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## **Article**

Macroeconomic determinants of the JSE size-base industries connectedness: evidence from changing market conditions

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# FINANCIAL ECONOMICS | RESEARCH ARTICLE



# Macroeconomic determinants of the JSE size-base industries connectedness: evidence from changing market conditions

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#### **ABSTRACT**

This study provides evidence and proof of dynamic return connectedness alongside the revelation that certain macroeconomic factors determine the return connectedness of size-based industries of the Johannesburg Stock Exchange (JSE). The objective of this study is to examine the effect of COVID-19 on the connectedness of JSE size-based indices and to investigate the effect of macroeconomic variables on JSE size-based index connectedness under changing market conditions. By employing the time varying parameter vector autoregressive (TVP-VAR) model alongside the Diebold and Yilmaz Connectedness framework to examine the time-varying connectedness and using the Markov regime-switching model to determine the drivers of the return connectedness for the period from 4 January 2017, to 30 June 2023. The findings of this study demonstrated that the return connectedness of the JSE-size-based indices vary over time, especially in extreme market conditions such as the pre, during and post-Covid-19 periods. Moreover, the Covid-19 pandemic period reveals a season of high correlation; hence, a heightened co-movement in the returns of all JSE sized-based indices. Moreover, macroeconomic variables have an alternating effect on the connectedness of JSE sized-based indices during bull and bear market conditions. That is, the effect is regime-dependent and time varying. These findings have serious implications for portfolio diversification, in which portfolio rebalancing is needed during alternating market conditions.

In recent years there have been problems in equity portfolio decision, formulation, and stability especially during economic turbulence. Hence making the task of investment portfolio formulation a difficult one. The size-based industries on the Johannesburg stock exchange (JSE) are eligible instruments that have the capacity to reflect the market performance of firms in each category (FTSE Russell, 2020), and hence capable to be used in enhancing portfolio decisions, formulation and further enhance return stability on the JSE. This is very important in turbulence periods such as the COVID-19 pandemic during which global and local economic activities was stalled, economic and financial uncertainties spiked and financial markets plunged, which led to global financial chaos that disturbed asset allocations. Hence this study used the sized-based industries on the JSE to establish possible correlations between them (JSE-LRG CAP, JSE-MID CAP, JSE-SML, and JSE-FLD industries) during extreme events that affected global economy such as the COVID-19 pandemic, and further investigates the macroeconomic factors that could determine their connectedness in different market conditions such as during the bullish or bearish regime of an economy.

#### ARTICLE HISTORY

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#### KEYWORDS

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#### **SUBJECTS**

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G11; G01; F21

#### 1. Introduction

Investigations of the spillover of economic risks have gained momentum in recent years. Significant global and regional extreme events have contributed to scholarly inquiry into the subject matter. The Johannesburg Stock Exchange (JSE) size-based industries have been classified into different listed industries based on size or market capitalization (JSE, 2023). Therefore, for ease of categorization, this study used the large-cap (JSE-LRG CAP) (J205), mid-cap (JSE-MID CAP) (J201), small-cap (JSE-SML) (J202), and fledging (JSE-FLD) (J204) as selected size-based industries on the JSE. These size-based industries are eligible instruments that have the capacity to reflect the market performance of firms in each category (FTSE Russell, 2020), and hence capable to be used in enhancing portfolio decisions, formulation and further enhance return stability on the JSE. This is very important in turbulence periods such as the COVID-19 pandemic during which global and local economic activities was stalled, economic and financial uncertainties spiked and financial markets plunged, which led to global financial chaos that disturbed asset allocations. Therefore, investigating the level of connectedness of these size-based industries on the exchange, would help establish their degree of correlation and the macroeconomic factors responsible for their interconnectedness, especially during one of the major global crises that affected global markets like the Covid-19 pandemic, is crucial for the JSE. Diebold and Yilmaz (2009, 2012, 2015) were the first to introduce the idea of connectedness along with suggestions for measurements. The goal of connectedness is to quantify how closely related and dependent various parts of a system are on each other while encapsulating this knowledge in a single number or index. Therefore, connectedness is a multidimensional concept that generally represents the components of a set, such as the system's agents or companies listed on a particular market or across several markets. When strong interdependence is established between the components of a given set, it is described as having a high connectedness. Moreover, market conditions such as bullish and bearish conditions, where investors buy and sell their stocks based on an anticipated rise or drop in stock prices, have become very interesting seasons in markets to study the connectedness and determinants of sized-based industries. This is due to key economic indicators such as GDP, inflation, and interest rates, which, whether positive or negative, could push bullish markets by boosting confidence or exacerbating bearish conditions, respectively.

Hence, this study considers the level of interconnectedness of size-based industries on the JSE during changing market conditions and identifies important macroeconomic conditions that drive their connectivity with the returns of the JSE-LRG CAP, JSE-MID CAP, JSE-SML, and JSE-FLD industries from 4<sup>th</sup> January 2017 to 29th December 2023.

Financial interconnectedness is a well-known potential source of systemic risk (Maggi et al., 2020). When market interdependence is high, volatility spillovers across and within markets are significant (Diebold & Yilmaz, 2012). Therefore, the Diebold and Yilmaz connectedness index of 2009, 2012, and 2014, with the time-varying parameter VAR (TVP-VAR) of Antonakakis et al. (2020), is used to establish the connectedness and propagation of shocks within the network of industries. The TVP-VAR has superior estimation capacity over rolling-window analysis in several ways: first, it eliminates the need to measure the rolling window's width; second, the number of observations that corresponds to the number of window sizes remains intact. Third, it is based on the Kalman Filter; in contrast to the rolling-window approach, which does not permit the identification of data points that contribute to a spike or a dip in the connectedness index inside a particular window, it generates coefficients that are matched to each data point in the sample, as mentioned above (Antonakakis et al., 2020). Moreover, the Markov regime-switching model is employed to examine how the connectedness of the JSE-LRG CAP, JSE-MID CAP, JSE-SML, and JSE-FLD indices is affected by macroeconomic variables under changing market conditions.

This study is centered on connectedness; however, it is unique in that it focuses on the interconnect-edness of size-based industries and its innovative application in using the regime-switching model to determine the drivers of connectedness in varying market conditions. Moreover, due to the very limited literature on the macroeconomic drivers of connectedness of the JSE sized-based industries in South Africa, in different economic changing conditions, this study bridges the gap in literature by providing insight first on the connectedness of the JSE sized-based industries. Moreso since the JSE-Sized base industries are used by investors to enhance portfolio return. However, it has not been established as to how the comovement of these JSE sized-based firms could affect returns and portfolio diversification. Therefore the first part of the objective of this study reveals the movement of these sized-based industries before, during and after the COVID-19 crisis so as to establish if there is any evidence of comovement. Furthermore the second part of the objective helps to identify the macro-economic factors that could determine the connectedness of the JSE-sized based industries under macro-changing conditions.

Moreover, the main result shows that connectedness varies over time during and after the Covid-19 pandemic, moreso, the study demonstrates that macroeconomic variables have an alternating effect on

size-based index connectedness. Section two describes a literature review. Section three provided the data and the empirical strategy, followed by the empirical results in Section four, and Section five revealed the discussion, and Section six revealed the conclusion.

## 2. Literature review

Empirical investigation into connectedness in different sectors, industries, and asset classes has gained significant recognition in the past few years (see Goswami et al. (2012); Chow (2017), Gabauer et al. (2024) and Costa et al. (2022)). In South Africa, limited efforts have been made to reveal the connectedness of assets, which is the inspiration for this study. Due to this limited effort on the South African terrane, this study investigates the connectedness of JSE size-based industries to the stock market and further estimates the macroeconomic determinants of their connectedness.

A substantial body of empirical studies investigate how the Great Recession of 2008 affected the relationships among different asset classes (Choudhry et al., 2015; Kang & Yoon, 2019; Mensi et al., 2016; Zhang & Broadstock, 2018) demonstrating how the GFC has changed asset allocation and hedging tactics, as well as strengthened market links. Investors seeking the benefits of diversification are very concerned about changes in the interconnectedness across financial markets (Brière et al., 2012). A rising corpus of study emphasizes how crucial it is to use the connectedness approach to identify shock spillovers in a specified network (Hussain Shahzad et al., 2019; Zhang, 2017). Importantly, there are advantages and disadvantages associated with a higher level of network interconnectedness, which indicates increased market risk. Initially, it can enhance risk distribution among the network's members by mitigating individual asset shocks to varying degrees, which can be asset-specific and improve risk diversification in a portfolio of assets with weak connections. Second, it can lead to financial contagion because shocks can propagate through the network, indicating instability in the financial system. Third, to draw conclusions about an asset's capacity to function as a hedge or safe haven against the downside risk of other assets, it can be utilized to identify which asset is mostly segmented (isolated) inside the system of return connectedness. Although this lacks a theoretical model (Baur & Lucey, 2010 and Bouri et al., 2020), It has been used in numerous current investigations (Mensi et al., 2017).

In spite of this, there is a dearth of research on return spillovers across a wide range of asset classes, including bonds, stocks, commodities, and currencies. Wang and Chueh (2013), for instance, examined the interconnections between the price of gold, oil, interest rates, and the currency market. They present data on the price transmission link between the majority of the studied market pairs as well as feedback effects in the relationship between interest rates and strategic commodities like gold and crude oil. Using MSCI energy equity indices for 29 countries, Akyildirim et al. (2022) examine the global connectivity between energy equity indices for oil-exporting and oil-importing nations. Time-varying measures of the quantity of shocks that each country sends and receives from other nations. They discover after examining the global network that shocks are mostly transmitted by countries that export oil and received by countries that import it. Furthermore, panel data regressions are employed to evaluate the potential influence of global COVID-19 outbreak, uncertainty, and economic attitudes on the degree of interconnectedness across nations. It was found that countries are significantly more interconnected when there is uncertainty, a weak economy, or COVID-19 difficulties. This shows that the benefits of diversity between countries substantially drop precisely during times of crisis, when the benefits of diversification are most important.

Little empirical evidence of financial connectivity has been established in the South African context, as it should consider the robustness of the South African economy and even as an emerging economy (McManus, 2018). Lawrence et al. (2024) investigated connectedness of the realized volatilities of the super sectors on the JSE during the GFC, European debt crises EDC), China-United States (US)-trade war, and COVID-19 pandemic. The results reveal that energy is the strongest net transmitter of shock during the full sample period and the EDC, while Automobile and Parts are the strongest transmitters of shocks during the US-China trade. The financial sector was the strongest net shock transmitter during the GFC and the COVID-19 period. The result further establishes that connectedness among the super sectors is dynamic and very high during these extreme periods.

In conclusion, the empirical literature on dynamic connectedness in developing economies such as South Africa has limited recognition; hence, there is little or no empirical emphasis on size-based

industries. Hence, there is a need to examine the dynamic connectedness among size-based industries on the JSE market and the direction of propagation among size-based industries. This study, for the first ever time, contributes to literature by revealing the connectedness level of the JSE size-based industries and further employing the Markov-switching model to determine the drivers of the connectedness of these selected size-base industries during bull and bear market conditions, which is the novelty for this study.

# 3. Data and empirical strategy

#### 3.1. Data

This study examines the connectedness of the South African headline to the JSE. Currently, there are four headlines<sup>1</sup> indices, namely JSE-LRG CAP, JSE-MID CAP, JSE-SML, and JSE-FLD on the JSE (JSE, 2022), based on the JSE classification. These indexes are divided into groups based on the size of the company (market capitalization) and consist of qualifying instruments that are listed on the JSE Main Board. The headline index returns are calculated in a full sample period from 4 January 2017 to 29 December 2023. Furthermore, this study considers the macroeconomic determinants of the connectedness of these headline indices. The daily indices provide sufficient data for the full, pre- during and post-Covid-19 pandemic analysis and allow for the observation of new events (Shen et al., 2020). The period allows for the pre-Covid-19 period (4 January 2017 to 31 December 2019), Covid-19 pandemic period (1 March 2020 to 31 August 2022), and post-covid-19 (1st August 2022 to 30 June 2023), and a comparison of risk contagion. Data is collected from the INET BFA website, Bloomberg Data Services, Capital IQ, and DataStream.

#### 3.2. TVP-VAR model

This study employs Antonakakis et al. (2020) TVP-VAR to establish connectedness and shock propagation among the selected sectors and markets. The TVP-VAR model with one lag can be expressed as follows:

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

$$vec(\theta) = vec(\theta_{t-1}) + r_t \ r_t \sim N(0, Q_t)$$
 (2)

where  $\Delta y_t$ ,  $\Delta y_{t-1}$  and  $\mu_t$  are vectors of  $N \times 1$  dimension,  $\theta_t$  and  $E_t$  are matrices of  $N \times N$  dimension,  $vec(\theta)$  and  $r_t$  are parameter matrices of  $N^2 \times 1$  dimension,  $Q_t$  is an  $N^2 \times N^2$  dimensional matrix for sectoral index returns. In line with Antonakakis et al. (2020), the TVP-VAR is estimated and then transformed into a time-varying parameter vector moving average (TVP-VMA) representation using the Wold representation theorem (WRT). WRT is defined as:

$$\Delta x_t = \sum_{i=1}^p \beta_{it} \Delta x_{t-1} + \varepsilon_t = \sum_{i=1}^\infty \gamma_{jt} \epsilon_{t-j} + \varepsilon_t.$$
 (3)

Subsequently, the TVP-VMA coefficients are mined to calculate the generalized forecast error variance decomposition (GFEVD) developed by Koop et al. (1996) and Pesaran and Shin (1998), from which the Diebold and Yilmaz connectedness index is constructed. The pairwise directional connectedness from j to i which portrays the impact of sector j on sector i in terms of its forecast error variance, is derived from the unscaled GFEVD, and defined as:

$$\emptyset_{ij,t}^{g}(J) = \frac{\sum_{ii,t}^{-1} \sum_{t=1}^{J-1} (I_j' A_t E_t I_j)^2}{\sum_{i=1}^{N} \sum_{t=1}^{J-1} (I_i A_t \sum_{t} A_i' I_i)}$$
(4)

$$\varphi_{ij,t}^{g}(J) = \frac{\emptyset_{ij,t}^{g}(J)}{\sum_{j=1}^{N} \emptyset_{ij,t}^{g}(J)}$$
 (5)

where  $\sum_{j=1}^{N} \varphi_{ij,t}^{g}(J) = 1$  and  $\sum_{i,j=1}^{N} \varphi_{ij,t}^{g}(J) = N$ , where J represents the forecast horizon and  $I_{i}$  is a selection vector that is equal to 1 at the ith position and 0 otherwise. Using the GFEVD, the total connectedness index is constructed as given by:

$$C_t^g(J) = 1 - N^{-1} \sum_{i=1}^N \varphi_{ii,t}^g(J)$$
 (6)

This connectedness approach demonstrates how a shock in one sector spills over into other sectors. Assume that sector I transmits its shock to the remaining sectors j, and the resulting total directional connectedness to others is given by:

$$C_{i \to j, t}^{g}(J) = \sum_{j=1, i \neq j}^{N} \varphi_{ji, t}^{g}(J)$$
 (7)

Furthermore, the directional connectedness sector i receives from sector j is termed total directional connectedness from others and is defined as

$$C_{i \leftarrow j, t}^{g}(J) = \sum_{j=1, i \neq j}^{N} \varphi_{ij, t}^{g}(J)$$
 (8)

Moreover, the net total directional connectedness, representing sector i's influence on the analyzed network, is obtained as the difference between connectedness to others and connectedness from others. This is given as:

$$C_{i,t}^g = C_{i \to i,t}^g(J) - C_{i \leftarrow i,t}^g(J) \tag{9}$$

A positive  $C_{i,t}^g$  suggests that sector i exerts a greater impact on the network than vice versa, while a negative value suggests that sector i is driven by the network. The  $C_{i,t}^g$  being an aggregated measure tends to mask central underlying dynamics; hence, the need to derive the net pairwise directional connectedness (NPDC), which discloses information about the bilateral transmission process between sectors i and j:

$$NPDC_{ij}(J) = \varphi_{ii,t}^g(J) - \varphi_{ii,t}^g(J). \tag{10}$$

If  $NPDC_{ij}(J) > 0$   $(NPDC_{ij}(J) < 0)$  variable i drives (is driven by) variable j. It is expected that connectedness among JSE sized-based industries will increase during the covid-19 period. In addition, more connectedness during the pre- and post-Covid-19 periods is expected. These results have important implications for portfolio managers in South Africa, Africa, and globally given that South African equities are a component of many global equity funds.

# 3.3. Markov regime-switching model

This study examines how the connectedness of the JSE-LRG CAP, JSE-MID CAP, JSE-SML, and JSE-FLD indices is affected by macroeconomic variables under changing market conditions. Consequently, the size-based connected index parameters are extracted from Section 3.1 and used as a dependent variable in the Markov regime-switching model. The study selects this particular model as it caters to regimeswitching, and it does not require inputs to determine the regimes, as the Markov chain obtains the regimes automatically. Moreover, the transition probabilities allow for time varying, whereas other nonlinear models do not. The two-state Markov regime-switching model is given by:

$$JSE_{Cor} = \mu_{ct} + B_{0ict}\Delta CPI + B_{1ict}\Delta M2 + B_{2ict}\Delta STJNT + B_{3ict}\Delta LT\_INT + B_{4ict}\Delta GDP + B_{5ict}\Delta REER + \varepsilon_{c_t}$$
(11)

where  $JSE_{Cor}$  is the size-based connectedness index,  $\mu_{ct}$  is the state dependent intercept, The explanatory factors dependent on the state are provided by the inflation rate, represented by  $\Delta$ CPI, the money supply rate by  $\Delta$ M2, the change in the short- and long-term interest rates by  $\Delta$ ST\_INT and  $\Delta$ LT\_INT respectively, the change in the gross domestic product by  $\Delta GDP$ , the real effective exchange rate by  $\Delta REER$ , and the state dependent error terms by  $\varepsilon_{ct}$ .  $C_t$  offers two state-dependent regimes: the bear regime (1) and the bull regime (2).

Each regime follows a Markov first-order process as provided by the transition probability matrix. The proposition of being in a bull or bear regime depends on the current state, as given by:

$$Prob(C_t = 2|C_{t-1} = 1) = Prob_{1,2}(t)$$
 (12)

where 1,2 is the probability of switching from a bull regime (1) in period t-1 to a bear regime (2) in a period denoted by t, such that the probability is constant  $(Prob(t) = Prob_{1,2})$  for both periods.

# 4. Empirical results

# 4.1. Preliminary analysis

Figure 1 shows the time series plots of the returns of the four headline groups included in this study from 4th January 2017 to 29 December 2023. According to Zhang et al. (2020), the price indices of each headline group are used to calculate the daily returns. The formula used to calculate the returns is provided by:

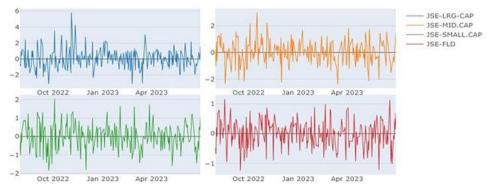
$$PR_{i,t} = \left(\frac{P_{ti-P_{to}}}{P_{to}}\right) \tag{1}$$

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

Figure 1 shows plots of the time series of the return indices of the four selected headline series. The plot clearly shows evidence of volatility clustering. This illustrates that the series stock returns have non-linear features. The tendency for large changes in stock prices, regardless of sign, to trail large changes and small changes, regardless of sign, to tail little change is known as volatility clustering (Brooks, 2014 p. 386).

Table 1 shows the descriptive statistics of the headline indices and stationarity test. The JSE-LRG CAP had the highest mean value of 0.027, whereas the JSE FLD had the lowest mean. The same goes for the median and maximum measures, as the JSE-LRG CAP has the highest values of 0.036 and 8.285, while the JSE FLD has the lowest values of 0.007 and 5.7021, respectively. The JSE-LRG CAP has the highest standard deviation of 1.2673. However, with a mean of 0.027, it shows that the volatility of the sector is not clustered around its means. Furthermore, the skewness of the headlines indices returns is negative, illustrating that the headline returns are skewed to the left with a long tail. Hence, the bulk of the returns are positioned on the right. The Jarque-Bera test at a 1 percent significance demonstrates that the variables are not normally distributed. It is interesting to note that the Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are all headline indices that are significant at the 1 percent level. This suggests that the null hypothesis of all the headline series having a unit root is rejected in favor of the alternative hypothesis, suggesting that the four series are stationary at level.

Table 2 provides descriptive statistics and stationarity tests associated with the connectedness index and macroeconomic variables. The connectedness index's average returns are positive over the sample period. Moreover, long-term interest has the highest average growth rate, whereas money supply has the lowest average growth rate. However, gross domestic product has the highest growth rate, whereas short-term interest has the lowest growth rate. Given that there was a higher-level change in the short-term interest growth rate, it was the most volatile, as presented by the standard deviation. The long-term interest growth rate, gross domestic product growth rate, and the real effective exchange growth



**Figure 1.** Return plot of South African headline series. Notes: 1. Source: Authors' estimation (2024).

Table 1. TPV-VAR descriptive statistics and stationarity tests results.

	JSE-LRG CAP	JSE-MID CAP	JSE-SML CAP	JSE-FLD
Mean	0.0270	0.0019	0.0095	0.0017
Median	0.0364	0.0234	0.0093	0.007
Maximum	8.2851	5.6495	10.2918	5.7021
Minimum	-10.0880	-11.2143	-11.2994	-6.0704
Std. Dev.	1.2673	1.1475	0.9670	0.7174
Skewness	-0.3655	-1.3937	-1.2036	-0.4547
Kurtosis	9.2381	17.1129	32.1439	14.8029
Jarque-Bera	2871.517	15063.86	62248.93	10200.79
Probability	0.0000	0.0000	0.0000	0.0000
Observations	1747	1747	1747	1747
ADF	-41.69271***	-13.6594***	-14.1859***	-14.1449***
KPSS	0.0220***	0.0777***	0.31408***	0.4753***
ARCH-LM	35.8487***	19.0765***	34.4826***	98.1802***

Notes: 1. Source: Authors' estimation (2024); 2. \*, \*\*, \*\* represent a significance level of 10, 5%, and 1%, respectively.

Table 2. Descriptive statistics and stationarity results of the connectedness index and macroeconomic variables.

	$\Delta$ DTC_INDEX	$\Delta$ CPI	<b>∆</b> M2	$\Delta$ ST_INT	$\Delta$ LT_INT	$\Delta$ GDP	$\Delta$ REER
Mean	0.2118	0.0527	-0.5087	0.2075	0.3229	-0.2687	0.0040
Median	-0.5096	0.0000	-0.3743	0.3085	-0.2191	-0.1262	-0.5929
Maximum	21.0545	20.0000	2.7974	13.4812	17.7859	20.6429	9.3843
Minimum	-3.1136	-21.2121	-5.8642	-23.9189	-9.9394	-17.9314	-6.2035
Std. Dev.	3.2546	4.9825	1.4631	4.7851	3.3786	3.5472	3.2498
Skewness	4.0875	-0.25825	-0.4228	-1.3687	1.5102	0.7665	0.5129
Kurtosis	23.7349	8.6341	4.0337	10.2152	10.7454	22.9522	3.0508
Jarque-Bera	1738.680	112.0346	6.2422	208.4349	241.9001	1401.545	3.6926
Probability	0.0000	0.0000	0.0441	0.0000	0.0000	0.0000	0.1578
Observations	84	84	84	84	84	84	84
ADF	-7.456047***	-7.861402***	-11.42275***	-4.055056***	-8.539757***	-3.491825**	-8.273136***
KPSS	0.078943***	0.638012*	0.129672***	0.384871**	0.052909***	0.095178***	0.056053***
ADF-Breakpoint	-12.56981***	-9.567872***	10.85339***	-7.866365***	-10.44600***	-6.691073***	-8.998125***

Notes: 1. Source: Authors' estimation; 2. \*, \*\*, \*\* represent a significance level of 10, 5%, and 1%, respectively.

rate are positively skewed, whereas the inflation growth rate, money supply growth rate, and short-term interest growth rate are negatively skewed. All variables, except the real effective exchange growth rate, exhibited a kurtosis of greater than 3, which indicates that the connectedness index returns, and the growth rate of macroeconomic variables do not follow a normal bell shape. This is further substantiated by the Jarque-Bera test, as all variables were not normally distributed.

Furthermore, Table 6 shows that the ADF test statistics for the connectedness index and macroeconomic variables are significant. Therefore, the alternative hypothesis—that the two series are stationary in levels—can be accepted in place of the null hypothesis, according to which the two series have a unit root. As the null hypothesis that the series is stationary cannot be rejected, the KPS test supports these conclusions. In the presence of structural breaks, the data must remain stationary in order for the Markov regime-switching model to be estimated. ADF breakpoint testing was carried out. The findings demonstrate that the test statistics are more negative than the associated critical levels. Therefore, the two series are stationary in the presence of structural breaks. Consequently, the connectedness index series and macroeconomic series are stationary in level and the presence of structural breaks.

#### 4.2. Empirical model results

In this section, we present and interpret the results of the models discussed and specified in Section 3.

# 4.2.1. Dynamic total connectedness index for full sample, pre-Covid-19, during-Covid-19, and post-Covid-19 period

Figure 2 shows the daily total connectedness index graphs for the pre-Covid, full period, during, and post-Covid-19 periods in descending order. The peaks in each plot reveal unique values at different periods. The full sample period shows a peak that hits a high value of 100% in the early months of 2020,

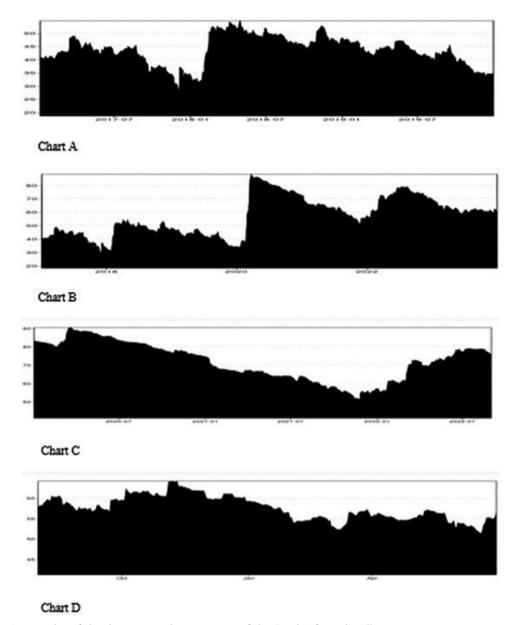


Figure 2. Return plot of the dynamic total connectivity of the South African headline series. Notes: 1. Source: Authors' estimation (2024); 2. The estimation was carried out with a lag length of 1, a forecast horizon (H) of 20 with Bayes prior, and a size of 200; 3. Charts A, B, C and D represent the pre-, full-, during and post-Covid periods, respectively.

coinciding with the start of the Covid-19 pandemic in South Africa. The South African president announced a national disaster state for the country on 5 March 2020 (Kotzé, 2020), after the first case of Covid-19 infection was tested and confirmed positive (Giandhari et al., 2021). The pre-Covid-19 graph shows a peak value at 85% around May-June 2018. The dynamic connectedness graph during Covid-19 reveals a peak that ranges from 95% to 100% between January and Charts 1, 2, 3, and 4 of Figure 3 show the return propagation of the full sample, pre-Covid, during and post-Covid period, respectively. It is evident that the Covid-19 pandemic significantly affected JSE-LRG CAP, JSE-MID CAP, JSE-SML and JSE-FLD company returns, and the overall business performance and output of companies listed under these indices. (Muthu & Wesson, 2023; Ngarava et al., 2022; Oni & Omonona, 2020). The post-covid-19 period reveals a connectedness value of 87%.

Tables 3, 4, and 5 show the average dynamic total connectedness index for the pre-Covid-19, full sample size and the post-COVID-19 pandemic periods. Due to cross-asset return connectivity, the average return variation of any headline over the course of the whole sample is 56.99%. The average TCI during the COVID-19 pandemic (76.91%) was much higher than that of the entire sample, the period

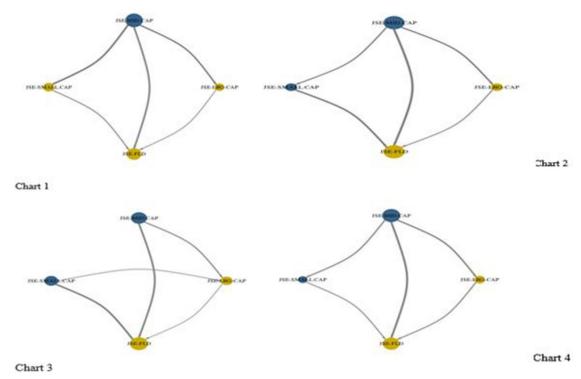


Figure 3. Network connectedness plots of all periods.

Note. 1. Source: Author estimation (2024); 2. Charts 1, 2, 3 and 4 represent the pre, full, during and post Covid periods, respectively.

Table 3. Average dynamic connectedness table before the COVID-19 pandemic.

	JSE-LRG CAP	JSE-MID CAP	JSE-SML CAP	JSE-FLD	FROM
JSE-LRG CAP	66.62	22.97	8.26	2.15	33.38
JSE-MID CAP	20.07	57.81	18.35	3.77	42.19
JSE-SML CAP	8.97	21.79	63.26	5.98	36.74
JSE-FLD	3.65	6.83	7.88	81.64	18.36
TO	32.69	51.59	34.49	11.90	130.66
Inc. Own	99.31	109.40	97.75	93.54	cTCI/TCI
NET	-0.69	9.40	-2.25	-6.46	43.55/32.67
NPT	2.00	3.00	1.00	0.00	

Notes: 1. Source: Authors' estimation (2024).

Table 4. Average dynamic connectedness table for the full sample.

	JSE-LRG CAP	JSE-MID CAP	JSE-SML CAP	JSE-FLD	FROM
JSE-LRG CAP	56.88	23.67	13.50	5.96	43.12
JSE-MID CAP	20.99	49.70	22.21	7.10	50.30
JSE-SML CAP	13.30	24.48	53.02	9.20	46.98
JSE-FLD	7.73	10.46	12.39	69.43	30.57
TO	42.02	58.60	48.10	22.25	170.97
Inc. Own	98.89	108.31	101.12	91.68	cTCI/TCI
NET	-1.11	8.31	1.12	-8.32	56.99/42.74
NPT	1.00	3.00	2.00	0.00	

Notes: 1. Source: Authors' estimation (2024).

before Covid-19, and the period after Covid-19 (57.57%). The pre-Covid-19 has the lowest connectedness value (43.55%). The post Covid-19 connectedness value was much higher that the pre-Covid-19 period. This suggests that the connectedness of these firms remains high even after the turbulence period in the market. This demonstrates how the global pandemic could affect the equities of the headline firms differently, with their connectedness responding differently in each period, with some firms not finding equilibrium in the potential of their returns. This finding is consistent with Ferrer

Table 5. Average dynamic connectedness table during COVID-19 pandemic.

	JSE-LRG CAP	JSE-MID CAP	JSE-SML CAP	JSE-FLD	FROM
JSE-LRG-CAP	46.63	23.66	18.45	11.26	53.37
JSE-MID-CAP	21.12	41.27	26.01	11.60	58.73
JSE-SML-CAP	16.79	26.91	42.22	14.07	57.78
JSE-FLD	12.75	15.13	17.98	54.15	45.85
TO	50.66	65.70	62.43	36.94	215.73
Inc. Own	97.29	106.97	104.65	91.09	cTCI/TCI
NET	-2.71	6.97	4.65	-8.91	71.91/53.93
NPT	1.00	3.00	2.00	0.00	

Notes: 1. Source: Authors' estimation (2024).

et al. (2018), who noted that the financial system is dynamic and likely to react differently to economic and financial stress.

# 4.2.2. Total directional connectivity from other headlines

Table 3 shows the average dynamic connectedness values for the sample period. The JSE-MID CAP has the highest TO-connectedness (shocks to other headlines) with a value of 94.22%, followed by the JSE-SML CAP, JSE-LRG CAP, and JSE FLD with 58.60%, 48.10%, 42.02%, and 22.25%, respectively. The TO-connectedness values during the COVID period were the highest for the four sample periods, with the JSE-MID CAP having the highest value of 65.70%. These figures show the self-generated shocks that were transferred from these headlines to other equities.

#### 4.2.3. Total directional connectedness from other headlines

The FROM-connectedness values for each headline firm in the full sample, pre-Covid-19, during-Covid-19, and post-Covid-19. Surprisingly, the JSE-MID CAP has the highest FROM connectedness value of 50.30% during the full sample period, indicating that the JSE-MID CAP received the highest total shock from the other headlines, whereas the JSE FLD has the least FROM-connectedness value of 30.57%. During the pre-Covid-19, post-Covid-19 period and during-Covid-19 periods the JSE-ASLI had the highest FROM connectedness total with values of 42.19%, 52.66%, and 58.73%, respectively. This indicates that the JSE-MID CAP plays a major role in absorbing shocks from the rest of the headline, even from the (JSE-LRG CAP) possibly owing to its robust stability as a JSE-MID CAP headline.

# 4.2.4. Net volatility connectedness

A snapshot of the net connectedness results for the different categories of headline firms for the full sample, pre-, during, and post-Covid reveals that the JSE-LRG CAP, JSE-SML CAP, and JSE-FLD headlines are the net receivers of shocks during the full-Covid sample period with (-0.69%), (-2.25%), and (-6.46), respectively, while the JSE-MID CAP headline is the net transmitter of shocks in the network with 9.40%. From Table 3, during the Covid-19 period, JSE-MID CAP is revealed to be the highest net transmitter at 6.97%, while JSE-FLD is the highest net receiver of shock (-8.91%). Similarly, during the pre-Covid-19 period 9.40% was recorded as a net-transmitting value for the JSE-MID CAP, while the JSE-FLD was the highest net receiver of shock from other headlines with a value of -6.46%. The post-Covid-19 period reveals that the JSE-MID CAP is the highest net transmitter of shock, while the JSE-FLD is the highest net receiver of shock, -7.34%. It is interesting to note that the JSE-MID CAP is the highest transmitter of shock during the pre-Covid-19, full sample, during the Covid-19, and in the post-Covid-19 periods. Surprisingly, JSE-LRG CAP and JSE-FLD remain net receivers of shocks throughout the different periods. However, the JSE-FLD had the highest connectedness (receiver) during the Covid-19 pandemic period. This shows the capacity of JSE-FLD firms as a huge shock absorber throughout the system, thus providing stability to the system during the pandemic. The capacity of a ledge cap to absorb shock remains a subject of debate.

# 4.2.5. Network propagation of return connectedness during

Charts 1, 2, 3, and 4 of Figure 3 show the return propagation of the full sample, pre-Covid-19, during and post-Covid-19 period, respectively. During the full sample period, it is evident that the JSE-MID CAP

industry sends shocks (spillover) to the other three industries, signifying that the JSE-MID CAP is the highest net transmitter of shock with the only blue node and largest in size. Chart 2 reveals that during the pre-Covid-19 period the JSE-MID CAP continues to be the highest net transmitter, as evident from Table 4 (9.4%), transmitting shock to the other three size-based industries, while the JSE-FLD is the highest receiver of shocks from all other industries when with the largest edge in yellow.

In Charts 3 and 4, the JSE-MID CAP remains the highest transmitter of shocks to other industries, as shown Charts 1, 2, 3, and 4 of Figure 3 show the return propagation of the full sample, pre-Covid, during and post-Covid-19 period, respectively in Tables 5 and 6, with 6.97% and 8.51% net connectedness, respectively, and with the largest blue nodes, respectively. The JSE-FLD remains the industry with the largest node in yellow and, hence, the industry with the highest shock receiver throughout all periods. Chart 3 shows that there is no connection between the JSE-MID CAP and the JSE-SML CAP; hence, there is no transmission of shocks between them.<sup>2</sup>

# 4.2.6. Markov regime-switching results

The Markov regime switching model results, expected duration, and probabilities are presented in Table 7. It is evident from the results that size-based connectedness index returns are negative in bull regimes and

**Table 6.** Average dynamic connectedness table after COVID-19 pandemic.

	JSE-LRG CAP	JSE-MID CAP	JSE-SML CAP	JSE FLD	FROM
JSE-LRG CAP	53.53	24.87	17.38	4.21	46.47
JSE-MID CAP	22.10	47.34	24.07	6.50	52.66
JSE-SML CAP	16.83	26.37	50.63	6.16	49.37
JSE-FLD	6.27	9.93	8.02	75.78	24.22
TO	45.21	61.17	49.46	16.88	172.72
Inc. Own	98.74	108.51	100.09	92.96	cTCI/TCI
NET	-1.26	8.51	0.09	-7.34	57.57/43.18
NPT	1.00	3.00	2.00	0.00	

Notes: 1. Source: Authors' estimation (2024).

Table 7. Markov regime-switch results.

$JSE_{Cor} = \mu_{ct} + B_{0ict}\Delta CPI + B_{1ic}$	$_{tt}\Delta M2 + B_{2ict}\Delta ST\_INT + B_{3ict}\Delta L$	$-T_{\perp}INT + B_{4ict}\Delta GDP + B_{5ict}\Delta RB$	$EER + \varepsilon_{c_{t_i}}$	
DTC_INDEX				
BULL REGIME				
	Coefficient	Std. Error	z-Statistic	Prob.
С	-0.6149	0.1565	-3.9289	0.0001
∆ CPI	0.0527	0.0294	1.7901	0.0734
∆ M2	0.0854	0.1045	0.8174	0.4137
∆ ST_INT	0.0583	0.0395	1.4763	0.1399
Δ LT_INT	-0.1082	0.0523	-2.0701	0.0384
∆ GDP	-0.0156	0.0548	-0.2855	0.7753
∆ REER	0.0102	0.0434	0.2361	0.8133
LOG (SIGMA)	0.0197	0.0946	0.2083	0.8351
Transition Probabilities				
P11	0.933339			
Τ11	15.00136			
BEAR REGIME				
	Coefficient	Std. Error	z-Statistics	Prob.
C	9.2861	0.4643	20.0010	0.0000
∆ CPI	-1.6753	0.0960	-17.446	0.0000
∆ M2	0.3539	0.2706	1.3077	0.1910
∆ ST_INT	1.2569	0.1031	12.1808	0.0000
∆ LT_INT	1.1605	0.0492	23.5778	0.0000
∆ GDP	0.1587	0.0763	2.0802	0.0375
∆ REER	1.1041	0.1573	7.0210	0.0000
LOG (SIGMA)	-0.4807	0.2737	-1.7563	0.0790
Transition Probabilities				
P22	0.464208			
T22	1.866395			
Diagnostic Test				
LM	0.733460	_	_	0.6930

Notes: 1. Source: Authors' estimation (2024).

positive in bear regimes. However, in bull market conditions, size-based connectedness index returns are less volatile than bear market condition returns. This suggests that the returns of the size-based connectedness index decrease during a bull regime but are not decreasing enough to enhance volatility, whereas in the bear regime, the size-based connectedness index returns increase, but are more volatile as during a bear market, returns vary continuously. It is also evident that only long-term interest rates significantly negatively affect size-based connectedness index returns in a bull regime. However, in a bear regime, the short-term interest growth rate, long-term interest growth rate, gross domestic product growth rate, and real effective exchange growth rate have a significant positive effect on size-based connectedness index returns.

However, in a bear regime, the inflation growth rate has a negative and significant effect on the return on the size-based connectedness index. The transition probabilities of the size-based connectedness index in the bull regime (0.933339) are greater than that of the bear regime (0.464208). This suggests that the size-based connectedness index is categorized as increasing over the sample period, and this is confirmed by the expected duration probabilities as the size-based connectedness index returns stay longer in a bull regime (15 months) as opposed to a bear regime (1.8 months). It is further evident that the Breusch-Godfrey LM test suggest that there is no autocorrelation in the residuals of the model as we fail to reject the null hypothesis (no autocorrelation in the residuals of the model). Consequently, this increases the robustness of the findings.

# 5. Discussion of results

#### 5.1. Headline TVP-VAR

In this study, the framework of Antonakakis et al. (2020) was employed to study the nature of the return transmission of the headline series of the JSE market. This result indicates that the return spillovers and return linkages vary over time, especially in extreme market conditions such as the pre, during, and post-Covid-19 periods. The study discovered that the JSE-LRG CAP and the JSE-FLD series are net receivers of shock during the pre, during and post-CovID-19 periods, as well as during the entire sample with the JSE-FLD attaining an average net receiving value of over -8%, higher than JSE-LRG CAP, whereas JSE-MID-CAP and JSE-SML CAP are the net transmitters of shocks for the entire different conditions with the exception of the pre-CovID-19 period. When examining the spikes in total connectedness values, it was observed that the heightened value was more differentiated during the Covid-19 period. This illustrates that the Covid-19 period reveals a season of very high correlation; hence, a heightened comovement in the returns of all headline series. This suggests that various firms under this headline would have made huge losses or gained whenever a shock affected the headline network.

# 5.2. Markov regime-switching model

It must be noted that no domestic or international study examines the effect of macroeconomic factors on the connectedness of sized base indices. Consequently, it is not possible to provide a comparison between studies or discuss the results according to empirical literature. Rather, the implications of the findings are discussed herein. The Markov regime-switching model's findings show that the size-based index connectivity is influenced by macroeconomic variables in a reversible manner. These findings are in line with the adaptive market hypothesis, which suggests that the effect should be time-varying, regime-dependent, and alternate with bull and bear regimes. Thus, the proposition of the efficient market hypothesis that all markets are efficient, macroeconomic variables do not affect asset prices, and their connectedness is not supported. The implications of the findings are as follows. If portfolio managers use size-based indices for added diversification in an investor's portfolio, they should consider that these size-based indices are connected and that this connection is influenced by macroeconomic variables, where it alternates with bull and bear market conditions. Moreover, policymakers should consider the condition of the market when conducting policy adjustments to inflation, interest rates, real effective exchange rate, and gross domestic product, as it affects the performance of size-based index returns and their connectedness. Hence, diversification benefits are affected, which effects investor portfolio formation, as portfolio rebalancing is required.



#### 6. Conclusion

At the beginning of this study, academics had two objectives. The first objective was to examine the effect of COVID-19 on the connectedness of JSE-size-based indices. The second objective was to investigate the effect of macroeconomic factors or variables on JSE-sized-based index connectedness under changing market conditions. The study used daily data from 4 January 2017 to 30 June 2023, to achieve the desired objectives. In Objective 1, the TPV-VAR model was used, where the sample period was subsampled to accommodate pre-COVID-19, during-COVID-19, and post-COVID-19. The findings of the study demonstrated that the return spillovers and return linkages of the JSE-size-based indices vary over time, especially in extreme market conditions such as the pre, during, and post-Covid periods. Moreover, the Covid-19 pandemic period reveals a season of very high correlation; hence, a heightened comovement in the returns of all JSE-size-based indices.

In the second objective, the Markov regime-switching model was administered, in which the derived connectedness index of the entire sample from Objective 1 was used as the dependent variable. Macroeconomic variables like the money supply, the short- and long-term interest rates, inflation, the gross domestic product, and the real effective exchange rate were among the independent variables. The findings suggest that macroeconomic variables have a time-varying effect on JSE-size-based indices under changing market conditions. That being, the effect was not the same under each regime; rather, it alternated with the specific market conditions.

The implications of these findings are as follows. First, JSE-size-based indices are highly correlated, and such correlations vary depending on market conditions, such as COVID-19. Consequently, portfolio managers should not consider companies that form part of the JSE-sized-based indices in investor portfolios during market conditions because they do not provide added diversification benefits. Second, the JSE large-cap index and JSE fledging index are net receivers of shocks during the COVID-19 period. Therefore, portfolio managers should conduct portfolio rebalancing during changing market conditions, as there will be added risk transmission if portfolios contain companies that are part of the JSE large cap index and JSE fledging index. Third, macroeconomic variables influence the returns of JSE-sizedbased indices under bull and bear market conditions. Hence, policymakers should consider the condition of the market when conducting policy adjustments to inflation, interest rates, the real effective exchange rate, and gross domestic product. Hence, diversification benefits are affected, which hampers investor portfolio formation, as portfolio rebalancing is required.

A limitation of the study is not easily derived as the following study is the first in South Africa to consider the two objectives presented. However, a future recommendation is that academics can extend the number of macroeconomic variables to determine if macroeconomic variables that are external to this study influence sized-based index returns connectedness.

#### **Notes**

- 1. All Share index represent 99% of the market capitalization of all eligible securities listed on the JSE Main Board. The Large Cap index represent the market capitalization of all qualifying securities listed on the JSE Main Board is represented by the Large Cap Index, which amounts to 85% of the total. 85% to 96% of the total market capitalization of all eligible securities listed on the JSE Main Board is represented by the Large & Mid Cap Index, while the Mid-Cap Index represents 85-96% of the full market capitalization value of all eligible securities on the main board of the JSE. The Small Cap Index is comprised of 96% to 99% of the total market capitalization of all eligible ordinary stocks that are listed on the JSE Main Board, and finally the Fledgling Index shows the bottom 1% of all qualifying ordinary stocks listed on the JSE Main Board in terms of market capitalization.
- 2. Figures 2 show the network plots of total connectedness index for the industries during the full sample period, the pre, during and post Covid. The plot is a series of nodes and edges. The nodes are in yellow and blue which represents the different industries while the 'arrows' linking one node to another or each other are called the edges.

#### Author's contribution

The three authors of the research article contributed significantly to its finality. That being, Dr. Babatunde Lawrence was tasked with writing the introduction, literature review, econometric methodology and interpretation of objective 1 of the research article. Mr. Fabian Moodley was responsible for writing the abstract, conclusion, econometric methodology and interpretation of objective 2 of the research study. Prof. Sune Ferreira-Schenk was responsible for data collection, discussion section, reviewing and editing of the manuscript.

### **Disclosure statement**

No potential conflict of interests was reported by the author(s).

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# Data availability statement

The data is available on request from the corresponding author.

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