Christie (1982) and the volatility feedback effect. According to the financial leverage hypothesis, financial leverage is increased by negative returns, increasing stock return volatility. Therefore, asymmetric volatility has been regularly associated with financial leverage effects, and the evidence of asymmetric volatility can reflect the existence of dynamic risk premiums (Mandimika and Chinzara, 2012; Muguto, 2021).

The effect of past shocks, β, was significant for all the sector indices in both sentiment-unaugmented and augmented results. This indicated that previous innovations could explain current volatility, suggesting market inefficiency. Therefore, future prices or price changes can only be rationalized in an inefficient market by information from past prices. Similar to the findings of the mean equation, these results challenge the efficient market hypothesis theory, which posits that market prices fully reflect all available information. The results further revealed that δ was greater than β for all sector indices, indicating that the impact of negative shocks outweighed that of positive shocks of equal magnitude. This asymmetry suggests that negative market shocks have a stronger and more lasting effect on volatility than positive shocks, highlighting the inherent dynamics of market reactions to adverse events.

The positive innovation contribution is equivalent to β, while $\beta+\delta$ represents the negative innovation contributions. This means that for a one-unit positive shock on the sentiment-unaugmented, the ALSI volatility would increase by 0.0287, whereas for the same magnitude of a negative shock, volatility would increase by 0.9260. According to Bohl and Siklos (2003), the $(\beta+\delta)/\beta$ ratio is an intuitive measure of asymmetry in volatility responses. The financial sector exhibited the highest volatility asymmetry levels for the sentiment-unaugmented results, whereas the technology sector had the lowest. The sentiment-augmented results also showed that the ALSI indicated the highest volatility asymmetry levels, whereas the travel and leisure sector had the lowest volatility asymmetry levels across all sectors.

The average asymmetry across all sector indices with significant leverage effects was approximately 22.5156 and 21.2495 for sentiment-unaugmented and augmented results, respectively. This suggested that, for example, in sentiment-augmented results, negative innovations increased volatility on average 21.2495 times more than positive innovations of equal magnitude. These findings highlight the pronounced asymmetry in market reactions to positive and negative shocks across different sectors, indicative of the complex dynamics of volatility and risk management in financial markets. That is, the substantial disparity in how markets respond to positive and negative shocks highlights the intricate interplay of factors influencing stock market volatility and the risk management strategies that allow investors to mitigate its effects in their portfolios.

The degree of volatility persistence, $\beta+\lambda$, was positive and less than one for all the sector indices in both the sentiment-unaugmented and augmented results. This finding suggests the presence of volatility clustering, a common feature across all indices, affirming that volatility persistence is a regular occurrence in financial time series data and meeting the stationarity condition for all sectors. According to Engle and Patton (2001), this implies that current volatility shocks influence the expected volatility in future periods. Examining the relationship between returns and volatility is crucial, as persistent volatility influences the risk premium significantly (Mandimika and Chinzara, 2012; Muguto, 2021). The sentiment-unaugmented and augmented results indicated that the ALSI and the financial sector exhibited the highest degree of persistence compared to other sector indices.

Table 4. 6 Selected models without sentiment

Index	J203	J510	J520	J550	J560	J575	J580	J590
Selected model	GJR-GARCH-M(1.1) – T-distribution	GARCH-M (1.1) – T-distribution	GJR-GARCH-M (1.1) – T-distribution	GJR-GARCH-M (1.1) – T-distribution	GARCH-M (1.1) – T-distribution	GARCH-M (1.1) – T-distribution	GJR-GARCH-M (1.1) – T-distribution	GARCH-M (1.1) – T-distribution
Parameters	CONDITIONAL MEAN EQUATION							
μ	2.8664***	4.5663***	2.7974***	4.5630***	7.2307***	3.5400***	1.0566***	1.3788***
θ	0.1705***	0.1749***	0.1227***	0.1252***	0.0803***	0.0177	-0.0309**	0.0372*
α	0.9948***	0.9984***	0.9899***	0.9961***	0.9950***	0.9938***	0.9464***	0.9974***
υ	-0.9521***	-0.9737***	-0.9480***	-0.9517***	-0.9487***	-0.9075***	-0.9683***	-0.9736***
	CONDITIONAL VARIANCE EQUATION							
ω	0.0213***	0.08177***	0.0212***	0.0623***	0.0741***	0.0502***	0.0283***	0.0320***
β	0.0287***	0.0757***	0.0610***	0.0408***	0.0627***	0.1081***	0.0155*	0.0821***
λ	0.1139***	-	0.0475***	0.0417***	-	-	0.1117***	-
δ	0.8973***	0.8901***	0.9015***	0.9107***	0.9161***	0.8605***	0.9047***	0.9083***
γ	10.3511***	14.5395***	15.4332***	10.2409***	5.7324***	6.5134***	10.7805***	4.0368***
(β + δ)	0.926	0.9658	0.9625	0.9515	0.9788	0.9686	0.9202	0.9904
(β + δ)/β	32.2648	12.7583	15.7787	23.3211	15.6108	8.9602	59.3677	12.0633
β + λ	0.1426	0.0757	0.1085	0.0825	0.0627	0.1081	0.1272	0.0821

***, ** and * denote significance at the 1%, 5% and 10% levels respectively. All mean equations were modelled as ARMA (1.1) processes.
Source: Own estimations (2024)

Table 4. 7 Selected models with sentiment

Index	J203	J510	J520	J550	J560	J575	J580	J590
Selected model	GJR-GARCH (1.1) – T-distribution	GARCH-M (1.1) – T-distribution	GJR-GARCH (1.1) – T-distribution	GJR-GARCH (1.1) – T-distribution	GARCH-M (1.1) – T-distribution	GARCH-M (1.1) – T-distribution	GJR-GARCH (1.1) – GED	GARCH-M (1.1) – T-distribution
Parameters	CONDITIONAL MEAN EQUATION							
μ	2.7756***	4.2796***	2.7769***	3.8546***	7.0660***	3.6076***	1.0344***	1.5813***
θ	0.1852***	0.1919***	0.1320***	0.1111***	0.0911***	0.0269	-0.0129	0.0361*
α	0.9927***	0.9989***	0.9897***	0.9963***	0.9965***	0.9940***	0.9540***	0.9981***
υ	-0.9481***	-0.9740***	-0.9453***	-0.9525***	-0.9506***	-0.9056***	-0.9774***	-0.9735***
Compsent	-0.0181	0.0560	-0.0676**	0.1089**	-0.0373	-0.0222	-0.0339***	-0.0423
	CONDITIONAL VARIANCE EQUATION							
ω	0.0236***	0.0829***	0.0354***	0.0644***	0.0932***	0.1129***	0.0467***	0.0528***
β	0.0212**	0.0739***	0.0611***	0.0390***	0.0613***	0.1165***	0.0228**	0.0928***
λ	0.1212***	-	0.0516***	0.0434***	-	-	0.1194***	-
δ	0.8967***	0.8902***	0.8871***	0.9103***	0.9092***	0.8008***	0.8776***	0.8905***
γ	10.7493***	14.8073***	15.9603***	10.0894***	5.8162***	7.0747***	1.5902***	4.0623***
Compsent	0.0046***	0.0052	0.0091***	0.0005	0.0054	0.0314***	0.0113***	-0.0099**
(β + δ)	0.9179	0.9641	0.9482	0.9493	0.9705	0.9173	0.9004	0.9833
(β + δ)/β	43.2972	13.0460	15.5188	24.3410	15.8320	7.8738	39.4912	10.5959
β + λ	0.1424	0.0739	0.1127	0.0824	0.0613	0.1165	0.1422	0.0928

***, ** and * denote significance at the 1%, 5% and 10% levels respectively. All mean equations were modelled as ARMA (1.1) processes.

Source: Own estimations (2024)

The models for the conditional variance were permissible for all the sector indices as the non-negativity conditions in the volatility equation ($\omega > 0$, $\beta > 0$, $\lambda \geq 0$, $\beta+\lambda \geq 0$) were all satisfied. The estimated degrees of freedom parameter, γ, for all the sector indices unaugmented and augmented with sentiment with a student's t-distribution was significant and low (below 30); this suggested that the distribution was not normally distributed and was heavy-tailed (Stoyanov et al., 2011). Further, the GED-distribution for the sentiment-augmented financial sector showed an estimated degree of freedom parameter that was significant and less than two, indicating that the GED was fat-tailed as suggested by the kurtosis and JB statistic in Table 4.1 (Brooks, 2019).

The analysis of sentiment-unaugmented versus sentiment-augmented models reveals key differences in how sentiment impacts sector indices' volatility and returns. In sentiment-unaugmented models, risk premiums were generally positive and significant except in travel and leisure and financial sectors, suggesting compensation for risk aligns with conditional variance. Conversely, sentiment-augmented models highlighted a more nuanced picture: the financial sector showed variable risk premium effects, and sentiment significantly influenced returns and volatility dynamics.

Both models demonstrated significant leverage effects, where negative shocks increased volatility more than positive ones, but sentiment-augmented results exhibited higher volatility asymmetry and persistence. For instance, sentiment-augmented models showed greater volatility response to negative shocks compared to sentiment-unaugmented models, with the ALSI and financial sector displaying the highest asymmetry. Overall, sentiment-augmented models provided more profound insights into the influence of market sentiment, revealing pronounced asymmetries and variations in volatility persistence that were less apparent in sentiment-unaugmented models.

4.4 Model adequacy tests

Table 4.8 displays the results of two model adequacy tests – the LB test for autocorrelation and the ARCH LM test for heteroscedasticity that were conducted to assess the validity of the chosen models. The standardised residuals should not be significant for autocorrelation and heteroscedasticity to ensure that the models were correctly specified. The LB statistic tested the independence of the residuals, and the test statistics were insignificant for all sector indices. This means the null hypothesis of no serial correlation in the standardised residuals could not be rejected. Therefore, the mean equation was correctly specified for all the sector indices. The ARCH LM test statistics were insignificant, and they showed that there were no ARCH effects in the standardised residuals of the indices. Therefore, the LB and ARCH-LM test results showed that the variance equations for the indices were correctly specified.

Table 4. 8 Model adequacy tests

	Unaugmented		Augmented	
	LB statistic	LM statistic	LB statistic	LM statistic
J203	37.761	37.827	35.9628	36.0254
J510	28.381	9.190	27.02948	8.7528
J520	41.683	28.365	39.6980	27.0141
J550	52.793	20.194	50.2794	19.2327
J560	24.785	39.810	23.6045	37.9138
J575	33.718	36.111	32.1125	34.3918
J580	25..625	44.270	24.4045	42.1624
J590	25.936	44.528	24.70113	42.4073

Source: Own estimations (2024)

4.5 Unconditional volatility correlations

Table 4.9 showcases the unconditional volatility correlations among sector and broad market indices, both with and without sentiment factored in. In the absence of sentiment, the most robust correlation was seen between the broad market index (J203) and the financial sector (J580), registering at 0.80***. In contrast, the weakest link was between basic materials (J510) and consumer services (J575), at -0.04. These connections remained largely unaltered even when sentiment was introduced into the analysis. The strongest correlation held steady between the broad market index and the financial sector (0.80***), while the weakest remained between basic materials and consumer services (-0.04). This steadfastness suggests that sentiment doesn't significantly sway the relative volatility relationships among these indices. The inherent volatilities of the sectors and the broad market appear resistant to sentiment fluctuations, retaining their correlation patterns even in the presence of sentiment considerations.

Table 4. 9 Unconditional correlations between volatilities

Unaugmented								
	J203	J510	J520	J550	J560	J575	J580	J590
J203	1.0000 ***	-0.0265	0.7334 ***	0.7905 ***	0.5696 ***	0.4214 ***	0.8030 ***	-0.0069
J510	-0.0265	1.0000 ***	-0.0006	-0.0419	-0.0106	-0.0141	0.0041	0.2953 ***
J520	0.7334 ***	-0.0006	1.0000 ***	0.4475 ***	0.5160 ***	0.4564 ***	0.7927 ***	0.0038
J550	0.7905 ***	-0.0419	0.4475 ***	1.0000 ***	0.3573 ***	0.2925 ***	0.4723 ***	-0.0356
J560	0.5696 ***	-0.0106	0.5160 ***	0.3573 ***	1.0000 ***	0.2886 ***	0.5337 ***	-0.014
J575	0.4214 ***	-0.0141	0.4564 ***	0.2925 ***	0.2886 ***	1.0000 ***	0.4981 ***	-0.0191
J580	0.8030 ***	0.0041	0.7927 ***	0.4723 ***	0.5337 ***	0.4981 ***	1.0000 ***	0.0124
J590	-0.0069	0.2953 ***	0.0038	-0.0356	-0.014	-0.0191	0.0124	1.0000 ***
Sentiment-augmented								
	J203	J510	J520	J550	J560	J575	J580	J590
J203	1.0000 ***	-0.0267	0.7315 ***	0.7885 ***	0.5699 ***	0.4204 ***	0.8046 ***	-0.0081
J510	-0.0267	1.0000 ***	-0.001	-0.0446	-0.0134	-0.0167	0.0027	0.2946 ***
J520	0.7315 ***	-0.001	1.0000 ***	0.4446 ***	0.5152 ***	0.4574 ***	0.7877 ***	0.0041
J550	0.7885 ***	-0.0446	0.4446 ***	1.0000 ***	0.3614 ***	0.2911 ***	0.4676 ***	-0.0365
J560	0.5699 ***	-0.0134	0.5152 ***	0.3614 ***	1.0000 ***	0.2857 ***	0.5245 ***	-0.0143
J575	0.4204 ***	-0.0167	0.4574 ***	0.2911 ***	0.2857 ***	1.0000 ***	0.4832 ***	-0.0179
J580	0.8046 ***	0.0027	0.7877 ***	0.4676 ***	0.5245 ***	0.4832 ***	1.0000 ***	0.011
J590	-0.0081	0.2946 ***	0.0041	-0.0365	-0.0143	-0.0179	0.011	1.0000 ***

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

Source: Own estimations (2024)

Both the sentiment-absent and sentiment-present results highlight the financial sector's greater interconnectedness with other sectors, whereas the basic materials sector appears the most isolated. This high degree of connection for the financial sector emphasizes its critical role in the overall market's behavior. Its strong correlations suggest substantial volatility spillovers to and from other sectors, indicating a significant interdependence and potential for systemic risk transmission. Conversely, the basic materials sector displays negative correlations with several other sectors, suggesting potential diversification advantages. These negative correlations imply that incorporating basic materials stocks into a diversified portfolio could reduce overall risk, thereby enhancing stability and resilience.

The observed differences in unconditional correlations among sectors reveal varying degrees of interdependence within the market. These variations can be attributed to sector-specific factors like differing economic cycles, regulatory environments, and market sensitivities. For instance, sectors like financials, closely tied to the broader economy, are more susceptible to macroeconomic indicators and policy changes, reflected in their interconnectedness. In contrast, sectors such as basic materials, exhibiting lower or negative correlations, are driven more by unique supply-demand dynamics, global commodity prices, and sector-specific risks. This disparity in correlations highlights the importance of sectoral analysis in portfolio diversification and risk management strategies, as it provides valuable insights into how different sectors respond to evolving market conditions and economic shifts.

4.6 Volatility correlations among the sector indices

This section shows the results from the ADCC-GARCH model of Cappiello et al. (2006) that was used to measure time-varying correlations in the volatilities among major sector indices in the South African market. The multivariate-GARCH (M-GARCH) framework used three GARCH specifications – the GARCH-M (1,1), GJR-GARCH (1,1), and E-GARCH (1,1). The optimal specification was selected based on minimising the information criteria in a particular sector. For both the sentiment unaugmented and augmented results, all the sectors chose the GARCH-M (1,1) and GJR-GARCH (1,1) specifications, except for the sentiment unaugmented technology sector for which the E-GARCH (1,1) was chosen. However, it was explosive ($\beta+\delta>1$); therefore, the second best model, GARCH-M (1,1), was selected. The sectors that selected the extended GARCH models indicated significant leverage effects.

Tables 4.10 and 4.11 show the effect of dynamic connectedness across different sector indices. The inclusion of sentiment-augmented sector indices addressed the objective of examining the influence of prevailing investor sentiment on the dynamic connectedness and hedging effectiveness among the major sector indices in South Africa. From the results, the θ_1 and θ_2 coefficients capture the effect of previous shocks and previous dynamic conditional correlations on current dynamic conditional correlations, respectively. The coefficients were statistically significant for 23 sector index pairs and 22 sector index pairs for Tables 4.10 and 4.11, respectively. This simultaneous significance indicated the presence of time-varying correlations within and across the sector indices on the South African market.

Although θ_2 was statistically significant for all the sector index pairs, for the sentiment unaugmented results, θ_1 was statistically insignificant in five sector index pairs. For the sentiment-augmented results, θ_1 was statistically insignificant in six sector index pairs. This suggests that while investor sentiment shapes the dynamic connectedness among sector indices, its impact may vary across different sectors. The statistical significance of θ_2 across all pairs highlights the persistent influence of previous dynamic correlations, emphasising the importance of historical interconnectedness in predicting future market behaviour. However, the variable significance of θ_1 indicates that the immediate effect of previous shocks can differ depending on whether sentiment is considered.

The results of the time-varying volatility correlations showed that the DCC-GARCH framework was suitable to model the correlations as the θ_1 coefficients were statistically significant. For all the 28 sector index pairs for the respective tables, the stationarity condition, $\theta_1 + \theta_2 <1$, was met. The time-varying correlations among the sector indices were higher and statistically stronger for the sentiment-augmented results, suggesting that sentiment plays a role in the correlations, although the sector indices showed heterogeneity in response to the shocks.. This was because sentiment significantly impacted the volatility of sector indices in the market. There is, thus, a need to incorporate sentiment indicators in volatility models to capture the full dynamics of market behaviour and improve hedging and risk management strategies.

The asymmetry parameter, g, was statistically insignificant in 10 sector index pairs and significant in 18 sector index pairs for the sentiment unaugmented table. In contrast, in the sentiment-augmented table, it was statistically insignificant in 7 sector index pairs and significant in 21 sector index pairs. Overall, the asymmetry parameter was statistically significant for most of the sector index pairs in both tables, implying that asymmetrical effects are prevalent in the volatility dynamics of sector indices. This suggests that negative shocks, or bad news, have a different impact on volatility compared to positive shocks, or good news, highlighting the importance of considering asymmetry in modelling and forecasting market behaviour, especially when accounting for sentiment factors in the volatility modelling.

The results from Tables 4.10 and 4.11 also addressed the objective of assessing the impact of dynamic connectedness among the sector indices on their hedging effectiveness. The daily average volatility correlations were positive but less than one; this implied that diversification benefits existed among the sector indices but varied across pairs. The mean daily volatility correlation of 0.8551 between the financial and technology sectors for the sentiment-augmented results was close to 1, suggesting homogeneity and minimal diversification benefits across these sector indices. The lowest correlations were between pairs that included the consumer services sector. This could be because this sector is less correlated with other sectors due to its unique demand drivers and market dynamics, in line with Bacilar et al. (2015).

For the unaugmented table, the highest standard deviation of 0.1036 was between the basic materials and technology sectors but 0.1341 between the same sectors in the sentiment-augmented table. In comparison, the lowest mean daily volatility correlation standard deviation for the sentiment unaugmented table was 0.0170, found between the ALSI and consumer services sector and also between the basic materials and consumer services sectors. For the sentiment-augmented table, the lowest mean daily volatility correlation standard deviation was 0.0220 for the same pairs. These variations in standard deviations indicate the differing levels of volatility and correlation stability among sector pairs, highlighting the potential for effective diversification strategies depending on the sector combinations.

The volatility correlations ranged from -0.0262 to 0.7285 across sector indices for the sentiment unaugmented table and from -0.0339 to 0.9430 for the sentiment augmented table. The results indicated higher levels of homogeneity and heterogeneity among the sentiment-augmented sector indices than unaugmented ones. Both the highest and lowest volatility correlations were found among the sentiment-augmented sector indices. The finding suggested that the sentiment-augmented table had the pairs with the highest correlation and diversification benefits. The results indicated evident linkages across the pairs of the sector indices. The findings showed that the conditional correlation estimates were higher than the static correlations, which confirmed an increased level of connectedness over time. The assumption that the correlations were static could result in an inefficient measurement of correlations.

Table 4. 10 ADCC-GARCH output – Sentiment

	θ_1	θ_2	g	ρ1.2 (μ)	ρ1.2 (max)	ρ1.2 (min)	ρ1.2 (σ)
J203 - J510	0.0080*	0.7093***	0.0027**	0.2366	0.4118	0.0690	0.0513
J203 - J520	0.0088*	0.6971***	0.0022**	0.1612	0.3352	0.0521	0.0375
J203 - J550	0.0041**	0.6604**	0.0064**	0.0933	0.2084	0.0353	0.0170
J203 - J560	0.0059*	0.7216***	0.0007	0.2468	0.3851	0.1081	0.0636
J203 - J575	0.0195***	0.6845**	0.0095***	0.3898	0.6723	0.1642	0.0868
J203 - J580	0.0146***	0.7018***	0.0039**	0.3022	0.5284	0.0989	0.0802
J203 - J590	0.0127***	0.7063***	0.0035**	0.2973	0.5129	0.0726	0.0798
J510 - J520	0.0114***	0.6789***	0.0071***	0.2061	0.4615	0.0018	0.0456
J510 - J550	0.0049*	0.6675**	0.0025**	0.1047	0.2378	0.0084	0.0170
J510 - J560	0.0132***	0.7073***	0.0061***	0.3278	0.5941	0.0436	0.0995
J510 - J575	0.0103***	0.7015***	0.0052**	0.2508	0.4505	0.0679	0.0591
J510 - J580	0.0196***	0.6937***	0.0080***	0.3372	0.6542	0.0004	0.0990
J510 - J590	0.0176***	0.7004***	0.0064**	0.3279	0.6354	-0.0262	0.1036
J520 - J550	0.0067*	0.7182***	0.0004	0.1328	0.2882	-0.0205	0.0493
J520 - J560	0.0093*	0.7058***	0.0046*	0.2838	0.5628	0.1468	0.0552
J520 - J575	0.0039	0.7171***	0.0009	0.1805	0.3123	0.1110	0.0277
J520 - J580	0.0117***	0.6960***	0.0043*	0.2569	0.5170	0.1135	0.0517
J520 - J590	0.0098*	0.7077***	0.0022**	0.2508	0.4793	0.1046	0.0507
J550 - J560	0.0029	0.7284***	0.0003	0.1463	0.2851	-0.0230	0.0707
J550 - J575	0.0050*	0.6912***	0.0038**	0.0990	0.2614	-0.0036	0.0244
J550 - J580	0.0022	0.7284***	-0.0003	0.0886	0.1576	-0.0072	0.0363
J550 - J590	0.0025	0.7280***	-0.0003	0.0871	0.1647	0.0027	0.0365
J560 - J575	0.0031	0.7274***	0.0002	0.2906	0.3935	0.1824	0.0500
J560 - J580	0.0132***	0.7039***	0.0031**	0.4086	0.6542	0.2298	0.0673
J560 - J590	0.0141***	0.7052***	0.0025**	0.4039	0.6436	0.2119	0.0733
J575 - J580	0.0104**	0.7059***	0.0024	0.3757	0.5884	0.1927	0.0528
J575 - J590	0.0098*	0.7084***	0.0025	0.3629	0.5870	0.1831	0.0551
J580 - J590	0.0278***	0.6869**	0.0009	0.6606	0.7285	0.4900	0.0290

Source: Own estimations (2024)

Table 4. 11 ADCC-GARCH output + Sentiment

	θ_1	θ_2	g	ρ1.2 (μ)	ρ1.2 (max)	ρ1.2 (min)	ρ1.2 (σ)
J203 - J510	0.0104***	0.9181***	0.0035**	0.3063	0.5330	0.0893	0.0664
J203 - J520	0.0114***	0.9023***	0.0029**	0.2087	0.4339	0.0674	0.0485
J203 - J550	0.0053*	0.8549***	0.0082***	0.1208	0.2698	0.0456	0.0220
J203 - J560	0.0076*	0.9341***	0.0009	0.3195	0.4985	0.1400	0.0823
J203 - J575	0.0253***	0.8861***	0.0123***	0.5045	0.8703	0.2125	0.1123
J203 - J580	0.0189***	0.9085***	0.0050**	0.3912	0.6840	0.1280	0.1039
J203 - J590	0.0165***	0.9143***	0.0045**	0.3848	0.6639	0.0940	0.1033
J510 - J520	0.0148***	0.8789***	0.0093***	0.2668	0.5974	0.0024	0.0590
J510 - J550	0.0064*	0.8641***	0.0033**	0.1355	0.3079	0.0109	0.0220
J510 - J560	0.0171***	0.9156***	0.0079**	0.4243	0.7691	0.0564	0.1288
J510 - J575	0.0133***	0.9081***	0.0067**	0.3247	0.5832	0.0879	0.0765
J510 - J580	0.0254***	0.8980***	0.0104**	0.4365	0.8469	0.0005	0.1281
J510 - J590	0.0228***	0.9067***	0.0083***	0.4245	0.8225	-0.0339	0.1341
J520 - J550	0.0087	0.9297***	0.0005	0.1720	0.3731	-0.0265	0.0638
J520 - J560	0.0120***	0.9136***	0.0059**	0.3673	0.7285	0.1901	0.0715
J520 - J575	0.0051	0.9282***	0.0012	0.2336	0.4043	0.1437	0.0359
J520 - J580	0.0151***	0.9010***	0.0055**	0.3326	0.6692	0.1470	0.0670
J520 - J590	0.0126***	0.9161***	0.0028**	0.3247	0.6205	0.1354	0.0656
J550 - J560	0.0037	0.9429***	0.0003	0.1894	0.3691	-0.0298	0.0915
J550 - J575	0.0065	0.8947***	0.0049**	0.1282	0.3384	-0.0046	0.0315
J550 - J580	0.0028	0.9429***	-0.0003	0.1147	0.2040	-0.0094	0.0470
J550 - J590	0.0032	0.9424***	-0.0004	0.1128	0.2133	0.0035	0.0473
J560 - J575	0.0040*	0.9416***	0.0002	0.3761	0.5094	0.2362	0.0648
J560 - J580	0.0170***	0.9112***	0.0041**	0.5289	0.8469	0.2975	0.0871
J560 - J590	0.0183***	0.9129***	0.0033**	0.5228	0.8331	0.2742	0.0949
J575 - J580	0.0135***	0.9138***	0.0031**	0.4864	0.7617	0.2494	0.0684
J575 - J590	0.0127***	0.9170***	0.0032**	0.4698	0.7598	0.2370	0.0713
J580 - J590	0.0360***	0.8892***	0.0012*	0.8551	0.9430	0.6343	0.0375

Source: Own estimations (2024)

4.7 Total directional volatility among sector indices

Table 4.12 shows the results from the static spillover estimations, without and with sentiment, based on the Diebold and Yilmaz index. The total directional connectedness sentiment-unaugmented results show that the financial sector (76.85%) was the largest transmitter of shocks to all the sector indices, followed by industrial (71.64%) and consumer services (42.02%). This could be because the financial sector is deeply intertwined with various economic activities and is a crucial intermediary, amplifying market shocks across sectors. Telecommunications (39.49%), travel and leisure (24.83%), technology (9.59%), and basic materials (9.34%) followed. Due to their specific market roles and dependencies, these sectors exhibited varying degrees of transmission capabilities influenced by sector-specific factors such as demand volatility and technological advancements.

The total directional connectedness in the "from" column showed a similar order except for basic materials and travel and leisure, where their positions were reversed compared to the transmission rankings. The financial sector (66.00%) received the most spillover from other sectors, followed by industrial (64.37%) and consumer services (51.51%). Telecommunications (51.23%), travel and leisure (37.76%), basic materials (13.56%), and technology (12.56%) followed. Again, the financial sector's prominent role as a receiver of spillovers highlights its sensitivity to external market shocks and its pivotal position in absorbing volatility from other sectors, reinforcing its interconnectedness and influence within the broader market dynamics. This means that during periods of market turbulence, the financial sector can be a barometer of overall market health and stability.

Like the dynamic connectedness results without sentiment, the results with sentiment showed a similar pattern of connectedness among the sector indices. The financial sector (76.60%) was the largest transmitter of shocks to all the sector indices, followed by the industrial sector (71.60%) and consumer services (42.17%). Telecommunications (39.38%), travel and leisure (24.66%), technology (9.61%), and basic materials (9.40%) followed. The total directional connectedness in the "from" column also showed a similar pattern to the sentiment-unaugmented results. The financial sector (65.87%) received the most spillover from other indices, followed by the industrial (64.31%) and consumer services (51.61%). Telecommunications (51.16%), travel and leisure (37.60%), basic materials (13.56%), and technology (12.58%) followed.

The value of connectedness among the sector indices showed a minor difference between the sentiment unaugmented and augmented dynamic connectedness tables, suggesting that sentiment had a marginal impact on the significance of connectedness among the sector indices. Specifically, the total connectedness over the sample period was 45.71%, indicating a substantial degree of system interdependence among the sector indices. In contrast, the total connectedness slightly decreased to 45.67% for the sentiment-augmented results. Overall, this implies that approximately 46% of the changes in the volatility of these sector indices were influenced by mutual interactions. This moderate level of interdependence highlights that about 46% of the forecast error variance stemmed from spillovers among the indices, underscoring their significant interconnectedness even during turbulent economic periods.

4.8 Net volatility spillovers among sector indices

The net volatility spillovers for the sentiment unaugmented and augmented dynamic connectedness tables indicate that the industrial and financial sectors were net transmitters of risk out of all the sector indices. The sentiment-unaugmented results show that the financial sector (10.86%) was the main exporter of risk, followed by the industrial sector (7.27%). The order of the sentiment-augmented results was the same – the financial sector (10.73%) and the industrial sector (7.29%). This consistent pattern emphasises the financial sector's significant role as a volatility transmitter, supported by findings from studies such as Shen et al. (2021), Chirilă (2022), and Khan et al. (2022) that highlight its prominence. On the other hand, travel and leisure (-12.93%) was the main receiver of risk, followed by telecommunications (-11.74%), consumer services (-9.49%), basic materials (-4.21%), and technology (-2.97%).

The sentiment-augmented results mirrored this order: travel and leisure (-12.93%), telecommunications (-11.78%), consumer services (-9.44%), basic materials (-4.16%), and technology (-2.97%). This indicates a consistent vulnerability among these sectors to volatility shocks, illustrating their roles as net risk recipients within the interconnected South African market environment. The results are in line with the findings of Chatziantoniou et al. (2021), Shahzad et al. (2021), and Dang et al. (2023), who observed that cyclical industries typically tend to be net recipients of shocks due to their sensitivity to economic cycles and market conditions. This contrasts defensive sectors such as utilities and healthcare, which often exhibit more resilience and may even act as net transmitters of risk during certain prevailing market conditions.

When the sentiment-unaugmented results were compared to the sentiment-augmented, it was found that the net spillover increased for four of the sector indices, stayed the same for two, and decreased for the remaining two, namely the telecommunications (-0.04%) and financial sector (-0.13%). This implied that when sentiment was included, most sector indices transmitted more shocks over time. This could be because sentiment triggers high volatility in the market, and this, therefore, increases net volatility spillover among the sector indices. However, although the intensity of the spillovers varied over time, the indices maintained their respective positions as net transmitters and net recipients with and without sentiment, suggesting fundamental stability in their relative positions within the interconnected market dynamics, even in turbulent periods.

The diagonal elements of the connectedness table represent the own connectedness of the sector indices. These are the largest values under both sentiment unaugmented and augmented tables – up to 87% for technology. This is consistent with Diebold and Yilmaz (2012), Ji et al. (2019), and Antonakakis et al. (2023) findings that own-volatility spillovers are likely to be higher than cross-volatility spillovers. This is because the variables tend to be more sensitive to their own shocks than external shocks (Muguto, 2021). Sector indices such as technology, basic materials, and travel and leisure were less open as they exhibited the highest sensitivity to their own spillovers. In comparison, the remaining sector indices, like the industrial, consumer services, telecommunications and financial sectors, were the most open indices as they appeared to be less sensitive to their own spillovers than external shocks.

4.9 Pairwise volatility spillovers among sector indices

The analysis of pairwise volatility spillovers reveals notable interactions between specific sector indices, with the financial and industrial sectors showing the most significant bidirectional influence. In the unaugmented models, the financial sector transmitted 21.36% of its volatility to the industrial sector, while the industrial sector reciprocated with 22.29% of its volatility affecting the financial sector. These results remained consistent in the sentiment-augmented model, with the financial sector transmitting 21.30% and the industrial sector transmitting 22.20% of their volatilities to each other. This strong interconnection highlights both sectors' critical roles in the economy, with the financial sector driving economic development through infrastructure and job creation and the industrial sector heavily interacting with financial markets.

The overall market index also demonstrated significant volatility spillovers, particularly influencing the industrial sector at 16.66% in the unaugmented model and maintaining similar levels in the augmented model. This could be because the industrial sector is closely tied to the overall economic performance, making it sensitive to broad market movements captured by the overall market index. The consumer goods sector J550 had a substantial spillover effect on the overall market index, transmitting 26.83% of its volatility. Additionally, the health care sector transmitted 13.16% of its volatility to the industrial sector. These substantial spillovers indicate that sectors such as consumer goods and health care, while less prominent in terms of bidirectional influence, still play a significant role in the volatility dynamics of the market, impacting the broader economic environment.

Conversely, some sectors exhibited minimal spillover effects. The telecommunications sector consistently had the least influence on other sectors, with the highest spillover being to the basic materials sector at 7.42% in the unaugmented model. This suggests that this sector operates relatively independently from the broader market volatility, potentially due to its unique market dynamics and steady demand for telecommunication services. Also, it could be that the telecommunications sector is more resilient to economic fluctuations. Similarly, the basic materials sector itself showed limited impact on other sectors, with only 7.48% of its volatility spilling over to telecommunications. This indicates that the basic materials sector may also be relatively insulated from external shocks, possibly due to its focus on essential commodities and raw materials that maintain consistent demand.

Overall, these minimal spillovers suggest that sectors like telecommunications and basic materials are relatively isolated regarding volatility transmission, which can be advantageous for investors seeking to minimize risk through portfolio diversification. By including sectors with minimal external volatility influences, investors can achieve more stable portfolio returns and mitigate the impact of market-wide shocks. However, sectors like financial and consumer goods exhibit significant volatility interactions with other sectors, suggesting that they are more susceptible to broader economic trends and market conditions. This heightened sensitivity can lead to greater potential returns but also increases risk, necessitating more active management and strategic planning in investment portfolios to navigate and capitalize on these fluctuations effectively.

Table 4. 12 dynamic connectedness among the indices

	J203	J510	J520	J550	J560	J575	J580	J590	FROM
Unaugmented									
J203	31.27	0.23	16.66	17.94	9.64	4.57	19.49	0.20	68.73
J510	1.26	86.44	0.88	1.26	0.96	0.64	1.08	7.48	13.56
J520	18.82	0.22	35.63	6.67	9.60	6.52	22.29	0.25	64.37
J550	26.83	0.42	8.04	48.49	4.45	2.63	8.76	0.38	51.51
J560	14.93	0.31	13.16	4.92	48.77	3.34	14.26	0.31	51.23
J575	8.25	0.45	10.64	3.42	4.16	62.24	10.18	0.65	37.76
J580	21.00	0.28	21.36	6.84	9.91	6.29	34.00	0.31	66.00
J590	0.87	7.42	0.90	0.95	0.77	0.84	0.80	87.44	12.56
TO others	91.95	9.34	71.64	42.02	39.49	24.83	76.85	9.59	365.71
+ Own	123.22	95.79	107.27	90.51	88.26	87.07	110.86	97.03	cTCI/TCI
Net spillovers	23.22	-4.21	7.27	-9.49	-11.74	-12.93	10.86	-2.97	52.24/45.71
Augmented									
J203	31.29	0.24	16.64	17.99	9.63	4.54	19.47	0.20	68.71
J510	1.26	86.44	0.87	1.27	0.93	0.64	1.06	7.51	13.56
J520	18.82	0.22	35.69	6.70	9.62	6.51	22.20	0.25	64.31
J550	26.86	0.43	8.06	48.39	4.46	2.62	8.80	0.38	51.61
J560	14.92	0.32	13.18	4.93	48.84	3.31	14.20	0.31	51.16
J575	8.23	0.46	10.64	3.43	4.13	62.40	10.07	0.65	37.60
J580	21.03	0.28	21.30	6.89	9.85	6.20	34.13	0.31	65.87
J590	0.86	7.46	0.91	0.96	0.76	0.83	0.80	87.42	12.58
TO others	91.97	9.40	71.60	42.17	39.38	24.66	76.60	9.61	365.40
+ Own	123.26	95.84	107.29	90.56	88.22	87.07	110.73	97.03	cTCI/TCI
Net spillovers	23.26	-4.16	7.29	-9.44	-11.78	-12.93	10.73	-2.97	52.20/45.67

Source: Own estimations (2024)

4.10 Hedging effectiveness

The analysis reveals a diverse range of potential hedging effectiveness across sector pairs. Financials and Industrials exhibit the most promising hedging potential, with near-unity hedge ratios suggesting that a near-equal and opposite position in one sector can effectively offset risk in the other. This is unsurprising given their strong economic interconnectedness, which reflects their joint sensitivity to broader market movements and economic cycles. A one-to-one relationship in hedging between these sectors indicates a robust mechanism for balancing portfolio volatility. However, for other sectors like Telecommunications, achieving effective hedges may require significantly larger positions due to their relative insulation from volatility spillovers. That is, the smaller hedge ratios observed suggest that a larger adjustment in one sector may be needed to offset volatility in the other.

This reflects the sector's lesser dependence on market-wide fluctuations and its distinct market dynamics driven by steady demand for services. Thus, investors aiming to hedge exposures involving Telecommunications would need to adjust their positions more substantially to achieve comparable risk mitigation. This highlights the importance of tailoring hedging strategies to specific sector pairs, considering their unique volatility transmission dynamics in relation to the other sectors on the South African market. While some sectors exhibit strong and direct hedging relationships due to their intertwined economic roles, others require more nuanced approaches that account for their insulation from broader market volatilities. By understanding these dynamics, investors can optimize their hedging strategies to manage risk and enhance portfolio stability effectively.

Interestingly, incorporating sentiment into the analysis does not substantially alter the hedge ratios or their statistical significance. This suggests that sentiment-driven volatility, while potentially impactful in the short term, does not fundamentally change the underlying hedging relationships between sectors. That is, the structural relationships captured by the unaugmented models remain robust even when sentiment factors are considered. This finding highlights the stability of hedging strategies based on long-term economic factors and market interdependencies, regardless of short-term sentiment fluctuations. It could be valuable for investors who primarily rely on fundamental factors for their hedging decisions, as it suggests that enduring economic linkages play a dominant role in determining effective hedging strategies across sectors.

However, it is essential to consider that the dataset may not fully capture the nuances of sentiment impact across all market conditions. Furthermore, the significance of sentiment may not have been adequately reflected in the analysis due to its inherently transient and often unpredictable nature. If that was the case, then sentiment-driven volatility might still play a role in extreme market conditions or during periods of heightened uncertainty, which were not fully represented in the dataset. This highlights the need for investors to remain vigilant and possibly incorporate sentiment analysis in conjunction with traditional economic factors during times of market stress, ensuring a comprehensive approach to risk management. Without that, investors may overlook critical short-term fluctuations that could undermine the effectiveness of their hedging strategies, leading to unanticipated risks and potential losses.

Table 4. 13 Hedge ratios across the sectors

Sector Pair	Unaugmented hedge ratios		Sentiment-augmented hedge ratios	
	Hedge ratios	P-values	Hedge ratios	P-values
J510 - J520	24.61	0.000	24.64	0.000
J510 - J550	1.48	0.000	1.47	0.000
J510 - J560	1.48	0.000	1.44	0.000
J510 - J575	1.30	0.000	1.32	0.000
J510 - J580	21.00	0.000	20.41	0.000
J510 - J590	0.11	0.000	0.10	0.000
J520 - J550	3.23	0.000	3.22	0.000
J520 - J560	1.45	0.000	1.44	0.000
J520 - J575	1.63	0.000	1.64	0.000
J520 - J580	0.96	0.000	0.96	0.000
J520 - J590	28.16	0.000	28.20	0.000
J550 - J560	2.25	0.000	2.25	0.000
J550 - J575	2.90	0.000	2.95	0.000
J550 - J580	3.28	0.000	3.24	0.000
J550 - J590	23.79	0.000	23.71	0.000
J560 - J575	2.83	0.000	2.90	0.000
J560 - J580	1.52	0.000	1.53	0.000
J560 - J590	21.87	0.000	21.74	0.000
J575 - J580	1.23	0.000	1.21	0.000
J575 - J590	12.68	0.000	12.68	0.000
J580 - J590	27.00	0.000	27.23	0.000

Source: Own estimations (2024)

These findings have significant practical implications for investors and risk managers. They emphasize the importance of carefully selecting hedging pairs based on their volatility spillover characteristics. While sectors like Financials and Industrials may offer robust hedging opportunities, others might require more complex or diversified strategies. Additionally, the limited impact of sentiment on hedging suggests that fundamental analysis remains a cornerstone of effective risk management. Future research could look deeper into the role of sentiment by exploring different sentiment measures and methodologies and examining how sentiment interacts with other market factors. Additionally, incorporating other factors like macroeconomic variables and company-specific events could provide a more comprehensive understanding of hedging dynamics.

4.11 Conclusion of chapter

This chapter analyzed the nature of return volatility, volatility spillovers, hedging effectiveness, and the impact of sentiment among sector indices in the South African market. The results showed that volatility clustering and sentiment significantly impacted sectoral returns. The time-varying correlations among the sector indices augmented with sentiment were higher and statistically stronger; this showed that when sentiment was included, shocks intensified. Basic materials and consumer services had the lowest correlations, suggesting they had high diversification benefits. The directional connectedness results showed that the financial sector was the largest transmitter and recipient of shocks among sector indices. This implied that it was the most sensitive to the changes that occurred in the financial market and instantaneously reflected the impact of turbulence.

Furthermore, the presence of the leverage effect confirmed that negative shocks increased volatility more than positive shocks of an equal magnitude. The results from the unconditional volatility correlations showed that the financial sector was more connected with the other sectors, whereas the basic materials sector was the least integrated. Pairwise volatility spillovers indicated that the financial sector transmitted most of its volatility to the industrial sector, and the industrial sector transmitted most of its volatility to the financial sector. This emphasized the symbiotic relationship between these two sectors and their critical role in the South African market. Overall, the analysis revealed a complex interplay of factors influencing volatility on the South African market. The findings highlight the importance of considering both historical patterns and investor sentiment for effective investment decision-making.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The phenomenon of sectoral return volatility remains a focal point of interest among diverse stakeholders within financial markets, intending to facilitate the implementation of effective regulatory frameworks by policymakers and the formulation of optimal portfolio management strategies by investors. It is imperative to understand the various characteristics of volatility, such as the risk-return relationship and mean-aversion implied by volatility, volatility asymmetry, and volatility clustering, as it is often viewed as a catalyst for risk. Although the patterns may vary based on the sector indices being investigated in a particular market, there still needs to be comparative analyses concerning the characteristics of return volatility across sector indices and financial markets not included in this study.

As more turbulent events occur in the financial market, studies tend to prioritise examining traditional factors pertinent to sector indices in financial markets. The increase in market interconnectedness, propelled by technological advancements and financial market liberalisation, is frequently demonstrated by global financial crises. This significantly influences the interaction across indices in the market dynamics and necessitates consideration when analysing volatility spillovers. Such considerations are necessary for adequate assessment of spillover risks, as is often observed in numerous studies. Moreover, most studies aiming to explore the determinants of sectoral return volatility and volatility spillovers exhibit a narrow focus on fundamental factors and the shocks affecting them.

During periods of heightened volatility, when market uncertainties prevail, investors frequently resort to hedging methods to safeguard their assets against adverse shifts in asset prices. Implementing effective hedging strategies enables the counterbalance of risks stemming from market fluctuations to reduce potential losses. This becomes particularly crucial during volatile periods characterised by intensified connectedness during turbulent events, as effective hedging plays a pivotal role in mitigating the transmission of risk and maintaining portfolio stability. Therefore, it is imperative to assess the hedging effectiveness in the financial market by examining the ability of sector indices to mitigate risk, enhance portfolio diversification, and exhibit safe haven characteristics during financial turbulence.

The volatility and volatility spillover patterns vary significantly during different financial periods and are characterised by bullish and bearish sentiment. This discrepancy arises because traditional finance theory often fails to account for behavioural biases influencing investors' attitudes and decision-making processes. Substantial evidence demonstrates the impact of prejudices, emotions, and cognitive biases on investors within the financial market, affecting their reactions and strategies. The ongoing identification of financial market anomalies that fall outside the scope of traditional finance theories highlights the necessity of integrating behavioural biases into any comprehensive analysis of financial markets. This integration can provide a more accurate understanding of market dynamics and improve investment strategies.

5.2 Objectives of the study

This study examined the dynamic connectedness and hedging effectiveness among sector indices in the South African stock market, considering their sensitivity to prevailing market-wide investor sentiment. It analysed volatility patterns, including asymmetry, persistence, mean reversion, and the risk-return relationship across sector indices, as well as volatility spillovers, focusing on systemic shocks and resilience to economic challenges. The study also assessed hedging effectiveness by identifying indices with low or no correlation during turbulent events, providing portfolio diversification benefits. A sentiment index was constructed to measure investor sentiment accurately, and its impact on dynamic connectedness and hedging among South African stock market sector indices was evaluated.

By including sector indices from various industries in the South African market, spanning nearly thirteen years of daily data, this study compared dynamic connectedness and hedging effectiveness across sector indices over an extensive period. This comprehensive perspective on sentiment led to more robust conclusions than most studies. The long sample period allowed for consideration of the impact of increased financial crises, driven by rising connectedness among indices due to rapid technological advancements and financial market liberalisation. Addressing the burgeoning behavioural finance theory and the shortcomings of traditional asset pricing models, this study examined the influence of investor sentiment on sectoral return volatility, dynamic connectedness, and hedging effectiveness.

5.3 Methodologies used to achieve study objectives

It is essential to employ a suitable approach to achieve the defined objectives of the study. Preliminary tests such as stationarity, normality, serial correlation, autocorrelation, and heteroscedasticity tests were employed on the data to understand the attributes of the return series before examining the nature of volatility. To evaluate the volatility among the sector indices, three GARCH models (Bollerslev, 1986; Nelson, 1991; Glosten et al., 1993) as the GARCH framework has proven its efficacy in quantifying and modelling volatility. Comprising the mean and variance equations, the GARCH models facilitated the examination of four primary volatility patterns that provide insights into their nature: the risk-return relationship, volatility persistence, volatility leverage effects, and volatility mean reversion.

To address the first objective of determining the level of dynamic connectedness among the major sector indices, the Asymmetric Dynamic Conditional Correlation (ADCC)-GARCH and the spillover index approach developed by Diebold and Yilmaz (2012, 2014, 2015) was employed. The ADCC-GARCH facilitates the estimation of time-varying volatilities, covariances, and correlations, and the Diebold and Yilmaz index enables the examination of the extent to which each index's forecast error variance can be attributed to external shocks originating from macroeconomic events. This combination of methodologies provided a comprehensive framework for analysing the intricate interdependencies and volatility spillovers among sector indices.

To address the second objective of assessing the impact of dynamic connectedness among major sector indices on their hedging effectiveness, the DCC-GARCH t-Copulas method was applied. This copulas-based framework, an extension of the GARCH model, was chosen for its capability to accurately capture the effects of economic shifts on the hedging effectiveness of variables. The student-t copulas are particularly effective in identifying and modelling correlated multivariate random variables, allowing for a nuanced analysis of dependencies. This methodology enables the determination of each index’s resilience to economic shocks and its potential to enhance portfolio diversification through effective hedging strategies. This component was central to the study.

The third objective involved measuring the influence of investor sentiment on the dynamic connectedness and hedging effectiveness among the sector indices. To achieve this, a composite index was constructed and then incorporated into the GARCH models, with residuals subsequently utilised in the ADCC-GARCH models and the Diebold and Yilmaz index. The results of these augmented models were compared with those from unaugmented models to identify differences arising from the inclusion of the sentiment index. Through these methodologies, the study aimed to provide a significant comparative contribution to the literature on dynamic connectedness, hedging effectiveness, and the impact of investor sentiment on these factors within the South African financial market.

5.4 Summary of key findings

The significance of dynamic connectedness and its impact on hedging effectiveness among South African stock market sector indices and their subjectivity to prevailing market-wide investor sentiment was examined in this study. This section notes the critical findings from Chapter 4, the data analysis and presentation of the results.

5.4.1 Nature of volatility among sector indices

In section 4.3.2, the equation for conditional variance indicated that the leverage effect parameter was consistently significant and positive across all sector indices. This affirmed the presence of the leverage effect, where negative shocks led to more substantial increases in volatility compared to positive shocks of the same magnitude. This finding aligns with the financial leverage hypothesis, which posits that negative returns amplify stock return volatility, suggesting the potential existence of dynamic risk premiums. Additionally, past shocks significantly affected all sector indices, indicating that current volatility could be explained by preceding innovations, which suggests market inefficiency. In inefficient markets, future prices or price changes could be rationalised only by past price information, contradicting the efficient market hypothesis.

The study also revealed that negative shocks had a more pronounced impact than positive shocks of equivalent magnitude. Notably, the financial sector displayed the highest asymmetry in volatility levels, while the technology sector exhibited the lowest volatility levels. Furthermore, the persistence of volatility highlighted the presence of volatility clustering, a common feature across all indices. It implied that future volatility expectations are influenced by current volatility shocks, underscoring the importance of examining the relationship between returns and volatility, as persistent volatility solely accounts for the risk premium. Specifically, the ALSI and financial sector displayed the highest persistence in return-generating processes compared to other sector indices, suggesting that shocks would persist over numerous future periods due to long memory in conditional variance.

5.4.2 Dynamic connectedness and hedging effectiveness

The analysis of unconditional volatility correlations among sector indices revealed the strongest and weakest correlations between the ALSI and the financial sector and between basic materials and consumer services, respectively. These findings indicated that the ALSI and the financial sector exhibited greater interconnectedness than other sectors, while the basic materials sector was the least interconnected. Some high correlations observed suggested significant volatility spillovers among other sectors, whereas the negative correlations that some sectors exhibited with each other indicated considerable diversification benefits. Simultaneously, the study unveiled dynamic correlations among sector indices, demonstrating robust time-varying volatility correlation across sector indices.

The asymmetry parameter was significant for most sector index pairs, suggesting that negative shocks among sectors tended to amplify co-movements compared to positive shocks of similar magnitude. Daily average volatility correlations were positive but below one, indicating the presence of diversification benefits among sector indices. Furthermore, the findings revealed clear linkages among sector index pairs and conditional correlation estimates surpassed static correlations, confirming an escalating interconnectedness over time. Relying on the assumption of static correlations could lead to inefficient correlation measurement. Additionally, the net volatility spillover analysis found that the financial and industrial sectors were the main transmitters of risk, highlighting the significant role these sectors play in the economy.

5.4.3 The influence of investor sentiment

In section 4.2.3, an investor sentiment index was constructed to evaluate its influence on connectedness and hedging effectiveness across sector indices. Principal component analysis highlighted the efficacy of ComSent as a sentiment measure, with the first four principal components explaining 87 per cent of the data variation. ComSent effectively captured shifts in investor sentiment during significant financial crises, such as the 2008-2009 global financial crisis, the 2015-2016 Chinese market crash, and the COVID-19 pandemic, demonstrating its capacity to explain variations in returns and volatility triggered by such events. Additionally, plots of sector indices' returns alongside the sentiment index visually depicted how turbulent periods aligned with declining sentiment and how calm periods aligned with rising sentiment.

The significant sentiment coefficient in sector indices' sentiment-augmented mean and variance equations affirmed that investor sentiment played a crucial role in the market. Sentiment also influenced risk premiums, past returns, and past shocks, with its inclusion leading to increased volatility in the variance equation. Analysing dynamic connectedness, sentiment-augmented sector indices exhibited higher and statistically more robust time-varying correlations. ADCC-GARCH results revealed more substantial leverage effects between sector index pairs augmented with sentiment. Moreover, volatility correlation results indicated higher homogeneity and heterogeneity among sentiment-augmented sector indices. Finally, net volatility spillover among sector indices increased when sentiment was considered, highlighting how sentiment-induced volatility led to increased spillovers among sector indices.

5.5 Study implications

The significant findings derived from the research objectives and questions outlined in the analytical chapters have essential implications that warrant attention. By focusing on the implications of these key findings, this section sheds light on their broader significance for various stakeholders in the financial market and academia alike.

5.5.1 Implications of the nature of volatility

The findings presented in section 4.3.2 hold significant implications for various stakeholders, from academics to policymakers. For academics engaged in volatility modelling, the discovery that specific sectors do not consistently incorporate volatility into pricing highlights the need for alternative risk measures like skewness. Investors must reconsider their strategies, particularly in discerning between efficient and inefficient markets, as positive correlations challenge market efficiency and present opportunities for abnormal returns through technical trading strategies. Firms navigating capital markets must factor in stock pricing and cost implications amidst varying market efficiencies. At the same time, policymakers are encouraged to prioritise initiatives to enhance market efficiency for broader economic benefit.

Furthermore, the study's examination of volatility patterns highlights the persistence of sectoral return volatility, possibly driven by irrational trading behaviours. This emphasises the imperative for policymakers to mitigate such behaviours, potentially through regulatory mechanisms, to effectively manage volatility shocks. Investors and firms can leverage these insights to devise portfolio strategies and time the issuance of shares during periods of low volatility, enhancing their risk management practices. Additionally, the study challenges conventional wisdom by advocating for tailored GARCH models and fat-tailed distributions like the student's t and GED across sector indices, emphasising the necessity of integrating behavioural factors like sentiment into volatility models for comprehensive analysis, thereby challenging the adequacy of traditional asset pricing models like CAPM.

5.5.2 Implication of dynamic connectedness and hedging effectiveness

Sections 4.6 to 4.10 shed light on the growing challenges investors face in diversifying portfolios to mitigate systemic risk, as observed similarities in volatility behaviours among sector indices in financial markets indicate. Heightened volatility connections during economic downturns emphasise the importance of understanding how different indices react to external shocks when assessing portfolio risks. For policymakers, these findings offer valuable insights into the spread of financial risks across various indices, their information efficiency, and the flow of information in the market. Armed with this knowledge, policymakers can devise strategies to prevent contagion risks among sectors in the financial market and implement effective measures to stabilise financial systems.

For firms, the increasing volatility connections among indices have significant implications. Understanding these dynamic interactions can help firms anticipate capital availability and costs from sector indices in the market. Moreover, firms must recognise that capital dynamics are influenced not only by shocks within their sector but also by volatility from other sectors. Academically, the evidence of fluctuating correlations and volatility spillovers highlights the limitations of static models in capturing the evolving nature of sector indices' interactions. Dynamic models that account for changing market structures are essential. Furthermore, the observed volatility correlations challenge existing notions of market efficiency, prompting a re-evaluation of what constitutes an efficient market.

5.5.3 Implication of significant investor sentiment impact

In Chapter 4, the results revealed that investor sentiment significantly influences both dynamic connectedness and hedging effectiveness across sector indices. This highlights the importance of investors incorporating sentiment into portfolio construction to maximise returns and diversification benefits effectively. Moreover, the impact of sentiment on volatility spillovers between indices suggests the necessity of integrating it into portfolio construction for optimal performance, prompting a reassessment of efficiency classifications for fund allocation. For policymakers, the substantial influence of sentiment on volatility and spillovers highlights the need to regulate noise trading and reduce risk among sector indices. Policies should aim to curb speculative and sentiment-driven behaviour in financial systems.

For firms, the influence of investor sentiment on sector indices affects the cost and accessibility of capital due to its impact on volatility and liquidity levels. However, there is variability in sentiment effects among indices, enabling firms to access and focus on less volatile sectors. Understanding the impact of dynamic connectedness and investor sentiment guides firms in timing their market entry or exit, acknowledging that capital factors are influenced by sentiment across multiple sectors and facilitating careful investment decisions. Scholars should acknowledge the significant impact of investor sentiment, prompting consideration of behavioural biases in asset pricing models and tests. Reliable sentiment measures and denoised data in asset pricing tests can enhance model accuracy and price discovery.

5.6 Conclusion and recommendations

5.6.1 Concluding remarks

This study shed light on the intricate dynamics within the South African stock market. It revealed distinct volatility patterns across various sector indices, even within groups like cyclical or non-cyclical sectors. Differences in volatility persistence, asymmetry, mean reversion, and risk premiums across individual indices highlight the limitations of broad assumptions about groups. Furthermore, the observed volatility patterns challenge the efficient market hypothesis, suggesting potential inefficiencies within the South African market. It then begs the question of why asset pricing analyses and models still utilise the platform of market efficiency. It also highlights the need for incorporating behavioural finance concepts into asset pricing models to account for the observed market inefficiencies.

The research also unveiled significant yet fluctuating interconnectedness among sectors. This interconnectedness intensified during turbulent market periods and among sectors heavily influenced by investor sentiment. Consequently, hedging effectiveness decreased as risk transmission surged across indices. Investor sentiment emerged as a key factor, heavily influencing dynamic connectedness and hedging effectiveness. Including sentiment in the models yielded statistically stronger coefficients and highlighted the amplification of external shocks on the market. The tight correlation between investor sentiment and return noise across sectors highlights the prevalence of behavioural biases, emphasising the importance of incorporating sentiment analysis into asset pricing models and future research.

5.6.2 Limitations to the study

Despite successfully achieving its goals, the study encountered limitations. The analysis, restricted to thirteen years of South African data, missed capturing the impact of major historical events on the market. Focusing solely on seven South African sector indices also overlooked potentially informative sectors like healthcare, oil and gas, and consumer goods. While the chosen indices provided sufficient diversity, including a broader range of sectors and incorporating data from BRIC and G7 economies could have revealed how volatility patterns and spillovers vary across regions and economic events. This wider scope would have provided a richer understanding of the complex interplay between market sentiment and volatility.

Furthermore, while valuable, the study's focus on investor sentiment could have been complemented by explicitly examining the influence of specific behavioural biases. While these biases might have been implicitly considered, a more nuanced understanding could have been gained by directly analysing how overreaction, herding, and similar biases affect volatility and market dynamics. The methodology, while sound, could also benefit from exploring alternative volatility analysis methods like the Heston and CEV models. Additionally, incorporating fat-tailed return distributions and conducting definitive tests on asset pricing models could have provided more profound insights into how investor sentiment interacts with established financial models through its influence on market behaviour.

5.6.3 Recommendations for future studies

Future research can significantly enhance the understanding of volatility dynamics and spillover effects by broadening the scope of investigations. Including a broader range of sector indices from diverse countries would provide a more holistic perspective. Focusing on sectors heavily impacted by recent events, like healthcare during COVID-19, can reveal how volatility patterns evolve under unique circumstances. Furthermore, incorporating other asset classes, particularly commodities markets, would broaden the applicability of the findings. This is especially important given the increasing role of retail investor speculation, which significantly influences commodity prices. Additionally, the interconnectedness between commodity futures and stock markets underlines the need to examine cross-market dynamics.

Future research should consider longer timeframes and data granularity to better understand sector behaviour. Analysing a broader period encompassing significant historical events beyond this sample period would allow for a more robust understanding of sector behaviour across different market conditions. For example, this could include events like the 2023 Israel-Hamas war or the FATF grey-listing on South Africa. Furthermore, analysing data at the individual firm level, rather than relying solely on indices, can provide a more nuanced picture of how sentiment affects volatility and returns across companies within the same sector. Finally, exploring Lo's adaptive market hypothesis and incorporating other behavioural biases can offer a more realistic lens for examining volatility and spillovers.

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APPENDIX

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

16 August 2023

Miss Thabile Siphesihle Nkosi (217002280)
School Of Acc Economics&Fin
Westville

Dear Miss Thabile Siphesihle Nkosi,

Original application number: 00021416
Project title: Dynamic connectedness, hedging effectiveness and investor sentiment among South African sector indices

Exemption from Ethics Review

In response to your application received on 14 Augsut 2023, your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted]

Prof Josue Mbonigaba
Academic Leader Research
School Of Acc Economics&Fin

UKZN Research Ethics Office
Westville Campus, Govan Mbeki Building
Postal Address: Private Bag X54001, Durban 4000
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Founding Campuses: Edgewood Howard College Medical School Pietermaritzburg Westville

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