"The determinants of volatility connectedness of South African equity super sectors"

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THE DETERMINANTS OF VOLATILITY CONNECTEDNESS OF SOUTH AFRICAN EQUITY SUPER SECTORS

Abstract

The paper aims to explore the determinants of total volatility connectedness of nine super sectors on the Johannesburg Stock Exchange (JSE) market from 3rd January 2006 to 31st December 2021. These sectors are Automobile and Parts, Chemical, Telecommunication, Technology, Energy, Health, Finance, Insurance, and General Industrials. The paper applied Diebold and Yilmaz connectedness matrix and the time-varying parameter – vector autoregressive (TVP-VAR) model to determine the sectorial total volatility connectedness index (STVCI). After that, the nonlinear autoregressive distributed lag model (NARDL) was used to determine the asymmetric effects and the drivers of STVCI. It was found that the partial sum decomposition of the South African volatility index (SAVI) and Economic Policy Uncertainty Index (EPU) are the key determinants of the STVCI both in the long and short run. However, domestic market return (DMR) shows no significant asymmetric effect on STVCI. The study concluded that SAVI and EPU are the key determinants of volatility connectedness among the JSE super-sectors. The results unveil important implications for sectorial investors and policymakers on potential regulations and stability of the significant determinants of spillover risk.

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INTRODUCTION

The Johannesburg stock exchange (JSE) market is made up of aggregated and disaggregated sector (Kawawa & Hoveni 2017). In a study by Moodley et al. (2022), it was found that the bullish market conditions was dominant among JSE disaggregated sector returns. This implies that the JSE disaggregated sector returns are high and stable. However, the recent surge in global turbulence caused by the financial crises, European Debt Crisis and Covid-19, among others, has significantly affected the stocks listed on the JSE (Lawrence et al. 2024). In this context, Muzindutsiet al. (2020) demonstrate that the JSE mining sector returns fluctuated during the 2008 global financial crisis. Similarly, Shi et al. (2021) discovered that the returns of information technology and industrials sectors co-moved during the 2017-2018 US-China trade war. Consequently, the JSE sectors are not completely insulated from the global financial crisis such as the European Debt Crisis, which effected the Paris, London, Frankfurt and New York stock exchanges. In the same vein, Akinola, Anderu and Mbonigaba (2021) demonstrated that Covid-19 pandemic was a global event that affected most financial markets including the JSE (Akinolaet al., 2021).

Over the years, the occurrences of global crises have resulted in contagion due to their impact on the volatility of asset markets (Fry-

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McKibbin et al., 2014) including the JSE market (Duncan, & Kabundi, 2011; Chokoe, 2022). However, other drivers of sectoral volatility connectedness are yet to be determined. Hence, investigating the drivers of sectoral volatility connectedness such as the macroeconomic factors that could influence the connectivity of the JSE super sectors will contribute to existing body of knowledge.

This study is related to a limited documentation of research focusing on connectedness of assets (Awartani et al., 2016; Su, 2020 ; Agyei & Bossman, 2023). However, it differs by applying the Diebold and Yilmaz connectedness matrix (2009, 2012, and 2014) alongside the TVP-VAR model of Antonakakis et al. (2020) to determine STVCI and NARDL to establish short and long run determinants of STVCI. This study contributes uniquely to literature because it is the first to determine STVCI and its determinants, especially in the South African context. The remainder of this article is organized as follows: section 2 provides both the theoretical and empirical review of literatures, section 3 contains the methodology and data, section 4 presents the empirical results and the conclusion is presented the last section.

1. LITERATURE REVIEW

There are several explanations for volatility spillovers in the financial markets. Engle et al. (1990) identified two hypotheses on volatility spillovers. The first hypothesis is known as "heat wave" hypothesis. The heat wave suggests that volatility in one market will only persist in the same market on the next day and would not spread to other markets. In contrast, the "meteor shower" hypothesis which is the second postulates that volatility in a market tends to transmit to another, hence, volatility in a market is followed by volatility in another market. The "meteor shower" hypothesis might be associated with the failures of market efficiency. Aside from these hypotheses, two other primary theoretical arguments are related to volatility transmission, including the "decoupling" and "contagion" hypotheses. The "contagion" hypothesis suggests that the benefits of portfolio diversification are limited because of the increasing intensity of volatility transmission across markets during a crisis (Hkiri et al. 2017). Alternatively, the "decoupling" hypothesis asserts that performance in emerging economies is independent of changes in the developed economies (Wyrobek et al., 2016).

Empirical literatures on the determinants of volatility has been documented in different markets around the globe. However, there are very limited literature on the determinants of sectorial total volatility connectedness. For example, Kurzet al. (2005) posit that stock market volatility are driven rationalizable over confidence by investors and second rationalizable asymmetry in frequencies of bull or bear states. Different studies had emerged with more emphasis on the macroeconomic factors that could have more impact on stock market volatility. For example, Batten et al. (2010) modelled the macroeconomic determinants of price volatilities of four precious metal (silver, gold, palladium and platinum) between January 1986 and May 2006. It was established that gold volatility could be explained by the monetary variables, however, these monetary variables could not explain silver and others. The paper further established that there is limited proof that the same macroeconomic factors jointly influence the volatility processes of the four precious metal prices.

Focusing on time-varying volatility and spillover effect of crude oil, heating oil and natural gas markets from 1994-2011, Karali and Ramirez (2014) show that the volatility of crude oil increases in response to major financial, political and natural events in the United State. Furthermore, by studying ten real estate investment trusts (REITS) over 2004-2017 period, Liow and Huang (2018) discovered that REITs volatility is significantly influenced by interest rate movement, market anxiety, economic policy uncertainty, and global stock market returns. Shahzad et al. (2019) studied 2,862 daily observations of Credit Default Swaps indices using Bayesian model averaging. The findings showed that stock market volatility and financial conditions were the main factors influencing corporate CDS connectivity in the Eurozone.

In the cryptocurrency market, Moratis (2020) studied the determinants of spillover risk by employing daily prices of the 30 largest cryptocurrencies from

2016-2018. The findings confirm that, Bitcoin as the cryptocurrency with the greatest network, significantly increases the market's spillover risk. Due to the fact that larger cryptocurrencies are associated with more cryptocurrencies than their counterparts, size, as determined by market capitalization, is a good predictor of spillover risk. Contrastingly, Ji et al. (2019) demonstrate that variables such as trading volume, global financial factors, economic policy uncertainty, and commodity prices influence the return and volatility connectedness of the cryptocurrency markets. Moreover, global shocks resulting from changes in the price of metals and oil are, according to Atenga and Mougoué (2021), the drivers of return and volatility connectivity across African stock markets. Similarly, according to Su (2020), within the G7 countries' real economic activities, oil price, industrial productivity, market anxiety, economic policy uncertainty, currency rate, and consumer confidence all have varying effects on the long- and short-term volatility connectedness among their equities markets.

In a more recent study, Bouri et al.(2021) illustrate that real economic activity, term spread of interest rates, and economic policy uncertainty are the main factors influencing volatility connectivity in the commodities futures market. To the knowledge of the authors, this is the only study that examines the determinants of connectedness using the TVP-VAR framework. In the study of liquidity connectedness, Inekwe (2020) uses the Diebold and Yilmaz framework to assess the degree of liquidity connectedness across 24 European and Asian economies, but the connectedness was not examined.

With the limited literature discussed above, authors across different countries have modelled the volatility of stocks and commodities. Moreover, it is evident from the above literature that time-varying volatility and spillover of commodities has been established alongside the determinants of their spillover. However no empirical study has established the determinants of total volatility connectedness at the sectorial level, especially when considering the asymmetric effect of these determinants on STVCI. It is, therefore, unknown how macroeconomic factors could impact the STVCI on the JSE. Hence, the purpose of this study is to investigate the determinants of sectorial total volatility connectedness on the JSE market, in South Africa, being one of the fast-growing emerging economies.

The novelty of this study is the application of the TVP-VAR framework and NARDL for examining sectoral volatility connectedness and its drivers. Literature reveals that while other drivers of connectedness have been determined for a few asset classes, there is a shortage of studies on the drivers of STVC in equity markets. Understanding the drivers of the STVCI could aid portfolio maximization, especially in an emerging market such as South Africa. Employing the novel NARDL model enables the capturing of the negative or positive functions of the explanatory variables and the effect of their changes on the sectoral volatility connectedness index. Consequently, the purpose of this study is to investigate the drivers of sectorial total volatility connectedness on the JSE market by employing the Diebold and Yilmaz connectedness index alongside the TVP-VAR framework to determine the STVCI and thereafter employing the NARDL model to establish the drivers of STVCI on the JSE market.

2. METHODS

Daily volatility of selected nine super sectors on the Johannesburg Stock Exchange, namely, Energy (ENE), Technology (TECH), General Industrial (IG), Financials (FIN), Health Care (HEC), Insurance (INS), Telecommunications (TEL), Chemicals (CHE), and Automobile and Parts (AM & P) (ICB 2019, 2021), was computed from their daily returns for the period January 3, 2006 to December 31, 2021. The sample period was informed by data availability and relevant regional and international extreme economic and market events, thus allowing for a better understanding of the dynamic spillover and shock propagation of the JSE super sectors. The research approach adopted for this study was quantitative, empirically investigating the connectedness of super sectors on the JSE and its determinants. Following Shahzad et al. (2018) and Liew et al. (2022), the monthly average of the daily STVCI connectedness would be generated and employed as the dependent variable denoted as $\Delta G_t Con_T$ in equation (8).

The daily returns of each super sector are computed from their price indices in equation (1) following Zhang et al. (2020).

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

where P_{ti}, P_{t0}, and PRi,t represent the price at the current time, the price at the initial time, and the price return, respectively.

2.1. Modelling shock propagation and connectedness of JSE super sectors

The paper examines shock propagation and connectedness among JSE equity sectors. The study followed Shen et al. (2020) and Garman and Klass (1980) to investigate the volatility spillover of the super sectors by first generating the daily realized volatility for each index, such that:

$$V_{it}^{GK} = 0.511\left(h_{it} - l_{it}\right)^2$$
$$-0.019\left[\left(c_{it} - o_{it}\right)\left(h_{it} - l_{it} - 2o_{it}\right)\right. \quad (2)$$
$$\left.-2\left(h_{it} - o_{it}\right)\left(l_{it} - o_{it}\right)\right] - 0.383\left(c_{it} - o_{it}\right)^2,$$

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 to determine the time series properties.

Subsequently, the time-varying parameter VAR (TVP-VAR) model, an innovation of Antonakakis et al. (2020), is employed to determine the connectedness of and shock propagation among the JSE super sectors. Following Antonakakis et al. (2020), the study combines the TVP-VAR methodology, which was first established by Koop and Korobilis (2013), to overcome the drawbacks of the rolling-window approach and the Diebold and Yilmaz (2009, 2012, 2014) connectedness index. The connectedness index computation of a TVP-VAR model with one lag can be expressed as:

$$\Delta y_t = \theta_t \Delta y_{t-1} + \mu_t, \quad \mu \sim N\left(0, E_t\right), \quad (3)$$

$$vec\left(\theta\right) = vec\left(\theta_{t-1}\right) + r_t, \quad r_t \sim N\left(0, Q_t\right), \quad (4)$$

where 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, $N = 9$, the series involved are the volatilities of the super sectors of the JSE.

Antonakakis et al. (2020) suggest that the Wold's representation is used to transform the estimated TVP-VAR into a time-varying-parameter vector-moving-average (TVP-VMA) representation. This theorem is expressed as:

$$\Delta x_t = \sum_{i-1}^{p} \beta_{it} \Delta x_{t-1} + \varepsilon_t = \sum_{j=1}^{\infty} \gamma_{jt} \int_{t-j} + \varepsilon_t, \quad (5)$$

x_t step, the TVP-VMA coefficients are extracted to compute the generalized forecast error variance decomposition (GFEVD) developed by Pesaran and Shin (1998). From there, the Diebold and Yilmaz 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:

$$\varnothing^{g}_{ij,t}\left(J\right) = \frac{\sum_{ii,t}^{-1} \sum_{t=1}^{J-1} \left(l_j' A_t E_t l_j\right)^2}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \left(l_i A_t \Sigma_t A_l' l_i\right)} \varphi^{g}_{ij,t}\left(J\right)$$
$$= \frac{\varnothing^{g}_{ij,t}\left(J\right)}{\sum_{j=1}^{N} \varnothing^{g}_{ij,t}\left(J\right)}, \quad (6)$$

with

$$\sum_{j=1}^{N} \varphi^{g}_{ij,t}\left(J\right) = 1, \text{ and } \sum_{i,j=1}^{N} \varphi^{g}_{ij,t}\left(J\right) = N,$$

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, the total connectedness index is constructed as:

$$C_t^g\left(J\right) = 1 - N^{-1} \sum_{i-1}^{N} \varphi^{g}_{ii,t}\left(J\right), \quad (7)$$

This total connectedness index ($C_t^g(J)$) estimated above is used as the dependent variable of the NARDL model used to investigate the drivers of the STVCI[1]. The daily STVCI estimated above is converted into a monthly series with E-views because the estimated determinants of the STVCI

1 See equation (9)

are available monthly. The precise measurement of the daily connectedness index proves that the Diebold and Yilmaz connectedness index is a justified index.

2.2. Modelling the determinants of sectorial total volatility connectedness with NARDL

This study uses the NARDL model to model the determinants of volatility connectedness of the super sectors. The model accommodates both the levels and differences of the relevant series (I (0) and I (1)) or combinations of both and accounts for 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 et al., 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 the context of this study, the estimated ARDL model is presented as follows:

$$\begin{aligned} G_tCon_T &= n_0 + \sum_{i=1}^{k}\partial_1 G_tCon_{Tt-1} \\ &+\sum_{i=1}^{t}\partial_2\Delta SAVI_{(t-i)} + \sum_{i=1}^{t}\partial_3\Delta DAMR_{(t-i)} \\ &+\sum_{i=1}^{t}\partial_4\Delta EPU_{(t-i)} + \ldots\partial_n X_{t-1} + \beta_1 G_tCon_{t-1} \\ &+\beta_2 SAVI_{t-1} + \beta_3 DAMR_{t-1} + \beta_4 EPU_{t-1} \\ &\ldots\ldots\beta_n X_{t-1} + e_t, \end{aligned} \tag{8}$$

where G_tCon_T represents monthly total connectedness index across the super sectors on the JSE, obtained by averaging the daily total connectedness index derived from equation (7) into monthly index. The practice of averaging daily total connectedness is consistent with Liew, Lim and Goh (2022). ∂_1, ∂_2, ∂_3, ∂_4, ..., ∂_n represents the short-run coefficients, and β_1, β_2, β_3, β_4, ..., β_n depict the long-run coefficients. The error term is represented by e_t. The null (H_0) hypothesis and the alternative (H_a) hypothesis for the ARDL bound test are depicted as

H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \ldots\ \beta_n = 0.$

H_a: $\partial_1 \neq \partial_2 \neq \partial_3 \neq \partial_4 \neq \ldots\ \partial_n \neq 0.$

To reject the null hypothesis, the F-statistics must be greater than both the lower and upper bound critical values. Once the series is not integrated at order (2), the NARDL model is implemented. This study appropriates the different parameters into corresponding shocks such that: Con^+, Con^-, $SAVI^+$, $SAVI^-$, $DAMR^+$, $DAMR^-$, EPU^+, EPU^-, ...$Xt\text{-}1^+$, $Xt\text{-}1^-$.

Equation (8) can be specified in the NARDL model as shown thus:

$$\begin{aligned} \Delta G_tCon_T &= \partial_0 + \sum\nolimits_{(i=1)}^{t}\partial_1 G_tCon_{T(t-1)} \\ &+\sum\nolimits_{(i=1)}^{t}\partial_2\Delta SAVI^{+}_{(t-1)} + \sum\nolimits_{(i=1)}^{t}\partial_3\Delta SAVI^{-}_{(t-1)} \\ &+\sum\nolimits_{(i=1)}^{t}\partial_4\Delta DAMR^{+}_{(t-1)} \\ &+\sum\nolimits_{(i=1)}^{t}\partial_5\Delta DAMR^{-}_{(t-1)} + \sum\nolimits_{(i=1)}^{t}\partial_6\Delta EPU^{+}_{(t-1)} \\ &+\sum\nolimits_{(i=1)}^{t}\partial_7\Delta EPU^{-}_{(t-1)}\ldots\sum\nolimits_{(i=1)}^{t}\partial_n\Delta X^{+}_{(t-1)} \\ &+\sum\nolimits_{(i=1)}^{t}\partial_n\Delta X^{-}_{(t-1)} + \beta_1 G_tCon_{(t-1)} + \beta_2 SAVI^{+}_{(t-1)} \\ &+\beta_3 SAVI^{-}_{(t-1)} + \beta_4 DAMR^{+}_{(t-1)} + \beta_4 DAMR^{-}_{(t-1)} \\ &+\beta_5 EPU^{+}_{(t-1)} + \beta_6 EPU^{-}_{(t-1)}\ldots + \beta_n X_{(t-1)} \\ &+\rho ECT_{(t-1)} + e_t, \end{aligned} \tag{9}$$

where ΔG_tCon_T represents $C^g_t(J)$, and $C^g_t(J)$ is the monthly total connectedness index obtained in equation (7). In identifying the major difference between the ARDL and the NARDL models, the linear ARDL model lacks the option of both positive and negative variations of the independent variables, which would have differing impacts on the dependent variable. The NARDL allows the identification of the nonlinear relationship between the dependent and explanatory variables, in addition to checking cointegration in a single-equation framework (Pesaran et al., 2001). Additionally, the study assesses the stability of the asymmetrical models using the Wald test. The Wald test was employed by the study to verify the long-term asymmetrical influence of the asymmetrical ARDL approach. The asymmetric causality, which enables the parameters to be separated into the corresponding shocks, tests their causal-

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ity from negative shocks to negative shocks and positive shocks to positive shocks under the VAR framework, using the Hatemi-j (2012) causality.

3. RESULTS AND INTERPRETATIONS

To generate the daily realized volatility in equation (2), this study examined daily opening and closing prices of the 9[2] JSE super sectors. The descriptive statistics of the daily realized volatility for each index, calculated following German and Klass's (1980) calculations of the sectors, are shown in Table A1 (see Appendix). The energy and health sectors have the highest and lowest mean of 0.000302 and –0.000572, respectively. The Energy and General Industrial sectors have maximum and minimum values of 0.2101 and 0.00000868, respectively.

Table 1. Unit root for volatilities of super sectors

Variables	REALISED SUPER SECTOR VOLATILITY Levels 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)

Note: *, **, and *** represent 10%, 5%, and 1%, respectively.

Moreover, the Health sector has the highest standard deviation of 0.0059, which signifies that its volatility is not clustered around its means. The statistics also show the kurtosis and the skewness coefficients, which indicate that the realized volatilities of the series are far from the normal distribution, all statistically significant at 1% significance level. This condition is formally confirmed by the Jarque-Bera test statistics. Table A2 (see Appendix) shows the pairwise Pearson correlation coefficients across the 9 super sectors. The correlations are positive and negative, varying from the lowest value of –0.0052 between chemical and Insurance and 0.5248 between general industrial and insurance super sectors, which have the highest correlation. This result was anticipated as the general industrial sector, being a capital-intensive sector, would rely on the insurance sector to meet the need for insuring the lives of staff, products, properties, etc., whether as life, nonlife, or General insurance services.

Tables A3 reveal that the Augmented Dickey-Fuller (ADF) test and the Philips-Perron (PP) test ascertain that both the STVCI and the determinant variables are not integrated at the second-level difference, which testifies to the trustworthiness of the F-test.

Table A4 reveals an average sectorial total dynamic volatility connectedness index (STVCI) of 62.0% and a conditional sectorial total dynamic volatility connectedness index (cSTVCI) of 69.74%. A STVCI of 62.0% reveals that the daily STVCI of each super sectors has a mean volatility connectedness value of 62.0%. The sectorial total volatility connectedness index graph shown in Figure 1 reveals some spikes, which are signs of extreme volatility connectedness across the different super sectors triggered by economic shocks. Figure 1 gives the graphical evolution of the sectorial total volatility connectedness over the sample periods. The much interesting spikes to note from Figure 1 are the 90% threshold in 2007–2008, the 100% threshold in 2015, and the 70% threshold of 2020. These volatility spikes coincide with the GFC, the civil unrest that lead to stoppage of production of coal and closure of mines in South Africa, and finally, the COVID-19 pandemic occurrence, which officially was announced in the country on March 26, 2020.

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

Determinants of the sectorial total volatility connectedness index

Table 2 presents the results of ARDL and NARDL equations and reveals that the F-statistics of 3.49 and 4.55 are larger than the upper bound critical value at 5% and 1% significance levels, respectively. This indicates the presence of a long-run relationship (occurrence of cointegration) between log of

2 There are 11 super sectors; two super sectors, such as utilities and real estate, are omitted due to data availability.

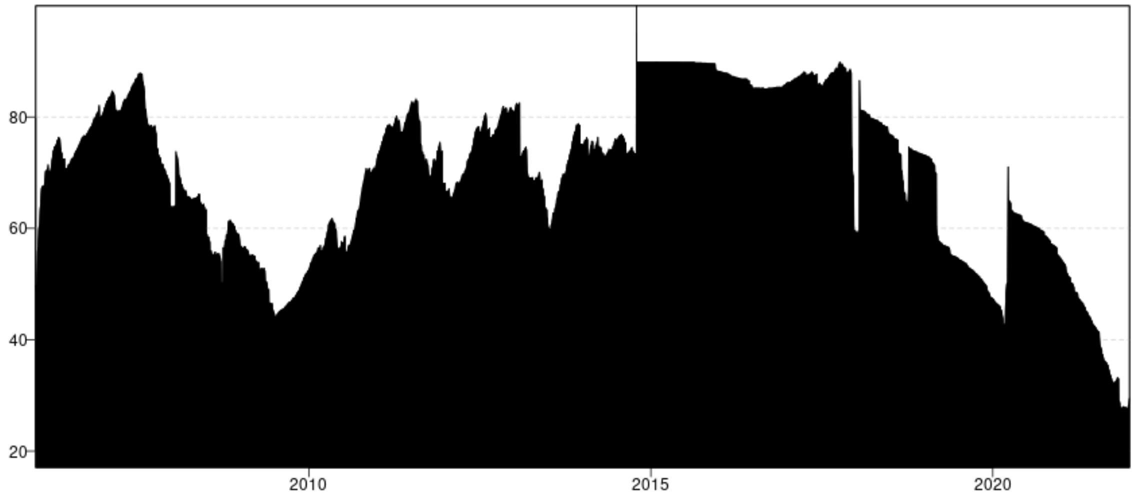

Figure 1. Total dynamic volatility connectedness between super sectors on the Johannesburg Stock Exchange for the full sample

the STVCI (LSTVCI) and its drivers. According to the AIC, the maximum lag order equals 4 to preserve the degree of freedom. Between ARDL and NARDL, the best model that minimizes information criterial is NARDL (LSTVCI) (4, 2, 0, 1, 1, 4, 3, 0, 2, 2, 2.).

Table 2 also shows that the LSTVCI is a positive and negative function of positive and negative changes in LSAVI. Hence, a 1% increase and decrease in LSAVI will increase and decrease LSTVCI by 0.8066 and 0.0547, respectively. However, LSTVCI is a positive function of both positive and negative changes in LEPU and LDMR. Hence, a 1% increase in the South African economic policy uncertainty Index will increase the LSTVCI by 0.001 unit, and a 1% decrease in the South African economic policy uncertainty will increase the log of total sectorial total volatility connectedness index of the JSE by 0.0021 units. Similarly, a 1% increase in the log of domestic market return (i.e. All Share Index) will increase the logarithm of the total connectedness index by 1.3952 units, while a 1% decrease will increase the LSTVCI index by 2.2793 units.

Table A5 presents the error correction model for ARDL and NARDL models. The estimated result of the asymmetric long run and the short run of the NARDL model is also revealed in Table 3 The error correction term of CointEq (–1) is negative and statistically significant at 1%. Hence, it reveals that there is cointegration among the independent and the dependent variables in the NARDL model, indicating that the speed of adjustment from the short to the long run is 12.2%. This means that at any disequilibrium, there is a correction back to equilibrium monthly at a rate of 12.20%, which is also -0.0594 for the ARDL model. These results show that only the negative impact of South Africa's volatility index, domestic market return, economic policy uncertainty, trade openness, manufacturing output, and money supply have a significant short-run effect on the total connectedness index.

Table 3 indicates the NARDL asymmetry test result. The NARDL asymmetric test 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. The null hypothesis of the Wald test implies that the relationship between the dependent variable, the logarithm of sectorial total volatility connectedness index (LSTVCI), 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. The alternative hypothesis states that there is an asymmetric relationship between the dependent variable (LSTVCI) and independent variables (LSAVI, LEPU, and LDMR). The evidence indicates strong evidence of asymmetric effects in the long run and short run in in-

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Table 2. Bounds test for cointegration for the long-run ARDL and NARDL

Bound Test Result for Cointegration Test and Long-run Equation									Outcome
F Statistic	99%		97.50%		95%		90%		
	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	I (0)	I (1)	
3.49**	2.88	3.99	2.55	3.61	2.27	3.28	1.99	2.94	COINTEGRATED
Long-run Equation ARDL D(LSTVCI)	$EC = \text{LSTVCI} - \left(\begin{array}{l} 0.2652 \cdot LSAVI - 1.7207 \cdot LMOP + 0.0013 \cdot LEPU \\ -3.4702 \cdot LM2 - 1.6131 \cdot LTO + 3.0958 \cdot LDMR + 15.3561 \end{array} \right)$								
F Statistic	99%		97.50%		95%		90%		
	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	COINTEGRATED
Long-run Equation NARDL LSTVCI	$\begin{array}{l} \text{LSTVCI} = 0.8066 \cdot LSAVI\_POS - 0.0547 \cdot LSAVI\_NEG \\ -0.1235 \cdot LMOP + 0.0010 \cdot LEPU\_POS \\ +0.0021 \cdot LEPU\_NEG - 4.3510 \cdot LM2 - 1.0182 \cdot LTO \\ +1.3952 \cdot LDMR\_POS + 2.2793 \cdot LDMR\_NEG + 30.115 \end{array}$								

Note: *, **, and *** are 10%, 5%, and 1% significance levels, respectively.

dependent 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, respectively, with the corresponding p-values of 0.0322, 0.0002, and 0.0000, all significant at the 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 LSTVCI and independent variable LSAVI and LEPU at the long-run, short-run and the strong asymmetry tests. Furthermore, there is a non-rejection of the null hypothesis of a symmetric effect of LSTVCI and LDMR in the long run. However, the study accepts the alternative hypothesis of an asymmetric relationship between LSTVCI and the variable LDMR in the short-run and strong effect asymmetry. This suggests that the partial sum decomposition of the log of the South African volatility index and the log of the economic policy uncertainty index in the long run and in the short run is important for determining the STVCI on the JSE market. In contrast, the decomposition of log of domestic market returns in the short run is negligible.

Figure 2 shows the CUSUM and CUSUMSQ tests and the multiplier graph test. The model is stable and reliable for estimating short-run and long-run coefficients because the cumulative sum of recursive residuals and the cumulative sum of the square of recursive residuals are within the critical bounds at the 5% significance level.

4. DISCUSSION

Table 3. NARDL asymmetry test result

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

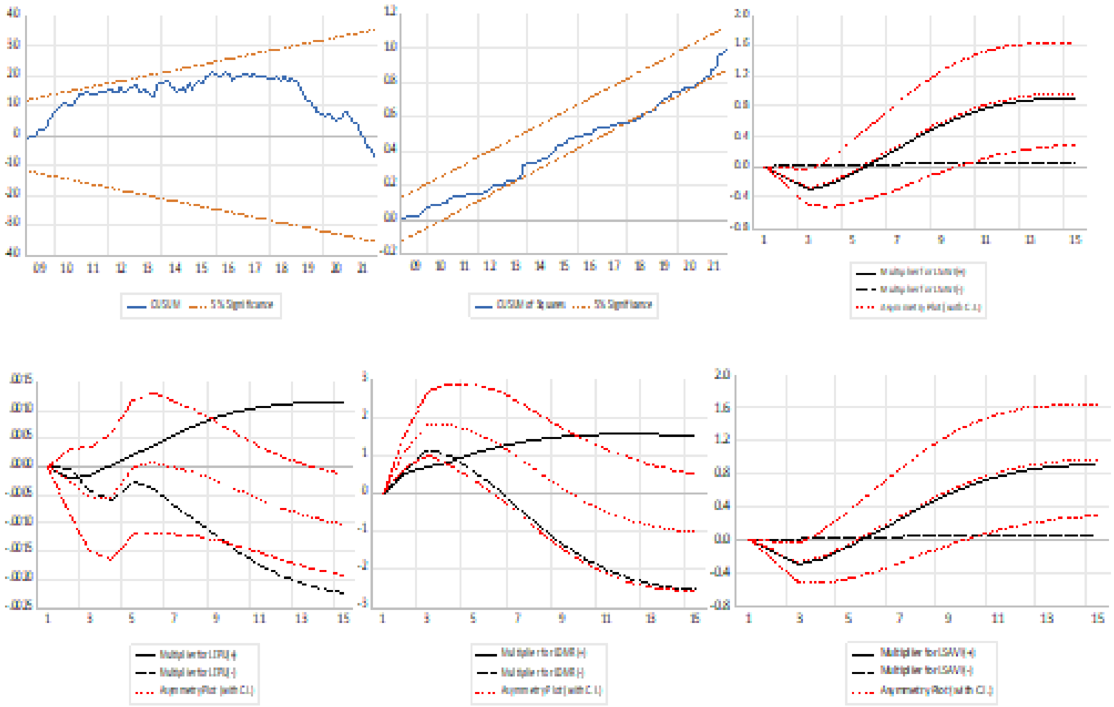

Figure 2. Graphs of CUSUM, CUSUMSQ, and multiplier graph

The NARDL model is employed to check the long- and short-run relationship between the dependent and independent variables. In this objective, there is a long-run significant relationship between the LSTVCI and independent variables, namely LSAVI, LDMR, and LEPU. This model simultaneously captures both short- and long-run relationships of variables with the negative and positive nature of the relationship. The results of this objective confirm the long-run relationship between LSTVCI and LSAVI, LDMR and LEPU on the JSE market.

Estimating the determinants of sectoral total volatility is crucial, as indicated by the gap in the literature; therefore, the result obtained above is interesting. The models' error-correcting terms were significant, as demonstrated by the t-Bounds results, which also support the short-run relationship. According to the ECT, there is a significant correction back to the long-run equilibrium for both the linear and nonlinear short-run models (Brooks, 2014).

The results also demonstrated that, among the six independent variables, the effects of the South African volatility index, the uncertainty surrounding economic policy, and domestic market returns impact the sectorial total volatility connectivity index. The LDMR only exposes its relevance in the short run and the strong asymmetry test, whereas the SAVI and EPU demonstrate long-run, short-run, and strong asymmetry significance.

Interestingly, the South African volatility index, the economic policy uncertainty index, and the logarithm of domestic market returns have the greatest effects on sectorial total volatility connectedness. As a result, these three variables have a significant effect. The significance of SAVI and EPU results corroborates with Shahzad et al. (2018a, 2018b), who discovered that selected market volatilities significantly explained overall spillovers across all credit industries and the connectedness between U.S. industry-level credit markets.

CONCLUSION

This paper aimed to examine the determinants of the sectorial volatility total connectedness index. Using the Diebold and Yilmaz connectedness matrix andTVP-VAR model, the study derived STVCI and determines its drivers using NARDL model. The findings from the study show that South African economic policy uncertainty and South African Volatility index are significant determinants of the sectorial total volatility connectedness index on the JSE. This study concludes that the South African volatility index and economic policy uncertainty index are essential drivers of the spillover risk among the JSE All Share Index (JSE ALSI) super-sectors in the short and long run. However, the general performance of the domestic market represented by the JSE is negligible. It is safe to conclude that the lack of clarity regarding future government policies and regulatory frameworks as well as market fear and market sentiment regarding the performance of domestic currency in relation to the US Dollar increase the spillover risk among JSE super sectors. Finally, the results have implications for sectorial market investors and policymakers in the sense that there must be a policy monitoring system to regularize and stabilize the fluctuations of the SAVI to ensure its use as a market timing tool and as an effective instrument to optimize portfolio return of the JSE super sectors. The results validate the need for government agencies to bring certainty and stability to economic policies, which would enhance the ease of doing business at the sectorial level, hence directly impacting business and investment positively in South Africa. Moreover, the study demonstrates that sentiments against the South African currency vis-à-vis US Dollar is a driver of systemic risk among the sector, hence, the need for policy makers to promote policies that strengthens domestic currency.

This study is limited to nine super sectors due to non-availability of data for some super sectors, namely Real estate and Utilities. Hence, these super sectors are excluded from this study. However, the selected super sectors are still good enough to establish the objectives of this study. Future studies could investigate the drivers of volatility connectedness of South African asset markets, n commodities such as Gold and other principal raw materials that form the main export products from which the South African economy receives external earnings.

AUTHOR CONTRIBUTIONS

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APPENDIX A

Table A1. Descriptive statistics for sector volatility

Variables	AM–VOL	ENE–VOL	CHE–VOL	FIN–VOL	HEC–VOL	G.I–VOL	INSUR–VOL	TEC–VOL	TELCOM–VOL
Mean	0.0002	0.0003	8.89E–05	6.82E–05	–5.72E–05	2.19E–05	0.0001	5.23E–05	6.13E–05
Maximum	0.0257	0.2101	0.0106	0.1787	0.0027	0.0016	0.0050	0.0029	0.0022
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.	0.0007	0.0051	0.0004	0.0028	0.0059	4.57E–05	0.0002	0.0001	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	146E+06***	31E+07***	31468020***	265E+07***	266E+07***	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.	0.0018	0.1034	0.0006	0.0319	0.1419	8.33E–06	0.0002	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

Table A2. Correlation of sectorial volatility

	AM–VOL	CHE–VOL	EN– VOL	FIN–VOL	G–I VOL	HEC–VOL	INSUR–VOL	TEC–VOL	TELECOM– VOL
AM–VOL	1	0.0064	0.0316	0.003	0.1125	0.0042	0.12892	0.0898	0.1194
CHE–VOL	0.0064	1	0.0265	–0.0005	0.0064	0.0014	–0.0052	–0.0012	0.0003
ENE–VOL	0.0316	0.0265	1	0.0004	0.1021	0.0015	0.0479	0.0773	0.1359
FIN–VOL	0.0030	–0.005	0.0004	1	0.0114	0.0001	0.0069	0.0247	0.0052
G–I–VOL	0.1125	0.0063	0.1021	0.0114	1	–0.0012	0.5248	0.3336	0.5247
HEC–VOL	0.0042	0.0014	0.0015	0.0001	–0.0012	1	0.0002	0.008	0.0053
INSUR–VOL	0.1289	–0.0052	0.0479	0.0069	0.5248	0.0001	1	0.3243	0.4831
TEC–VOL	0.0898	–0.0012	0.0773	0.0247	0.3336	0.0085	0.3243	1	0.3177
TELECOM–VOL	0.1194	0.0003	0.1359	0.0052	0.5247	0.0053	0.48314	0.3177	1

Table A3. Unit root test for determinants (returns)

Variables	Levels		First difference		Integration Order
	ADF t-statistic	Phillips-Perron Test-statistic	ADF t-statistic	Phillips-Perron Test-statistic	
LSTVCI	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					
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)

Note: *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

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Table A4. Average sectorial dynamic volatility connectedness table for the full sample period

	A M–& P Vol	TELECOM–Vol	INSUR–Vol	CHE–Vol	TEC–Vol	G.I–Vol	FIN–Vol	ENE–Vol	HEL–Vol	FROM
A M–& P 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	cSTVCI/STVCI
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	

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

Table A5. Error correction model for ARDL and NARDL models

Error Correction Regression					
Model	**Variables**	**Coefficients**	**Standard Error**	**t-Statistics**	**Probability**
ARDL (LSTVCI)	D(LSTVCI (–1))	0.4530	0.053714	8.434124	0.0000
	D(LSTVCI (–2))	–0.1066	0.060758	–1.755274	0.0814
	D(LSTVCI (–3))	0.1422	0.053961	2.635341	0.0094
	D(LSTVCI)	–0.0609	0.035418	–1.719093	0.0878
	D(LSTVCI (–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 (LSTVCI)	D(LSTVCI (–1))	0.4762	0.05709	8.341352	0.0000
	D(LSTVCI (–2))	–0.0249	0.065194	–0.37885	0.7054
	D(LSTVCI (–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