“Volatility transmission and dynamic conditional correlations in South African equity markets: An in-depth cross-index examination”

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VOLATILITY TRANSMISSION AND DYNAMIC CONDITIONAL CORRELATIONS IN SOUTH AFRICAN EQUITY MARKETS: AN IN-DEPTH CROSS-INDEX EXAMINATION

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Abstract

To enhance risk management techniques, this study attempts to evaluate the feasibility of treating volatility as a distinct asset class in portfolio diversification strategies. In particular, it examines dynamic conditional correlations and spillover effects between equity returns across Johannesburg Stock Exchange (JSE) indices and volatility (as determined by the VIX and the South African Volatility Index – SAVI), both before and during the COVID-19 pandemic (2010 to 2022). By extending the analysis beyond the global VIX to also include the local SAVI, the study provides insights into the role of volatility in emerging economies. The study employed the Multivariate GARCH models: the Dynamic Conditional Correlation (DCC) GARCH of Engle and the Baba, Engle, Kraft, and Kroner (BEKK) model proposed by Engle and Kroner. We found evidence of volatility spillovers from the VIX to the South African equity indices. However, the VIX did not exhibit a significant response to volatility in the South African market. The study revealed consistent and significant negative correlations between volatility (VIX & SAVI) and JSE broad market indices, with these correlations further decreasing during the pandemic. Additionally, the SAVI showed notably lower correlations with the JSE market compared to the VIX, suggesting its distinct role in conveying risk perception and market expectations specific to the JSE.

Keywords volatility, VIX, SAVI, spillover, conditional correlations, DCC GARCH, BEKK

JEL Classification G11, G12

INTRODUCTION

In the dynamic financial market landscape, risk assessment and effective hedging strategies remain crucial for investors and portfolio managers. The nexus between market volatility and asset returns shapes risk management practices. Volatility, a barometer of market sentiment and investor fear, provides insights into future market direction, allowing market participants to make effective investment decisions. The VIX is globally recognised as a benchmark for equity market volatility and has evolved into a tradable asset class, allowing investors to long or short volatility through derivatives (Liu et al., 2022). Empirical evidence highlights an inverse relationship between volatility and stock returns – intensifying during periods of market stress (Cheuathonghua et al., 2019; Auinger, 2015). For example, declines in the S&P 500 index are often accompanied by surges in the VIX, underscoring its role as a hedge against downturns. However, most studies have focused on the U.S. market, particularly the S&P 500, leaving gaps in understanding how volatility-return dynamics unfold across other indices and within emerging economies.

South Africa offers a compelling case, with the availability of a local benchmark – the SAVI – and its integration into global financial markets. Volatility shocks in emerging markets can reverberate internationally, influencing global risk perceptions and prompting hedging behaviour among investors with emerging market exposure (Karanasos et al., 2022). Emerging markets are generally more sensitive to global financial conditions, with local volatility often serving as an early warning signal for broader systemic risk. This interconnectedness underscores the need to investigate volatility transmission and diversification dynamics not only in relation to the VIX but also through the SAVI. A cross-market index perspective is especially valuable, as different indices may exhibit unique responses to macroeconomic shifts and global events, offering deeper insights into volatility's role in hedging and diversification.

1. LITERATURE REVIEW

The Modern Portfolio Theory (MPT) developed by Markowitz (1952) shaped portfolio management by emphasising efficient construction based on the risk-return trade-off. Its cornerstone is diversification aimed at maximising returns while minimising risk. According to the MPT, diversification reduces risk by selecting a weighted set of assets whose combined risk is lower than that of individual assets. It follows the principle of "never put your eggs in one basket" . The risk-reduction potential depends on asset return volatility and correlations of asset pairs (Just & Echaust, 2020). The lower the correlation, the greater the diversification benefits. Assets with low correlations offset each other's downside risk, lowering portfolio risk without equivalent return reduction (Markowitz, 2014).

Markowitz's mean-variance model (1952) optimised the balance between risk and return through asset correlations. Later models refined this: Fishburn (1977) introduced the Mean-Gini (MG) model for non-normal return distributions, improving flexibility; Shalit and Yitzhaki (2005) developed the MG efficient frontier to address quadratic utility and normality limitations; Konno and Yamazaki (1991) proposed the Mean-Absolute Deviation (MAD) model for real-time optimisation of large portfolios; Rockafellar and Uryasev (2000) introduced Conditional Value-at-Risk (CVaR) for better tail risk management; Krokhmal et al. (2002) showed CVaR constraints create more stable portfolios; Alexander and Baptista (2002) compared VaR and mean-variance, noting VaR can increase volatility in some portfolios; Agnesens (2013) found extensive constraints are often needed for effective diversification.

These developments highlight the evolving nature of diversification while reaffirming Markowitz's principle that low correlations significantly reduce portfolio risk. This paper builds on that foundation, integrating modern approaches to analyse diversification's role in financial risk management. Koumou (2020) argues that diversification within the same sector offers limited protection against industry-wide risks, emphasising cross-industry diversification. However, cross-industry diversification cannot hedge against cyclical factors affecting all industries, showing that diversification mainly offsets uncertainty from incomplete information (Koumou, 2020).

Traditionally, investors diversified between equity and fixed income. Within equities, global investing historically improved diversification (Binstock et al., 2017). Recently, however, correlations between global stock indices have risen, especially during downturns, eroding these benefits (Moran & Liu, 2020). Lan et al. (2023) found heightened volatility spillovers during COVID-19, signalling stronger market interconnectedness. Siriopoulos and Fassas (2013) reported increased conditional correlations in implied volatility indices during turbulence, reducing diversification opportunities.

In response to changing markets, new asset classes have emerged, including derivatives, hedge funds, alternative investments, and ETFs. Volatility has evolved from a market uncertainty indicator to a distinct asset class, with the S&P Volatility Index (VIX) as its benchmark. Initially designed for equity markets, the VIX now enables active trading for hedging or diversification.

Recent studies reinforce volatility's role. Bouri et al. (2017) examined cryptocurrency diversification in international stock markets, emphasising

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volatility spillovers; Alexander and Lazar (2006) used a multivariate GARCH model to manage risk and optimise portfolios; Engle and Colacito (2006) assessed how volatility and correlation forecasts improve diversification; Guidolin and Timmermann (2008) explored stochastic discount factor (SDF) volatility timing in global portfolios; Maghyereh et al. (2017) analysed spillovers and cross-hedging in commodity markets.

Empirical evidence shows a negative, asymmetric relationship between the VIX and equity returns, especially in stress periods (Badshah et al., 2016; Chichilnisky & Rezai, 2017; Padungsaksawasdi & Daigler, 2014). Just and Echaust (2020) found close dependence between returns, implied volatility, and implied correlation in US markets. Cheuathonghua et al. (2019) reported that even small changes in VIX affect global markets in extreme conditions, with more pronounced effects in developed markets and on volatility in emerging markets. Jackwerth and Vilkov (2019) found evidence of a significant risk premium for market volatility correlation.

While much research examines volatility spillovers between equity markets (Atenga & Mougoué, 2021; Bhar & Nikolova, 2009; Lan et al., 2023), fewer studies focus on volatility as an asset class in developing economies. Most existing work targets the US and EU using the VIX and broad market indices. From a South African perspective, Peerbhai et al. (2024) examined SAVI–equity return relationships, finding a positive correlation – unlike many developed markets. However, they did not study dynamic correlations and relied on static GARCH models. This study focuses on South Africa, comparing the evolution of dynamic equity–volatility correlations for the VIX and the local volatility index (SAVI) under different market conditions, exploring cross-index rather than broad-index relationships. Cheuathonghua et al. (2019) note that the VIX's impact varies with market conditions. This study examines dynamic conditional correlations between volatility and equity returns for various South African stock indices before and during the pandemic to assess the possibility of using volatility as a standalone asset class for diversification.

2. METHODS

To examine the dynamic conditional correlation, spillovers, and hedging effectiveness of the VIX and SAVI on South African cross-market indices, the study employed Multivariate GARCH models: the Dynamic Conditional Correlation (DCC) GARCH of Engle (2002) and the BEKK model of Engle and Kroner (1995). The BEKK model provides a useful framework for examining cross-asset and market volatility spillovers, but is complex, requiring many parameter estimates (Ghorbel & Jeribi, 2021). Alternatives, such as the Constant Conditional Correlations (CCC) and DCC models (Engle, 2002), offer more streamlined specifications.

Multivariate GARCH models explore temporal dependence in conditional variance between variables. They are widely used in financial literature due to their simplicity and ability to generalise other volatility measures. Financial time series often exhibit fat-tailed returns, volatility clustering, time-varying volatility, asymmetry, persistence, co-movements, and mean-reverting volatility. GARCH-type conditional volatility models, the most commonly used family of volatility models, are specifically designed to address these characteristics (May & Farrell, 2018).

2.1. MDCC GARCH

Following Ceylan (2021)'s approach, we employed the Engle (2002) DCC GARCH model to analyse the time-varying conditional correlations and volatilities among the VIX/SAVI and several equity indices within the South African market. The Dynamic Conditional Correlation (DCC) GARCH model by Engle (2002) is a powerful tool for analyzing dynamic correlations. The DCC GARCH model is favored for its flexibility and simplicity in estimating time-varying correlations, making it computationally efficient and ideal for large datasets (Engle, 2002). Unlike the constant correlations observed in a CCC model, the DCC GARCH model permits dynamic conditional correlations that fluctuate over time. The notable benefit of the DCC model lies in its independence from the number of series being estimated, providing computational efficiency, especially when dealing with large covariance matrices (Engle, 2002). However, it may struggle with capturing non-linear dependencies in extreme market conditions.

Specifically, in a DCC GARCH (1,1) model, where r_t represents a vector of two returns, denoted as $r_t = (r_{1t};\ r_{2t})'$,

$$A(L)r_t = \omega + \varepsilon_t \ , \qquad (1)$$

where $A(L)$ is a lag polynomial and ε_t is the error term. The DCC model is based on the assumption that conditional returns follow a normal distribution with a mean of zero and a conditional variance matrix.

$$h_t = E\left[r_t r_t'\right] \qquad (2)$$

expressed as.

$$H_t = D_t R_t D_t \ , \qquad (3)$$

where D_t represents the conditional covariance diagonal matrix defined as

$$D_t = \left[diag(h_t)\right]^{1/2}, \qquad (4)$$

where the elements of D_t are estimated using the univariate GARCH. The conditional correlation matrix (R_t), varies over time and is defined as:

$$R_t = diag\left(q_{11,t}^{-1/2} \dots q_{nn,t}^{-1/2}\right) Q_t diag\left(q_{11,t}^{-1/2} \dots q_{nn,t}^{-1/2}\right), \qquad (5)$$

where represents the n x n symmetric positive definite matrix, and the DCC (1,1) model can be formulated as follows:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon_{t-1} + \beta Q_{t-1}, \qquad (6)$$

where Q_t represents the conditional covariance matrix of the error terms, while $\bar{Q}$ denotes the unconditional covariance matrix. The scalar parameters $\beta\, and\, \alpha$ are non-negative, satisfying $\beta + \alpha < 1$. When $\alpha = \beta = 0$, Q_t equals $\bar{Q}$, making the CCC model suitable for correlation matrix estimation. According to Engle (2002), $\bar{Q}$ is the second moment of the error term (ε_t) often approximated by sample moments of estimated returns in large systems. In this section, the primary focus is on R_t, which denotes the conditional correlations given as:

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \ . \qquad (7)$$

2.2. MGARCH-BEKK

The Baba, Engle, Kraft, and Kroner (BEKK) model by Engle and Kroner (1995) is a robust technique for analysing volatility spillovers. The BEKK model ensures the positive definiteness of the covariance matrix and provides a detailed view of volatility spillovers, though its complexity can lead to computational challenges and overfitting in large systems (Engle & Kroner, 1995). Diebold and Yilmaz's (2012) methodology for measuring spillover effects through forecast error variance decompositions has gained popularity for its straightforward and intuitive approach. However, it tends to focus on aggregate spillover indices and may miss the detailed dynamics captured by multivariate GARCH models (Diebold & Yilmaz, 2012). The DCC and BEKK models offer a more granular analysis of volatility and correlation dynamics, which is essential for effective hedging and risk management.

The Engle and Kroner (1995) BEKK model can be defined as follows:

$$H_t = C'C + \sum_{i=1}^{k} A_i'\varepsilon_{t-1}\varepsilon_{t-i}'A_i + \sum_{i=1}^{k} G_i'H_{t-1}G_i, \qquad (8)$$

where H_t represents the conditional variance matrix in the MGARCH BEKK model; A_i and G_i are $N\ x\ N$ matrices of parameters, while C is an $N\ x\ N$ upper triangular matrix of constants; ε_{t-1} denotes the residual matrix at time t–1. Equation 8 ensures that all diagonal representations are positive definite. In accordance with Mohammadi and Tan (2015), we set the lag length to one, resulting in a concise specification of the BEKK model as follows:

$$H_t = C_t + A_i'\varepsilon_{t-1}\varepsilon_{t-i}'A_t + G_i'H_{t-1}G_t, \qquad (9)$$

In this context, C_t, A_t, and G_t denote the coefficients of the BEKK-GARCH model, as expressed by Engle and Kroner (1995) as follows:

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}, \ C = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix},$$

$$A = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \ G = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix},$$

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$$H_t = (h_{it}), \text{ where } i = 1,2\ldots,N;$$

$$C_t = (C_{i;j-t}), \text{ where } i,j = 1,2\ldots,N,$$

$$A_t = (\propto_{ij,t}), \text{where } i,j = 1,2\ldots,N;$$

$$G_t = (\mathrm{G}_{ij,t}), \text{where } i,j = 1,2\ldots,N.$$

The symmetric BEKK model can be transformed into an Asymmetric BEKK model (Park et al., 2020) as follows:

$$\begin{gathered} H_t = C_t + A_i^{'}\varepsilon_{t-1}\varepsilon_{t-i}^{'}A_t \\ +G_i^{'}H_{t-1}G_t + D'\eta_{t-1}\,\eta_{t-1}, D, \end{gathered} \tag{10}$$

where

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix},\ C = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix},$$

$$A = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix},\ G = \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix},$$

$$D = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix},\ \eta_{t-1} = \begin{bmatrix} \max(0, -\int_{1,t-1} \\ \max(0, -\int_{2,t-1} \end{bmatrix}.$$

The Engle and Kroner BEKK model effectively decomposes each conditional variance into its GARCH and ARCH components. The volatility of each Index return under the ARCH framework is influenced by the squares and cross-products of the preceding period's shocks associated with each asset return utilised. In this context, $\alpha_{11}\ldots;\ \alpha_{N1}$ encapsulate the impact of each asset's past squared shocks on today's volatility in the current index returns (Ghorbel & Jeribi, 2021).

$$\begin{aligned} &h_{11,t} = c_1 + \alpha_{1,1}^2\varepsilon_{1,t-1}^2 + \alpha_{2,1}^2\varepsilon_{2,t-1}^2 \ldots + \alpha_{N,1}^2\varepsilon_{N,t-1}^2 \\ &+2\alpha_{11}\alpha_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1}\ldots + 2\alpha_{11}\alpha_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ &+2\alpha_{11}\alpha_{N1}\varepsilon_{1,t-1}\varepsilon_{N,t-1} + 2\alpha_{21}\alpha_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ &+2\alpha_{21}\alpha_{41}\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 2\alpha_{N-1,1}\alpha_{N1}\varepsilon_{N-1,t-1}\varepsilon_{4,t-1}, \end{aligned} \tag{11}$$

Similarly, the volatility of each Index under the GARCH component is influenced by the prior covariance and conditional variances associated with each of the N corresponding indices. Here, $g_{11}\cdots g_{N1}$ represent the effect of each asset's preceding volatility on today's volatility of the Index in question (Ghorbel and Jeribi (2021).

$$\begin{aligned} &h_{11,t} = c_1 + g_{1,1}^2h_{11,t-1}^2 + g_{2,1}^2h_{22,t-1}^2\cdots \\ &+g_{N,1}^2h_{N,N,t-1}^2 + 2g_{11}g_{21}h_{12,t-1} \\ &+2g_{11}g_{31}h_{13,t-1}\cdots + 2g_{11}g_{N,1}h_{1,N,t-1} \\ &+2g_{21}g_{31}h_{23,t-1} + 2g_{21}g_{41}h_{24,t-1} \\ &+2g_{N-1,1}g_{N1}h_{N-1,N,t-1}. \end{aligned} \tag{12}$$

This study seeks to evaluate the dynamic correlations and volatility dynamics between the VIX and different indices of the South African market. Consequently, the investigation focuses on α_{1t} and β_{1t} to analyze spillover effects. The estimated BEKK parameters $(A.\,,i)$ and $B(.\,,i)$ correspond to the ARCH and GARCH parameters pertaining to each asset or series i. The ARCH term $(A.\,,i)$ captures the response of asset i 's volatility to squared standard innovations in each asset. In equation 12, the diagonal parameters g_{1i} signify the GARCH effects from asset/return 1 to asset/return i, while the diagonal matrix A, $\alpha_{1,i}$ in equation 11 denotes the ARCH effects from asset 1 to asset i (Mohammadi & Tan, 2015).

2.3. Data and the variables

The analysis used daily time-series price data from January 1, 2010, to December 31, 2022, divided into two samples: the pre-COVID-19 period (January 1, 2010, to November 30, 2019) and the COVID-19 period (December 1, 2019, to December 31, 2022). This window was chosen to capture the broader market dynamics associated with the pandemic, including the initial volatility shock, the recovery driven by stimulus, and the normalization phase that followed in 2022. Even though the most severe financial effects of the pandemic happened in early 2020, volatility models such as BEKK and DCC depend on persistent correlation structures that evolve over long periods. Hence, using a longer window makes sure that all the different kinds of uncertainty related to the pandemic are taken into account. We recognize that different definitions, like shorter event windows or the establishment of a post-COVID period, may yield further insights. This opens up important paths for future research.

Study variables included the CBOE VIX, the SAVI, and four South African equity indices: the JSE All Share, Top-40 (40 most valuable firms), Mid Cap, and Small Cap. The VIX, a primary measure of expected market volatility, is derived from S&P 500 Index option prices and is recognised as a leading US equity market volatility indicator (Lin, 2013). It is calculated by aggregating weighted prices of SPX puts and calls across various strike prices (Moran & Liu, 2020), incorporating SPX weekly option expirations – only options expiring on Fridays with valid non-zero bid and ask prices are included. This reflects market sentiment on which strike prices are likely to be reached before expiry. By enabling volatility exposure replication through an SPX option portfolio, this methodology has turned the VIX from a theoretical measure into a practical benchmark for volatility trading and hedging (Moran & Liu, 2020). Consistent with prior research, daily closing prices of the equity indices were used. Prices were converted into continuously compounded log returns. Data came from the S&P Capital IQ online database.

The data were aligned using synchronous daily closing prices because the trading hours of the JSE and US markets do not completely match. Many international volatility spillover studies use this method because daily VIX values account for all of the US trading session, including the opening period that overlaps with the last 90 minutes of JSE trading. Because volatility is persistent and has a long memory, daily MGARCH models can accurately capture spillovers even without intraday alignment. Therefore, even though intraday analysis could provide additional granularity, the closing-price alignment approach used here is consistent with established literature and suitable for examining volatility transmission at the daily frequency.

3. RESULTS

3.1. Descriptive statistics

Table 1 presents the descriptive statistics of returns for the JSE broad indices. Over the sample period, all assets had positive mean returns except for the SAVI, which was negative. During the sample period, the JSE All Share and Top 40 indices both had the highest average daily returns (0.027). These similar return levels reflect the broad market performance captured by the JSE's largest and most representative segments. In the pre-COVID period, the Midcap index had the highest mean return, while the VIX and SAVI showed negative returns, reflecting lower volatility. During the pandemic, the Small-cap index posted the highest mean return among the four JSE indices. Both the VIX and SAVI had significant positive returns, likely due to heightened volatility. Volatility indices showed greater deviations from the mean, with higher standard deviations than the JSE equity indices in both periods.

3.2. Correlation analysis

Table 2 shows the static correlations of returns from the four JSE broad indices and the Volatility Indices (VIX and SAVI) during pre- and post-COVID-19 periods. A significant negative correlation exists between all equity and volatility indices in both periods, suggesting potential diversification benefits. The negative correlations are stronger during the pandemic, supporting the view that the inverse relationship between equity returns and volatility is more pronounced in crises (Chichilnisky & Rezai, 2017), implying that volatility can hedge equity returns. Results also show a weak positive, statistically significant correlation between

Table 1. Descriptive statistics

	ALSH	MIDCAP	SMLCAP	TOP40	VIX	SAVI
Mean (Overall)	0,027%	0,023%	0,024%	0,027%	0,002%	–0,001%
Pre COVID	0,029%	0,032%	0,020%	–0,007%	–0,016%	–0,018%
COVID	0,036%	0,005%	0,052%	0,025%	0,034%	0,070%
Std. Dev. (Overall)	1,224%	0,994%	0,780%	1,320%	7,710%	6,374%
Pre COVID	0,951%	0,772%	0,558%	1,361%	3,608%	7,763%
COVID	1,437%	1,438%	1,292%	2,982%	5,006%	8,316%
Maximum	7,262%	5,650%	10,29%	7,907%	76,82%	230,7%
Minimum	–10,23%	–11,21%	–11,30%	–10,45%	–35,06%	–230,0%
Observations	4248	4248	4248	4248	4248	4225

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Table 2. Static correlations

Panel A: PRE-COVID PERIOD						
	VIX	SAVI	ALSH	Top40	MIDCAP	SMCAP
VIX	1					
SAVI	0.1443*	1				
ALSH	–0.3489*	–0.4291*	1			
Top40	–0.3474*	–0.4302*	0.9963*	1		
MIDCAP	–0.2411*	–0.2762*	0.7286*	0.6705*	1	
SMCAP	–0.2022*	–0.2464*	0.5120*	0.4685*	0.6173*	1
Panel B: COVID PERIOD						
	VIX	SAVI	ALSH	Top40	MIDCAP	SMCAP
VIX	1					
SAVI	0.1571*	1				
ALSH	–0.3581*	–0.3779*	1			
Top40	–0.3541*	–0.3782*	0.9976*	1		
MIDCAP	–0.3149*	–0.3200*	0.8201*	0.7850*	1	
SMCAP	–0.2780*	–0.2550*	0.7178*	0.6768*	0.8153*	1

Note: * Significant at 5% .

VIX and SAVI, indicating a marginal simultaneous increase in their volatility. The Small Cap index has the lowest correlation with the other JSE broad indices, highlighting potential diversification benefits. Static correlations among the JSE broad indices increased during the pandemic, indicating risk concentration and reduced diversification.

3.3. Unit root and ARCH effects

For GARCH models to be fitted, data series must exhibit stationarity, heteroskedasticity, and evidence of volatility clustering. A battery of tests, including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS tests, was conducted to assess stationarity. Results from Table 3 indicate that all return series are stationary at levels, evidenced by significant p-values of the ADF and PP tests and p-values above 5% for the KPSS test. The Engle Lagrange multiplier (LM) test of ARCH effects, also presented in Table 3, confirms the presence of heteroskedasticity, with p-values of the ARCH effects test below 5% for all series, rejecting the homoskedasticity null hypothesis. Furthermore, residual plot trends depicted in Figure 1 illustrate volatility clustering, where periods of low/high volatility are followed by similar periods, supporting the notion that error terms are conditionally heteroskedastic and can be represented by ARCH/GARCH models (Miah & Rahman, 2016).

3.3.1. Volatility clustering

Figure 1 illustrates notable increases and spikes in volatility during crisis periods- the global financial crisis (2008–2009) and the COVID-19 period (2019 to 2022), across all the indices. These spikes indicate heightened market uncertainty and increased investor risk aversion during these turbulent periods.

Table 3. Unit root and ARCH tests

Index	ADF		Phillips–Perron		KPSS	ARCH TEST	
	t-Stat	Prob.	t-Stat	Prob.	LM-Stat.(5%)	F-statistic	Prob. Chi2
ALSH	–64.5308	0.0001	–64.8518	0.0001	0.463	154.805	0.0000
MIDCAP	–60.0751	0.0001	–60.0161	0.0001	0.463	94.8975	0.0000
SMLCAP	–24.6899	0.0000	–61.3260	0.0001	0.463	6.70664	0.0096
TOP40	–65.1558	0.0001	–65.6846	0.0001	0.463	145.318	0.0000
VIX	–50.8699	0.0001	–80.3418	0.0000	0.347	24.41360	0.0000
SAVI	–42.0213	0.0001	–114.8334	0.0001	0.463	69.8590	0.0000

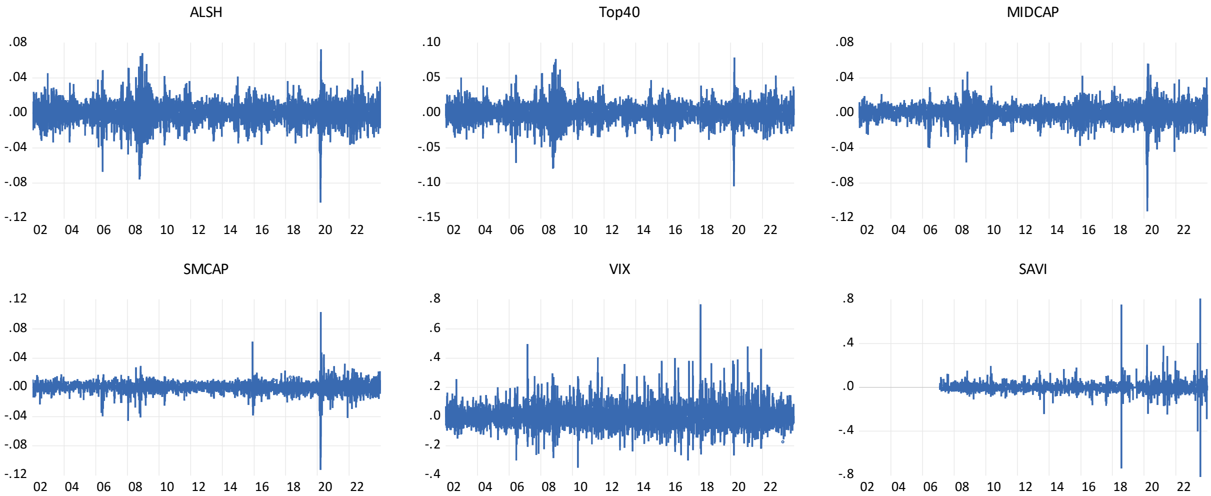

Figure 1. Returns plot

3.4. Spill-over effects: VIX and JSE broad indices

Tables 4 and 5 present the estimation results of the BEKK-GARCH models examining the spillover effects between the VIX and the broad JSE indices. The coefficients of the ARCH terms A (1,1) and A (2,2) are positive and statistically significant for all indices pre and post-COVID-19 periods, indicating that the volatility of these JSE indices, along with the VIX and SAVI, significantly responds to past squared shocks in its own market, suggesting that past news and shocks in these indices positively affect the current Index conditional volatility. Similarly, the diagonal GARCH parameters B (1,1) and B (2,2) for all indices and the VIX are positive and statistically significant, implying that their conditional variances positively respond to their historical variances and spillovers within their own market. The coefficient estimates for A (1,1) and B (1,1) remain relatively stable across both periods, indicating that past squared shock volatility dynamics of the VIX and JSE indices did not change significantly due to the COVID-19 pandemic. Nevertheless, noticeable variations emerge in the coefficients for A(2,2), which increased, and B(2,2), which declined, implying shifts in own conditional variances of the VIX amidst the COVID-19 period.

The coefficient of parameter B (2,1) shows the response of the broad JSE indices' conditional variances to the previous day's volatility shock in the VIX. The results in Tables 4 and 5 indicate that the JSE All-Share Index and the Top40 negatively responded to volatility shocks in the VIX both before and during the pandemic, with a slight increase in magnitude during the pandemic. Meanwhile, the SAVI shows a positive response to shocks in the VIX, suggesting that current conditional vol-

Table 4. Estimates of ARCH and GARCH parameters in the BEKK model (pre-COVID-19)

Volatility Index (VIX): Pre-COVID-19 Jan 2010 to November 2019										
	ALSH_VIX		TOP40_VIX		MIDCAP_VIX		SMLCAP_VIX		SAVI_VIX	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
A (1,1)	0.203*	0.012	0.199*	0.013	0.238*	0.014	0.232*	0.013	0.3616*	0.031
A (1,2)	–0.231	0.187	–0.207	0.178	–0.606*	0.196	0.416*	0.210	–0.004	0.008
A (2,1)	–0.001	0.003	–0.002	0.003	–0.001	0.002	–0.004*	0.002	0.0348*	0.013
A (2,2)	0.422*	0.022	0.422*	0.022	0.410*	0.021	0.435*	0.022	0.418*	0.020
B (1,1)	0.966*	0.004	0.966*	0.004	0.966*	0.004	0.968*	0.004	0.251*	0.102
B (1,2)	–0.118	0.084	–0.114	0.076	0.052	0.082	–0.266	0.112	0.024	0.055
B (2,1)	–0.003*	0.002	–0.004*	0.002	0.000	0.002	0.002	0.001	0.036*	0.020
B (2,2)	0.740*	0.022	0.742*	0.022	0.747*	0.023	0.733*	0.023	0.777*	0.019

Note: A (i, i) and B (i, i) are the corresponding ARCH and GARCH parameters for return i. * Significant at 5% or better; Standard errors next to coefficients.

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Table 5. Estimates of ARCH and GARCH parameters in the BEKK model (during COVID-19)

Volatility Index (VIX): COVID-19 PERIOD November 2019 to December 2022										
	ALSH_VIX		TOP40_VIX		MIDCAP_VIX		SMLCAP_VIX		SAVI_VIX	
	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error	Coeff	Std Error
A(1,1)	0.210*	0.013	0.206*	0.013	0.258*	0.016	0.271*	0.016	0.313*	0.023
A(1,2)	–0.284*	0.171	–0.268	0.169	–0.919*	0.191	0.260	0.207	–0.003	0.007
A(2,1)	–0.001	0.003	–0.001	0.003	0.004	0.003	–0.005*	0.002	0.039*	0.014
A(2,2)	0.433*	0.022	0.431*	0.023	0.421*	0.022	0.446*	0.023	0.431*	0.022
B(1,1)	0.964*	0.004	0.965*	0.004	0.945*	0.007	0.955*	0.005	0.380*	0.083
B(1,2)	–0.065	0.073	–0.058	0.074	0.091	0.084	–0.186*	0.112	0.010	0.083
B(2,1)	–0.004*	0.002	–0.005*	0.002	–0.007*	0.002	0.002	0.002	0.020	0.019
B(2,2)	0.703*	0.026	0.708*	0.025	0.693*	0.025	0.6957*	0.026	0.752*	0.021

Note: A (i, i) and B (i, i) are the corresponding ARCH and GARCH parameters for return i. * Significant at 5% or better; Standard errors next to coefficients.

atility on these indices is influenced not only by their own previous volatility but also by historical volatilities of the VIX, indicating the existence of volatility spillovers between these indices and the VIX. Before the pandemic, previous VIX volatility had no significant effect on the Midcap and small-cap indices. However, during the pandemic, the Midcap also responds negatively to shocks in the VIX. The results also show that the VIX does not significantly respond to volatility in the JSE All Share, Top40, Midcap, and SAVI, as indicated by insignificant coefficients of B(1,2) before and during the pandemic.

3.5. Dynamic conditional correlations VIX and JSE broad indices

The BEKK model has drawn criticism for its extensive parameter estimation requirements. Engle (2002) introduces the DCC-GARCH model, which demands fewer parameter estimates. In our analysis, we employed a VAR-DCC model, and the findings are detailed in Tables 6 and 7. Panel A of each table presents the parameters of the VAR model. The results illustrate that none of the indices' returns responded significantly to past returns during the pandemic.

Table 6. Dynamic conditional correlation (DCC) – MGARCH model PRE-COVID

Index								
A: Estimates of VAR-DCC Parameters								
	ALSH		TOP40		MIDCAP		SMCAP	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Return L.1	–0.101*	0.025	–0.108*	0.025	0.010	0.024	0.053	0.036
VIX.L1	–0.029*	0.003	–0.031*	0.003	0.002*	0.000	–0.014*	0.002
B: Estimates of the DCC GARCH Parameters								
α	0.041*	0.005	0.040*	0.005	0.056*	0.006	0.140*	0.022
β	0.861*	0.049	0.899*	0.055	0.847*	0.269	0.899*	0.205
C: Conditional quasicorrelations								
ρ [Index, VIX]	–0.265*	0.046	–0.264*	0.045	–0.249*	0.022	–0.261*	0.028
ρ [Index, SAVI]	–0.415*	0.088	–0.492*	0.038	–0.366*	0.028	–0.324*	0.025
ρ [ALSH, Top40]	0.997*	0.000		ρ [Top40, MIDCAP]			0.752*	0.014
ρ [ALSH, MIDCAP]	0.802*	0.012		ρ [MIDCAP, SMCAP]			0.699*	0.016
ρ [ALSH, SMCAP]	0.584*	0.002		ρ [Top40, SMCAP]			0.543*	0.013
D: Adjustment								
λ_1 (DCC α1)	0.0178*	0.0011						
λ_2 (DCC β1)	0.9465*	0.0037						
$\lambda_1+\lambda_2$			0.9642					
Wald test $\lambda_1=\lambda_2=0$			330000			Prob > chi2		0.0000
Log likelihood			43374					
Wald chi2			195067			Prob > chi2		0.0001

Note: * Significant at 5% or better; Std Errors are standard error values presented next to coefficient estimates; λ1 and λ2 are the conditional correlation parameters; α and β are ARCH and GARCH parameters. ρ [i, i] are quasicorrelation estimates from the DCC model.

Panels B in Tables 6 and 7 present the estimates of the ARCH $\left(\varepsilon^2_{t-1}\right)$ and $GARCH\left(h_{t-1}\right)$ parameters. The large GARCH coefficients for all indices indicate that shocks in conditional variance take longer to dissipate, suggesting long memory and volatility persistence. The results indicate a significant change in volatility both before and during the COVID-19 pandemic. Panel C depicts the conditional quasi-correlations between the VIX and JSE broad indices. There is a consistently significant negative relationship between the VIX and all JSE indices both before and during the pandemic, indicating the possible presence of diversification benefits and hedging ability of the VIX on the JSE broad equity indices.

Among the JSE indices, the results in Tables 6 and 7 and Figure 2 reveal significant, high positive correlations between the indices, suggesting that movements in one index tend to be accompanied by similar movements in others, implying a possible decline in diversification benefits. Specifically, the JSE All Share and Top40 exhibit a close to perfect positive correlation, suggesting a lack of diversification between these two indices. The small-cap index appears to have the lowest correlation with the rest of the indices both before and during the pandemic, suggesting that small-cap stocks can offer diversification benefits to investments in the top JSE indices due to their relatively independent behaviour.

3.5.1. Dynamic conditional correlations between volatility and the JSE market indices

Figure 3 illustrates a persistent negative relationship between the JSE Broad indices and the VIX. The figure indicates that the Top 40 and the JSE All Share Index have the lowest correlation with the VIX over the sample period, suggesting that the VIX can provide the highest diversification to these two indices. It is worth noting that, although slightly higher, the correlations of the VIX with the Small and Medium caps remain very low, below –0.1, which still presents a promising diversification avenue for investors holding these indices, given that they are not in perfect sync. The chart also depicts a decline in correlations during the COVID-19 pandemic, with the Top 40 reaching lower values of below –0.6 (the lowest during the sample period), potentially offering maximum diversification benefits during this period.

Table 7. Dynamic conditional correlation (DCC) – MGARCH model COVID PERIOD

Index								
A: Estimates of VAR–DCC Parameters								
	ALSH		**TOP40**		**MIDCAP**		**SMCAP**	
	Coeff.	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
return L.1	–0.021	0.716	0.059	0.665	–0.156	0.104	0.068	0.073
VIX.L1	–0.038*	0.006	–0.040*	0.007	–0.025*	0.006	–0.022*	0.005
B: Estimates of the DCC GARCH Parameters								
α	0.061*	0.015	0.056*	0.015	0.105*	0.025	0.205*	0.046
β	1.107*	0.246	1.237*	0.291	0.153	0.141	0.394*	0.149
C: Conditional quasicorrelations								
ρ [Index, VIX]	–0.370*	0.037	–0.363*	0.038	–0.323*	0.038	–0.298*	0.039
ρ [Index, SAVI]	–0.488*	0.098	–0.484*	0.100	–0.325*	0.036	–0.267*	0.038
ρ [ALSH, Top40]	0.998*	0.000			ρ [Top40, MIDCAP]		0.762*	0.015
ρ [ALSH, MIDCAP]	0.796*	0.013			ρ [MIDCAP, SMCAP]		0.784*	0.015
ρ [ALSH, SMCAP]	0.677*	0.020			ρ [Top40, SMCAP]		0.638*	0.022
D: Adjustment								
λ_1 (DCC α1)	0.034*	0.011						
λ_2 (DCC β1)	0.403*	0.168						
$\lambda_1+\lambda_2$	0.437							
Wald test $\lambda_1=\lambda_2=0$	12.20	Prob > chi2		0.000				
Loglikelihood	12532							
Wald chi2	199.65	Prob > chi2		0.002				

Note: * Significant at 5% or better; Std Error are standard error values presented next to coefficient estimates; λ1 and λ2 are the conditional correlation parameters; α and β are ARCH and GARCH parameters. ρ [i, i] are quasicorrelation estimates from the DCC model.

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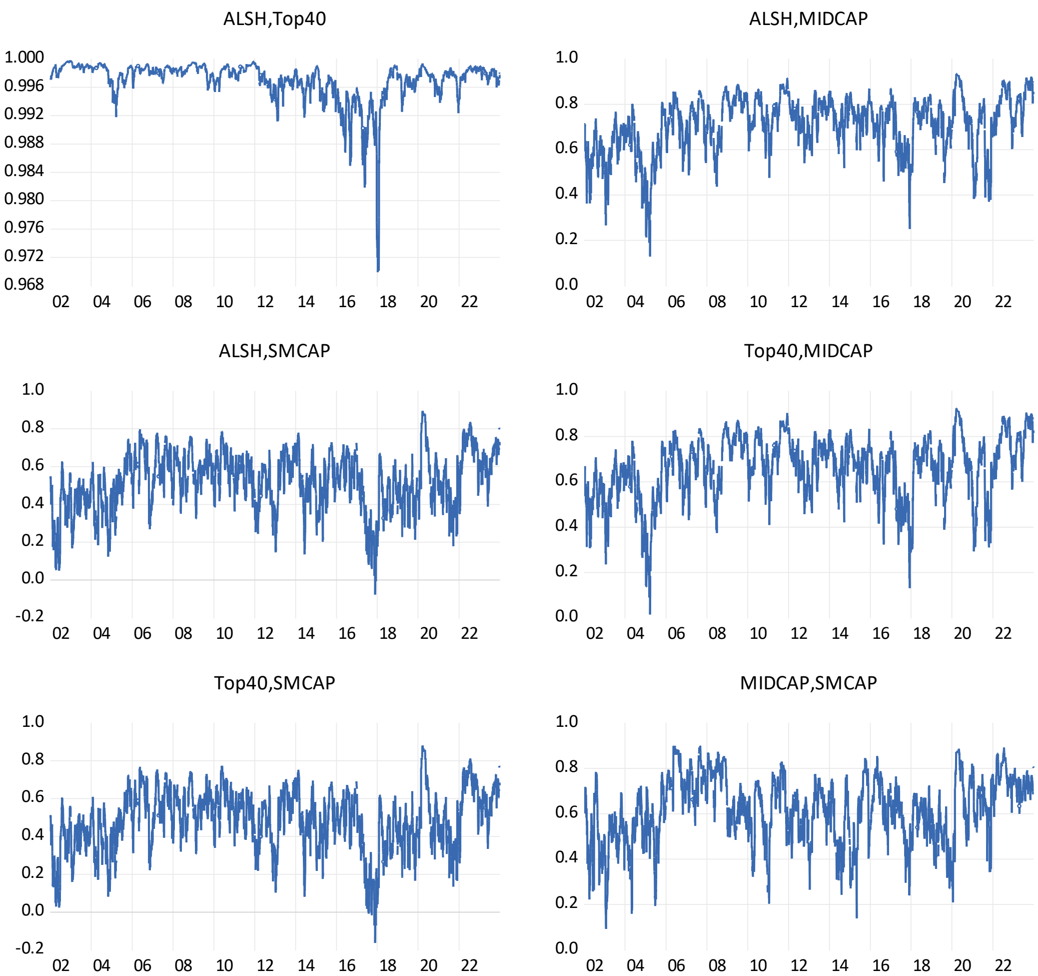

Figure 2. Conditional correlations between JSE broad indices

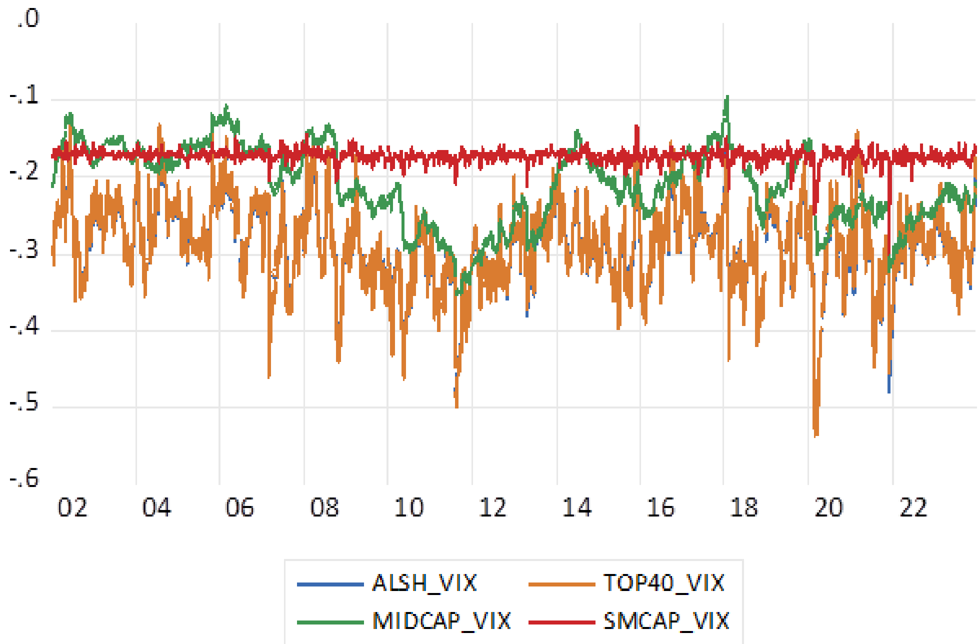

Figure 3. Conditional correlations between the VIX and JSE market indices

3.5.2. Dynamic conditional correlations between SAVI and the JSE market indices, pre-COVID

Figure 4 displays the dynamic conditional correlations between the SAVI and the JSE market indices. The SAVI also demonstrates negative correlations with the JSE market indices. Interestingly, the results reveal that the SAVI has lower correlations (below −0.4 for most of the sample period) with the JSE indices compared to the VIX. These low correlations are also evident in Tables 6 and 7. The findings suggest that the SAVI may offer more diversification and hedging benefits for JSE indices.

3.5.3. Dynamic conditional correlations between VIX and the JSE market indices, COVID period

Figure 5 depicts a significant decline in correlations between the VIX and JSE indices at the onset of the COVID-19 pandemic, observed across all indices. The results show that the small-cap index experienced the highest decrease in correlation with the VIX, dropping below −0.7. Additionally, the small-cap Index exhibited the most volatile correlation with the VIX. This result suggests that the small-cap index behaved differently from other indices during the pandemic, indicating specific structural and sectorial factors influencing its behaviour independent of broader market volatility. In contrast, the All Share and Top 40 indices, despite experiencing significant declines at the start of the pandemic, demonstrated more stable correlations with the VIX, oscillating around −0.3 to −0.4 over this period. This stability offers a more reliable and predictable diversification avenue.

3.5.4. Dynamic conditional correlations between the SAVI and the JSE market indices, COVID period

Figure 6 also illustrates a notable decrease in correlations between the SAVI and JSE market indices at the beginning of the pandemic, reflecting heightened market expectations and fear. The JSE Top 40 registered the lowest correlations below −0.6 during that period. Compared to the results in Figure 5, the findings demonstrate a divergent response of JSE indices to the VIX and SAVI. The Small Cap exhibited the lowest correlations with the VIX during the pandemic, while with SAVI, it was the Top 40 that recorded the lowest conditional correlations. Additionally, the findings reveal that the SAVI displays considerably lower correlations with the JSE indices during the pandemic than the VIX, indicating a divergence in local market sentiment from the global indicator. Notably, the JSE Top 40 and All Share indices demonstrated the lowest correlations with the SAVI over the sample period.

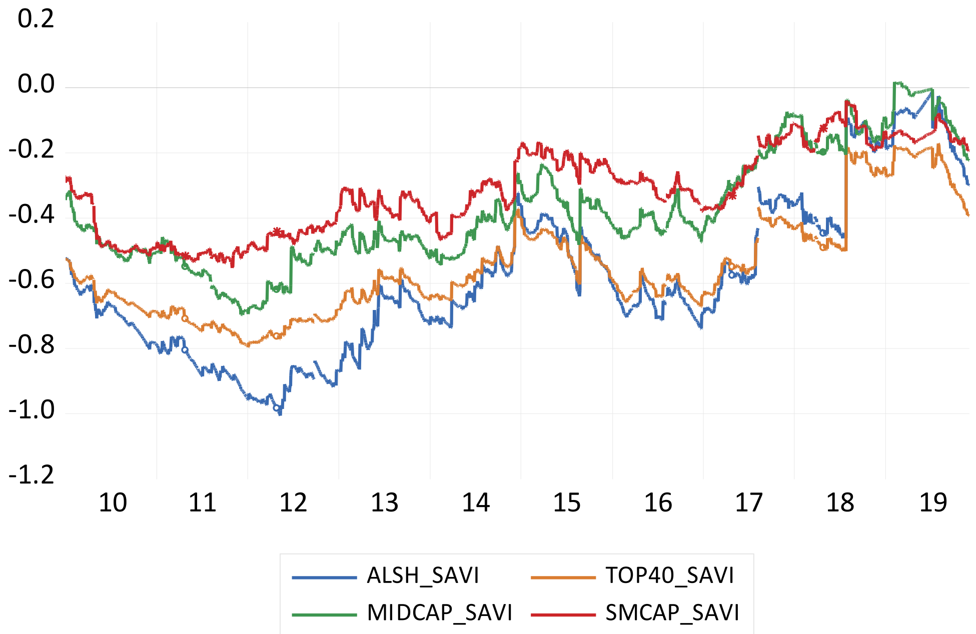

Figure 4. Conditional correlations between the SAVI and JSE market indices

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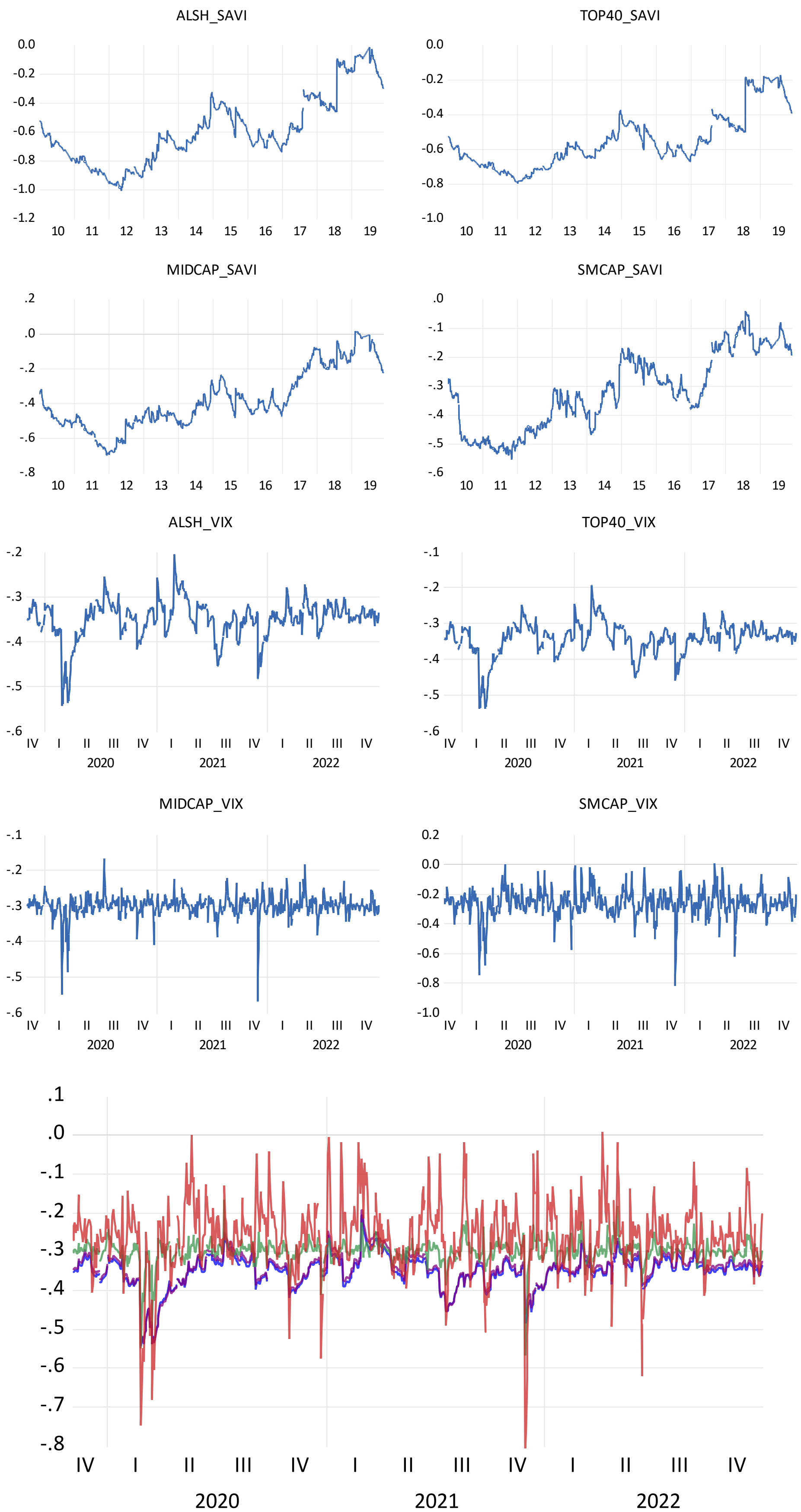

Figure 5. Conditional correlations between the VIX and JSE market indices during COVID-19

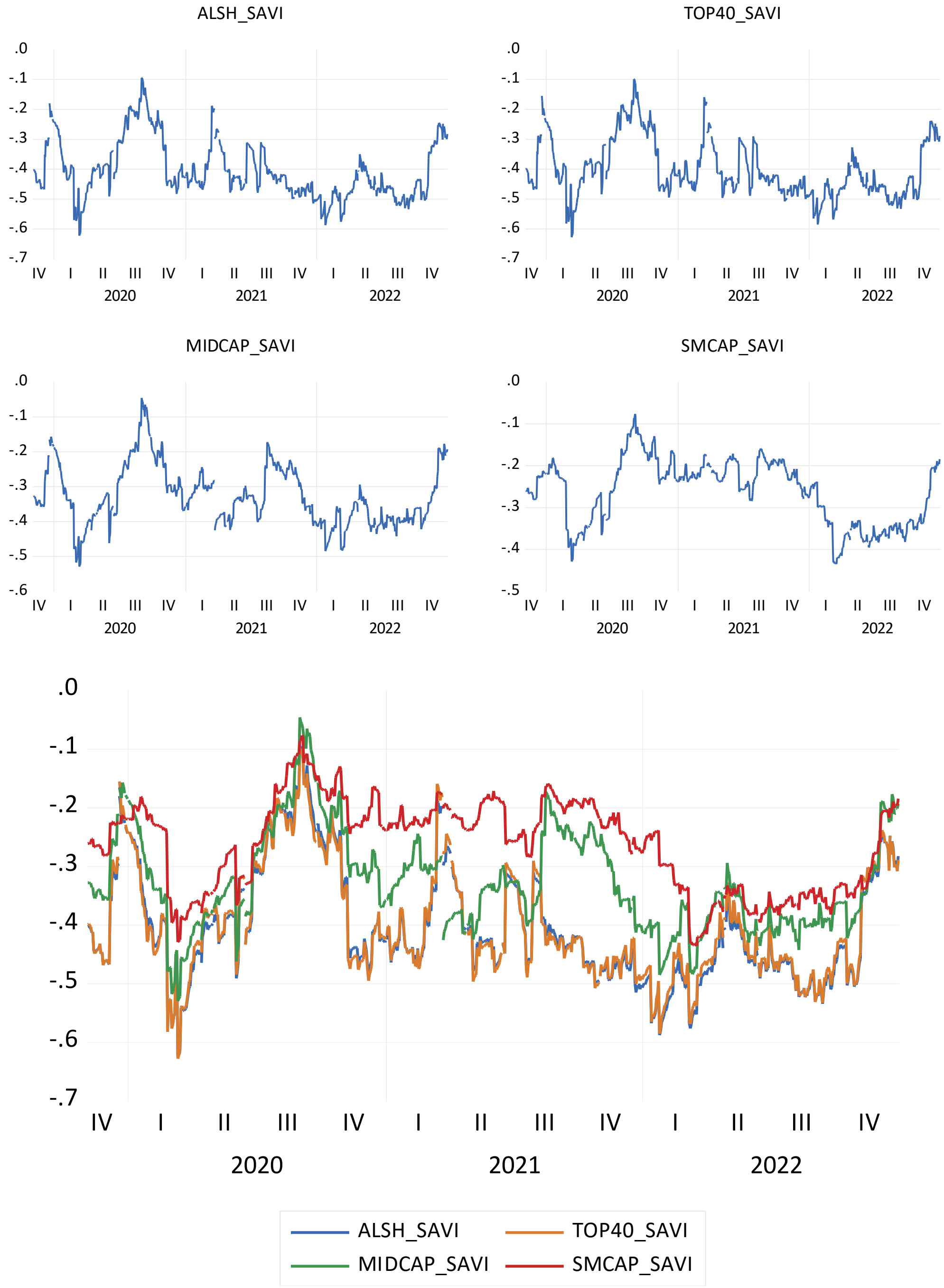

Figure 6. Conditional correlations between the SAVI and JSE market indices during COVID-19

4. DISCUSSION

The study found evidence of unidirectional volatility transfer from the VIX to the JSE broad indices, suggesting that the JSE market has little significance in driving volatility in the US market, while it is highly responsive to global market shocks. The asymmetry in information flow means that volatility in emerging markets may be reflected in global risk measures more rapidly than the reverse, which helps explain the unidirectional spillover effect. Hence, market participants in South Africa should closely monitor the VIX volatility due to its spillover impact on the South African market. Therefore, decoupling strategies should be implemented on the South African equity portfolios to insulate them from contagion. The results are consistent with Atenga and Mougoué (2021),

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who found evidence that African markets are net receivers of volatility spillovers. In addition, the results align with those of Cheuathonghua et al. (2019), who found that the VIX spillovers exhibit a more substantial impact on volatility in emerging markets.

Regarding dynamic conditional correlations, the negative and statistically significant relationship between the returns of the VIX and all JSE broad market indices confirms the phenomenon of asymmetric volatility, where equity indices and volatility indices exhibit a negative correlation, suggesting the potential existence of diversification benefits. This asymmetric volatility effect, marked by rising volatility during market downturns, can be attributed to investor behaviour. In such periods, investors typically become more risk-averse and uncertain about future market conditions, leading to greater demand for hedging and protection, which subsequently drives up volatility. This phenomenon aligns with the concept of loss aversion, where investors are more reactive to losses than to gains, driving them to seek protective measures during market declines. Empirical studies also demonstrate that market volatility rises more sharply during downturns than it falls during upturns, highlighting the asymmetric nature of volatility (Auinger, 2015; Cheuathonghua et al., 2019).

The coefficients of the ARCH (a) and GARCH (β) terms are statistically significant for all indices both before and during the pandemic (Tables 6 and 7), suggesting that internal shocks influence volatility in the JSE Broad indices. Highly significant α and β parameters provide evidence of volatility clustering (May & Farrell, 2018). The results in Table 6 (pre-COVID) show that α + β parameters are statistically less and close to one in all indices, indicating the decay in shock effects over time and the persistence of shocks in volatility for extended periods (Engle & Bollerslev, 1986). During the pandemic, the (α + β) parameters for the All Share Index and the Top40 are equal to one, suggesting persistence in conditional variance across all finite horizons . Holding both VIX and JSE stocks may reduce severe losses during market downturns; as stocks fall, gains from the VIX offset some of the losses, thereby providing a hedge to equity positions.

The parameters α and β (λ_1 and λ_2) associated with dynamic conditional correlations exhibit statistical significance (Tables 6 and 7), suggesting that the conditional correlations are dynamic and time-varying (Wang et al., 2023). The statistically significant (DCC α1) indicates the persistence of standardised residuals from previous periods, implying the presence of volatility spillovers and information transmission between the VIX and JSE broad market indices over shorter periods. Similarly, the significant (DCC β1) indicates the persistence of the conditional correlation process and volatility spillovers over the long run. The sum of $\lambda_1+\lambda_2$ is less than 1 in all models (pre- and during the pandemic), indicating that the conditional correlations are not constant both before and during the pandemic.

The low correlations between the SAVI and the JSE market suggest that the SAVI may offer more diversification and hedging benefits for JSE indices. However, limited avenues for trading the SAVI on the JSE may hinder investors from employing such strategies. The results align with Cheuathonghua et al.'s (2019) findings that the impact of VIX is asymmetric, more pronounced in highly volatile and bearish markets. They also showed that the impact of VIX spillovers is more substantial in developed market returns than in emerging markets.

It is important to note that all indices displayed very low correlations (predominantly negative), which is beneficial for diversification purposes, aligning with the MPT diversification principle. Cheuathonghua et al. (2019) argue that the VIX effect on international markets is expected to diverge in diverse financial market conditions. Consistent with the findings by Kotzé et al. (2009), the results suggest that the SAVI provides distinct information about risk perception and market expectation about the JSE market compared to the broader global market, represented by the VIX. The results suggest that the SAVI could provide superior diversification advantages and hedging potential for investors in the JSE market, particularly during turbulent market conditions such as the COVID-19 pandemic, hence acting as a hedge asset. Moreover, the consistently minimal correlations between the SAVI and JSE indices throughout the observation period suggest promising opportunities for investors to enhance diversification by integrating the SAVI into their investment portfolios. The interpretation of pre- and during-COVID dynamics should be viewed in light of the asymmetric lengths of the two subsamples and market conditions that characterise these periods. This study encompasses the complete volatility cycle associated with the pandemic. Alternative periodisations may delineate shorter event windows or establish a post-COVID era, encompassing the initial shock, subsequent recovery, and eventual normalization. Although these refinements fall outside the scope of the current study, they present valuable avenues for future research and could help in further understanding the evolution of correlation dynamics and volatility transmission over distinct market phases.

CONCLUSION

The paper analyzed volatility spillovers and dynamic conditional correlations between volatility indices and JSE broad market indices using multivariate GARCH, BEKK, and DCC models. Evidence shows volatility spillovers from the VIX to the JSE's major indices. Pairwise correlations indicate significant negative relationships between volatility indices (VIX & SAVI) and JSE broad indices, suggesting that volatility as an asset class can provide diversification and hedging, especially during market turmoil, as correlations between volatility indices and JSE indices further decline. The SAVI exhibits lower correlations with the JSE market than the VIX, implying that integrating the SAVI could offer superior diversification and hedging opportunities. These findings highlight SAVI's unique insights into risk perception and market expectations, distinguishing it from the broader global market represented by the VIX.

The results have important implications for market participants and investors. Negative correlations between JSE indices and volatility indices suggest that incorporating volatility indices into portfolios can enhance diversification, particularly during turbulent periods. Understanding dynamic conditional correlations can help investors manage risk by adjusting portfolio allocations in response to market fluctuations. Compared to the VIX, the SAVI's lower correlations offer unique hedging and diversification opportunities for South African investors, potentially improving risk-adjusted returns and portfolio diversification. Overall, considering correlations between volatility and market indices can improve investment decisions, portfolio diversification, and risk management. A limitation is that the analysis focuses solely on the South African market. Future studies could examine hedging efficiency using volatility across other South African and global indices.

AUTHOR CONTRIBUTIONS

Conceptualization: Edson Vengesai.
Data curation: Edson Vengesai.
Formal analysis: Edson Vengesai.
Investigation: Edson Vengesai.
Methodology: Edson Vengesai.
Project administration: Edson Vengesai.
Software: Edson Vengesai.
Supervision: Edson Vengesai.
Validation: Edson Vengesai.
Visualization: Edson Vengesai.
Writing – original draft: Edson Vengesai.
Writing – review & editing: Edson Vengesai.

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