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Connectedness and Shock Propagation in South African Equity Sectors during Extreme Market Conditions

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Abstract: This study examined the connectedness and propagation of risk in the South African equity sectors during the Global Financial Crisis (GFC), the European Debt Crisis (EDC), the US–China trade war, and the COVID-19 pandemic. Daily returns of nine Johannesburg Stock Exchange (JSE) super sectors were examined from 3 January 2006 to 31 December 2021. Applying the connectedness matrix and time-varying parameter vector autoregressive (TVP-VAR) model, in full sample and sub-periods, the study showed that dynamic total connectedness of the super sectors is high in absolute form (62%). Furthermore, it was found that the highest volatility connectedness was during the EDC (68.83%) and during the COVID-19 pandemic (68.57%), followed by the GFC (63.16%) and lastly the US–China trade war (42.09%), respectively. This suggests that the tendency for a systemic risk is highest during the EDC, COVID-19, and GFC periods, and lowest during the US–China trade war. The financial sector was the primary net-transmitter of shocks during the COVID-19 period, while the automobile and parts sector was the strongest net-transmitter of shocks during the GFC, EDC, and US–China trade war. Similarly, the strongest net recipient of shocks during GFC, EDC, and COVID-19 is the chemical super sector. The study concludes that there is a significant volatility connectedness among JSE super sectors. In addition, the JSE super sectors exhibit time-varying connectedness during extreme events. Moreover, the net-transmitter and net-receiver of shock do not change significantly during different crisis periods. The policy implications of the findings are highlighted in the concluding section.

Keywords: dynamic connectedness; TVP-VAR; financial networks; equity sectors; volatility; spillovers

JEL Classification: C05; C32; G1

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1. Introduction

The interlinkages between financial markets have increased in the past two decades (i.e., from the early 2000s) 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 has affected international finance and investment, resulting in a global finance[1] phenomenon (Bekaert et al. 2005). 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 markets. This phenomenon is often referred to as financial contagion[2] (Bekaert et al. 2005).

The contagion effects noted across international markets have implications for domestic equity sectors too. It has been shown that during a crisis, stock volatility increases due to uncertainty created through negative shocks. In this context, negative shocks arising from the global or international crises may have a direct impact on sectors. Quite a number of empirical studies have been carried out on risk contagion in diverse financial markets

(Elyasiani et al. 2015; Fry-McKibbin et al. 2014; Jung and Maderitsch 2014). However, limited efforts have been directed to uncover the risk transmission between different equity sectors, especially in South Africa. This study was motivated by the dearth of studies on risk spillovers in the JSE equity sectors, in light of numerous recent extreme market events. Extant studies such as Lawrence et al. (2024a) and Nyakurukwa and Seetharam (2023) established correlations among JSE sectors; however, it remains to be seen how shocks are propagated. 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 risk propagations on the JSE equity sectors 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 a negative shock event is the US–Chinese trade war and COVID-19 pandemic. The trade war between the US and China was based on trade restrictions and counter-retaliations between them (Annan 2020; Mao and Görg 2020; SCMP 2021). The attendant negative shocks could directly impact the export sectors on the US tariff list and then be transmitted to other sectors, which have direct and indirect connections to the affected sectors. For example, shock from the US–China trade war can affect their trading partners through a direct impact on the latter's sectors, which export goods, and such shocks are propagated to sectors with indirect and direct links with the primary sectors facilitated through interdependency in value chains (Egger and Zhu 2020). The US–China trade war has significant implications for South Africa as China and the United State of America (USA) occupy the first and third positions as South Africa's import and export trade partners, respectively (WITS 2021). The EDC impacted economic sectors globally (Zamora-Kapoor and Coller 2014). 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) and resulting in uncertainty in the financial markets, exports, and trade flow. Furthermore, understanding the risk transmission mechanism is crucial for the stability of the South African economy, taking the COVID-19 pandemic which significantly impacted South Africa into consideration (Giandhari et al. 2021).

This study unravels the interconnectedness of the super sectors on the JSE market; a connectedness network is constructed using the connectedness matrix of Diebold and Yilmaz (2009, 2012, 2014) and the time-varying parameter VAR (TVP-VAR) model innovation of Antonakakis et al. (2019) and Antonakakis et al. (2020). We produce the first attempt to empirically investigate connectedness and risk-propagating mechanisms in extreme risk conditions, especially in the South African context. The remainder of this paper is organised as follows: Section 2 provides both the theoretical and empirical literature reviews, Section 3 gives the methodology and data, Section 4 presents the empirical results, and the conclusion is presented in Section 5.

2. Literature Review

2.1. Theoretical Concept of Contagion and Spillovers

The theoretical literature on how shocks are propagated internationally is quite extensive; however, the literature has sub-divided these broad sets of theories into two groups, namely crisis-contingent theories and non-crisis-contingent theories. The former are those that explain why transmission mechanisms change during a crisis; therefore explaining why cross-market linkages increase after a shock (Rigobon 1999). The latter assumes that transmission mechanisms are the same during a crisis as during more stable periods; 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. Moreover, the two theories can be expressed in terms of contagion and interdependence, respectively (Rigobon 1999).

2.2. Empirical Studies on Dynamic Return and Volatility Connectedness

Regarding the connectedness of equities under different conditions, several researchers favour using volatility-spillovers[3] as a gauge of market connectivity. For example, Jung and Maderitsch (2014) examined the transfer of volatility in the international equities markets. The findings showed time-variation volatility spillovers and traced significant contagion to the 2007 GFC. Similarly, Tsai (2014) employed a GARCH (1, 1)-M model and demonstrated that for the time period before 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. The findings also reveal that for close-to-open returns, this effect on the conditional mean is consistent with international financial integration. According to the results, information was mostly transmitted to other significant international markets from Germany and the USA. The authors further revealed that the African economies were greatly affected by the EDC from the onset of the crisis, emphasising that the spillovers from major European nations such as Germany, France, and the United Kingdom to the African nations were more than the spillovers from the USA after the sub-prime crisis.

Risk transmission has been investigated amidst stock, bond, commodities, and economic growth. For example, Berg and Vu (2019) investigated the link between the USA bond and stock markets and economic activity of 17 developed markets using panel VAR. They showed that the volatility of the US financial markets exerts a significant impact on the output growth of these economies, showing that the US market has a greater impact on these economies' performances than do their domestic financial markets. In a network of American and European (Belgium, Germany, France, Italy, Netherlands, Spain, UK, Switzerland) financial institutions, Fry-McKibbin et al. (2014) investigated the interconnectivity of stock return volatility. The variance decomposition matrix of a vector-autoregressive approximating model was used to create a novel connectedness measure from 2004 to 2014. 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 addition, Akyildirim et al. (2022) employed the Diebold–Yilmaz (DY) on global and Chinese crude oil markets and found bidirectional volatility spillover, while Awartani et al. (2016) found that the oil market transmits both return and volatility spillover to other equity markets in the Arabian Gulf using the DY method.

On the Asian terrain, Manopimoke et al. (2018) investigated the dynamic connections between emerging Asian equities markets and important global markets, using the VAR model. The study showed that international stock markets have become more connected over time, with a gradual rise since the Asian financial crisis (AFC) and a sharp increase during the GFC. The authors found that developed markets are net-transmitters of shocks while the Asian markets are net-receivers. In addition, connectedness is very strong between Asian economies (Malaysia, India, China, Korea, Hong Kong, Thailand).

On the African terrain, Claassen (2019) investigated the return and volatility spillovers in five African markets using the time-domain technique of Diebold and Yilmaz (2012) and the frequency-domain approach of Baruník et al. (2017). The findings suggest that the return connectedness index is relatively moderate over the full sample period. South Africa and Egypt are identified as the net-transmitters, while Morocco, Nigeria, and Tunisia are the net-receivers of these spillovers. In Nigerian financial markets, Udeaja (2019) used the Diebold and Yilmaz (2012, 2014) methods to examine the degree of connectedness between the Naira/USD exchange rate and the All Share Index return and volatility. With higher connectedness during the Nigerian currency's depreciation in 2014 and 2016 and the domestic economic crisis, this study showed that spillovers in the financial market can be traced to domestic crises as opposed to external shocks. The outcome also demonstrated that the Nigerian financial market's connectedness varies over time.

Using MSCI energy equity indices for 29 countries, Akyildirim et al. (2022) investigated the connectedness among energy equity indices around the globe of oil-exporting and oil-importing countries. It was found that shocks are primarily sent by oil-exporting nations and received by oil-importing nations. Additionally, 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, when diversification is most crucial, the benefits of diversity between countries are drastically decreased. By using 12 commodity sectors and stocks from African markets, Agyei and Bossman (2023) investigated the dynamic connectedness between commodities and African equities from 23 February 2010 to 4 February 2022 using the TVP-VAR connectedness approach. The findings indicated that, particularly during times of financial and economic stress, African stocks and commodities are not completely immune to shocks and contagion from the global market. Additionally, it was found that idiosyncratic spillovers play a substantial role in the connection between African equity returns and commodity returns.

More recently, in a bid to examine the connectedness of industry sectors on the JSE in both the time and frequency domain, Nyakurukwa and Seetharam (2023) employed wavelet multiple correlation and wavelet scalogram difference to reveal the evolution of interconnectedness of the sectors over time and at different frequencies. The results revealed that the sectors on the JSE are integrated at lower frequencies. The study also emphasised that the sectorial correlation is in tandem with local and global shocks such as the downgrading of the South African debt by Fitch in 2013 and the COVID-19 pandemic. Lawrence et al. (2024a) established the need to investigate the volatility connectedness of the JSE sectors for the purpose of portfolio formation. Furthermore, contemporary financial market theories such as the adaptive market hypothesis (AMH) have established that changing market conditions and events have a force to bear on markets outcomes (Lawrence et al. 2024b). In this context, market behaviours and risk-return relationships should not be viewed from an absolute or 'all or nothing' perspective. In other words, market events should not be analysed only on a full sample basis; hence, events affecting stock markets should be taken into consideration and tracked using rolling or sub-period analyses. It is noteworthy that different events are not likely to have similar effects on the relationship and connectedness between the sectors. In other words, the shock propagator and recipient may change depending on the particular crisis.

Drawing from the forgoing review of empirical studies, we hypothesised in null form as follows:

Hypothesis 1. *There is a significant connectedness among JSE super sectors.*

The hypothesis is derived from the extant literature (Longin and Solnik 1995; Diebold and Yilmaz 2009; Tsai 2014) that revealed that correlation, volatility and equity connectedness exist among different markets and sectors, though the subject has not been extensively documented on the JSE.

Hypothesis 2. *The JSE super sectors exhibit significant time-varying connectedness during extreme events.*

The hypothesis is derived from the extant literature (Tsai 2014; Udeaja 2019; Manopimoke et al. 2018) that showed that returns and volatility connectedness do vary and change during crisis periods, though this remains to be seen among equity sectors, especially on the JSE. The hypothesis is corroborated by contemporary financial theories such as the AMH (Lo 2004), which argues that changing market conditions and events tends to produce time variation in market behaviour and risk-return relationships.

Hypothesis 3. *Certain super sectors on the JSE act as the net-transmitters or receivers of shocks during different crisis periods.*

This hypothesis is derived from the extant literature (Agyei and Bossman 2023; and Akyildirim et al. 2022) that showed that certain markets transmit more shocks that they receive while some receive more shocks than they transmit. However, it is apparent that connectedness and the direction of propagation of shocks within sectorial equities are yet to be established during extreme periods such as the GFC, EDC, the US–China trade war, and the COVID-19 pandemic among sectorial equities on the JSE market in South Africa.

3. Data and Methods

3.1. Data Collection and Sampling

Daily volatility of the selected nine sectors[4] on the JSE, namely Energy (ENE), Technology (TECH), General Industrial (IG), Financials (FIN), Health Care (HEC), Insurance (INS), Telecommunications (TEL), Chemicals (CHEM), and Automobile and Parts (AMP) (ICB 2019, 2021), was computed from daily returns for the period from 3 January 2006 to 31 December 2021. The research approach adopted for this study was quantitative, empirically investigating the connectedness and risk propagation of super sectors on the JSE during the GFC, EDC, the US–China trade war, and the COVID-19 pandemic risk events.

3.2. Empirical Model

The daily returns of each super sector are computed from their price indices using Equation (1), as outlined in Lawrence et al. (2024a) and Zhang et al. (2020).

$$PR_{i,t} = \left(\frac{P_{ti-P_{to}}}{P_{to}}\right) \tag{1}$$

$P_{ti},\ P_{to},\ and\ PR_{i,t}$ denote the price at current and previous times, and price return, respectively. The study employed the formula by Garman and Klass (1980) to generate the daily realised volatility for each sectorial index, as used in Zhang et al. (2020).

$$V\binom{GK}{it} = 0.511(h_{it} - l_{it})^2 - 0.019[(c_{it} - o_{it})(h_{it} - l_{it} - 2o_{it}) - 2(h_{it} - o_{it})(l_{it} - o_{it})] - 0.383(c_{it} - o_{it})^2 \tag{2}$$

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

Subsequently, this study employed Diebold and Yilmaz (2009, 2012, 2014) alongside the time-varying parameter (TVP-VAR) model. Following Antonakakis et al. (2020), the study combined the TVP-VAR methodology, which was first established by Koop and Korobilis (2013), to overcome the drawbacks of the rolling-window approach in Diebold and Yilmaz (2009, 2012, 2014)'s connectedness index. The connectedness index computation of a TVP-VAR model with one lag can be expressed below:

$$\Delta y_t = \theta_t \Delta y_{t-1} + \mu_t \tag{3}$$

$$\mu \sim N(0,\ E_t)$$

$$vec(\theta) = vec(\theta_{t-1}) + r_t \tag{4}$$

$$r_t \sim N(0,\ Q_t) \tag{5}$$

where Δy_t, Δy_{t-1} and μ_t are vectors of $N \times 1$ dimension, θ_t and E_t are $N \times N$ matrices of dimension, $vec(\theta)$ and r_t are parameter matrices of $N^2 \times 1$ dimension, and lastly, Q_t is an $N^2 \times N^2$ matrix. In this study, $N = 9$ where 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.[5] This theorem is expressed as:

$$\Delta x_t = \sum_{i-1}^{p} \beta_{it} \Delta x_{t-1} + \varepsilon_t = \sum_{j=1}^{\infty} \gamma_{jt} \epsilon_{t-j} + \varepsilon_t. \tag{6}$$

In the next step, the TVP-VMA coefficients are extracted to compute the generalised forecast error variance decomposition (GFEVD) developed by Koop and Korobilis (2013). From there, the DY connectedness index is built.

The unscaled GFEVD, $\varnothing^{g}_{ij,t}(J)$¯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:

$$\varnothing^{g}_{ij,t}\,(J) = \frac{\sum_{ii,t}^{-1} \sum_{t=1}^{J-1} \left(l_j' \, A_t \, E_t \, l_j\right)^2}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \left(l_i A_t \sum_t A_l' l_i\right)} \qquad \varphi^{g}_{ij,\,t}(J) = \frac{\varnothing^{g}_{ij,t}\,(J)}{\sum_{j=1}^{N} \varnothing^{g}_{ij,t}\,(J)} \tag{7}$$

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

$$C^{g}_{t}(J) = 1 - N^{-1} \sum_{i-1}^{N} \varphi^{g}_{ii,\,t}\,(J) \tag{8}$$

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 another sector j, called total directional connectedness to others:

$$C^{g}_{i\to j,t}(J) = \sum_{j=1,\, i\neq j}^{N} \varphi^{g}_{ji,\,t}(J) \tag{9}$$

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

$$C^{g}_{i\leftarrow j,t}(J) = \sum_{j=1,\, i\neq j}^{N} \varphi^{g}_{ij,\,t}(J) \tag{10}$$

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 sector's influence on the analysed network.

$$C^{g}_{i,t} = C^{g}_{i\to j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \tag{11}$$

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 and vice versa (Antonakakis et al. 2020). We generate the net pairwise directional connectedness (NPDC), a measure which provides information about the bilateral transmission process between variable i and variable j:

$$NPDC_{ij}(J) = \varphi^{g}_{ji,\,t}(J) - \varphi^{g}_{ij,\,t}(J). \tag{12}$$

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

4. Empirical Findings

4.1. Descriptive Statistics and Correlation Results

The descriptive statistics of the daily realised volatility for each index calculated following Garman and Klass (1980) are shown in Table 1. The energy sector has the highest mean of 0.0003, while the health sector has the lowest mean of −0.0006, respectively. The insurance sector and financial sector have the lowest median values. The energy sector has the highest maximum value of 0.2101, while the general industrial sector has the lowest minimum value of 0.00001. Notably, the energy sector has the highest mean and standard deviation, demonstrating a high risk-return relationship. The statistics also show the kurtosis and the skewness coefficients, which indicate that the realised volatilities of the series are far from a normal distribution, with all results being significant at the 1% level. This condition is formally confirmed by the Jarque–Bera test statistics, also significant at 1% significance level.

Table 1. Descriptive statistics for sector volatility.

	AM	ENE	CHE	FIN	HEC	G-I	INSUR	TEC	TELCOM
Mean	0.0002	0.0003	0.0001	0.0001	−0.0000	0.0000	0.0001	0.0001	0.0001
Median	0.00003	0.00004	0.00003	0.0000	0.00002	0.00001	0.0001	0.00003	0.00004
Maximum	0.0258	0.2101	0.0107	0.1787	0.0027	0.0017	0.0050	0.0029	0.0022
Minimum	−0.00003	−0.00001	−0.00004	−0.0000	−0.3767	−0.0000	−0.0000	−0.0000	−0.0000
Std. Dev.	0.0007	0.0051	0.0004	−0.0028	0.0051	0.0000	0.0002	0.0001	0.0001
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	0.9371 ***	1.3659 ***	0.436 ***	3.9922 ***	3.9949 ***	0.5343 ***	0.1494 ***	0.2401 ***	0.1303 ***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jarque–Bera	146 ***	310 ***	31.46802 ***	2650 ***	2660 ***	47.25765 ***	3.625887 ***	9.460527 ***	2.752864 ***
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	0.621	1.2086	0.3555	0.2727	−0.2289	0.0875	0.5179	0.2092	0.2452
Sum Sq. Dev.	0.0018	0.1033	0.0006	0.0319	0.1419	0.0000	0.0002	0.0000	0.0000
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	3.1400	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

Note: Kurtosis and Jarque–Bera are divided by 1000. *** represents statistical significance at 1%.

Table 2 shows the pairwise Pearson correlation coefficients across the nine super sectors. In general, the correlations are both positive and negative. The correlation of −0.0005 between chemicals and financials suggests the possibility of combining them in the same portfolio to reduce risk while the high correlation between insurance and industrial goods and services super sectors, and telecommunications and general industrial goods and services suggests otherwise. This result was anticipated between the industrial goods and services sectors; the IGS, being a capital-intensive sector, would rely on the insurance sector for the protection of life and other liabilities.

Table 2. Correlation of sectorial volatility.

	AM	CHE	EN	FIN	G-I	HEC	INSUR	TEC	TELECOM
AM	1	0.0064	0.0316	0.0030	0.1125	0.0043	0.1289	0.0899	0.1194
CHE	0.0064	1	0.0265	−0.0005	0.0064	0.0014	−0.0052	−0.0012	0.0003
ENE	0.0316	0.0265	1	0.0004	0.1021	0.0015	0.0479	0.0773	0.1359
FIN	0.003	−0.0005	0.0004	1	0.0115	0.0001	0.0069	0.0247	0.0052
G-I	0.1125	0.0063	0.1021	0.0115	1	−0.0012	0.5248	0.3337	0.5248
HEC	0.0042	0.0014	0.0015	0.0001	−0.0012	1	0.0002	0.0085	0.0053
INSUR	0.1289	−0.0052	0.0479	0.0069	0.5248	0.0002	1	0.3243	0.4831
TEC	0.0898	−0.0012	0.0773	0.0247	0.3337	0.0085	0.3243	1	0.3177
TELECOM	0.1194	0.0003	0.1359	0.0052	0.5247	0.0053	0.4831	0.3178	1

Source: Authors' Estimation (2023). Note: Jarque–Bera values in Table 1 are divided by 1000 and other values also in Table 2 are approximated to 4 decimal places.

4.2. Analysis of Super Sector Connectedness for Full Sample Period

Table 3 shows the decomposition of super sectors into transmitters and receivers in full sample. 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 sectors. The total connectedness index (TCI[6]) for the period among the sectors is 62.0% and the dynamic conditional total connectedness index (cTCI[7]) is 69.74%. This means that the average realised volatility spillover is 62% across all sectors. A sector is considered as a net-receiver of shocks if its net-connectedness value is negative and a sector with a positive net-connectedness value is considered a net-transmitter of shocks (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. Technology, finance, energy, and health sectors are net-transmitters of shocks with 9.3%, 9.47%, 13.00%, and 9.72%, respectively.

Table 3. Average sector volatility connectedness table for full sample period.

	AM	TELCOM	INSUR	CHE	TEC	G.I	FIN	ENE	HEL	FROM
AM	42.02	6.75	5.97	6.73	7.02	6.88	7.28	9.21	8.14	57.98
TELCOM	5.74	34.46	8.89	6.36	8.33	13.34	7.29	8.27	7.33	65.54
INSUR	5.92	9.69	39.66	5.27	7.94	11.24	7.9	7.12	5.26	60.34
CHE	6.16	6.12	4.86	38.58	5.76	6.27	9.07	11.13	12.05	61.42
TEC	7.05	9.07	8.00	6.57	34.43	10.22	8.73	8.18	7.76	65.57
G.I	5.81	12.28	10.33	6.26	8.93	31.01	9.64	9.39	6.34	68.99
FIN	5.58	5.84	5.86	7.7	6.95	8.12	41.12	11	7.85	58.88
ENE	7.02	6.58	5.34	9.23	5.59	6.84	11.19	36.99	11.22	63.01
HEL	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: Authors' Estimation (2023).

It is interesting to note that the energy sector is the highest contributor to connectedness/spillover among the JSE equity sectors with realised volatility of 76.02%, while financial and general industrials are the 2nd and 3rd most significant contributors with 68.36% and 68.27%, respectively. Automobile and parts is the least significant contributor with 49.59%. It can be observed that each diagonal element in the matrix represents each 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 sector originate from itself, where the diagonal volatility connectedness ranges from 31.01% to 43.77%. It could be deduced from the result that the automobile and parts sector has the smallest net spillover in the system. It is observed that the health sector generated the strongest self-volatility connectedness (43.77%), illustrating that the health sector has the greatest self-shock amongst all the sectors, followed by the automobile and parts (42.02%) and financial sectors (41.12%), while the general industrial sector has the least self-volatility connectedness at 31.01%.

The non-diagonal section of the average dynamic connectedness in Table 3 represents the volatility shocks that sector j transmits to sector i. It can be observed that volatility spillover from general industrial to telecom (13.34%) has the highest value, followed by telecom 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 sector and the health sector with 11.77%, while the volatility connectedness from insurance to health sector (4.16%) has the minimum value.

4.3. Analysis of Super Sector Connectedness in Extreme Periods

Table 4 depicts that the total connectedness index is high during the GFC. This established the fact that 63.16% and 71.05% of the realised volatility connectedness is the average level of risk spillover through all sectors during the GFC. Telecommunications, chemicals, technology, and health are net-receivers with −4.28%, −17.87%, −12.63%, and −29.83%, respectively. Among these, the health and chemical sectors are the biggest receivers of shocks with −29.83% and −17.87%, respectively, while the automobile and parts, insurance, general industrial, financial, and energy sectors are net-transmitters with realised volatilities of 35.80%, 4.98%, 3.50%, 14.62%, and 5.71%, respectively. The financial sector, as the second-highest shock transmitter during the GFC, demonstrates how the sector serves as a conduit for the propagation of global crises to other super sectors.

Table 4. Average dynamic sectorial volatility connectedness during GFC.

	AM	**TELCOM**	**INSUR**	**CHE**	**TEC**	**G.I**	**FIN**	**ENE**	**HEL**	**FROM**
AM-	48.00	7.27	9.60	0.33	6.34	6.95	8.59	10.21	2.71	52.00
TELECOM	11.63	28.33	10.45	0.41	9.05	12	14.3	9.26	4.57	71.67
INSUR	12.99	9.59	28.94	0.54	9.98	10.78	13.12	10.05	3.99	71.06
CHE	5.47	2.42	3.39	79.44	1.83	2.48	2.2	2.28	0.49	20.56
TEC	13.41	9.79	11.91	0.41	23.35	12.3	13.9	9.99	4.94	76.65
G-I	12.13	10.53	10.83	0.32	10.19	24.13	16.69	10.3	4.89	75.87
FIN	11.02	11.54	11.84	0.24	10.74	15.58	24.02	9.90	5.11	75.98
ENE	11.83	8.53	10.09	0.25	7.59	10.41	11.39	35.92	3.98	64.08
HEL	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	135.80	95.72	104.98	82.13	87.37	103.5	114.62	105.71	−70.17	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: Authors' Estimation (2023).

From Table 5, the static total connectedness index (TCI) and the conditional total connectedness index (cTCI) are seen to have a value of 77.10% and 68.83%, respectively, in realised volatility. This depicts that the total connectedness index is high on average over the period of the EDC, with an average level of risk spillover of 77.10% across all sectors during the EDC. It is observed that chemicals, technology, financial, energy, and health are net-receivers with −20.28%, −8.55%, −16.52%, −3.1%, and −10.15%, respectively, in realised volatility. This suggests the chemical, technology, financial, and energy sectors during the EDC period receive shocks from others, playing the role of shock absorbers from the transmitters, with automobile and parts, telecommunication, insurance, and general industrial having 35.80%, 4.98%, 3.50%, 14.62%, and 5.71%, respectively, in realised volatilities, as they play the role of net-transmitters, transmitting shocks from one sector to another. The result shows that the biggest transmitters of shocks are the automobile and parts (19.22%) and general industrial (18.91%) sectors, respectively, while the biggest receivers of shocks are the chemical and financial sectors, 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 sectors with realised volatility of 79.17% and 78.44%, respectively, with the chemical sector standing as the least receiver of risk with 39.85%. The financial sector is seen to switch roles as a transmitter of shock during the GFC to a receiver of shock during the EDC, hence standing as the second-highest shock receiver in this period.

Table 5. Average dynamic sectorial volatility connectedness during EDC.

	AM	TELCOM	INSUR	CHE	TEC	G.I	FIN	ENE	HEL	FROM
AM	45.98	8011	1.77	3.57	1.49	13.66	8.94	8.57	7.91	54.02
TELECOM	10.04	21.56	12.03	2.20	10.77	14.43	9.28	9.65	10.03	78.44
INSUR	5.84	14.91	30.23	2.09	15.64	10.17	5.74	7.30	8.08	69.77
CHE	6.03	5.22	4.75	60.15	3.28	7.16	3.34	5.67	4.41	39.85
TEC	6.23	14.98	16.54	1.60	29.23	10.12	8.99	7.39	7.92	70.77
G.I	12.72	13.99	8.69	2.99	7.33	20.83	13.08	9.79	10.57	79.17
FIN	10.95	13.21	11.26	2.05	8.42	16.13	20.00	8.00	9.77	79.80
ENE	9.18	12.26	8.48	2.66	7.57	12.37	7.28	32.03	8.17	67.97
HEL	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: Authors' Estimation (2023).

Table 6 shows the shock propagation during the US–China trade war. The average total connectedness index of 47.35% is relatively low when compared to other extreme periods and the full sample periods. The automobile and parts sector shows some evidence of high values in volatility. The sector has the highest self-volatility connectedness of 90.67% followed by telecommunications with 61.11%. These two sectors happen to be two among other sectors involved in production line or consumption of goods affected by US–China tariffs, such as automobiles, electronic chips, and metal materials (Annan 2020). This suggests that the tariffs cost had a significant impact on the volatility of these two sectors, resulting in higher values compared to other sectors.

Table 6. Average dynamic sectorial volatility connectedness during the US–China trade war.

	AM	TELCOM	INSUR	CHE	TEC	G.I	FIN	ENE	HEL	FROM
AM	90.67	0.81	1.44	0.74	1.3	1.58	1.20	1.6	0.65	9.33
TELECOM	4.23	61.11	2.85	1.98	2.84	8.67	4.97	6.01	7.36	38.89
INSUR	6.90	2.63	55.62	2.28	3.43	12.25	5.34	5.27	6.28	44.38
CHE	9.43	1.55	1.94	57.09	3.16	4.34	7.93	9.46	5.1	42.94
TEC	8.18	2.20	2.97	3.26	59.65	4.36	7.35	7.48	4.55	40.35
G-I	6.45	6.06	10.06	3.72	3.64	45.94	6.70	6.44	10.99	54.06
FIN	9.23	2.38	2.70	5.18	4.73	5.07	53.54	11.36	5.81	46.46
ENE	9.88	3.70	2.73	6.69	4.96	5.00	11.51	48.9	6.64	51.1
HEL	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: Authors' Estimation (2023).

In addition, the FROM-connectedness result (54.06%) shows the general industrial sector as the major receiver of risk from other sectors. These values suggest that this super sector, which is heavily involved in converting raw materials into finished products for export and other sectors of the economy, may have been affected by the trade war, considering that approximately 10% of South Africa's manufacturing exports are linked to China (SA Oil 2019). The sector with the least FROM-connectedness is the automobile and parts sector with 9.33%, indicating it receives the least risk 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 transmit shocks to other sectors, especially during the trade war period. The energy, general industrial, and financial sectors have a similar capacity to send shocks. The insurance (−14.97%), chemical (−14.73%), telecommunications (−14.25%), technology, general industrial, and health sectors are all net-receivers of shocks with general industrial being the least net-receiver with −1.66%. This shows that the insurance sector is the largest receiver of shocks during the US–China trade war.

The COVID−19 pandemic estimation spanned from 1 October 2019 to 31 December 2021 as presented in Table 7. This helps us to cover the timeline of the prevalence of pandemic in South Africa. Even though the pandemic started in China in November 2019, the first cases of the pandemic hit the country of South Africa in March 2020 with the nation declaring a national state of disaster in the same month (Giandhari et al. 2021). The average TCI from Table 7 is 68.57% while the conditional TCI is 77.14%. Both indicate the heightened level of average realised volatility within the sectors.

However, the chemicals sector has the highest self-volatility connectedness of 75.22%, followed by the energy sector with 56.69%. It is important to note that, despite being under significant pressure during this period, the health sector has one of the lowest self-volatilities at 22.36%. Table 7 also shows that the general industrial sector has the highest FROM-connectedness at 85.81%, indicating that it received the largest shocks from other sectors, followed by the financial sector with 79.34%. The health sector is the fourth-largest receiver of shocks.

The biggest net-transmitter of shock is the financial sector with 22.65%. This indicates that, while the sector provided funds to support other sectors during the pandemic and to revive economic activities, it transmitted more shocks than it received. The health sector, on the other hand, acted as a risk receiver during this period, demonstrating the critical supporting roles of healthcare in serving the populace during the pandemic (Lawrence et al. 2024b).

Table 7. Average dynamic sectorial volatility connectedness during COVID-19 pandemic period.

	AM	TELCOM	INSUR	CHE	TEC	G.I	FIN	ENE	HEL	FROM
AM	26.72	6.57	7.82	2.34	16.25	3.98	15.87	6.66	13.78	73.28
TELECOM	11.7	20.03	11.42	1.19	13.33	7.03	13.72	9.33	12.25	79.97
INSUR	10.97	12.27	22.84	1.46	12.18	7.57	13.86	7.13	11.71	77.16
CHE	5.4	1.67	1.97	75.22	4.11	1.02	3.68	3.4	3.54	24.78
TEC	15.01	8.22	7.72	1.86	24.18	5.68	15.76	7.9	13.68	75.82
G-I	10.74	9.97	8.38	1.44	12.64	14.19	16.27	13.38	12.99	85.81
FIN	13.36	8.55	9.05	1.44	14.48	9.86	20.66	7.91	14.69	79.34
ENE	7.53	5.67	6.18	1.36	8.11	1.78	6.27	56.69	6.41	43.31
HEL	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: Authors' Estimation (2023).

4.4. Network Plot of Volatility Connectedness of Full Sample and the Extreme Periods

Figure 1 shows the network plot of the volatility connectedness for the full sample period. The plot shows that the energy sector has the biggest blue node, making it the strongest net-transmitter of shock. The energy 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 complex value chain within the economy and the domestic and non-domestic demand of its products by the entire population (NAAMSA 2022). The automobile and parts sector acts as the highest receiver of shocks, receiving links from five different sectors (health, energy, financial, general insurance, and telecommunications). The widths of the edges are quite significantly thick, making the sector the highest in net-connectedness receiver, with a value of −8.39%. In contrast, the general industrial sector has the smallest node size, indicating it is the smallest net-receiver.

Figure 2 shows the network plot of the period of the GFC. The plot shows that the automobile and parts sector is the highest transmitter of shock, hence the reason why it has the biggest node (confirming the highest net-connectedness value of 35.80% in Table 4), with its strongest edge (shock) propagated to the technology and health care sectors. This indicates that during this period, the technology and health sectors were heavily affected by shocks from the automobile and parts sector within the business value chain. However, the health sector is the highest receiver of shocks, receiving shocks from six sectors, evidenced by its node size and lowest net-connectedness value of −29.83%. This demonstrates its role as a stable and defensive sector (Novy-Marx 2014). Figure 3 shows the network plot of the EDC period. The plot shows that the automobile and parts, general industrial, and telecoms sectors are the highest transmitters of shocks, as indicated by the size of their nodes and their propagation of shocks to six sectors. However, the chemical sector is the highest receiver of shocks as it receives shocks from six sectors (general industrial, energy, health, automobile and parts, technology, and insurance), with the lowest net-connectedness value of −20.28%. The decline in FDI inflow could have affected South Africa, Africa's largest chemical producer, through the EDC's impact on other sectors and industry (Kganyago 2012).

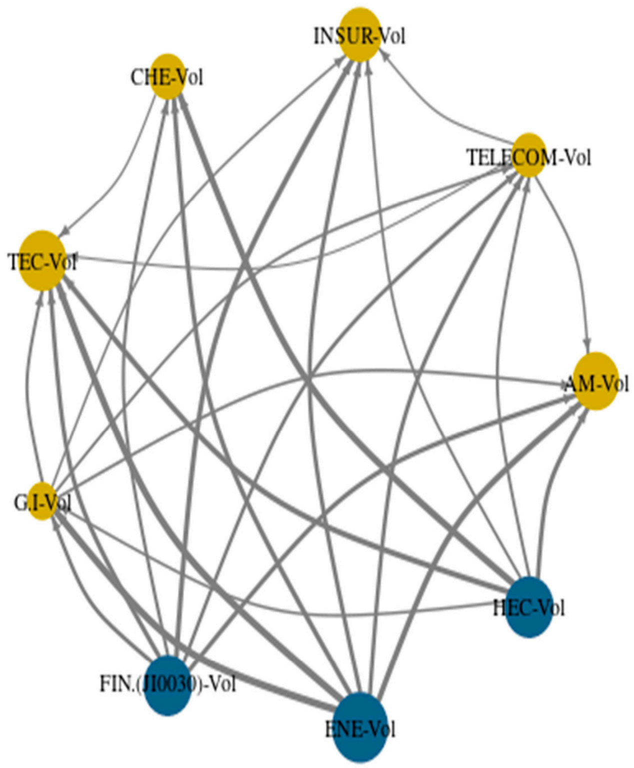

Figure 1. Network plot of volatility connectedness of full sample period. Source: Authors' Estimation (2023). Note: The yellow and blue nodes represent the receiving and transmitting sectors, respectively. The nodes are linked to one another through the edges. The edges differ in thickness due to how strong the shock transmitted in-between.

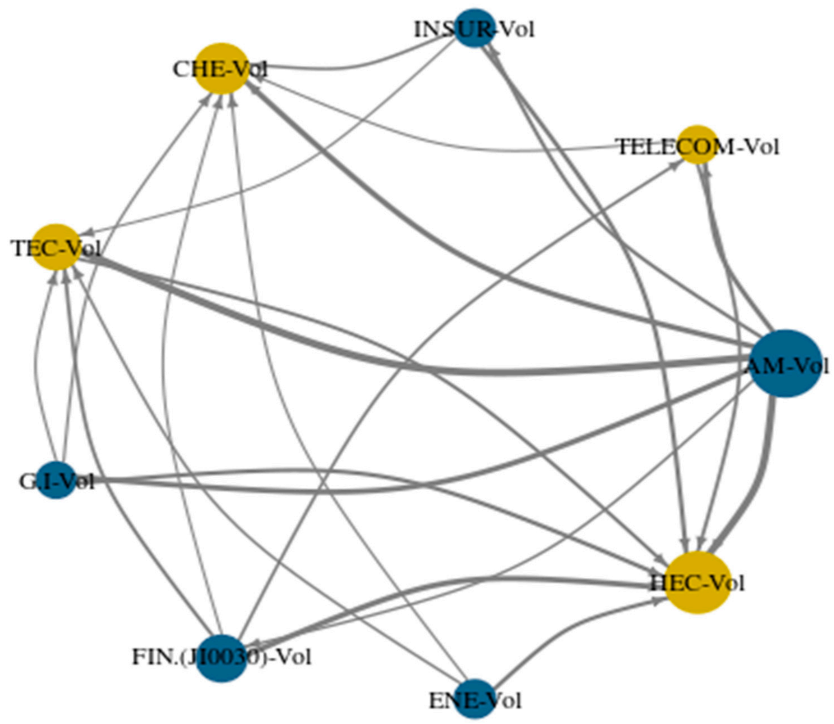

Figure 2. Network plot of volatility connectedness of GFC. Source: Authors' Estimation (2023). Note: The yellow and blue nodes represent the receiving and transmitting sectors, respectively. The nodes are linked to one another through the edges. The edges differ in thickness due to how strong the shock transmitted in-between.

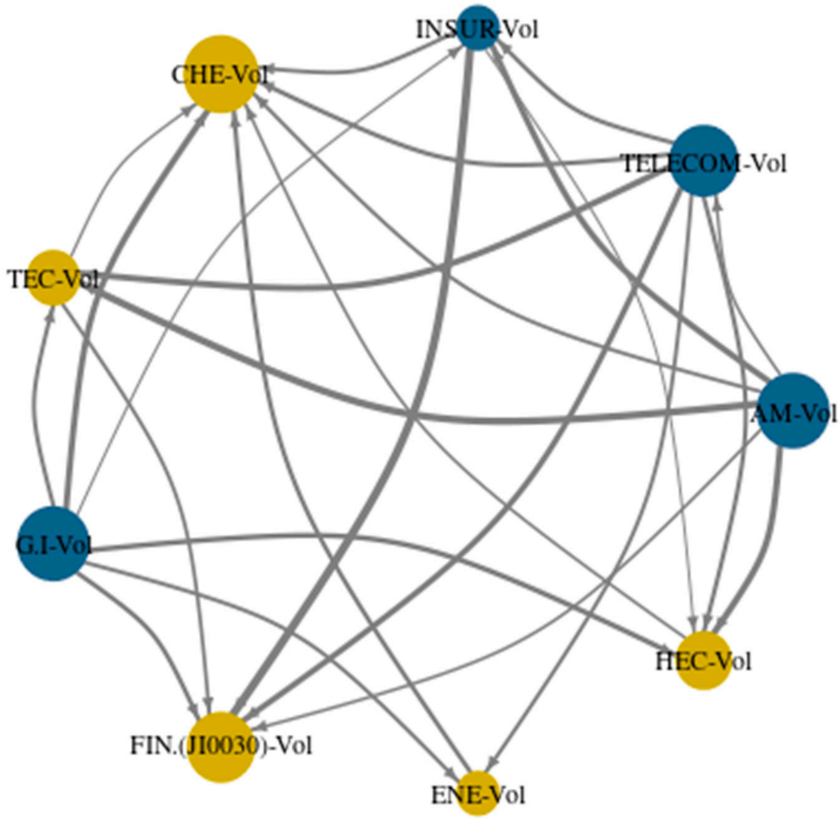

Figure 3. Network plot of volatility connectedness of the – EDC. Source: Authors' Estimation (2023). Note: The yellow and blue nodes represent the receiving and transmitting sectors, respectively. The nodes are linked to one another through the edges. The edges differ in thickness due to how strong the shock transmitted in-between.

Subsequently, Figures 4 and 5 illustrate how each crisis impacts volatility connectedness of the JSE sectors differently. Figure 4 shows the network plot under the US–China trade war period. The plot reveals that the automobile and parts sector is the main propagator of shocks, with the biggest blue node. It sends shocks to the remaining eight sectors through eight edges, with stronger shocks to the chemical, telecommunication, insurance, and general industrial sectors, as shown by the thicker width of the edges. This suggests that the automobile and parts sector is highly connected with these sectors, making it the highest net-transmitter with 51.2%. It also generated the highest self-induced volatility in the network of 90.67% (see Table 6). Figure 5 also shows the network plot under the COVID-19 pandemic period, revealing the general industrial sector as the main shock receiver, receiving shocks from the automobile and parts sector. Figure 5 reveals that the insurance and telecommunications sectors acted as shock receivers. This network confirms the finance sector as the highest net shock transmitter with 22.65%.

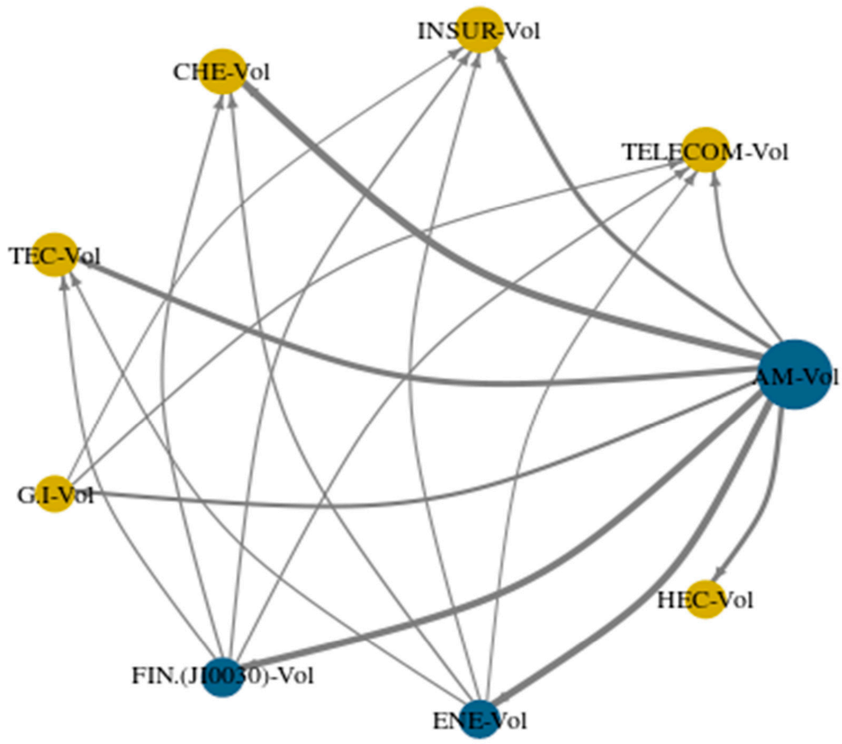

Figure 4. Network plot of volatility connectedness of the– US–CHINAR TRADE WAR. Source: Authors' Estimation (2023). Note: The yellow and blue nodes represent the receiving and transmitting sectors, respectively. The nodes are linked to one another through the edges. The edges differ in thickness due to how strong the shock transmitted in-between.

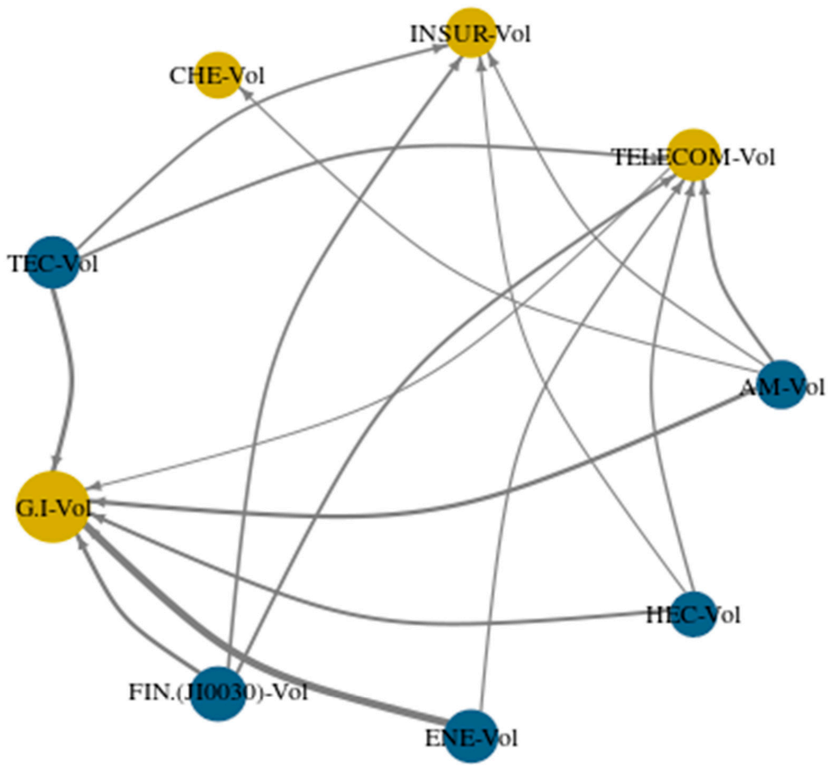

Figure 5. Network plot of volatility connectedness of the COVID-19. Source: Authors' Estimation (2023). Note: The yellow and blue nodes represent the receiving and transmitting sectors, respectively. The nodes are linked to one another through the edges. The edges differ in thickness due to how strong the shock transmitted in-between.

5. Discussion

The study shows that the TCIs are significantly high during extreme periods like the GFC, EDC, and the COVID-19 pandemic. The high TCI confirms a significant volatility connectedness amongst the sectors on the JSE, an indication of the high risk spillover and limited diversification possibilities. The GFC results reveal that the health and chemical sectors are the highest net-receivers of shocks with −29.83% and −17.87%, respectively, while the highest net-transmitters are the automobile and parts and finance sectors during the GFC. The net-transmitters of risk, transmit risk of cyclical nature to other sectors during the crises. In contrast, non-cyclical[8] sectors such as telecoms, chemicals, and health absorb these shocks. This result corroborates the findings of Chowdhury and Irfan (2022), which indicate that cyclical stocks are net-transmitters of risk in the Indian stock market. It is not surprising that the financial sector is a transmitter of risk during the GFC, as the crisis originated in the financial sectors (Baily et al. 2008).

In the EDC period, the risk transmitters are the automobile and parts, general industrial, telecoms, and insurance sectors, while the risk receivers are the chemical, finance, health, technology, and energy sectors. According to Fuchs et al. (2012), South Africa has the largest economy in Africa, with a developed and internationally integrated financial sector; it is both the most significant recipient of portfolio inflows and the biggest borrower from European banks. In late 2011, there was a significant decline in portfolio inflows, which affected 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 their businesses, which were already under pressure. The average amount of loans from foreign banks as a percentage of GDP is low in most African nations, but for South Africa and some other African nations, it exceeds 20% (Fuchs et al. 2012). These are suggestive of the fact that the financial sector could be an external shock receiver during the EDC crisis; hence, a distortion in the business value chain of these sectors could be inevitable, as sectors close to them in the chain will be first to experience a distortion in their business flow.

The average TCI for all sectors during the US–China trade war stood at 47.35%, which is quite low compared to the GFC of 71.05%; EDC of 77.10%; and COVID-19 pandemic period of 77.14%. This suggests that the impact of the trade war on the sectors within the JSE is not as significant compared to the three other notable extreme events that affected the whole globe. As shown in Figure 4, the risk-receiving sectors include the insurance, telecommunications, chemical, tech-nology and general industrials sectors. One major channel of external risk transfer to the economy is through cumulative tariff effects in global supply chains (Mao and Görg 2020). Moreover, Egger and Zhu (2020) documented 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 during the trade war. This suggests reasons why from Table 6 some of the sectors that are net-receivers of shocks during this period are export-driven in nature; for example, general industrials, technology, telecoms, and chemicals.

The finding of this study worth discussing is the identification of sectors that transmit more shock to other specific sectors. This could have implications for changing diversification opportunities during different market events. As highlighted through the network plot of the full sample period, the energy sector directly transfers more shocks (thicker edges) to general industrials, technology, and automobile and parts super sectors. Also, the automobile and parts sector transferred more shocks (thicker edges) to technology, health, general industrials, chemicals, and telecoms sectors during the GFC. During the EDC, the automobile and parts sector also had more shocks (thicker edges) transfer to technology, health, and insurance sectors. Similarly, during the US–China trade war, the automobile and parts sector transferred more shocks (thicker edge) to energy, financial and chemical sectors and fewer shocks (thinner edges) to general industrial, insurance, and telecommunications. For the benefits of diversification, sectors with a tendency to transfer highest shocks to one another must not be combined and vice versa.

Similarly, the EDC is another finance-related crisis where portfolio diversification with telecommunications could be considered, given the fact that it is a sector that received far fewer shocks (very thin edge) from the automobile and parts sector. Finally, since the automobile and parts and the finance sectors had greater shock exposure during the US–China trade war and the COVID-19 pandemic periods, respectively, it may be wise to avoid portfolios that include these two sectors. These results differ from Dang et al. (2023) 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.

Drawing from the analysis of different market conditions, the volatility spillover varies in magnitude over time but is generally high, with the exception of US–China trade war period. For example, the highest volatility connectedness was during the EDC (68.83%), and during the COVID-19 pandemic (68.57%), followed by the GFC (63.16%) and lastly the US–China trade war (42.09%). It is safe to state that the higher the magnitude of a crisis, the higher the volatility spillovers and tendency for a systemic risk among JSE super sectors. The financial sector was the primary net-transmitter of shocks during the COVID-19 period, while the automobile and parts sector was the strongest net-transmitter of shocks during the GFC, EDC, and US–China trade war. Similarly, the strongest net recipient of shocks during GFC, EDC, and COVID-19 is the chemical super sector. Thus, the automobile and parts sector and chemical super sector are of systemic importance in the JSE.

6. Conclusions

The study analysed dynamic volatility connectedness and shock propagation of the JSE super sectors using the TVP-VAR approach developed by Antonakakis et al. (2019) and Antonakakis et al. (2020), along with the connectedness model of Diebold and Yilmaz (2009, 2012, 2014). This study established that the average TCIs of the super sectors are high and dynamic, thus confirming hypotheses one and two. Sectorial volatility connectedness does exist on the JSE during extreme events such as those mentioned. This establishes that the average sectorial volatility spillover is significant, over 60% for each event, except for the US–China trade war. The automobile and parts sector was the strongest net-transmitter of shocks during the GFC, EDC, and US–China trade war, emphasising the systemic importance of the super sector in South Africa. The Automobile sector in South Africa is the third largest economic sector in the country. It is the world's eighteenth largest industry for the production of automobiles South African Embassy (SAE 2002). The South African automobile and parts sector plays a vital role in the South African economy. The sectors has capitalised on the economic interest from countries like the Japanese, European, and American vehicle manufacturers, considering the wealth of experience of these countries (NAAMSA 2022). Similarly, in terms of the net shock recipient, the strongest net recipient of shocks during GFC, EDC, and COVID-19 is the chemical super sector. The results show that Africa's largest chemical producer, through external crises' impact on other sectors and industries, is affected. A significant portion of the South African manufacturing activities is in 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). We conclude that automobile and parts and chemical super sectors are the major net-risk transmitter and recipient, respectively, refuting the third hypothesis of the study which states the net-transmitters and recipients are not likely to remain the same during different market conditions. It is safe to exclude these two sectors from the portfolio of the JSE equity super sectors for the purpose of diversification.

The study concludes that there is a significant volatility connectedness among JSE super sectors. In addition, the JSE super sectors exhibit significant time-varying connectedness during extreme events. Moreover, the net-transmitters and net-receivers of shock do not change significantly during different crisis periods. Thus, portfolio managers and investors in South Africa could leverage sectorial net-connectedness outputs to predict suitable sectorial equities to include in a portfolio. Therefore, this study provides insights for investors on sectorial stock volatility and correlation with a clear understanding of portfolio formation strategies. The study further recommends a strong governance and sectorial-business risk administration during turbulent periods. Finally, future research could focus on empirical estimations of the weights of equity sectors in a possible simulated environment for portfolio diversification.

The limitation of this study includes nonavailability of data for certain super sectors, such as real estate and utilities. These two sectors did not have readily available data in the IRESS data bank. Knowing the economic importance of these two super sectors to the South African economy, future study must consider these super sectors when the data are available data.

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Notes

1. This is a worldwide integration of the financial system where financial institutions, economies and markets are interlinked (Valdés 2000).
2. Contagion is the propagation of market disturbances, from one economy to another through the movement of assets. It could also be defined as a considerable rise in cross-market linkages due to shock to an economy or groups of economies. (Dornbusch et al. 2000).
3. Volatility spillover refers to the transmission of instability from market to another. It occurs when price volatility change in one market causes a lagged impact on price volatility in another market above the local market effects.
4. In this study, sector (s) is used to connote super sector (s) of the JSE market which are samples for the study.
5. Wold representation theorem states that every covariance-stationary time series decomposed into the sum of two time series, a deterministic component and a stochastic component.
6. Total connectedness index (TCI) refers to the average impact a shock in one series has on all others (Antonakakis et al. 2019). Assessed 3 March 2024. https://gabauerdavid.github.io/ConnectednessApproach/Rpackage#dynamic-connectedness-measures. Assessed on 15 July 2024
7. Conditional dynamic total connectedness Index (cTCI) refer to the measure of the dynamic connectedness patterns between financial assets or series.
8. 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. Examples of cyclical sectors in South Africa include financial, industrial, energy, automobile and parts and technology.

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