EQUITY SUPER SECTORS CONNECTEDNESS AND ITS DETERMINANTS: EVIDENCE FROM THE JOHANNESBURG STOCK EXCHANGE

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DECLARATION

I, Babatunde Samuel Lawrence, declare that:

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DEDICATION

This PhD thesis is dedicated to my maker and LORD, Elohim Adonai. To God the father, to God the Son, to God the Holy Spirit and to my dear wife Dr (Mrs) Tolulope Ibukun Lawrence.

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ABSTRACT

Everything depends on everything else. More importantly, macroeconomic and financial connections have proved to be more fundamental compared with others. The reality of dynamic connectedness and time varying correlation as precursors to contagion and systemic risk are proven through the super sectors, namely the Automobile and Parts, Chemical, Telecommunication, Technology, Energy, Health, Finance, Insurance and General Industrial super sectors of the Johannesburg Stock Exchange, with daily sample period from 1 January 2006 to 31 December 2021. The first objective is to determine the systematically important super sectors in the different extreme periods. The second objective is to determine the return linkages of the equity super sector, while the third objective is to examine the dynamic connectedness and the shock propagation among the super sectors during the extreme risk events. Finally, the fourth objective is to evaluate the determinants of volatility connectedness of the JSE equity super sectors. The different extreme events considered alongside the full sample periods for this study are the 2007/2008 Global financial crisis (GFC), the 2009-2011 European Debt Crisis (EDC), the 2017-2018 U.S-China trade war (U.S-China TWR) and the late 2019-2021 COVID-19 pandemic.

This study employs the Page et al., (1999) model with the Granger causality model of Billio et al., (2012) to accomplish objective one. While in objective two, the DECO-GARCH model of Engle and Kelly (2012) was employed to establish the time varying equicorrelations status of the super sectors through the rolling window analysis. For objective three, the realised volatilities of the super sectors were obtained through the Garman and Klass (1980) model and thereafter, the dynamic connectedness and direction of propagation were determined through the Diebold and Yilmaz (2009, 2012 and 2014) model alongside the TVP-VAR of Antonakakis et al., (2020). The study further employed the nonlinear autoregressive distributed lag (NARDL) model to determine the asymmetrically significant determinants of total sectorial volatility connectedness of the JSE market in the fourth objective.

Findings from this study revealed the Telecommunication super sector is the most systematically important super sector during the full sample size analysis. It was revealed that the equicorrelation of the super sectors is positive and high, this was also the case for the rolling window results except for the years not within the extreme period, yet the least equicorrelation was 0.1491 for the year 2012-2013, while the highest was 0.7022 for the COVID-19 pandemic period. It was also established that the total connectedness of the sample period and the different extreme periods were high, suggesting a high interconnectedness of the super sectors. Lastly, the determinant estimation results show LSAVI, LDMR and LEPU as the asymmetrically significant drivers of total sectorial volatility connectedness on the JSE market.

This study is the first to investigate sectorial connectedness, equicorrelation and the determinants of volatility connectedness in South Africa and in Africa at large. This study contributes to the limited literature on systemically important equity super sectors and sectorial dynamic connectedness and dynamic equicorrelation in the emerging market. First the result shows that the Telecommunication sector is the most important node for the EDC, the U.S-China trade war and the COVID-19 pandemic periods. While the Insurance and the Energy are the highest ranked super sectors amongst the network of super sectors for the full sample period and for the GFC period, hence making these super sectors the most systemically important nodes during these selected periods. It also shows that the sectorial common equicorrelation on the JSE is high and time varying with higher values for the year where extreme events occurred such as the GFC, EDC, and the COVID-19 pandemic period. This result is also a revelation that during the period of financial or economic crisis correlation of sectors are high compared to non-crisis periods. Third, the dynamic connectedness results show that the sectors on the JSE are interconnected and a shock to one sector can have a spillover effect on another close sector in the value-chain. Fourth, the South African volatility index, the Economic Policy Uncertainty and the Domestic Market Return are symmetrically and asymmetrically significant determinants of the sectorial volatility connectedness of JSE market. These findings from this study have implications for economic policy makers, portfolio and fund managers, foreign and local investors, sector regulators and researchers/academics in the field of finance.

Keywords: Sectorial Equity Returns, Dynamic Volatility Connectedness, Dynamic Equicorrelation

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AM & P	Automobile and Parts
ARDL	Autoregressive distributive lag
CCC	Constant conditional correlation
CHE	Chemical
COVID-19	COVID-19 pandemic
DECO	Dynamic equicorrelation
ECM	Error Correction Model
EDC	European Debt Crisis
ENE	Energy
FIN	Financial
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GFC	Global Financial Crisis
GFEVD	Generalised Forecast Error Variance Decomposition
G.I	General Industrial
HEL	Health
INSUR	Insurance
JSE	Johannesburg Stock Exchange
LDMR	Logarithm of Domestic Market Return
LEPU	Logarithm of Economic Policy Uncertainty
LMOP	Logarithm of manufacturing Output
LM2	Log of Money Supply
LSAVI	Logarithm of South African Volatility Index
LTCI	Logarithm of Total Connectedness Index
LTO	Logarithm of Trade Openness
MRP	Market Risk Premium
NARDL	Nonlinear Autoregressive Distributive Lag
NPDC	Net Pairwise Directional Connectedness
PP	Philip and Perron
SIFI	Systemically Important Financial Institutions
SIS	Systemically Important Sectors
TCI	Total Connectedness Index

TDW	Trade war
TECH	Technology
TELECOM	Telecommunication
TR	Trade Ratio
TVP	Time Varying Parameter
U.S	United State
U.S-China TDW	U.S China Trade war
VAR	Vector Autoregression
VIX	Volatility Index

LIST OF PUBLICATIONS

Published Articles

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND TO THE STUDY

Everything depends on everything else. More importantly, macroeconomic and financial connections have proved to be more fundamental compared with others (Diebold & Yilmaz, 2015). The interlinkages between financial markets have increased in the past two decades (i.e. from the 2000s and 2010s) through globalisation and advances in technology, providing free and accessible market information to investors and removing foreign barriers to investments. The increase in financial, economic and political integration of different economies has affected the international market linkages. Therefore, because of increasing correlation of markets, the global finance[1] phenomenon happened (Longin & Solnik, 1995). For example, the volatility of stock markets and their correlations have been understood to be influenced by global shocks, which often come as important news and cause fluctuations in share prices with a rapid influence on other market stocks. Such intensive interrelations of crises between one market and others, which give rise to a global crisis, is often referred to as "financial contagion[2]" (Bekaert, Harvey & Ng 2005).

The different economic sectors in a country can been seen as the driver of wealth and prosperity for such when they work efficiently. However, it is important to understand their interconnections because their interdependence and connectedness with each other and sectors may sometimes come at a cost. The contagion effects noted across international markets have implications for domestic equity sectors too. It has been shown that during crisis stock volatility increases due to uncertainty created through negative shocks. Hence, markets exhibit contagion, with devastating consequences for the economy at large (Sugimoto, Matsuki & Yoshida, 2014). Consequently, negative shocks of such may have a direct impact on sectors

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[1] This is a worldwide integration of the financial system where financial institutions, economies and markets are interlinked (Paul & Heikki 2007)

[2] Contagion is the propagation of market disturbances, from one economy to another through the movement of assets. Dombusch et al., (2000) also defined contagion as a considerable rise in cross-market linkages due to shock to an economy or groups of economies.

which export goods and such shocks are propagated to sectors with indirect and direct links with the target sectors facilitated through interdependency in value chain (Egger & Zhu, 2020).

This study was motivated by the dearth of studies on JSE equity sector equicorrelation in light of numerous recent extreme market events. Boako and Alagidede (2017) posit that developing and emerging economies have become the main drivers of global economic growth since the global financial crisis. Emerging markets such as South Africa offer diversification benefits to investors during global crises (Cayón and Sarmiento, 2020) as crises in advanced markets do not result in losses in these markets. However, South Africa's strong ties with other emerging and developed markets tend to expose its economy to external events. Given the attraction of the South African economy to foreign and domestic investments, it is important to shed light on the equity sector co-movement amidst recent and previous events such as the GFC, the EDC and the recent US-China trade war and the COVID-19 pandemic.

The Global financial crisis of 2008/2009 constitutes a risk contagion event. However, the most recent example of such negative shock event is the U.S-Chinese trade war, which was stimulated through the increase in tariffs on specific Chinese products, which weakens investor's confidence and hence, transfers negative shocks to the market. Logically, such negative shocks could directly impact the export sectors on the U.S tariff list and then are transmitted to different other sectors, which have direct and indirect connections to the target sectors, which is facilitated through interdependence in the global value-chain (Egger & Zhu, 2020). Quite a number of empirical studies have been carried out on risk contagion in diverse financial markets Jung and (Maderitsch, 2014; Fry-McKibbin, Martin and Tang (2014); and Elyasiani, Kalotychou, Staikouras and Zhao (2015)). However, limited efforts have been directed to uncover the risk transmission between different sectors within the economy, especially in South Africa.

After the global financial crisis of 2008, financial markets around the world have become very volatile. This has been a source of concern for stakeholders in regulatory institutions and academics to understand the pattern, the propagation of financial risk and the possible way of modelling interconnectedness in financial markets. The widespread of risk across different assets, sectors, markets and countries with unclear contagious patterns cause significant damage to local and the global economy at large (Zhang, Zhuang, Wang, & Lu 2020). Hence, proper understating of the system or mechanism by which financial risk are transferred from one sector to another has become imperative. Dornbusch, Park and Claessens (2000) illustrate that connectedness of markets and spillover of risk in relation to the origin (source) of shocks are vital in understanding risk contagion.

Understanding the risk transmission mechanism is crucial for the stability of South African economy, taking the recent 2018-2019 U.S-China trade crisis into consideration. The trade war between the U.S and the China was founded based on trade restrictions and counter-retaliations between them (SCMP 2021, Annan, 2020).

The U.S-China trade war has significant implications for South Africa. Both countries occupy crucial position in the South African international trade (export and import), as China and the United State of America occupy the first and third position as South Africa's import and export trade partners respectively (Santander Trade Market, 2021). The trade war has had an adverse impact on South African exports with around 10 percent of the country's total export destined for China, which has put a strain on export coupled with a direct and indirect spillover effect on other sectors. The South African economy surpasses its worse performance estimations as the manufacturing sector had a greater impact on the country's poor GDP for 2018 and 2019. Internal issues within the manufacturing sectors and the emergence of US-China trade war were the main causes of its poor performance. The manufacturing sector of the South African economy is one of the most lucrative amongst other sectors enjoying export activities to Latin America, Europe, the United States and China, with the country exporting almost 20% of its total exports in manufactured goods, services and commodities and deriving most of its income from the last two economies (U.S and China) (SA Oil, 2019).

According to 2018 statistics, a total sum of U.S$24.3billion in manufactured goods such as iron, machinery, steel and plastics were exported to these countries, with high tendencies of this export figure increasing through the imposed tariffs due to the unresolved persistent war between the two countries, especially with the U.S refusing to include South Africa in the list of exempted countries on tariffs (SA Oil, 2019). Imposed tariffs increase the cost of exportation for the manufacturing industries to export their goods into the U.S and China, thereby making such goods expensive for the average Americans and for organisations procuring SA's goods, which are exported to China and then sold to the American markets, as the cost of imported goods rise and exports declining, or an outright plummet of goods purchased by these markets. With aluminium and steel tariffs set at 10% and 25% respectively, the SA manufacturing sector is already affected due to the hike in tariffs. For example, the car manufacturers in SA faced similar hikes in tariff, which they were given exemption from before, under the African Growth and Opportunity Act (AGOA), which aided duty-free trade access into the United States markets. Such hikes in tariffs not only cause industries to lose massive income but also pose an enormous threat to the SA job holders who face retrenchment (SA Oil, 2019). The effect is reflected on the first quarter GDP growth of the year 2018 for SA economy, which gave a negative digit, with the economy experiencing a sharp output decline for the year 2018 to 2019 in sectors such as manufacturing, mining, agriculture and utilities, which was as a result of a 3.2% contraction year-on-year following (Mathews 2019). In this context, negative shocks as such could have a direct impact on specific sectors of the economy that directly deal with exportation of goods and services (e.g., the manufacturing sector) to other countries and, hence, transmits the risks to other sectors that indirectly related to these target sectors facilitated by interdependence in global value-chain (Egger & Zhu, 2020).

Therefore, due to shocks initiated from one sector, risks could be easily transferred to other sectors because of possible connectedness of these sectors to each other and ultimately causing a systemic risk in the whole economy. In this context, risk contagion is important and prerequisite in plotting the connectedness amongst economic sectors[3], identifying risk spillover mechanism within these sectors and as well as the sources of shocks (Wu, Zhang, & Zhang 2019). The concept of systemically important financial institutions (SIFI) could be deployed to nonfinancial institutions, markets and economic sectors. It is vital to establish the systematically important sector for the economic managers to prioritise them. From the portfolio management viewpoint, understanding the linkages and interconnection among the economic sector or equity sectors will enable investors and fund managers to make sound decisions to reap the benefit of sectorial portfolio diversification. A couple of empirical studies such as Ewing (2002), Ewing, Malik and Ozfidan (2002) and Ranjeeni (2014) show that due to risk characteristics, market and industrial heterogeneities, markets react to shocks differently and propagation of shocks from market to market is inevitable. In this light, the multifaceted association between markets and their internal elements (which includes market conditions, macroeconomic variables, etc.) is a carrier of risk transmission and their connectedness patterns or structures play a vital function in the development and spread of systemic risk.

[3] Economic sectors and equity sectors are used interchangeably.

Thus, the study filled this gap in the literature by first determining the systematic important sectors on the JSE through the PageRank method developed by Page et al. (1999) and the pairwise Granger causality test of (Billio *et al.*, 2012). Followed by investigating the equicorrelations of these sectors of these sectors, namely technology, energy, chemical, financial, insurance, health care, industrial goods and services, Automobile and Parts and telecommunications with each other. This would involve deploying DECO-GARCH of Engle and Kelly (2012) method. Also, a connectedness network will be constructed with reference to the connectedness matrix of Diebold and Yilmaz (2014) and the time-varying parameter VAR (TVP-VAR) model innovation of Antonakakis, Chatziantoniou and Gabauer (2020) to investigate the connectedness of the super sectors amongst each other. This would also unravel the transmission mechanism of risk spillover from one sector to another. In addition, this study investigated the drivers or determinants of sectorial volatility connectedness of the sectors in the Johannesburg stock exchange (JSE) through the nonlinear autoregressive distribution lag method (NARDL). Therefore, the results of this study would help to unveil the systematically important JSE equity sectors, their interlinkages, volatility spillover connectedness and determinants during periods of crisis or extreme periods.

1.2 STATEMENT OF THE PROBLEM

The mechanisms of financial systemic risks transfer across markets have been a persistent problem for regulators and policymakers to understand during financial crises. The global financial crisis of 2008-09, the European debt crisis of 2010-12 with the recent U.S-China trade war which started in 2018 shown that during periods of financial crises, volatility increases sharply due to uncertainty and markets are known to display contagion effects, which have negative economic outcomes on society at large (Sugimoto *et al.*, 2018).

Contagion across international markets around the globe causes problems for international diversification, thereby presenting opportunity for investigation of alternative investment vehicles for the purpose of portfolio formation; for example, alternative to international diversification is domestic asset diversification and sectorial asset diversification.

In practical terms, international diversification is becoming less attractive due to growing contagion, presenting a serious problem for selection of securities to be included in a diversified portfolio. The alternatives such as sectorial diversification have not received sufficient research attention.

The U.S-China trade war, which started in 2018, has significant contagious implication for South Africa within the economic sectors. This is because both economies are South Africa's major export and import trading partners. South Africa exports many products to China, which undergoes processing and are subsequently re-exported to the U.S as finished products and some of these products are re-imported to South Africa with higher tariffs (Tshitiza 2019).

Moreover, Mao and Grog (2019) report that tariff increase could have a direct impact on countries through direct trading activity and an indirect (cumulative tariffs) effect on a third country via links in global supply chains. Such countries indirectly get hurt through cumulative tariff cost. The ripple effect of this is evident in the emerging markets sell-off of investments, as the MSCI[4] emerging market index for South Africa annual performance declined from 36.12% in 2017 to -24.76% in 2018 (MSCI 2021).

Hence, without the evaluation of alternative diversification opportunities, investors, portfolio managers and other stakeholders will continue to be exposed to the negative effect of contagion without or with limited alternatives. In other words, studying the connectedness and interlinkages of JSE super sectors during periods of extreme event such as U.S-China trade war and other extreme events would shed light on the sectorial diversification opportunities.

A study of sectorial co-movement and interconnectedness in a major emerging market like South Africa will assist the stakeholder to determine the appropriateness of sectorial diversification for portfolio formation. Investigation of correlation and connectedness during periods of extreme market events will also provide insight as to whether sectorial diversification is also affected by contagion against the belief that an emerging market such as SA can be considered a separate asset class (i.e. not majorly/usually affected by international events).

In addition, product exporting sectors are usually first in line to be impacted with these negative shocks and then through global value chain interdependencies other sectors which have direct or indirect links in value chain with the target sectors are then affected with the shock (Egger & Zhu, 2020). As a result of the frequent financial crises around the world, more research has

[4] The MSCI South Africa index is designed to determine the large and mid-cap segment's performance in the South African market. Having 37 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in South Africa

focused on the risk contagion in different markets (Jung and Maderitsch 2014), in financial institutions and in assets (Fry-McKibbin et al. (2014); Elyasiani et al. (2015), also at country level (Corradi et al. (2012); Cotter and Suurlaht, (2019); Kenourgios et al. (2011). Nevertheless, this study is not aware of any empirical study that has been channelled towards discovering risk transmission among super sectors within South Africa, which is particularly critical to understand the stability of the South African economic system. This is particularly essential given the China-US trade conflicts and previous financial crises over the last two decades.

1.3 STUDY AIM AND OBJECTIVES

Haven identified the study motivation, the study background and the problem statement, the main objective of this study is to analyse the volatility spillover dynamics among the selected super-sectors on the Johannesburg Stock Exchange (JSE) during the full sample period and during extreme events such as the 2008/2009 GFC, European debt crisis, the China-U.S trade war and the COVID-19 pandemic crisis. The specific objectives of this study are to:

i. Determine the systemically important equity super sectors within the JSE
ii. Determine return linkages of JSE equity super sectors.
iii. Examine the connectedness and shock propagation among JSE equity super sectors during extreme risk events (2008/2009 GFC, European debt crisis and the China-U.S trade war and the COVID19 pandemic crisis).
iv. Evaluate the determinants of connectedness in JSE equity super sectors.

1.4 Research Questions

Based on the statement of the problem and the research or study objectives, it is important to provide answers to the following research questions:

i. Which of the JSE equity super sectors are the systemically important.
ii. Do JSE equity super sector returns a common equicorrelation and does the equicorrelation change over time?
iii. What is the nature of shock propagation and connectedness of the JSE equity super sectors during extreme market events?
iv. What are the determinants of connectedness of JSE super sectors

1.5 Methodological Scope

This study is anchored on a quantitative research approach. Secondary data on JSE equity super price indices were collected from the Johannesburg stock exchange for the 2006-2021 period based on data availability. The study employs different econometric models to achieve the study's objectives. The study employs the use of the dynamic equicorrelation GARCH (DECO-GARCH) model, which is a distinct variant of the dynamic conditional model (DCC-model) formulated by Engle and Kelly (2012) to discover the return linkages or the common time varying equicorrelation of the super sectors. The study proceeds to model the volatility connectedness of the super sectors, by first determining the daily volatility for each index through the application of the Garman and Klass (1980) model. Thereafter, the estimated daily volatility will be used to measure the connectedness in the time-domain under the vector autoregressive technique (VAR). By applying the forecast error variance decomposition framework based of the VAR model of Diebold and Yilmaz (2009, 2012 & 2014) method, along with the time-varying parameter VAR (TVP-VAR) model of Antonakakis, Chatziantoniou and Gabauer (2020), the different sets of connectedness matrices is obtained which help to reveal the dynamic spillover within the super sectors. The study will further estimate the systemically important super sector taking the various crisis periods into consideration, by employing the PageRank algorithm procedure discovered by Page et al. (1999), which would identify the super sectors that are crucial to the stability of the entire South African economic system. The study employs the nonlinear autoregressive lag distribution model (NARDL) model to further investigate the variables responsible for determining the total connectedness index of the JSE equity super sectors volatility.

1.6 SIGNIFICANCE OF THE STUDY

Apart from uncovering the spillover effect among the equity super sectors in South Africa, the study also unveils the risk contagion pattern, which would give insight to understand connectedness of super sectors in the JSE. The net volatility spillovers results may inform policy makers in identifying which super sectors are the transmitters and the receivers of risk information including the connectedness information of the return series of the super sectors. Therefore, the knowledge of the nature of relationship amongst JSE equity super sectors through the degree of their connectedness or spillovers are of valuable information for regulatory authorities, financial and non-financial firms in diversifying their business portfolios, in hedging risk and strategies in their investments (Hamori & Toyoshima, 2018).

Moreover, for regulators and policy makers, the identification of systemically important sectors (SIS) would inform them on how best policies can be employed in mitigating different risk characteristics.

Diversification benefit of assets has gained a lot of attention in recent years as it is an important decision to consider in allocation of assets for any portfolio manager (Umar 2017). Assets with better diversification benefits display correlation of lower values compared to assets of lower benefits in a portfolio mix and vice versa. In periods of financial crisis when markets display high propagation risk across other assets classes, a well-diversified portfolio would be better protected from such spillover effect (Zaremba et al. 2019), hence, evidence of contagion across equity super sector returns or markets would be of great interest to know how strong the correlations of assets of these sectors are during low or high volatility periods.

1.7 JUSTIFICATION FOR THE STUDY

With the advent and frequency in recurring financial and economic crises all over the word, with African countries being adversely affected. The study on the super sectors of the South Africa economy is significant because the country has the largest stock market in Africa (Ntim 2012; Boako, 2016), one of the top two most diversified economies in sub-Saharan (Usman and Landry, 2021) the second largest economy in Africa and the EU's, U.S and Asia largest trading partner in Sub-Sahara (EU, 2020). Also, the South African stock market (JSE) is one of the three African stock markets opened to foreign participation (Boako 2016) with some foreign industries and financial firms being listed on the JSE and fully integrated into the South African economic system over the years. This implies that the JSE and possibly the entire South African economy could respond to movement in international decisions and policy changes. Hence, this provides possibility of sectorial connectedness with foreign markets and interlinks within the JSE. Therefore, this study ranks the foremost in South Africa to study the interconnectedness among the super sectors of the JSE as it seeks to unravel the risk transmission mechanism from one super sector to another in economy, which is not clear from the literature. Thereafter, establish the economic variables that can be monitored to prevent or lessen sectorial instability from shocks. The outcome of the study would inform regulators of the need to provide accurate and timely policy measures to prevent sectorial instability and failure.

1.8 RESEARCH APPROACH AND DESIGN

A quantitative research approach, descriptive, cause-effect and correlational research design was employed in this PhD research thesis. A quantitative design approach involves objective measurements through the statistical analysis of numerical data collected, to explain or describe an issue or a phenomenon (Apuke 2017). Devi, Lepcha and Basnet (2023) define a correlational research design as a non-experimental technic which involves the use of statistical analysis to examine the relationship between two variables. Singh (2020) defines a cause-effect research design as a research design employed to gather proof of a cause-and-effect relationship between two or more variables, with one variable acting as the dependent and another as the independent variable. This type of research approach allows for an in-depth systematical view and analysis of the different data characteristics, which allows for a better understand of the super sectors used as sample for this research. Moreover, the approach also establishes the relationship between the different super sectors in this study and the reason why such a relationship exists between them, without room for manipulation. In addition, the research designs allow for the detailed and methodological study of the effect of a potential cause in a variable which cannot be manipulated (Devi, Lepcha & Basnet 2023).

Furthermore, the research design is quantitative because it involves the use of numerical data which suits this study. Descriptive design enables the researcher to ascertain the characteristics of the study variables, for example the different super sectors, such as Technology, Telecommunication, Health, Financial and Insurance sectors. Correlational design is relevant for establishing relationships between financial variables such as super sector returns as well as their connectedness and determinants. Cause-effect design is relevant for determining the systematically important sector and establishing the effect of certain variables, namely the South African Volatility Index (SAVI), the local economy policy uncertainty index (EPU), the domestic market return (DMR), Money supply (M2), the manufacturing Output (MOP) and Trade openness (TO) on the connectedness index of super sectors on the JSE.

1.9 ORGANISATION OF THE STUDY

This PhD research thesis would be structured into seven chapters. Chapter one gives the introductory background to the study, statement of problem, research objectives, the research questions and significance of the study. Chapter two provides theoretical review of the literature on connectedness, correlation, contagion, interdependence, spillover, modern portfolio theory and their relationships with this study.

Chapter three provides the detailed review of the empirical literature, the methods employed in such analysis and the conclusions drawn from such works and hence, reveals the gaps in the literature as far as the South African context is concerned.

In chapter four, the study seeks to describe the methodology and all the empirical models employed to achieve all the objectives. To model the return linkages and time varying common equicorrelation, the study shall employ the novel DECO-GARCH model. The aim of three is modelling connectedness under the time domain spillover approach using Diebold and Yilmaz (2014) VAR and the TVP-VAR framework. While in objective one the study will seek to rank the super sectors in order of the PageRank score using PageRank algorithm method. The study will finally investigate the possible determinants responsible for sectorial connectedness on the JSE.

Furthermore, in Chapter 5, the results of the various estimated models are presented. The chapter presents and interprets the results from each estimated model in the order of the objectives. Chapter 6 describes the discussions of the main findings of the results with the purpose of establishing if the findings conform with other works and the conclusions of existing empirical works. Finally, chapter 7 provides the summary of the thesis, implications of findings, limitations and suggestions for further study.

CHAPTER 2: THEORETICAL REVIEW

2.1 INTRODUCTION

The concept of portfolio diversification is rooted in the earlier work of Markowitz. However, over the past two decades certain theories have emerged to explain the changes in correlations of assets, even at the international level. The literature on the theoretical concept of how shocks are propagated and how financial entities are connected is often summarised under the concepts of contagion, spillover and connectedness. Therefore, theories of contagion, interdependence and connectedness are very relevant in the discussion of domestic assets and sectorial diversification. This chapter, therefore, expounds and discusses these theories. In addition, this section is further divided into five main subsections, namely discussing the Modern Portfolio Theory (MPT), Conceptual Clarifications, Theoretical Concept of Contagion and Spillovers, The Concept of Connectedness, Financial Connectedness through Asset and Liability Management (ALM) and The South African Economic Sectors and Industry Classification.

2.2 CONCEPT OF SYSTEMATICALLY IMPORTANT SECTORS

The recent financial crisis has exposed serious flaws in the oversight and regulation of the global banking industry. To increase the resilience of the banking system generally and importantly in times of financial and economic turmoil, comprehensive reforms packages like the Dodd-Frank Act or Basel III by the Basel Committee on Banking Supervision (BIS 2010, 2011) have been devised. Two of these reforms' most important components are the establishment of globally standardised liquidity norms and a significant increase in capital requirements, both quantitatively and qualitatively.

The G20-countries and different international institutes such as the Financial Stability Board (FSB), the Basel Committee on Banking Supervision (BCBS), the International Association of Insurance Supervisors, or the International Organisation of Securities Commissions, have addressed the issue of financial institutions potentially being "too big to fail" or "too interconnected to fail" (Brühl 2017). Therefore, due to their size, complexity and systemic interconnectivity, financial institutions have been classified as systemically important if their crisis or disorderly breakdown would result in a severe disruption to the entire financial system and economy (FSB 2010).

Due to the potential for spillover effects to other financial institutions, as well as to private and institutional investors, a failure of such systemically important financial institutions (SIFIs) could substantially harm the stability of the financial system. Brühl (2017) posits that the failure of a SIFI would have detrimental externalities effect on real economy activities in a variety of ways. On the other hand, to avoid moral hazard and take into account the unique significance of SIFIs for stability of the global financial system, SIFIs are anticipated to have stronger loss-absorbency capacities and are subject to more intensive monitoring and resolution plans.

Furthermore, Brühl (2017) in his article offers a three-part test logic that allows us to categorise financial institutions as systemically significant - regardless of the particular business sector they may majorly operate in. This technique for determining SIFIs proposed in this proposal is predicated on the idea that a SIFI is systemically important if it possesses the following characteristics: global market importance, high-risk potential and high interconnectedness with other financial institutions. A minimum criterion for total assets could be used as a preliminary filter for choosing which financial institutions to examine. This suggests that financial firms with total assets below this threshold would likely be too large to fail.

2.2.1 Non-Bank Entities

Presently in the U.S, the concept of a systemically important financial institution goes far beyond conventional banks and is frequently referred to as a non-banking financial corporation. It includes large hedge funds and traders, large insurance companies and various and sundry systemically important financial market utilities

Regarding which entities will be so designated, the Dodd–Frank Act of 2010 contains the following in Title I—Financial Stability, subtitle A—Financial Stability Oversight Council (FSOC), Sec. 113. Authority to require supervision and regulation of certain nonbank financial companies (2) considerations:

- the extent of the leverage of the company;
- the extent and nature of the off-balance-sheet exposures of the company;
- the nature, scope, size, scale, concentration, interconnectedness and mix of the activities of the company;
- any other risk-related factors that the Council deems appropriate, amongst others

The Financial Stability Oversight Council later issued clarification under the Final Rule on Authority to Designate Financial Market Utilities as Systemically Important, which recasts the aforementioned statutory requirements into a six-category FSOC analytical framework including:

- size
- interconnectedness
- lack of substitutes
- leverage
- liquidity risk and maturity mismatch
- existing regulatory scrutiny

Having enough regulations behind the non-bank institutions has enhanced the systemic importance of these institution has been established over the years (Miller 2019).

It has been reported, in general, how crises affected economies in regions via decreased capital flows, specifically a decrease in investments, a decrease in domestic production and exports and a decrease in remittances (World Bank 2009b). For instance, Eastern Europe and Central Asia have had a thriving economy after the 1998 Russian crisis, which has had a good impact on agriculture sector output and poverty.

Jiang, Koller and Williams (2009) posit that sectors do undergo sequences of decline and recovery during a period of crisis. This suggests that certain sectors of the economies are crucial to the survival of the entire economies beside the financial sector, whose survival is central to the stability of the economy at large; because when they thrive the economy does stabilise. Hence, the concept behind the first objective is to implement the idea of systemically important financial institutions on economic sectors, therefore, substituting financial institutions with super sectors on the JSE, using PageRank algorithm to examine the centrality of each super sector on the JSE.

2.2.2 Theory of Centrality Measure

The first objective of this study seeks to measure the systemically important super sectors on the JSE market through the concept of centrality measurement. Therefore, the theory discussed in this subsection helps to give an understanding of the methodological model used to provide the solution to the first objective. The theory and concept of centrality measure can be explained with the graph theory. Understanding how things are connected through nodes (locations where different paths meet) or edges (paths connecting the nodes) is provided by the graph theory. The most well-known varieties of graphs are digraphs (directed graphs in which A may lead to B but the reverse may not be true), undirected graphs (in which there is no implicit directionality). The study of networks is one of its main applications and when graph theory is used to study complicated networks, the insights it yields can resemble more magic than math. (Shetty 2020).

The semantic relationships between various entities are stored and retrieved by Google using a graph representation, these are referred to as the Knowledge Graph. Google also employs the graph theoretic PageRank algorithm to show someone the most pertinent webpages for their search. For example, friendship links between distinct groups within social networks may be more sporadic and comprise closely knit circles of friends (Shetty 2020).

Communities emerge in a network because not all nodes are equally crucial, some have more "influence" over others than the rest, some are more accessible to others, or some act as a middleman in the majority of node-to-node communications (Shetty 2020). The most frequently employed measures of centrality analysis, which identifies the most crucial node in a network, are closeness centrality, degree centrality and betweenness centrality. The following details these centrality measures:

Closeness centrality

How close one entity is to the other network members may be another factor that is of interest in network analysis. Information could reach other entities much faster through one entity than the other within a network, whereas others may take several steps if information needs to travel across the network (Hansen, Shneiderman, & Smith 2010). Therefore, closeness centrality is the measure of the average shortest distance from each vertex to each other vertex. It is specifically the opposite of the typical shortest distance between the vertex and all other network nodes (Hansen, Shneiderman, & Smith 2010). The closeness centrality is shown as:

Closeness centrality $Cl_c = \frac{1}{Average\ Distance\ to\ all\ Other\ Vertices}$

Higher closeness centrality corresponds to a higher centrality score that is more desirable (i.e., has a shorter average distance to other vertices), using the inverse.

(i) **Degree centrality**

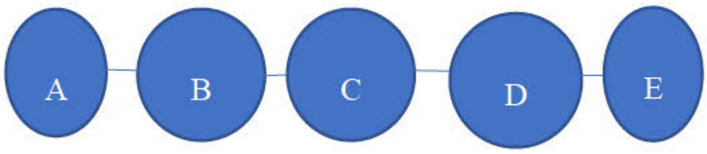
In a network graph, the total number of direct linkages between each node is known as the degree centrality. Equation (i) expresses the formula for degree centrality (Bolland Nieminen 1988; Marvin 1954).

$$C_{De}\ (No_i) = \ \sum_{j=1}^{n} X\ ij\ (i = j) \qquad (1)$$

From equation 1 $C_{De}(No_i)$ connotes the centrality degree, n is the size of the network, while $i\ and\ j$ are points of nodes in the network. The equation also accommodates the size of the network with time, which may increase or decrease. Hence, standardising equation (1), equation (2) is derived:

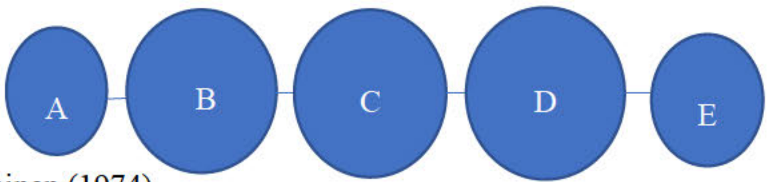
$$C'_{De}(No_i) = \frac{\sum_{j=1}^{n} X\ ij\ (i = j)}{(n-1)(n-2)}\ (i \neq j) \qquad (2)$$

This illustrates that the number of links directly connected with node No and n means the total number of the nodes in focal network (Nieminen 1974).



Source: Nieminen (1974)

Figure 2.1: Degree Centrality Direct Links



Source: Nieminen (1974)

CDE	**1**	**2**	**2**	**2**	**1**
C'_{De}	**0.083**	**0.167**	**0.167**	**0.167**	**0.083**

Source: Nieminen (1974)

Figure 2.2: Degree Centrality Direct Links

Take a network graph like Figure 2.1 as an example, the number of direct links connected with point C obviously is 2, in other words C point's C_{De} is 2, after standardisation C'_{De} is approximately equal to 0.167. In the same way we can calculate Cde and C'_{De} of point A, point B, point D and point E. See the results on Figure 2.2.

Betweenness Centrality

Higher closeness centrality corresponds to a higher centrality score that is more desirable (i.e., has a shorter average distance to other vertices), using the inverse. One node would be significant and most likely have a high betweenness centrality if it serves as the only point of connection, transportation, or transaction for other nodes (Freeman 1977). It could also be referred to as metric that can be used to quantify how important an entity is to the flow of information inside a network. Technically, it determines the percentage of shortest paths that must go via a specific node. It is critical to understand that betweenness evaluates a node's importance to the information flow via a network (Golbeck 2015).

The degree to which a specific vertex is located on the shortest paths connecting other vertices is captured by the measure of betweenness centrality, which represents a fundamentally distinct kind of significance. Hence, it aids in locating people who act in a "bridge-spanning" capacity inside a network (Hansen, Shneiderman & Smith 2010).

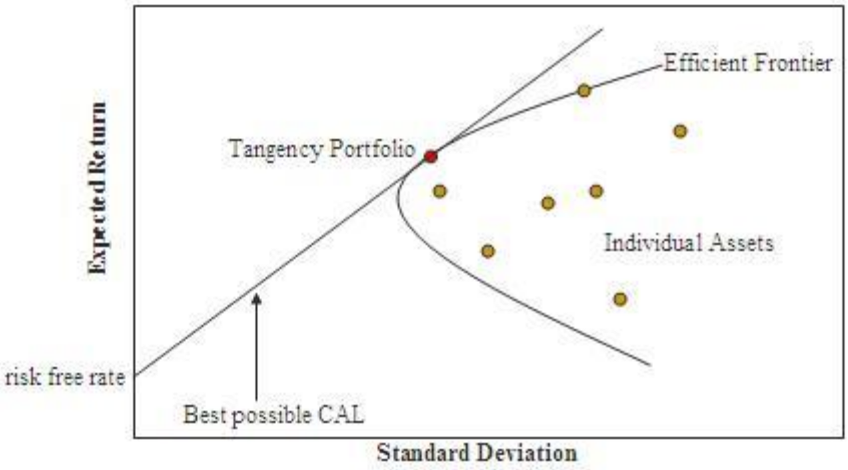
The Eigenvector centrality is employed to estimate the level of influence of a node within a network. Every node within the network will be given a score or value: the higher the score the greater the level of influence within the network. This score is relative to the number of connections a node will have to other nodes. Hence, the score of a node is increased by links to high-scoring eigenvector centrality nodes compared to low-scoring nodes on an equal basis (Shaw 2019).

2.3 THE MODERN PORTFOLIO THEORY (MPT)

The second objective of this study seeks to measure the common equicorrelation of the super sectors on the JSE market and also examining if the common equicorrelation is time-vary. Therefore, the MPT discussed in this subsection helps to give an understanding of assets correlation, portfolio management and formulation. This theory give the foundational background to the second objective of this study. The modern portfolio theory, otherwise known as the mean-variance analysis, is a mathematical framework that can be used to put together a portfolio of assets so that the expected return is maximised for a specific degree of risk (Wigglesworth 2018). It is a formalisation and expansion of diversification in investing, the idea that holding a variety of financial assets reduces risk compared to owning a single type. Its main emphasis is that an asset's risk and return should not be evaluated on its own, but rather in the context of the risk and return of the entire portfolio. The proxy for risk is the variance of asset prices (Wigglesworth 2018).

MPT asserts that investors will select the less risky portfolio if given two portfolios with the same expected return because they are risk averse. Thus, investors would take on increased risk only if there is compensation for a high expected return. Conversely, an investor must take on more risk if they want larger predicted profits. Although all investors will face the same exact trade-off, they will each assess it differently depending on their unique risk aversion characteristics. By holding combinations of instruments that are not fully positively correlated, an investor can lower portfolio risk. If all the asset pairs have correlations of 0, they are perfectly uncorrelated—the portfolio's return variance is the sum over all assets of the square of the fraction held in the asset times the asset's return variance (and the portfolio standard deviation is the square root of this sum (Setayesh 2017).

Figure 2.3 shows the efficient frontier graph. Showing the expected return (vertical axis) against the standard deviation (horizontal axis), depicting the more the increase in risk, the more the returns expected. This is called the 'risk-expected return space.' This risk-expected return space allows for the plotting of every possible combination of risky assets and the region in this space is defined by the collection of all such possible portfolios.



Source: Markowitz (1952)
Figure 2.3 The Efficient frontier plot

The two-mutual fund theorem is a major result of the above diagram. This theorem states that by combining any given two portfolios, an efficient frontier can be generated; the latter two given portfolios are the "mutual funds" in the theorem's name. Therefore, even if all that is available is a pair of efficient mutual funds, an investor can still create any desired efficient portfolio in the absence of a risk-free asset. If the location of the desired portfolio on the frontier is between the locations of the two mutual funds, both mutual funds will be held in positive quantities. If the desired portfolio is outside the range spanned by the two mutual funds, then one of the mutual funds must be sold short (held in negative quantity) while the size of the investment in the other mutual fund must be greater than the amount available for investment (the excess being funded by the borrowing from the other fund).

Regardless of the MPT's theoretical importance, due to the several ways in which its financial models do not align in real world scenarios, its value has been questioned as an ideal investment tool (Damghani M. 2013; Wigglesworth 2018).

The risk, return and correlation measures used by MPT are based on expected values, which means that they are statistical statements about the future (the expected value of returns is explicit in the above equations and implicit in the definitions of variance and covariance). Such metrics frequently fall short of capturing the underlying statistical characteristics of risk and return, which frequently exhibit highly skewed distributions (e.g. the log-normal distribution), which can result in excess growth of return as well as decreased volatility (Hui, Fox & Gurevitch 2017). Investors must actually replace these values in the equations with forecasts based on previous assessments of asset return and volatility. Very often such expected values fail to take account of new circumstances that did not exist when the historical data were generated (Low, Faff & Aas 2016).

Fundamentally speaking, MPT seeks to represent risk in terms of the chance of losses, but says nothing about why those losses may occur, leaving investors stuck with estimating important parameters from historical market data. The risk evaluations conducted are probabilistic rather than structural. When compared to many engineering methods to risk management, this is a significant difference.

The MPT expounds that diversification and risk reduction can be achieved through the reduction of the overall volatility of the returns of the assets selected for the portfolio. The aim is to maximise expected return against a certain risk level. Followers of MPT seek a zero or near-zero correlation in the price movements of the various assets in a portfolio. That is, they seek assets that respond to macroeconomic trends in distinctly different patterns. The ideal selection of assets will have the highest possible return for the desired level of risk (Ross 2022).

The modern portfolio theorist suggests that investors compute the correlation coefficients between the returns of multiple assets in order to select assets strategically that are less likely to depreciate at the same time. It entails figuring out to what extent macroeconomic factors tend to cause the prices of the assets to move in the same direction. The theory seeks to find the most favourable correlation between the anticipated return and the anticipated volatility of several potential investments. The optimal risk-reward relationship was titled the efficient frontier by economist Harry Markowitz, who introduced the modern portfolio theory in 1952 (Goetzmann 2011). A portfolio is referred to as "Markowitz-efficient" if the assets it has chosen have the highest predicted return at a specific level of risk (Ross 2022).

The creation of an efficient-portfolio selection from sectorial perspective would be a perfect application of the MPT for this study. With 11 industries and over 45 sectors as categorised by the international classification benchmark (ICB 2019), the combination or choice of assets of different sectors to form an efficient portfolio is key in maximising expected returns. First, it must be noted that if the correlation of the assets of any two sectors is zero, the two assets of the sectors have no predictive relationship, therefore, the efficient frontier for such a sectorial-portfolio is when the investor finds the combination of sector-assets that offer the best return for a given risk level. Such sectorial assets demonstrate the optimal correlation between return and risk. For instance, if two sectors have an expected return correlation of 100% this implies, they are perfectly correlated. If one sector gains 20%, the other sector gains 20%, if one drops 5%, so does the other. A perfectly negative correlated sector (-100%) denotes one sector's loss is equally matched by another sector's gain. Therefore, for an efficient sectorial portfolio, through the MPT, an investor should look for formulating a sectorial-portfolio, which has assets that are from different sectors/industries and are consistently uncorrelated, possible a near-zero correlation to limit risk, hence, practically demonstrating a diversified sectorial portfolio.

2.4 CONCEPTUAL CLARIFICATIONS

This subsection defines the different definitions of contagion and the different authors that supports these definitions.

2.4.1 Contagion and Spillovers (Definition)

Contagion presents the risk of a singular nature to financial institutions. It is a structural feature of the financial system that is endogenous to the economics of maturity transformation and, in is endogenous to the economics of maturity transformation and, in is judgement or improved prudential oversight (Scott 2016). In the absent affirmative steps to contain it, the problem of contagion will continue to hunt the financial system. While there is no consensus on what contagion is, Pericoli and Sbracia (2003) document a few definitions, which are commonly used in the literature. This study discusses the five most representative:

Definition One: Contagion is a significant increase in the probability of a crisis in one country, conditional on a crisis occurring in another country (ECB 2005). Forbes and Rigobon (2001) explanation of the concept of contagion agrees with this definition.

Usually, empirical research on the effects of exchange rate collapse on the global scale is linked to this definition. It explains why a large number of nations are typically involved in exchange rate crises, even though some of those nations may be able to resist devaluation despite being subject to intense waves of speculative pressure.

Definition Two: Contagion happens when the crisis country's asset price volatility spreads to other nations. The spike in asset price volatility that occurs during times of financial unrest is a stylised fact in international financial markets. Utilising this empirical evidence, our concept characterises contagion as a volatility spillover from one market to another. Asset price volatility is generally regarded as a good approximation of market uncertainty. Hence, interpreting this definition, the spread of uncertainty across global financial markets is referred to as contagion (Dornbusch, Park & Claessens 2000). The causes of contagion in the above definition are highlighted and supported by Wolf (1999), Forbes & Rigobon (2000) and Pritsker (2000).

Definition Three: Contagion occurs when cross-country co-movement of asset prices cannot be explained by fundamentals.

This definition of contagion is theoretically accurate within the context of models that permit numerous instantaneous equilibria in the presence of a coordination issue. Fundamentals alone cannot explain a crisis' time and modalities if it reflects an arbitrary movement from one equilibrium to another. Hence, the state of fundamentals may nonetheless explain why some economies are susceptible to crises while others are not. An economy is at risk, for instance, if contagion spreads due to liquidity problems (Liew, Lim & Goh 2022), because of its low number of international reserves in comparison to its short-term liabilities denominated in foreign currencies. The findings in the Forbes and Rigobon (2000) study align with the above definition.

Definition Four: Contagion is a major or 'a significant' rise in co-movement of prices and quantities across markets, as a result of crisis taking place in a market or group of markets (Forbes and Rigobon 2002). The merit of this definition is its immediate appeal: it fits what is commonly perceived as contagion, such as the spread of financial instability after the Hong Kong stock market crash in October 1997, or after the Russian crisis in the summer of 1998. By stressing the quantitative dimension (a 'significant increase'), this concept characterises contagion as "excessive co-movement" relative to some standard. Furthermore, this definition also presents major problem for international diversification because it has become prominent in the light of different extreme market events in recent times.

Definition Five: (Shift-) Contagion occurs when the transmission channel[5], intensifies or, more generally, changes after a shock in one market. European Central Bank (2006) establish that there are two main channels by which contagion can emerge in financial systems. First is through physical exposure and the other through asymmetric information. The international transmission mechanism may strengthen in response to a crisis in one country (crisis in the financial system). For instance, some channels of transmission might be active only during

[5] Transmission channels are the causal chains that explain how risk drivers impact its targets directly and indirectly through their counterparties, assets, and the economy in which they operate (BCBS 2021).

financial crises. More generally, we could simply identify shift-contagion could be identified with a change in the transmission mechanism[6] contingent on a crisis: there is no reason why the concept of contagion should be confined to the hypothesis of stronger than normal cross-country linkages.

The implications of contagion, according to this definition, are somewhat similar to those of the previous two definitions. As in the third definition, the phenomenon could be due to a jump between multiple equilibria; nevertheless, the definition of shift-contagion also includes discontinuities in the behaviour of economic variables which are produced by learning processes or by informational cascades and herding by market participants. Similarly to the fourth definition, shift-contagion could be measured in terms of excessively strong (or weak) movements of prices and quantities across countries. However, tests for structural breaks in the data-generating process would probably be more appropriate.

All the definitions above clearly, in one way or the other, give a true picture of what contagion means. The bottom line in contagion is a movement in correlation of assets from one market to another. Hence, we could tentatively accommodate all these definitions as correct for the purpose of this study. However, for the deeper emphasis, definition five is the most relevant for this study.

2.5 Theoretical Concept of Contagion and Spillovers

The third objective of this study seeks to examine the connectedness and shock propagation among JSE equity super sectors during different extreme risk events on the JSE market through the Diebold and Yilmaz (2009, 2012 and 2014) Connectedness index and the time-varying parameter VAR framework of Antonakakis, Chatziantoniou and Gabauer (2020). These models have the capacity to capture and quantify spillovers (connectedness) among assets (entities), hence the theories of spillover and contagion discussed in this subsection helps to understanding the concept behind the third objective of this study. Financial contagion is reminiscent of disease transmission. Just like individuals can be either in a state of illness or health, financial markets can generally be classified to be in a crisis state or a non-crisis state. While links between individuals in disease transmission usually describe some form of contact

[6] This is the process through which monetary or financial policy decisions affect the economy in general and the price level in particular (ECB 2023).

or interaction that would allow for the infection to spread, links in a financial network[7] are typically approximated through the similarity of characteristics among the financial entities (Vodenska & Becker 2019). Stock markets usually serve as proxies for the health and robustness of the underlying economies and foreign exchange markets encode macroeconomic fundamentals like GDP growth, inflation rate and unemployment (Taulbee 2000). Therefore, studying the network structure[8] of global financial markets becomes critical to anticipate how a shock may propagate through the system. It is generally assumed that a high degree of correlation suggests a larger likelihood of crisis spreading from one node to another. In particular, tightly knit communities are more likely to react to a given shock in a similar way; therefore, identifying these communities may help to anticipate the dynamics of the shock throughout the network (Vodenska & Becker 2019).

The theoretical literature on how shocks are propagated internationally is quite extensive, however literature has sub-divided these broad set of theories into two groups, namely crisis-contingent theories and non-crisis contingent theories. The former is those that explain why transmission mechanisms change during a crisis and, therefore, why cross-market linkages increase after a shock (Valdes 1996). The latter assumes that transmission mechanisms are the same during a crisis as during more stable periods and, therefore, cross-market linkages do not increase after a shock. As a result, evidence of shift-contagion would support the group of crisis-contingent theories, while no evidence of contagion would support the group of non-crisis-contingent theories (Rigobon 1999). Moreover, in addition to the above two theories, this study further expatiated briefly on other three theories on contagion and spillover which are the financial view, the coordination view and the fundamental view.

2.5.1 Crisis-Contingent Theory

There are three major mechanisms to illustrate how shocks transmit internationally, namely endogenous liquidity, political economy and multiple equilibria. The multiple equilibria theory is used to explain when financial or economic crisis in an economy is used to sunspot for other

[7] A financial network is a term that describes any grouping of financial institutions (such as traders, corporations, banks, and financial exchanges) and the connections that exist between them, ideally through direct transactions or the capacity to mediate a transaction.

[8] Network structure refers to a general system, or pattern of inter-relationships that can be derived from the observable behaviour of entities in a given population.

economy. For instance, Manson (1998) illustrates how crisis in an economy has the potential in coordinating investor’s perception and expectation from good to a bad equilibrium for another economy; hence, resulting a burst in the second economy. Escalation of such events results in negative comovements in asset prices; these occur due to correlation of bad memories rather than market fundamentals. Therefore, the equilibrium shift couple with shock transmission occur as a result of beliefs and expectation of investors instead of real linkages.

In the *endogenous liquidity* category of the crisis contingency theories Valdes (1996) propounds a model where the liquidity of investors in a market can be reduced when crisis occur in an economy. In such a condition, investors are compelled to reformulate their portfolios, sell their assets in other countries to continue to operate in the market and satisfying margin calls. Conversely, in a large enough liquidity shock, the degree of credit rationing could increase in a country and force market participants to sell off assets in economies not affected by the initial crisis. In the political economy mechanism, Drazen (1998) stipulates that central bank of different economies may be forced through political pressure to maintain a fixed exchange rate, as a result there could be a clumping of exchange rate of these economies, hence, spread of original shock via a pattern not in existence before the initial crisis. Calvo (1999) develops a different model of endogenous liquidity. In this model, there is asymmetric information among investors. Informed investors are affected by liquidity shocks (margin calls), which drive them to liquidate their holdings, after receiving warnings about a country's fundamentals. Uninformed investors charge more when informed investors are net sellers because they are unable to differentiate between a liquidity shock and a poor signal. The liquidity shock increases the correlation of asset prices in each of these models. This transmission-mechanism only operates after the initial shock and does not operate during stable times.

2.5.2 The Non-crisis-contingent Theory

This theory expounds the way shocks from an economy can be transmitted across countries and yet do not result in a shift-contagion. It explains that the mechanism of propagation of shock is not different from before the crisis, hence, any correlation of sectors or markets or economic fundamentals before a crisis are continuation of the linkages which exists before such crisis. The theory has four basic channels in which they can be explained which are: country revaluation, trade, random aggregate shocks and policy coordination.

The trade transmission mechanism could occur through several ways. The devaluation of a country's currency puts enormous pressure on the relative competitiveness of that country's goods as regards exportation or importation. When exports in such economies increases local sales of such exported goods are adversely affected. Also, this devaluation could adversely affect export sales from other countries competing in the same market. Therefore, if loss in competitiveness is much it may cause an increasing expectation for devaluation of exchange rate and result to an attack on another country's currency (Gerlach & Smets 1995; Corsetti et. al. 2000).

The second transmission mechanism, policy coordination, links economies together because a nation's response to a financial shock may compel another to adopt similar measures. For instance, a trade agreement might include a clause in which lax monetary policy in one nation forces other member countries to raise trade barriers (Forbes & Rigobon 2001).

The third propagation mechanism, country re-evaluation or learning, maintains that investors could apply the lessons learnt after a shock in a specific economy (for instance a developing economy) to other countries with similar macroeconomic structures and policies (Rigobon 1998; Chari & Kehoe 1999; Calvo & Mendoza 1998). For instance, if a country is vulnerable to currency crisis due to a weak banking system, investors could reassess the health of the financial systems in other nations and modify their anticipated crisis probabilities accordingly.

The final non-crisis-contingent transmission mechanism argues that random aggregate or global shocks could simultaneously affect the fundamentals of several economies. For example, a rise in the international interest rate, deduction in the volume of global money supply, or reduction in global demand in commodities (such as for commodities), even the frequent changes in global crude oil prices could have the capacity to simultaneously slow growth in some economies. Asset prices in any countries affected by this aggregate shock would move together (at least to some degree), so that directly after the shock, cross-market correlations between affected countries could increase (Forbes & Rigobon 2001).

2.5.3 Fundamental View

The fundamental view of contagion and spillover explains the propagation of shocks across countries by appealing to real channels[9]. The papers on contagion and spillover in this literature include explanations based on bilateral trade, trade of similar goods with a common market and monetary policy coordination and macroeconomic similarities (Corsetti, Pericoli & Stracia 2005; Corsetti et al. 1999; Gerlach & Smetts 1995). For example, on the bilateral trade explanation (which happens to be the first paper on contagion!), if a country has a crisis and its consumption declines, then the country's imports are likely to decline as well (Gerlach & Smets 1995). Therefore, the trading partners experience a decline in the demand for their exports: either their prices drop—a deterioration in the terms of trade—or they reduce production. In both cases, their GDP declines and there is a recession and quite likely a depreciation. All international real business cycle models exhibit this transmission channel. According to (), this can easily be extended to two unrelated countries (peripheral countries) trading with a third one (the centre country). If the country at the centre suffers from a crisis, the demand for the exports of the peripheral countries declines. So, the two seemingly unrelated economies experience common shocks that are transmitted through the trade channel.

Monetary policies and other macroeconomic policies are also linked by trade. Therefore, the transmission is not exclusively through relative prices but can also occur through monetary policy coordination and other similar macroeconomic policies. For example, if the US increases its interest rates, other countries have to evaluate their monetary policy paths. The increase in the US is a common shock to the world and several emerging markets would suffer the negative consequences. In Latin America, Argentina, Brazil and Venezuela have undergone massive recessions in 2016–2019—though Venezuela's is self-inflicted. Countries such as Chile, Colombia and Mexico are slowing down, but to a much lesser extent. Interestingly, the best predictor of "suffering" is if the country exclusively touches the Atlantic Ocean.

The theories based on fundamental transmission mechanisms were used to explain the transmission from the Great Depression and European crises in the 1970s and 1980s. In those instances, trade played a very important role in the transmission of the shocks. Most of these papers study the interaction between real shocks, real variables and nominal exchange rates,

[9] Real channels are non-financial mediums by which shocks within the economy are propagated.

even though most of the contagion was evaluated in countries depreciating their currencies (Forbes & Rigobon 1999; Forbes 2001).

The finance literature combines trade and asset prices in a single framework. Pavlova and Rigobon (2007) use a general equilibrium model to analyse the interactions between international asset prices, the exchange rate and trade in goods. Furthermore, Martin (2013) studies asset prices in a multi-country model and shows how shocks from one country change conditional correlations exactly in the spirit of contagion. These two papers put together the simple intuitions of trade within asset price models.

2.5.4 Financial View

Rigobon (2019) that the financial view concentrates on constraints and inefficiencies in banking sectors and international equity markets. The idea of this channel is that imperfections in the financial system are exacerbated during a crisis and such imperfections limit the extent to which financial services can be provided to different countries—which ex ante might have been seen as independent. This theory, in general, implies that a shock increases the propagation of shocks across countries. In most of these models, trade channels—and other fundamental channels—are shut down. In other words, the theories based on financial linkages assume that real linkages are not present and that the only reason behind the propagation of shocks is that financial markets are imperfect and subject to a variety of constraints (Rigobon 2019). This is obviously an extreme assumption, but it allows for a clearer analysis of the reasons behind the transmission mechanisms.

Generally, the argument on contagion goes as follows: Assume that two countries receive financial services from a third party. The financial services can be direct lending, insurance, the provision of liquidity and so forth. The assumption is that a shock in one country affects the balance sheet of the financial intermediary, limiting its ability to continue offering the same services to the other country. The reduction in the service to the second country has real effects owing to the presence of financial imperfections. In the end, this affects asset prices and exchange rates as well (Rigobon 2019).

Therefore, the countries are interrelated because both are receiving financial services from a common financial institution or market. For instance, the common-lender theory by Goldstein, Kaminsky and Reinhart (2000) and by Kaminsky & Reinhart (1999) assumes that a single bank is leading to two countries whose outputs are in principle unrelated (Goldstein, Kaminsky, &

Reinhart (2000); Kaminsky & Reinhart (2003)). A crisis in one country affects the bank's balance sheet, forcing the bank to stop lending to the second country. So, even if two countries are independent in terms of real linkages, their international flows still co-move, as do other macroeconomic variables. These theories were developed to study the Asian crises in 1997. In this case, the Japanese banks were the culprit of the contagion. The theories based on margin calls, liquidity aspects, or wealth effects are similar in spirit to the common lender. In these cases, the financial intermediary is the capital market instead of the banking sector. The most prominent example of these theories is documented by Calvo and Mendoza (2000). In these models, a shock in one country lowers the value of the portfolio holdings of the intermediary.

The fall in wealth implies that financial intermediaries behave either as if they have a higher degree of risk aversion or are subject to margin calls. Both reasons force them to sell off assets in the same asset class. In the end, this implies downward pressure on all the assets held by the intermediary, causing contagion. Most of these theories were developed to understand the transmission during the 1998 Russian crisis and the aftermath of the Long-Term Capital Management (LTCM) crisis. Finally, new theories of financial spillover highlight the network across financial institutions as the vehicle of propagation (Allen & Gale, 2000). This is a promising area of research, although measurement of the interconnections in the network is still an open question. In particular, what makes two markets connected? Is it their high correlation or their conditional distribution? What if the high correlation is the outcome of an omitted variable? These are all still open questions in the literature.

2.5.5 Coordination View

The third class of theories is based on coordination failure. The coordination view investors and policymakers' behaviour and coordination problems as the explanation behind contagion. In these theories, most of the contagion comes from investors' actions and is usually a learning or herding problem. Theories based on the coordination of market participants include explanations where the spillover is due to multiple equilibrium, herding, learning and political contagion (Rigobon, 2019).

The transmission of shocks occurs because there is an informational problem that drives market participants (investors) to withdraw resources jointly across countries. In addition, policymakers can coordinate and decide to abandon a particular macroeconomic policy—usually the exchange rate regime—when another country implements the same policy. In the end, the transmission exists because the actors in the market coordinate and move from one equilibrium to the other and not because the countries have something in common—except for the policy shift. In the first multiple equilibrium framework of contagion, contagion is defined as a shift from a good to a bad equilibrium (Masson 1998). When the herding informational cascades are applied to capital flows, the spillover occurs because information in one country leads investors to take actions in another (Chari & Kehoe 1999; Calvo & Mendoza 2000). Theories of learning or herding problems have also been used to explain contagion (in particular) (Rigobon 1998; Kodres & Pritsker 2002).

Finally, political contagion is one preferred theories of spillover. Drazen (2000) examines why the Exchange Rate Mechanism (ERM) was abandoned in Europe in 1991. The assumption is that being a member of the ERM was like being a member of a gentlemen's club. Although being a member of the club had its advantages in terms of prestige and class, it also demanded substantial sacrifice. According to Drazen's concept, when a nation decides to leave the club, two things happen: one, leaving has a lower cost for the subsequent gentleman and second, staying in a smaller club has a lower value. As a result, the likelihood that other countries will follow suit increases when one does. According to his theory, the variation in reputational cost drives all nations to collectively accept or reject a specific policy. One could contend that Drazen's processes were followed by the political rise of populism in Latin America. Chávez came to power in Venezuela in 1999 (elections in 1998), at a time when Latin America was mostly following policies close to the centre of the political spectrum. Chávez's political triumph spread to neighbouring nations in varying degrees. The worst-hit countries were Bolivia, Brazil, Ecuador, El Salvador and, of course, Argentina. But by 2018, the menace of radical populism had to be addressed in all of Latin America.

2.6 CONCEPT OF CONNECTEDNESS

2.6.1 Selected Events as the Basis for the Investigation of Contagion and Connectedness

Extreme financial and economic crisis from major developed nations such as the US subprime mortgage crises and other extreme events have successfully spurred the interrogation of connectedness and contagion in recent time and its impac.t in other markets. Therefore, this sub-section gives a brief information on connectedness of assets, businesses and institutions.

Due to a fast increase in subprime mortgage foreclosures and delinquencies, the subprime mortgage crisis was one of the early warning signs of the late 2000s financial crisis, which originated in the U.S and led to a sharp decline in the value of assets backed by mortgages. As a result, the mortgage crisis had a significant negative economic impact on the United States. By mid-2008, total home equity in the U.S had fallen to $8.8 trillion from $13 trillion at its 2006 peak and property prices had fallen by 20% since that year's peak. Savings and investment assets loss $1.2 trillion during this time period and pension assets lost another $1.3 trillion. Summing this up, Americans lost more than 25% of their net worth between June 2007 and November 2008. The effects on financial institutions, banks and SMEs were unquestionably the most severe. The collapse or forced mergers/bailouts of Bear Stearns, AIG, Fannie Mae, Freddie Mac, Lehman Brothers, IndyMac Bank, Merrill Lynch, Wachovia, Washington Mutual and many more companies in 2008 sent the markets into a tailspin (Francis, 2008).

Since the middle of the 1990s, nations have interacted with one another more and more as a result of the globalisation of their sovereigns', financial institutions' and enterprises' asset and liability management (ALM) strategies (Moghadam & Vinals 2010). However, this financial globalisation has both advantages, such as the pooling of risks and drawbacks, such as the spread of crises. Common intermediaries following global ALM strategies that collectively become overexposed to risk in the upswing of a credit cycle and unduly risk-averse in the downswing can amplify and propagate shocks in one area of the system (Moghadam & Vinals 2010). It spreads quickly from the U.S to the rest of the world. Both developed and developing economies were somewhat impacted by the crisis. Institutions around the developed world, including the G7 nations, have experienced financial shock connected to the subprime crisis on the side of developed countries. For instance, numerous banks throughout the globe are reporting significant losses brought on by the subprime crisis. The Citigroup in the United States, Crédit Agricole in France, HSBC in the United Kingdom, CIBC in Canada, or Deutsche Bank in Germany (Paulo, Carlos, & Isabel, 2008) are only a few examples of the banks that are available worldwide. Similarly across the developing countries the crisis resulted in huge downturn in their economy (Paulo, Carlos & Isabel, 2008).

The negative effects of the crisis in developing countries were further amplified by the deepening recession in the U.S and other developed nations (Stephany & Jose, 2009). In other words, most African, Asian, Latin American countries GDP growth was slower after the mid of 2008 according to IMF’s data. However, it was documented that the levels of financial contagion that the United States has on various nations are highly diverse. Additionally, there is a difference in the timing of the financial contagion effect.

2.6.2 Financial Connectedness through Asset and Liability Management (ALM)

Through the asset and liability management (ALM) policies of their sovereigns, financial institutions and enterprises, countries are financially interconnected. Benefits and vulnerabilities have both been brought about by this financial globalisation. The risks of interconnection are particularly highlighted by the speed with which illiquidity and losses in specific markets can result in global asset recomposition. Therefore, tracking the development of systemic risk concentrations, identifying the fault lines down which financial shocks propagate and improving macroprudential surveillance and policy making all depend on knowing the nature of these interconnections (Moghadam & Vinals 2010).

Most the world's financial transactions are handled by a small number of large, complex financial institutions (LCFIs), which operate out of a select few nations that act as the world's primary lenders and borrowers. These nations serve as the hub of cross-border financial flows of assets and liabilities, linking nations together. These core economies have a significant role in the dissemination of shocks as well as the spillover of policies and financial circumstances.

The global desire for income caused a trend away from more expensive deposit funding in the run-up to the GFC, which led to an increase in LCFIs' reliance on market-sensitive funds. This liability recomposition was made possible by regulatory arbitrage and reflected developments on the asset side brought about by securitisation, ratings creep and leverage. Balance sheet expansion and improved cross-border and nonbank banking links were the outcomes of this approach. Additionally, it led to the accumulation of systemic risk concentrations and created the crucial fault lines along which global liquidity shocks were later conveyed.

As regards the relationship between international connectedness and its implications for domestic assets or sectorial connectedness, Costa, Matos and da Silva (2022) document that there exists an increase in a system-wide asymmetric changes for domestic sectors in the United State of America. They further document that the COVID-19 pandemic induces factors such as fire sales, herd behaviour policy action and feedbacks which in a concerted way contributed to the retraction in economic activities among the sectors. Moreover, through trade and financial channels Cesa-Bianchi, Dickinson, Kösem, Lloyd and Manuel (2021) assert that events abroad have affected the UK in both positive and negative ways due to this deep integration within the global financial and trading system. Emphasising that foreign developments account for around half of the variation in UK GDP and for over two thirds of the variation in a measure of tail risk.

Moghadam and Vinals (2010) posit that in order to further develop an accurate understanding of financial interconnections and the build-up of systemic risk concentrations, large data gaps need to be bridged and additional analytical tools developed. In this context, understanding the equity super sectors is relevant in terms of their network, interlinkages and connectedness. For bilateral and multilateral surveillance, a deeper appreciation of interconnections beyond simply aggregated country-level analysis is required. Hence, it is vital to pay attention to the sub-periods of extreme market events from the external sources in the analysis of sectorial diversification. Further dialogue with policy makers is also needed on the macro-prudential policies to address risks.

2.7 THE SOUTH AFRICAN ECONOMIC SECTORS AND INDUSTRY CLASSIFICATION

The super sectors identified and used for this study are appropriately classified by employing the industry classification Benchmark (Equity) (ICB) system published in June 2021. The ICB classifies companies into subsector, sector, super sector and industry through the nature of their business, (e.g. Energy (as industry), Energy (as super sector) and Oil, Gas and Coal (as sector)) as whether they are involved in via their revenue sources or the source where the highest percentage of their revenue is sourced from. The ICB classification system allows for a comprehensive structure to be allotted to the industry and sector of the South African economy allowing the possibility of proper analysis and comparison across all the four major levels of classification (FTSE Russell, 2021).

Under the ICB classification, the super sectors in the Johannesburg stock exchange (JSE), entail, Technology (Tech), Telecommunications (Tel), Health care (HEL), Financial services (FIN), Automobiles and Parts (AM & P), Industrials (IGS), Chemicals (CHE), Energy (ENE) and Insurance (INSUR).

Technology: South Africa is home to one of Africa's largest information and communications technology (ICT) markets. It depicts the state of online banking, security software and mobile applications as technologically advanced. South Africa has a sophisticated and developed ICT and electronics sector, which is increasingly contributing to the GDP of the nation. Companies with subsidiaries based in South Africa include IBM, Cisco, Unisys, AWS, Microsoft, Intel, Systems Application Protocol (SAP), Dell, Novell and Compaq. It is regarded as a regional centre and a supply base for nearby nations (ITA 2023). South Africa's ICT goods and services industry is growing and entering the rapidly developing African market. Most of the new fixed and wireless telecommunications networks installed on the continent in recent years have been supplied by South African companies and locally based affiliates of foreign corporations. (ITA 2023).

Companies in the Technology sector are primarily involved in the development and the advance of information technology and electronics industries. It comprises businesses that create integrated computer systems and services, application software that is not particular to industry market sectors and suppliers of digital platforms that make money from displaying advertisements and charging advertisers membership fees. Companies that create subsequent-generation electronics and associated components are also featured (ICB 2021). The contribution of the entire Technology sector in 2022 to the GDP of the South African economy was 8%, this figure includes the information and communication technology (ICT) subsector (Trade Commissioner 2023). When a nation imports more than it exports, a trade deficit is created. ICT imports have continuously outpaced exports in South Africa. However, between 2011 and 2014, trade deficits have increased from R42billion to R97billion (Statistic SA 2017).

Telecommunication: The country's expanding economy depends heavily on the telecommunications industry. The service provider and telecommunications equipment sectors make up the majority of it, with the former including service providers and cable television services. (ICB 2019).
In 2020, the overall telecommunications income climbed somewhat by 3.6%. In 2020, the total income from mobile services increased by 7.8%. 2020 saw a 5.4% decline in overall fixed internet and data revenue and a 24.1% decline in total fixed line revenue. Over a period of 6 years from 2015 to 2020, the total Telecommunication revenue increased by 5.3%. The total mobile services revenue and total fixed internet and data revenue increased by 6% and 2.8%, respectively, however fixed line revenue decreased by 12.6% for the same period (ICASA 2021). In addition, the contribution of the telecommunication sector to the gross domestic product of the South African economy was 3.0% in 2017 and has increased marginally since then (Statistics SA 2017; Sinclair & Barros 2019).

In South Africa, the demand for telecommunications services has dramatically expanded during the past five years. Due to emerging technology (including artificial intelligence and the internet of things) as well as the COVID-19 pandemic, data requirements have recently increased particularly swiftly. The "to Business" (2B) and "to Consumers" (2C) markets make up the SA Telecom market's two main segments. There are two main telecom infrastructures in each of the two key markets: fixed network and wireless. Currently, they provide wireless service to roughly 9M South Africans (Gao 2021).

Health Care: Currently, South Africa has a two-tiered healthcare system with a larger public sector and a much smaller but quickly expanding private sector. While 80% of the population receives healthcare from the public sector the private sector caters for the balance of 20% (Africa Health 2019).

Healthcare services range from the most fundamental primary care, which is provided free by the government, to highly specialise hi-tech health services, which are supplied in both the public and commercial sectors. Middle- and high-income earners who frequently participate in medical plans make about 18% of the population and the private sector, which is mostly managed on commercial principles, caters to them. The majority of the nation's health professionals are attracted to the private sector. With a focus on public-sector healthcare, the Department of Health is in charge of the nation's healthcare generally. There are 211 private hospitals and about 400 governmental hospitals in the nation (Africa Health 2019).

In 2017, the nation spent 9% of its GDP on healthcare, which is 4% more than the WHO suggests for a nation of its socioeconomic standing. Health outcomes fall short of those of comparable middle-income countries despite these high costs, mostly due to differences between the public and private sectors (Africa Health 2019).

Moreover, the South African Health system has transited through diverse challenges and phases since pre-apartheid and post-apartheid. The apartheid era (1948–1993), during which the healthcare system was incredibly fragmented and had a discriminatory impact on four separate racial groups, is where the current health sector difficulties originate (Maphumulo & Bhengu, 2019). Even 26 years post-apartheid, health care inequality in South Africa is worse for low-income, black South Africans than it was under apartheid, despite the fact that access to health care services is a fundamental human right protected by the Constitution (Norris, 2010).

Despite tremendous efforts since independence in 1994 to raise the standard of healthcare delivery in South Africa, there are still many obstacles to overcome. Increased demand for medical services, widespread corruption, brain drain, deteriorating infrastructure and these factors all contribute to the growth of the healthcare sector.

In spite of these difficulties, the South African government has pushed for the implementation of the National Health Insurance Scheme, which will pool funds to provide all South Africans with access to high-quality, reasonably-priced personal health services based on their individual health needs, regardless of their socioeconomic status (Hlatshaneni, 2019).

In research conducted by PWC, in order to give insight and direction to the growth, development and stability of the South African health sector for the benefit of all the South African populace, a few key recommendations were made which are in line with international studies which can be employed by health parastatals, which could lead to the health sectors transformation (PWC 2022):

- South Africa's healthcare system will undergo a revolution through the empowerment of National Health Insurance (NHI), which will also foster innovative public-private partnerships.
- With cutting-edge innovations and technical support progressing in leaps and bounds, the future of the healthcare is brighter and secured.
- The South African healthcare sector needs an undivided attention on social, environmental, government initiatives and measures.

Financial Services: The commercial banking business, insurance industry, retirement fund industry, investment and asset management industry, financial advising and intermediary industry, financial market infrastructures, retail lending industry and payment providers are all included in the financial services sector. The financial sector in South Africa is sophisticated with an asset to growth domestic product ratio above most emerging market. Domestic credit to the private sector as a percentage of GDP stood at 129%, the highest amongst all African countries (FSCA 2022).

Significant progress has been made to expand financial services to the unbanked with a good number of the population owing individual bank account. Major local banks are highly regarded and South Africa's banking sector is recognised as one of the best globally. The top Five JSE-listed banking groups are FirstRand (FNB), Absa, Standard Bank, Nedbank and Capitec and also dominate South Africa's retail banking market. But with the entry of new banks to the market, the banking landscape is becoming less consolidated and increasingly competitive. The banking sector consists of 10 locally controlled banks, 7 foreign controlled banks, 3 mutual banks, 2 co-operative banks as about 50 branches and representative offices of foreign banks, with a total banking asset of approximately R6Trillion (SARB 2019). However, active usage remains at low levels due to real access to financial services (FSCA 2022). In the face of competitive entrance into the changing banking landscape in the country Tyme bank, Discovery bank and Bank Zero have gained entrance into the sector in the last four years, yet the largest banks hold over 85% of the industry’s assets as at 2020 (FSCA 2022).

The occurrence of the July 2021 civil unrest in the country lead to considerable damage in banking infrastructure such as buildings, ATMs and shortage in cash for clients. Whereas, just a year before, the insurance industry experienced a huge increase in the number of claims due to the 2020 COVID-19 pandemic prevalence, with quite a number of customers and businesses reporting failures of the insurance firms to pay the claims to them (FSCA 2022). However, quite a number of insurers have increased premiums on policies to cater for the increase in the risk of death, arising from the pandemic (FSCA 2022). Masondo (2020) reports that the South African banking sector is the engine of the South African economy and arguably one of the most important sectors, which has made important internal transformation and hence, made an impact in the transformation to the economy.

The South Africa’s retirement segment of the financial sector seats on assets in excess of ZAR4.6trillion with one of the highest ratios to GDP in the world. With an active fund of 1, 580 funds out of 5,154 demonstrating 31% active funds. Coverage remains a major constraint in the retirement sector with an estimation of 7-10 million individuals having retirement savings products out of an employed labour force of about 15 million (FSCA 2022).

Several million consumers are served by the South African investment and asset management sector, which has had continuous expansion in terms of consumer numbers, investment activity and assets under management (FSCA, 2022). As of September 2021, the investment industry held an estimated ZAR 4.26 trillion in total assets under management; 79% of the total assets under management were held by local CIS, 18% by foreign CIS, while CIS in hedge funds held 2%. While growth of the private equity sector over the last 20 years has been significant, year on year growth has been more volatile (FSCA 2022).

Although the formal loan market in South Africa is well developed and serves over half of the country's population, the informal credit market is nonetheless pervasive. Unregistered lenders have been in business for a while in South Africa and are seen as socially rooted in lower-class areas. However, over-indebtedness is still an issue, as more than 50% of credit-active customers in South Africa fall into this category (FSCA 2022). As more people obtain credit since 2009, the value of consumer credit has continuously increased. The number of persons with active credit accounts peaked in 2020 as more people turned to loans as a result of increased financial strain brought on by the COVID-19 outbreak.

Automobile and Parts: After mining and financial services, the Automobile sector in South Africa is the third largest economic sector in the country. Currently, it is the world's eighteenth largest industry for the production of Automobiles (South African Embassy 2021). The South African Automobile and parts sector plays vital role in the economic strength of the country. With the economic interest of countries like the Japanese, European and American vehicle manufacturers, the wealth of experience of these countries has been capitalised on (NAAMSA 2022). Due to the investment opportunities such as well-established infrastructure, developed manufacturing capacity, diversified economy and sophisticated capital market, the country has become a destination choice and production-base for automobiles to be exported to continental markets and even to the global market with much easier logistic and low production cost (NAAMSA 2022).

In 2004, South Africa exported assembled cars to 53 nations, including Germany, Japan, the US, the United Kingdom and Australia. Toyota Motor Corporation has picked South Africa as its manufacturing hub for 200 000 vehicles, 100 000 of which was exported in 2010, these vehicles will include Hilux vans and SUVs, contributing 6.7% to the total GDP of the country (SAE 2022).

But by 2020, the country’s statistics show that the Automobile and Parts sector's overall GDP contribution was 4.9% (i.e. 2,8% manufacturing and 2,1% retail), which is a reduction from the 2019 contribution of 6.4%. Which was due to the severe effects of COVID-19 on automotive manufacturing and retail as a result of the country lockdown restrictions that were in place during the year. Vehicle and automotive component manufacturing activity, the largest manufacturing sector in the economy, contributed a significant 18.7% of value addition to domestic manufacturing output, maintaining the industry's position as a major player in South Africa's industrialisation process. Vehicle and automotive component manufacturing activity, the largest manufacturing sector in the economy, contributed a significant 18.7% of value addition to domestic manufacturing output, maintaining the industry's position as a major player in South Africa's industrialisation process (NAAMSA 2022).

The South African Embassy in The Netherlands, in its report in 2021, documents that the South African Automobile and Parts sector has the following comparative advantages compared to other African countries which includes the following: good infrastructure, availability of raw materials, emerging market cost advantages, low tool cost, competitive industrial based and first-class production tests.

Insurance: The life-insurance and non-life insurance super sectors are classified under the insurance industry. Companies that engage in mainly life and health insurance are categorised under the life insurance and those involved in wide range of insurance combination products which includes property/casualty and specialty insurance are categorised under the nonlife insurance companies (FTSE 2021). In addition, reinsurance brokers and property and casualty insurance which provide insurance services against accident, fire marine, are other classes of nonlife insurance (FTSE 2021).

In addition to the life-insurance and non-life insurance markets under the insurance industry, the reinsurance market is another market under the insurance industry. The South African Insurance sector has 34 non-life insurers, 19 life insurers and 4 reinsurers within its markets (KPMG 2021). Below are the statistics of the industry for the year 2020 to 2021.

Non-Life Insurance

- Profit after tax rises from R5.6 billion to R11.7billion which is a 110% increase.
- Gross Written Premium (GWP) rose by 7% from R123 billion to R132.6 billion in 2021
- 76.5% of the contribution in Gross Written Premium (GWP) was accounted for by the top 10 largest insurer.

Life-Insurance

- Net Written Premium (NWP) rose up to R595 billion (10.4% increase)
- New policies were sold in 2021 (10.4 million), compared to 2020 (8.9 million).
- A rise in Total assets from R3.2 billion to R3.7 billion
- Profit after tax was a loss of R5 billion in 202 but rose to R17.7 billion in 2021.

Reinsurance

- Underwriting losses up from R50 million to R3.8 billion
- Gross Written Premium rose by 1% (3rd year of declining growth).
- Investment income down 11% (with a declining investment base) (KPMG 2021)

General Industrials: Consists of businesses that specialise in the creation, manufacturing and distribution of capital goods as well as the provision of business support services, includes producers of commercial vehicles, industrial machinery and equipment, weapons and defence, aerospace and commercial vehicles. The service segment consists of diverse logistic support services, international trade, business support, maintenance and security services and commercial transportation services (FTSE Russell, 2021).

SARB (2020) documents that the South African manufacturing sector as one of the industrial arms of the country has witnessed series of evolution in performance. Despite having peaked at about 23% in the early 1980s, manufacturing still plays a significant role in South Africa’s economy. With 42% in exports achieved the sector made 12% as contribution to GDP in 2019 alongside a 12% contribution to employment in the formal sector. South Africa’s manufacturing performance is behind the environmental monitoring (EM) average even if the evolution of manufacturing value added (MVA) looks to be in step with global trends.

The South African general industrial: (manufacturing, distribution of goods and services, industrial machinery and equipment etc.) remains concentrated in energy-and capital-intensive subsectors because the sector has been unable to diversity. The aforementioned highlights the requirement for (industrial) policies focused at establishing capabilities and creating fresh sources of competitive advantage in order to halt/reverse deindustrialisation (SARB 2020).

A key indication of the strength and competitiveness of the general industrial and manufacturing sector, sophistication or technology intensity of manufacturing is a measure of the direct research and development (R&D) intensity and R&D incorporated in intermediate and investment goods (Hatzichronoglou 1997). Despite being the lowest-ranked BRICS member, South Africa is placed first in sub-Saharan Africa and 45th globally in terms of the competitiveness and industrial development index (CIP) (UNIDO 2019).

Chemical Sector: A significant portion of the South African manufacturing economy is the chemicals sector. According to the Chemical and Allied Industries' Association, it represents 25% of the nation's manufacturing sales and is the most advanced of its sort in Africa (KPMG 2019). The chemical super sector in South Africa has a self-sufficient chemical manufacturing base, however exportation and importation of chemical-based products are a way of maintaining trade relationships with key trade partners such as the US, Germany and China (Majozi & Veldhuizen 2015).

The industry has a diversified and complex nature with different subsectors. This is due to the fact that the industry’s outputs are mostly essential and used across other sectors of the economy, hence, it plays a critical role in the South African economy (DTIC 2018). Sales of domestic chemicals increased significantly in recent years, with a CAGR of 7.6% between 2006 and 2016 (MarketLine, 2016). Despite demonstrating resilience in the face of increasing exposure to global competition, with local manufacturing output growing at a CAGR of 3.6% between 2001 and 2016, the local chemicals manufacturing sector has been unable to take advantage of local market growth, with imports being the main beneficiary (DTIC 2018).

The emerging threat to South Africa's chemical production and related industries is another crucial resource, water. The country is one of the 30 driest countries in the world and the need to use water more efficiently has never been more urgent, hence, the much dependence on water by several companies in the chemical sector such as the pulp and paper companies, is a cause for serious concern (Majozi & Veldhuizen 2015). The South African chemical industry is part of the international market; however, the sector must move away from the apartheid philosophy of isolationism and protectionism, which it was founded on and it's shielding it from global competition so it can be sustainable (Majozi & Veldhuizen 2015).

About 3.0% of South Africa's GDP and 22% of all manufacturing production are contributed by the chemical industry, which significantly boosts our country's economy. Demand for chemical sector products rises as a result of economic expansion, which in turn spurs product innovation. However, the sector's economic contribution is decreasing as a result of, among other things, the rising cost of doing business in South Africa, which includes the increasing application of regulatory and economic tools (CAIC 2020).

Energy: The energy super sector is at the centre of the economy due to the nation's high energy intensity despite the country's recent electricity struggles, the country has a robust and developed electricity network, which makes it one of the highest rates of electricity access in sub-Saharan Africa (IEA, 2020). For both domestic and non-domestic use, the department of Mineral Resources and Energy is required to guarantee that energy resources are accessible, trustworthy, economical and sustainable while reducing any resulting negative environmental effects. (Ratshomo & Nemba 2021). Under the 2021 JSE Industrial classification benchmark, the energy super sector contains companies which are directly involved in energy extraction, process and production activities, including the manufacturing of related energy equipment. The renewable, non-renewable energy companies and energy distribution companies are also classified amongst these companies.

An extensive summary of the South African energy sector's contribution to GDP, employment, taxes and the balance of payments is provided in the White Paper on the Energy Policy, published in December 1998. It concludes that the industry can significantly contribute to an effective and long-term national growth and development strategy (Ratshomo & Nemba 2021). As of 2018, the country’s primary energy supply was coal (65%), Therefore, 92% of the electric-power supply is generated through coal, crude Oil (18%), renewable and waste (11%), gas (3%), nuclear (2%) and geothermal (1%) (Ratshomo & Nemba 2021), hence, with total consumption per GDP* of 87.6 (2005=100) (Enerdata 2020).

Crude oil, which is the second-largest energy source, is mainly imported from the Middle East and other African nations. Most of the liquid fuels that power the nation's automobile industry are produced using crude oil. Through the open-cycle gas turbine, Oil is used to generate electric power and the nuclear resource is used in to supply electricity through the Koeberg nuclear power station. Lastly, the renewables are also a source of energy used to generate power through the Renewable Energy Independent Power Produces Procurement Programme (REIPPP) (IEA, 2019; International Renewable Energy Agency [IRENA], 2021a). Categorically documents that the objective of the Integrated Energy Plan (IEP) for the South African energy sector includes the following:

- Ensure security of supply
- Minimise cost of energy
- Promote job creation and localisation
- Minimise environmental impacts
- Minimise water consumption
- Diversify supply sources
- Promote energy efficiency and to increase access to energy (DMRE 2016).

Globally speaking, South Africa has ratified the Paris Agreement and updated its Nationally Determined Contribution in September 2021. The updated Nationally Determined Contribution increases the country’s climate ambition, is a step toward keeping warming below 2°C and “is found to be consistent with a 1.5°C pathway” (Climate Action Tracker, 2021; Steyn & Tyler, 2021).

While all the sectors are important to the South African economy in providing real economic activities, it is not clear which sector is more important than the other in the context of risk propagation or structure. Therefore, this study would help bring to light sectors that are relevant in risk propagation within the economy.

SUMMARY AND CONCLUDING REMARKS

The cascading event of the subprime rate that led to the global financial crisis of 2007/2008 is a proof that indeed we live in a connected globe. The different definitions and views on contagion gave a series of concise understanding on contagion and how contagion could evolve from different channels and tools within an economy and have an international implication on other economies. The non-crisis-contingent theory reveals that certain mechanism such as country revaluation, trade, random aggregate shocks and policy coordination are channels by which shocks are propagated from one country to another. The fundamental view of contagion and spillover further explains the propagation of shocks across countries are carried out through real channels.

The concept of connectedness has revealed how nations have interacted with one another more and more as a result of the globalisation of their sovereigns', financial institutions' and enterprises' asset and liability management (ALM) strategies (Moghadam & Vinals 2010). The understanding of connectedness has revealed that no economy is 100% independent of the other because nations would continue to interconnect through financial globalisation of assets and markets.

A review of the South African sectors reveals that the economy is largely dependent on the growth, development and the commercial activities of these sectors both locally and internationally. Hence, since the sector has been a major player in international trade and commerce, then there exists a possibility of connectedness of the South African sectors with other economies around the globe. Hence, the insights from the application of most of the theories from this chapter clarifies the fact that South African equity sectors could also be having its share in contagion and interconnectedness share in line with international periods of financial and economic crisis, since it enjoys its share on international trade with nations like the US and China to mention a few.

Therefore, the theoretical literature has established the fundamental fact and possible proofs that interlinkages and eventual connectedness of assets, bonds, commodities and other real and market indices do exist. The following chapter presents the review of the empirical literature on connectedness at different areas, correlation of assets and markets, PageRank and drivers of assets connectedness around the globe.

CHAPTER 3: REVIEW OF EMPIRICAL STUDIES

3.1 INTRODUCTION

This chapter reveals the relevant empirical studies that have been presented on the determination of systemically important sector, dynamic linkages or equicorrelation, equity/market connectedness and on the drivers of volatility connectedness across various economies. This empirical review starts with an exposure into the studies on PageRank on equity and markets also delving into studies on the concept of too-big-to-fail and too-central-to-fail. These are followed by the literatures on contagion, then followed by the empirical studies on time varying equicorrealation, then the empirical studies on dynamic connectedness on returns and volatilities at different markets and economies are documented. Finally the empirical review ends with the documented studies on the determinants of volatility connectedness. The presentation of the empirical literature gives a detailed understanding of the study; hence, the empirical studies have revealed some of the gaps within the literature.

3.2 EMPIRICAL REVIEW ON SYSTEMATICALLY IMPORTANT INSTITUTIONS

This sub-section reveals the literature documented under systemically important institutions and how the PageRank model and a few other models was employed to rank the institutions, in addition to documenting other empirical literature where the concept of too-central-to-fail concept was adopted in non-financial institutions. Therefore this section documents the empirical review relating to the first objective of this study which is to determine the systematically important equity super sectors within JSE.

3.2.1 Empirical Studies on PageRank on Equity and Markets

The PageRank algorithm was created by Larry Page and Sergey Brin at Stanford University to rank the importance of online sites and assign numerical values to indicate that importance (Christenson, & Nathan ND). PageRank employs an algorithm that is made to rank web pages according to the quantity and quality of the backlinks they receive. In order to address the Link-Based Object Ranking (LBR), this algorithm is generally used (Chakraborty, Wilson, Green, Alur, Ergin, Gurumurthy & Chinta 2013).

Although PageRank is interested in the quantity of back links a page has, it also considers the authority of the pages that the back links are on. As a result, a page with a higher ranking boosts the rating of the websites it links to more than a page with a lower ranking (Christenson, & Nathan ND). For instance, if page A has a higher rank than page B and pages C and D both have one back link from those pages, respectively, then page C will rank higher than page D. Phil Craven uses the metaphor of casting votes to highlight the fact that "the relevance of the page casting the vote dictates how important the vote itself is" (Craven 2022).

The algorithm takes into account a model in which a person opens a webpage and proceeds to take a ‘random walk’ by clicking links from the page he is currently on. Occasionally, a new webpage might be accessed to begin another such walk. The probability of a website being viewed in a specific random walk is its PageRank (Chakraborty *et al*. 2013).

Yun, Jeong and Park (2019) disclose that there is a second level in studies on PageRank, which emphasises on weights or weights with directions to links. Direct interaction between entities is represented as a link, which can be a transaction, ownership, or credit relation, in the case of financial institutions. The top level assigns a degree of freedom to nodes that proceed to a non-topological variable to shape the network. This is in line with recent research that accounts for the dynamics of nodes through centrality. Degree, closeness, betweenness and eigenvector centrality are the most commonly used centrality measures derived from a social network analysis.

In finance and economics, Battiston et al. (2012b) employs Debt-Rank to identify systemically important nodes. A dataset on the USD 1.2 trillion Federal emergency loans program to global financial institutions during 2008-2010 was analysed and the result revealed that majority of the institutions which received the loan formed a strong connected graph where each node becomes systematically crucial at the peak of the crisis. While Soramäki and Cook’s (2013) used SinkRank to determine systemically important banks in a payment system. Kuzubaş, Ömercikoğlu and Saltoğlu (2014) claim that centrality measures perform well in predicting SIFIs. In this study, degree centrality, betweenness centrality, closeness centrality and Bonacich centrality measures were constructed for the Turkish financial institutions using the banks business statistics such as volume, links, connectivity, reciprocity and transactions on pre and post financial crisis. An increasing trend in all centrality measures was detected for the Demirbank (main borrower institution). Ex-post examination of the financial crisis shows that Turkish interbank market centrality values are effective in identifying systemically important institutions.

3.2.2 The 'Too big to fail'/'Too interconnected to fail' and the 'Too central to fail' (PageRank) Centrality Measure

The theory in banking and finance known as 'too big to fail' (TBTF) contends that some businesses, particularly financial institutions, are so big and interconnected with each other and with the real economy that their failure would be catastrophic for the larger economic system and should, therefore, be supported by the government when they face potential failure (Lin 2012).

U.S Congressman Stewart McKinney coined the phrase 'too big to fail' during a 1984 Congressional hearing while he was debating the Federal Deposit Insurance Corporation's intervention with Continental Illinois (Dash, 2009). The term had previously been used occasionally in the press (Stern & Feldman 2004) and similar thinking had motivated earlier bank bailouts (Nurisso & Prescott 2017).

Some economists such as Paul Krugman hold that financial crises arise principally from banks being under-regulated rather than from their size, using the widespread collapse of small banks in the Great Depression to illustrate this argument (Krugman 2009; Krugman 2010). In 2014 the International Monetary Fund and other financial regulatory institutions claimed that the issue was still unresolved (Harding & Atkins 2014; Wolf 2014). The existence of a specific list of systemically important banks that are deemed TBTF has a partially offsetting impact, even though the individual elements of the new regulation for systemically important banks (additional capital requirements, enhanced supervision and resolution regimes) likely reduced the prevalence of TBTF (Moenninghoff, Ongena & Wieandt 2015).

Bernanke (2010) states that a financial institution is considered too big to fail if its size, complexity interconnection and key functions are such that, should it unexpectedly go out of business, the rest of the financial system and the economy would suffer significant negative effects. Several risks, which include taking more risk than desirable and having less resources in securing such risk. Benefiting from economies of scale compared to other small financial institutions and (iii) absence of adequate monitoring and resolution tools were some of the risks these banks undertake (Bernanke 2010). Therefore, in the process of resolving the TBTF challenges and reducing the detrimental effect of these banks in the face of a collapse, introduction of strict regulations, breaking the banks into smaller banks, levying of higher taxes for bigger institutions and increasing monitoring through oversight committees were some of the measures that was put in place (Ritholtz 2013).

Battiston, Puliga, Kaushik, Tasca and Caldarelli (2012) employed Debtrank (which is a novel measure motivated by feedback centrality, which can be used to construct ranking but it is not itself the rank of the nodes) on daily time series data of outstanding debt and market capitalisation of 407 institutions in a period of 1 004 days spanning from August 2007 to June 2010. They established that 22 institutions from sample institutions formed a strongly connected network graph and each institution's (nodes) becomes systemically important at the peak of the crisis. Moreover, a systemic default could have been triggered even by small, dispersed shocks. The results suggest that the debate on TBTF institutions should include the even more serious issue of too-central-to-fail.

Centrality measures and community identification methods are useful for assessing systemic risk in the financial system. Centrality measures are suitable to capture the too-connected-to-fail dimension of systemic risk, while community identification methods serve to single out groups of firms where some of them may play a too-important-to-fail role (Chan-Lau, 2018). Chan-Lau (2018) arrived at the above conclusion after examining the performance of these measures in a variance decomposition of global financial networks of firms. The author also revealed from the overall analysis that centrality measures and community identification methods complement each other for assessing systemic risk in financial networks and that the PageRank centrality measure yields ranking of firms.

To quantify the centrality of 92 financial institutions in the United States, Yun Jeong and Park (2019) contrasted the PageRank algorithm with conditional value at risk (CoVaR) and marginal expected shortfall (MES), which both successfully capture the network relationships between all the institutions. It was determined that Rank, rather than CoVaR and MES, can better describe the network structure among financial institutions. Further, PageRank does not have procyclical properties; therefore, it is not dependent on market conditions. This study contributes to the development of a timely measure using publicly available market data. Furthermore, because financial institutions report balance sheets on a quarterly basis, the metric avoids the drawbacks of the balance sheet-based method, which is prone to time lags. The authors also include assets of the equity and liability types since systemic hazards primarily spread through intricately intertwined liability obligations in these asset classes. The conclusions will aid policymakers and regulators in comprehending the consequences of keeping an eye on systemic risks from a network perspective.

Zhang, Zhuang, Wang and Lu (2020) adopted PageRank index to identify systemically important sectors when they analysed weekly closing prices of 24 Chinese sectors for a period 4 January 2007 to 31 December 2018. The PageRank index was used to identify systemically important sectors released by utilities and financial sectors. It was revealed that the tail risk network of Chinese sectors can be divided into four different spillover function blocks. The role of blocks and the spatial spillover transmission path between risk blocks are time-varying. The result provides useful and positive implications for market participants and policy makers dealing with investment diversification and tracing the paths of risk shock transmission. The financial and the utilities sectors are systemically important within the network.

Mishra, Srivastava and Chakrabarti (2022), in their study, proved that systemic risk within an asset category is related to firm size indicating that too-big-to-fail financial institutions tend to be too-central-to-fail by employing Granger causal network and PageRank centrality (Page et al. 1999) on bond and stock price data of 282 firms from February 2013 to December 2018. The study revealed two separate results. First institutions with higher systemic risk on the stock market typically usually have higher risk ramifications on the bond market. Secondly, the relationship between systemic risk and firm size within an asset class suggests that too-big-to-fail enterprises also frequently have a too-central-to-fail characteristic. These findings have significant policy ramifications for identifying weaknesses and implementing focused remedies in financial networks.

Chaturvedi and Singh (2022), used the returns of non-banking financial companies (NBFCs) in India to examine systemic risk during crisis and no-crisis periods. The authors acknowledged the concept of too-central-to-fail is crucial in recognising the sources of systemic risk. The study uses a complex Granger causality network based on returns data to explain how NBFCs are connected to the other financial institutions. PageRank algorithm was employed to identify the central and very important nodes (companies/financial institutions) and ranks financial institutions in pre-crisis and crisis periods based on their maximum percentage loss suffered during the crisis.

Using non-parametric rank-based regression, the PageRank ranking of financial institutions in the pre-crises period (explanatory variable) is regressed with the ranking of financial institutions based on maximum percentage loss suffered by them during the crises period (dependent variable) along with leverage and size as control variables. The authors concluded that PageRank from pre-crisis can identify most financial institutions that suffered losses during NBFCs crises even in the presence of control variables.

Kumar and Mukhtar (2023) developed an algorithm called CentralityCosDis, a derivative of different centrality measures (CentralityCosDis, combines nine centrality measures to prioritise nodes in PPI and co-expression networks, including degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, PageRank, Personalised PageRank, information centrality, eigenvector centrality and clustering coefficient). This ranks nodes using a combination centrality metrics and seed nodes. Using NetworkX (2.8.8) Python package to analyse multiple co-expression and (protein-protein-interaction) PPI networks, the authors were able to rank and identify the 10 nodes (the proteins) based on their centrality measures. It was discovered that CentralityCosDis identified more plant–pathogen interactions and related functions and pathways compared to the other algorithms.

Objective one of this research is to determine the systematically important super sectors on the JSE, from the too-central-to-fail perspective, which helps to establish the super sectors that are central and important to the stability of the South African economic sector network. To achieve objective one of this study, PageRank Centrality (Page et al., 1999), with Granger causality index, would be applied to compute the centrality score of each super sector and, hence, rank sectors on their scores. This would be done following the study done by Billio et al. (2012), Yun et al. (2019) and Chaturvedi and Singh (2022), who employed PageRank to measure the centrality of financial institutions from a too-central-to-fail perspective. This objective bridges the literature gap especially on the JSE sectorial market by identifying the super sectors that are crucial in attaining economic stability.

3.3 LITERATURE ON CONTAGION

The frequency in the occurrence of financial crisis in recent years has attracted a lot of attention. Contagion and interdependency (Karolyi & Stulz 1996; Allen & Gale 2000; Pericoli & Sbracia 2003; Forbes & Rigobon 2002; Broner et al. 2006), respectively, have attracted significant interest in research. Allen and Gale (2000) and Forbes and Rigobon (2002) defined contagion as an adverse event that manifests in a particular market and has an amplifying and implicative impact upon other markets, regions, or countries. Contrary to contagion, these authors defined interdependence as the cross-linkage of market fundamentals. Pericoli and Sbracia (2003) expounded that contagion and interdependence could both be propagated by negative shocks through financial and real channels. Although there are differences between these two phenomena, the spillover index, which is a financial interdependence index, could be used to represent co-movements of markets, especially in risk contagion in crisis period (Broner et al. 2006). Financial connectedness would be better understood with the good knowledge and understanding of the concept of the contagion and interdependence of assets, sectors and international markets.

Two strands of the literature stand out in expounding the financial contagion concept. The first elaborated on pairwise correlation among institutions and markets on the basis of correlation measures (Baele, 2005; Chiang & Jeon, 2007; Teply & Kvapilikova, 2017; Wang et al. 2017). GARCH-models of (Engle, 2002), Granger causality technique of Sander and Kleimeier, 2003) Patton (2006) and Ning (2010) Copular models the CoVaR models and the Quantile regression technique of Nusair and Olson (2019) are some of the employed methods of measuring contagion. In studying the spillover of different assets, the multivariate-GARCH models were at first used. However, computational difficulties in estimating parameters have been a problem in the use of these models (Shen, Jiang, Ma, Wang & Zhou 2020). Therefore, Engle and Sheppard (2001) devised a model called the dynamic conditional correlation known as DCC-GARCH model which handles high dimensional systems and estimate up to 100-assets. Engle & Kelly (2002) later documents that the DCC-GARCH model is yet confronted with computational and presentation limitations. Hence, the DECO-GARCH model was devised to resolve these limitations, which better captures the dynamic correlations of different assets class (Engle & Kelly, 2012). The direction of contagion was yet a possibility to capture by the GARCH models, therefore, the Granger test is then developed to determine the direction of risk patterns and hence, direction of the contagion (Billio, Getmansky, Lo and Pelizzon, (2010); Corsi, Lillo, Pirino and Trapin, (2018).

Sander and Kleimeier (2003) employed the Granger causality test to give the pattern and direction of risk spillover using the Asian crisis at the regional level as a case, while Kalbaska and Gostkowski (2012) confirmed the existence of contagion effects using direct causality networks within the UK, West Germany, France and other economies. Underestimation of both tail dependence and risk occur when Granger test and GARCH models are employed (Shen, *et al.*, 2020), therefore, more sophisticated models were developed, for instance, the CoVaR &

Copula. Wen, Wei & Huang (2012) employed CoVaR and Copula in examining contagion effect between energy market and stock markets in the financial crises of 2008/2009 and obtain a significant characteristics of increasing tail dependence illustrating as evidence that contagion existed during the period.

The second strand of the literature uncovers the aspect of financial contagion from the view of complex-networks. Compared to the rumour spreading on social networks, financial networks[10] shape the risk contagion, hence, they play a crucial role to stabilise the financial systems (Shen, *et al.* 2020). Gai and Kapadia (2010) empirically deduce that the probability of risk contagion in markets is influenced by the changes developed in these network structures. Huang et al. (2016) worked on financial system stability and examined the impact of local structures[11] of financial networks and claimed that financial nodes have more strength and tightness, greater centrality and clustering-coefficients contribute more to systemic risk. This depicts that financial network that have higher interwoven local structures have a magnifying effect on local risk. Nevertheless, this magnifying effect is not 100% true. Acemoglu, Ozdaglar & Tahbaz-Salehi (2015) posits that with a small enough negative impact, financial systems stability can be affected.

3.4 EMPIRICAL STUDIES ON TIME-VARYING EQUICORRELATION (TVE)

Time varying equicorrelation is a phenomenon that explains the possibility of the correlations of assets changing through time, but constant across the cross-section of the assets (Engle and Kelly (2007). This subsection reviews empirical studies carried out at different regions and market, to proof the possibility of assets or stocks obeying the concept of TVE. Hence the empirical review discussed in this subsection and subsection 3.5 relates to the second objective of this study which is to determine the return linkages of JSE equity super sectors.

Aboura and Chevallier (2014) was the first literature to document the time varying qualities of assets using dynamic equicorrelation (DECO) model to a cross market dataset which consist of exchange rates, bonds and equities alongside commodities through the period 1983-2013. The uniqueness of this work lies in the equicorrelation of the volatilities of these assets. The

[10] Financial networks are the concept that explains the interactions and links between financial entities such as banks, financial exchangers, traders etc. in relation to the direct and indirect transaction mediated with them (Nagurney and Ke 2001).

[11] Local structures describe the geometry details of the welded joint lines, the weld seam and the immediate adjacent joint components

results show that the average volatility equicorrelation across markets is around 15%, showing time-varying evidence with regime shifting and with a low mean reversion level.

The effect of a crisis on correlation levels has been the subject of numerous research. Financial and non-financial crises' effects on the correlation among U.S financial markets were studied by Tsai and Chen (2010) and Garnaut (1998), by employing dynamic conditional correlation (DCC) analysis, which is multivariate GARCH method. Evidence was discovered that the crises were associated with considerable short-term increases in correlation. Furthermore, similar findings for some emerging markets were found by Schwebach, Olienyk and Zumwalt (2002) (on Australia, Austria, France, Germany, Italy, Mexico, Singapore and the U.K using Markowitz (1952) framework of mean-variance efficient portfolio frontiers), Cho and Parhizgari (2008) (between Thailand and Hong Kong using dynamic conditional correlation (DCC)) and Medo, Yeung and Zhang (2009) (using the mean–variance portfolio and the Kelly portfolio on selected assets). As a result, the financial crisis of 2007 offers a great illustration of how and to what extent correlation is impacted.

Niklewski (2014) suggests that correlation seems to be greater in emerging/developing markets. He argues that the increases in correlation may be the consequence of two factors: First the tightening of regulations in combination with the deleveraging that took place in financial markets and sectors worldwide and, secondly, the impact of the crisis on relative market conditional volatilities. It was revealed that market conditions such as extreme market conditions have a big impact on correlation, which in turn have a considerable impact on portfolio weights, but no significant increase in portfolio returns was reported. Tolgahan and Yilmaz (2010) employed the DCC and DECO-GARCH models to examine the performance of global minimum variance portfolios (GMVP) and compared it with that of GMVP constructed by sample of covariance and constant correlation methods in terms of reduced volatility from the stocks listed on the Istanbul Stock Exchange 30 index in Turkey. The results indicate that the GMVP constructed with the DCC and the DECO-GARCH performed far better than that of the other GMVP. The result also illustrates the pronounced effect of time varying variance and dynamic correlations on portfolio optimisation in the stock market, when the calibration method of the DECO-GARCH and DCC was improved and simultaneously reducing the rolling window to one day from one week, as the other GMVP decreases.

Kearney and Poti (2005) examined correlation dynamics using daily data from 1993 to 2002 on the five largest Eurozone stock market indices. They estimated conditional correlations using the symmetric and asymmetric dynamic conditional correlation multivariate GARCH (DCC-MGARCH) model and their results suggested that there are very small benefits to be gained in diversifying across Eurozone market indices, although there were significant gains to be exploited in diversifying across different stocks. Comparing sectorial and market indices, Meric, Ratner and Meric (2008) studied the portfolio diversification implications of the co-movements of sector indexes in the U.S, the UK, German, French and Japanese stock markets in bull and bear markets (1997–2002). Their findings indicated that all the sectors are highly correlated with each other and with the national benchmark stock market index in France and Japan in the bull market. They found that, in a bull market, investors can obtain more benefits with global diversification than with domestic diversification. This suggests that sectorial diversification benefit differs from international diversification benefit in the selected advanced markets. Studies of sectorial diversification are limited; there is need for more studies in the emerging market setting.

Cao, Long and Yang (2013) examined the relationship between the stock market indices of China's stock market (July 2007–December 2012). They divided the period into two stages. One stage represents the drastic shock periods in 2007 and 2008 and the other represents the general ups and downs periods. In the first stage when the market experiences drastic ups and downs, the sector indices tend to rise or fall together and exhibit very close correlations between each other. In the second stage, however, much smaller correlations appear, this depicts that the stock price indices reflect the cyclical characteristics of the real sector economy. The study gave an investment perspective for investors and supervisors to make positive decisions in investments. Yilmaz (2010) used both DCC- and DECO-GARCH methods to track the performance of global minimum variance portfolios investing in the Istanbul Stock Market. His results seem to suggest that the performance of those portfolios estimated by DCC- and DECO-GARCH outperformed all other portfolios and, furthermore, the performance of the portfolios improved when the sample period was extended.

Kang and Yoon (2019) estimate three different vector autoregressive multivariate GARCH (VAR-MGARCH) models in an effort to address the issue of correlation and volatility transmission between Chinese stock and commodity futures markets from August 2004 to May 2016. They found that the DCC-GARCH model performed best in estimating the dynamic conditional correlation. The findings suggested that in optimal portfolios, stocks should outweigh commodity futures and optimally weighted commodity-stock portfolios may help investors reduce risks. As regards portfolio risk management analysis, the study calculates optimal hedge ratios for different commodities and thus determining optimal portfolio weights for reducing portfolio risk. However, from the work of Kang and Yoon (2019) and Tolgahan and Yilmaz (2010), it seems to suggest that DCC is a better model compared to others, but the DECO-GARCH model comes with a far better computational capacity for better result output.

Alkan and Cicek (2020) employed a BEKK (Baba, Engle, Kraft & Kroner) parameterisation of the multivariate GARCH model to test for spillover effects in Turkish financial markets between 2006 and 2018. Their results supported the existence of a strong spillover effect from global markets to Turkish stock and bond markets and from the Turkish stock and exchange markets to the bond market. Strong volatility spillover effects between each market pair were also present. Using the conditional mean and the conditional covariance equations to capture the spillovers, the results indicate that a shift in volatility in a global market spread to other domestic markets almost immediately.

Kang, McIver and Yoon (2017) in their study investigated the spillover effects among six commodity futures markets by employing the multivariate DECO-GARCH model and a spillover index. They examined the period from January 2002 to July 2016 and included six commodities, namely gold, silver, oil, corn, wheat and rice trading in U.S markets. The findings suggested the existence of positive equicorrelation between commodity futures market returns and this impact was found to be stronger during periods of economic downturns and financial turbulence. Moreover, they compared optimal portfolio weights and hedge ratios, assigning higher values for the hedge ratios during periods of crises, which may influence portfolio trading strategies and investment decisions.

Chimwal, Bapat and McMillan (2020) used autoregressive moving average (ARMA) and threshold GARCH (TGARCH) models to estimate the effect of both domestic and foreign investment flows on the volatility of stocks trading in Indian markets. The results indicated that foreign investment flows have a positive impact on market volatility but this effect is reduced when domestic investment flows are taken into account. This impact may assist portfolio managers in developing successful volatility strategies in order to optimise returns.

Several studies have explored the issues of correlations and comovement by examining various European markets. Corbet and Twomey (2015) investigated the Irish debt crisis. They found evidence of the so-called contagion effect that is an unusually high correlation between the

Irish and several European equity markets, during the Irish financial crisis. In addition, Gjika and Horváth (2013) found that the correlations among stock markets in Central Europe and between Central Europe, *vis–à–vis* the Euro area remained at high levels during the financial crisis. Dajcman and Festic (2012) showed that the global financial crisis of 2007–2008, had a major impact on the increased co-movement of the Slovenian stock market with European stock markets. Dajcman, Festic and Kavkler (2012) examined the dynamics of the United Kingdom, Germany, France and Austria stock markets. They concluded that the global financial crisis of 2007–2008 only slightly and temporarily increased the already high level of co-movement between these European stock markets. Denkowska and Wanat (2020) investigated the weekly return rates of eight insurance companies (five from Europe and the biggest insurers from each of USA, Canada and China) during the period 2005 to 2018. They concluded that all the considered insurance companies are positively correlated and this correlation is stronger in times of turbulences. Finally, Tevdovski and Stojkoski (2021) discovered that there are strong persistence effects and significant linkages between south-eastern European stock markets. In addition to GARCH, a variety of alternative volatility models have been applied in the literature, namely implied volatility, realised volatility, range-based volatility and stochastic volatility (Danielson, 2011). The empirical studies discussed reveals that correlation among institutions and different economies are significantly time varying. The next subsection further establishes the existence of dynamic equicorrelation among different equities in from different countries.

3.5. EMPIRICAL STUDIES ON DYNAMIC EQUICORRELATION ON EQUITY MARKET

Thai Hung (2021) studies the interlinkages between Bitcoin and Central Eastern Europe (Hungary, Czech Republic, Poland, Romania and Croatia) stock market by applying both multivariate DECO-GARCH model of Engle and Kelly (2012) and quantile methodology proposed by Sim and Zhou (2015) using daily data spanning from 6 September 2012 to 12 August 2019. First, the findings show that the average return equicorrelation across Bitcoin prices and CEE stock indices are positive, even though it is found to be time-varying over the research period shown. Second, the Bitcoin-CEE stock market association has positive signs for most pairs of quantiles of both variables and represents a rather similar pattern for the cases of Poland, the Czech Republic and Croatia. However, a weaker and primarily negative connectedness is found for Hungary and Romania, respectively. Furthermore, the interconnectedness between the co-movements in the Bitcoin market and stock returns changes significantly across quantiles of both variables within each nation, indicating that the Bitcoin-stock market relationship is dependent on both the cycle of the stock market and the nature of Bitcoin price shocks. The study has significant implications for divergent economic agents, including global investors, risk managers and policymakers, who would benefit from a comprehensive knowledge of the Bitcoin-stock market relationship to build efficient risk-hedging models and to conduct appropriate policy reactions to information spillover effects in different time horizons.

Since the 2008 global financial crisis, an emerging strand of the literature employing different datasets and various econometric frameworks focuses on the connectedness dynamics among emerging markets assets such as American depository receipt (ADR), exchange traded fund (ETF) and foreign exchange rate (Forex). Hwang (2014) employs DCC-GARCH model to analyse the transmission of the 2008 U.S financial crisis to four Latin American stock markets. The sample covers daily stock returns from 2006 to 2010 related to specific markets, namely Merval (Argentina), Bovespa (Brazil), Bolsa de Santiago (Chile) and Bolsa Mexicana de Valores (Mexico). The evidence of financial contagion by showing that pair-wise conditional correlations are relatively higher and more volatile during the period of crisis. In other words, empirical findings show that stock markets in Argentina, Brazil and Mexico are heavily affected by the 2008 U.S financial.

The multivariate DCC-GARCH model has also been employed by Rodriguez-Nieto and Mollick (2020) to identify contagion from the U.S.A to the largest developed and emerging markets in the Americas (Argentina, Brazil, Canada, Chile, Colombia, Mexico and Peru) during the U.S financial crisis. Their sample considers daily closing prices from 1 January 2002 to 31 December 2015 and includes changes in the general economy's credit risk represented by the TED spread and changes in the U.S market volatility represented by the CBOE Volatility Index (VIX). Results suggest that increases in VIX have a negative intertemporal and contemporaneous relationship with most of the stock returns and these relationships increase significantly during the U.S financial crisis. Moreover, they also find evidence of significant increases in contemporaneous conditional correlations between changes in the TED spread and stock returns. Increases in conditional correlations during the financial crisis are associated with financial contagion from the U.S.A. to the Americas. Those findings illustrate that during periods of financial distress, U.S stock volatility and weakening credit market conditions could promote financial contagion to the Americas. In their article, Marçal et al. (2011) used DCCGARCH model to investigate the existence of contagion among countries on the basis of an analysis of returns for stock indices over the period 1994 to 2003. Results show that contagion spread from the Asian crisis to Latin America, but not in the opposite direction. A possible explanation for Latin America's vulnerability to financial crises lies in the weakness of its economic fundamentals during the period.

Esqueda et al. (2015) employ GARCH-M model to examine the effects of the U.S investor sentiment on American depository receipts (ADR) premiums by using daily prices from 1995 to 2009. The volatility index (VIX) is used as a proxy for investor expectations about the stock market while liquidity, transaction costs and domestic and U.S stock exchange returns are controlled. They find that deviations from the law of one price in ADRs can be partially explained by the lag of the smoothed volatility index. Those findings have important implications for portfolio diversification on emerging markets as investment managers can improve hedging strategies by incorporating known values of the volatility index. In the other hand, Costa Correa et al. (2018) use VAR-MGARCH multivariate skewness models, with diagonal VECH representation to detect and measure the phenomenon of interdependence of ADR indices on the main Latin American capital markets (Brazil, Argentina, Chile and Mexico) and developed (United States, Japan, United Kingdom and France) given the 2008 financial crisis scope. They found that the ADR indices presented greater interdependence with the developed countries, compared to the analysed Latin American equity markets.

In a research paper, Diamandis (2009) uses weekly observations for the period January 1988–July 2006 and examines long-run relationships between four Latin America stock markets and a mature stock market that of the U.S via the autoregressive and moving average representations of a VAR model. The main finding of the analysis suggests that there are significant common permanent components driving the examined stock markets in the long run. Moreover, results also indicate that those five equity markets are partially integrated, implying small, long-run benefits from international portfolio diversification since the stock prices adjust very slowly to these common trends. Extending this framework, Esqueda and Jackson (2012) analyse the behaviour of 74 American depository receipts (ADR) and exchange rate returns from Argentina, Brazil, Chile and Mexico by employing seemingly unrelated regressions (SUR) and multivariate regression models (MVRM) during the period May 1994 to May 2009. Results show that ADR prices are determined primarily by the underlying stock, exchange rates, host country index as well as U.S stock market. Moreover, monitoring the underlying stock and local and host country stock indexes, they find that ADRs generate significant negative abnormal returns during currency crises, due to conversion exposure. Those findings confirm the predominance of the American stock exchanges in terms of ADR price discovery and market integration.

Forestal and Pi (2021) employ the multivariate autoregressive moving average-generalised autoregressive conditional heteroscedastic-dynamic equicorrelation (ARMA-GARCH-DECO) to determine contagion among Latin American financial markets during financial turmoil period, by analysing dynamic conditional correlations among 18 American Depositary Receipts (ADR), eight Exchange Traded Funds (ETF) and six Foreign Exchange Rates (Forex). The sample includes daily closing prices from 1 April 2014 to 29 January 2021, for Argentina, Brazil, Chile, Colombia, Mexico and Peru. Results find long-run properties in the volatility of most instruments including those belonging to defensive super sector implying that defensive super sector and basic materials are the most impacted sectors during the last financial crises.

It is presented that in times of economic disruption like in the midst of the COVID-19 pandemic, those financial assets do not act as safe harbour investments since they are relatively more correlated during period of financial crises than in normal periods. The findings have policy implications and are of interest to practitioners who seek a better understanding of the dynamics of spillovers among the behaviour of emerging financial assets.

One key advantage for the proposed study is the examination of the sectorial correlation to determine diversification opportunities in the emerging market such as South Africa. Existing studies have focused on international stock and other markets, not domestic economic sectors. This would also reveal the possibility of the evidence of contagion among these JSE sectors.

3.6 EMPIRICAL STUDIES ON DYNAMIC RETURN AND VOLATILITY CONNECTEDNESS

This subsection gives an exposition on different empirical literature on volatility and return connectedness across different regions around the globe. Since the aim of objective three is to examine the connectedness and shock propagation among the equity sectors on the JSE market under extreme risk events such as the 2007/2009 global financial crisis, the European debt crisis, the U.S China trade war and the COVID-19 pandemic period. Conversely, this subsection shed light on existing connectedness work under different conditions and how such conditions enhanced the degree of connectedness.

Early studies, such those by Arshanapalli and Doukas (1993) and Karolyi (1995), concentrated on the correlations between the mature markets since, before to the mid-1990s, investors were not very interested in emerging economies. Several researchers favour using volatility spillovers[12] as a gauge of market connectivity. King and Wadhwani (1989) examines the transfer of volatility between equities markets. Sensitive information may circulate between markets when investors gather information from them, increasing the interconnectivity of all markets. Their findings demonstrate that an increase in volatility leads to further increases in volatility.

Probably the first study to use univariate GARCH models to examine relationships across cross-border markets is one by Hamao, Masulis & Ng (1990). They employ a two-stage methodology in this study to examine the transmission of volatility among the stocks listed on the New York, London and Tokyo stock exchanges. The result reveals that for the time period before to October 1987, there is evidence of price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London, but none in other directions. According to Tsai (2014), information was mostly transmitted to other significant international markets from Germany and the United States. Berg & Vu (2019), follow the economic activity of 17 developed markets as it is affected by the volatility of the U.S stock market. Their findings demonstrate that the U.S market has a greater impact on these economies' performances than do their domestic financial markets.

The recent and frequent financial crises have compelled research into the how markets and assets are connected, regardless of the different geographical locations of these markets. Hence, there is a need to sub-categorise the relevant literature in these fields as it relates to the objectives of this study.

[12] Volatility spillover refers to the transmission of instability from market to another. It occurs when volatility price change in one market cause a lagged impact on volatility price in another market above the local market effects.

3.6.1 Dynamic Connectedness in Euro-area and U.S. (Trans-Atlantic)

The 2008–2009 global financial crisis, which began in the U.S sub-prime mortgage market and progressed through numerous stages over the course of a year and a half, provides a greater understanding of connectedness in the modern era than any other recent financial catastrophe. Later, in late 2008, it spread internationally, hurting numerous markets and nations. This resulted in a global recession and a significant fall in global trade in 2009 (Diebold & Yilmaz 2015). Between 2009 and 2011, peripheral EU countries were hammered particularly hard, with numerous financial institutions and governments on the verge of insolvency (Diebold & Yilmaz 2015). Because it serves as a guide for this research, a thorough analysis of the empirical results from Europe and the U.S provide a solid understanding of the topic of financial connection.

In a network of significant American and European financial institutions, Diebold and Yilmaz (2015) described the interconnectivity of stock return volatility. The variance decomposition matrix of a vector-autoregressive approximating model was used to create a novel connectedness measure, which was then applied to daily data of financial institutions from countries including Belgium, Germany, France, Italy, Netherlands, Spain, UK, Switzerland and the U.S from 2004 to 2014. The techniques enabled detailed characterisation of the timing and development of significant elements of the financial crisis. Initially, it was determined that the 2007–2008 financial crisis was unquestionably tied to the United States–European Union relationship, but that connection began to shift towards a bidirectional relationship in late 2008. Second, it was discovered that in June 2011, there was an extraordinary increase in the direction of connection between European and American financial institutions, which was compatible with a significant decline in the health of EU financial institutions. In conclusion, it was seen that specific institutions were discovered that had disproportionately significant roles in creating connection throughout the American and European crises (Diebold & Yilmaz 2015). Connectivity became bidirectional in late 2008.

The transmission of volatility risks across multiple frequency bands between the E.U carbon market and various commodities and financial markets, while considering the impact of the uncertainty in U.S economic policies (EPU). The research demonstrates that the carbon market's connections to other markets are complex and varied. Particularly, the correlation between volatility and frequency cycle rises, showing that the intensity of risk transmission is greatest when assets are kept for a longer period. Further, Huynh et al. (2020) show the return and volatility connectedness and spillovers related to the nine U.S dollar exchange rates of the most globally traded currencies and how it is affected by trade policy uncertainty. They find an asymmetry in the spillovers and connectedness between the exchange rates in times of high trade policy uncertainty.

The price volatility of EU carbon allowances, commodities (gold, silver, copper, natural gas and crude oil), financial markets (the U.S dollar and the S&P 500 index) and how these connections relate to the unpredictability of U.S economic policy are all examined by Adekoya et al. (2021a). According to the findings, the U.S EPU significantly influences how connected the carbon market is to other markets. Yaya, Gil-Alana, Adekoya and Vo (2021) investigate the long-term relationships between U.S stock, commodity and energy sector fear indices and the global stock and oil fear indices, establishing that there is a fractional cointegrating relationship between each of the global and oil fear indices and other fear indices. But a weak long-term relationship amongst technology stock. In addition, the cointegrating framework reveals a nonstationary mean-reverting behaviour in the long-run relationship, implying that the effect of shocks from financial, economic, or other exogenous sources will be temporary though with long-lasting effects. These findings have crucial policy inferences for portfolio managers concerning investment decisions.

Moreover, Antonakakis and Kizys (2015) demonstrate the dynamic relationship between commodity and currency market returns and volatility. They discovered that the informational contents of gold, silver, platinum and the CHF/USD and GBP/USD exchange rates helped predict the returns and volatilities of palladium, crude oil and the EUR/CHF and GBP/USD exchange rates with greater precision. They note that while gold, silver and platinum volatility shocks continued to have relatively significant net transmission roles, those of platinum returns shocks worsened during the financial crisis. Mensi et al. (2021) have looked at the volatility spillovers and hedging traits between four main PMs Futures and seven major currencies at different time horizons. To analyse the spillover between the currency and precious metal markets, they employ the index methodologies of Diebold and Yilmaz (2012, 2014) and Barunk and Krehlk (2018). They show that the currency-precious metal spillovers were primarily asymmetric across time horizons and more pronounced in the short run, although they become more pronounced during periods of economic instability. Reboredo et al. (2021) investigated the connections and spillovers between three distinct market fronts, including currencies (EUR, GBP, CHF, JPY, AUD and CAD), six main stock markets and commodities (agricultural, industrial metals, PMs, energy and They find that stock markets contribute the largest spillovers to the commodity and currency markets. Meanwhile, the commodity markets obtain the largest spillovers from the commodity and currency markets.

Bossman, Junior and Tiwari (2022) used the D-Y (2012, 2014), while Barunk and Krehlk (2018) employed the connectedness index with daily stock indices from 23rd November 2015 to 8th September 2021 to study the dynamic connectivity and spillover between Islamic and conventional stock markets. They discovered that volatility spillovers between and within Islamic and/or G7 markets are frequency and time dependant, but that during market turmoil, conventional stocks are more vulnerable to volatility than Islamic stocks. Additionally, our research reveals infectious spillovers between Islamic and conventional stocks during the Brexit and the COVID-19 study period. They emphasised the dominance of short-term spillovers between Islamic and G7 economies relative to mid- and long-term spillovers. Investors should use their understanding of market volatility and patterns to hedge their holdings against reduced stock returns during tumultuous trading periods when spillover is more intense. Spillovers should be closely monitored by regulators because they jeopardise cross-market relationships.

Umar, Nasreen, Solarin and Tiwari (2019) investigate the time and frequency connectedness among metal prices and oil prices between 1980 and 2017-month-5, using the Diebold & Yilmaz (2014), Barunik & Krehlik (2017) and DECO-GARCH model to ascertain the time, frequency domain and the equicorrelation among the commodities, respectively. The time domain result depicts that overall connectedness is as small as 3.39%, whereas the frequency domain output shows that short-term frequency (1-4 months) exhibits the highest contribution (1.6%) whereas medium-term frequency (8-15 months) exhibits the lowest contribution (0.45%). The maximum frequency's contribution, which covers a period of more than 15 months, is only 0.56%. According to the network analysis, Zinc is a net receiver.

Umar, Polat, Choi and Teplova (2022), in relation to the Russian-Ukrainian, war examined the geopolitical risks associated with European financial markets, global commodity markets and the Russian financial market in order to assess the influence of the war on the interconnectedness of financial markets. The time and frequency dynamic connectivity metrics were evaluated using the (TVP-VAR). The empirical finding indicates that the conflict has significantly altered how these markets are related to one another. Furthermore, volatility and return connectedness were impacted in terms of short- and long-term frequency, respectively and the net-transmitters of shocks are Russian bonds and European stocks.

In addition, Benlagha and El Omari (2022), utilising data from 14 November 2018 to 24 March 2021, examined the dynamic connection of the top five stock markets worldwide, including the New York Stock Exchange (NYSE), with stocks related to oil and gold. It was determined that these markets were more dynamically connected during the COVID-19 epidemic than they were prior to it. Oil was found to be a net-transmitter of shocks, but Gold was found to be a net-receiver of shocks from the five markets.

The subsection successfully highlights the existence of empirical studies on connectedness of assets and commodities. It is important to emphasise that the direction and propagation of volatility spillover has not been covered especially within sector, which objective three of this study would examine. However, the next subsection reveals the existence of dynamic connectedness among some emerging economies.

3.6.2 Empirical Studies on Dynamic Connectedness in Developing or Emerging Economies

The aim of this subsection is to emphasise the empirical literature on dynamic connectedness of assets in emerging markets or economy.

Due to specific economic and industrial characteristics of these countries, which have not yet met the standards of a developed nation, such countries are categorised as emerging countries (MSCI 2014). Some of these characteristics include GDP and opportunities for investments (Statistia 2023); however, with a record high of market hedge fund capital of $121 billion and a global market share of PPP-adjusted GDP which rose from 27% to 53% in 2013 (Zhang & Gao 2015). These are proofs of the risen level of economic development which came as a result of increased investment relationship with the global economy. Therefore, incisive empirical studies of some of the emerging countries on how the study connectedness has evolved is very crucial.

Zhang and Wang (2014) examine return and volatility spillovers between the Chinese and global oil markets (WTI and Brent), extending the Diebold and Yilmaz (2012) method of capturing spillover dynamics. They show that the Chinese oil market was strongly affected by world oil markets via both return and volatility spillovers during the GFC. Batten et al. (2015)

also apply the Diebold and Yilmaz (2009) method of identifying spillover, including surface time-varying spillover, for four main precious metals (i.e., gold, silver, platinum and palladium). It was found that geopolitical and economic events alter the trend in spillover effects. The findings show that the market is only marginally integrated, that this degree of integration varies over time and that it varies depending on the market's volatility and returns. Similarly, Gomes and Chaibi (2014) indicate considerable shock transmission between changes in oil prices and some of the 21 frontier markets or economies[13] under consideration over the years 2008 to 2013.

Further, Diaz et al. (2016) and Zhang (2017) both find insignificant results on monthly data using VAR and DY-method, respectively. Other papers applying DY on volatility spillovers in the oil market includes Baruník et al. (2015), which use the DY-method on energy commodities and their results indicate no dominant energy commodity. In addition, Zhang and Wang (2014) employ DY on global and Chinese crude oil market and find bidirectional volatility spillover, while Awartani and Maghyereh (2013) find that the oil market transmits both return and volatility spillover to other equity markets in the Arabian Gulf using the DY-method.

Ahmad, Mishra and Daly (2018) examined the financial connectedness between three global sovereign bond markets (U.S, European Monetary Union (EMU) and Japan) and the BRICS nations. Extracted weekly return data for a period 1 January 1997 to 27 July 2016 was estimated with the Diebold and Yilmaz (2009, 2012) index. The study shows that South Africa and Russia are the net-transmitters of shocks, indicating that shocks from these two markets could have an adverse impact on other BRICS nation. Also the economies of India and China show a weak level of connectedness which suggest that these two economies may be a safe haven for diversification benefits and hedging opportunities. Furthermore, the results show a high level of connectedness between China and the United States, with the U.S identified as the strongest shock transmitter to the BRICS nations.

Manopimoke, Prukumpai and Sethapramote (2018) investigate the dynamic connections between emerging Asian such as (Malaysia, India, China, Korea, Hong Kong, Thailand)

[13] Frontier markets as defined by the International Finance Corporation (IFC), as a subset of emerging market economies that are investable but have lower market capitalization (usually under 17% of GDP) and liquidity than the more developed traditional emerging markets which makes them inherently riskier investments but also provides potential opportunities for investors to take advantage of privatisations and increased listings on local exchanges over time.

equities markets and compare them to other important global markets, using daily stock market returns which were calculated from nominal local currency stock market indices from 1 January 1992 to 30 November 2017. The study revealed that through VAR model over 50% of the volatility and equity returns are from external markets compared to own-shocks. Moreover, the study shows in accessing the degree of connectedness over time that international stock markets have become more connected over time, with a gradual rise since the Asian financial crisis (AFC) but a sharp increase during the global financial crisis (GFC).

Although Asian developing markets are becoming more crucial to the global economy, the study shows that their impact on advanced economies such as the U.S and Europe, is still very moderate and has not increased much over time. The authors also found that developed markets over a decade has consistently been the net-transmitters of shocks and the Asian economies have been the net receivers. In addition connectedness is very strong between Asian economies of same region. The study opens the flow for futuristic guarded open policy of effective trade within the emerging and developed markets.

Akram and Malik (2020), using Diebold and Yilmaz (2009, 2012) spillover index approach with daily data of return from 4th May 2011 to 30th July 2019 in capturing cyclical and secular movement through rolling window approach. The study reveals that there is evidence of dynamic connectedness among the bond markets of major trading partners. Additionally, the main source and originator of shock spillover are the USA, EU, Singapore and Malaysia, whereas Pakistan, India and Japan are the net shock receivers in this group. China, on the other hand, appears to be the lone market shock recipient. The results of the rolling window analysis show that during periods of financial or economic stress, relevant plots of returns and volatility spillovers increase. The implication of this result has practical relevance for stakeholders in investments, research and economic institutional policy makers.

Chowdhury (2020) investigated the presence and direction of stock market sentiment spillover between the GCC stock markets. The findings of this study indicate that Kuwait and Qatar stock market sentiments are not connected to other markets' sentiment and that the stock market sentiments of Saudi Arabia and the UAE are connected as well as bi-directional. The results of this study show that while the stock market feelings of Saudi Arabia and the UAE are connected and reciprocal, the stock market sentiments of Kuwait and Qatar are not connected to that of other markets. In addition, the pair-wise spillover of returns and volatility shocks between nine developed and 11 emerging futures markets is tested by Yarovaya et al.

(2017), who discover that there is an asymmetry in the spillover of returns and volatility between these markets. Arin et al. (2020) explore financial spillovers between the four main GCC stock markets in a recent study. There is proof that Saudi Arabia's volatility affects Qatar, Abu Dhabi and Dubai. Moreover, during the time following the 2014 oil crisis, spillovers from the bigger markets have grown.

Academicians conducted testing of spillover between these markets in the 1990s due to the growing significance of emerging markets in the global economy. According to Abbas et al. (2013), volatility transmission occurs when multiple regional markets are connected economically. Allen, Amram and McAleer (2013) study if the Chinese stock market's volatility affects its surrounding markets and developed countries. The empirical results show some evidence of volatility spillovers across these markets in the pre-GFC periods, but there is little evidence of spillover effects from China to related markets during the GFC.

Furthermore, DY method is also employed to assess volatility spillovers in the seafood markets (Dahl & Jonsson, 2018). The connectedness matrix generated by DY method is also used to construct risk spillover networks. Yang and Zhou (2017) identify networks of volatility spillovers and investigate time-varying spillover among the U.S Treasury bonds, global stock indexes and commodities. Besides the markets mentioned in Yang and Zhou (2017), Yoon et al. (2019) also add the currency markets to investigate the risk spillover within the markets of bond, stock, commodity and exchange. Both studies report that the U.S stock market is the greatest single risk contributor in the global financial markets (Yang & Zhou, 2017; Yoon et al. 2019). By building the connectedness network of EMU countries using the sovereign bond data, Fernández-Rodríguez et al. (2016) identify the countries whether they locate in the network core or network periphery and find that the risk transmits from the core to the periphery. More importantly, such connectedness network can be further used of bank supervision and financial stability monitoring (Wang et al. 2018; Hale & Lopez, 2019).

The degree of liquidity connection between Malaysia's stock, bond, money and foreign exchange markets is quantified by Liew, Lim and Goh (2022). The liquidity connectedness index from the time-varying parameter vector autoregression model shows sensitivity to extreme market shocks but low average cross-asset liquidity contagion, suggesting minor risk of a systemic liquidity dry-up in the Malaysian financial markets. Additional investigation reveals that perceived credit risk, global market uncertainty and international crude oil prices all contribute to the explanation of cross-asset liquidity connectivity. The impact of outside variables highlights the necessity for small, open economies like Malaysia to increase market surveillance in order to track cross-border liquidity shocks. It is interesting to note that the Republic of South Africa is an emerging economy (McManus 2018), however, no empirical evidence of dynamic connectedness has been documented like other emerging economies, hence the more reason why examining the dynamic connectedness among her super sectors in of crucial importance.

3.6.3 Empirical Studies on Dynamic Connectedness among Commodities

Subsection 3.6.2 fully documents the existence of dynamic connectedness in developing or emerging economies involving different stocks. This subsection further reveals the empirical studies on dynamic connectedness on different commodities. Modern empirical studies on the connectedness of commodities around the globe date back to the early 2000s, where Nazliogu (2011) examined the relationship between oil and agriculture products using the Toda-Yamamoto: Non-parametric causality using price index for a period 1994 to 2010. The author revealed that there is a nonlinear feedback relation between agricultural and Oil commodities.

Further down period of investigations different authors with diverse methods revealing different outputs in their investigation. With ARMA-GARCH, Zhang and Qu (2015) reveal a high vulnerability of commodities, using copular model Koirala et al., (2015) reveals that agricultural and oil commodities have high positive correlation between each other. While in 2016 Awartani et al. (2016) and Chen and Wu (2016) worked on precious metals, crude oils, grains, soft, livestock and agricultural commodities for a period of (2012-2015) and (1995-2015) with VAR and DCC;VAR respectively. The result of these investigation reveals that there is a little transmission of volatility which is moderate from oil to precious metal, while comovement and interconnection exist in an increasing manner between all commodities during the GFC of 2007-2008, with a weak volatility transmission between crude oil and rapeseed respectively.

The DY technique is used to examine the dynamic spillover effects between commodity futures (crude oil, precious metals and agricultural items) by Kang, McIver and Yoon, (2017) and to identify asymmetric volatility connections in exchange markets during financial crisis periods (Barunik et al. 2017). In contrast to the wide application of DY method in empirical studies, little attention has been paid to the spillover effects within sectors. A handful papers report the credit risk transmission within CDS sectors in the credit markets (Collet & Ielpo, 2018; Da Fonseca & Ignatieva, 2018; Shahzad et al. 2019).

Particularly, Collet and Ielpo (2018) investigate the cross-sector volatility spillovers in the US credit market and find that the sectors exhibit very high spillover effects and the risk contributors are comprised of insurance, commodity and energy sectors. By performing very similar analysis on the sectors in stock markets, Nguyen et al. (2018) move one step further to construct a complete tail risk connectedness network for the entire U.S industrial system and find that the tail risk dependence is mainly driven by the trade flow within sectors. Practically, examining the sectorial spillover effects in stock markets is helpful to find potential sector-based hedging opportunities for investors. As no market is isolated in the global financial markets, the sectors in one market could receive risk shocks from other markets. By investigating the dynamic risk spillovers across two major commodity markets (crude oil and gold), the aggregate Dow Jones.

Balli, Naeem, Shahzad and Bruin (2019) investigate the frequency and time connectedness of 22 commodities uncertainty indices such as sugar, cocoa, palladium, Brent crude oil nickel, silver, natural gas, WTI crude oil, coffee, cotton, wheat, corn, gasoline, aluminium, using data of spot and futures from January 2007 to 31 December 2016. Using network graphs and spillover analysis, we discover that there is an overall rise in connection among commodity uncertainty during the Global Financial Crisis (GFC) and the 2014–2016 oil price drop. The network study reveals more spillover within a particular commodity class, precious metals act as a haven during the crisis due to less spillover with other commodities. The spillover index's breakdown demonstrates that over time commodity markets are more connected. The implication for investors is to better inform them on better and efficient commodity hedging strategies.

The oil and gold markets, as well as the industries of energy, finance, technology and telecommunication, are net risk takers, receiving risks from the DJIM index and the other sectors, according to Mensi, Hammoudeh, Al-jarrah, Sensoy and Kang (2017) analysis of the Islamic (DJIM) index and 10 stock sectors, the result revealed that the spillover of risk is time-varying, and an increased correlation after the 2008-2009 GFC was observed. Moreover, it was shown that the Gold stock has diversification benefit. In another study by Yu et al. (2018) an analysis of the risk that crude oil market transfer to different U.S stock market sectors, it was observed that the crude oil market transmits the most risk to the energy sector and the least risk to the consumer staples sector.

Bouri, Lucey, Saeed and Vo (2021) examine the dynamic connectedness among commodities such as heating oil, crude oil, natural gas, copper, platinum, cocoa, coffee, cotton, corn, orange juice, soybean, sugar, Soybean meal and wheat from 2008 September to 2020 May. The findings demonstrate both strong and moderate degrees of volatility connectivity between energy and metals, as well as moderate connectedness levels within the group of agricultural commodities. In some circumstances, cross-commodity connectedness can account for a significant amount of volatility connectedness, underscoring the significance of conducting realised volatility connectedness inside a model that permits realised volatilities to be calculated endogenously and simultaneously. The degree of connectedness fluctuates over time and is resilient to different standards. The term spread of interest rates and real economic activity are two macroeconomic variables and uncertainties that primarily influence it. The analysis, however, reveals that some connectedness-related factors are different between the upper and lower quantiles.

The connectedness among natural resource index (precious metal, crude oil, livestock, crude oil, agriculture products) and stock indices was examined in the Chinese economy by Chang and Fang (2022) between 2001 and 2019. The results showed that crude oil, precious metals, livestock and agricultural products commodity indexes have a positive linkage with Chinese stock market indices. This article offers policymakers a framework for reference as they create legislation pertaining to natural resources and stock market indices. The Augmented Dickey-Fuller (ADF) test was carried out to look at the unit root among the variables and the correlation matrix was utilised to investigate the correlation between the variables. The Granger causality test was used to evaluate the causal nexus between the constructs and the relationships between them using the autoregressive distributed lag (ARDL) model. The results showed that crude oil, precious metals, livestock agricultural products commodity indexes have a favourable relationship with Chinese stock market indices.

Akyildirim, Cepni, Molnár and Uddin (2022), using MSCI energy equity indices for 29 countries, investigate the connectedness among energy equity indices around the globe of oil-exporting and oil-importing countries. Time-varying metrics of the number of shocks that each nation transmits to other countries and the number of shocks that each country receives from other countries for each country. After analysis of the network of countries, shocks are primarily sent by oil exporting nations and received by oil importing nations. Additionally, we utilise panel data regressions to assess if economic sentiments, uncertainty and the worldwide

COVID-19 epidemic have an impact on the degree of connectedness across countries. It was discovered that when there is uncertainty, a depressed economy and COVID-19 issues, countries are substantially more interconnected. This suggests that precisely during crises, that is, when diversification benefits are most crucial, the benefits of diversity between countries are drastically decreased.

By applying a network theory approach that incorporates a bivariate spillover model to reveal the structure of magnitude and direction of spillover across mineral futures, An, Gao, An, Liu, Sun and Jia (2020) investigate the dynamic evolutionary spillover process among 19 bulk mineral futures, which include energy, (natural gas, heating oil, coal, RBOB regular gasoline) precious metal (gold, palladium, silver, platinum) and industry metals (copper, lead, nickel, cobalt, iron ore, aluminium and U.S steel). Using daily futures data prices from 3 February 2011 to 30 April 2019, it was established that network structure evolves over time. Generally speaking, an industrial metal commodity like U.S steel acts as the net highest spillover receiver, whereas an energy bulk mineral commodity like natural gas acts as the net highest spillover transmitter. There are a few spillover flows across bulk mineral markets and each market tends to have more spillovers across interconnected groups of neighbours, according to the network's general structure. Although the collapse of the European debt and oil crises in 2014–2016 caused the general structure to become complex, after the end of 2017 when its range of fluctuation widened, the structure has returned to simplicity. The study not only offers a process orientation to investigate the nonlinear dynamic process of spillovers across markets, but it also has significant ramifications for market management and the pricing mechanics of items related to bulk minerals.

Using daily data ranging from June 2008 to December 2020, Gong and Xu (2022) demonstrate that the commodity markets for energy, industrial metals and precious metals serve as information transmitters in the market for commodities, whereas the commodity markets for agricultural and animals serve as information receivers. In addition, the impact of geopolitical risk on the dynamic connectedness of the five commodities markets is also investigated using the GARCH-MIDAS model. It was discovered that the degree of interconnectedness of the commodities markets is highly impacted by geopolitical risk, particularly geopolitical act risk. More significantly, there are differences in the effects of different commodities markets' net spillover. The net spillover of the commodity markets for energy, agriculture and livestock is positively impacted by geopolitical risk, whereas the precious metal and industrial metal markets are adversely impacted (Gong & Xu 2022).

In conclusion, the empirical literature on dynamic connectedness among developing economies has gradually gained recognition, but little or no emphasis in an emerging economy like South Africa, beside not much work has been done with respect to the economic sectors, hence, the need for examining the dynamic connectedness among the JSE sectors and the direction of volatility propagation among these sectors.

3.6.4 Empirical Studies on Dynamic Connectedness in African Economies

The literature on equity connectedness within the African economies is very limited. Ogbuabor, Orji, Aneke and Erdene-Urnukh (2016) investigates the real and financial connectedness of selected African economies which are Nigeria, South Africa, Egypt and Angola with the global economy USA, UK, Eurozone, China, Japan, India, Canada, Indonesia, Mexico and Australia, using a network approach. It was discovered that the connectedness of the African economies was quite sizable with the global economy. The result established that the African economies are much interconnected but systemically unimportant with high vulnerability to shocks emanating from the global economy.

Claassen (2019) investigates the return and volatility spillovers in South Africa, Morocco, Egypt, Nigeria and Tunisia markets. The empirical measurement of spillovers is examined using the time-domain technique of Diebold and Yilmaz (2012) and the frequency-domain approach of Barunik and Khrehlik (2018) to determine the type and level of interconnectedness among the African stock markets. The findings suggest that these African equity markets' total return connectedness indices are relatively moderate at an average of 9.7% over the full sample period between 11 January 2002 and 2 November 2018. These results suggest that South Africa and Egypt are usually the net transmitters of both return and volatility, while Morocco, Nigeria and Tunisia are usually the net receivers of these spillovers.

Udeaja (2019) uses the Dynamic Return and Volatility (DY-2014, 2014) to examine the degree of connectedness between the All Share Index, the Naira/USD Exchange Rate and the All Share Index with the aim of examining the dynamic return and volatility connectedness among the Nigerian financial markets. The findings show that connectedness was higher during the Nigerian currency's depreciations in 2014 and 2016, which occurred during the country's domestic economic crises brought on by the decline in oil prices. This shows that relative to external shocks, connectedness in the financial market is increased during domestic crises. The outcome also demonstrates that the Nigerian financial market's connectedness varies over time. It was strongly advised that a more inward-policy focused evaluation be taken into account while integrating financial markets.

Using monthly data from 1996 to 2017, Boako and Alagidede (2020) used wavelet-based coherency, wavelet multiple cross-correlation analysis, wavelet-based Sharpe ratio and generalised Sharpe ratio diversification analysis to examine the time-scale connections between African stock market returns and commodities like agriculture, metals, energy and beverage markets. The findings demonstrate a lead-lag relationship between the markets as well as co-movements across various scales and long-term co-integration of commodity prices and returns on African stocks. Among the African economies, Boakye, Mensah, Kang and Osei, (2023) investigate foreign exchange return spillovers and network connectedness by employing the generalised VAR framework and network theory of Diebold and Yilmaz, 2012, 2014, 2016 connectedness index between June 2004 and June 2021. It was observed that the total spillover index increased during the global financial crisis and the Eurozone sovereign debt crisis which is an indication of contagion effect. This offers good diversification opportunities in the African currency market during crisis periods. In addition, the study also found no significant evidence of spillover effects among African currencies. The network connectedness analysis did, however, discover positive significant pairwise return spillovers from the South African rand, Moroccan dirham and CFA francs to the Botswana pula, as well as from the Moroccan dirham to the CFA francs and South African rand. The study also discovered that the Kenyan shilling and Botswana pula are the net recipients of return shocks from other currencies, whereas the South African rand, Moroccan dirham and CFA francs are the most important net-transmitters of return shocks to other currencies. These findings have ramifications for the interventions made by African central banks to stabilise their currency rates and allow intra- and inter-African commerce as well as for foreign portfolio investors to control their exposure to foreign exchange risk.

In an attempt to measure the time-frequency connectedness during the COVID-19 pandemic period, of developing economies in East Africa, Katusiime (2022), by employing Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), revealed that a strong interdependence exists within the east African communities (EAC), which is an indication of high volatility and return spillover index, giving an affirmation to previous study on the economic integration of the region. Additionally, the dynamic spillover study shows that connectedness among various EAC markets is extremely time-varying and seems to be heightened during major global crises like the COVID-19 epidemic, the Kenyan elections, the European debt crisis and shocks to commodity prices. According to the findings, however, financial market connectedness in the EAC is more likely to become enhanced during times of external global shocks than it is during times of domestic turmoil. The study, moreover, discovered that for the EAC market, Brent crude oil served as a major significant source of return and volatility spillover in crises periods.

By using 12 commodity sectors and stocks from African markets, Agyei and Bossman (2023) investigated the dynamic connectedness between commodities and African equities using data from 23 February 2010 and 4 February 2022; they used the TVP vector autoregression connectedness approach. The analysis's findings indicate that, particularly during times of financial and economic stress, African stocks and these 12 commodities are not completely immune to shocks and contagion on a global scale. Additionally, it was found that idiosyncratic spillovers play a substantial role in the connection between African equity returns and commodity returns. The conclusion of their investigations suggested that investment managers concentrate on the non-homogenous functions of assets as diversifiers, hedges and safe havens throughout a range of time periods.

The empirical literature on dynamic volatility connectedness in the African context is very limited, even within the largest African economies. Even though some work has been centred on a few African stock markets and some commodities and some measures of connectedness have been revealed, no empirical examinations have been done on the economic sectors of these largest African countries. Even with the emergence of trade relationships between African countries and some major developed nations like China and United States, it has become important for the dynamic volatility connectedness of the sectors within a major African economy like South Africa to be investigated. Hence, the reason to carry out objective three of this study.

3.7 EMPIRICAL STUDIES ON DETERMINANTS OF VOLATILITY CONNECTEDNESS

Having measured the connectedness the super sectors, investigating the underlying determinants of sectorial volatility connectedness index is of utmost importance in this study. Hence, this subsection reviews the empirical studies carried out in estimating the drivers of connectedness index around the globe. Therefore, the empirical review discussed in this subsection relates to the fourth objective of this study which is to evaluate the determinants of sectorial volatility connectedness index of JSE.

Fernandez-Rodríguez et al., (2015) discovered the significant influence of the fiscal position and market sentiment on sovereign bond market volatility connectedness in Europe. Liow and Huang (2018) find economic policy uncertainty, interest rate, market fear and world stock market returns to be significant drivers of volatility connectedness among the real estate investment trusts (REITs). Shahzad et al. (2019) identified financial conditions and stock market volatility as determinants of corporate CDS connectedness in the Eurozone. Ji et al. (2019) cite trading volume, global financial factors, economic policy uncertainty and commodity prices as factors driving return and volatility connectedness of the cryptocurrency markets. Atenga and Mougoué (2021) find global shocks emanating from oil and metal prices to be drivers of return and volatility connectedness across African stock markets. Su (2020) reports different effects of exchange rate, industrial productivity, market fear, economic policy uncertainty, oil price, real economic activity and consumer confidence on long- and short-term volatility connectedness among the G7 equity markets.

The work of Bouri et al. (2021) that finds economic policy uncertainty, term spread of interest rates and real economic activity as the significant drivers of volatility connectedness in the commodity futures market is the only study that applies the TVP-VAR framework to explore the connectedness determinants. In the only study on liquidity connectedness, Inekwe (2020) merely measures the extent of liquidity connectedness in 24 countries using the DY framework but does not explore its underlying determinants. The application of the TVP-VAR framework for examining liquidity connectedness and finding the drivers of liquidity connectedness thereon are the key novelties of our study.

A daily return data set that spans between 3 January 2012 and 29 November 2019, which covers the Wilderhill clean energy index and the solactive green bond index to represent clean and green energy assets is used. The significance of macroeconomic conditions is demonstrated by an analysis of the return connectedness determinants, particularly at the middle and lower quantiles. Saeed, Bouri and Alsulami (2021) document that the volatility in the crude oil market exacerbates the return spillovers at the lower quantile; the U.S currency has a beneficial effect in all circumstances. In addition, the results showed that macroeconomic conditions such as the term spread and interest rate are important, especially at the middle and lower quantiles, while crude oil market uncertainties intensify the return spillover at the left tail. The outcome of the results indicates a positive decision making particularly with regards to the stability of the system of return connectedness within the clean energy and dirty energy markets during extreme occurrences.

Liew, Lim and Goh (2022) estimated the total liquidity connectedness of stock, bond, money and foreign exchange markets in Malaysia, thereafter they investigated the determinants on liquidity connectedness using the ordinary least squared with heteroscedasticity and autocorrelation corrected errors with monetary policy uncertainty index, implied volatility of the Chicago Board of Options, the TED spread measured as the difference between the 3-month U.S Treasury bill rate and the 3-months U.S dollar London Interbank Overnight Rate, the West Texas Intermediate crude oil price index and the global real economic activity index constructed by Kilian (2009, 2019) as the independent variables. The OLS results show that there is a positive association between liquidity connectedness and heightened fear and credit risk, while an increase in international crude oil price (WTICO) gave a negative association with liquidity connectedness. Reduced liquidity connectedness during periods of rising global oil prices may be attributable to the upbeat sentiment brought on by Malaysia's revenue from oil exports, which is a significant source of funding for the country's budget. The demand-driven increase in the price of crude oil internationally is also a sign of rising economic activity, which is positive for investor sentiment and risk-taking tendencies.

To bring about robust and comprehensive results of the determinants of dynamic total connectedness within the sectors, the novel NARDL is employed. No study, to the best of the author’s knowledge, has employed this model to determine dynamic connectedness. The advantage of the NARDL is that it permits incorporating the possibility of asymmetric effect of positive and negative changes in explanatory variables on the dependent variables. In addition, the NARDL model provides graphs of cumulative dynamic multipliers used to trace out the adjustment patterns following the positive and negative shocks to explanatory variables. More importantly and interestingly, the model is simple and comprehensive enough to permit any asymmetry switching from short-run to long-run or vice versa.

3.8 SUMMARY AND CONCLUDING REMARKS

This chapter presents the relevant empirical literature on equicorrelation, contagion, correlation, connectedness (both time connectedness and the network emphasis) and the determinants of sectorial volatility connectedness. Throughout the connectedness literature regardless of the region of assessment or data fundamentals involved (market indices) one thing is clear; assets and markets connectedness is a phenomenon that does exist; however the level of interconnections does vary depending on how integrated the indices or markets (if it involves different countries) are.

First, it would be important to note that the concept of systemically important financial institution has been broadly emphasised in the literature with great applications in the financial industry. However as this application has been deployed into non-banking financial intuitions for example (Chaturvedi & Singh 2022), with huge success. Therefore, this study's first objective is to apply the concept of too-central-to-fail as a sector on the JSE which is first of its kind in empirical study. Therefore, since several studies has been carried out on centrality with the PageRank or its variant models as revealed from the literature review, there exists a gap in the literature to explore the centrality of sectors.

The empirical study on dynamic equicorrelation is fast-growing from its application on equity markets to commodities and so on, which this chapter has reviewed extensively. However, there is a gap in this study on the African sectorial markets, hence, the focus of this study on the largest economy in Africa, which is South Africa[14]. The application of the DECO model of Engle and Kelly (2002) on the JSE sectors will go a long way to reveal if indeed the correlation on the sectors are time varying and to know if the sectors are integrated, especially during crisis periods; hence, the possibility of the existence of contagion could be ascertained. Thirdly, this chapter expatiates on the existing literature on return and volatility dynamic connectedness in developing, developed and the in the African markets. Volatility connectedness of sectorial equity is crucial not just in determining the sectors that are connected, but knowing the propagation of shocks that led to how the sectors are connected in the first place is of utmost relevance. Hence, the reason for carrying out objective three of this study.

The existence of dynamic volatility connectedness among economic sectors has not been fully established, as some sectors tend to be cyclical[15] to economic movement or progress. Lastly, the investigation of the drivers or determinants of sectorial volatility connectedness of the JSE

[14] According to statista.com/statistic (2023): The JSE is the leading stock exchange on the African continent with a total market capitalization of over U.S 1 trillion dollars in 2022.

[15] Cyclical sectors are sectors which the business cycle of the country they exist has huge and direct effect on their business operations. Hence, there stocks profitable when the country experience economic growth.

is very crucial as this is yet to be investigated even within the body of the literature. The application is very crucial for sectorial investors to equip them with factors that triggers volatility connectedness on the JSE market, hence, this study helps to fill this huge gap in the South African stock market.

Therefore, from the empirical literature, it has been established that there exist gaps in the African market especially at the sectorial level, on dynamic equicorrelation, contagion and connectedness of sectors, which this study aims to fill through the provisions of answers to the research questions.

CHAPTER 4: DATA AND METHODOLOGY

4.1 INTRODUCTION

The objective of this study is to first identify the systemically important super sectors on the JSE, followed by determining the return linkages of the super sectors, in addition to this, is to examine the shock propagation and connectedness among the JSE super sectors and lastly, is evaluating the determinants of volatility connectedness of the super sectors. A brief history of the JSE and sample population is described and in addition the descriptive statistics of the data (returns and volatilities) are given. Lastly, details of the subsections under this chapter are given in the following order; Market, sample and data property, a brief of the JSE market, sample population, data description and sources, data properties, determine the systematically important super sectors, modelling time-varying equicorrelation (equity-return linkages), modelling the shock propagation and connectedness of JSE super sectors and lastly, this chapter expatiates on the modelling the determinants of volatility connectedness. In describing the methodologies involved in each objective, a detail breakdown of the different models employed to achieve each objective are given with the corresponding equations involved.

4.2 MARKET, SAMPLE AND DATA PROPERTY

In this section, the sample selection process is explained along with a brief description of the JSE. The data source, calculation and attributes are further discussed for each of the chosen super sectors.

4.2.1 A Brief on the Johannesburg Stock Exchange Market

Founded on 8 November 1887, during the South African gold rush, by Ben Woolman, the mission was to enable new mining firms and their investors to raise the capital required for the mining industry (Samkange, 2010). Within a period of 80 years (i.e. from 19832 to 2014) the number of firms listed from the industrials, financials and mining sectors on the JSE rose from 151 to 402. This business expansion necessitated the move to a larger facilities six times in nine decades, which was a reflection of the JSEs rapid growth (Moolman & Du Toit, 2005).

The JSE is ranked by market capitalisation the 17th largest stock exchange in the world, with a total market capitalisation of R 24.8 trillion ($1.36trillion), the oldest and the largest exchange in African continent (JSE, 2022). The exchange trades shares for a wide variety of industries, sectors with the largest fraction of market capitalisation coming from the mining industry (Chimanga & Kotze, 2009).

In the study of market efficiency, the JSE appears to have drawn more attention than other African markets. It has been highlighted that the JSE has more characteristics of stock markets in industrialised economies, making it the most developed and having one of the robust sectors in the African stock exchanges. In other to promote capital market activities and competitiveness, the JSE issued a consultation Paper in May 2022 with the aim of obtaining public input on various proposals regarding its listing frameworks considering the recent international developments and JSE initiatives. This plan is to put the JSE among the leading stock markets in the globe (Visser & Reddy 2022). The South African economy enjoys integration with the global economy through the platforms and trading instruments provided by the JSE, with the banking sector playing a role in the whole process, however, with implications (Mboweni, 2000).

The JSE's equities trading methodology was synchronised with that of Europe through cooperation with the FTSE Group and its instruments were reclassified to comply with the FTSE Global Classification framework. Hence, the JSE index series comprises of two benchmark indices, the FTSE/JSE All Share Index and the FTSE/JSE Top 40 Index. The FTSE/JSE Top 40 Index follows the top listings in a representative variety of industries, while the FTSE/JSE All Share Index encompasses 99 percent of market capitalisation (JSE, 2014). Through the industrial classification benchmark (ICB) companies on the JSE are classified into industries, super sectors, sectors and subsectors for detailed and comprehensive structure and nature of business (FTSE, 2021).

4.2.2 Population and Sampling

The JSE uses the industrial classification Benchmark (ICB) method to categorise companies. Under this classification system the JSE consist of 11 industries, 19 super sectors, 41 sectors and 114 subsectors (JSE 2022). The classification method assigns businesses to the sector that best captures the nature of their operations as indicated by the source of their revenue or the source of the majority of their revenue. This grouping enhances the investment demands of an ever-changing global equity market (FTSE Russell 2021). The South African sector markets have revenues and market capitalisation range in billions of Rands. This study chooses nine super sectors out of the 19 super sectors for the analysis of the four objectives.

The choice of selected super sectors is due to availability of data, super sectors such as Utilities, Real Estate and Consumer Products and Services could not be sourced from the available data sources. Moreover, secondly the super sectors selected contains the major equities within their different economic groups, they reflect the accurate asset price behaviour of the firms within the super sectors. Moreover, the selected super sectors are well capitalised within the industry that they exist under, hence, the better capitalised super sectors are selected. In addition, some super sectors such as Travel and Leisure, Media, Banks, Retail and Banks do not meet the heteroscedasticity test, which is a major preliminary test hence were omitted from the sample size.

Therefore, the selected super sector-sample are a good representation of the population of the entire sector/industry. In addition the super sectors selected contains the majority of the equities within their different economic groups (JSE 2023). In other words, the selected super sectors are the accurate reflection of the asset price behaviour of the companies/ firms within the sectors they track

4.2.3 Data Description and Sources

Due to the unavailability of data and classification criteria, this study employs the prices of stock indices for the selected nine JSE super sectors that was sourced from McGregor BFA. These super sectors are: Automobiles and Parts (AM & P), Energy (ENE), Financials (FIN), General Industrials (IGS), Chemicals (CHE), Health Care (HEL), Technology (TECH), Telecommunications (TEL), Insurance (INSUR) (ICB 2019, 2021). Daily return dataset spanning 3 January 2006 to 31 December 2021, would be required for objectives one to three. The choice of daily data is because it allows to detect immediate response to new event (Shen, Jiang, Ma, Wang and Zhou 2020). Further monthly data on (South Africa Volatility Index (SAVI), Domestic Asset Market Return (DAMR), Economic Policy Uncertainty (EPU), Trade Openness (TO), Manufacturing Output and macroeconomic variables such as Money Supply (M2) would be obtained from Statistics SA and SA Reserve Bank for the purpose of objective four.

Following Shahzad, Kayani, Raza, Shah and Yahyee (2018) and Liew, Lim and Goh (2022), monthly average of the daily sectorial total volatility connectedness index would be generated and employed as the dependent variable for objective 4, denoted as G_tCon_T in equation 3.7.1.7. The choice of this data period is that the data covers not only the 2017 to 2019 U.S-China trade war, but also covers the global financial crisis periods such as 2008/2009 financial crisis, European debt crisis of 2009/2012 and the COVID-19 pandemic, which allows the study to compare the risk contagion behaviours triggered by these events in the South African economic sectors. The daily returns of each super sector would be computed from their price indices following (Zhang, Zhuang, Wang and Lu. 2020) and the formula to be employed in calculating the returns is explained subsequently in equation (3).

$$PR_{i,t} = \left(\frac{P_{ti - P_{to}}}{P_{to}}\right) \tag{3}$$

$\boldsymbol{P_{ti}}$, $\boldsymbol{P_{to}}$ ***and*** $\boldsymbol{PR_{i,t}}$ represent the price at current time, price at initial time, and Price return respectively.

4.2.4 Data Property

This section treats the different tests of the stock return's data-generating and their distributional properties. Typically performed for robustness reasons, the tests include the common characteristics of stock returns. These tests are listed below.

Unit Root Tests: One major objective of the unit root test is to help in determining if trending data should be first differenced or regressed on deterministic functions of time to render the data stationary. Therefore, the test is to determine whether the stochastic component contains a unit root or is stationary. In statistics, a unit roots test whether a time series variable is non-stationary and possesses a unit root. The null hypothesis is generally defined as the presence of a unit root and the alternative hypothesis is either stationarity, trend stationarity or explosive root, depending on the test used. A simple and general approach to unit root is shown below (Kočenda & Černý 2015). This approach assumes that the time series to be tested $\boldsymbol{A_{t}{}_{t=1}^{T}}$ can be shown in equation (4) as:

$$\boldsymbol{A_t = D_T + Z_T + e_T} \tag{4}$$

$\boldsymbol{D_T}$ stands for the deterministic component components
$\boldsymbol{Z_T}$ is the stochastic component
$\boldsymbol{e_T}$ is the error component
This study would employ the augmented Dicky Fuller (ADF) test and the Philip-Perron test.

ADF-Test: In statistics, the null hypothesis that a unit root exists in a time series sample is tested using the augmented Dickey-Fuller test (ADF). Depending on the test version being utilised, the alternative hypothesis may vary, but it is typically stationarity or trend-stationarity. It is a supplement to the Dickey-Fuller test for a more extensive and intricate collection of time series models. The augmented Dickey–Fuller (ADF) statistic, used in the test, is a negative number. The rejection of the hypothesis that there is a unit root at some level of confidence is a function of the negative number of the ADF statistic (William 1997).

Testing procedure: The testing procedure for the ADF test is the same as for the Dickey–Fuller test but it is applied to the model.

$$\Delta_{yt} = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \mathrm{e_t} \qquad (5)$$

where α is a constant, β the coefficient on a time trend and *p* the lag order of the autoregressive process. Imposing the constraints $\alpha = 0$ and $\beta = 0$ corresponds to modelling a random walk and using the constraint $\beta = 0$ corresponds to modeling a random walk with a drift. Consequently, there are three main versions of the test, analogous to the ones discussed on Dickey–Fuller test (see that page for a discussion on dealing with uncertainty about including the intercept and deterministic time trend terms in the test equation.)

By including lags of the order *p* the ADF formulation allows for higher-order autoregressive processes. This means that the lag length *p* has to be determined when applying the test. One possible approach is to test down from high orders and examine the *t*-values on coefficients. An alternative approach is to examine information criteria such as the Akaike information criterion, Bayesian information criterion or the Hannan–Quinn information criterion (Dickey & Fuller, 1979).

The unit root test is then carried out under the null hypothesis $\gamma = 0$ against the alternative hypothesis of $\gamma < 0$. once a value for the test statistic

$$DF_T = \frac{\gamma}{SE\ (\gamma)}$$

is computed it can be compared to the relevant critical value for the Dickey–Fuller test. As this test is asymmetrical, we are only concerned with negative values of our test statisticDF_T. If the calculated test statistic is less (more negative) than the critical value, then the null hypothesis of $\gamma = 0$ is rejected and no unit root is present (Kočenda & Černý 2015).

Philip-Perron Test: This is a unit root test used in time-series analysis to test the null hypothesis that a time series is in integrated of order 1 Phillip & Perron (1988). It builds on the Dickey–Fuller test of the null hypothesis $P = 1$ in $\Delta yt = (\rho - 1)y_{t-1} + \mu_t$, where Δ is the first difference operator. Like the augmented Dickey–Fuller test, the Phillips–Perron test addresses the issue that the process generating data for y_t might have a higher order of autocorrelation than is admitted in the test equation—making y_t endogenous and thus invalidating the Dickey–Fuller t-test. Whilst the augmented Dickey–Fuller test addresses this issue by introducing lags of Δy_t as repressors in the test equation, the Phillips–Perron test makes a non-parametric correction to the t-test statistic. The test is robust with respect to unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation. Davidson and MacKinnon (2004) report that the Phillips–Perron test performs worse in finite samples than the augmented Dickey–Fuller test (Russell & James (2004).

Normality Test: The normality test is used to examine whether a data set can be adequately described by a normal distribution and to calculate the likelihood that a random variable underlying the data set will be normally distributed. Specifically, the tests are a type of model selection and depending on how one understands probability, they can be interpreted in the ways:

i.) In descriptive statistics terms, one measures a goodness of fit of a normal model to the data – if the fit is poor then the data are not well modelled in that respect by a normal distribution, without making a judgment on any underlying variable.

ii.) In frequentist statistics statistical hypothesis testing, data are tested against the null hypothesis that it is normally distributed.

iii.) In Bayesian statistics, one does not "test normality" per se, but rather computes the likelihood that the data come from a normal distribution with given parameters μ,σ (for all μ, σ) and compares that with the likelihood that the data come from other distributions under consideration, most simply using a Bayes factor (giving the relative likelihood of seeing the data given different models), or more finely, taking a prior distribution on possible models and parameters and computing a posterior distribution given the computed likelihoods.

A normality test is used to determine whether sample data has been drawn from a normally distributed population (within some tolerance). The normality test is important for objective two of this study.

One application of normality tests is to test the residuals of a linear regression model (Portney & Watkins 2000) if they are not normally distributed, the residuals should not be used in Z tests or in any other tests derived from the normal distribution, such as t-tests, F-tests and chisquared tests. If the residuals are not normally distributed, then the dependent variable or at least one explanatory variable may have the wrong functional form, or important variables may be missing. Correcting one or more of these systematic errors may produce residuals that are normally distributed; in other words, non-normality of residuals is often a model deficiency rather than a data problem (Jolynn, Octavia, & Augustine 2018).

4.3 DETERMINE THE SYSTEMICALLY IMPORTANT SUPER SECTORS WITHIN THE JSE

The first objective of the study is to determine the systemically important equity super sectors within the JSE. This entails the application of PageRank of Page et al., (1999) and Granger causality model of Billio *et al*. (2012).

4.3.1 PageRank Centrality Measure

To assess the relative importance of entities within a network, centrality measures are employed. Several centrality measures have been developed in literature which includes between centrality Newman (2001), closeness centrality of Newman (2001), degree centrality Freeman (1978), Katz centrality of Katz (1953), eigenvector centrality of Bonacich (1972) and PageRank of Page, Brin, Motwani and Winograd (1999) amongst many others. Centrality measures have been applied to different types of real networks; for instance, ranking the cities with at least one operating airport in the air transport network of China (Wang, Mo, Wang & Jin 2011) and evaluating the impact of research papers in a citation network (Hirsch 2005).

Therefore, to determine the systematically important super sector on the JSE, PageRank algorithm is employed. The PageRank developed by Page and Brin (1999) is an algorithm that the link-based object ranking (LBR) problem. It assigns numerical ranks to pages based on backlink counts and ranks of pages providing those backlinks (Chat) (Billio et al., 2012).

To determine the systematically important super sector on the JSE, the PageRank algorithm is employed. This study quantifies the centrality of the super sectors through ranking. Rank represents the link between one super sector and another while considering the other super sector's weight (Billio et al., 2012). First, an 'effect matrix', which depicts the extent to which each super sector is connected to the other is estimated. This study follows Billio et al., (2012) and Jeong and Park's (2018) Granger causality network to create the effect matrix. These studies employ a p-value to calculate each super sector' connectedness, the study will use the

F-statistics of the Granger causality network as the entity of the effect matrix (ω_{ijt}). The use of F-statistics, rather than p-values, give room for more specific by accounting for wider variations.

Secondly, this study estimates the value of super sector's centrality. Based on entity (i, j) of the effect matrix, the effect weight of each super sector is as follows:

$$E_{ijt} = \frac{\omega_{ijt}}{\sum \omega_{ijt}} \tag{6}$$

where ω_{ijt} represents the extent of the effect by super sector *i* on super sector *j* at time *t* and E_{ijt} is the effect weight on super sector *j* by super sector *I* at time *t*. Thereafter, the PageRank algorithm established by Page et al., (1999) is adopted to get PageRank (PR) such that:

$$Rank_{it} = \frac{(1-d)}{N} + d \sum_{i=1}^{N} E_{ijt}\, Rank_{jt} \tag{7}$$

As the damping factor is denoted as d (generally set to 0.85) (Page et al., 1999), E_{ijt} is the effect weight on super sector $j\ by\ super\ sector\ i\ at\ time\ t. Rank_{it}$ is the rank of super sector i and its value is always positive. Higher value of PR_i^s implies that super sector *i* contributes more to systemic risk of network. This would help to rank the super sectors in order of their importance in contribution to systemic risk. In this study we follow Yun, Jeong and Park (2019) and Zhang, Zhuang, Wang and Lu (2020) who adopted Page et al., (1999) model in their studies to determine the systemically important sectors on the Chinese stock market, respectively.

4.3.2 The Granger Causality Test

The Granger causality test was initially developed in 1969 by CWJ Granger (Granger 1969). It is a statistical hypothesis test for detecting if one time series is important in predicting another. Regressions typically only show mere correlations, but according to Clive Granger (Granger 1969), one way to test for causation in economics is to measure how well one time series can predict future values using data from a different time series.

Econometricians claim that the Granger test only detects "predictive causality" since the concept of "true causality" is highly philosophical and because it is fallacious to believe that the mere fact that one event occurs after another proves a connection by means of causation is post hoc ergo propter hoc (Diebold 2007). Using the term causality alone is a misnomer, as

Granger causality is better described as precedence (Leamer 1985), or, as Granger himself later claimed in 1977, "temporally related" (Granger & Newbold 1977). Rather than testing whether X causes Y, the Granger causality tests whether X forecasts Y (Hamilton 1994).

A time series is said to be Granger-caused if it can be demonstrated, typically by a sequence of t-tests and F-tests on lagged values of X (and with lagged values of Y also included); those X values convey statistically significant information about future values of Y. Granger emphasised the "ridiculous" results of some research that applied Granger causality testing outside of the field of economics (Thurman 1988). However, due to its computational simplicity, it continues to be a well-liked technique for causality analysis in time series (Seth 2007; Eichler 2012). Although numerous improvements have been made to address these concerns, the original definition of Granger causality does not take into account latent confounding effects or capture instantaneous and non-linear causal linkages (Eichler 2012).

The Granger causality test (Granger 1969) can be described as follows: for two variables v_x and v_w, where Vx causes W_v (written as $v_x \rightarrow v_w$) and where ($v_w \rightarrow v_x$) a bivariate linear autoregressive model is created:

$$\mathrm{V_x} = \sum_{\mathrm{j-1}}^{\mathrm{p}} \mathrm{A_{1i}} \mathrm{V_x}\,(\mathrm{t-j}) + \sum_{\mathrm{j-1}}^{\mathrm{p}} \mathrm{A_{2j}}\,\mathrm{V_w}\,(\mathrm{t-j}) + \mathrm{e_1} \qquad (8a)$$

$$\mathrm{W_v} = \sum_{\mathrm{j-1}}^{\mathrm{p}} \mathrm{A_{11i}} \mathrm{V_x}\,(\mathrm{t-j}) + \sum_{\mathrm{j-1}}^{\mathrm{p}} \mathrm{A_{21j}}\,\mathrm{V_w}\,(\mathrm{t-j}) + \mathrm{e_2} \qquad (8b)$$

P is the maximum number of lagged observations, $\mathrm{e_1}$ and $\mathrm{e_2}$ denotes the residual error for the time in each time series. $\mathrm{A_{1i}}$, $\mathrm{A_{2j}}$ $\mathrm{A_{11i}}$, and $\mathrm{A_{21j}}$ are matrixes that contains the coefficients of the model (i.e. the contributions of each lagged observation to the predicted values of $\mathrm{V_x}$ and $\mathrm{W_v}$ are free variables that are chosen via least squares regression. This model is then compared via a hypothesis test to the restricted model: If the variance of $\mathrm{e_1}$ and $\mathrm{e_2}$ is reduced by the inclusion of the $\mathrm{V_x}$ and $\mathrm{W_v}$ terms in the first or second equation, then it connotes that $\mathrm{W_v}$ Granger causes $\mathrm{V_x}$ and vice versa. Therefore $\mathrm{W_v}$ Granger causes $\mathrm{V_x}$ if the coefficient in ($\mathrm{A_{2j}}$) are jointly significantly different from zero (0).

This can be tested by performing an F-test with the null hypothesis that $\mathrm{A_{2j}} = 0$, with the assumptions of stationarity of covariance of $\mathrm{V_x}$ and $\mathrm{W_v}$. Therefore, for a causal link to be detected the null hypothesis must be rejected. The F-test, which is a popular choice for Granger analysis (Bressler & Seth, 2011; Jiang, Gao, An, Li, & Sun 2017).

$$\boldsymbol{F-Test} = \frac{(\boldsymbol{RSS_{re}} - \boldsymbol{RSS_{un}})/\boldsymbol{q}}{\boldsymbol{RSS_{un}}/(\boldsymbol{S}-\boldsymbol{p}-\boldsymbol{q}-\mathbf{1})} \quad (\mathbf{9})$$

Where $\boldsymbol{RSS_{re}}$ and $\boldsymbol{RSS_{un}}$ are the residual sum of squares for the restricted and unrestricted model respectively and S denotes the sample size (Jiang, Gao, An, Li, & Sun 2017). A significance level of 5% is employed in this study.

Following the work of Jiang *et al*,. (2017), the network of causality links in a multivariate system can be captured in a causality pattern. This can be seen as an n-by-n matrix, with each element representing the causal link from $\boldsymbol{i}$ to $\boldsymbol{j}$. The system's evolution can, therefore, be captured by creating a series of causality patterns via a sliding window of fixed length (the start of each window is one time step after the start of the previous).

4.3.3 Granger Causality Network

The pairwise Granger causality test Billio *et al*., (2012) measures the dynamic propagation of shocks to the financial system. The Granger causality test is employed on the volatility of super sectors obtained from Garman and Klass (1980) model in Section 4.5 to build the network parameters.

Let r_t^i and v_t^j be the two stationary volatility time series of super sectors assumed to have zero mean. If v_t^j contain information that helps in predicting v_t^i beyond the information that is contained in lagged values of v_t^j alone then v_t^j is said to be Granger cause v .

$$v_{t+1}^i = a^i v_t^i + b^{ij} v_t^j + e_{t+1}^j \quad (10)$$

$$v_{t+1}^j = a^j v_t^j + b^{ji} v + e_{t+1}^i \quad (11)$$

Where, e_{t+1}^j, e_{t+1}^i are uncorrelated residual series assumed to be white noise and a^i, b^{ij}, a^j, b^{ji}. are coefficients of the model. Then v_t^j Granger causes v_t^i if b^{ij} is different from zero. Using AIC (Akaike information criteria) the lag number is determined to be two (2) for the model, following (Chaturvedi and Singh 2022).

The Granger causality helps to model a matrix relationship among the super sectors. An adjacency matrix of the network of N super sectors is defined as:

$$(j \to i) = \begin{cases} 1, \\ 0, \end{cases} (1 \; if \; j \; Granger \; causes \; i \, , otherwise \; 0$$

and define $(j \to i) = 0$.

Essentially in studying the connectedness of super sectors, ranking the super sectors with the PageRank model reveals how the systematically important sectors could be close or interconnected with each other. Therefore, by determining the score ranks of each super sector through the PageRank-Granger Causality model, the connectivity of the important super sectors to each-other is ascertained.

4.4 MODELLING TIME-VARYING EQUICORRELATION (EQUITY-RETURN LINKAGES) OF JSE SUPER SECTORS

The problem of constant correlation is solved by the dynamic conditional correlation GARCH (DCC-GARCH), first suggested by Engle (2000). The mathematical framework of this model first estimates the conditional standard deviations through the univariate GARCH and secondly, it calculates the time-varying correlations relying on lagged values of residuals and covariance matrices (Engle & Sheppard, 2001). After that, the conditional covariance matrix is formulated by using conditional standard deviations and dynamic correlations.

The first adaptation of a GARCH process was carried out by Bollerslev, Engle and Wooldridge (1988). They employ the univariate GARCH process to do multivariate parameterisation. However, when the sample size is very large the computational problems are quite considerable and thus it is hard to achieve a feasible estimation. Bollerslev (1990) introduces a variation of this GARCH model, namely the constant conditional correlation GARCH (CCC-GARCH) model. In this framework, standard deviations of each asset are produced by a univariate GARCH process. The standard deviations within the covariance matrix are calculated relying on the GARCH constraints.

The DCC-GARCH model is a very well-structured model employed to estimate the time-varying covariance matrix. However, when we have a very large number of observations, the estimation of conditional correlation matrix becomes very difficult. Engle and Kelly (2012) reduced the burden of large-scale parameterisation, thus reducing the scale of estimation by averaging pair dynamic correlations. This process is called dynamic equicorrelation GARCH (DECO-GARCH).

The second objective of this study is achieved by using DECO-GARCH model. The DECO-GARCH model is a distinct variant of the dynamic conditional correlation model DCC-model formulated by Engle and Kelly (2012), which expatiates and explains the time-varying common equicorrelation and dynamic correlation of all pairs of assets. A major unique advantage of the GARCH-DECO model over the DCC model is that it removes presentational and computational difficulties during estimation, especially with big data. Kang et al., (2017) document that GARCH-DECO has a superior forecasting capacity even during crisis period across different assets classes. Umar, Nasreen, Solarin and Tiwari (2019) and Kang and Yoon (2019) employed this model in related studies to quantify the dynamic linkages between seven different assets involving oil price and some precious metals and between CSI 300 index and some commodities, respectively. This objective starts with the estimation of the mean equation below in equation (12) using the vector of r_t return series:

$$r_t = \mu_t + \vartheta r_{t-1} + \epsilon_t \tag{12}$$

Where r_t is the return value at time t, μ_t and $\in_t$ is the vectors that contains the constant term and the model residual at time t, or the error terms, respectively. The volatility coefficient for the mean is ϑ.The estimation procedure of conditional volatilities $h_{i,t}^2$ from the univariate GARCH (1, 1) procedure is shown in equation 13:

$$h_{i,t}^{2} = v_i + \alpha_i \varepsilon^2{}_{i,t-1} + \beta_i h^2{}_{i,t-1} \tag{13}$$

Where $v > 0, \alpha_i \geq 0, \beta_i \geq 0, and\ \alpha_i + \beta_i < 1.$ α_i and β_i are the parameters of the ARCH and GARCH components respectively, while ε^2 is the model's residual at time t.

Furthermore, to estimate the dynamic correlation between the examined super sectorial return this study derived DECO- from the DCC-model of Engle (2002). Assuming that $G_{t-1}[\varepsilon_t] = 0$ and $G_{t-1}[\varepsilon_t \varepsilon^{`}] = H_t$. As $G_t[.]$ is the conditional expectation for using the information set available at time t, the conditional variance covariance matrix H_t can be presented as:

$$H_t = E^{1/2} R_t E_t{}^{1/2} \tag{14}$$

where $R_t = [\rho_{ij,t}]$ denotes the conditional correlation matrix, while the diagonal matrix of the conditional variance is given by $E_t = diag[h_{i,t} \ldots\ldots h_{n,t}]$. In following the dynamic structure of correlation, H_t is estimated as:

$$R_t = \{Q_t^*\}^{-1/2} Q_t \{Q_t^*\}^{-1/2} \tag{15}$$

$$Q_t{}^* = diag(Q_t) \tag{16}$$

$$Q_t = [q_{it,t}] = (1 - C - D)S + C\mu_{t-1}\mu_{t-1} + bQ_{t-1} \tag{17}$$

Where u_t represents the standard residuals, with C and D being positive scalars satisfying $C + D < 1$. The resulting model is known as the DCC procedure. Aielli (2013) validates that $[R_t] \neq E[Q_t]$. To estimate a covariance matrix by this means is inconsistent, hence, a consistent DCC (cDCC) model was proposed for the correlation driving process:

$$Q_t = (1 - C - D)S^* + \left(Q^* 1_{t-1}\mu_{t-1}\,\mu_{t-1}\,Q_{t-1}^{*1/2}\right) + bQ_{t-1} \tag{18}$$

S* signifies the unconditional covariance matrix of $Q_t^{*1/2}\mu_t$. Engle and Kelly (2012) proposed that ρ_t is modelled by using the DCC-procedure to produce conditional correlation matrix Q_t, after which the average of its off-diagonal elements is taken. The model derived is called the DECO model. g_n is a vector of ones and $q_{ij,t}$ is the (i, j)th components of the matrix Q_t from the DCC model.

(ρ_t) is the scalar equicorrelation and shown as:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}\left(g_n R_t^{cDCC}\, g_n - n\right) = \frac{2}{n(n-1)} \sum_{i-1}^{n-1} \sum_{j=i+1}^{n} \frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{jj,t}}} \tag{19}$$

Hence, according to Yoon (2019) and Tsiaras (2020), the scalar equicorrelation can be used to compute the conditional correlation matrix as seen in equation (20) below:

$$R_t^{DECO} = (1 - \rho_t)I_n + \rho_t g_n \tag{20}$$

Where ρ_t represents the conditional equicorrelation, I_n represents the n-dimensional identity matrix and g_n represents the nxn matrix of ones.

As earlier stated the DECO-GARCH model set the average of conditional correlation equal to all pair correlations and haven earlier determined the score ranks of the super sectors in objective one. The DECO-GARCH estimation enables to show how possibly connected are the super sectors in other words how positively or negatively correlated to each other. These procedures allow to determine the extent of co-movement of a cluster of sectorial returns series under consideration with a single time-varying correlation coefficient. If the results from the ARCH and GARCH terms are significant and close to unity, then there is high possibility that the results would produce high persistence of volatility across the super sectors. In addition, if the dynamic equicorrelation value is positive and high, it indicates a possibility of contagion among the sectors (Tsiaras 2020). The reliability of the DECO-GARCH model has been proven and established by different authors in investigating the equicorrelations of cryptocurrency and in the direction of spillovers for example (Demiralay & Golitsis 2021; Bouri, Vo & Saeed 2021; Hung 2021). The DECO-GARCH model was suitable to capture the time-varying co-movements and the interlinks among the cryptocurrency markets in the different periods.

The analysis was carried out through the GARCH-DECO model with the full sample from 3 January 2006 to 31 December 2021 and also the rolling window at yearly intervals (2006-2007, 2007-2008, 2008-2009, 2009-2010, 2010-2011, 2012-2013, 2013-2014, 2014-2015, 2015-2016, 2016-2017, 2017-2018, 2018-2019, 2019-2020 and 2020-2021) to demonstrate how equicorrelation varies between normal and the different extreme event periods.

4.5 MODELLING SHOCK PROPAGATION AND CONNECTEDNESS OF JSE SUPER SECTORS

The third objective of this study is to examine shock propagation and connectedness among JSE equity super sectors during extreme risk events. This entails estimating the spillover connectedness across all super sectors on the JSE. The study followed Shen, Jian, Ma, Wang and Zhou (2020) to investigate the volatility spillover connectedness of the super sectors, by first generating the daily realised volatility for each index, following Garman and Klass (1980):

$$V_{it}^{GK} = 0.511(h_{it} - l_{it})^2 - 0.019[(c_{it} - o_{it})(h_{it} - l_{it} - 2o_{it}) - 2(h_{it} - o_{it})(l_{it} - o_{it})] - 0.383(c_{it} - o_{it})^2: \quad (21)$$

where h_{it}, l_{it}, o_{it} and c_{it} are the natural logarithm of high, low, open and close values of index (using returns), (*i)* on day (*t*). For each index once volatility is obtained, the corresponding mean, median, standard deviation, minimum and maximum, kurtosis, skewness and ADF statistics are estimated.

In their first paper, Diebold and Yilmaz (2009) introduce a connectedness index derived from the factor error variance decomposition (FEVD) of a Cholesky-type VAR model. Subsequently, Diebold and Yilmaz (2012) present two improvements. First is the use of the generalised VAR framework to replace the Cholesky-type VAR, hence, solving the problem of variable ordering when extracting variance decompositions from the VAR model. The second improvement is the introduction of directional connectedness – to a market, (or super sector in the context of the present study), -from a market and -net connectedness, as opposed to their earlier framework which relies only on the total connectedness in a system. Later, Diebold and Yılmaz (2014) link their framework to the network theory to show how the connectedness measures proposed in their earlier works are closely related to key measures of connectedness in the network literature.

Diebold and Yilmaz (2009, 2012, 2014) compute their time-varying connectedness index from models estimated through a rolling windows approach. The rolling window estimation technique has a few disadvantages, which could be detrimental to the results of this objective. First the rolling window approach will need to determine the width of the rolling window which often times is an arbitrary figure with little or no statistical background (Liew, Lim & Goh 2022). Second, the rolling window analysis has the tendency to lose some number of observations, which is often equal to the width size and lastly, the rolling-window approach does not allow the identification of data points that contribute to a spike or a dip in the connectedness index within a specific window (Antonakakis & Gabauer, 2017; Antonakakis et al. 2018; Gabauer & Gupta, 2018; Korobilis & Yilmaz, 2018). Therefore, due to the above important factors, this study employs the time-varying vector autoregression model, which has the capacity to overcome the mentioned disadvantages.

4.5.1 Dynamic Connectedness Index in Time-varying Parameter Vector Autoregression Model

The time-varying parameter VAR (TVP-VAR) model, an innovation of Antonakakis, Chatziantoniou and Gabauer (2020), is employed to determine the connectedness of, and shock propagation among the JSE super sectors. As indicated in section 4.5.1, the TVP-VAR is superior to the rolling-window approach in certain ways. First, it avoids the need to determine the width of rolling window, second it does not lose the number of observations that is equal to the number of widths of the window size and thirdly it is based on Kalman Filter, which produces coefficients that are matched to each data point in the sample, unlike the rolling-window approach, which does not allow the identification of data points that contribute to a spike or a dip in the connectedness index within a specific window as mentioned above (Antonakakis et al., 2020).

Antonakakis et al., (2020) combine the TVP-VAR methodology of Koop and Korobilis (2013) and the connectedness index computation of Diebold and Yilmaz (2009, 2012, 2014) to overcome the drawbacks of the rolling-window approach. The use of this combined model ensures measurability of the spillover effect among the different super sectors without the error rolling window bring especially in relation with the extreme subperiods. A TVP-VAR model with one lag can be written as follows:

$$\Delta y_t = \theta_t \Delta y_{t-1} + \mu_t \tag{22}$$
$$\mu \sim N\ (0, E_t)$$

$$vec(\theta) = vec(\theta_{t-1}) + r_t \tag{23}$$

$$r_t \sim N(0, Q_t) \tag{24}$$

Where, y_t represents the N x 1 vector, Δy_t, Δy_{t-1} and μ_t are vectors of $N \times 1$ dimension, θ_t and E_t are matrices of $N \times N$ dimension, $vec(\theta)$ and r_t are parameter matrices of $N^2 \times 1$ dimension and lastly, Q_t is an $N^2 \times N^2$ dimensional matrix. In this study, $N = 9$ whereby the series involved are the volatilities of the super sectors of the JSE.

Following the suggestion by Antonakakis et al., (2020), the TVP-VAR is estimated and then transformed to a time-varying parameter vector moving average (TVP-VMA) representation using the Wold representation theorem[16]. This theorem is expressed as:

$$\Delta x_t = \sum_{i-1}^{p} \beta_{it}\, \Delta x_{t-1} + \varepsilon_t = \sum_{j=1}^{\infty} \gamma_{jt}\, \epsilon_{t-j} + \varepsilon_t. \tag{25}$$

In the next step, the TVP-VMA coefficients are extracted to compute the generalised forecast error variance decomposition (GFEVD) developed by Koop et al., (1996) and Pesaran and Shin (1998). From there, the DY connectedness index is built.

The unscaled GFEVD, $\emptyset^{g}_{ij,t}(J)$ – representing the pairwise directional connectedness from *j* to *i* which in turn is the influence variable *j* has on variable *i* in terms of its forecast error variance share – is defined as follows:

$$\emptyset^{g}_{ij,t}\,(J) = \frac{\sum_{ii,t}^{-1} \sum_{t=1}^{J-1} \left(l'_j\, A_t\, E_t\, l_j \right)^2}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \left(l_i A_t \Sigma_t A'_l l_i \right)} \qquad \varphi^{g}_{ij,t}(J) = \frac{\emptyset^{g}_{ij,t}\,(J)}{\sum_{j=1}^{N} \emptyset^{g}_{ij,t}\,(J)} \tag{26}$$

[16] Wold representation theorem says that every covariance-stationary time series can be written as the sum of two time series, one deterministic and one stochastic.

With $\sum_{j=1}^{N} \varphi_{ij,t}^{g}(J) = 1$ and $\sum_{i,j=1}^{N} \varphi_{ij,t}^{g}(J) = N$, where *J* represents the forecast horizon and l_i a selection vector with a one on the *i*th position and zero otherwise. Using the GFEVD, we construct the total connectedness index by:

$$C_t^g(J) = 1 - N^{-1} \sum_{i-1}^{N} \varphi_{ii,t}^{g}(J) \tag{27}$$

This connectedness approach shows how a shock in one super sector spills over to the other. First, the study looks at the case where variable *I* transmits its shock to all other super sector *j*, called *total directional connectedness to others:*

$$C_{i\to j,t}^{g}(J) = \sum_{j=1,i\neq j}^{N} \varphi_{ji,t}^{g}(J) \tag{28}$$

Second, this study calculates the directional connectedness super sector *i* receives from super sector *j*, called *total directional connectedness from others* and defined as:

$$C_{i\leftarrow j,t}^{g}(J) = \sum_{j=1,i\neq j}^{N} \varphi_{ij,t}^{g}(J) \tag{29}$$

Finally, this study subtracts the *total directional connectedness to others* from the *total directional connectedness from others* to obtain the *net total directional connectedness*, which can be interpreted as super sector *i* influence on the analysed network.

$$C_{i,t}^{g} = C_{i\to j,t}^{g}(J) - C_{i\leftarrow j,t}^{g}(J) \tag{30}$$

If the net total directional connectedness of variable *i* is positive, it means that variable *i* influences the network more than being influenced by it (Antonakakis et al., 2020). By contrast, if the net total directional connectedness is negative, it means that variable *i* is driven by the network. Since the net total directional connectedness is an aggregated measure and sometimes masks important underlying dynamics, this study is interested in the net pairwise directional connectedness (NPDC). This measure provides us with information about the bilateral transmission process between variable *i* and variable *j*:

$$NPDC_{ij}(J) = \varphi_{ji,t}^{g}(J) - \varphi_{ij,t}^{g}(J). \tag{31}$$

If $NPDC_{ij}(J) > 0$ ($NPDC_{ij}(J) < 0$) variable i is driving (driven by) variable j.

A number of studies centered on the connectedness of assets markets employed the Diebold and Yilmaz (2009, 2012, 2014) model alongside the time-varying parameter VAR (TVP-VAR) model of Antonakakis, Chatziantoniou and Gabauer (2020) proving the reliability and validity of the model. Such studies include (Antonakakis, Gabauer, Gupta & Plakandaras, 2018; Huang, 2020; Bossman, Junior & Tiwari, 2022; Alshater, Polat, El Khoury & Yoon, 2022). The Diebold and Yilmaz (2009, 2012, 2014) and the VAR (TVP-VAR) model from these studies was suitable and accurate enough to quantify the connectedness (spillover) of the variables (equities) in relation to each other.

4.6 MODELLING THE DETERMINANT OF VOLATILITY CONNECTEDNESS IN ECONOMIC SUPER SECTORS ON THE JSE

There is limited or no recognised empirical study on the determinants of volatility connectedness at the sectorial level, in particular in emerging African markets. To investigate the determinants of sectorial volatility connectedness, the nonlinear autoregressive distributed lag (NARDL) model is proposed and compared with the ARDL model.

4.6.1 Model Selection

This study employs the use of the NARDL model to model the determinants of volatility connectedness of the super sectors due to the following advantages: first, it has the merit of including both the levels and differences of the relevant series and that the bounds testing framework means that it can accommodate I (0) and I (1) sequences of variables, or combinations of both and accommodating complex asymmetry (Allen & McAleer 2021). In addition, the NARDL model explicitly captures the short-run and long-run equilibrium volatility changes that follow uncertainty shocks (Liang, Troy, & Rouyer 2020).

In the ARDL model, the current values of the response variable can be predicted based on the current and lagged values of the independent variable (Chen, 2010), which are the possible determinants of super sector connectedness. In situations where there is only one independent series, with orders p and q the ARDL mode is denoted as ARDL (p, q), which consists of p lags of explanatory and q lags of response series. The lags of the response series make the model autoregressive. According to Demirhan (2020), when the number of ith explanatory series is shown by p_i, $i = 1, \ldots, k$, the ARDL model is given as:

$$G_t = n_0 + \sum_{i=1}^{k} B_{0i}X_{ti} + B_{1i}X_{(t-1)i} + \cdots + B_{pi}X_{(t-p_{i)}i} + A_1G_{t-1} + \cdots + A_qG_{t-q} + e_t \quad (32)$$

Where G_t and X_t are expected to be stationary and are the response and *i*th explanatory series respectively, p_I is the lag order of the explanatory series, q is the autoregressive order of the model and e_t is the error term and it is a white noise process if each value in the sequence has a mean of zero, a constant variance and its serially uncorrelated (Chen 2010). n_0 is the constant term, it is assumed that the error-term is a white noise process for each of period (t) (Demirhan 2020).

In ARDL model the selection of the maximum lag order can be obtain through a couple of options which includes the Akaike information criterion (AIC) for optimal selection, the Bayesian information criterion (BIC), fixed lag order for some or all variables (Pesaran, Shin, & Smith, 2001).

Moreover, the existence of a long-run / cointegration relationship can be tested based on the error correction representation (EC). The optimal model is the one with the smallest value (most negative value) of the AIC or BIC, with the BIC tends to select more parsimonious models (Kripfganz & Schneider 2018). A bound testing procedure is used to draw conclusive inference on whether the variables are integrated in the order of zero or one, $I(0) or\ I(1)$, respectively (Pesaran, Shin, & Smith, 2001).

The popularity of the ARDL model comes from the fact that cointegration of nonstationary variables is equivalent to an error correction (EC) process and the ARDL model has a re-parameterisation in EC form (Engle & Granger, 1987; Hassler & Wolters, 2006).

Estimation: The ordinary least squares (OLS) model would be suitably employed if the value of X_t are uncorrelated with e_t, but OLS would not be suitable if $R(X_t e_t) \neq 0$ and X_t is determined simultaneously with G_t . On condition that e_t is white noise process and must be stationary, likewise not dependent of $X_t,\ X_{t-1}, \dots and\ G_t\ G_{t-1}, \dots$ the autoregressive distribution lag models can be estimated with OLS (Chen 2010).

Dynamic Effect Interpretation: The model in equation 32 can be inverted as the lag polynomial in *G* as:

$$G_t = \left(1 + A_1 + {A_1}^2 + \cdots\right)n_0 + (1 + A_1 L + A_1^2 L^2 + \cdots)(B_0 X_t + B_{1i} X_{ti-1} + e_t). \quad (33)$$

The current value of G depends on the current and all the previous values of *X* and *e*.

Where $\frac{\partial G_t}{\partial X_t} = B_0$ (34)

and it is known as the impact multiplier. However, the effect after one period is given as:

$$\frac{\partial G_{t+1}}{\partial X_t} = B_1 + A_1 B_0 \tag{35}$$

The effect after two periods will be

$$\frac{\partial G_{t+2}}{\partial X_t} = A_1 B_1 + A_1^2 B_0, \tag{36}$$

Therefore, the long-run effect, also known as the long-run multiplier, is:

$$\frac{B_0 + B_1}{1 - A_1} \text{ if } |A_1| < 1. \tag{37}$$

Generalisation: In the ARDL (p, q) model: where $A(L)G_t = n_0 + B(L)X_t + e_t$,

With $A(L) = 1 - A_1 L - A_2 L^2 - \cdots A_p L^p$,

$$B(L) = B_0 + B_1 L + B_2 L^2 + \cdots + B_q L^q.$$

From the general ARDL $(p, q_1, q_2, \ldots, q_k)$ model:

$$A(L)G_t = n_0 + B_1(L)X_{1t} + B_2(L)X_{2t} + \cdots + B_k(L)X_{kt} + e_t \tag{38}$$

Therefore, equation 38 can be extended to give the equation:

$$G_t Con_T = n_0 + \sum_{i=1}^{k} B_{0i} X_{ti} + B_{1i} X_{(t-1)i} + \cdots + B_{pi} X_{(t-p_i)i} + A_1 G_{t-1} + \cdots + A_q G_{t-q} + e_t \tag{39a}$$

In the context of this study, equation 39a can also be represented as follows:

$$G_t Con_T = n_0 + \sum_{i=1}^{k} \partial_1 G_t Con_{T_{t-1}} + \sum_{i=1}^{t} \partial_2 \Delta SAVI_{(t-i)} + \sum_{i=1}^{t} \partial_3 \Delta DAMR_{(t-i)} + \sum_{i=1}^{t} \partial_4 \Delta EPU_{(t-i)} + \cdots \partial_n X_{t-1} + \beta_1 G_t Con_{t-1} + \beta_2 SAVI_{t-1} + \beta_3 DAMR_{t-1} + \beta_4 EPU_{t-1} \ldots \ldots \beta_n X_{t-1} + e_t \tag{39b}$$

Where $G_t Con_T$ represents monthly total connectedness across the super sectors on the JSE, obtained by averaging the daily total connectedness index derived from objective three (3) into monthly index. The practice of averaging daily total connectedness is consistent with ∂_1 ,∂_2, ∂_3, $\partial_{4\ldots}\partial_n$ represents the short run coefficients and $\beta_1, \beta_2, \beta_3, \beta_4 \ldots \beta_n$ depicts the long run coefficients. The error term is represented by e_t. The null (H_o) and the alternative (H_a) hypothesis for the ARDL bound test are depicted by equation 40a and 40b, respectively.

$$H_o: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \cdots \beta_n = 0 \tag{40a}$$

$$H_a: \partial_1 \neq \partial_2 \neq \partial_3 \neq \partial_4 \neq \cdots \beta_n \neq 0 \tag{40b}$$

To reject the null hypothesis, the F-statistics must be greater than both the lower and upper bound critical values. Once the series is confirmed as non-stationary at $\boldsymbol{I(2)}$, (i.e. not integrated at order 2) the Non-linear autoregressive distributed lag (NARDL) model would be implemented. This study will appropriate the different parameters into corresponding shocks such that: ($\boldsymbol{Con^{+}}, \boldsymbol{Con^{-}}, \boldsymbol{SAVI^{+}}, \boldsymbol{SAVI^{-}}, \boldsymbol{DAMR^{+}}, \boldsymbol{DAMR^{-}}, \boldsymbol{EPU^{+}}, \boldsymbol{EPU^{-}} \ldots . \boldsymbol{X_{t-1}}^{+}, \boldsymbol{X_{t-1}}^{-}$)

Equation (39b) can be revamped into the following NARDL model shown as:

$$\Delta G_t Con_T = \partial_0 + \sum_{i=1}^{t} \partial_1 G_t Con_{T_{t-1}} + \sum_{i=1}^{t} \partial_2 \Delta SAVI_{t-1}^{+} \sum_{i=1}^{t} \partial_3 \Delta SAVI_{t-1}^{-} + \sum_{i=1}^{t} \partial_4 \Delta DAMR_{t-1}^{+} + \sum_{i=1}^{t} \partial_5 \Delta DAMR_{t-1}^{-} + \sum_{i=1}^{t} \partial_6 \Delta EPU_{t-1}^{+} + \sum_{i=1}^{t} \partial_5 \Delta EPU_{t-1}^{-} \ldots \sum_{i=1}^{t} \partial_n \Delta X_{t-1}^{+} + \sum_{i=1}^{t} \partial_n \Delta X_{t-1}^{-} + \beta_1 G_t Con_{t-1} + \beta_2 \mathrm{SAVI}_{t-1}^{+} + \beta_3 \mathrm{SAVI}_{t-1}^{-} + \beta_4 \mathrm{DAMR}_{t-1}^{+} + \beta_4 \mathrm{DAMR}_{t-1}^{-} + \beta_5 \mathrm{EPU}_{t-1}^{+} + \beta_6 \mathrm{EPU}_{t-1}^{-} \ldots \ldots \beta_n \mathrm{X}_{t-1} + \rho \mathrm{ECT}_{t-1} + \mathrm{e}_t \qquad (35)$$

The distinctiveness between the ARDL and the NARDL model is that the linear ARDL model does not provide the option of negative and positive variations of the independent variables that have different effects on the dependent variable. The NARDL model not only permits to identify the presence of nonlinear relationship that independent variables may have on the dependent variable, but NARDL model also allows for checking cointegration in a single equation framework (Pesaran, Shin, & Smith 2001).

In the NARDL model, non-linear cointegration is examined using the bounds test. To reject the null hypothesis in NARDL, the F-stat must be greater than both the lower and upper bound critical values. Further, the study uses various diagnostic measures to examine the stability of the asymmetrical models. In the asymmetrical ARDL method, the study utilised the WALD test to validate the long-term asymmetrical impact. The asymmetric causality, which enables the parameters to be separated into the corresponding shocks, then test their causality from negative shocks to negative shocks and positive shocks to positive shocks under the VAR framework, using the Hatemi-j (2012) causality.

Lastly, the validity and reliability of the NARDL model has been established through different work from different authors for example in the analysis of the FTSE and S & P 500 indexes, the determinants of crude oil prices and in the determinant of Vietnam's stock market (Allen, & McAleer, 2021; Salem, Nouira, Jeguirim & Rault, 2022; Phong, Van & Bao, 2019) respectively.

4.6.2 Description of Determinants or Drivers of Sectorial Volatility Connectedness

Certain financial and economic variables such as the stock market volatility index (VIX), market risk premium (MRP) and trade ratio (TR), the Chicago Board Options Exchange (CBOE) have been identified to influence risk spillover in different markets in Europe and Asia, (Longstaff et al., (2011); Luchtenberg & Vu (2015); Bijsterbosch & Falagiarda (2015); Price & Young (2018); and Shahzad, Bouri, et al., (2019)). Hence, this study uses the South Africa volatility index (SAVI), which is the equivalent of the VIX in this study. Also, the economic policy uncertainty index (EPU), is employed as a variable for Investor sentiment that proxy for behavioural determinants amongst other possible factors that would be investigated as determinants of the super sector connectedness on the JSE. Subsequently, the variables, which are identified for the purpose of this study, are described below:

SAVI: The SAVI (South Africa Volatility Index) is the equivalent of the CBOE-VIX also known as the Chicago Board Options Exchange on the Johannesburg stock exchange. Both indexes measure implied market volatility. Also, the SAVI is a measure of market sentiment and employed as a market fear index. Subsequently it was standardised to reflect expected market volatility consistent with theoretical framework and risk management. The SAVI was also designed to measure three month at-the-money volatility accurately, adjusted for the contribution from the skew volatility, as determined by the actively traded options in the market (Kotze, Joseph & Oosthuizen 2010). As the VIX (volatility index) is designed to measure the S&P 500 index options, the SAVI is also employed to measure the volatility on the JSE. Kenmore and Tafou (2014) document that the SAVI is an index built to respond to volatility spillover. Hence, the study investigates its capacity as a determinant of super sector connectedness on the JSE.

Domestic Market Return (DMR): Following Fontana & Scheicher (2010), Longstaff et al., (2011), Dieckmann & Plank (2011) and Fender et al., (2012), this study employs domestic stock market return as a proxy for economic state of the country. Longstaff et al., (2011) employs total market returns which includes dividends. Employing total return which includes dividends is advantageous, since important information such as the different company's performance, are contained in company's dividends (Blommestein et al., 2016). An economy with an already weak status could be worsened by external trade conflicts and such a negative impact would also be felt by the importing and exporting firms on the stock market (World Bank, 2019). The study uses FTSE/JSE All-Share Index return as the proxy for domestic market return, which represent 99% of the full market capitalisation of JSE and measures the performance of the major industry and sectors segments of the South African market (FTSE Russell 2021).

The FTSE/JSE Africa Index Series provides investors with a complete and complementary series of indexes that measure the performance of the main capital and industry segments of the South African market. It is structured to represent the performance of South African companies (FTSE Russell 2023). Oberholzer and von Boetticher (2015) posit that there exists a small directional volatility spillover from the South African currency (RAND) to the JSE All Share Index which is based on the positive correlation which exist between the two, when the inter-market relationship between the main five indices on the JSE market and the RAND was studied. The study established that the ALSI is not a volatile as the RAND. This result suggests that the ALSI is a relatively stable index. The ALSI of the JSE market was used as an index to proxy South African economic performance in a study to measure the spill-over effects of foreign markets on the JSE before, during and after the global financial crises. The results demonstrate that the returns of the economy where the GFC starts have a direct spillover effect on the JSE All Share index through contagion. Moreover the findings further demonstrate that South Africa has made strides in recent years to protect its stock market against financial disasters (Heymans & Da Camara 2013). These findings show the robust properties of the ALSI reflect performance of registered company returns and the economic performance of the Country.

Economic Policy Uncertainty: Also known as regime uncertainty, it is a form of economic risk where government policy for the future is uncertain, hence, leading to increased risk premium and resulting in delayed spending and investment until such uncertainty is resolved. Uncertainty of such can include electoral outcome, monetary, fiscal and taxation policies (Scott, Davis & Steven, 2011). Baker et al., (2016) document that three major components are involved in constructing the economic policy uncertainty index. The first component is economic forecasts on government expenditures and inflation, followed by the list of tax code provisions to explore in the next ten years and the third component is the monthly data of news articles and information from media coverage on policy uncertainty, predominantly from 10 largest newspapers of the specific country, containing uncertain, economic or policy relevant terms. These components are aggregated to derive an index. With similar components as that of Baker et al., (2016), Makololo & Seetharam (2020) constructed the EPU for South and extends the index to cover international scenery.

Kundu & Paul (2022) investigate the effect of economic policy uncertainty on volatility of the stock market under different market characteristics and the estimated findings imply that an increase in EPU only reduces return when the time period is contemporaneous, while increasing market volatility. According to the estimation results, EPU has a considerable impact during a bad market and a negligible impact during a bull market. Moreover, EPU has been established to have influence on volatility of stock markets in emerging countries. Ghani and Ghani (2023) investigate EPU on the stock market volatilities of emerging markets such as Pakistan, China and developed markets such as the US and United Kingdom. The empirical findings show that the US economic policy uncertainty index is a more powerful predictor of the Pakistan stock market volatility. In addition, the EPU index for the UK also provides valuable information for equity market volatility prediction. This result reveals that a significant relationship does exist between EPU and market volatility.

EPU is included in this study to ascertain its ability to determine the connectedness of economic sectors, since economic policies influence trade, business, the stock market (Caldara, Iacoviello, Molligo, Prestipino & Raffo, 2019, Ofori-Abebrese, Amporfu & Sakyi. 2016) and market volatility (Ghani & Ghani 2023).

Trade Openness: Trade openness refers to the sum of export and import values were normalised by the GDP of the same year (Alotaibi & Mishra 2014). Also known as the trade-to-GDP ratio of a nation, which is estimated by finding the mean of total trade relative to the GDP. The word openness may not necessarily mean low import and export activity, but could connote other factors such tariff issues, size of the economy, geographical remoteness from trade partners (etc.) interplaying in the whole trade transaction (OECD 2011). Luchtenberg and Vu (2015) document that the more a country's bilateral trade is dependent on another country's economy, the more likely shocks can be transferred to the former and fluctuations or contagion in such economy could be easily transferred to the other country. Luchtenberg and Vu (2015) found a significant relationship between contagion and trade ratio and further established that trade ratio can predict contagion between two countries. This strengthens the conviction for this study to include trade openness as possible determinants of sector financial connectedness on the JSE.

Manufacturing Output: Manufacturing is an important part of South Africa's economy, contributing 12% of GDP, 12% to formal sector employment and 42% of the rand value of exports in 2019. Manufacturing has strong linkages with a variety of suppliers and supporting industries, particularly mining and agriculture, as well as service providers (IDC 2019). The sector, which contributed about 23% of GDP at its height in the early 1980s has been in sharp decline since the early 1990s. Manufacturing's share of formal non-agricultural employment has followed a similar trend, declining from 25% in 1970 to reach an all-time low of 12% in 2019. Adverse global economic events have over time impacted adversely on the output of the manufacturing sector. SARB (2020) asserts that capacity utilisation and capital stock declined sharply following the 2009 recession and have stabilised at lower levels, consistent with deindustrialisation. The manufacturing output index is also known as the index of the volume of manufacturing production or the production index, is the statistical measure of the change in the volume of production. In simple terms it is the volume of output generated by the entire manufacturing or production sectors of a country (OECD 2023). This study includes the manufacturing output index as an independent variable to investigate its impacts on with the sectorial total connectedness index, as its response to volatility changes.

Money Supply (MS): Money supply refers to the sum of the volume of money held in the public within an economy at a given point in time (Brunner 2018). This study will consider M2 as proxy for money supply, since it consists of the notes and coins in circulation, traveller's cheques, demand and savings deposits, time deposits and other checkable deposits (OCDs) majorly consisting of negotiable order of withdrawal accounts in deposit institutions and credit union share draft accounts. Market volatility is thought to be influenced by changes in monetary policy factors such as money supply, interest rates and exchange rates. Hence, capital markets are crucial for the transmission of monetary policy conversely, monetary policy has a considerable impact on how stock market returns behave (Zare, Azali & Habibullah 2013).

Moreover, this study considers money supply as a possible determinant of sectorial volatility connectedness, according to Kontonikas and Ioannidis (2006) and Maskay (2007). Their studies consider the stock market to be the primary indication of the health and direction of the economy, which has a significant impact on and precedes it. Additionally, according to these studies, the money supply has a significant impact on the economy as a whole, including the stock market. When there is more money in the economy than can be used, it is allocated to investments (i.e., trades, manufacturing, services etc.) which has a direct impact on stock prices.

Additionally, a monetary policy that expands the money supply however in a high level of inflation have a considerable and detrimental effect on industrial production (Tule, Egbuna, Akinboyo, Afangideh & Oladunni (2016); Orji, Ekeocha, Ogbuabor & Anthony-Orji (2022)). Hence, the inclusion of money supply also helps to determine sectorial productivity level during the U.S-China trade war. Tchereni & Mpini (2020) established a negative relationship between M2 and stock market volatility on the JSE within the period of 2000Q1 and 2016Q4. In addition, money supply is known to have a positive relationship with the return of the FTSE/JSE All Share index. These result shows that money supply could have an impact on sectorial connectedness and, hence, a possible determinant of super sector volatility connectedness of the JSE market.

4.7 SUMMARY OF THE CHAPTER

The empirical ranking of sample super sectors, the certainty of whether dynamic equicorrelation exist among the super sectors, the revelation of the propagation of the shocks coupled with the identification of super sectors whether as net-transmitters and net-receivers and finally, the estimation of the determinants of sector volatility connectedness on the JSE are the summary of the objective of this chapter

It can be deduced that the PageRank model of Page et al., (1999) and the Granger causality network of Billio et al., (2012) were precise and well-suited for ranking the super sectors on the JSE through their centrality scores. While the GARCH-DECO model of Engle and Kelly (2002) were fit enough to be applied on the whole sample size and also on the rolling window framework. The robustness and the computation ease of the model proved good to ensure the appropriateness of the results. Similarly, the Diebold and Yilmaz (2009, 2012 and 2014) in combination with the TVP-VAR of the (Antonakakis et al., 2019) effectively modelled the connectedness and propagation of volatility spillover amongst the super sectors. The TVP-VAR of (Antonakakis et al., 2019) was a model introduced to overcome the computational errors in rolling window analysis of this type of objective, hence, was very effective. Finally, the use of NARDL to model the determinants of sectorial volatility connectedness was equally effective, given the attributes of the MARDL model over the ARDL (i.e. to capture both the symmetric and asymmetric long run and short run relationships). Therefore, the models and methodologies discussed in this chapter are perfectly fit to examine the objectives and also give the best result output to be discussed in the next chapter.

CHAPTER 5: DATA ANALYSIS AND INTERPRETATION OF RESULT

5.1 INTRODUCTION

The focus of this study is to determine the systematically important super sectors, determine the return linkages of the equity super sector, followed by examining the dynamic connectedness and the shock propagation among the super sectors during the extreme risk events and finally, evaluate the determinants of volatility connectedness of the JSE equity super sectors. Hence, the analysis and the interpretation of the results of the models specified in chapter four are presented in this chapter. The analysis covers the PageRank centrality results, the dynamic return equicorrelation results, the dynamic volatility connectedness results and the determinants of sectorial volatility connectedness on the JSE.

5.2 DESCRIPTIVE STATISTICS

The descriptive statistics of the equity returns and the volatilities of the nine super sectors for the full sample are shown in Tables 5.1 and 5.2, respectively. It was crucial to perform the descriptive statistics of both the return and volatility data for this study because the return descriptive statistics are essential for objective one, two and four, the volatility descriptive data are equally important for objective three. The major importance of carrying out the descriptive statistics for these two sets of data is because it helps to provide the measures of central tendency and measures of spread for both data sets, in addition to determining the distribution of the data set (Wiedmaier 2017).

The equity returns summary statistics from Table 5.1 show that energy and Health sectors have the highest and lowest mean of 0.000609 and -0.0000415 respectively. A possible reason for this is because of the high dependence and consumption rate of electricity and power by the economy and the population of the entire South Africa. In addition, the highest mean return by the Energy super sector is also a reflection of the confirmation of the principle of the higher the risk, the higher the return. Considering the risks and challenges that have besieged the energy and power enterprise (ESKOM) of South Africa in recent times (Kamanzi 2022). Yet there is substantial profitability and significant revenue from export activities and local commercial activities from the sector (Hanto, Schroth, Krawielicki, Oei, & Burton 2022).

The Insurance sector has a median value of 0.000501 and it is the highest among the sectors, while Chemical has the lowest median value of -0.0000608. Moreover, the Energy sector happens to have the highest standard deviation of 0.037433 and with a mean of 0.000609, it is an indication that the returns of the Energy super sector are not clustered around the mean. Furthermore, the Automobile super sector has a maximum value of 0.579582, while the health sector has the lowest maximum return value of 0.062229. It is quite interesting to note that even when the Automobile super sector has the highest maximum return value, it does not possess the highest mean value. This illustrates the fact that Automobile data are not evenly distributed with high returns over the period of years, while the energy data has high return values well distributed over the same period.

The skewness values for all returns, which is the measure of the distortion of symmetric or asymmetric distribution of the returns are negative for all super sectors, which signifies that the distributions of the sectorial returns are towards the left. In addition, the negative skewness suggests a higher probability of large negative returns compared to large positive returns. Moreover, kurtosis statistics are all greater than three in all super sectors, which denotes a higher possibility of an extreme outcome in the return distributions. The results from skewness and kurtosis statistics suggest skewed fat tails and leptokurtic patterns of the return distribution, as the probability values of the Jarque-Bera test reject the hypothesis of normality. The test of the normality of financial data is an important step to decide the measures of central tendency and statistical methods for data analysis (Mishra, Pandey, Singh, Gupta, Sahu & Keshri 2019).

Table 5.1 Descriptive Statistics for Super Sector Returns

	AM & P	CHE	ENE	FIN	G.I	HEL	INSUR	TECH	TELECOM
Mean	0.000329	6.56E-05	0.000609	-0.000211	2.38E-05	-4.15E-05	0.000148	0.000197	0.000147
Median	0	-6.08E-05	0	0.000482	0.000395	0.000412	0.000501	0.000495	0.000268
Maximum	0.579582	0.354643	0.386829	0.077764	0.079425	0.062229	0.075455	0.163155	0.144134
Minimum	-1	-1	-1	-1	-1	-1	-1	-1	-1
Std. Dev.	0.030043	0.028356	0.037433	0.026231	0.020106	0.025393	0.020795	0.023018	0.02552
Skewness	-7.454878***	-11.59081***	-7.22976***	-27.75329***	-30.79491***	-26.37034***	-27.83981***	-20.56521***	-15.06087***
	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Kurtosis	364.3476***	417.8839***	217.7192***	1057.33***	1532.461***	994.0157***	1340.116***	895.601***	593.6055***
Jarque-Bera	21788165***	28763280***	7715039***	186000000***	390000000***	164000000***	298000000***	133000000***	58257887***
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Sum	1.317038	0.262119	2.436365	-0.842388	0.095019	-0.165766	0.590878	0.787818	0.587738
Sum Sq.Dev.	3.607557	3.213838	5.600611	2.749467	1.61584	2.577281	1.72847	2.117673	2.603049
Q(10)	99.006	37.571	26.216	3.817	3.583	3.323	6.055	5.296	11.519
	0.00000	1.535	9.526	0.695	0.732	0.772	0.359	0.462	0.034
Q2(10)	12.856**	1.535	9.526*	0.002	0.001	0.001	0.001	0.002	0.003
	0.017	0.972	0.087	1	1	1	1	1	1
Observations	3998	3998	3998	3997	3998	3998	3998	3998	3998

Source: Author’s Estimation (2023)

The descriptive statistics of the daily realised volatility for each index calculated following German and Klass (1980) of the sectors are shown in Table 5.2. The Energy super sector has the highest mean as Health super sector with the lowest mean of 0.000302 and -0.000572, respectively. The Insurance super sector has the highest median, while the Financial super sector has the lowest mean; their values of 0.0000729 and 0.000012, respectively. The Energy super sector has a maximum value of 0.2101 and the General Industrial has a minimum value of 0.00000868 in realised volatility index. It is quite interesting to note that Energy super sector has the highest mean and maximum values of realised volatility. Moreover, the Health super sector has the highest standard deviation of 0.005958, followed by the Energy super sector with a value of 0.005083, this signifies that these two sectors' volatilities are not clustered around their means. Again this illustrates that the Energy super sector obeys the principle of the higher risk (high standard deviation), the higher the return (high mean return).

The statistics also show the kurtosis and the skewness coefficients, which indicate that the realised volatilities of the series are far from the normal distribution, all with 1% significance level. This condition is formally confirmed by the Jarque-Bera test statistics, also significant at 1% confidence level.

Descriptive statistics of the volatility of the entire super sectors, namely the Automobile and Parts (AM &P), Chemical (CHE), Energy (ENE), Finance (FIN), General industrial (G.I), Health (HEL), Insurance (INSUR), Technology (TECH) and Telecommunications (TELECOM) are shown in Table 5.2.

Table 5.2 Descriptive Statistics for Super Sector Volatility

	AM-VOL	ENE-VOL	CHE-VOL	FIN-VOL	HEC-VOL	G.I-VOL	INSUR-VOL	TEC-VOL	TELECOM-VOL
Mean	0.000155	0.000302	8.89E-05	6.82E-05	-5.72E-05	2.19E-05	0.00013	5.23E-05	6.13E-05
Median	3.49E-05	4.90E-05	3.34E-05	1.20E-05	2.16E-05	1.24E-05	7.29E-05	2.69E-05	3.58E-05
Maximum	0.02578	0.2101	0.010671	0.178718	0.002742	0.001666	0.005013	0.002957	0.002226
Minimum	-3.25E-05	-1.54E-05	-4.27E-05	-2.13E-06	-0.37669	-8.68E-06	-3.51E-05	-1.71E-05	-2.24E-05
Std. Dev.	0.000679	0.005083	0.000376	0.002827	0.005958	4.57E-05	0.000209	0.000104	9.93E-05
Skewness	26.73196***	36.53***	18.72451***	63.16678***	-63.19345***	18.28349***	9.083418***	11.76709***	8.853478***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Kurtosis	937.0748***	1365.923***	436.0129***	3992.354***	3994.944***	534.3667***	149.411***	240.1449***	130.326***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jarque-Bera	146000000***	310000000***	31468020***	2650000000***	2660000000***	47257650***	3625887***	9460527***	2752864***
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	0.621265	1.208575	0.355497	0.272652	-0.228871	0.087488	0.517877	0.209233	0.245227
Sum Sq. Dev.	0.001843	0.103266	0.000564	0.031934	0.141906	8.33E-06	0.000175	4.33E-05	3.94E-05
Q(10)	84.579***	451.590***	3822.012***	0.002	0.002	3059.439***	2213.643***	2056.388***	2157.862***
	0.000	0.000	0.000	1.000	1.000	0.000	0.000	0.000	0.000
Q2(10)	0.253	377.508***	857.141***	0.001	0.001	3.14E+02	494.434***	977.959***	585.017***
	1.000	0.000	0.000	1	1.000	0.000	0.000	0.000	0.000
Observations	3998	3998	3998	3997	3998	3998	3998	3998	3998

Source: Author’s Estimation (2023)

5.3 STATIONARITY TEST (UNIT ROOT) RESULTS

The unit root tests are usually used to test the stationarity of stock-returns. This is based on the assertion that stock returns often take a random walk if they reject stationarity or have unit root (Lim & Brooks 2011). A time series or stock data are said to be stationary when the statistical characteristics of the data remain stable over time, for instance, when data mean, variance and autocorrelation structure do not vary over time (Lim & Brook 2011). The stationarity of the data for this study is crucial to be ascertained so that the data would not give erroneous and misleading results.

In this study, the augmented Dickey-fuller test (ADF) and the Philip Perron tests (PP) are employed to examine the stationarity of both the returns and volatility data. The study examined the ADF test at the level and first difference for both (ADF) and (PP) tests for each super sectors returns, their realised volatilities and the determinants data. Table 5.3 shows the result of the ADF test statistics and their integrated order. First, all the data for the determinants of sectorial volatility have been converted into their logarithm forms. From Table 5.3, it is interesting to note that the log of economic policy uncertainty (LEPU), log of South African volatility index (LSAVI) and log of manufacturing output (LMOP) were all integrated at level. This implies that the null hypothesis of unit root against alternative hypothesis of stationarity was carried out. Hence, for these variables it implies that the test statistics is greater than that of the critical values in absolute term, therefore, the null hypothesis that the return series contains a unit root is rejected. This is also confirmed by their p-values, which are less than 1%.

Similarly, log of total connectedness index (LTCI), the log of domestic market returns (LDMR), log of trade openness (LTO) and log of money supply (LM2) were all integrated at order one (1). Hence, at this order the test statistics for these variables were greater that their respective critical values and the null hypothesis of the presence of unit root was also rejected. The Phillips-Perron test statistics for LEPU, LSAVI, LMOP, LTCI, LTO, LDMR and LM2 were examined and variables were integrated at order I (0) and I (1).

In addition, Table 5.3 reveals the ADF and the PP tests for the returns of the super sectors. It is important to note that all the p-values of the Automobile and parts, energy, technology, telecoms, financials, health, insurance, chemical and general industrials are less than 1%. In addition, the test statistics of each of these super sectors are greater than the critical values in absolute terms. Therefore, the null hypothesis, which suggests the presence of unit root is rejected and the alternative hypothesis of no unit root, is accepted, hence, the super sector data are stationary, even at level I (0). The Philips-Perron test also reveals the rejection of the null hypothesis and that the returns data are stationary at order I (0). The ADF test was also conducted for the realised volatilities for the super sectors for the purpose of objective one. It was revealed that the test statistics were greater that the critical values and the p-values for the super sectors were less than 1%, hence, confirming the rejection of the null hypothesis of the presence of unit root and acceptance of the alternative. Therefore, the realised volatilities of the super sectors are stationary at level.

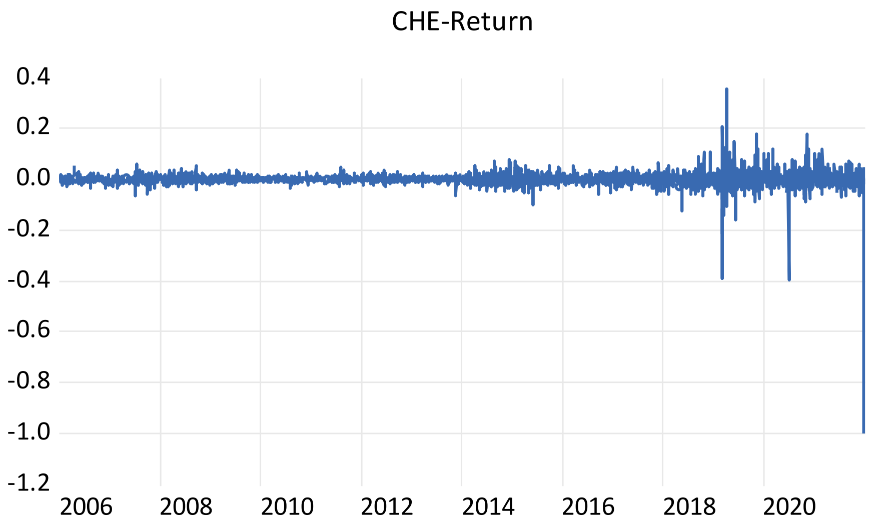
Examining the stationarity property through the ADF and the PP tests for the determinants variables indicates that there exists no unit root at level and even at first difference. It shows that all the variables are either integrated at level or at first difference. Also, the returns and the realised volatilities of each super sector examined reveal that the data are stationary at level, hence, revealing the existence of stationarity in the property of the data.

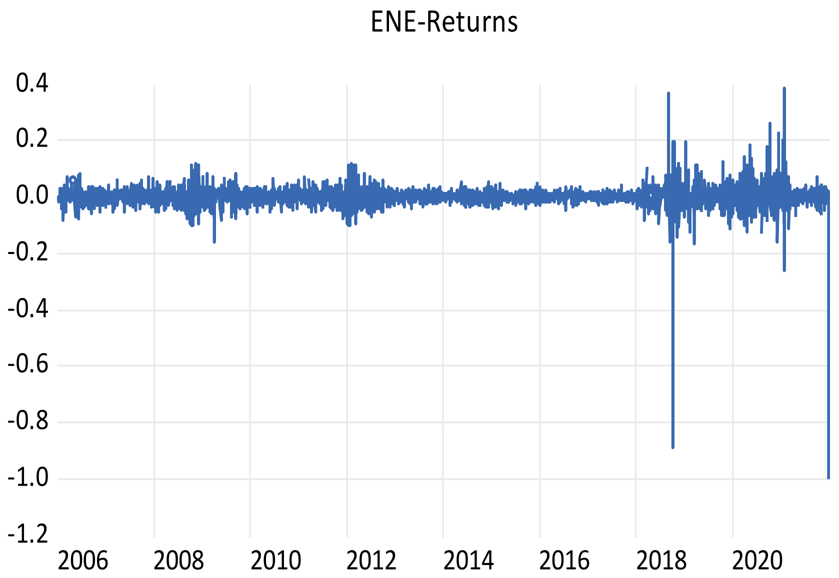
Furthermore, it is crucial to note that besides the relevance of stationarity test on the data for this study, it is also important to document that some of the models or estimation techniques for this study require the stationarity status of the data, hence, the data will be appropriate for the model. For instance, the nonlinear autoregressive distributed lag (NARDL) model requires data to be stationary at level or at first difference. This connotes that once the series is non-stationary at I (2) the NARDL model cannot be employed to estimate the data series. From the stationarity results it is clear that the NARDL can be employed with the both the determinant and the log of total connectedness index to estimate objective four of this study.

Moreover, the Granger causality framework Billio et al., (2012) for objective one, the Diebold and Yilmaz (2009, 2012 and 2014) and the TVP-VAR of Antonakakis et al., (2020) for objective three require that the realised volatility data be all stationary before use with the models. Therefore, the confirmation of stationarity shows that the data (both returns and volatilities) are appropriate for the models estimated in this study.

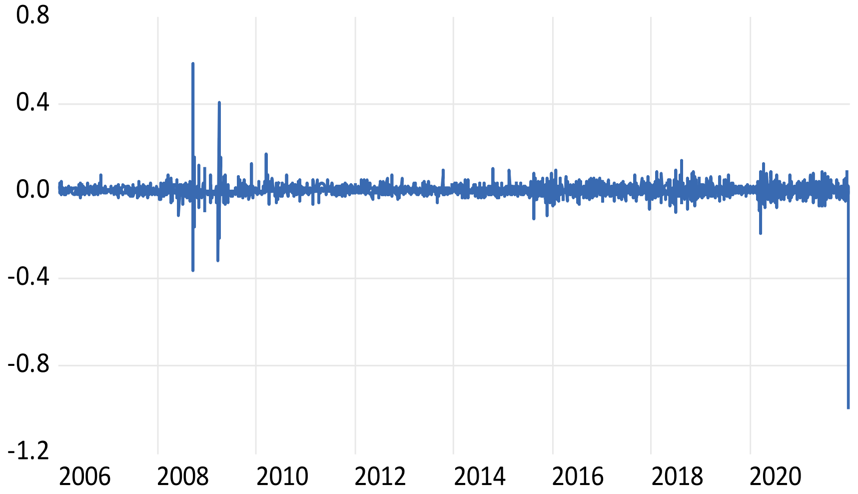
5.4 GRAPHICAL PLOT OF SECTORIAL RETURNS

Through the use of Eviews 13.0 application software, the graphical view of the returns of each super sector is shown in Figure 5. The daily time series returns of the super sectors were first transformed into logarithm form through equation 1 and then represented graphically. The graphical representation shows that the returns of the super sectors are non-stationary. The plots for each super sector also show heightened spikes in notable time periods, such as the 2007-2008, 2018-2019 and the 2020 periods, which corresponds to the GFC, the U.S-China TDW and the COVID-19 periods. However, the Telecommunication, Automobile and Parts, Technology and Energy super sectors show higher spikes during the above-mentioned periods compared to other super sectors.

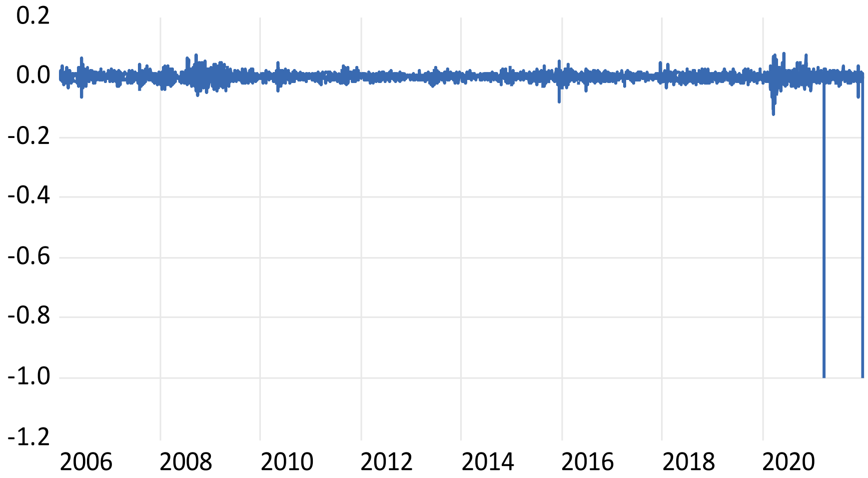




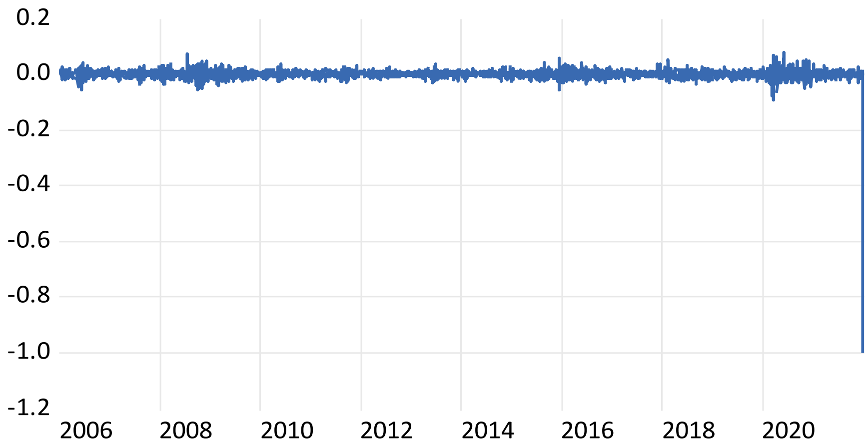
AM & P-Returns

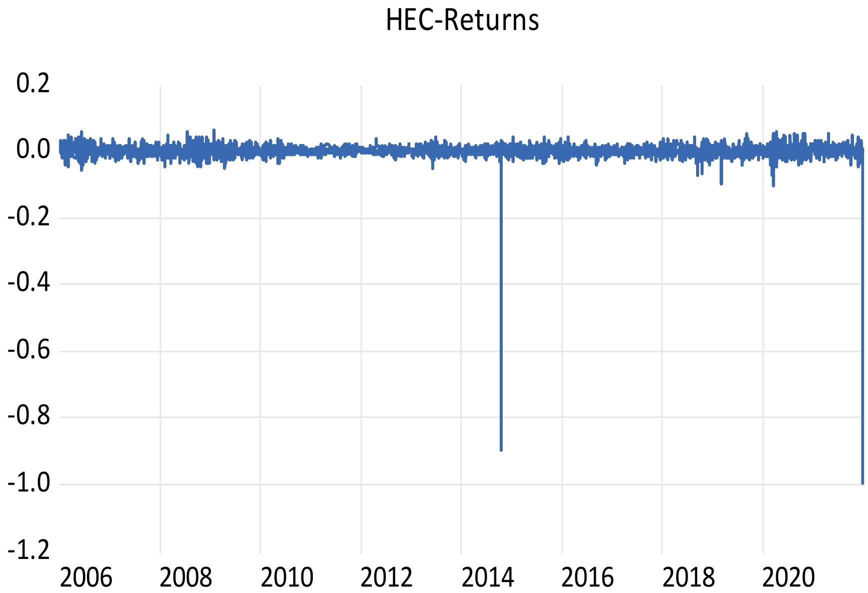


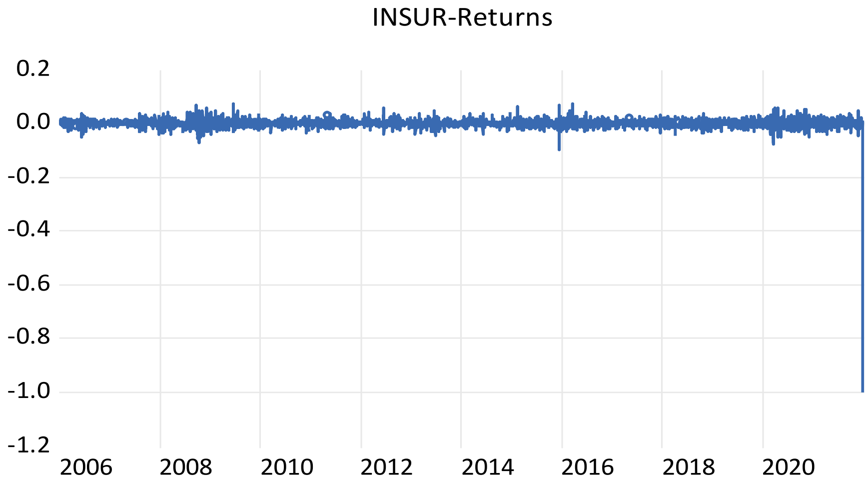
FIN J10030Returns



G.I-Returns




HEC-Returns
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
2006
2008
2010
2012
2014
2016
2018
2020


INSUR-Returns
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
2006
2008
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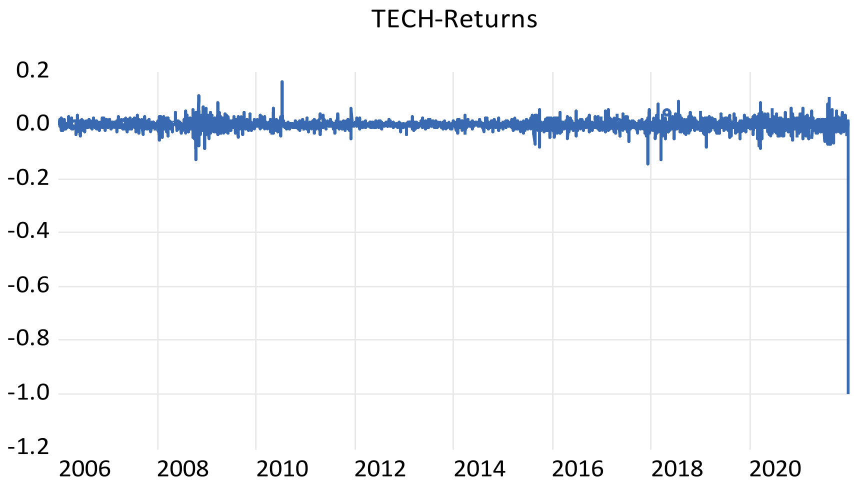
2012
2014
2016
2018
2020


TECH-Returns
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
2006
2008
2010
2012
2014
2016
2018
2020

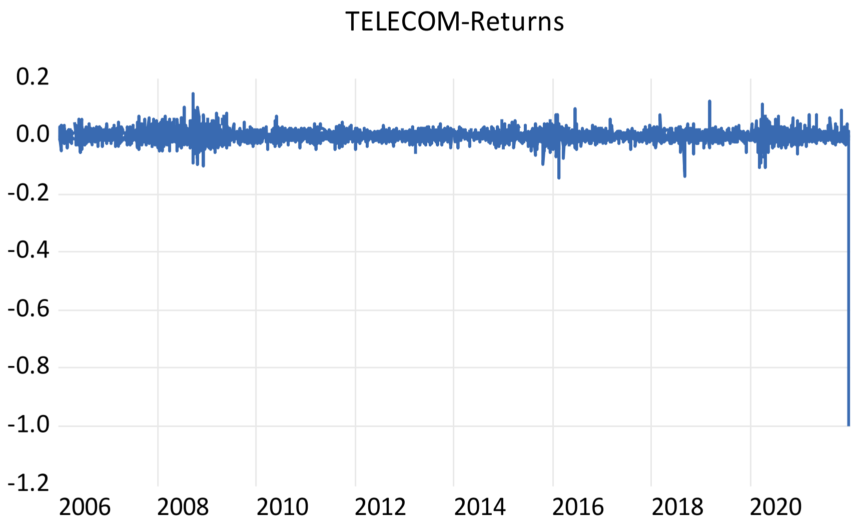


Figure 5.0: Time plot of Automobile and Parts, Chemical, Energy, Finance, General Industrial, Health, Insurance, Technology, Telecommunication Super Sectors

Source: Author's own Estimations (2023).

5.5 PEARSON'S CORRELATION

Table 5.3 explains the correlation between the returns of all nine super sectors. From Table 5.3, it is obvious that none of the super sectors are adversely correlated with other, in other words, no single super sector return has a negative correlation.

The lowest correlation value exists between Automobile and Parts and Energy sector with 0.21761, while the highest correlation of 0.8196 exists between Insurance and General Industrials. The average correlation value is 0.3321. This is an indication that there exists a strong correlation between the Insurance super sector and the General Industrial super sector. A possible reason for this is due to the fact that most industries in South Africa are regulated and there is high demand for insurance for regulated industries (Mayers & Smith 1982). Moreover, Motsepe (2018) documents that industries and firms are well regulated in South Africa, hence, a need for a mandatory purchase of insurance policies to hedge against any risk.

There exists a weak correlation between Automobile and Parts and the Energy super sector. Machivha (2021) documents that the Automobile and Parts is a sector that consumes a lot of energy through its production stages of the different kinds of vehicles. However, Venage (2019) posits that the rolling power cuts across South Africa have, over time, has threatened the automotive production and logistics chain, as the nation's overburdened state power supplier, Eskom, struggles to meet the needs of businesses. Hence, there exists a gradual degrading business interlink between these two sectors. This could suggest the reason for the low correlation between the Automobile and parts and Energy super sectors.

Table 5.3: Unit Root Test for Variables (RETURNS)

	Levels		First difference		
Variables	**ADF t-statistic**	**Phillips-Perron Test-statistic**	**ADF t-statistic**	**Phillips-Perron Test-statistic**	**Integration Order**
LTCI	0.976796***	0.086346***	-9.826266***	-9.826266***	I(1)
LEPU	-3.962503***	-3.97472***	-3.97472***	-15.06036***	I(0)
LSAVI	-3.13806***	-3.151274***	-3.682072***	-13.66901***	I(0)
LDMR	-1.301589***	-1.301589***	-12.01311***	-12.01311***	I(1)
LTO	-2.473232**	-2.597083***	-13.78534***	-13.26802***	I(1)
LM2	-2.049663***	-2.156678***	-14.13246***	-14.16585***	I(1)
LMOP	-6.12381***	-6.128606***	-6.128606***	-25.13997***	I(0)
RETURNS					
	Levels		**First difference**		
Variables	**ADF t-statistic**	**Phillips-Perron Test-statistic**	**ADF t-statistic**	**Phillips-Perron Test-statistic**	**Integration Order**
AM & P	-33.00101***	-47.75009***	-101.9052***	-124.2562***	I(0)
ENE	-45.09287***	-47.75009***	-102.2404***	-124.2562***	I(0)
TEC	-42.5474***	-41.17167***	-77.40496***	-85.96048***	I(0)
TELECOM	-35.96697***	-46.57627***	-84.68298***	-104.7792***	I(0)
FIN	-30.3187***	-28.46108***	-58.73551***	-54.66793***	I(0)
HEL	-47.41724***	-46.48382***	-85.45521***	-110.1091***	I(0)
INSUR	-41.45546***	-39.38669***	-75.01627***	-78.79808***	I(0)
CHE	-25.62023***	-47.75009***	-88.02635***	-124.2562***	I(0)
G.I	-36.98848***	-35.81249***	-69.3813***	-69.23035***	I(0)

Source: Author's Estimation (2023)

Table 5.4: Unit root for Volatilities

	REALISED SUPER SECTOR VOLATILITY	
	Levels	
Variables	**ADF t-statistic**	**Integration Order**
AM & P	-33.00101***	I(0)
ENE	-45.0928***	I(0)
TEC	-42.5474***	I(0)
TELECOM	-35.9669***	I(0)
FIN	-30.3187***	I(0)
HEL	-47.4172***	I(0)

INSUR	-28.8647***	I(0)
CHE	-25.6202***	I(0)
G.I	-36.98848***	I(0)

Source: Author's estimation (2023). Please note that asterisks (*), (**) and (***) represent 10%, 5% and 1% respectively.

5.6 Results of Systematically Important Super Sectors

The first objective of this study is to determine the systematically important equity super sectors using the centrality scores, through Page et al., (1999) with the pairwise Granger causality test (Billio *et al*., 2012). This involves the application of PageRank algorithm on the volatilities of the super sectors with a view to estimate the centrality score for each super sector for the whole sample period and for the four sub-periods, namely the GFC, EDC, U.S-China trade war and the COVID-19 periods. The four sub-period analyses will shed light on the stability of the systematically important super sectors during extreme events. The PageRank centrality score of the institution in the financial network represents its ability to receive incoming links from high centrality neighbours. The algorithm dilutes the incoming centrality in proportion to the outgoing links from that high centrality neighbours. Unlike eigenvector centrality, in PageRank, the incoming connection from a parsimonious (low degree node) node is worthier than connections from a high degree centrality node. Therefore, PageRank also represents systemic vulnerability and, in a true sense, captures the too-central-to-fail concept (Chaturvedi & Singh 2022).

Following Yun, Jeong and Park (2019), Zhang, Wang and Lu (2020) and Chaturvedi and Singh (2022), the centrality scores were obtained using Granger causality relationships to build an adjacent matrix whose entity (e_{ijt}) uses F-values of the Granger causality network to account for wider variations, hence, centrality scores were estimated for the super sectors for different extreme periods as shown in Table 5.6. Adopting the realised volatilities of the super sectors, the centrality scores results show that the Telecommunication has the highest centrality score of 0.2827 and, hence, is ranked as number one among all the sectors, followed by General industrial and Insurance with centrality scores of 0.2081 and 0.1604 respectively, having the 2nd and 3rd rank, respectively. The Financial and Chemical sectors both occupy the 8th rank with no centrality scores, while Technology, Health, Energy and Automobile and Part super sectors occupy the 4th, 5th and 6th ranks, as also shown in Figure 5.3.1a.

Generally speaking, the full sample result implies that the Telecommunication, General Industrial and Insurance sectors are very central to the stability of the sector on the JSE market full sample (within the period 3 January 2006 to 31 December 2021), hence, systemically important to the South African economy as any negative shock to any or one of these three sectors could trigger the instability of other sectors in South Africa. Furthermore, from Table 5.6, the technology, health and energy sectors occupy the middle, while the Automobile, financial and chemical are the last three sectors with least centrality scores for the whole sample period.

The Global Financial Crisis (GFC) occurred during the period January 2007 to last quarter of 2008 and extended into early 2009 (Wild 2012). In this study, a separate analysis was carried out for the GFC with the sample period spanning from January 2007 to first quarter 2009. It is suggestive from the Table 5.6 that the Energy super sector is the most volatile and has the highest centrality score of 0.1555. Therefore, the Energy super sector is ranked as number 1 among all the super sectors, followed by Health and Technology super sectors in the 2^{nd} and 3^{rd} positions respectively with centrality scores of 0.1538 and 0.1512, respectively. The Financial, General Industrial and Insurance sectors occupy the 4^{th}, 5^{th} and 6^{th} ranks with centrality scores of 0.1475, 0.1320 and 0.1307 respectively, while Telecommunication, Automobile and Chemical super sectors were 7^{th}, 8^{th} and 9^{th}.

The result indicates that during the global financial crisis period which is known generally as a turbulent period the Energy, Health and Technology super sectors are central to the stability of the South African economic super sector on the JSE and any problem in these super sectors will affect the stability of the whole sectors in the economy. It is quite interesting to note that the Financial sector (Banks and financial services) seats at the middle position of the ranking with 0.1475 score, suggesting the fact that the Financial super sector enjoy some stability during the turbulent period. Gordhan (2011) documents that the South African banks and financial sector successfully weathered the Global financial crisis due to, a sound framework for financial regulation and well-regulated institution, appropriate and conservative risk management practices at domestic banks, subsidiary structure and listing requirements amongst other implemented monetary policy decisions. In addition, the financial institutions have been fairly exposed to foreign structured financial products in addition to having a fairly conservative financial regulation and risk management practices within the context of sound macroeconomic policies (SARB 2011). They are, however, not as stable as what was witnessed in absolute form (full sample).

Subsequently, a separate analysis was carried out for the European Debt Crisis (EDC) period. This is another crisis that impacted economic sectors globally (Zamora-Kapoor & Coller 2014). Furthermore the crisis has been known to affect the South African economy adversely through the channel of foreign direct investment (FDI) inflows from the European Union, which reduced significantly affecting business and investments (Kganyago 2012). Including uncertainty in the financial markets, exports and trade flow (Horn 2015). Since the European Sovereign Debt Crisis occurred from 2009 to late 2010, the data for the PageRank equally covers for this period. The Telecommunication, General Industrial and Financial sectors have top-3 PageRank scores of 0.1636, 0.1618 and 0.1597 respectively during EDC. Hence, occupying the 1st, 2nd and 3rd ranks, respectively. It is important to note that Chemical Automobile and Parts occupy the 7th and 8th rank, respectively. Since the higher the centrality score of the super sector, the more relevant the super sector to that period or extreme situation.

The U.S-China trade war (U-CTW) peaked between mid of 2017 to 2018 and South Africa is a major country that trade with both U.S and China. The trade war tends to have a cumulative negative effect on the sectors which directly involve in trade exports and imports. The results in Table 5.6 shows that Telecommunications has the highest centrality score of 0.2321, while General Insurance and Health super sectors are joint second with centrality score of 0.1572. Hence, this makes these super sectors occupies the 1st, 2nd and 3rd positions amongst the super sectors. It is interesting to note that Telecommunication and General insurance are both export-import oriented and this quality has positioned them as the highest PageRank score. Energy and Finance super sectors occupy the least rank and with the lowest score. While Insurance and Chemical super sectors occupy the mid-positions with same rank score of 0.12115, respectively. This illustrates that these two super sectors are not significantly affected by the U-CTW during the period.

The COVID-19 pandemic is another extreme event with a significant implication for the South African economy. The last sub-period analysis is for the COVID-19 pandemic, which sampled period October 2019 to December 2021. The results in Table 5.6 shows that the Telecommunication, General Industrial and Insurance has the top 3 highest centrality score of 0.2827, 0.2081 and 0.16044 respectively, as the Technology, Health and Energy super sectors making them the 4th, 5th and 6th rank. It is interesting to observe that the Health super sector occupies the 5th rank with a centrality score of 0.07188, which is the same rank and score as the general sample period and lower than other periods. The COVID-19 pandemic affected all sectors of the entire South African economy (Arndt, Davies, Gabriel, Harris, Makrelov, Modise, & Anderson (2020); Ngarava, Mushunje, Chaminuka, & Zhou 2022) and it is expected that the Health super sector would show a high centrality score as it was during the GFC, U.S-China TDW and the EDC but rather the contrary. This illustrates that, despite the pressure on the Health super sector during the COVID-19 pandemic period, the sector does not appear to be central to the instability of the economy. The implication of the COVID-19 pandemic result is that the Telecommunication, Industrial and Insurance super sectors are very central to the stability of the South African economy during the COVID-19 pandemic.

Table 5.5 Correlation of Super Sector Returns

	AM	CHE	ENE	FIN	G.I	HEL	INSUR	TECH	TELECOM
AM & P	1	0.29383769	0.217605456	0.36823877	0.480059372	0.389356126	0.446151499	0.409812945	0.383557615
CHE	0.29383769	1	0.234982593	0.377165765	0.479212124	0.377514068	0.443693051	0.387243316	0.369646187
ENE	0.217605456	0.234982593	1	0.305306544	0.3950647	0.305295767	0.370544558	0.321992155	0.338352372
FIN	0.36823877	0.377165765	0.305306544	1	0.731585351	0.548733422	0.676471705	0.533238455	0.616916978
G.I	0.480059372	0.479212124	0.3950647	0.731585351	1	0.66958424	0.819639832	0.686676661	0.747185243
HEL	0.389356126	0.377514068	0.305295767	0.548733422	0.66958424	1	0.621120338	0.533057417	0.560749575
INSUR	0.446151499	0.443693051	0.370544558	0.676471705	0.819639832	0.621120338	1	0.649171235	0.671798166
TECH	0.409812945	0.387243316	0.321992155	0.533238455	0.686676661	0.533057417	0.649171235	1	0.555665671
TELECOM	0.383557615	0.369646187	0.338352372	0.616916978	0.747185243	0.560749575	0.671798166	0.555665671	1

Source: Author’s Estimation (2023)

Table 5.6 Systematically Important Sectors Results

	TOTAL PERIOD				GFC				US-China TDW	
Nodes	PageRank Scores	PageRank		Nodes	PageRank Scores	PageRank		Nodes	PageRank Scores	PageRank
TELE-Vol	0.282736121	1		ENE-Vol	0.155598858	1		TELE-Vol	0.234209121	1
G.I-Vol	0.208142556	2		HEC-Vol	0.153880184	2		G.I-Vol	0.157222873	2
INSUR-Vol	0.160448679	3		TEC-Vol	0.151200969	3		HEC-Vol	0.157222873	3
TEC-Vol	0.133025952	4		FIN	0.147518354	4		INSUR-Vol	0.121157183	4
HEC-Vol	0.071882231	5		G.I-Vol	0.132003775	5		CHE-Vol	0.121157183	5
ENE-Vol	0.071882231	6		INSUR-Vol	0.130701213	6		TEC-Vol	0.100462762	6
AM-Vol	0.071882231	7		TELE-Vol	0.110346647	7		AM-Vol	0.054284003	7
FIN	0.0000	8		AM-Vol	0.01875	8		ENE-Vol	0.054284003	8
CHE	0.0000	9		CHE	0.0000	9		FIN	0.0000	9
	EDC				COVID					
Nodes	PageRank Scores	PageRank		Nodes	PageRank Scores	PageRank				
TELE-Vol	0.163671104	1		TELE-Vol	0.282736121	1				
G.I-Vol	0.161843849	2		G.I-Vol	0.208142556	2				
FIN	0.159703846	3		INSUR-Vol	0.160448679	3				
HEC-Vol	0.14531145	4		TEC-Vol	0.133025952	4				
INSUR-Vol	0.137568469	5		HEC-Vol	0.071882231	5				
TEC-Vol	0.099102644	6		ENE-Vol	0.071882231	6				
CHE-Vol	0.076818571	7		AM-Vol	0.071882231	7				
AM-Vol	0.055980067	8		FIN	0.0000	8				
ENE	0.0000	9		CHE	0.0000	8				

Source: Author's Estimation (2023)

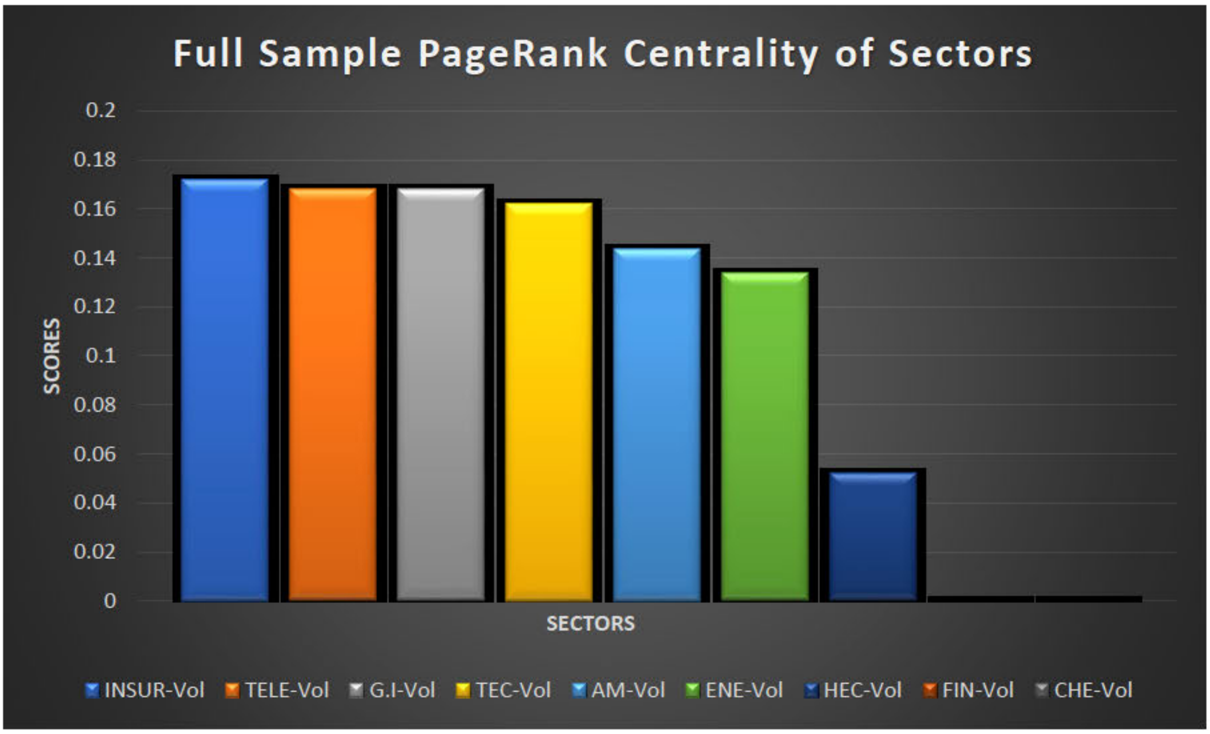


Figure 5.1a PageRank Plot of Full Sample Size

Source: Author's Estimation (2023)

Figure 5.1a, Figure 5.1b, Figure 5.1c , Figure 5.1d and Figure 5.1e reveal the graphs of the PageRank centrality scores of each super sector and in different sample periods representing the full sample size, the GFC period, the EDC period, the U.S-China trade war and the COVID-19 pandemic period, respectively.

The graph depicts a decreasing slope which is as a result of decrease in the value of the centrality scores from Telecommunication super sector to Chemical super sector. However, the graph plot for the GFC shows that there was a General Increase in the centrality scores for each super sector except for the Automobile and Parts and Chemical super sector. This suggests that the global financial crisis was an extreme event that predisposed many sectors of the economy into a position of instability. Hence, creating susceptibility to systemic risk, since the higher the centrality score the more central the sector to fail (too-central-to-fail).

In a similar scenario, the European debt crisis plot reveals a high centrality score for each of the sectors with the exception of Automobile and Parts and Chemical super sector. This is also a reflection that during extreme periods, for example, financial, or economics crisis the entire sectors of an economy are liable to instability. The U.S-China-TDW is another crisis that impacted South Africa as a third-party in the in the global value-chain. Figure 5.1d shows that the telecoms sectors had the highest impact with the highest centrality score. As a sector it could have been impacted negatively through the dependence on the raw materials such as iron, metals, chips etc. used in the production process of Telecommunication end-products, which were major items under ban by the U.S government (Annan 2020).

Finally, Figure 5.1e also reflects a downward slope of centrality score with telecoms having the highest centrality score, followed by the general industrial. Again, this plot showing the centrality of the Telecommunication, General Industrial and possibly the Insurance super sectors to extreme periods and need for more economic-policy attention to be given to these super sectors.

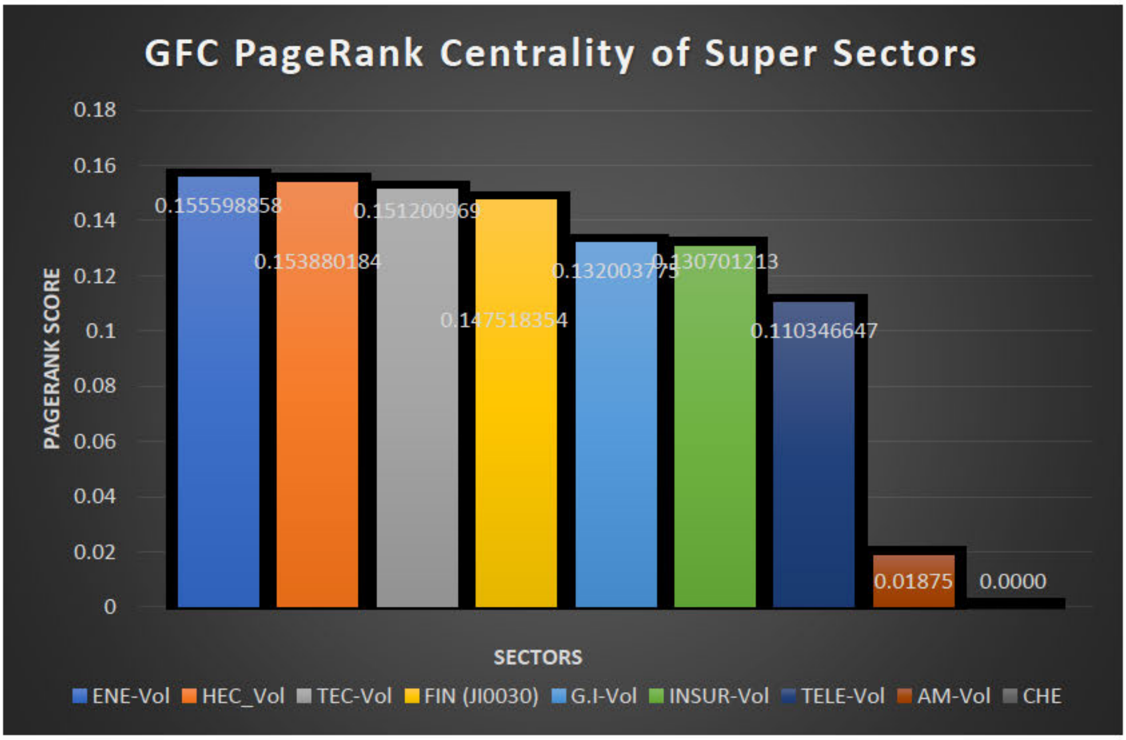


Figure 5.1b PageRank Plot of GFC Period
Source: Author's Estimation (2023)

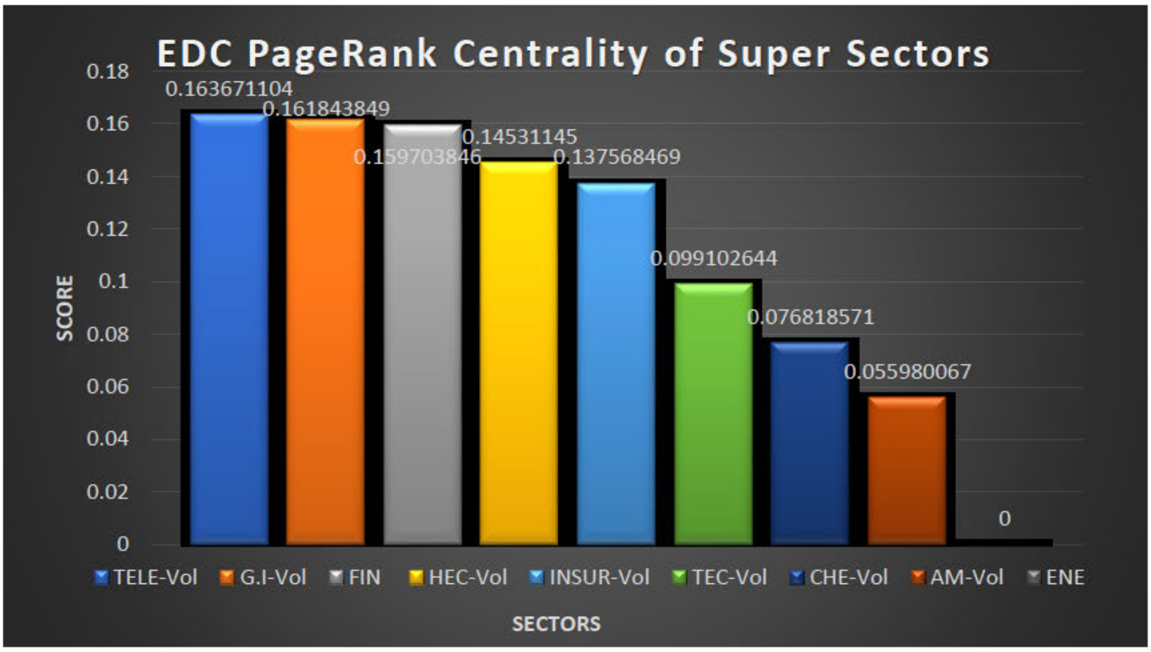


Figure 5.1c PageRank Plot of EDC Period.
Source: Author's Estimation (2023)

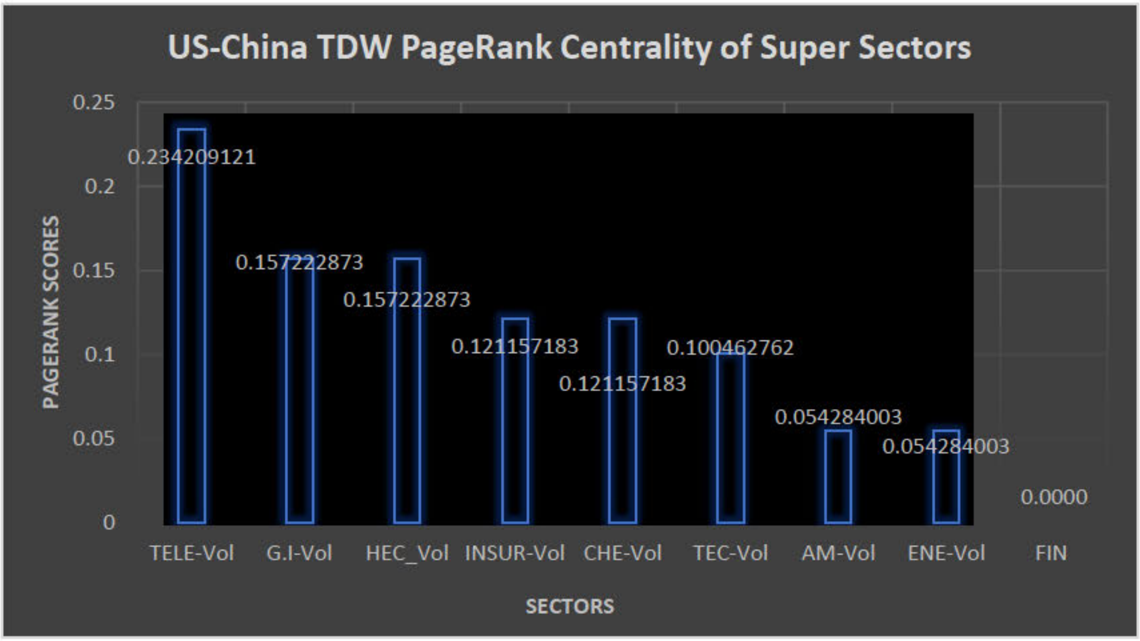


Figure 5.1d PageRank Plot for U.S-China Trade war Period
Source: Author's Estimation (2023).

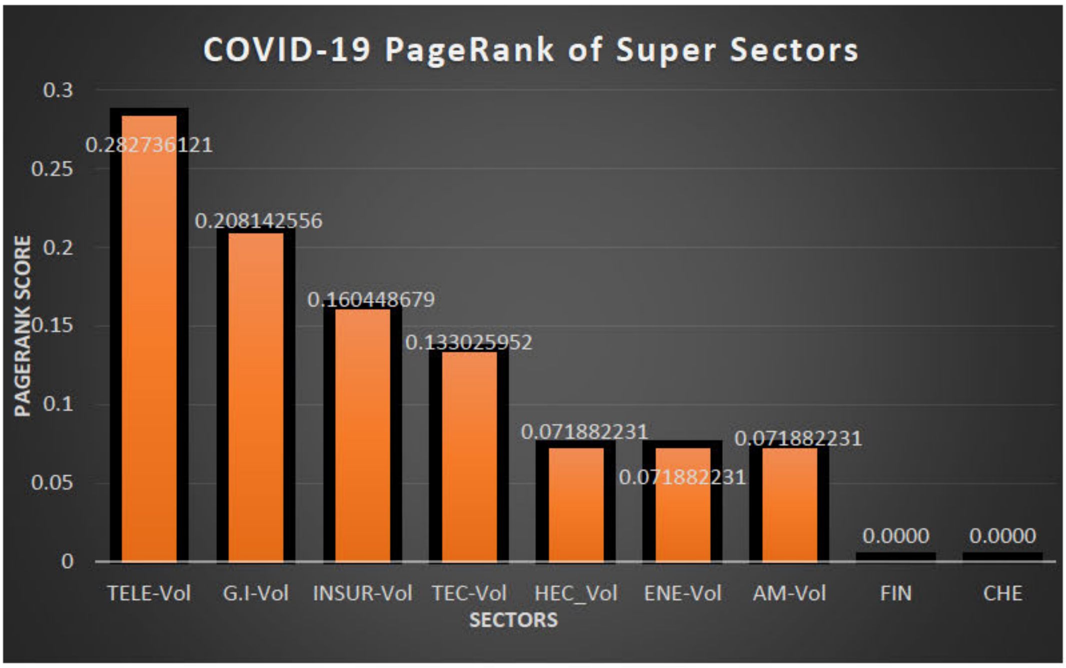


Figure 5.1e PageRank Plot of COVID-19 Period
Source: Author's Estimation (2023).

5.7 SUMMARY OF OBJECTIVE ONE

The purpose of objective one is to rank the super sectors on the JSE market through the PageRank centrality scores. To achieve this objective, the Page et al., (1999) model with the with the pairwise Granger-causality test Billio *et al*., (2012) was employed. The result of the objective shows that the aforementioned models are suitable to reveal the solution of the objective. The results show that Insurance and the Energy are the top-ranking super sectors for the full sample and the GFC periods respectively, while Telecommunication is the top ranked super sector during the EDC. The Telecommunication is the top ranked super sector during the U.S-China Trade War and the COVID-19 pandemic. The results also show that both Finance and Chemical super sectors have the least rank scores, each with zero (0.000); hence, these sectors were ranked 8th and 9th respectively for the full sample periods. The Chemical super sector is also revealed to be the sector ranked 9th with a score of (0.000) for the GFC and the EDC, and the COVID-19 pandemic periods, while the Financial super sector is ranked least with 0.0000 score for the U.S-China Trade war.

Furthermore, the results indicate that during the U.S-China trade war and the COVID-19 pandemic, the General industrial sector occupies the 2nd position, hence having the 2nd highest PageRank scores. Additionally the full sample period shows that the Telecommunication, General industrial, and Technology super sectors occupying the 2nd, 3rd, and 4th positions, while the 2nd, 3rd, and 4th positions were occupied by the Health, Technology and Financial super sectors during the GFC. It is crucial to note that the ranking positions of these super sectors has systemic importance in the network of the super sectors which would be discussed further in the discussion chapter of this study for each of the sub-periods.

5.8 TIME VARYING SECTORIAL EQUITY RETURN EQUICORRELATION RESULTS

The objective of this section is the second objective for this study, which is to determine the return linkages of the JSE equity super sectors. The estimation technique employed to achieve this objective is the DECO-GARCH model formulated by Engle and Kelly (2012). The result from Table 5.8 reveals that indeed there exists a time-varying equicorrelation with evidence of integration amongst the super sectors, as the equicorrelation parameter (Average ρ_{ij}) was significant and high.

5.8.1 Estimates of the Univariate GARCH of Super Sectors

The GARCH (1, 1) model in this study is a parsimonious model. The model is very good because it fits into the return data of the super sectors. The major two parameters in the GARCH (1, 1) model for estimation are the ARCH term beta-1(b) and GARCH term theta-1 (θ). It is important for these two parameters to be significant because it validates the appropriateness and the use of the DECO model.

As shown in Panel A of Table 5.8, on the estimates on the GARCH model, the results of all the super sectors, namely Automobile and Parts, Telecommunications, Insurance, Chemical Technology, General Industrials, Finance, Energy and Health have the sum of their ARCH and GARCH terms approximately equal to one (1) Automobile and Parts (0.9821), Telecommunications (0.9886), Insurance (0.9968), Chemical (0.9807), Technology (1.0039), General industrials (0.9855), Finance (0.9761), Energy (0.9984) and Health (0.9619). Furthermore, the corresponding p-values of the ARCH and GARCH terms of each of these super sectors are significant at 1% level (0.000) with the exception of Telecommunication super sector with a p-value of 0.1115 for its ARCH term. Moreover, Table 5.8 also shows that coefficients of the ARCH and GARCH terms of each of the super sectors are positive and all significant at 1% level as stated earlier. In addition, the coefficients of the mean equation are positive and also significant. This connotes that the past values of the returns of the super sector significantly predict the current values of the super sectors. It is interesting to note that the coefficient of the ARCH and GARCH terms are also positive, hence, satisfying the stability condition.

The result of the GARCH (1, 1) model for the super sectors clearly establish the presence of time varying conditional volatility of the returns of the super sectors on the JSE. The result also indicates that the persistence of the volatility shocks as represented by the sum of the ARCH and GARCH parameters ($b_1 + \theta_1$) is large. Therefore, it denotes that the effect of today's shock remains in the forecasts of variance for many periods in the future for the super sectors. The implication of this is that all the volatility of the super sectors returns display high persistence and their conditional volatility is mean reverting (Hung, 2020).

5.8.2 Results of the Dynamic Equicorrelation-GARCH Model Specification for full sample period (2002-2021).

Dynamic equicorrelation connotes a state at which at every time period all pairwise correlations are equal. In application, the model DECO involves first adjusting for individual volatilities and then estimating correlations. The aim of this subsection is to measure the return equicorrelation (linkages) of the super sectors.

The Panel B of Table 5.8 shows the result of the equicorrelation parameter estimates. It shows that the DECO parameters lie in the range of standard estimates stemming from GARCH (1, 1) models. First, the parameter (α) is positive with a value of 0.03381. In addition the beta parameter (β) is also positive with a value of 0.8767, with their p-values statistically significant at 1% level. The sum of these two estimates (α + β) is nearly equal to one unity (0.9105), indicating a high persistence and integration of volatility among the super sectors.

Second, the output of dynamic equicorrelation parameter ($\rho_{i\,j}$) is found to be positive and statistically significant at 1% level (0.0000) with a value of (0.1830), showing a high degree of integration and suggestive of correlation among the super sectors. This signifies that a significant degree of integration exists among the super sectors on the JSE, in absolute form (full sample), hence, the returns equicorrelation of the super sectors are integrated (Bouri, Vo, & Saeed 2021; Thai Hung 2021).

Moreover, the use and the appropriateness of the DECO-GARCH model is justified by the statistical significance of the parameter (α) and (β). In addition, the DECO parameter lies within the range of standard estimates, which originates from the GARCH (1, 1) models. This suggests the stability of the equicorrelation among the super sectors on the JSE market. This result is consistent with Umar et al., (2019), Liu et al., (2021) and Bouri et al., (2021).

Table 5.8 Estimation Result of the DECO-GARCH model with DECO specification

Panel A: Estimates of the univariate GARCH

	AM & P	TELECOM	INSUR	CHE	TECH	G.I	TELECOMS	FIN	ENE	HEL
Constant	0.0005	0.00037	0.0008	0.00027	0.0006	0.0005	0.0003	0.0005	0.0007	0.0006
z-Statistic	3.2397	1.5913	4.4880	3.6820	3.9453	3.7477	1.5913	3.9302	2.8101	3.4239
P-value	0.0012	0.1115	0.0000	0.0002	0.0001	0.0002	0.1115	0.0001	0.0050	0.0006
ARCH (α)	0.0903	0.0523	0.0957	0.1019	0.1215	0.0929	0.0522	0.1427	0.1074	0.1335
z-Statistic	7.9978	7.1403	1.5830	7.0040	8.6046	8.5926	7.1403	9.8416	9.0140	8.8350
P-value	0.0000	0.0000	0.0014	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GARCH (β)	0.8918	0.9363	0.9011	0.8788	0.8824	0.8926	0.9363	0.8334	0.8910	0.8284
z-Statistic	69.9466	110.9873	3.1970	53.5500	81.7400	74.9502	110.9873	61.4923	93.1342	54.4341
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(α + β)	0.9821	0.9886	0.9968	0.9807	1.0039	0.9855	0.9885	0.9761	0.9984	0.9619

Panel B: Estimates of the DECO model

Average ρij	0.1830
t-Statistic	6.4870
p-Value	0.0000
Alpha (α)	0.0338
p-Value	0.4932
Beta (β)	0.8767
t-Statistic	10.4500
P-value	0.0000
(α + β)	0.9105

Source: Author's own Estimation (2023)

5.8.3 Dynamic Equicorrelation (Rolling Window Analysis)

This subsection reveals the results of the rolling window analysis of the DECO model on the returns of the super sectors. Even though the rolling window analysis has its flaws, to a reasonable extent it has its advantages, especially for this objective. For instance, the study employs rolling window analysis, which helps to capture the periods of extreme events or crises and otherwise normal periods too; hence, revealing more details about dynamic equicorrelation of each year even within an extreme period.

Figure 5.2 shows the two-year rolling window estimations plots (with interval or step size of 1 year) of the dynamic equicorrelation of the super sectors over the period of time for this study. This plot is derived from Table 5.7, which shows the rolling window results and the corresponding equicorrelation. The graph gives the idea of the correlation of the super sectors indicating the variation over time with a correlation level varying from a minimum value of 0.0953 to a maximum value of 0.7022, with an average return equicorrelation of 0.2562. It is interesting to note that each year's rolling DECO estimate is positive and significant at 1%. This indicates a high degree of integration through the sample period year.

Table 5.7 Dynamic Equicorrelation with One-year Intervals

Years	Equicorrelation
2006-6007	0.2814
2007-2008	0.5528
2008-2009	0.2278
2009-2010	0.2278
2010-2011	0.0953
2011-2012	0.2032
2012-2013	0.1491
2013-2014	0.1836
2014-2015	0.1996
2015-2016	0.2203
2016-2017	0.1813
2017-2018	0.1877
2018-2019	0.2184
2019-2020	0.2132
2020-2021	0.7022

Source: Author's Estimation (2023).

The plot gives a proof of occurrence of high integration of the super sectors during the 2007/2008 great financial crisis with 0.2814 for year 2006-6007 and much higher dynamic correlation value of 0.5528 in 2007/2008, indicating a more heightened level of integration of the super sectors. The DECO parameters for these periods were statistically significant. This shows the response of the South African super sectors to the global financial crisis. The European sovereign debt crisis of 2009-2010 also had a relative high value of 0.2278, which is also an indication of an integrated super sectors during the same period.

The period 2017 to 2018 was the peak of the U.S-China trade war which affected all major trade partners (export and import) of China and the U.S (Annan 2020), with South Africa being one of the major trading economies with these two countries (especially with China). The return equicorrelation for three windows between 2017 and 2019 (0.1813, 0.1877 and 0.2184) respectively grew steadily, which could be as a response to the ripple effect of the increase in tariffs affecting the correlations among SA equity super sectors.

Finally, the COVID-19 pandemic, which started globally in the last quarter of 2019 up till late 2021, is reflected in the graph and has the highest return equicorrelation with a value of 0.7022, which is proof that the South African economy also had its share of the adverse impact to the COVID-19 pandemic with highly integrated equity super sectors.

The Pearson’s correlation analysis of Table 5.5 is a positive affirmation of the DECO results. The positive pairwise correlation between the super sectors suggests that the super sectors move in the same direction. In other words, if a crisis or a shock happens to one super sector, others could also be impacted or affected in the same direction across the JSE market.

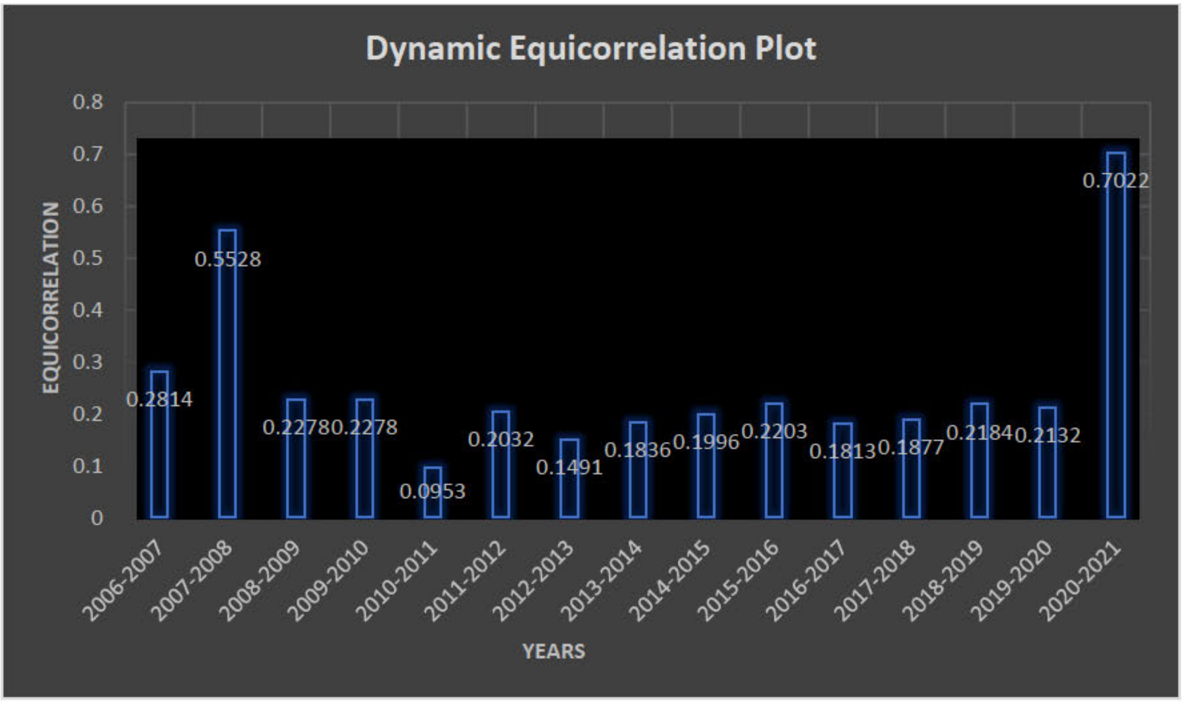


Figure 5.2 Time varying Dynamic Equicorrelation Graph
Source: Author's Estimation (2023).

5.9 Summary of Objective

The objective of this subsection is to determine the return linkages of the JSE equity super sectors on the JSE through the use of the DECO-GARCH model of Engle and Kelly (2002). On the basis of the result of the objective, the research question which says: Does the JSE equity super sector returns have a common equicorrelation? and Does the equicorrelation change over time? Yes, there is a common equicorrelation and it does change over time. Therefore, the equicorrelation of the super sectors of the JSE is time-varying.

The study applied the univariate GARCH (1, 1) model on the returns of the super sectors which revealed that there is the presence of time varying conditional volatility on the super sector returns. Moreover, the model also confirmed the persistence of volatility shocks which was large as evident by the sum of the ARCH and GARCH terms which was near equity for each of the super sectors with the exception of Technology super sector, which was 1. The overall GARCH results is a perquisite needed for estimating the DECO model.

The DECO model results were in two parts, first the dynamic equicorrelation results for the entire sample period (2006-2021) and the rolling window estimation. The first part, which was the full sample size gave a positive equicorrelation measure of 0.1830, with a p-value of less than 1%. In addition, the sum of alpha and beta values is near equity (0.9105), with statistically significant p-values. Which illustrates that there is high persistence and integration of the volatilities of the returns of the super sectors. Finally, the rolling window results further confirmed that the return equicorrelations of the super sectors is time varying with high positive values especially for the extreme crisis periods.

5.10 VOLATILITY CONNECTEDNESS RESULTS

The objective three of this study, which is explained in this section, is to examine the volatility connectedness and the shock propagation among the equity super sectors during the extreme risk events of 2008/2009 Global financial crisis, the European debt crisis of 2010-2012, the U.S-China trade war of 2017-2018 and, finally, the COVID-19 pandemic of 2019/2020. The TO-connectedness, FROM-connectedness, NET-connectedness and the TOTAL-connectedness results for the entire sample period and all the extreme periods were presented to ascertain whether there exists high volatility connectedness among the super sectors. Furthermore, this study went on to reveal the mode or sequence of propagation of shocks from one super sector to another, identifying the net-connectedness (the receivers and the transmitters) of shocks for each period under investigation.

As a point of emphasis, the TO-connectedness is calculated by estimating the shocks transmitted from one super sector to all other super sectors. The FROM–connectedness is the amount of shock received by one super sector from other super sectors, also the NET-connectedness is the shock obtained by subtracting the TO-connectedness from the FROM-connectedness of a particular super sector.

Table 5.9a Average Sector Volatility Connectedness Table for full Sample Period

	AM-Vol	TELECOM-Vol	INSUR-Vol	CHE-Vol	TEC-Vol	G.I-Vol	FIN-Vol	ENE-Vol	HEL-Vol	*FROM*
AM-Vol	42.02	6.75	5.97	6.73	7.02	6.88	7.28	9.21	8.14	57.98
TELECOM-Vol	5.74	34.46	8.89	6.36	8.33	13.34	7.29	8.27	7.33	65.54
INSUR-Vol	5.92	9.69	39.66	5.27	7.94	11.24	7.9	7.12	5.26	60.34
CHE-Vol	6.16	6.12	4.86	38.58	5.76	6.27	9.07	11.13	12.05	61.42
TEC-Vol	7.05	9.07	8.00	6.57	34.43	10.22	8.73	8.18	7.76	65.57
G.I-Vol	5.81	12.28	10.33	6.26	8.93	31.01	9.64	9.39	6.34	68.99
FIN-Vol	5.58	5.84	5.86	7.7	6.95	8.12	41.12	11	7.85	58.88
ENE-Vol	7.02	6.58	5.34	9.23	5.59	6.84	11.19	36.99	11.22	63.01
HEL-Vol	6.31	6.09	4.16	9.59	5.76	5.36	7.24	11.72	43.77	56.23
TO	49.59	62.41	53.40	57.69	56.28	68.27	68.36	76.02	65.95	557.96
Inc. Own	91.61	96.87	93.07	96.27	90.7	99.28	109.47	113	109.72	**cTCI/TCI**
NET	-8.39	-3.13	-6.93	-3.73	9.3	-0.72	9.47	13.00	9.72	69.74/62.0
NPT	1.00	3.00	2.00	4.00	0.00	5.00	7.00	7.00	7.00	

The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200.

Source: Author's Estimation (2023).

From Table 5.9a the ***TO*** represents the total directional connectedness from one super sector to all other super sectors excluding its own spillovers. Total ***FROM*** represents the total connectedness received by a super sector from others excluding own spillovers, while NET connectedness is estimated by deducting total connectedness received from total connectedness transmitted (**Total FROM –Total TO**).

Table 5.9a shows the decomposition of Automobile and Parts, Telecommunications, Insurance, Chemicals, Technology, General Industrial, Finance, Energy, Health super sectors into transmitters and receivers. The TVP-VAR model with the sample period from 3 January 2006 to 31 December 2021 is used to estimate the average connectedness values of the super sectors. The static total connectedness index (TCI[17]) for the period among the super sectors is 62.0% and the dynamic conditional Total Connectedness Index (cTC[18]I) is 69.74%; this established the fact that 69.74% of the realised volatility connectedness is spillover from other super sectors on the average. A sector is known as a net receiver of shocks if NET-connectedness value is negative and while a positive value for net transmitter of shock (Antonakakis et al., 2019). It is observed that Automobile and Parts, Telecommunications, Insurance, Chemicals and General Industrials super sectors are net receivers of shocks with -8.39%, -3.13%, -6.93%, -3.73% and -0.72% in realised volatility estimations, respectively. While the role of Technology, Finance, Energy and Health super sectors became net transmitters of shocks with 9.3%, 9.47%, 13.00%, 9.72% with realised volatilities, respectively.

Moreover, it is interesting to note that Energy super sector is the highest contributor connectedness/ spillover among the JSE equity super sectors with realised volatility of 76.02% while financial and general industrials coming as the 2nd and the 3rd most significant contributors with 68.36% and 68.27% respectively, as Automobile and parts is the least contributor with 49.59%.

It can be observed that each diagonal element in the matrix represents each super sector's own connectedness ($C_{i\leftarrow i}$). It can also be observed that in each row or column, the diagonal volatility connectedness is the largest, indicating that the largest volatility shocks of each super sector

[17] Total Connectedness Index (TCI) refers to the average impact a shock in one series has on all others (Gabauer, 2021). https://gabauerdavid.github.io/ConnectednessApproach/Rpackage#dynamic-connectedness-measures

[18] Dynamic Conditional Total Connectedness Index (cTCI) is

originates from itself, where the diagonal volatility connectedness range from (31.01% to 43.77%). It could be deduced from the result that Automobile and Parts super sector has a net spillover/connectedness in the system. It is observed that the Health super sector generated the strongest self-volatility connectedness (43.77%), followed by Automobile and Parts and Financial super sector with (42.02%) and (41.12%) respectively, with the General Industrial having the least self-volatility connectedness of (31.01%), illustrating that the health sector has the greatest self-shock volatility from amongst all the sectors.

In addition, it can also be deduced that the self-volatility connectedness ($C_{i\leftarrow i}$) on the average, half of the total FROM-connectedness ($C_{.\leftarrow i}$) for almost all the sectors like Telecommunication, Technology, General industrial and Energy, it suggests that each super sector's volatility connectedness consist of, its total external shock and its self-shock almost in equal contributions. However, sectors such as Automobile and Parts, Insurance, Chemicals, Finance, Health has well over 50% of its volatility connectedness as self-volatility. In other words, external shocks are lesser than the self-shocks.

The non-diagonal section of the average dynamic connectedness in Table 5.9a represent the volatility shocks sector j is transmitting to sector i. It can be observed that volatility spillover from General industrial to Telecommunication (13.34%) has the highest value while, followed by Telecommunication to General Industrials (12.28%) and Health to Chemical (12.05%). It can be noticed that there is also a high volatility connectedness between the Energy super sector and the Health super sector with 11.77%, while the volatility connectedness from Insurance to Health super sector (4.16%) has the minimum value.

5.10.1 FROM-Connectedness, TO-Connectedness and Net-Connectedness for entire Sample Period.

Table 5.9a also reports the FROM-connectedness of the average dynamic volatility connectedness. It shows that the FROM-connectedness value ranges narrowly from 56.23% to 68.99%, with Health and General Industrial being the super sectors with the lowest and highest FROM-connectedness. This signifies from the range values for each super sector that 62% of its volatility shocks are contributed by other sectors. The results also show that the health sector has the lowest volatility shock of 56.23%. In addition, the Insurance and the Financial sectors have very close FROM-connectedness of 60.34% and 58.88% respectively, signifying that these sectors receive comparable volatility shocks compared with other sectors.

Interestingly, the Industrial super sector has the highest volatility shock from other sectors. This illustrates that General Industrial the very important role the sector has as a central-sector in the South African economy, depicting that almost all other sectors are one –way or the other connected with the engineering sector, making it a very important sector of the South African Economy.

For TO-Connectedness, the Energy sector shows to have the strongest volatility spillover effects on the other sectors with a value of 76.02%, followed by the Financial and General Insurance sectors with 68.36% and 68.27% respectively. Automobile and Parts seats at the bottom of the rank as the super sector with the least volatility spillover effects on other sectors.

The high TO-connectedness of Energy illustrates the vital role the sector plays as the power generating sector, which provides a source of energy to drive the productivity in all other sector and even the country at large. This could be the same reason for the high TO-connectedness values for the Financial and General Insurance super sectors, as they are both seen as drivers of other super sectors (in the sense that they provide funds, credits and finance for other sectors). However, the General industrial stood as a net-receiver of shock while the Financial and Energy super sectors play the role of net-transmitters.

The NET-connectedness results are also depicted on the average dynamic connectedness table. The difference between the TO-connectedness and the FROM-connectedness is known as the NET-connectedness. When a super sector has a positive value as NET-Connectedness it means the super sector is a risk transmitter and are known to transmit shocks to other super sectors. While a super sector with a negative NET-connectedness value is a shock receiver, receiving more shocks from other super sectors than it transmits. It can be observed that the Automobile and Parts, Telecommunication, Insurance, Chemicals and general industrial sectors are all shock receivers with -8.39%, -3.13%, -6.93%, -3.73% and -0.72% in realised volatility estimations, respectively. While Tech, Financial, Energy and Health super sectors are the shock transmitters with 9.3%, 9.47%, 13.00%, 9.72% with realised volatilities, respectively.

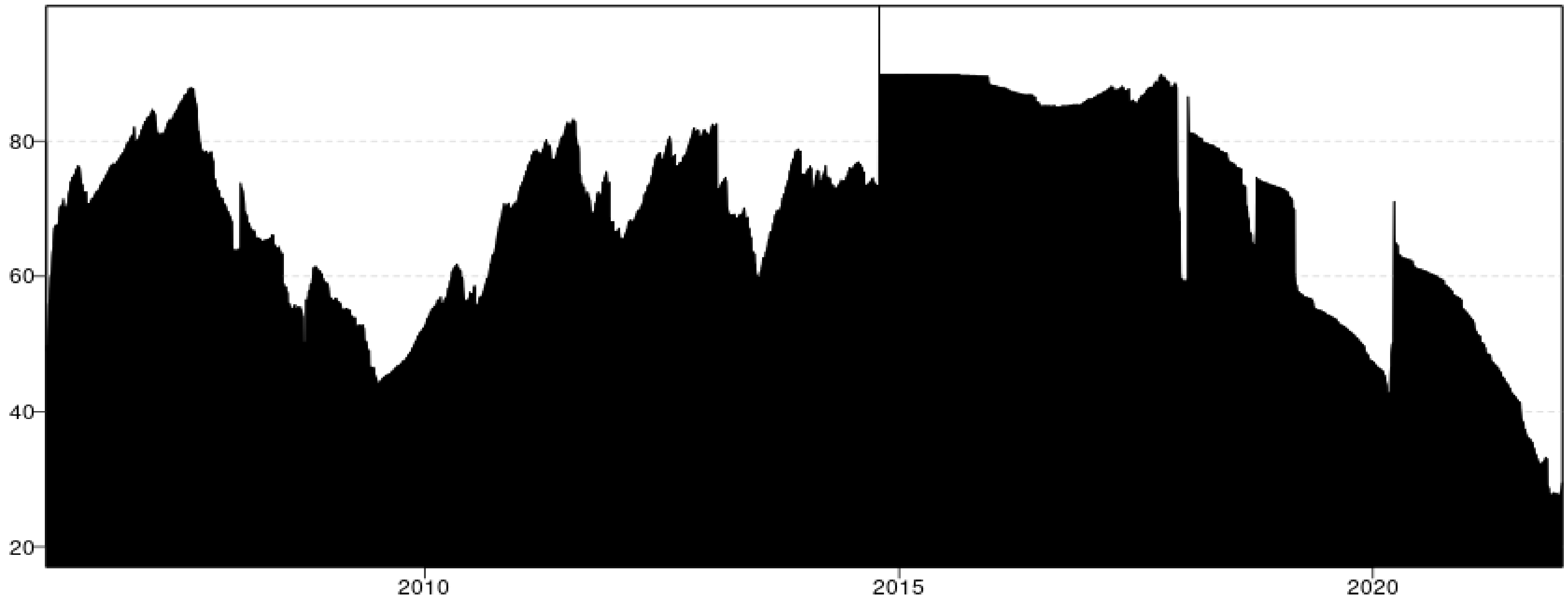


Figure 5.3 Total Dynamic Connectedness between Super Sectors in the Johannesburg Stock Exchange for Full Sample

Note: The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200. Source: Author’s Estimation (2023)

Figure 5.3 shows the average super sector volatility connectedness and the graph respectively; included are the decompositions as transmitters and receivers among the different super sectors, namely Automobile and Parts, Telecommunications, Technology, Health, Chemical, Energy, Finance, General Industrials and Insurance.

5.10.2 Dynamic Total Connectedness between Sectors in the JSE throughout Sample Period.

It can be understood that the average total volatility connectedness of any one super sector due to cross-sector volatility connectedness throughout the sample period is 62.0% (cTCI/TCI). Figure 5.3 gives the graphical plot of the evolution of the TCI over time through the sample period. It is quite important to note that there are couple of spikes with the highest spike at 100% in 2015 and then between 2006 and 2015 there are series of fluctuation.

With an average total connectedness of 62%, this gives the average risk spillover within all the super sectors on the JSE. It is obvious that at this total connectedness value the one can suggest that the risk spillover in the Johannesburg stock exchange exhibits a relatively above-average spillovers. Noticeable spikes are between May-September 2007, May 2011, January 2011 and January 2015 where connectedness rose to 100%.

5.10.3 Total Dynamic Connectedness in Extreme Periods

This subsection presents the dynamic connectedness for the four different sub-periods, which are the Global Financial Crisis (GFC), the European Debt Crisis (EDC), the U.S-China trade war (U.S-China TW) and the COVID-19 pandemic. The aim is to establish how the spillover varies during extreme events, as opposed to the absolute form (full sample) presented in section 5.10.2 immediate previous subsection. For each of the sub-periods, the data ranged within the period of occurrence of events. For example, the GFC starts from 3 January 2006 to 31 March 2009, the EDC starts from 2 January 2009 to 31 March 2011, U.S.-China TW starts from 3 October 2016 to 31 December 2018 and the COVID 19 period starts from 1 October 2019 to 31 December 2021. The purpose of this is to determine the properties of the super sectors, whether as a risk transmitter or risk receiver and also determine the degree (high or low) of total connectedness of the super sectors through these extreme periods.

5.10.3.1 Total and Net-Connectedness during GFC

Table 5.9b shows the result of the average total volatility connectedness across the nine super sectors during the GFC. On a more detailed note, the results for the GFC estimation show from the dynamic connectedness measures as at 1st of December 2006 the Total Connectedness Index is 43.1% but rose to 70.8% by the 29th of same month. The TCI rose to an average of 75.6% in the 1st quarter of 2007 and had an average of 81%, 80.2% at the 2nd, 3rd quarters and dropped to 71% 4th quarter of the same year. The TCI is maintained at 71.3% at the 1st quarter of 2008, 72.3% in the 2nd quarter and at dropped significantly to 57.3% and 60.8% in the 3rd and 4th quarter 2008, respectively. The TCI rose significantly to 69% by the 1st quarter 2009 most possibly due to the beginning of the EDC. The impact of the quarterly TCI is reflected in the total average connected table shown in Table 5.9b.

Table 5.9b Average Dynamic Connectedness Table during GFC

	AM-Vol	TELECOM-Vol	INSUR-Vol	CHE-Vol	TEC-Vol	G.I-Vol	FIN-Vol	ENE-Vol	HEL-Vol	**FROM**
AM-Vol	48.00	7.27	9.60	0.33	6.34	6.95	8.59	10.21	2.71	5.2
TELECOM-Vol	11.63	28.33	10.45	0.41	9.05	12	14.3	9.26	4.57	71.67
INSUR-Vol	12.99	9.59	28.94	0.54	9.98	10.78	13.12	10.05	3.99	71.06
CHE-Vol	5.47	2.42	3.39	79.44	1.83	2.48	2.2	2.28	0.49	20.56
TEC-Vol	13.41	9.79	11.91	0.41	23.35	12.3	13.9	9.99	4.94	76.65
G.I-Vol	12.13	10.53	10.83	0.32	10.19	24.13	16.69	10.3	4.89	75.87
FIN-Vol	11.02	11.54	11.84	0.24	10.74	15.58	24.02	9.90	5.11	75.98
ENE-Vol	11.83	8.53	10.09	0.25	7.59	10.41	11.39	35.92	3.98	64.08
HEL-Vol	9.32	7.71	7.92	0.20	8.29	8.86	10.42	7.80	39.47	60.53
TO	87.8	67.39	76.05	2.70	64.02	79.37	90.6	69.79	30.69	56.84
Inc. Own	35.8	-4.28	4.98	-17.87	-12.63	3.5	14.62	5.71	-29.83	cTCI/TCI
NET	35.80	-4.28	4.98	-17.87	-12.63	3.50	14.62	5.71	-29.83	71.05/63.16
NPT	8.00	3.00	6.00	0.00	2.00	5.00	7.00	4.00	1.00	

Note: The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200.

Source: Author's Estimation (2023)

The static total connectedness index (TCI) and the conditional total connectedness index (cTCI), are shown in the table as 63.16% and 71.05% respectively. This depicts that the total connectedness index is high on an average over the period of the GFC. This established the fact that 63.16% and 71.05% of the realised volatility connectedness is the average level of risk spillover within all super sectors during the GFC.

It is observed that Telecommunications, Chemicals, Technology and Health are net receivers with -4.28%, -17.87%, -12.63% and -29.83% in realised volatility respectively, as health and Chemical super sectors are the biggest receivers of shocks with -29.83% and -17.87% respectively, while the role of Automobile and Parts, Insurance, General Industrial, Financial and Energy super sectors are net transmitters with 35.80%, 4.98%, 3.50%, 14.62% and 5.71% of realised volatilities, respectively. It is interesting to observe that the Financial super sector, being the major source-distressed sector (with respect to global value chain), has the 2nd highest realised volatility of (14.62%), while Automobile and Parts is the biggest net transmitter of risk with 35.80%, since the net transmitters are known to distribute shocks from them to other super sectors.

However, is important to also observe that the Financial super sector contributes the highest risk spillover with realised volatility of 90.6%; this is proof and an indication of the risk confronted with the Financial super sector during GFC, while Automobile and Parts and Insurance are the 2nd and the 3rd most significant contributors of risk with 87.80% and 76.05% respectively and the Chemical super sector is the least contributor with 2.70%.

In addition, the FROM-connectedness result, the Technology and Financial super sectors are the largest and 2nd receivers of risk from other super sectors with realised volatility of 76.65% and 75.98% respectively and general industrial being the 3rd receiver of risk with 75.87%. This result is quite interesting showing the Financial super sector with dual risk duty, in other words, both transmitting and receiving a very high amount of risk to and from other sector, due to the central role the Financial super sector plays during the global financial crisis and its role as a financial provider within the South African economy.

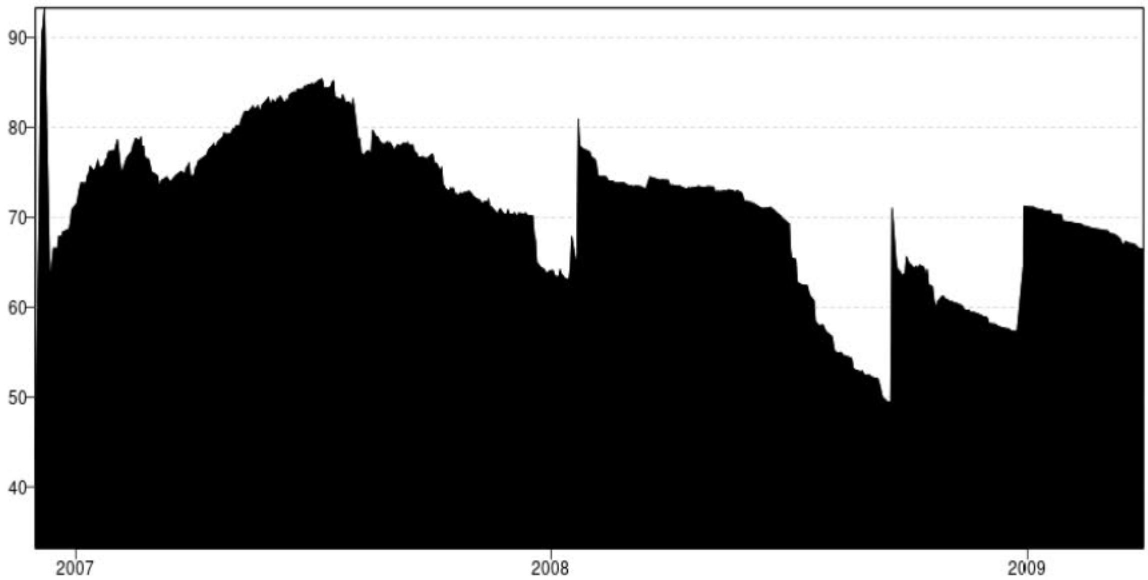


Figure 5.4: Averaged Dynamic Connectedness Graph for GFC Period

Note: The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200. Source: Author's Estimation (2023).

Table 5.9c Average Dynamic Connectedness Table during EDC

	AM-Vol	TELECOM-Vol	INSUR-Vol	CHE-Vol	TEC-Vol	G.I-Vol	FIN-Vol	ENE-Vol	HEL-Vol	**FROM**
AM-Vol	45.98	8011	1.77	3.57	1.49	13.66	8.94	8.57	7.91	54.02
TELECOM-Vol	10.04	21.56	12.03	2.20	10.77	14.43	9.28	9.65	10.03	78.44
INSUR-Vol	5.84	14.91	30.23	2.09	15.64	10.17	5.74	7.30	8.08	69.77
CHE-Vol	6.03	5.22	4.75	60.15	3.28	7.16	3.34	5.67	4.41	39.85
TEC-Vol	6.23	14.98	16.54	1.60	29.23	10.12	8.99	7.39	7.92	70.77
G.I-Vol	12.72	13.99	8.69	2.99	7.33	20.83	13.08	9.79	10.57	79.17
FIN-Vol	10.95	13.21	11.26	2.05	8.42	16.13	20.00	8.00	9.77	79.80
ENE-Vol	9.18	12.26	8.48	2.66	7.57	12.37	7.28	32.03	8.17	67.97
HEL-Vol	12.25	12.98	9.48	2.42	7.72	14.03	9.63	8.50	23.00	77.00
TO	73.24	95.65	73.03	19.57	62.22	98.07	63.29	64.87	66.85	616.79
Inc. Own	119.22	117.21	103.26	79.72	91.45	118.91	83.48	96.9	89.85	cTCI/TCI
NET	19.22	17.21	3.26	-20.28	-8.55	18.91	-16.52	-3.10	-10.15	77.10/68.83
NPT	7.00	6.00	5.00	0.00	3.00	8.00	1.00	3.00	3.00	

Note: The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200. Source: Author's Estimation (2023).

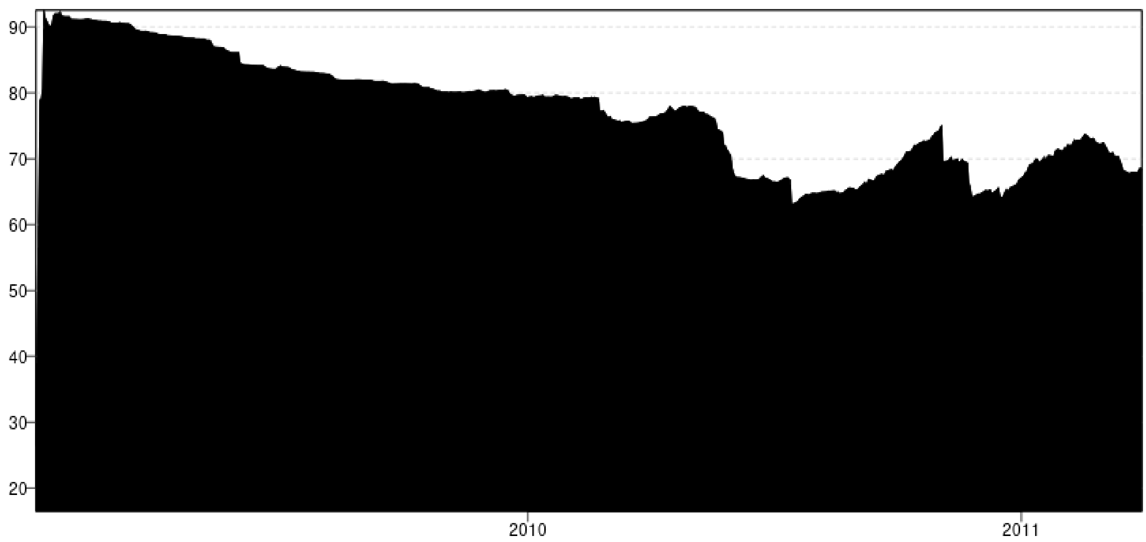


Figure 5.5 Averaged Dynamic Connectedness Graph for EDC Period

Note: The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200.

5.10.3.2 Total and Net-Connectedness during EDC

Table 5.9c shows the result of the average total volatility connectedness across the nine super sectors during the EDC. The EDC result shows that as at 1st quarter of 2009 the TCI had an average value of 89.13% the 2nd, 3rd and 4th quarter of the same year had a value of 86.5%, 81%, 80.3% respectively. This suggests that the TCI for the year 2009 although high in the first quarter but remained between 80% and 86%, indicating the TCI for the year 2009 maintained an average high level. However, at the last quarter of 2011, shows that the average of TCI has dropped to 70.6%. This result indicates that the TCI during EDC from a high value of 89.13% in the 1st quarter of 2009 dropped to an average of 71.3% in 2010 and a further drop to 70.6% in 2011, which suggest that as the impact of the EDC was more pronounced through 2009 than in the rest of the years.

From Table 5.9c, the static total connectedness index (TCI) and the conditional total connectedness index (cTCI) is seen to have a value of 77.10% and 68.83% in realised volatility. This depicts that the total connectedness index is high on an average over the period of the EDC. This established the fact that 77.10% of the realised volatility connectedness is the average level of risk spillover within all super sectors during the EDC.

It is observed that Chemicals, Technology, Financial, Energy and Health are net receivers with -20.28%, -8.55%, -16.52% and -3.1% and -10.15% in realised volatility, respectively. This suggests the Chemical, Technology, Financial and Energy super sectors during the EDC period receives shocks from others, playing the role of shock absorber from the transmitters. With Automobile and Parts, Telecommunication, Insurance and General Industrial, with 35.80%, 4.98%, 3.50%, 14.62% and 5.71% in realised volatilities respectively they play the role of net transmitters, transmitting shocks from one super sector to another. The Financial super sector is seen to have the 2nd highest realised volatility since the net transmitters are known to distribute shocks from themselves to other sectors.

The result shows that the biggest transmitters of shocks are the Automobile and Parts (19.22%) and General industrial (18.91%) respectively, while the biggest receivers of shocks are Chemical and Financial with net values of -20.28% and -16.52% respectively. In addition, the FROM-connectedness result reveals that the Financial and General industrial sectors are the largest receivers of risk from other super sectors with realised volatility of 79.17% and 78.44% respectively, with the Chemical super sector standing as the least receiver of risk with 39.85%.

Table 5.9d Average Dynamic Connectedness Table during the U.S-China Trade War

	AM-Vol	TELECOM-Vol	INSUR-Vol	CHE-Vol	TEC-Vol	G.I-Vol	FIN-Vol	ENE-Vol	HEL-Vol	***FROM***
AM-Vol	90.67	0.81	1.44	0.74	1.3	1.58	1.20	1.6	0.65	9.33
TELECOM-Vol	4.23	61.11	2.85	1.98	2.84	8.67	4.97	6.01	7.36	38.89
INSUR-Vol	6.90	2.63	55.62	2.28	3.43	12.25	5.34	5.27	6.28	44.38
CHE-Vol	9.43	1.55	1.94	57.09	3.16	4.34	7.93	9.46	5.1	42.94
TEC-Vol	8.18	2.20	2.97	3.26	59.65	4.36	7.35	7.48	4.55	40.35
G.I-Vol	6.45	6.06	10.06	3.72	3.64	45.94	6.70	6.44	10.99	54.06
FIN-Vol	9.23	2.38	2.70	5.18	4.73	5.07	53.54	11.36	5.81	46.46
ENE-Vol	9.88	3.70	2.73	6.69	4.96	5.00	11.51	48.9	6.64	51.1
HEL-Vol	6.24	5.31	4.73	4.33	3.82	11.12	7.59	8.16	48.69	51.31
TO	60.53	24.64	29.41	28.18	27.89	52.39	52.59	55.79	47.37	378.79
Inc. Own	151.2	85.75	85.03	85.27	87.54	98.34	106.13	104.69	96.06	***cTCI/TCI***
NET	51.2	-14.25	-14.97	-14.73	-12.46	-1.66	6.13	4.69	-3.94	47.35/42.09
NPT	8.00	0.00	1.00	3.00	2.00	5.00	7.00	6.00	4.00	

Note: The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200.

Source: Author's Estimation (2023)

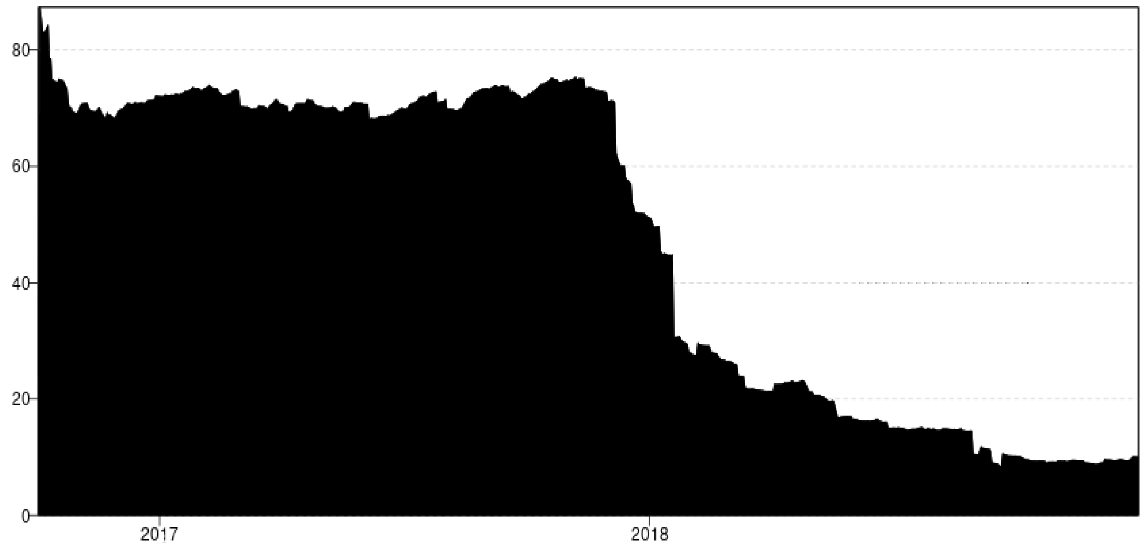


Figure 5.6 Averaged Dynamic Connectedness Graph for the U.S-China Trade War Period

Note: The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200. Source: Author's Estimation (2023).

Table 5.9e Average dynamic connectedness table during COVID-19 pandemic period

	AM-Vol	TELECOM-Vol	INSUR-Vol	CHE-Vol	TEC-Vol	G.I-Vol	FIN-Vol	ENE-Vol	HEL-Vol	***FROM***
AM-Vol	26.72	6.57	7.82	2.34	16.25	3.98	15.87	6.66	13.78	73.28
TELECOM-Vol	11.7	20.03	11.42	1.19	13.33	7.03	13.72	9.33	12.25	79.97
INSUR-Vol	10.97	12.27	22.84	1.46	12.18	7.57	13.86	7.13	11.71	77.16
CHE-Vol	5.4	1.67	1.97	75.22	4.11	1.02	3.68	3.4	3.54	24.78
TEC-Vol	15.01	8.22	7.72	1.86	24.18	5.68	15.76	7.9	13.68	75.82
G.I-Vol	10.74	9.97	8.38	1.44	12.64	14.19	16.27	13.38	12.99	85.81
FIN-Vol	13.36	8.55	9.05	1.44	14.48	9.86	20.66	7.91	14.69	79.34
ENE-Vol	7.53	5.67	6.18	1.36	8.11	1.78	6.27	56.69	6.41	43.31
HEL-Vol	13.74	8.28	8.59	1.46	14.15	7.25	16.56	7.62	22.36	77.64
TO	88.44	61.21	61.14	12.55	95.25	44.17	101.99	63.32	89.04	617.1
Inc. Own	115.71	81.24	83.97	87.77	119.43	58.36	122.65	120.01	111.4	***cTCI/TCI***
NET	15.17	-18.76	-16.03	-12.23	19.43	-41.64	22.65	20.01	11.4	77.14/68.57
NPT	5.00	3.00	2.00	1.00	7.00	0.00	7.00	6.00	5.00	

Note: The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200.
Source: Author's Estimation (2023).

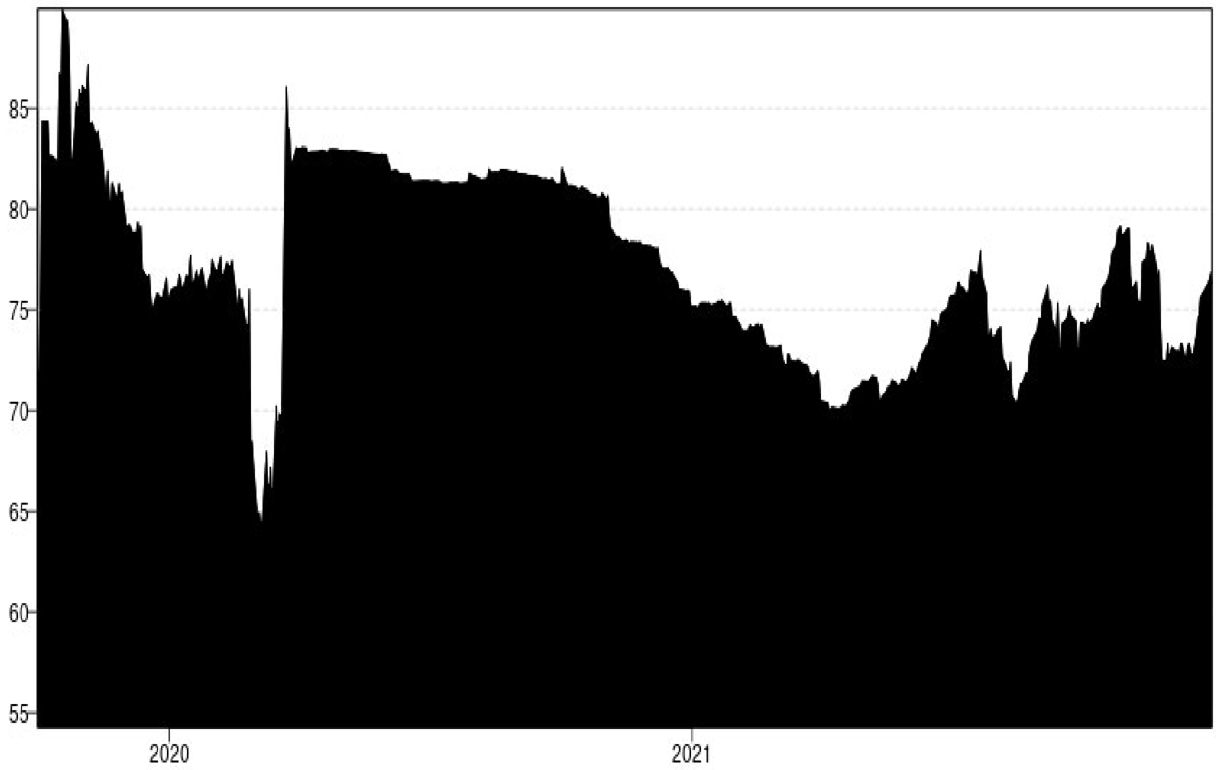


Figure 5.7 Averaged dynamic connectedness graph for COVID-19 pandemic period

Note: The estimation was carried out with lag length 1, forecast horizon (H) of 20 with Bayes prior and with size 200. Source: Author's Estimation (2023).

5.10.3.3 Total and Net-Connectedness during the U.S-China Trade war

The results for the U.S-China trade war estimation span from 3rd of October 2016 to 31st December 2018. The quarterly TCI were calculated so observe the trend-increase or decrease through the period of analysis and compared to the averaged TCI shown in the Table 5.9d. The quarterly result of the last quarter 2016 shows a 71.30% TCI, however, this does not necessarily reflect the impact of the trade war on the South African super sectors.

During the 3rd and the 4th quarter of 2018, the average quarterly TCI was 13.26% and 9.37% respectively, with the TCI for the 1st quarter being 18.79%. This suggest that the TCI shows no response through the cumulative effect from the several impositions of tariffs from U.S to China and vis-a-vis on the different trade product between the two economies. Despite the cumulative impact of the trade war documented on different countries most especially their trade partners, yet the realised volatility through the year 2018 gives very low value.

The average total connectedness index in Table 5.9d shows a value of 47.35%, which is a reflection of the realised volatilities; this suggests a relatively low value when compared to other extreme periods, even lower than the full sample periods.

The Automobile and Parts super sector shows some evidence of high values in volatility. The super sector has the highest self-volatility connectedness ($C_{i\leftarrow i}$) of 90.67% followed by Telecoms with 61.11%. These two super sectors happen to be the two among other super sectors involved in production line or consumption of the tariffs-imposed goods such as automobiles, electronic-chips, metals-materials etcetera. This suggests the resultant effect on the volatility connectedness of these two sectors and, hence, higher in value compared to other sectors.

In addition the FROM-connectedness result shows the General industrial as the largest receiver of risk from other super sectors with realised volatility of 54.06%. These values suggest the nature of the super sector being involved in the recipient and conversion of most raw-materials into finished product, from the other different super sectors of the economy, hence, it has the highest received volatility compared to others. The sector with the least FROM-connectedness is the Automobile with 9.33%, indicating the super sector with the lowest shock received from other sectors. Furthermore, the Automobile and Parts sector, again, has the highest To-connectedness with a value of 60.53% indicating its capacity to send shocks to other sectors, especially during this trade war period, with the Energy, General industrial and financial sectors having a similar capacity to send shocks to others too.

The TO and FROM connectedness results of the Automobile and Parts positions the super sector as the greatest significant transmitter of shocks (i.e. risk transmitter) with a volatility of 51.2% within the network with Finance and Energy with 6.13% and 4.69% respectively. The Insurance (-14.97%), Chemical (-14.73%), Telecoms (-14.25%), Technology, General Industrial and Health super sectors are all net-receivers of shocks with General Industrial the least net-receiver with -1.66%. This shows that the Insurance super sector is the biggest receiver of shock during the U.S-China trade war.

5.10.3.4 Total and Net-Connectedness during COVID-19 pandemic

The COVID-19 pandemic estimation spanned from 1 October 2019 to 31 December 2021. This helps us to cover the timeline of the prevalence in South Africa. Even though the pandemic started in China in November 2019, the first bunch of cases of the pandemic hit the country of South Africa in March 2022, with the nation declaring a national state of disaster in same month (Giandhari, Pillay, Wilkinson, Tegally, Sinayskiy, Schuld, Lourenço, Chimukangara, Lessells, Gazy, Moosa, Fish, Singh, Khanyile, Fonseca, Giovanetti, Carlos, Alcantar, Petruccione & de Oliveira 2021). By the end of the 2nd quarter 2020 the TCI was standing at 82.44%, a rise of 7.78% from the 1st quarter. The 3rd and 4th quarter of the same year stood at a TCI of 81.54% and 78.9% respectively, reflecting the negative impact of the pandemic on economic activities and triggering the spread of shocks through the entire super sectors on the JSE.

At the 3rd quarter 2021 the TCI has risen to record value of 99.28% but dropped to a value of 75.5% at the last quarter of 2021, which reflects the measures implemented to ease economic and social activities in the country. The averaged TCI from Table 5.9e stood at 68.57% while the conditional TCI is 77.14%, both indicate the heightened level in the average realised volatility within the super sectors.

However, the Chemical super sector has the highest self-volatility connectedness ($C_{i \leftarrow i}$) of 75.22%, followed by Energy with 56.69%. It is important to note that the Health sector being obviously the most pressured sector during this period has one of the least self-volatilities of 22.36%. Table 5.5.6 also shows that the General industrials has the highest FROM connectedness with 85.81%, indicating that the sector received the largest shock from other super sectors of the economy followed by the financial sector with 79.34%, while the health sector is the 4th receiver of shocks.

The general industrial became the second to last transmitter of shock with a TO-connectedness value of 44.17%, while the financial super sector became the largest transmitter of shock to the entire system with 101.99% of TO-connectedness (shock spillover), with the health sector becoming the second largest transmitter of shocks. These resultant effects of the TO and FROM connectedness values puts the General industrial as the highest net-receiver of shock with a value of -41.64%. The biggest net-transmitter of shock is the Financial super sector with 22.65%, showing its capacity as ‘risk’ giver super sector, in providing funds into business or sectors to relieve the devastating effect of the pandemic and in reviving economic activities, hence, such funds may be seen as liabilities (risk) to the receivers. The Health super sector, however, functions in the capacity of a risk receiver during this period but in the lowest capacity with a net value of 11.4%.

5.11 EVOLUTION OF SECTORIAL TOTAL VOLATILITY CONNECTEDNESS DURING FULL SAMPLE PERIOD

With respect to Figure 5.3, which shows the plot result of the dynamic total connectedness from 3 January 2006 to 31 December 2021 reveals that TCI of the super sectors hit an average height of 80% during the 2007-2008 global financial crisis and came down to an approximate minimum of

42% Thereafter between 2010 to 2015 where different periods of spikes ranging .from a minimum of 65% to 83%.

Moreover, the period witnessed the highest total connectedness value of 100% between December 2014 and January 2015 and thereafter dropped to an average of 90% through a long period of time, until around February 2018 that the super sector recorded a sharp drop in TCI to 60% and then picked up to a height of around 87%. However from February 2018 the super sectors experienced a steady drop in TCI till late 2019 and further pick up to around 70% in 2020 during the COVID-19 pandemic. Through different economic measures and lockdown restriction measures being eased there was a gradual drop in TCI till end of the 2021 sample period.

5.12 EVOLUTIONARY TRENDS OF SECTORIAL VOLATILITY CONNECTEDNESS DURING EXTREME PERIODS

This section considers the evolution of all the connectedness measures (TO-connectedness, FROM-connectedness and NET-connectedness) of the super sectors through the different extreme periods which are the GFC, EDC, U.S-China Trade War and the COVID-19 pandemic from the average connectedness results of each extreme periods.

It is of interest to note that during the GFC and EDC the super sectors of Telecommunication, Insurance, Technology, General Industrial and Financial maintained a FROM-connectedness of above 70% when compared to other sectors whose connectedness ranges between of 20% to 64%. This suggest that the Financial, Telecommunication, Insurance, Technology and General Industrial sectors respond sensitively with increased volatility to financial-crash events, international or global economic challenges etc. In addition it is quite noticeable that the TO-connectedness is greater compared to FROM-connectedness of Automobile and Parts, Telecommunication, Insurance, General Industrials, Energy and Financials, with the exception of Chemical, Technology and Health. This suggests that no super sector is independent in the market and there is spillover of from one super sector to another to a considerable level.

Moreover, the stability of the super sectors throughout the extreme periods are worthy of identification. The Automobile and Parts and Chemical super sectors are shown to remain as risk transmitter and receiver respectively throughout the four extreme periods. This shows their stability capacity during the periods of extreme market conditions, hence, maintaining their stability regardless of policies or economic adjustment strategies.

In contrast, other super sectors show their tendency to fluctuate from being a risk-transmitter or risk-receiver under the different extreme risk event. For example, the Technology super sector maintained its identity as a risk receiver during the GFC, EDC and the Trade war and under the COVID-19 period became a risk transmitter. Meanwhile, the financial super sector changed from risk transmitter during the GFC to a risk receiver during the EDC and later stabilised as a risk-transmitter during the U.S-China trade war and the COVID-19 pandemic. Similarly, the General Industrial super sector exists as a risk transmitter during the GFC and the EDC and operates as a risk receiver during COVID-19 and trade war period.

The Insurance super sector exists as a risk-receiver and risk-transmitter during the (trade war and COVID-19 pandemic) and the (GFC and EDC) respectively, while Health was a risk receiver during the (GFC, EDC and Trade war) and later became a risk-transmitter during the COVID-19 pandemic, respectively. These changes in net-connectedness properties, from a net-receiver to a net-transmitter of risk, show the capacities of the Financial, General Industrial, Insurance, Technology, Energy, Telecoms and Health super sectors adaptability to different shocks events in the economy and, hence, function to the stability of the entire sectorial system.

In summary, the connectedness results of objective three, reveals that indeed in the full sample period there exist a high connectedness across the super sector based of the cTCI of 69.74% with the Technology, Energy, Financials and Health super sectors being the net transmitters of shocks to other super sectors, while the shocks were received by Automobile and Parts, Telecommunication, Insurance, Chemicals and General Industrials. Moreso, for the GFC period, cTCI had increased to 71.05%, indicating an increased connectedness among the super sectors on the JSE compared to during the full sample periods. However, with super sectors like Telecommunication, Chemical, Technology, Health super sectors were the shock receivers, super sectors like Automobile and Parts, Insurance, General Insurance, Financials and Energy were the shock transmitters during the global financial crisis. The cTCI stood at 77.10% during the EDC, which was much higher than during the GFC and the full sample period. Technology, Chemicals, Financial, Health and Energy sectors were the receivers of shocks while Automobile, Telecoms, Insurance and General Industrials, were the transmitters of those shocks.

During the U.S-China trade war the cTCI dropped to 47.35%, which is significantly lower compared to aforementioned dynamic total connectedness in. The highest net transmitter of shock is the Automobile and Parts super sector while the highest receiver of shock is the Insurance super sector. Furthermore, during the pandemic period the sectors witnessed an increased cTCI of 77.14%, which was particularly the highest for all the extreme periods, indicating a significant connectedness level among the super sectors on the JSE. The General Insurance sector was the highest receiver of shock among the network of sectors while the Financial super sectors was the greatest transmitter of shock to other super sectors during this period. The results provide significant evidence that sectors on the JSE experienced high connectedness especially during the extreme or crisis event and some sectors do contribute to the transfer of shocks and the receiving of shocks during the full sample period and during the extreme period. The transfer of shocks is an important pointer to the fact that direction of propagation or movement of these shocks could be traced from source super sectors to the receiving super sectors.

5.13 NETWORK PLOTS OF VOLATILITY CONNECTEDNESS FOR FULL SAMPLE AND THE EXTREME PERIODS

This section is in continuation of objective three (3) of this study, having established that connectedness does exist on the JSE, hence, with the aid of a network plot this study examines the direction of propagation or movement of shocks from one super sector to the other – from the super sector which transmits to that which receives shocks. This section helps to isolate shock-originating or shock-contributing super sectors and the corresponding receivers with the aid of a network plot of the different sample periods.

In each network plot, the arrow coming from a super sector (transmitter) pointing towards another super sector (receiver) illustrates a shock is transmitted or propagated. The yellow and blue node represent (net-receivers) and (net-transmitters) respectively. Also the size of the nodes and width of the link or edges are proportional to the net-connectedness (values) and pairwise directional connectedness, respectively.

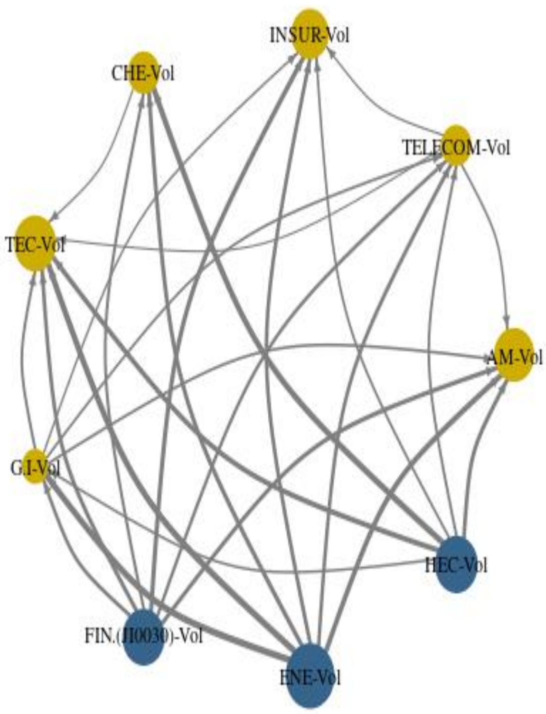


Figure 5.8 Sectorial Volatility Network plot for Full Sample Period
Source: Author's Estimation (2023).

5.13.1 Network Plot of Volatility Connectedness of Full Sample

Figure 5.8 shows the network plot of the entire sample period and it reveals the movement of shocks from one super sector to another via the links. The plots show that the Energy super sector has the biggest blue node with the highest net-connectedness value of 13.0%, making it the strongest net-transmitter of shock. The Energy super sector transmits shocks to every other sector within the network with the exception of the Health and Finance super sector. The Energy super sector plays a huge role in the fuelling of the day-to-day business activities of the South African economy; it emphasises its role within the value chain and the domestic demands of the entire population (Ratshomo 2021).

The Automobile and Parts super sector seats as the highest receiver of shocks receiving links from five different super sectors (Health, Energy, Financial, General Insurance and Telecommunications) the widths of these links are quite significant, making the super sector the highest in net-connectedness (receiver) value of 8.39%; whereas, general industrial has the smallest node size as a net-receiver, accepting shocks from just three super sectors and equally sending out shocks to three super sectors, hence, with very small net-connectedness (net-receiver) value of -0.72 almost at equilibrium (i.e. a state where net-received equals net-transferred).

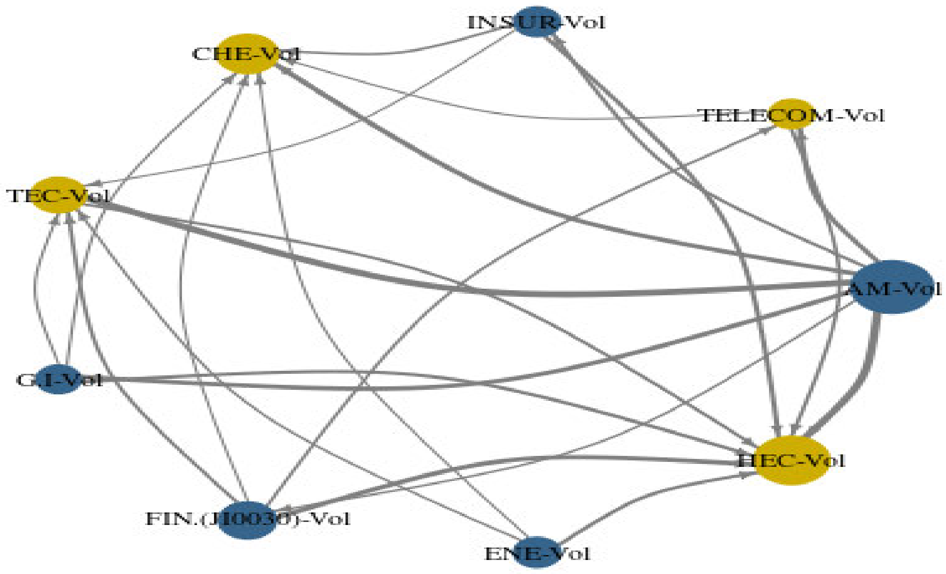


Figure 5.8.1 Sectorial Network Plot of Volatility Connectedness for the GFC Period
Source: Author's Estimation (2023).

5.13.2 Network Propagation during GFC

Figure 5.8.1 shows the network plot of the period of the GFC and it reveals how shocks are propagated from one sector to another. The plot shows that Automobile and Parts is the highest transmitter of shock since it transmits to all other sectors except the Energy, hence, the reason why it has the biggest node, with the highest net-connectedness positive value of 35.80%, with its strongest link (shock) propagated to the Technology and Health care super sectors. This depicts that during this period the Technology and Health are heavily dependent on the Automobile and Part super sector in the business value chain. However, the Health super sector is the highest receiver of shocks as it receives shocks from six sectors, as proven by the size of the node (i.e. lowest net connectedness value of -29.83%).

It is quite important to give an insight on the propagation of shock as regards the financial super sector as it relates to the GFC period. It is interesting that the Financial super sector is a net transmitter of shock (with 14.62%) during the GFC period from the network with the second biggest node size after the Automobile and Parts, hence, transmitting risk to the Technology, Chemical, Telecommunication and the Automobile sectors.

5.13.3 Network Propagation during EDC

Figure 5.8.2 shows the network plot of the period of the EDC and it reveals how shocks are propagated from one sector to another within the network.

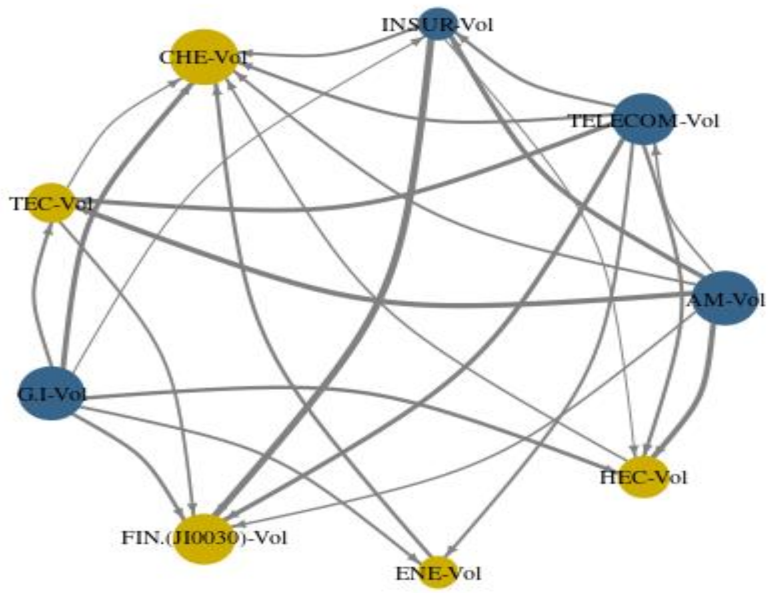


Figure 5.8.2 Sectorial Network Plot of Volatility Connectedness for the EDC Period
Source: Author's estimation (2023).

The plot shows that Automobile and Parts, general Industrial and telecoms sectors are the highest transmitters of shocks, based on size of nodes and propagating shocks to six sectors, respectively. However, the Automobile and Parts has the three strong links to sectors of insurance, technology and health compared to general industrial and telecoms, which has just one strong link each, hence, making Automobile and Parts the highest net-transmitter of shock with highest connected value of all the three with 19.22%. However, the Chemical super sector is the highest receiver of shocks as it receives shocks from six super sectors (the Technology, General Industrial, Energy, Health, Automobile, Technology and Insurance), as proven by the size of the node (i.e. lowest net connectedness value of -20.28%). It is important also to note that the Chemical super sector receives the strongest link from the General industrial during the period. This suggests the heavily-dependent relationship the General Industrial has on the chemical super sector, which produces raw materials (chemicals) for its manufacturing processes.

In addition, it is obvious from the network plot the width (thickness) of the nodes between Financials and Insurance, Technology and Telecommunications, Technology and Automobile and Parts and Health, revealing the strength of the shock propagated from Telecoms, Automobiles and General Industrials.

5.13.4 Network Propagation during U.S.-China Trade war

Figure 5.8.3 shows the network plot under the U.S-China trade war period. It is revealed that Automobile and Parts super sector is the main propagator of shocks and with the biggest blue-node, sending shocks to the remaining eight super sectors through eight edges with stronger shocks to Chemical, Financial, Energy, Insurance and Health super sectors with the evidence of thicker width of the edges. This suggests that the Automobile and Parts is more highly connected with these sectors, making it the sector with the highest net-transmitter with 51.2%, having generated the highest self-induced volatility of 90.67% (see Table 5.9c) in the network.

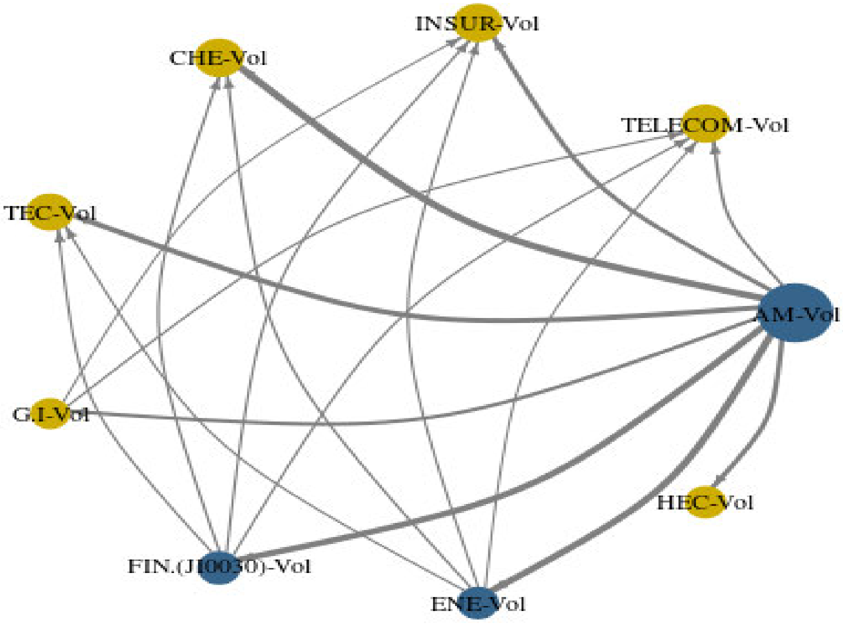


Figure 5.8.3 Sectorial Network Plot of Volatility Connectedness for the Trade War Period

Source: Author’s Estimation (2023).

The network plot also reveals that the super sectors of Telecommunications, Insurance and Chemicals are the greatest shock receivers, receiving (shocks) from the Automobile and Parts super sector, each with over -14%. Particularly, these sectors including financials and energy received shocks with thicker edges. Interestingly General Industrial super sector is the least shock receiver with net-connectedness of -1.66%, receiving link from only the Automobile and Parts sector.

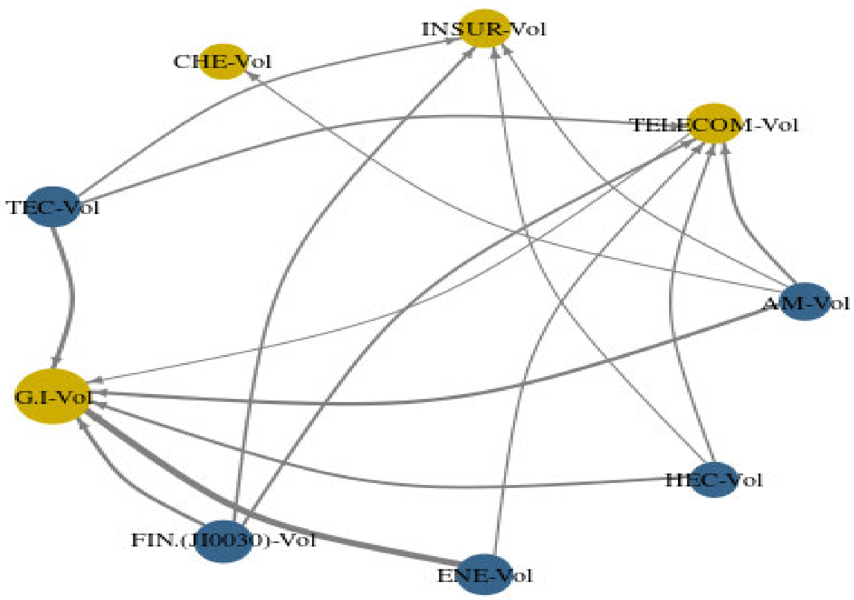


Figure 5.8.4 Sectorial Network Plot of Volatility Connectedness for the COVID-19 Period
Source: Author's Estimation (2023)

5.13.5 Network propagation during COVID-19 pandemic period

The network plot under the COVID-19 pandemic period reveals the General Industrial super sector as the main shock receiver from Technology, Financial, Energy, Health, Automobile and Parts, Insurance, Chemicals and Telecommunication super sector, hence, having the biggest size in yellow-node. In addition the general industrial sector is the receiver of the strongest links as depicted by the thicker widths coming mainly from the Energy and Technology sectors; for these reasons the General Industrial has the highest net-connectedness (net-receiver) shock of -41.64% during the pandemic period. The network plot of figure 5.8.4 also reveals that the Insurance and the Telecommunication super sectors stood as a shock receiver or absorber next to General Industrial receiving shocks from Financial Energy, Technology, Health and Automobile and Parts making them the next two net receivers with -18.76 and -19.03 respectively. This network also reveals energy sector with a huge shock propagator or transmitter (as evident by the thickest edge), sending shocks to general industrial with a 20.01 net connectedness.

In summary, the network plot of the full sample period and the four extreme periods show that there is evidence of propagation or movement or transfer of shocks from one sector to the other, as some sectors are targets sectors and some sectors are initiators of shocks. It is quite interesting to note that from one period to another, the net-connectedness status of some sectors changed from a net-transmitter to net-receive possibly due to the nature or the kind of extreme event of crisis involved.

For instance, during the full sample period the Insurance super sector was a net receiver of shock with the identity as a yellow node, receiving shocks or four edges into itself, however during the GFC and the EDC the Insurance super sector status changed into a net-transmitter with a blue node. Similarly the industrial sector stood as a net receiver with a yellow node during the full sample period but during the GFC became a net transmitter of shock. Furthermore, during the full sample period the Automobile and Part super sector was a small net-receiver of risk but ding the U.S-China trade war became a greatest net–transmitter of shock in the entire network. This is a pointer to the fact that roles of super sectors could change depending on the crisis. However, this does not apply to all the super sectors on the network. The Chemical super sector is revealed to be a net-receiver of shock in the full sample period and throughout the remaining extreme period remained as a net-receiver of shock. Moreso, super sector such as the Financials remained as a net-transmitter of shocks in all the different periods with the exception of the EDC period where it stood as a net-shock receiver.

The result further strengthens the fact that size of the node, whether blue or yellow, is a function of the net-figure (i.e. either positive or negative). Therefore, the higher the figure the larger the size of the nodes in the network, hence, corroborating with the net-connectedness values of each super sectors on the average connectedness tables for each period under observation. In addition, the results also show that the thinker the links or edges between two super sectors the stronger the shock transferred or received between them and also reveals values of the net-connectedness values.

5.14 DETERMINANT OF CONNECTEDNESS ON THE JSE EQUITY SUPER SECTORS

The fourth objective of this study is to investigate the determinants or drivers of sectorial volatility determinants on the JSE market. Hence, this section presents how this objective is achieved. The nonlinear autoregressive distribution lag (NARDL) model of Shin, Yu and Greenwood-Nimmo (2014) was employed to achieve the objective. The chapter starts with the unit root test results followed by the estimated results of both the ARDL and the NARDL results for both the long and the short run forms.

Table 6.1 the unit root test result

	Levels		First difference		
Variables	**ADF t-statistic**	**Phillips-Perron Test-statistic**	**ADF t-statistic**	**Phillips-Perron Test-statistic**	**Integration Order**
LTCI	0.976796	0.086346	-9.826266	-9.826266	I(1)
LEPU	-3.962503	-3.97472	-3.97472	-15.06036	I(0)
LSAVI	-3.13806	-3.151274	-3.682072	-13.66901	I(0)
LDMR	-1.301589	-1.301589	-12.01311	-12.01311	I(1)
LTO	-2.473232	-2.597083	-13.78534	-13.26802	I(1)
LM2	-2.049663	-2.156678	-14.13246	-14.16585	I(1)
LMOP	-6.12381	-6.128606	-6.128606	-25.13997	I(0)

Source: Author's Estimation (2023).

Table 6.1 shows the results of the unit root test. The ADF unit root test and the Phillips-Perron test were carried out to determine the stationarity of the variables, namely LTCI[19] (log of total connectedness index), LEPU (log of economic policy index), LSAVI (log of South Africa volatility index), LDMR (log of domestic market index), LTO (log of Trade Output), LM2 (log of Money Supply) and LMOP (log of Manufacturing Output). Hence, the Unit root test is important to be carried out to ascertain the stationarity of the above-mentioned variables in the in ARDL and the NARDL model. It reveals that variables are not cointegrated at order 2, (i.e. 1(2)). The NARDL model is not suitable if the variables are integrated into two I (2) (Greenwood-Nimmo & Shin, 2013; Shin et al., 2014). The result of the unit root test shows

[19] Log of Total Connectedness Index (LTCI) refers to the logarithm value of the monthly average of the daily total connectedness index of the whole sectorial volatility. This is computed from the David Gabauer ConnectednessApproach application.

that EPU, SAVI and LMOP were all integrated of order zero (0), with the ADF and the Phillip-Perron test. However, LTCI, LDMR, LTO and LM2 were stationary at first difference. Using the ADF and PP test, the PP test applies a nonparametric correction to the standard ADF test statistics. The section discusses the results of ARDL and the NARDL.

5.14.1 ARDL and NARDL Analysis Result

This section reveals the result of the ARDL and NARDL model. This study analysed both the ARDL and the NARDL model. The reason for this is for robustness purpose and to select the best based on the information criteria.

Table 6.2 The Bound test for Cointegration for the Long run of ARDL and NARDL

Bound Test Result for Cointegration Test and Long-run Equation									
	99%		97.50%		95%		90%		**Outcome**
F Statistic	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	COINTEGRATED
3.49**	2.88	3.99	2.55	3.61	2.27	3.28	1.99	2.94	
Long-run Equation ARDL D(LTCI)	EC=LTCI-(0.2652*LSAVI - 1.7207*LMOP + 0.0013*LEPU - 3.4702*LM2 - 1.6131*LTO + 3.0958*LDMR + 15.3561)-----(1)								
	99%		97.50%		95%		90%		COINTEGRATED
F Statistic	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I ()	
4.55***	2.5	3.68	2.24	3.35	2.04	2.08	1.8	2.8	
Long-run Equation NARDL (LTCI)	LTCI = 0.8066*LSAVI_POS - 0.0547*LSAVI_NEG - 0.1235*LMOP + 0.0010*LEPU_POS + 0.0021*LEPU_NEG - 4.3510*LM2 -1.0182*LTO + 1.3952*LDMR_POS + 2.2793*LDMR_NEG + 30.115-----(2)								

Note that asterisks *, ** and *** are respectively the 10%, 5% and 1% significance level. Source: Author’s estimation (2023)

5.14.1.1 ARDL and NARDL Long-Run Relationship Analysis

Table 6.2 shows the output of the ARDL and the NARDL F-Bounds test and the long-run equation. With respect to the AIC the best models are for NARDL (LTCI) (4, 2, 0, 1, 1, 4, 3, 0, 2, 2.) and the ARDL (LTCI) is (4, 2, 2, 1, 0, 0, 2). Represented in the parenthesis are the lag-number of each of the variables estimated in the model. It can be observed that the F-statistic value for both the ARDL (LTCI) and NARDL (LTCI) exceed the both upper and lower bound critical values at 5% significant level, while the F-statistics for the NARDL model stood at 4.55***; hence, significant at 1% level. Hence, this ascertains the need to reject the null hypothesis of no cointegration relationship among the response and explanatory variables. The result signifies that there exists a long-run relationship between logarithm of total connectedness index (LTCI) and the independent variables of logarithms of South Africa volatility index (LSAVI), Domestic market return (LSAVI), Economic policy uncertainty (LEPU), Trade openness (LTO), Manufacturing output (LMOP) and Money supply (LM2). The result also suggests that the long run relationship between the dependent and independent variables is asymmetric in nature. The asymmetric relationship between the variables were strengthened by the AIC lag results, which boost the output of the NARDL model.

Having confirmed the asymmetric long-run equation and relationship in the LTCI (NARDL) model. Table 6.2 shows that from the long-run components both positive shock in the past period of the South African Volatility index has a positive causal effect on total connectedness index and negative shock in South African volatility index in the current period do not have significant effect on the LTCI. Also it can be deduced that positive shock in the past period of EPU has no significant effect on LTCI while negative shock in the past period of EPU has a positive causal significant effect on LTCI. Likewise, both positive and negative shock to the past period of lag of domestic market return has positive significant effect on LTCI.

Moreover, from the short run components both positive shock (in the present period) and (in the past period) in the South African Volatility index have significant negative causal effect on TCI. It also shows that both positive and negative shock in the present period of EPU has no significant effect on the TCI. However, there is a negative significant effect on TCI from the negative shock (in the past 3 period) of EPU. The results also indicate that negative and positive shock in the present period of domestic market return has a significant negative and positive effect on TCI respectively. Also, there is a significant negative effect on TCI from a negative shock on the past period of domestic market return, but positive shock to the past value of domestic market return has no significant effect on TCI.

It is essential to note that the NARDL model allows the decomposition of the explanatory variables into partial sum, which helps to give an insight of how the variation in the explanatory variable affects the sectorial volatility connectedness of the JSE market. From the asymmetric long-run levels in equation (2) of Table 6.2, it can be deduced that total volatility connectedness index is a positive function of both positive and negative changes in LSAVI. Therefore, it implies that a 1% increase in the logarithm of South African volatility index will increase the logarithm of total sectorial volatility connectedness index by 0.8066 unit and a 1% decrease in the South African volatility index will increases the logarithm of total sectorial connectedness index of the JSE by 0.0547 unit. Also from the equation (2) it can be deduced that LTCI is positive function of both positive and negative changes in LEPU hence, when a 1% increase in the logarithm of South African Economic Policy Uncertainty Index will increase the Logarithm of total sectorial volatility index by 0.001 unit and a 1% decrease in the South African Economic Policy Uncertainty will decrease the log of total sectorial volatility connectedness index of the JSE by 0.0021 units. Furthermore, it is observed that LTCI is a positive function of both positive and negative changes in LDMR, hence, a 1% increase in the log of domestic market return (i.e. All Share Index) will increase the logarithm of total connectedness index by 1.3952 units while a 1% decrease in the logarithm of domestic market return (All Share Index of the JSE) will decrease the logarithm of total sectorial volatility connectedness index by 2.2793 units.

Table 6.3 Error Correction Model for ARDL and NARDL Models

Error Correction Regression					
Model	**Variables**	**Coefficients**	**Standard Error**	**t-Statistics**	**Probability**
ARDL (LTCI)					
	D(LTCI (-1))	0.4530	0.053714	8.434124	0.0000
	D(LTCI (-2))	-0.1066	0.060758	-1.755274	0.0814
	D(LTCI (-3))	0.1422	0.053961	2.635341	0.0094
	D(LSAVI)	-0.0609	0.035418	-1.719093	0.0878
	D(LSAVI (-1))	-0.0894	0.035444	-2.522331	0.0128
	D(LMOP)	-0.1875	0.045669	-4.106302	0.0001
	D(LMOP (-1))	0.0634	0.038636	1.642772	0.1027
	D(LEPU)	-0.00009	0.000113	-0.839417	0.4027
	D(LDMR)	0.1407	0.101151	1.391128	0.1664
	D(LDMR (-1))	-0.4048	0.100053	-4.046067	0.0001
	CointEq (-1)*	-0.0594	0.010957	-5.419126	0.0000
NARDL (LTCI)		**Coefficients**			**Probability**

(Response variable)	**Asymmetric Short-run coefficients**		**Standard Error**	**t-Statistics**	
	D(LTCI (-1))	0.4762	0.05709	8.341352	0.0000
	D(LTCI (-2))	-0.0249	0.065194	-0.37885	0.7054
	D(LTCI (-3))	0.1481	0.052342	2.830908	0.0054
	D(LSAVI-POS)	-0.1446	0.054725	-2.643472	0.0092
	D(LSAVI-POS(-1))	-0.2011	0.056437	-3.564143	0.0005
	D(LMOP)	-0.2053	0.054798	-3.746789	0.0003
	D(LEPU_POS)	-0.0002	0.000149	-1.417197	0.1589
	D(LEPU_NEG)	0.000039	0.00022	0.17799	0.859
	D(LEPU_NEG(-1))	0.00013	0.000237	0.548816	0.5841
	D(LEPU_NEG(-2))	-0.00023	0.000217	-1.092648	0.2766
	D(LEPU_NEG(-3))	-0.00058	0.000238	-2.447728	0.0157
	D(LM2)	-0.1965	0.173158	-1.135358	0.2583
	D(LM2 (-1))	0.2035	0.181393	1.122111	0.2639
	D(LM2 (-2))	0.3958	0.173589	2.280418	0.0242
	D(LDMR_POS)	0.5408	0.119456	4.527484	0.0000
	D(LDMR_POS(-1))	-0.2231	0.112363	-1.985656	0.0492
	D(LDMR_NEG)	-0.6088	0.15758	-3.863562	0.0002
	D(LDMR_NEG (-1))	-0.6062	0.168135	-3.60519	0.0004
	CointEq (-1)*	-0.122	0.016607	-7.348714	0.0000

Source: Author's Estimation (2023).

5.14.1.2 NARDL Model Asymmetry Test (Analysis of Short-run Relationships)

The error correction models are estimated as a result of the cointegrated long-run relationships and are given in Table 6.3. The output illustrates the short-run relationship and also the speed of adjustments of the models back to equilibrium. The t-bounds statistics shows that the error correction terms (ECT) of the models were significant as the t-statistics is greater than the lower and the upper bound t-values at 1% significance level. The negative value and the significance at 1% level indicate the ECT confirms an existence of a long-run relationship.

The value -0.0594 and -0.1220 represent the ECT of the LTCI-(ARDL) and the LTCI-(NARDL) respectively. This indicates that at any disequilibrium there is a correction back to equilibrium monthly at a rate of 5.94% and 12.20% for the ARDL and the NARDL model, respectively. This indicates that the adjustment speed of NARDL model is significantly double, compared to the ARDL. These results show that only negative impact of South Africa volatility index, Domestic market return, Economic policy uncertainty, Trade openness, Manufacturing output and Money supply have a significant short-run effect on total connectedness index.

Due to the robustness and the effectiveness of the NARDL model over the ARDL model and based on the information criteria. This study chooses the nonlinear autoregressive lag distribution lag as the most appropriate model and the conclusions on this objective will be based on the NARDL model. The result of the asymmetric test further strengthens the selection of the NARDL model over the ARDL.

5.15 DIAGNOSTIC TEST

5.15.1 CUSUM and CUSUM Q Tests

The cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals (CUSUMSQ) test established by (Brown, Durbin and Evans, 1975) are used to investigate the stability of the long-run and short-run coefficients obtained from the ARDL framework. The residuals' CUSUM test and the CUSUMQ, which is plotted in Figure 5.9 and Figure 5.10 respectively shows that the residuals remain firmly inside the red borderline boundary at the 5% level, while the model iterates through the observations of the whole sample of monthly values, suggesting that they are stationary. Hence, the plot depicts that both the short-run and the long-run coefficients estimated are stable.

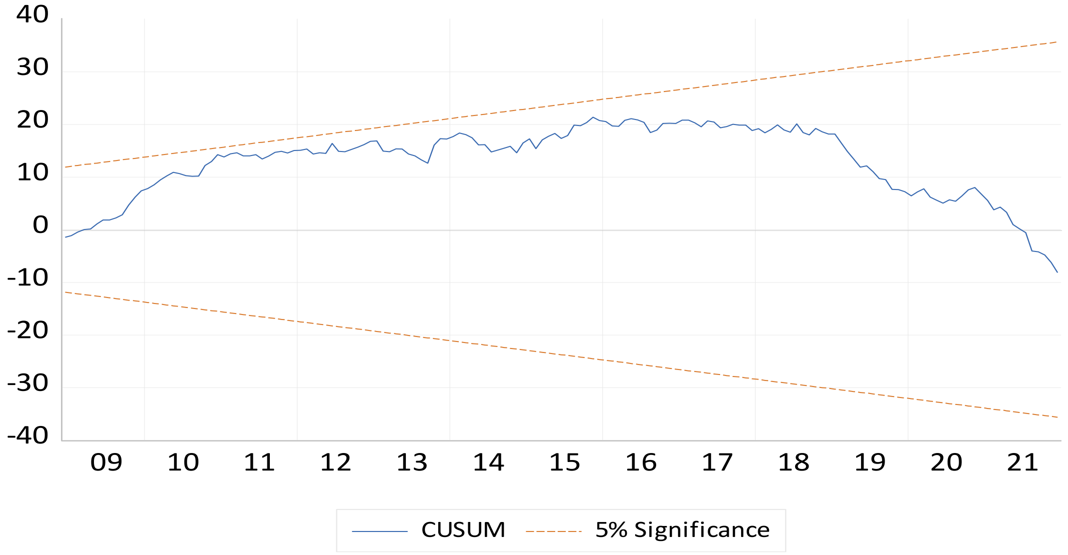


Figure 5.9: CUSUM Plot of Residual

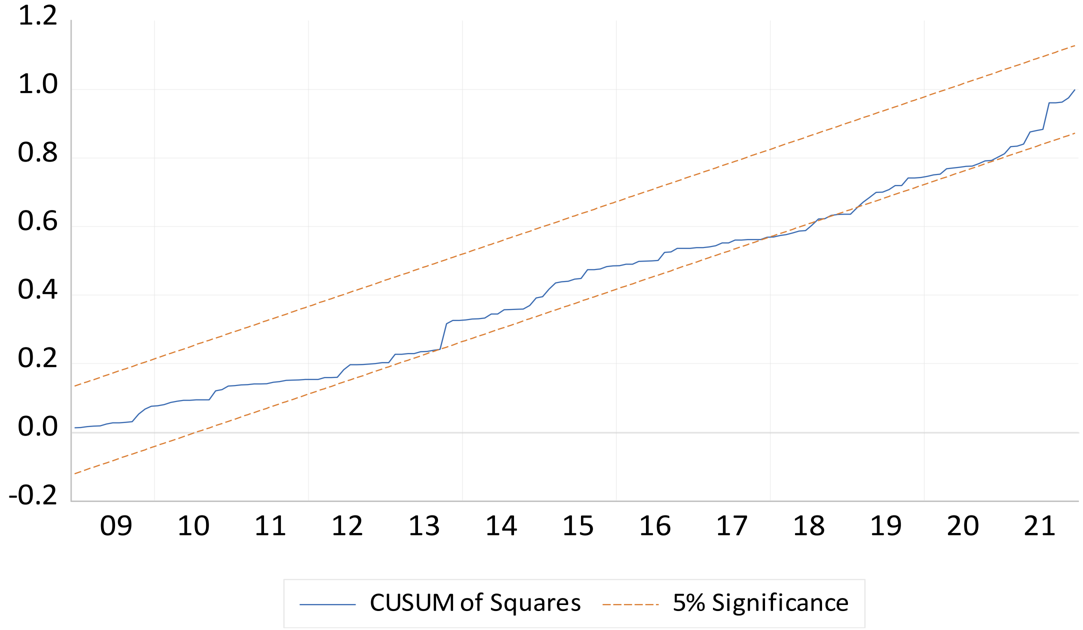


Figure 5.10: CUSUM of Squares Plot of Residual

5.15.2 NARDL Multiplier Graph

The NARDL multiplier graph test enables the study of the movement of both the positive and negative changes of the decomposed independent variables in the NARDL model. In addition, the graphs enable a view of if there is asymmetry in the model or in the decomposed independent variables. Figure 5.11, Figure 5.12 and Figure 5.13 show the multiplier graphs for LSAVI, LEPU and LDMR, respectively.

Note: The black line represents the movement of the independent variable, due to a positive change in the dependent variable LTCI. The dotted black line represents the movement of independent variable due to negative changes in the dependent variable LTCI. In addition, the dotted red line represents the asymmetry plot, while the dotted thin red line represents the confidence band.

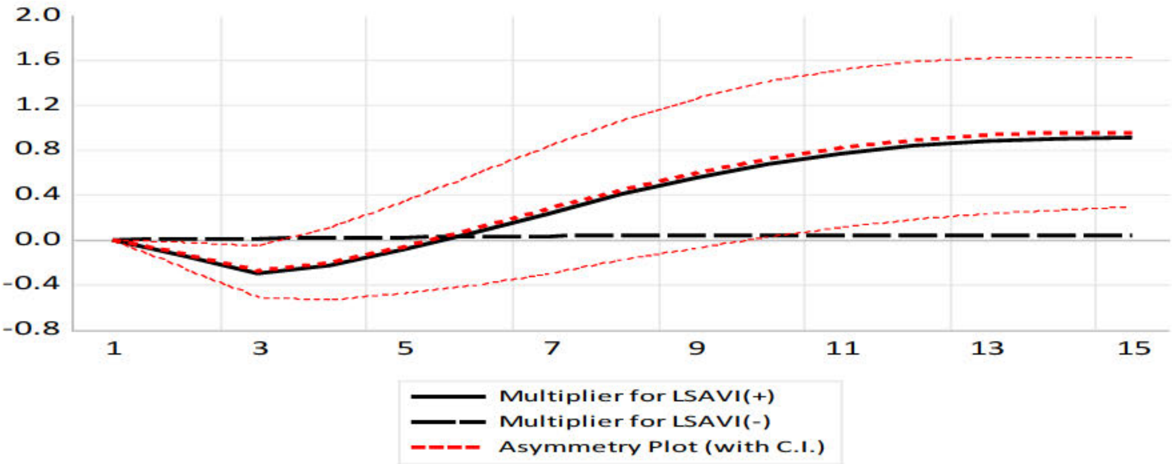


Figure 5.11: Multiplier Graph for LSAVI

Source: Author's Estimation (2023)

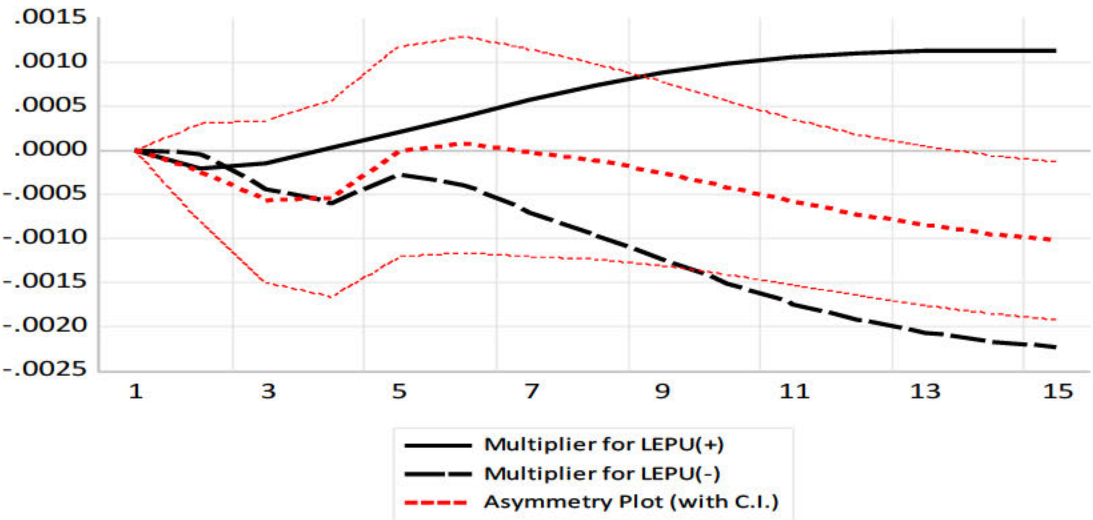


Figure 5.12: Multiplier Graph for LEPU

Source: Author's Estimation (2023)

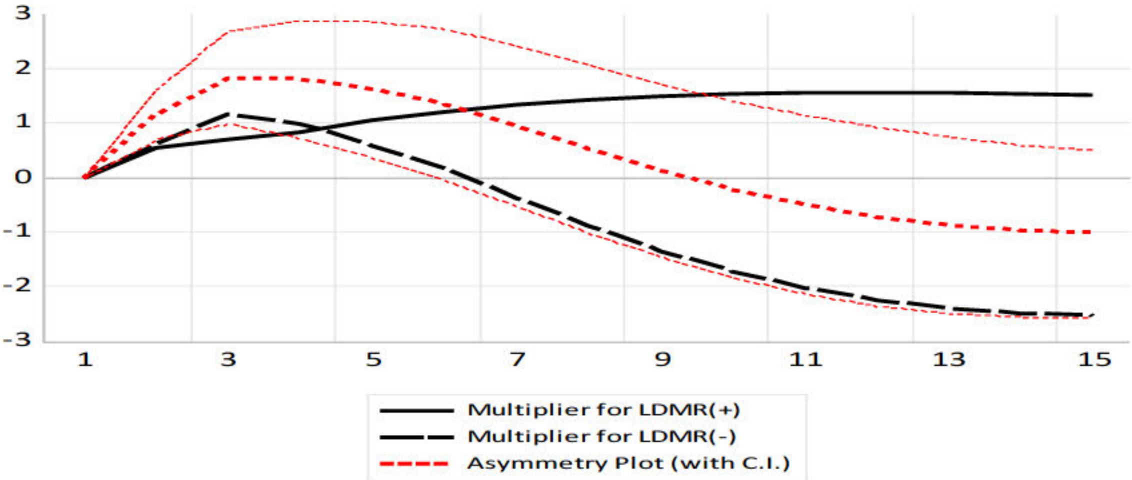


Figure 5.13: Multiplier Graph for LDMR

Source: Author's Estimation (2023).

Figure 5.11 shows that the independent variable (LSAVI) responds positively to a positive shock of the dependent variable (LTCI). The dotted black line indicates that the independent variable (LSAVI) responds with a relatively constant movement just a little above zero (0) to a negative shock in the dependent variable (LTCI). This signifies that the magnitude of the positive shock is stronger in the independent variable (LSAVI). Also Figure 5.11 shows that the on the long run the positive changes in the independent variables are more prominent compared to the short run. Even though at the short run the positive change in the independent variable responded negatively to a shock in the dependent variable. However, in comparison, the shocks have a positive stronger impact on the long run. The asymmetry plot indicates that there is no asymmetry in the dependent variable LSAVI.

Similarly, Figure 5.12 reveals that the dependent variable (LEPU (-)) responds positively to a positive shock in the dependent variable. In the opposite direction, the dotted line movement signifies that the independent variable (LEPU (-)) responds negatively to a negative shock in the dependent variable (LEPU). This implies that the magnitude s in the magnitude of the negative shock is stronger in the independent variable (LEPU). In the long run it shows that the negative changes in the independent variable (LEPU) are more relatively more prominent compared to the short run. However, at the short run the positive change in the independent variable (LEPU) responded negatively to a shock in the dependent variable (LTCI). The graph also reveals that there is no asymmetry in the variable (LEPU), since the asymmetry plot lies in between the confidence bands.

Finally, as depicted in Figure 5.13, the independent variable (LDMR) responded positively to a positive shock of the dependent variable (LTCI). Moreso, the dotted black line indicates that the independent variable (LDMR (-)) responded positively to a negative shock in the dependent variable (LTCI), but on the long run there was a negative response in the variable. Figure 5.13 shows that the on long run the negative changes in the independent variables are more prominent compared to the positive change. Even though at the short run the positive and the negative change in the independent variable responded positively to a shock in the dependent variable (i.e. both movements are above zero). However, in comparison of the long run and the short run, the shocks are likely to have a stronger impact. The asymmetry plot indicates that there is no asymmetry in the dependent variable LDMR.

5.14.3 NARDL Asymmetry Test

Following the multiplier graph test, the next test is the asymmetry test. The NARDL asymmetry test is a co-efficient diagnostic test, which uses the WALD test co-efficient restriction to test for the asymmetric properties of each coefficient in both the long run and the short run model or relationships. The null hypothesis of the Wald test implies that the relationship between the dependent variable, logarithm of total volatility connectedness index (LTCI) and the decomposed independent variables, log of South African Volatility Index (LSAVI), log of Economic Policy Uncertainty Index (LEPU) and log of Domestic Market Returns (LDMR) is symmetric in the long- and short-run. Whereas the alternative hypothesis states that there exists an asymmetric relationship between the dependent variable (LTCI) and independent variables (LSAVI), (LEPU) and (LDMR).

The test establishes whether the partial sums of the decomposed independent variables components are necessary, hence, significant. Table 6.4 shows the result of the long run and the short run of the WALD test and also the strong asymmetry test[20]. The evidence indicates strong evidence of asymmetric effects in the long run and short run in independent variable LSAVI indicated by significant coefficients of their F-statistic of 4.6886, 15.0305 and 17.7062 for the long run, short run and the strong asymmetry test respective respectively with corresponding p-value of 0.0322, 0.0002 and 0.0000 all significant at 1% level.

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[20] Strong asymmetry test models the combination of the long run and the short run asymmetry test.

Table 6.4: NARDL Asymmetry Test Result.

SN	Independent Variables	F-Statistics	P-value
1	**LSAVI**		
	Long Run Asymmetry test	4.6886	0.0322
	Short Run Asymmetry Test	15.0305	0.0002
	Strong Asymmetry Test	17.7062	0.0000
2	**LEPU**		
	Long Run Asymmetry test	4.3923	0.0381
	Short Run Asymmetry Test	11.235	0.0011
	Strong Asymmetry Test	11.2328	0.0011
3	**LDMR**		
	Long Run Asymmetry test	1.4647	0.2284
	Short Run Asymmetry Test	15.3577	0.0001
	Strong Asymmetry Test	14.1325	0.0003

Source: Author's Estimations (2023).

The second decomposed independent variable log of Economic Policy Uncertainty Index (LEPU) reveals strong evidence of asymmetric effects in the long run, short run and strong asymmetry effect. The result gave a F-statistic of 4.3923, 11.235 and 11.2328 for the long run, short run and the strong asymmetry test respective respectively with corresponding p-value of 0.0381, 0.0011 and 0.0011 all significant at 5%, 1% and 1% levels, respectively. Finally, the decomposed LDMR gave an F-statistic value of 1.14647, 15.3577 and 14.1325 for the long run, short run and strong asymmetry test, respectively. These gave a p-value of 0.2284 for the long-run test, which is not significant, however p-value of 0.0001 and 0.0003 value for the short run and the strong asymmetry tests both significant at 1% level.

Therefore, the WALD test shows the rejection of the Null hypothesis of symmetric effects and the acceptance of the alternative hypothesis of asymmetric relationships between LTCI and independent variable LSAVI and LEPU at the long run, short run and the strong asymmetry test. Furthermore, there is a non-rejection of the null hypothesis of a symmetric effect of LTCI and LDMR in the long run, however the study accepts the alternative hypothesis of an asymmetric relationship between LTCI and the variable LDMR at short run and strong effect asymmetry. This suggests that the partial sums decomposition of log South African Volatility Index and the log of Economic Policy Uncertainty Index in the long-run and in the short run is important for determining the sectorial total volatility connectedness index (LTCI) on the JSE market. In contrast, the decomposition of log of domestic market returns in the short run, is only important for determining the sectorial total volatility connectedness index (LTCI) and has symmetric effects on the sectorial total volatility connectedness index of the JSE market on the long run.

In summary, both the results of the ARDL and NARDL would be specifically discussed. The ARDL results shows the bound test which an important because it helps to eliminate the problem of serial correlation and endogeneity of variables (Rahman & Kashem, 2017). The ARDL result also reveals the error correction term (ECT) which captures the long run relationship between the variables and their coefficient. The coefficient measures the speed of adjustment to long run equilibrium in the presence of any shock to the system. The result from Table 6.3 shows that the ECT is (-0.0594), which is negative and significant at 1% level. This means it would take the model a speed of 5.94% for an adjustment back to equilibrium. It is also revealed that the F-statistic of the model is 3.49 which is greater that the upper bound of 3.28 at 5% significance. The ARDL result also reveals an adjusted –squared of 97.9% Therefore, this study confirms that there is cointegration between logarithm of total sectorial volatility connectedness index and logarithms of the independent variables South African Volatility index, manufacturing output, Economic policy uncertainty, Money supply, Trade openness and Domestic market returns; hence, suggesting a long-term nexus between the independent and dependent variables.

The NARDL results reveals an ECT of (-0.122), which is significant at 1% level, which is a speed of adjustment of (-12.2%) to equilibrium. This shows the existence of a long-term relationship between the dependent variable (LTCI) and the independent variables (LSVI), (LMOP), (LEPU), (LM2), (LTO) and (LDMR). The bound test of the NARDL model shows that an asymmetric relationship between the independent and dependent variables. The long run model from Table 6.2 reveals the decomposed independent variables are SAVI_POS, SAVI_NEG, LEPU_POS, LEPU_NEG and LDMR_POS, LDMR_NEG. These variables were further tested for asymmetric through the WALD test.

5.16 SUMMARY OF CHAPTER

This chapter is to provide the empirical result and interpretations of the models that are estimated in this study. The purpose of this chapter is to show the results of the objectives, hence, providing answers or solutions to the research questions which serve as motivations for the study. The aims of the chapter are to achieve the empirical objectives of the study which are to: Determine the systemically important super sectors within the JSE. Secondly, determine equity return linkages of JSE super sectors. Third, examine shock propagation and connectedness among JSE super sectors during extreme risk events (2008/2009 GFC, European debt crisis and the China-US trade war). Forth, evaluate the determinants of connectedness of JSE equity super sector super on the JSE.

First, this chapter reveals the results of the descriptive statistics in order to show how well the sectorial data is suited for the objectives. After this the chapter present the Insurance and the Energy super sectors as the highest ranked super sectors amongst the network of sectors for the full sample period and for the GFC period respectively. The Telecommunication is revealed as the highest ranked super sector during the EDC period. Lastly the Telecommunication super sector also has the highest score for the US-China trade war and the COVID-19 pandemic periods respectively, hence making each of these super sectors as a systematically important super sector for the network of super sectors on the JSE during the different periods.

Subsection (5.5) reveals the analysis of the equity equicorrelation of the super sectors. The result shows that univariate GARCH model rightly explains that there is high persistence in the volatility of the sectorial returns and their conditional volatility is mean reverting. Also, the DECO estimations shows that there is a high degree of integration suggestive of persistence correlation among the super sectors. In addition the rolling window analysis shows that return equicorrelation among the super sectors is time-varying. This result reveals that the year 2007-2008 which is the period for the GFC has an equicorrelation of 0.5528, the year 2009-2010 which is the period for the EDC has an equicorrelation of 0.2278, the year 2018-2019 which is the year for the U.S-China trade war has an equicorrelation of 0.2184 and finally, the year 2020-2021 which is the period of for the COVID-19 pandemic has an equicorrelation of 0.7022. These adverse periods are the periods with the most significant equicorrelation. The implication of these helps to answer the research question two; do JSE equity super sector returns have a common equicorrelation and does the equicorrelation change over time? The result evidently answers this question that indeed there is a high and common equicorrelation on the JSE and the equicorrelation do change over time.

Segment (5.6) reveals interesting volatility connectedness results. It shows that the conditional total connectedness index for the extreme periods is significantly high with the GFC, EDC and the COVID-19 pandemic periods showing a TCI of over 70% with the exception of the U.S-China trade war with a TCI of about 47%, hence, lower to another extreme period. The TCI for the entire sample period is over 69%, which is also significantly high. The high TCI s is a confirmation of a significant volatility connectedness amongst the sectors on the JSE. Also, the connectedness of each extreme and full sample period results reveals that:

- Full sample: Energy and Automobile and Parts super sectors as the biggest risk/shock transmitters and receivers, respectively.
- GFC period: Automobile and Parts, and Health super sectors as the biggest risk/shock transmitters and receivers, respectively.
- EDC period: Automobile and Parts and the Chemical super sectors as the biggest risk/shock transmitters and receivers, respectively.
- U.S-China Trade war period: Automobile and Parts and Insurance super sectors as the biggest risk/shock transmitters and receivers, respectively.
- COVID-19 period: Financial and General Industrials super sectors as the biggest risk/shock transmitters and receivers, respectively.

This further reveals that energy super sector is the highest net-transmitter of shocks with a value of (+13.00) during the full sample periods and transfer this shock (thick edges) to general industrials, technology and automobile and parts super sectors. The Automobile and Parts super sector is the highest net-transmitter of shock during the GFC with a value of (+35.80) and poses more this shock (thick edges) to Technology, Health, General Industrials, Chemicals and telecoms super sectors with the evidence of thicker edges compare to other super sectors which it transmits shocks to. Similarly automobile and parts also has the highest net-transmitter during the EDC period with a value of (+19.22) and poses more shock (thick edges) to Technology, Health and Insurance super sectors. Furthermore, Automobile and Parts is the highest net-transmitter for the US-China trade war period with a value of (+51.20) and poses more stronger (thick edges) shocks to Energy, Financials, Technology, Chemicals, Insurance, Finally, the Financial super sector has the highest net-transmitter of shocks during the COVID-19 period with a value of (+22.65), posing more shocks General Industrial, Insurance and Telecommunication super sectors. The implication of this evidence is helpful for changing diversification opportunities and options during different extreme events.

Finally, it was found in subsection (5.8) based on the NARDL results that the South African Volatility index, Economic Policy Uncertainty and Domestic Market Returns possess as significant determinants of sectorial volatility connectedness index on the JSE. This suggests that the partial sums decomposition of log South African Volatility Index and the log of

Economic Policy Uncertainty Index in the long-run and in the short run is important for determining the sectorial total volatility connectedness index (LTCI) on the JSE market. In contrast, the decomposition of log of domestic market returns in the short run, is only important for determining the sectorial total volatility connectedness index (LTCI) and has symmetric effects on the sectorial total volatility connectedness index of the JSE market on the long run.

CHAPTER 6: DISCUSSION OF FINDINGS

6.1 INTRODUCTION

Haven empirically determine the systemically important super sectors within the JSE in objective one of this study, followed by determining the equity return linkages of JSE super sectors for objective two and, thirdly, having examined the shock propagation and connectedness among JSE super sectors during extreme risk events (2008/2009 GFC, European debt crisis, the China-U.S trade war and the U.S-China trade war and, finally, evaluating the determinants of connectedness of JSE equity super sector on the JSE for the forth objective of this study, this chapter is devoted to discussing the main findings from the results of each objective. The discussion is based on the linkage between the findings of this study and the findings of the possible existing studies and the proposition of the relevant theories. The discussion of the result is in relation to the literature in previous studies for each objective.

6.2 DISCUSSION OF PAGERANK RESULTS (SYSTEMATICALLY IMPORTANT SUPER SECTORS)

The concept of 'too-big-to-fail' or 'too-central-to-fail' is commonly applied when categorising financial institutions into a group, whose failure could trigger a network of financial crisis to the whole financial system of an economy. This group of institutions are called systematically important financial institution (SIFI), namely banks, insurance, or other institutions (FSB 2011). An extension of this concept is what is known as 'too central to fail'. This concept investigates financial institutions network structures, which enhance their important influence on the entire financial system (Yun, Jeong, & Park 2019). This study investigates the 'too-central-to-fail' theory in the context of the South African economic sectors on the JSE by determining the centrality of the super sectors on the JSE, for the entire sample period and the four different extreme periods/events namely the Global Financial Crisis of 2007-2008 (GFC), the European Debt Crisis of 2009-2011 (EDC), the U.S-China Trade War of 2017-2018 (U.S-China TDW) and, finally, the COVID-19 pandemic of late 2019 to 2021. This is a novel study in the South African context.

From the page rank estimation of the whole sample period, it is quite obvious that the Insurance super sector emerges as the highest, from Table 5.4 and Figure 5.1a, with a score of 0.172194, which places the super sector at the top of the ranking. The Telecommunication and General Industrial sectors come second and third in ranking, respectively. By implication this shows that the Insurance sector is the most important node during the full sample periods based on connections with other super sectors in the network. Hence revealing that the Telecommunication super sector receives the maximum number of shocks directly or indirectly from other super sectors during the full sample periods. The Health super sector which has the lowest score of 0.052157 during the full sample period, reveals that it is the most insulated super sector from shock due to its lowest score. In addition the result also shows how important the top three super sectors (Insurance, Telecommunication, and General Industrials) with the highest scores are in the entire South African economy due to the fact that they receive more shocks from the remaining super sectors; hence, their instability may cause a huge shock and disruption to the entire sectorial market.

The PageRank result was somewhat different when the four sub-periods were investigated. During the GFC, the Energy, Health and Technology super sectors come in as the first, second and third super sectors, being the highest ranking super sectors, indicating that the Energy super sector is the most vital node during the GFC and most systemically important super sector during the period, hence crucial to the stability of the other sectors in the economy during the GFC. This is contrary to the finding of Shen, Jiang, Ma, Wang and Zhou (2020) that the sectors of banks and nonbanks finance possess the top PageRank score, indicating their role as the buffer in turbulent periods. The proper functioning and stabilisation of the Energy, Health and Technology super sectors would be crucial to managing systematic risk in the South African Economy. The Chemical super sector, on the other hand is the most insulated from shocks due to its lowest rank during the GFC.

The PageRank result for the European debt crisis reveals its unique ranking for the sectors, as the Telecommunication, General Industrial and Financial super sectors occupy the top three highest ranks. Indicating that the Telecommunication super sector is the most systemic important node during the EDC. It is the node which receives maximum number of shocks due to its connections with other super sectors in the network during the EDC. The surprising result is observing the Financial super sector not occupying the top ranking during the EDC and the GFC as seen in literatures (Shen et al., 2020). Hirsch, Kanbur and Ncube (2014) reveals that the financial institution in South Africa especially the banks were able to weather the shocks from the sub-prime markets during the period of GFC due to their capitalization, and firm economic management policies in place. This is a possible reason why the financial institution occupies almost mid rank positions (4th and 3rd) during the GFC and EDC respectively, due to their relatively fair stability.

The COVID-19 pandemic PageRank result is similar to the EDC, as Telecommunication and General industrial occupies the first and second rank score, respectively, showing the vital role these two super sectors play in the stability of the whole economy within the JSE stock market and the economy at large. It reveals that the Telecommunication super sector is the most systemic important node during the COVID-19 period due to its connections with other sectors. The Insurance super sector came third in ranking, as this emphasises the form of security the super sector provides to the economy in reducing risk and cushioning the effect of losses within these super sectors in the face of crisis periods such as the COVID-19 pandemic. The Financial and Chemical super sectors are the least ranked sectors due to the fact that they are the least connected to another super sector.

The last sub-period is the trade war between the United States and China. The PageRank result shows that, similar to the COVID-19 pandemic results, the Telecommunication and the General Industrial super sectors are the first and the second ranked super sectors. This is due to the fact that the Telecommunication super sector is the sector with the highest connections with other super sectors; hence, the most systemically important node during the U.S-China trade war. Again, this depicts the central role the Telecommunication, General Industrial and Energy sectors play during crises or extreme periods in the South African economy. This result strengthens the facts that these super sectors are central to the stability (high connections from other sectors), proper functioning and management of systemic risk in the economy. Therefore Telecommunication, General Industrial and Energy super sectors are too central to fail in the South African sectorial system. The result leaves the Financial super sector as the least connected super sector in the network; hence, its lowest rank during this period.

6.3 DISCUSSION OF TIME VARYING EQUITY EQUICORRELATION RESULTS

One of the core motivations of this objective is to ascertain the evidence of sectorial integration and to determine the integration of the economic sectors through their JSE sectorial equity return equicorrelation in absolute form and over time. The results estimate DECO-GARCH model applied to achieve this objective reveals that there is high integration in the equity returns of the selected super sectors. The DECO-GARCH model established by Engle & Kelly (2012) is novel covariance matrix estimator that operates on the assumption that any pair of series are equicorrelated at every period but this correlation varies over time. Panel B of Table 5.8 shows the estimates of the DECO model is a welcome prove that there exists evidence of sectorial integration on the JSE within the estimated sample period. The average return equicorrelation ($\boldsymbol{\rho_{ij}}$) which has a value of 0.1830 which is positive and statistically significant is an indication that the super sectors on the JSE are highly integrated, hence, a shock received by one super sector could lead to similar direction in correlation with other super sectors. The result corroborates with (Bouri, Vo, & Saeed 2021, Hung 2021 & Umar et al., 2019).

The results from section 5.5.3 on the full sample size shows again that there is a positive high correlation among the super sectors, in order words, the super sectors are integrated. Therefore, it could suggest that the full sample sectors may not be an ideal vehicle for portfolio diversification. This simply means that it would not be advisable to have all the super sectors in an investment portfolio, suggesting that all super sectors' returns would possibly move in the same direction whether during good shocks or negative shocks. This could be positive for investors under a positive shock and possible loss when a negative shock impact on one super sector.

The graphical plot of the sectorial equicorrelations in Figure 5.3 provides evidence of variation in its time evolution through the full sample period. This confirms the fact that sectorial return equicorrelation on the JSE is time varying. In the context of the AMH, risk and returns are likely to change over time due to changing environmental conditions which may be economic, political, financial technological (Lo, 2017). It is quite obvious that sectorial correlation heightens during the GFC of 2007-2008 with equicorrelation of 0.5528 and also during the COVID-19 period with correlation of 0.7022, which are the two extreme periods from the graphical plot. These two crises obviously put the economy into stress and the returns of the super sectors during these periods are evidence of such stress. This result corroborates with Liu, Bouri and Jalkh, (2021), Cai, Tian and Hamori (2016) who confirms market integration during the GFC and the COVID-19 periods. Other significant periods of high equicorrelation, but lower than 2007-2008 and 2020-2021 are the periods 2008-2009, 2009-2010, 2015-2016, 2018-2019 and 2019-2020. These periods have minimum equicorrelation value of 0.2132 and highest of 0.2278. The period 2009 to 2010 was externally associated with the European debt crisis (EDC), which spanned into end of 2012 (Beker, 2014). There are a couple of internal and external economic factors that could be possible reasons for the relatively high equicorrelation in 2015-2016. Hence, in such a scenario where integration is higher during certain extreme periods and not in other periods, the former would suggest that contagion is present within the economics sectors, hence, not limited to international market.

Faure (2017) posits that the exposure of the South African economy to highly correlated external shocks, such as the drop in demand of commodities by China, resulted in declined iron ore price. In addition to this, there was the labour unrest from 2012 to 2015, which ultimately resulted in the closure of the mines and the suspension of coal and other mineral output. Together with this, mining products experienced a significant reduction of, on average, 60% (IMF, 2016). Furthermore, the pick of the 2017-2018 U.S-China trade war also came as an external shock to the JSE All Share Index, which was a measure of the economic sector performance. The JSE All Share came down by 1.53% with the JSE Top-40 also dropping by 1.64% due to volatility during this period (Cronje, 2019). Also Tencent's share price downward fluctuation as a response to Chinese economic vulnerability to the trade war (PKZNT 2018). Finally, the COVID-19 was a global phenomenon which held all economy to ransom with the South African sectors having their share of the crisis. These crisis events are a suggestive proof of how the South African super sectors moves in correlation with event from external market.

6.4 DISCUSSION OF SECTORIAL DYNAMIC VOLATILITY CONNECTEDNESS RESULTS (TIME-DOMAIN)

The main focus of this objective is to determine the connectedness among the super sectors on the JSE during extreme periods (2008/2009 GFC, European debt crisis and the China-U.S trade war and the COVID-19 period) and further determine the direction of propagation of shocks. This involves identifying the net-receivers and net-transmitters of shock during these periods and during the entire sample periods, by employing the connectedness matrix of Diebold and Yilmaz (2009, 2012, 2014) and the Time-varying Parameter Vector Autoregression model of Antonakis et al., (2018, 2020), to overcome the shortfall of rolling window sizes and the outlier's selection.

The findings of this objective reveal that the estimation result shows the average conditional total connectedness index (cTCI) of 69.74% over the sample period. However, this figure is less informative when compared to the TCI of the whole sample period from Figure 5.3, which fluctuates between 27.05% and 89.84% with sectors such as Automobile and Parts, Telecommunication, Insurance, Chemicals and General Industrials operating as net-receivers while Technology, Finance, Energy and Health super sectors are the net-transmitters. This result shows the characteristics of each super sector through a long period of time, identifying them as a risk taker or risk giver within the economy.

Furthermore, the result of dynamic connectedness during the GFC period reveals a value of 71.05% in TCI, which is the average realised volatility of risk spillover across all super sectors, which is higher than average TCI for the entire sample period, which varies with time. However, the average TCI of 71.05% during the GFC indicates that there is a large degree of interconnectedness and dependence among these super sectors. The result corroborates with Bouri, Lucy, Saeed and Vo (2021) who investigate the realised volatility of commodities with sample spanning over similar period. Billio et al., (2012) established that increased interconnections are a significant systemic risk indicator during financial crisis such as the GFC. Therefore, having a (cTCI) of 71.05%, 77.10% and 77.14% for the GFC, EDC and the COVID-19 periods respectively, coupled with how interconnected, these super sectors are through the network graph suggests an implication for systemic risk within the sectorial network.

In addition, the estimation result of this GFC period reveals that Telecommunication, Chemicals and Health super sectors are the net receivers of risk with Health super sector with the Health super sector with (-29.83%), which has the highest absolute-value and the net transmitters are Automobiles, Insurance, General Industrials, Energy and Finance during the GFC. This suggest that the net transmitters of risk which assume a cyclical nature with the South African economy transmit risk to other super sectors during this crisis period, while the sectors of Telecommunication, Chemicals and Health which are non-cyclical[21] absorbs the shocks transmitted during the crisis. This result corroborates with Chowdhury and Irfan (2022) who found that cyclical stocks are net-transmitters of risk in India stock market. It is not surprising that the Financial super sector is a transmitter of risk during the GFC, since the GFC originates from the financial sectors (Johnson et al., 2008).

In the EDC estimation of volatility connectedness, the risk transmitters are the super sectors of Automobile, Telecoms, Insurance and General Industrial while the risk receivers during are the

[21] Non-cyclical or defensive stocks are stocks which performance is not dependent of economic growth. Often, they out-perform the market when there is even slow growth in the economy (Cheng and Schmitt 2022). Examples of cyclical sectors in South Africa includes financials, industrials, energy, automobiles &technology (MSCI ACWI 2023).

Financial, Technology, Chemical, Health and Energy super sectors. According to Fuchs, M., Losse-Mueller, Strobbe and Witte (2012), South Africa, the region's largest economy by a wide margin with a developed and internationally integrated Financial sector, is both the most significant recipient of portfolio inflows and the biggest borrower from European banks. Late in 2011, there was a significant decline in portfolio inflows, which had an effect on currency and stock market performance. However, certain South African Tech operators had significant credit from the European Bank before the EDC and during the crisis the majority of them were obliged to look for new sources of finance to maintain a business that was already under pressure. The average amount of loan from foreign banks as a percentage of GDP is low in most African nations, but South Africa and some other smaller African nations, it exceeds 20%. (Fuchs, M., Losse-Mueller, Strobbe, & Witte, 2012). These are suggestive of the fact why the Financial super sector could be an external shock receiver during the EDC crisis and, hence, a distortion in the business value chain of these super sectors could be inevitable, as sectors close to them in the chain will be first to experience a distortion in their business flow.

Thus, portfolio flow reversals are a significant risk entry point for super sectors during the crisis. Global portfolio flows to Africa are decreased due to a lack of liquidity, rising risk aversion and a decline in bond and equities prices and market liquidity. Performance of the African equities market is correlated with portfolio flow rates. Bond markets are primarily driven by domestic capital, but some frontier markets, like South Africa and Ghana, also see a sizable amount of foreign investment. The majority of portfolio movements are sent to South Africa, where they account for a smaller percentage of overall investment, but significant enough to impact on the Financial, Telecommunication and other sectors who receives funds from the European Banks. This again is suggestive of the reason why the Finance super sector is the largest receiver of risk from other super sectors with a value of 79.17%, with a high average total connectedness index of 77.10% across all super sectors.

The average TCI for all super sectors during the U.S-China trade war stood at 47.35%, which is quite low compared to the GFC (71.05%) and the EDC (77.10%). This suggests that the impact of the trade war on the super sectors on the JSE is not as significant as during the two aforementioned crisis. As shown in Table 5.6.4, the risk receiving super sectors include Telecommunication, Insurance, Chemical, Technology, General Industrials and Health. One of the major channels of external risk transfer to the economy is through cumulative tariff effect via links in global supply chains Görg (2019). Moreover, Egger and Zhu, (2020) document that sectors which export products are first in line to receive negative shocks and other sectors which are directly or indirectly linked to them in the value chain are then affected. This suggest reason why from Table 5.6.4 some of the sectors that are net-receivers during this period are export-driven in nature, for example, general industrials, technology, telecoms and chemicals.

From the industrial and manufacturing point of view, negative shocks from the U.S.-China Ann could have more effect on companies majorly into production of finished or semi-finished goods, which employ items that are on the U.S high-tariffs lists, such as iron, machinery, steel and aluminium as raw materials. This was evident at the height of the trade war, ArcelorMittal SA and Hulamin, two significant suppliers of aluminium to Tesla (a U.S.-based electric vehicle and clean energy company), saw declines in their share prices of 5% and 4%, respectively (Kohnert 2018). Therefore, negative risk through sectors involved in the value-chain of production or manufacturing would be affected with the South African economy, hence, as suggested by the negative net volatility connectedness of the general industrials, telecoms, technology.

Among the net-transmitters of risk is the Automobile and Parts, Finance and Energy super sectors. Table 5.6.4 shows that Automobile and Parts has the highest self-volatility connectedness of 90.67% and also as the highest giver of risk with 51.2%. This is suggestive of the fact that the Automobile and Parts super sector is also directly involved in the production line and value chain export and import business, as South Africa remains one of the highest export and import partners with China and the U.S. (SA Oil, 2019, SCMP 2021).

The COVID-19 estimation result shows a total connectedness index of 77.14%, which is quite high and a reflection of how connected the super sectors were due to the pandemic. It is quite interesting to note the super sector with the highest single transmitter of shock is the Financial super sector with 101.99% TO-connectedness, in addition to a 79.34% FROM-connectedness (shocks from other super sectors, which is the 2nd highest among the super sectors) this is a reflection of its net-connectedness value of (+22.65%), which made the super sector the highest transmitter of shock within the system. This is due to the financial super sector acting as a buffer within the system. For instance, some of the major South African banks have put relief measures in place to assist clients that have been directly impacted by the COVID-19. One of these measures are in the form of payment holidays. This is a system where customers of the banks who are supposed to make their loan payments are given waiver for up to a period of three months on different products and services such as home and personal loans, credit card loans, vehicle asset finance, credit life insurance claims. Such delay in payment could put most banks in strenuous positions, even considering the fact the banks are one of the institutions mandated by the government to continue to carry out their operations despite the lockdown in the economy (FSCA 2021)

Equally we find that the general industrial become the highest receiver of shock from the system, with -44.64%. A critical explanation for this is the South African government declaring a state of national disaster on 15 March 2020 after cases of COVID-19 were detected in the country, the manufacturing industries are forced to shut down production with certain exemption to food, non-alcoholic beverages, hygiene and medical products. Hence, having a negative impact of the GDP (Ngarava et al., 2022).

One of the most important investigations of objective four of this study that is worth discussing is the identification of super sectors that pose more shock to other specific super sectors. This could have implications for changing diversification opportunities during different market event. As highlighted in the summary of chapter 5, through the network plot of the full sample period the Energy super sectors directly transfer more shocks (thinker edges) to general industrials, technology and Automobile and Parts super sectors. Also Automobile and parts transferring more shocks (thinker edges) to Technology, Health, General Industrials, Chemicals and Telecommunications super sectors during the GFC. In the EDC, the Automobile and Parts super sector also had more shocks (thicker edges) transfer to Technology, Health and Insurance super sectors, while during the U.S-China TDW same Automobile and Parts super sector transfer more shocks (thinker edges) to Energy, Financials, Technology, Chemicals, Insurance and finally, the Financial super sector transferring more shocks (thinker edges) to General Industrials, Insurance and Telecommunications super sectors during the COVID-19 period. This has important emphasis for the normal periods (full sample) and the crisis periods (the different crisis periods). First, investment in the Energy super sector in same portfolio with the above-mentioned super sectors which more shock could be avoided or reduced and diversification of investment portfolio with super sectors with (thinner edges) for example, Telecommunications and Insurance super sectors could be of better investment choice. The Insurance and Finance super sectors could be a safe haven for portfolio diversification with Automobile and Parts super sectors due to the far less shock (thinner edges) transfer to these super sectors in financial crisis events such as the GFC.

Similarly, the EDC is another finance-related crisis where portfolio diversification with Telecommunications could be considered given the fact that it is a super sector that received a far less shock (very thin edge) from Automobile super sector. Finally, since the Automobile and the Finance super sectors are sectors with greater shock exposure during the U.S-China TDW and the COVID-19 periods respectively, it could be a better investment choice to avoid portfolios that include these two sectors. This study differs from Vo (2023) and Dang, Nguyen and Vo (2023), who discovered volatility spillover across the Australian and Vietnam sectors respectively but did not investigate or identify the sectors that pose more shocks to other sectors as this study has emphasised, which calls for policy implications to protect those sectors that receive more shocks from other sectors, could be formulated to insulate them form heavy shocks from other sectors.

6.5 DISCUSSION OF DETERMINANTS OF SECTORIAL VOLATILITY CONNECTEDNESS RESULTS

The need to estimate the determinants of sectorial volatility connectedness is crucial; hence, this was investigated and the result was interesting. The t-Bounds results show that the models' error correction terms were significant and provide evidence for the short-run relationship. The ECT for both the linear and nonlinear short run models shows that there is a large correction back to the long run equilibrium (Brooks, 2014).

The discovery of long-run, short-run and strong asymmetry relationships between sectorial total volatility connectedness index and economic policy uncertainty (LEPU), South African volatility index (LSAVI), domestic market returns (LDMR), trade openness (LTO), Manufacturing Output (LMOP) and money supply (LM2) has enabled not just the discovery of determinants of sectorial connectedness, but has enhanced the estimation of the asymmetric properties of these determinants as its relates to the total volatility connectedness (LTCI) of the super sectors on the JSE market, through the Nonlinear Autoregression Distribution Lag model (NARDL). To the knowledge of the author, no study has investigated the determinants of (LTCI) nor employed the NARDL model to estimate the determinants of sectorial volatility connectedness, hence, making this objective unique with its findings.

The major findings of objective four of this study show that the South African Volatility index, Economic Policy Uncertainty and Domestic Market Returns are significant determinants of sectorial volatility connectedness index on the JSE market. This suggests that the partial sums decomposition of log South African Volatility Index and the log of Economic Policy Uncertainty Index in the long-run and in the short run is important for determining the sectorial total volatility connectedness index (LTCI) on the JSE market. However, the decomposition of log of domestic market returns in the short run and the strong asymmetric significant are only important for determining the sectorial total volatility connectedness index (LTCI) and have symmetric effects on the sectorial total volatility connectedness index of the JSE market on the long run. The significance of the strong asymmetry test puts the log of domestic market return in a sufficient position as a significant determinant of the sectorial volatility connectedness index of the JSE market.

The findings further established the fact that from all six independent variables, the impact of South African volatility index, Economic policy uncertainty and domestic market return on sectorial total volatility connectedness index was not only significant but also asymmetric in nature. Where the SAVI and EPU show to exhibit long run, short run and strong asymmetry significance, the LDMR reveals its significance only in the short run and the strong asymmetry test. It is interesting to note that the logarithm of Domestic market returns has the greatest effect on sectorial volatility connectedness, followed by the South African volatility index and the Economic Policy Uncertainty index, hence, these three variables significantly affect the volatility connectedness of the super sectors on the Johannesburg stock exchange market compared to others. The significance of SAVI and EPU result corroborates with (Shahzad, Kayani, Raza, Shah, & Al-Yahyaee 2018a, 2018b) who discovered selected market volatilities significantly explained overall spillovers across all credit industries and in connectedness between U.S. industry level credit markets.

The nonlinear autoregressive distributed lag (NARDL) or asymmetric ARDL model is employed to check the long- and short-run relationship between the dependent and independent variables in this objective; indeed, there is a long run significant relationship between the (LTCI) and independent variable LSAVI, LDMR and LEPU. This model’s constructive contribution is to simultaneously capture both short- and long-run relationships of variables with negative and positive nature of the relationship. The results of this objective confirm the long-run relationship between LTCI and LSAVI, LDMR and LEPU on the JSE market. These results have implications for sectorial stock market investors in South Africa. First, for the JSE market regulators there must be a conscious policy monitoring system to regularise or stabilise the fluctuations or volatility in the South African Volatility index, to give stability to the index, so as to ensure its use as a market timing tool and as an effective instrument to optimise returns on sectorial investment on the JSE market. Secondly, Ekeocha, Ogbuabor, Ogbonna and Orji (2023) assert that domestic EPUs in Africa are yet to have any impact on economic development. Hence, the result validates the need for government agencies to bring certainty and stability in economic policies, which directly impacts business and investment positively in South Africa, as this directly reduces sectorial volatility on the JSE market. Lastly, this study used domestic market return to proxy the FTSE/JSE All Share Index of the JSE. Hence, the consistency in performance and stability of the All Share index is a tool to effectively regularising the total volatility connectedness index of the JSE.

The significance of domestic market returns in determining sectorial volatility connectedness on the JSE is quite interesting and good news for both local and foreign market analysts and investors, since good news for the local stock market in terms of performance is positive feedback for investors. However, when domestic market return increases the positive impact on the sectorial total connectedness index is lesser to the negative impact it has on LTCI when compared to when DMR it increases, this result corroborates with by Longstaff, Pan, Pendersen and Singleton (2011).

6.6 SUMMARY OF THE CHAPTER

The findings of this study from each objective has been extensively discussed in this chapter. The study reveals that the super sectors on the JSE market assume different centrality scores, which is a basis for their ranking in reference to their systemic impact in the sectorial network. The study determined the return linkages of the selected super sectors on the JSE, the sectorial returns on the JSE is time-varying and it has a significant common equicorrelation. This study submits, through evidence from the literature and the findings, that the super sectors on the JSE are highly integrated. Hence, an external or internal shock could significantly lead to contagion within the whole sectorial network.

In terms of the volatility connectedness of the super sectors. This study establishes that the super sectors on the JSE have high volatility connectedness index during extreme periods or periods of economic turmoil, in addition to its being relatively high in the main sample period between 3 January to 31 December 2021. Estimation of the entire sample period reveals that JSE sectorial volatility index is on an average high, which is a call for concern for the relevant authorities. Furthermore indexes such as the SAVI, EPU and the domestic market return proxy by FTSE/JSE All-Share Index return should be closely measured because they are important determinants of sectorial volatility connectedness on the JSE market.

CHAPTER 7: SUMMARY AND CONCLUSION

7.1 SUMMARY

This study was motivated by the dearth of studies on JSE equity super sector equicorrelation in light of many recent extreme market events. Boako and Alagidede (2017) posit that developing and emerging economies has become the main drivers of global economic growth since the global financial crisis. Emerging markets such as South Africa offer diversification benefits to investors during global crises (Cayón & Sarmiento, 2020) as crises in advanced markets do not result in losses in these markets. However, South Africa's strong ties with other emerging and developed markets tend to expose its economy to external events. Given the attraction of the South African economy to foreign and domestic investments, it is important to shed light on the equity sector co-movement amidst recent and previous events such as the GFC, the EDC, the recent U.S-China trade war and the COVID-19 pandemic.

This study consists of seven chapters, namely the introduction, theoretical review, empirical literature review, data and methodology, data analysis and interpretation of result, discussion of findings and, lastly, summary and conclusion. The study primarily contributes to the body of knowledge by presenting the systemically important super sectors in the sample period and in the individual crisis periods. Second, an account on how connected the realised volatility of the sectorial returns of the JSE was revealed, thirdly, the dynamic equicorrelation of the JSE market was established and, lastly, the study determined the explanatory variables for the sectorial volatility total connectedness index in the market.

The first chapter of this thesis provides the background, the problem of the study and motivation for the study, based on the need to reveal the systematically important super sectors, determine the dynamic equicorrelation of the super sectors, evaluate the level of volatility connectedness of the economic sectors and establish the determinants of total sectorial volatility connectedness of the JSE. Therefore, the chapter also provides the justification and the main objectives of the study.

Chapter 2 starts with the theoretical layout and background concepts for the study through extensive review of the major theories on returns and volatility connectedness, contagion in assets market, the MPT (Markowitz, 1952), the concept of assets and market integration and in general how these theories have been employed to support the objectives of this study and eventually to yield the result of the objectives. This chapter explores the MPT and how it helps in understanding portfolio diversification and underpins one of the objectives of this study. For example, by holding a portfolio or asset from a sector with a low level of correlation or equicorrelation, risk can be minimised. In addition, the theoretical concept of contagion, which reveals the crisis-contingent theory, the non-crisis-contingent theory and the fundamental view and the financial view coordination view are used to expatiate on connectedness of asset or equity, which are relevant for understanding the objective three of this study.

Chapter 3 gives insight into the detailed empirical literature that revolves around this study. First, is the documented literature on systematically important institutions, PageRank on equity and market, the 'Too big to fail/Too central to fail' (PageRank) centrality measure and literature on contagion. The empirical literature informs that there is a possibility between two or more markets to be interdependent on each other and this interdependency can bring contagion through negative shock from either of the markets. Additionally, the studies on time-varying equicorrelation were adequately expatiated. Furthermore, empirical literature on the studies of dynamic connectedness in Euro-area and the U.S, in the emerging economies or nations and the African economies are documented. The chapter also provided extensive literature on studies that have employed the PageRank algorithm in relation to centrality of assets and institutions. Hence, the literature indicates that there exists a research gap in the area of sectorial ranking, even globally. The objective two of this study helps to cover the research gap in the study of dynamic equicorrelation. In the South African context, no study has been done to fill the gap. Objective three fills the gap in the African and South African context of sectorial dynamic volatility connectedness. Moreover, objective three of this study helps to reveal the major super sectors which pose more direct shocks to specific super sectors through the edge-widths, as revealed by the network plot under different extreme periods. Finally, the study reveals the results of studies on the determinants of total connectedness index, which help to unveil the drivers or factors responsible for sectorial volatility connectedness on the JSE market.

Chapter 4 contains the full description of the methodology and empirical models, which are employed to achieve the objectives of the study. Objective one employed the Page et al., (1999) model alongside the Granger causality measure of Billio et al., (2012) to determine the systemically important equity super sectors at different periods. The DECO-GARCH model was employed to achieve objective two, which involves the investigation of time varying equicorrelation on the JSE sectorial market. For objective three, this study employed the Diebold and Yilmaz (2009, 2012, 2014) connectedness index alongside the novel TVP-VAR model established by Antonakakis et al., (2019), to substitute the rolling window approach and, finally, the nonlinear autoregression distributed lag (NARDL) was deployed to estimate the determinant of sectorial volatility connectedness index.

In Chapter 5, the results of centrality scores of the JSE equity sectors relating to objective one are presented, revealing that the Insurance and Energy super sectors are most systemically important super sector during the full sample periods and the GFC, respectively. While the Telecommunication super sector is the most systemically important super sector for the EDC, the U.S-China trade war and the COVID-19 pandemic period, respectively. From the second objective, the absolute and time-varying equicorrelation of the JSE equity super sectors are presented showing that the common equicorrelation value of the super sectors is positive and high, confirming that the super sectors on the JSE are integrated. Objective three reveals that the total sectorial volatility dynamic connectedness is high for the whole sample periods, the GFC, the EDC and the COVID-19 pandemic periods. Also, objective three results shows that some super sectors are revealed as net-receivers and some as net-transmitters of shocks during extreme market periods. Finally, the results relating to objective four reveals that SAVI, EPU and IDMR have asymmetric properties as a determinant of total sectorial dynamic volatility connectedness on the JSE market.

7.2 CONCLUDING REMARKS

The objective of this study is first to determine the systemically important super sectors within the JSE, followed by determining the equity return linkages and to ascertain if the equicorrelation is time-varying. Third, this study examined the connectedness and shock propagation among JSE super sectors during extreme risk events (2008/2009 GFC, European debt crisis, the China-U.S. trade war and the U.S-China trade war and finally, investigated with the determinants of sectorial dynamic volatility connectedness of JSE equity super sector.

The PageRank score shows that the Telecommunication super sector is the most ranked super sector for the entire sample periods and throughout the extreme periods with the exception of GFC which has the Energy super sector as the highest ranked super sector. Therefore, the following super sectors are top ranked for each period: Insurance (full period), Energy (GFC), Telecommunication (EDC), Telecommunication (U.S-China TDW) and Telecommunication

(Covid-19). This means that the Telecommunication super sector carries a weight of (23.42%), (16.36%), and (28.27%) for the U.S-China trade war, the EDC and the COVID-19 pandemic period, respectively. While the Insurance and the Energy super sectors carry a weight of (17.21%) and (15.56%) for the full sample and the GFC periods, respectively. This study concludes that the identification of the nodes (super sectors) that are central to systemic risk are important for policy direction for protection and proper administration during extreme events in South Africa. Employing their volatilities to study their centralities informs policy makers of the possible signs or outcomes to expect during crisis, which can be incorporated into their returns.

Moreover, this study reveals that there exists connectedness in the realised volatility in the selected economic sectors on the JSE. The notion that sectors are interconnected is real and empirically confirmed in this study. Through the realised volatility computed from sectorial returns, the total connectedness through the whole sample period and the different extreme period investigated in this study showed that total connectedness is dynamic with changes at different periods of events, but high. It can be concluded that the JSE equity super sector, as a whole, is integrated and one super sector is exposed to internal or external shock from the other. Also, the Energy and Automobile and Parts super sectors are the strongest net-transmitter of shocks for the full sample period, the EDC and U.S-China trade war, respectively. It is interesting to note that the Financial sector is the highest net-transmitter of shocks for the COVID-19 period. This helps to emphasise the importance on portfolio return maximisation. Super Sectors such as Energy, Automobile and Parts and the Financial could be selected in lesser weights or all three super sectors may not be allocated in the same portfolio to minimise their negative impacts on other super sectors. Furthermore, the results also confirm super sectors such as Financials as net transmitter of shock through three of the four extreme periods, namely during the GFC, the U.S.-China trade war and the COVID-19 pandemic crisis. This establishes the crucial importance of the super sector because instability of the Financial sector within the economy has a tendency to destabilise the entire economy. The position of the Financial super sector as a net transmitter of risk is also established from the result of the entire sample period as the Financial super sector remained a risk transmitter. Another super sector to be given consideration is the Automobile and Parts, which remains as a net shock or risk transmitter throughout the four extreme periods.

Notwithstanding, from the network graph super sectors such the Insurance, General Industrials and Financial super sector received a shock each from other super sectors while the Energy super sector received no shock at all during the GFC. While Telecommunications received one shock from a sector, both General Insurance and Automobile and Parts received no shock during the EDC. Similarly, during the U.S-China trade war the Health super sector received just one shock from one sector as General Industrials, Finance and Energy super sectors received no shocks from any super sectors. The COVID-19 period shows that the Chemical super sector received just one shock from one super sector. These results could have policy implications for changing diversification opportunities during different extreme events.

It also worthy to be noted that the high equicorrelation value from the DECO-GARCH model estimation should be considered. This is a sign of tendency of contagion to take effect whenever there is a prolonged negative shock into the market. Moreover, the study concludes that there exists a long run asymmetric relationship between sectorial total volatility connectedness index and local domestic market return, the South African volatility index and the economic policy uncertainty index, as these market indicators should be closely monitored for favourable policy implications.

7.3 CONTRIBUTIONS AND IMPLICATIONS OF FINDINGS

The objective of this study is first to determine the systemically important super sectors within the JSE, followed by determining the equity return linkages and to ascertain if the equicorrelation is time-varying and thirdly, examined the connectedness and shock propagation among JSE super sectors during extreme risk events (2008/2009 GFC, European debt crisis, the China-U.S. trade war and the U.S-China trade war) and, finally, investigate the determinants of sectorial dynamic volatility connectedness of JSE equity super sector.

This study contributes to the limited literature on systemically important equity sectors and sectorial dynamic connectedness and dynamic equicorrelation in the emerging market. Secondly, it shows that the sectorial common equicorrelation on the JSE is high and time varying with higher values for the year where extreme events occurred such as the GFC, EDC and the COVID-19 period. This result is also a revelation that during the period of financial or economic crisis correlation of sectors are high compared to non-crisis periods. Thirdly, the dynamic connectedness results show that the super sectors on the JSE are interconnected and a shock to one super sector can have a spillover effect on another close super sector in the value-chain. Fourthly, the South African volatility index, the Economic Policy Uncertainty and the Domestic Market Return are symmetrically and asymmetrically significant determinants of the sectorial volatility connectedness of JSE market. The implication of the high connectedness and equicorrelation findings could be a pointer to systemic risk. In addition, contagion among sectors, which usually affect international asset diversification can also affect domestic sectorial diversifications.

These findings from this study have implications for economic policy makers, portfolio and fund managers, foreign and local investors, sector regulators and researchers/academics in the field of finance. Based on the literature, the ranking of super sectors from this study suggests that a sector with a positive and high value denotes that the sector has a greater contribution to systemic risk in the network structure of sectors. Hence, the implication of the findings from the first objective of this study is that Telecommunication s super sector has a greater contribution to systemic risk and also central to stability of the whole economy and during extreme or crisis periods in the country. This study recommends that economic managers, policymakers and the government should develop policies early enough that could fortify and strengthen the business stability in the Telecommunication super sector. Furthermore, for policymakers a good understanding of super sectors that are central to the stability of the entire JSE sectorial market is valuable for crucial decision making.

The implication of the high connectedness and equicorrelation findings is that contagion, which usually affects international asset diversification can also affect domestic sectorial diversifications. Hence for portfolio managers if local investment portfolio formulation involving sectorial assets are poorly selected without adequate market information and empirical strategies, returns on investment could be negatively affected.

The findings of this study could be interest to sectorial investors who want to learn more about sectorial stock volatility and correlations, to assist them with better understanding of the sectorial market dynamics and making better investments, especially during extreme periods in building new diversification strategies in periods of financial and economic uncertainties. In addition the highly volatility connectedness and high return equicorrelation of super sectors may have a significant impact in inducing contagion effect across the JSE markets

In addition, this study reveals that a super sector does generate huge shock to itself as shown by the connectedness values allocated diagonally on the average connectedness tables for each period. Hence, this study further recommends that stronger governance and business risk administrations should be recommended to sectorial administrators, by government, to lessen internally-generated risk by a sector. Also the separation of super sectors into risk transmitters and risk receivers further reveals the importance of portfolio diversification. Having the right proportions of risk transmitters and risk receivers in a portfolio will be one of the best possible strategies in averting loss as the return lost due to shock from a super sector could be easily gained from other shock receiving-sector.

Finally, the determination of drivers of sectorial volatility connectedness is another contribution of this study. This study empirically contributes that the sectorial volatility connectedness index is driven by internal factors such as the South African volatility index, the local domestic market return, as well as economic policy uncertainty. For instance, a percentage increase in SAVI will cause an increase in LTCI by 0.8066 unit and a percentage decrease in SAVI will cause an increase in LTCI of the JSE by 0.0547 unit. Therefore, proper monitoring of these drivers by portfolio managers is important because any negative internal shock that affects any of these indexes or drivers will cause a change in the volatility connectedness index of the super sectors. Moreover, for sectorial investors and portfolio managers this result would enhance them with adequate information and understanding on the SAVI, EPU and the DMR as main drivers that triggers sectorial volatility connectedness on the JSE market. In addition policy makers would be well informed on the appropriate policy steps to take in to minimize propagation of shocks across the super sectors on the JSE market. To sum up on the contributions and implications, the degree of sectorial volatility connectedness index in any period should be closely monitored since it reflects how connected the super sectors are, in addition, it is empirically confirmed that connectedness and equicorrelation is time-vary on the JSE.

7.4 LIMITATIONS

Despite the achievement of the study objectives, this thesis has some limitations, which are common to research of this nature. First, the study examines nine super sectors/industries on the JSE, without considering some super sectors, which could have provided further information. However, the selected super sectors are still good enough to reveal the connectedness and the level of equicorrelation that exist on the JSE within the time period of analysis. Also the length of the period of analysis was chosen so as to cover the periods of extreme risk event such as the 2008/2009 GFC, the 2009-2010 EDC, 2017-2018 U.S.-China

Trade war and the 2019-2021 COVID-19, hence, the data range from 3 January 2006 to 31 December 2021. Yet some super sectors exist (e.g. real estate, utilities) where data are not available for this period, hence, data availability was a challenge in this study. In addition, due to same super sectors existing also as industry, for example, Energy, Telecommunications and Technology, the study selected such industries as super sectors for ease of data handling and collation.

7.5 SUGGESTIONS FOR FUTURE RESEARCH

Empirical work on dynamic connectedness and equicorrelation is fast gaining attention in finance and economics. Hence, there are still gaps to cover in research on this field. For example, more studies could be conducted on equities and commodities such as gold and other precious metals that have a strong influence on South African trade, to determine the extent to which these commodities are connected with the external commodities around the world.

Having investigated the determinants of the sectorial volatility connectedness index, it is of utmost importance to investigate the determinants of sectorial equicorrelation of the JSE, as this would enable the factors that could determine the correlation of assets and super sectors on the South African market at large. Global factors such as global policy uncertainty (GPU) could be investigated to determine their significance as a factor that could determine sectorial dynamic volatility connectedness on the JSE market. Furthermore, objective one of this study could be further researched by involving the returns series, for example using GARCH-adjusted returns. This would capture several properties of the returns of the super sectors

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APPENDICES

APPENDIX I: UNIT ROOT RESULT FOR NARDL VARIABLES

Null Hypothesis: EPU has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.962503	0.0020

Test critical values:	1% level	-3.464643
	5% level	-2.876515
	10% level	-2.574831

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(EPU)

Method: Least Squares

Date: 01/31/23 Time: 15:06

Sample (adjusted): 2006M02 2021M12

Included observations: 191 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EPU(-1)	-0.147751	0.037287	-3.962503	0.0001
C	4.240085	1.241281	3.415896	0.0008

R-squared	0.076704	Mean dependent var	0.116238
Adjusted R-squared	0.071819	S.D. dependent var	9.704728
S.E. of regression	9.349744	Akaike info criterion	7.318991
Sum squared resid	16521.95	Schwarz criterion	7.353046
Log likelihood	-696.9636	Hannan-Quinn criter.	7.332785
F-statistic	15.70143	Durbin-Watson stat	1.870014
Prob(F-statistic)	0.000105		

Null Hypothesis: D(LDMR) has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.02049	0.0000
Test critical values:	1% level	-3.464827	
	5% level	-2.876595	
	10% level	-2.574874	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LDMR,2)

Method: Least Squares

Date: 01/31/23 Time: 15:52

Sample (adjusted): 2006M03 2021M12

Included observations: 190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LDMR(-1))	-0.869026	0.072295	-12.02049	0.0000
C	0.002599	0.001272	2.043445	0.0424

R-squared	0.434573	Mean dependent var	-3.28E-06
Adjusted R-squared	0.431566	S.D. dependent var	0.022911
S.E. of regression	0.017274	Akaike info criterion	-5.268777
Sum squared resid	0.056096	Schwarz criterion	-5.234598
Log likelihood	502.5339	Hannan-Quinn criter.	-5.254932

F-statistic	144.4922	Durbin-Watson stat	1.988921
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LM2) has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.13246	0.0000
Test critical values:	1% level	-3.464827	
	5% level	-2.876595	
	10% level	-2.574874	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LM2,2)

Method: Least Squares

Date: 01/31/23 Time: 16:04

Sample (adjusted): 2006M03 2021M12

Included observations: 190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LM2(-1))	-1.018935	0.072099	-14.13246	0.0000
C	0.003028	0.000485	6.248711	0.0000

R-squared	0.515122	Mean dependent var	-7.61E-05
Adjusted R-squared	0.512543	S.D. dependent var	0.008528
S.E. of regression	0.005954	Akaike info criterion	-7.399109
Sum squared resid	0.006664	Schwarz criterion	-7.364930
Log likelihood	704.9153	Hannan-Quinn criter.	-7.385263
F-statistic	199.7265	Durbin-Watson stat	2.025911
Prob(F-statistic)	0.000000		

Null Hypothesis: LMOP has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.123810	0.0000
Test critical values:	1% level	-3.464643	
	5% level	-2.876515	
	10% level	-2.574831	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LMOP)

Method: Least Squares

Date: 01/31/23 Time: 16:05

Sample (adjusted): 2006M02 2021M12

Included observations: 191 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LMOP(-1)	-0.331484	0.054130	-6.123810	0.0000
C	0.659764	0.107774	6.121728	0.0000

R-squared	0.165567	Mean dependent var	-0.000136
Adjusted R-squared	0.161152	S.D. dependent var	0.026672
S.E. of regression	0.024429	Akaike info criterion	-4.575712
Sum squared resid	0.112787	Schwarz criterion	-4.541657
Log likelihood	438.9805	Hannan-Quinn criter.	-4.561918
F-statistic	37.50105	Durbin-Watson stat	2.066707
Prob(F-statistic)	0.000000		

Null Hypothesis: LSAVI has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.688122	0.0050
Test critical values:	1% level	-3.464643	
	5% level	-2.876515	
	10% level	-2.574831	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LSAVI)

Method: Least Squares

Date: 01/31/23   Time: 16:07

Sample (adjusted): 2006M02 2021M12

Included observations: 191 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LSAVI(-1)	-0.078792	0.021364	-3.688122	0.0003
C	0.103696	0.027307	3.797394	0.0002

R-squared	0.067138	Mean dependent var	0.006813
Adjusted R-squared	0.062202	S.D. dependent var	0.106434
S.E. of regression	0.103071	Akaike info criterion	-1.696379
Sum squared resid	2.007871	Schwarz criterion	-1.662324
Log likelihood	164.0042	Hannan-Quinn criter.	-1.682585
F-statistic	13.60224	Durbin-Watson stat	1.926703
Prob(F-statistic)	0.000295		

Null Hypothesis: D(LTCI) has a unit root

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.786672	0.0000
Test critical values:	1% level	-3.465202	
	5% level	-2.876759	
	10% level	-2.574962	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LTCI,2)

Method: Least Squares

Date: 01/31/23 Time: 19:58

Sample (adjusted): 2006M05 2021M12

Included observations: 188 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LTCI(-1))	-0.642740	0.094706	-6.786672	0.0000
D(LTCI(-1),2)	0.122907	0.081836	1.501865	0.1348
D(LTCI(-2),2)	-0.156515	0.070931	-2.206588	0.0286
C	-0.001551	0.001377	-1.126282	0.2615

R-squared	0.360112	Mean dependent var	-0.000170
Adjusted R-squared	0.349679	S.D. dependent var	0.023249
S.E. of regression	0.018748	Akaike info criterion	-5.094386
Sum squared resid	0.064675	Schwarz criterion	-5.025525
Log likelihood	482.8723	Hannan-Quinn criter.	-5.066486
F-statistic	34.51677	Durbin-Watson stat	1.950621
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LTO) has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

	t-Statistic	Prob.*

Augmented Dickey-Fuller test statistic		-13.78534	0.0000
Test critical values:	1% level	-3.464827	
	5% level	-2.876595	
	10% level	-2.574874	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(LTO,2)

Method: Least Squares

Date: 01/31/23 Time: 20:01

Sample (adjusted): 2006M03 2021M12

Included observations: 190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LTO(-1))	-1.005385	0.072931	-13.78534	0.0000
C	-0.009157	0.009077	-1.008852	0.3143

R-squared	0.502692	Mean dependent var	0.000000
Adjusted R-squared	0.500047	S.D. dependent var	0.176472
S.E. of regression	0.124779	Akaike info criterion	-1.314082
Sum squared resid	2.927100	Schwarz criterion	-1.279903
Log likelihood	126.8378	Hannan-Quinn criter.	-1.300237
F-statistic	190.0356	Durbin-Watson stat	2.000058
Prob(F-statistic)	0.000000		

Phillips-Perron Test

Null Hypothesis: EPU has a unit root

Exogenous: Constant

Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.974720	0.0019
Test critical values:	1% level	-3.464643	
	5% level	-2.876515	
	10% level	-2.574831	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	86.50234
HAC corrected variance (Bartlett kernel)	87.18030

Phillips-Perron Test Equation

Dependent Variable: D(EPU)

Method: Least Squares

Date: 02/01/23 Time: 15:22

Sample (adjusted): 2006M02 2021M12

Included observations: 191 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EPU(-1)	-0.147751	0.037287	-3.962503	0.0001
C	4.240085	1.241281	3.415896	0.0008

R-squared	0.076704	Mean dependent var	0.116238
Adjusted R-squared	0.071819	S.D. dependent var	9.704728
S.E. of regression	9.349744	Akaike info criterion	7.318991
Sum squared resid	16521.95	Schwarz criterion	7.353046
Log likelihood	-696.9636	Hannan-Quinn criter.	7.332785
F-statistic	15.70143	Durbin-Watson stat	1.870014
Prob(F-statistic)	0.000105		

Null Hypothesis: D(LDMR) has a unit root

Exogenous: Constant

Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-12.01311	0.0000
Test critical values:	1% level	-3.464827	
	5% level	-2.876595	
	10% level	-2.574874	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000295
HAC corrected variance (Bartlett kernel)	0.000293

Phillips-Perron Test Equation

Dependent Variable: D(LDMR,2)

Method: Least Squares

Date: 02/01/23   Time: 15:34

Sample (adjusted): 2006M03 2021M12

Included observations: 190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LDMR(-1))	-0.869026	0.072295	-12.02049	0.0000
C	0.002599	0.001272	2.043445	0.0424

R-squared	0.434573	Mean dependent var	-3.28E-06
Adjusted R-squared	0.431566	S.D. dependent var	0.022911
S.E. of regression	0.017274	Akaike info criterion	-5.268777
Sum squared resid	0.056096	Schwarz criterion	-5.234598
Log likelihood	502.5339	Hannan-Quinn criter.	-5.254932
F-statistic	144.4922	Durbin-Watson stat	1.988921
Prob(F-statistic)	0.000000		

Null Hypothesis: LMOP has a unit root

Exogenous: Constant

Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.128606	0.0000
Test critical values:	1% level	-3.464643	
	5% level	-2.876515	
	10% level	-2.574831	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000591
HAC corrected variance (Bartlett kernel)	0.000592

Phillips-Perron Test Equation

Dependent Variable: D(LMOP)

Method: Least Squares

Date: 02/01/23 Time: 15:39

Sample (adjusted): 2006M02 2021M12

Included observations: 191 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LMOP(-1)	-0.331484	0.054130	-6.123810	0.0000
C	0.659764	0.107774	6.121728	0.0000

R-squared	0.165567	Mean dependent var	-0.000136
Adjusted R-squared	0.161152	S.D. dependent var	0.026672
S.E. of regression	0.024429	Akaike info criterion	-4.575712
Sum squared resid	0.112787	Schwarz criterion	-4.541657
Log likelihood	438.9805	Hannan-Quinn criter.	-4.561918
F-statistic	37.50105	Durbin-Watson stat	2.066707
Prob(F-statistic)	0.000000		

Null Hypothesis: LSAVI has a unit root

Exogenous: Constant

Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.682072	0.0051
Test critical values:	1% level	-3.464643	
	5% level	-2.876515	
	10% level	-2.574831	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.010512
HAC corrected variance (Bartlett kernel)	0.010143

Phillips-Perron Test Equation

Dependent Variable: D(LSAVI)

Method: Least Squares

Date: 02/01/23   Time: 15:40

Sample (adjusted): 2006M02 2021M12

Included observations: 191 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LSAVI(-1)	-0.078792	0.021364	-3.688122	0.0003
C	0.103696	0.027307	3.797394	0.0002
R-squared	0.067138	Mean dependent var		0.006813

Adjusted R-squared	0.062202	S.D. dependent var	0.106434
S.E. of regression	0.103071	Akaike info criterion	-1.696379
Sum squared resid	2.007871	Schwarz criterion	-1.662324
Log likelihood	164.0042	Hannan-Quinn criter.	-1.682585
F-statistic	13.60224	Durbin-Watson stat	1.926703
Prob(F-statistic)	0.000295		

Null Hypothesis: D(LTCI) has a unit root

Exogenous: Constant

Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-9.826266	0.0000
Test critical values:	1% level	-3.464827	
	5% level	-2.876595	
	10% level	-2.574874	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000367
HAC corrected variance (Bartlett kernel)	0.000395

Phillips-Perron Test Equation

Dependent Variable: D(LTCI,2)

Method: Least Squares

Date: 02/01/23   Time: 15:42

Sample (adjusted): 2006M03 2021M12

Included observations: 190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LTCI(-1))	-0.632013	0.064986	-9.725352	0.0000
C	-0.001452	0.001401	-1.036461	0.3013

R-squared	0.334708	Mean dependent var	-0.000453
Adjusted R-squared	0.331169	S.D. dependent var	0.023547
S.E. of regression	0.019258	Akaike info criterion	-5.051352
Sum squared resid	0.069721	Schwarz criterion	-5.017173
Log likelihood	481.8785	Hannan-Quinn criter.	-5.037507
F-statistic	94.58248	Durbin-Watson stat	1.842532
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LTO) has a unit root

Exogenous: Constant

Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-13.78534	0.0000
Test critical values:	1% level	-3.464827	
	5% level	-2.876595	
	10% level	-2.574874	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.015406
HAC corrected variance (Bartlett kernel)	0.015405

Phillips-Perron Test Equation

Dependent Variable: D(LTO,2)

Method: Least Squares

Date: 02/01/23 Time: 15:45

Sample (adjusted): 2006M03 2021M12

Included observations: 190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LTO(-1))	-1.005385	0.072931	-13.78534	0.0000
C	-0.009157	0.009077	-1.008852	0.3143

R-squared	0.502692	Mean dependent var	0.000000
Adjusted R-squared	0.500047	S.D. dependent var	0.176472
S.E. of regression	0.124779	Akaike info criterion	-1.314082
Sum squared resid	2.927100	Schwarz criterion	-1.279903
Log likelihood	126.8378	Hannan-Quinn criter.	-1.300237
F-statistic	190.0356	Durbin-Watson stat	2.000058
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LM2) has a unit root

Exogenous: Constant

Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-14.16585	0.0000
Test critical values:	1% level	-3.464827	
	5% level	-2.876595	
	10% level	-2.574874	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	3.51E-05
HAC corrected variance (Bartlett kernel)	3.23E-05

Phillips-Perron Test Equation

Dependent Variable: D(LM2,2)

Method: Least Squares

Date: 02/01/23 Time: 16:06

Sample (adjusted): 2006M03 2021M12

Included observations: 190 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LM2(-1))	-1.018935	0.072099	-14.13246	0.0000
C	0.003028	0.000485	6.248711	0.0000

R-squared	0.515122	Mean dependent var	-7.61E-05
Adjusted R-squared	0.512543	S.D. dependent var	0.008528
S.E. of regression	0.005954	Akaike info criterion	-7.399109
Sum squared resid	0.006664	Schwarz criterion	-7.364930
Log likelihood	704.9153	Hannan-Quinn criter.	-7.385263
F-statistic	199.7265	Durbin-Watson stat	2.025911
Prob(F-statistic)	0.000000		

APPENDIX II: UNIT ROOT RESULTS FOR SECTORIAL VOLATILITIES

Null Hypothesis: **AM_VOL has a unit root**

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-28.42671	0.0000
Test critical values:	1% level	-3.431996	
	5% level	-2.862153	
	10% level	-2.567140	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(AM_VOL)

Method: Least Squares

Date: 01/21/23 Time: 17:26

Sample (adjusted): 1/06/2006 12/31/2021

Included observations: 3568 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AM_VOL(-1)	-0.735685	0.025880	-28.42671	0.0000
D(AM_VOL(-1))	-0.118246	0.022703	-5.208378	0.0000
D(AM_VOL(-2))	-0.062516	0.017296	-3.614529	0.0003
C	0.000112	1.01E-05	10.99284	0.0000

R-squared	0.424103	Mean dependent var	1.53E-07
Adjusted R-squared	0.423618	S.D. dependent var	0.000739
S.E. of regression	0.000561	Akaike info criterion	-12.13136
Sum squared resid	0.001123	Schwarz criterion	-12.12444
Log likelihood	21646.35	Hannan-Quinn criter.	-12.12889
F-statistic	874.8674	Durbin-Watson stat	2.062255
Prob(F-statistic)	0.000000		

Null Hypothesis: **ENE_VOL has a unit root**

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-30.69186	0.0000
Test critical values:	1% level	-3.431996	
	5% level	-2.862153	
	10% level	-2.567140	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(ENE_VOL)

Method: Least Squares

Date: 01/21/23   Time: 17:27

Sample (adjusted): 1/06/2006 12/31/2021

Included observations: 3568 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ENE_VOL(-1)	-0.700161	0.022813	-30.69186	0.0000
D(ENE_VOL(-1))	0.079377	0.019647	4.040118	0.0001
D(ENE_VOL(-2))	-0.054344	0.016722	-3.249793	0.0012
C	0.000221	8.45E-05	2.611982	0.0090

R-squared	0.343110	Mean dependent var	-2.33E-06
Adjusted R-squared	0.342557	S.D. dependent var	0.006201
S.E. of regression	0.005028	Akaike info criterion	-7.746390
Sum squared resid	0.090108	Schwarz criterion	-7.739463
Log likelihood	13823.56	Hannan-Quinn criter.	-7.743920
F-statistic	620.5226	Durbin-Watson stat	2.067990
Prob(F-statistic)	0.000000		

Null **Hypothesis: INSUR_VOL has a unit root**

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-17.99287	0.0000

Test critical values:	1% level	-3.431996
	5% level	-2.862153
	10% level	-2.567140

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(INSUR_VOL)

Method: Least Squares

Date: 01/21/23 Time: 17:28

Sample (adjusted): 1/06/2006 12/31/2021

Included observations: 3568 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INSUR_VOL(-1)	-0.352537	0.019593	-17.99287	0.0000
D(INSUR_VOL(-1))	-0.343164	0.022166	-15.48158	0.0000
D(INSUR_VOL(-2))	-0.103944	0.018492	-5.621034	0.0000
C	4.77E-05	3.98E-06	11.96651	0.0000

R-squared	0.319413	Mean dependent var	1.63E-06
Adjusted R-squared	0.318840	S.D. dependent var	0.000225
S.E. of regression	0.000186	Akaike info criterion	-14.34210
Sum squared resid	0.000123	Schwarz criterion	-14.33517
Log likelihood	25590.31	Hannan-Quinn criter.	-14.33963
F-statistic	557.5520	Durbin-Watson stat	1.995154
Prob(F-statistic)	0.000000		

Null Hypothesis**: TELECOM_VOL has a unit root**

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-20.17744	0.0000
Test critical values:	1% level	-3.431996	
	5% level	-2.862153	
	10% level	-2.567140	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(TELECOM_VOL)

Method: Least Squares

Date: 01/21/23 Time: 17:29

Sample (adjusted): 1/06/2006 12/31/2021

Included observations: 3568 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TELECOM_VOL(-1)	-0.394756	0.019564	-20.17744	0.0000
D(TELECOM_VOL(-1))	-0.346204	0.019838	-17.45197	0.0000
D(TELECOM_VOL(-2))	-0.164258	0.016493	-9.959512	0.0000
C	2.41E-05	1.94E-06	12.44194	0.0000

R-squared	0.360993	Mean dependent var	1.45E-07

Adjusted R-squared	0.360455	S.D. dependent var	0.000114
S.E. of regression	9.08E-05	Akaike info criterion	-15.77451
Sum squared resid	2.94E-05	Schwarz criterion	-15.76758
Log likelihood	28145.72	Hannan-Quinn criter.	-15.77204
F-statistic	671.1333	Durbin-Watson stat	2.063436
Prob(F-statistic)	0.000000		

Null **Hypothesis: CHE_VOL has a unit root**

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.88739	0.0000
Test critical values:	1% level	-3.431996	
	5% level	-2.862153	
	10% level	-2.567140	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(CHE_VOL)

Method: Least Squares

Date: 01/21/23   Time: 17:30

Sample (adjusted): 1/06/2006 12/31/2021

Included observations: 3568 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CHE_VOL(-1)	-0.260041	0.016368	-15.88739	0.0000
D(CHE_VOL(-1))	-0.284580	0.018357	-15.50244	0.0000
D(CHE_VOL(-2))	-0.288618	0.016790	-17.19025	0.0000
C	2.42E-05	5.38E-06	4.499173	0.0000

R-squared	0.288770	Mean dependent var	2.66E-07
Adjusted R-squared	0.288171	S.D. dependent var	0.000367
S.E. of regression	0.000309	Akaike info criterion	-13.32378
Sum squared resid	0.000341	Schwarz criterion	-13.31686
Log likelihood	23773.63	Hannan-Quinn criter.	-13.32131
F-statistic	482.3447	Durbin-Watson stat	2.060187
Prob(F-statistic)	0.000000		

Null Hypothesis: HEC_VOL has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-62.05356	0.0001
Test critical values:	1% level	-3.431863	
	5% level	-2.862094	
	10% level	-2.567108	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(HEC_VOL)

Method: Least Squares

Date: 01/21/23 Time: 17:31

Sample (adjusted): 1/04/2006 12/31/2021

Included observations: 3849 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HEC_VOL(-1)	-1.000473	0.016123	-62.05356	0.0000
C	-6.10E-05	9.79E-05	-0.623059	0.5333

R-squared	0.500237	Mean dependent var	-1.92E-07
Adjusted R-squared	0.500107	S.D. dependent var	0.008590
S.E. of regression	0.006073	Akaike info criterion	-7.369253
Sum squared resid	0.141905	Schwarz criterion	-7.366003
Log likelihood	14184.13	Hannan-Quinn criter.	-7.368099
F-statistic	3850.645	Durbin-Watson stat	2.076611
Prob(F-statistic)	0.000000		

Null Hypothesis: TEC_VOL has a unit root

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-23.22343	0.0000
Test critical values:	1% level	-3.431996	
	5% level	-2.862153	

	10% level	-2.567140

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(TEC_VOL)

Method: Least Squares

Date: 01/21/23   Time: 17:32

Sample (adjusted): 1/06/2006 12/31/2021

Included observations: 3568 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TEC_VOL(-1)	-0.423908	0.018253	-23.22343	0.0000
D(TEC_VOL(-1))	-0.144533	0.019117	-7.560346	0.0000
D(TEC_VOL(-2))	-0.036319	0.016685	-2.176716	0.0296
C	2.25E-05	1.84E-06	12.25908	0.0000

R-squared	0.263662	Mean dependent var	3.69E-09
Adjusted R-squared	0.263042	S.D. dependent var	0.000109
S.E. of regression	9.32E-05	Akaike info criterion	-15.72188
Sum squared resid	3.10E-05	Schwarz criterion	-15.71495
Log likelihood	28051.83	Hannan-Quinn criter.	-15.71941
F-statistic	425.3896	Durbin-Watson stat	2.036270
Prob(F-statistic)	0.000000		

Null Hypothesis: **G_I_VOL has a unit root**

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.02231	0.0000
Test critical values:	1% level	-3.431996	
	5% level	-2.862153	
	10% level	-2.567140	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(G_I_VOL)

Method: Least Squares

Date: 01/21/23 Time: 17:34

Sample (adjusted): 1/06/2006 12/31/2021

Included observations: 3568 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
G_I_VOL(-1)	-0.338660	0.018791	-18.02231	0.0000
D(G_I_VOL(-1))	-0.343107	0.019671	-17.44228	0.0000
D(G_I_VOL(-2))	-0.258284	0.017766	-14.53815	0.0000
C	7.47E-06	7.98E-07	9.360255	0.0000

R-squared	0.342104	Mean dependent var	-5.64E-08
Adjusted R-squared	0.341550	S.D. dependent var	5.03E-05
S.E. of regression	4.08E-05	Akaike info criterion	-17.37425
Sum squared resid	5.94E-06	Schwarz criterion	-17.36732

Log likelihood	30999.66	Hannan-Quinn criter.	-17.37178
F-statistic	617.7563	Durbin-Watson stat	2.097019
Prob(F-statistic)	0.000000		

Null Hypothesis: FIN__JI0030__VOL has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-62.03730	0.0001
Test critical values:	1% level	-3.431864	
	5% level	-2.862094	
	10% level	-2.567108	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: **D(FIN JI0030 VOL)**

Method: Least Squares

Date: 01/21/23   Time: 17:38

Sample (adjusted): 1/04/2006 12/31/2021

Included observations: 3848 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FIN__JI0030__VOL(-1)	-1.000342	0.016125	-62.03730	0.0000

C	7.00E-05	4.65E-05	1.506340	0.1321

R-squared	0.500171	Mean dependent var	-1.86E-07
Adjusted R-squared	0.500041	S.D. dependent var	0.004075
S.E. of regression	0.002882	Akaike info criterion	-8.860480
Sum squared resid	0.031934	Schwarz criterion	-8.857229
Log likelihood	17049.56	Hannan-Quinn criter.	-8.859326
F-statistic	3848.627	Durbin-Watson stat	2.076628
Prob(F-statistic)	0.000000		

APPENDIX III: UNIT ROOT RESULT FOR SECTORIAL RETURNS.

Null Hypothesis: AM_RETURNS has a unit root

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-33.00101	0.0000

Test critical values:	1% level	-3.431996
	5% level	-2.862153
	10% level	-2.567140

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(AM_RETURNS)

Method: Least Squares

Date: 01/21/23 Time: 15:40

Sample (adjusted): 1/06/2006 12/31/2021

Included observations: 3568 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AM_RETURNS(-1)	-1.385628	0.041987	-33.00101	0.0000
D(AM_RETURNS(-1))	0.162655	0.033053	4.921004	0.0000
D(AM_RETURNS(-2))	0.043602	0.021856	1.994983	0.0461
C	0.000380	0.000511	0.744142	0.4568

R-squared	0.516513	Mean dependent var	-0.000245
Adjusted R-squared	0.516106	S.D. dependent var	0.043875
S.E. of regression	0.030521	Akaike info criterion	-4.139704
Sum squared resid	3.319909	Schwarz criterion	-4.132776
Log likelihood	7389.232	Hannan-Quinn criter.	-4.137234
F-statistic	1269.147	Durbin-Watson stat	1.409138
Prob(F-statistic)	0.000000		

Null Hypothesis: ENE_RETURN has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-45.09287	0.0001
Test critical values:	1% level	-3.432294	
	5% level	-2.862284	
	10% level	-2.567210	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(ENE_RETURN)

Method: Least Squares

Date: 01/21/23   Time: 15:46

Sample (adjusted): 1/04/2006 12/31/2021

Included observations: 3065 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ENE_RETURN(-1)	-1.081587	0.023986	-45.09287	0.0000
C	-3.91E-05	0.000847	-0.046133	0.9632

R-squared	0.398984	Mean dependent var	-0.001153
Adjusted R-squared	0.398787	S.D. dependent var	0.060456
S.E. of regression	0.046876	Akaike info criterion	-3.281957

Sum squared resid	6.730597	Schwarz criterion	-3.278024
Log likelihood	5031.599	Hannan-Quinn criter.	-3.280544
F-statistic	2033.367	Durbin-Watson stat	1.432950
Prob(F-statistic)	0.000000		

Null Hypothesis: TEC_RETURNS has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-42.54746	0.0000
Test critical values:	1% level	-3.431863	
	5% level	-2.862094	
	10% level	-2.567108	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(TEC_RETURNS)

Method: Least Squares

Date: 01/21/23 Time: 15:47

Sample (adjusted): 1/04/2006 12/31/2021

Included observations: 3849 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TEC_RETURNS(-1)	-0.958058	0.022517	-42.54746	0.0000

C	0.000153	0.000375	0.408111	0.6832

R-squared	0.319992	Mean dependent var	-0.000241
Adjusted R-squared	0.319815	S.D. dependent var	0.028201
S.E. of regression	0.023258	Akaike info criterion	-4.683775
Sum squared resid	2.081060	Schwarz criterion	-4.680525
Log likelihood	9015.925	Hannan-Quinn criter.	-4.682621
F-statistic	1810.286	Durbin-Watson stat	1.534926
Prob(F-statistic)	0.000000		

Null Hypothesis: TELECOM_RETURNS has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-35.96697	0.0000
Test critical values:	1% level	-3.431928	
	5% level	-2.862123	
	10% level	-2.567124	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(TELECOM_RETURNS)

Method: Least Squares

Date: 01/21/23   Time: 15:48

Sample (adjusted): 1/05/2006 12/31/2021

Included observations: 3706 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TELECOM_RETURNS(-1)	-1.098985	0.030555	-35.96697	0.0000
D(TELECOM_RETURNS(-1))	0.083098	0.021337	3.894618	0.0001
C	0.000201	0.000425	0.473821	0.6357

R-squared	0.380160	Mean dependent var	-8.78E-05
Adjusted R-squared	0.379825	S.D. dependent var	0.032855
S.E. of regression	0.025874	Akaike info criterion	-4.470347
Sum squared resid	2.479025	Schwarz criterion	-4.465314
Log likelihood	8286.553	Hannan-Quinn criter.	-4.468556
F-statistic	1135.559	Durbin-Watson stat	1.604774
Prob(F-statistic)	0.000000		

Null Hypothesis: G_I_RETURNS has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.98848	0.0000
Test critical values:	1% level	-3.431863	
	5% level	-2.862094	
	10% level	-2.567108	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(G_I_RETURNS)

Method: Least Squares

Date: 01/21/23 Time: 15:50

Sample (adjusted): 1/04/2006 12/31/2021

Included observations: 3849 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
G_I_RETURNS(-1)	-0.980343	0.026504	-36.98848	0.0000
C	8.97E-06	0.000328	0.027386	0.9782

R-squared	0.262341	Mean dependent var	-0.000190
Adjusted R-squared	0.262149	S.D. dependent var	0.023664
S.E. of regression	0.020327	Akaike info criterion	-4.953256
Sum squared resid	1.589464	Schwarz criterion	-4.950005
Log likelihood	9534.541	Hannan-Quinn criter.	-4.952101
F-statistic	1368.148	Durbin-Watson stat	1.394019
Prob(F-statistic)	0.000000		

Null Hypothesis: CHE_RETURN has a unit root

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=2)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-25.62023	0.0000

Test critical values:	1% level	-3.431996
	5% level	-2.862153
	10% level	-2.567140

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(CHE_RETURN)

Method: Least Squares

Date: 01/21/23 Time: 16:50

Sample (adjusted): 1/06/2006 12/31/2021

Included observations: 3568 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CHE_RETURN(-1)	-0.827069	0.032282	-25.62023	0.0000
D(CHE_RETURN(-1))	-0.077719	0.027375	-2.839045	0.0046
D(CHE_RETURN(-2))	-0.032589	0.020378	-1.599233	0.1099
C	-0.000136	0.000487	-0.280051	0.7795

R-squared	0.356424	Mean dependent var	-0.000348
Adjusted R-squared	0.355882	S.D. dependent var	0.036228
S.E. of regression	0.029075	Akaike info criterion	-4.236723
Sum squared resid	3.012946	Schwarz criterion	-4.229795
Log likelihood	7562.314	Hannan-Quinn criter.	-4.234253
F-statistic	657.9346	Durbin-Watson stat	1.362257
Prob(F-statistic)	0.000000		

Null Hypothesis: INSUR_RETURNS has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-28.86475	0.0000
Test critical values:	1% level	-3.431928	
	5% level	-2.862123	
	10% level	-2.567124	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(INSUR_RETURNS)

Method: Least Squares

Date: 01/21/23 Time: 16:56

Sample (adjusted): 1/05/2006 12/31/2021

Included observations: 3706 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
INSUR_RETURNS(-1)	-1.083109	0.037524	-28.86475	0.0000
D(INSUR_RETURNS(-1))	0.045443	0.026074	1.742874	0.0814
C	0.000211	0.000350	0.603507	0.5462

R-squared	0.300999	Mean dependent var	-0.000214
Adjusted R-squared	0.300621	S.D. dependent var	0.025441

S.E. of regression	0.021276	Akaike info criterion	-4.861696
Sum squared resid	1.676178	Schwarz criterion	-4.856663
Log likelihood	9011.723	Hannan-Quinn criter.	-4.859905
F-statistic	797.2789	Durbin-Watson stat	1.420339
Prob(F-statistic)	0.000000		

Null Hypothesis: HEC_RETURNS has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-47.41724	0.0001
Test critical values:	1% level	-3.431863	
	5% level	-2.862094	
	10% level	-2.567108	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(HEC_RETURNS)

Method: Least Squares

Date: 01/21/23   Time: 16:57

Sample (adjusted): 1/04/2006 12/31/2021

Included observations: 3849 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

HEC_RETURNS(-1)	-0.983035	0.020732	-47.41724	0.0000
C	-5.93E-05	0.000415	-0.142809	0.8864

R-squared	0.368868	Mean dependent var	-0.000182
Adjusted R-squared	0.368704	S.D. dependent var	0.032404
S.E. of regression	0.025746	Akaike info criterion	-4.480546
Sum squared resid	2.550034	Schwarz criterion	-4.477295
Log likelihood	8624.810	Hannan-Quinn criter.	-4.479391
F-statistic	2248.395	Durbin-Watson stat	1.644350
Prob(F-statistic)	0.000000		

Null Hypothesis: FIN_J10030RETURNS has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on AIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-30.31870	0.0000
Test critical values:	1% level	-3.431864	
	5% level	-2.862094	
	10% level	-2.567108	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(FIN_J10030RETURNS)

Method: Least Squares

Date: 01/21/23 Time: 16:58

Sample (adjusted): 1/04/2006 12/31/2021

Included observations: 3848 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FIN_J10030RETURNS(-1)	-0.949722	0.031325	-30.31870	0.0000
C	-0.000229	0.000429	-0.533982	0.5934

R-squared	0.192903	Mean dependent var	-0.000450
Adjusted R-squared	0.192693	S.D. dependent var	0.029601
S.E. of regression	0.026597	Akaike info criterion	-4.415542
Sum squared resid	2.720593	Schwarz criterion	-4.412291
Log likelihood	8497.504	Hannan-Quinn criter.	-4.414388
F-statistic	919.2237	Durbin-Watson stat	1.293734
Prob (F-statistic)	0.000000		

9 June 2022

Mr Babatunde Samuel Lawrence (217081567)
School Of Acc Economics&Fin
Westville

Dear Mr Babatunde Samuel Lawrence,

Original application number: 00016944
Project title: Equity sector connectedness and its determinants: Evidence from the Johannesburg Stock Exchange.

Exemption from Ethics Review

In response to your application received on 1 June 2022, 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