THE VOLATILITY SPILLOVER EFFECT OF COVID-19 ON INVESTOR SENTIMENT IN JOHANNESBURG STOCK EXCHANGE

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ABSTRACT

This study investigates the volatility spillover effect of the COVID-19 pandemic on investor sentiment for the Johannesburg Stock Exchange (JSE). The study analyses how new cases and deaths affected the sentiment of participants in the stock market during the pandemic. It uses the South African Volatility Index (SAVI) as the main measure of market sentiment and the returns of the JSE main index. Daily data on the pandemic from 03/01/2020 to 19/03/2023 was obtained from the World Health Organisation (WHO) while the rest of the financial data was obtained from Yahoo Finance. The methods used are the Baba, Engle, Kraft and Kroner (BEKK) and dynamic conditional correlation (DCC) multivariate GARCH with the mean equations as a Vector Auto-Regressive (VAR) system. The results show that the pandemic had a spillover effect on investor sentiment. This spillover was asymmetric implying that negative news had more effect than positive news. Furthermore, new cases had more spillover effects on investor sentiment than new deaths recorded. The study recommends that investors should trade cautiously during pandemics considering the increased volatility and that policymakers need to minimise contagion effect from the virus to financial markets by calming down the markets or even halting trading temporarily.

1. INTRODUCTION

The COVID-19 virus changed how investors perceive, look at and understand markets during sustained periods of pandemics. One of the most pertinent topics for consideration is gaining insight how sentiment changes during different phases of the cyclical market. In this study, investor sentiment is defined as the belief about the prospect of future cash flows and investment risks that are not justifiable by any current factual information in possession (Baker & Wurgler, 2007).

Even though it has been universally accepted, this behavioural finance concept continues to interest researchers. What is known though is that investor sentiment affects stock returns and that when investors are more bullish and optimistic, returns tend to be high and vice versa (Kim & Lee, 2022). Much of this field's work has investigated how this sentiment affects stock makets (Ángeles López-Cabarcos et al., 2020). This study contributes to the body of literature by analysing the effect of COVID-19 on investor sentiment. Previous research investigated how this sentiment affects stock market performance during periods of financial turmoil, especially in 2008 but little work has been done to study how pandemics affect it. Only a few papers have tried to gain insight into this topic but unfortunately, not enough research has been conducted to tackle this problem. Fundamentally it would make reasonable sense to assume that the virus was fear-inducing, making market participants more fearful.

In this paper, we empirically test whether, during the pandemic in South Africa, there was a spillover effect from new infections and new deaths on investor sentiment. Theoretically, it would make sense that during this time, the pandemic induced widespread fear that affected the behaviour of investors, making markets volatile. This fact, compounded by other aspects including lockdowns which were also caused by the virus, means that the risk perceived by the market was heightened and, therefore, trading was abnormal for the Johannesburg Stock Exchange (JSE).

In simple terms, this study investigates whether the pandemic caused investors to be more fearful when trading in the JSE at a time when the virus was highly prevalent. Furthermore, it also seeks to look into whether this spillover was asymmetric or not. This is rather important because we need to understand if good news about the virus had the same effect as bad news on investor sentiment. It has been shown that in finance, bad news has more impact than good news on financial performance (Eil & Rao, 2011; Gambetti et al., 2023; Soroka, 2006), therefore, this needs to be tested in the South African context. This research also tries to establish if there is a dynamic conditional correlation (DCC) between COVID-19 and investor sentiment.

In developing the hypothesis for the theory, this research article came up with proximate variables that can be tested. Most studies construct complex indices, however, there is no need for that as there are already instruments in the market which are good enough proxies. One hypothesis this investigation tries to develop is to test if COVID-19 has a spillover effect on investor sentiment for the JSE by looking at the South African Volatility Index (SAVI) and the returns of the JSE main index. Furthermore, it will also analyse if the spillover effect is asymmetric both in the short-run and long-run periods. Finally, the paper will determine the most appropriate model for forecasting in such an environment in South Africa.

2. THE THEORY OF IATROGENIC PANDEMIC AND MARKET PERFORMANCE

The effect of the virus on the stock market has been of recent interest to most researchers since the World Health Organisation declared it a global pandemic. Bonneux & Van Damme (2006) studied why pandemics induce fear in the general public, and they argue that firstly the perception of risk by an individual is solely subjective to the feeling of control. The authors further explain that the fear of pandemics makes human nature feel out of control of their current situation hence leading them to partake in aimless activities like panicking. Worse still, people tend to perceive unlikely catastrophes and disasters as more threatening than regular risks with COVID-19 as an example of a catastrophic event. It has been shown that this iatrogenic panic leads to panic with buying or selling as individuals try to regain control of their current situation (Arafat et al., 2020). The same thing can be said about investors who in panic sell and cash in on the gains so that they feel in control during pandemics. This can lead to volatility in the market as everyone is trying to offload their portfolio stock while no one wants to buy them. Henceforth the perceived sense of losing control, especially during flu-like pandemics can be linked to panic behaviour in financial markets resulting in market volatility.

There is one aspect that has recently been noticed about the psychology of pandemics, especially during the COVID-19 pandemic. It has been observed that most media including social and mainstream contributed to the panic behaviour because of how fast news travels (Taylor, 2022). Some of this news which has the inherent risk of being false also worsens the panicking of individuals during this period.

The literature further shows that when the pandemic started, global financial markets did not react to the news regarding it. However, when human-to-human transmission was confirmed, markets reacted negatively (Khan et al., 2020; Ngwakwe, 2020; Okorie & Lin, 2021). It has also been shown that global markets suffered a negative shock when the pandemic started and that there was a bidirectional spillover effect between Asian, European and American markets (He et al., 2020; Yu, Xiao & Liu, 2022). In China, Mezghani, Boujelbène and Elbayar (2021) found that there is a dynamic connectedness and dual causality between investor sentiment and financial markets in both optimistic and pessimistic situations during COVID-19, indicating that the pandemic affected sentiment. In emerging markets, it has been indicated that the virus brought about asymmetric volatility spillover and that Russia, India, Brazil, and Peru were more volatile during the disease than during the global financial crisis (GFC) of 2008 (Rakshit & Neog, 2022). When focusing on Africa, Takyi & Bentum-Ennin (2021) also concluded that most countries had no chance of escaping the negative effects of the illness on the performance of African stock markets.

By looking at COVID-19 and investor sentiment, Reis & Pinho (2020) analysed how the pandemic affected market returns and investor sentiment. They concluded that since the United States of America (USA) has mass news informational sources, the virus had a negative impact on investor sentiment. This is also shared by Yarovaya et al. (2022). Some of the research has focused on designing a sentiment index to test against COVID-19 and measure its predictive power in stock markets. The studies conclude that there is some connection between the pandemic and the constructed sentiment indices (Huynh et al., 2021; Jiang et al., 2021). Other studies have looked at the asymmetric spillover nature of the pandemic. Hanif, Mensi & Vo (2021) provide evidence of asymmetric tail dependence during the COVID-19 pandemic breakout in the US across different industry sectors. They find time-varying bidirectional asymmetric spillover from the US to the Chinese market and vice versa. The spillover effect of news of the pandemic on travel and leisure stocks has also been recorded. It was found that the effect was mainly due to volatility induced by panic sentiment (Wang et al., 2023).

It is noted that at the beginning of the pandemic in the US and Chinese markets, the markets experienced extreme volatility as a result of pessimistic investor expectations that was caused by the virus (Nian et al., 2021). The two markets, however, had a negative correlation and, as the pandemic progressed, the effect of the virus was different in these markets. In the USA, China, and Japan, further studies suggest that the pandemic caused investors' psychological behaviours to be negative, leading to lower returns (Naseem et al., 2021).

3. MATERIALS AND METHODS

This study uses the multivariate GARCH (M-GARCH) method to test for conditional covolatility among the time series that are investigated (Bauwens et al., 2006). The M-GARCH approach is most appropriate for this analysis, as our goal is to test the time-varying conditional variance between variables (Hemche et al., 2016). Particularly in this paper, the two main M-GARCH models that are employed are the BEKK (BABA, Engle, Kraft and Kroner) by R. F. Engle & Kroner, (1995) and the DCC (Dynamic conditional correlation) method. Specifically, the asymmetric VAR-BEKK-GARCH model is used to test for volatility spillovers and asymmetric behaviour among multiple time series (Arfaoui & Yousaf, 2022; Hashmi et al., 2022).

3.1 Asymmetric VAR-BEKK-GARCH model

As an extension from the VAR-GARCH that was presented by Ling and McAleer (2003) and applied in multiple volatility spillover studies, (Kuhe, 2019; Manasseh et al., 2019; Thiem, 2018) the asymmetric VAR-BEKK-GARCH will be implemented. This is a variance decomposition approach which is ideal to study conditional means and variances/volatilities efficiently as the estimated parameters are not computationally intensive. The model comprises of two components which are the VAR and the regular asymmetric BEKK-GARCH. It is an appropriate model in this study as it can be used to study the combined evolutionary dynamics of spillovers from multiple time series.

The vector autoregressive (VAR), is an extension of the univariate autoregressive (AR) and also achieves its purpose by using the main variables of the problem as endogenous variables and using their previous lags to construct the model. This VAR model can be expressed in the following way:

$$R_t = C + \sum_k A_k R_{t-k} + \varepsilon_t \quad \text{..........(1)}$$

$$\varepsilon_t | I_{t-1} \sim N(0, H_t) \quad \text{..........(2)}$$

where it is given that R_t is the value of the vector of endogenous variables at time t, C is the constant vector, and A is the estimated coefficient matrix. Furthermore, ε_t is the residual vector that is assumed to be distributed with zero mean and constant variance while k is the lag order and I_{t-1} is all the market information available at the time t-1. Usually, the lag order (k) is chosen using the Akaike information criterion (AIC), and the likelihood ratio. For simplicity, the VAR(1) with one lag for each endogenous variable is used in this paper.

The BEKK(p,q)–GARCH model proposed by Engle and Kroner (1995) has some special properties that make it ideal for the problem in this study. This is because the model guarantees that the variance-covariance is always positive-definite without imposing any restrictions on the parameters to be estimated. This makes it easy to estimate as the model reduces parsimony. Also, as mentioned before for the VAR portion of the model, a lag order of one is employed such that $p=q=1$, therefore the formulation of the model is:

$$e_{i,t}=v_{i,t}h_{i,t},\ \ v_{i,t}\sim N(0,1) \quad (3)$$

$$h_{i,t}=c_i+\alpha_i e_{i,t-1}^2+\beta_i h_{i,t-1} \quad (4)$$

$$H_t=C^T C+A^T e_{t-1}e_{t-1}^T A+B^T H_{t-1}B \quad (5)$$

From the equations above, eq.(3) represents the relationship between the residual term $e_{i,t}$ and the conditional variance $h_{i,t}$ with $v_{i,t}$ as the standard normal distribution residuals. α, β are coefficients while $H_{i,t}$ is the conditional variance-covariance matrix. C indicates the lower triangular matrix while A and B are square arrays. It is given that if C^TC is positive, then it is almost positive everywhere. H_t, A, B, and C can be formalised in the following way:

$$H_t=\begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{pmatrix} \quad C=\begin{pmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{pmatrix}$$

$$A=\begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \quad B=\begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix}$$

The main diagonal of H_t symbolises the main variables of interest. In this case, $h_{11,t}$ represents the proxy for investor sentiment, the JSE main index returns and the SAVI index. Furthermore, $h_{22,t}$ denotes the COVID-19 infection rate, while $h_{33,t}$ is the COVID-19 death rate and $h_{ij,(ij)}$ is the conditional covariance of i and j. Matrix A displays the ARCH coefficients of the model, with the main diagonal a_{11}, a_{22} and a_{33} representing the three-time series of interest. It is the same interpretation as H_t except that it shows the ARCH effect. B is the GARCH effect coefficient matrix of the model with the main diagonal being the GARCH effects of the main time series. It is reflective of the persistence of the volatilities in the series themselves, while the off-diagonals show the spillover effects between different series. If the sum of the ARCH effect and the GARCH effect approaches one, then there is evidence of a longer volatility spillover effect.

When considering the asymmetric effect, the asymmetric BEKK (1,1) is applied in this investigation and is shown as:

$$H_t = C_0^T C_0 + A_1^T (e_{t-1} e_{t-1}^T) A_1 + B_1^T H_{t-1} B_1 + D_1^T (z_{t-1} z_{t-1}^T) D_1 \quad (6)$$

Matrix *D* is formulated similarly to *A* and *B*, and z_{t-1} is the *k*-dimensional column vector. Therefore, if $e_{t-1} \leq 0$ then it implies that there is bad news or negative shocks, then $z_{t-1} = e_{t-1}$, else $z_t = 0$. Therefore, matrix *D* measures the asymmetric effects of the time series being analysed.

3.2 Asymmetric DCC-GARCH model

The DCC-GARCH model (Engle 2002) is based on the constant conditional correlation (CCC) model. The CCC model assumes that the correlations are constant over time. However, in reality, correlations vary over time as the conditional correlations are updated by conditional volatility. The DCC-GARCH model solves this problem by relaxing the constant correlation condition and accounts for time-varying correlation which is what this study aims to investigate. The DCC-GARCH model is an effective tool for examining the conditional covolatility across several time series since it may consider time-varying correlation. It is a better strategy than the present time-varying approaches because it offers a more flexible and realistic approach to modelling and forecasting volatility and correlation.

The model decomposes the covariance matrix H_t as follows:

$$e_t | \psi_{t-1} \sim N(0, H_t), \quad H_t = D_t R_t D_t \quad (7)$$

where *it* is the residual vector comprising the residues of each series, the available market information available at time *t-1* is given by ψ_{t-1}, while H_t is the dynamic condition covariance matrix. $D_t = diag\left\{\sqrt{h_{it}}\right\}$ is a *k* x *k* diagonal matrix time varying standard deviations estimated from the univariate GARCH processes and R_t is the dynamic correlation coefficient matrix.

The standardised residuals, given as $\alpha_{it} = e_{it} / \sqrt{h_{it}}$, are given as an expression for measuring the dynamic correlation matrix, R_t:

$$R_t = diag(Q_t)^{-1}(Q)diag(Q_t)^{-1} \quad (8)$$

where $Q_t = (q_{ij,t})$ is a positive definite matrix with the conditional variances covariance of e_{it} and $diag(Q_t)^{-1}$ is the inverted diagonal matrix given as:

$$diagQ_t = \begin{pmatrix} \sqrt{q_{11,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{q_{kk,t}} \end{pmatrix} \quad (9)$$

In this regard, the DCC model can be estimated by the unconditional covariance of the standardised distribution $\bar{Q}$, of the univariate GARCH model:

$$Q_t = (1-\theta_1-\theta_2)\bar{Q} + \theta_1 \tilde{e}_t \tilde{e}_t^{'} + \theta_2 Q_{t-1} \quad (10)$$

Then the dynamic conditional correlation is given by:

$$p_{ij} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \quad (11)$$

It should be noted that θ_1 and θ_2 are non-negative scaler parameters that satisfy $\theta_1 + \theta_2 < 1$.

3.3 COVID-19 Data

Daily smoothed data on new cases and new deaths related to the virus are obtained from the World Health Organisation (WHO) spanning from 03/01/2020 to 19/03/2023. WHO uses a 7-day rolling average method to remove noise which is preferred in this analysis (McConnel, 2020). The author uses the rolling average of a time series to estimate parameters throughout a rolling window with a defined size that runs through the sample. This is a frequent method to evaluate a model's parameter consistency. The estimations over the rolling windows should not change significantly if the parameters are consistent over the whole sample. The rolling estimates ought to account for any instability caused by parameter changes that occur during the sample (Zivot & Wang, 2003). The proxy variables will then be new cases for new infection rates and new deaths for new death rates as a result of the virus using the rolling method.

The following chart shows the trend for the two series.

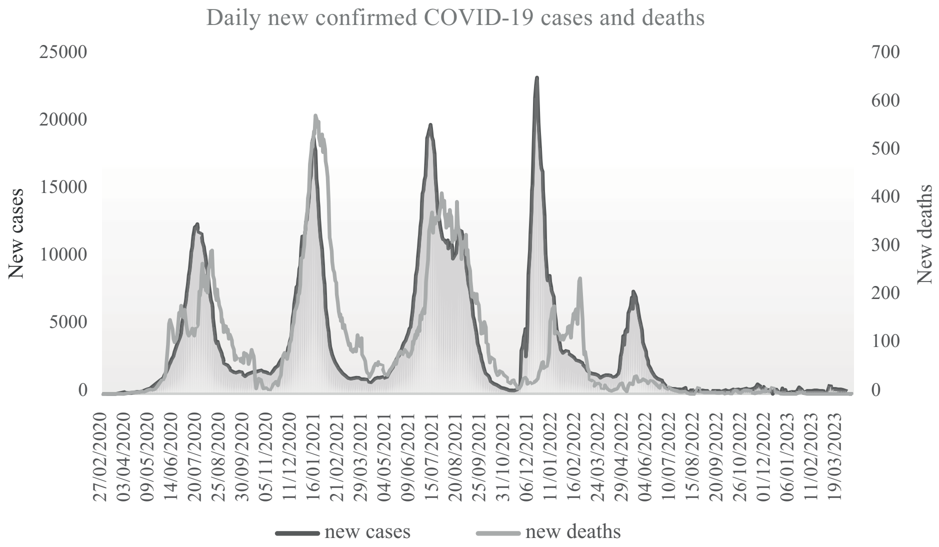

Figure 1. Daily new confirmed COVID-19 cases and deaths

Notes: Data was obtained from the World Health Organisation (WHO) for new COVID-19 infection rates and new death rates. The data was smoothed using the seven-day rolling method.
Source: Authors' calculations

Figure 1 above shows that South Africa went through approximately 5 waves of the pandemic. During the period under investigation, the daily infection rate peaked at around 23,000 cases infected in the fourth wave. Death rates also peaked at around 600 in the second wave.

3.4 Investor sentiment data

This study will use data ranging from 03/01/2020 to 19/03/2023 in the analysis.

The first proxy used to measure investor sentiment is the South African Volatility Index (SAVI). The SAVI was launched in 2007 as a gauge to measure market expectation of three-month market volatility. It is not a tradeable index and has been thought of as a 'fear' index (Kotze et al. 2009). It was updated by the JSE in 2009 to be an index more reflective of expected market volatility. When it was updated a new method of estimating the projected 3-month volatility was incorporated. Currently, the SAVI is calculated using the at-the-money volatilities and is based on the FTSE/JSE Top40 index level. Since the new SAVI includes a market crash protection volatility premium, it can be considered a more effective "fear" indicator, since the volatility skew represents the market's expectation of a crash. The weighted average prices of calls and puts with a wide variety of strike prices that expire in three months are used to determine the index.

Therefore, it is intuitive to say that the index can be used to measure investor sentiment (Harrilall & Seetharam, 2015). It should be noted that since the SAVI is a volatility index, there is no need for any transformation for this analysis and in this study, this name is referred to throughout the paper.

The second proxy used in this study is the daily return of the JSE main index (JSER) and it is chosen because similar studies have also utilised it (Huang et al. 2015; Yadav and Chakraborty 2022; Zi-Long, Su-Sheng & Ming-Zhu 2021). The data is obtained from Yahoo Finance and transformed accordingly. The adjusted closing price for the JSE main index is transformed into a daily log return calculated as, *log*(current price/previous price) as in previous studies (Jaffe et al., 1989; Zi-Long, Su-Sheng & Ming-Zhu, 2021). The log transformation is frequently used in time series analysis to stabilise the series' variance. Lütkepohl & Xu, (2012) look at the circumstances in which logging data is useful for predicting. They compare log-based forecasts with forecasts based on the original series in their study. It is discovered that the preference for the former or the latter depends on the data-generating procedure. If the log transformation really stabilises the volatility of the underlying series, then taking logs for a variety of economic variables results in significant forecasting benefits. For this analysis, the variance must be stable, hence the need for the log transformation.

The raw data chart for the period under analysis is shown below. The adjusted closing price for the JSE main index and SAVI trend can be seen in Figure 2 below.

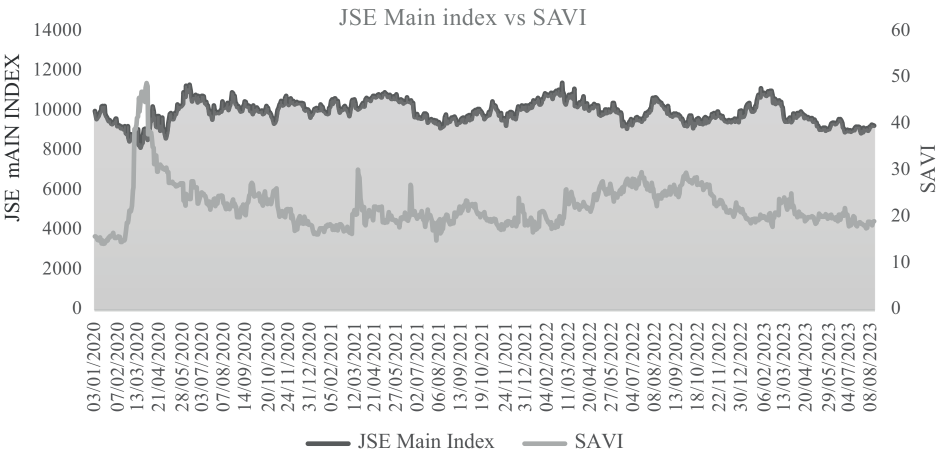

Figure 2. Adjusted closing price of the JSE main index and the SAVI

Notes: Data obtained from Yahoo Finance. The graph shows the SAVI against the adjusted closing price of the JSE for the period under review.

Source: Authors' calculations

Figure 2 above shows the results for the SAVI and the JSE Main index. During the beginning of the pandemic, the SAVI spiked to almost 50 indicating that as new cases started to increase, volatility also rose considerably showing that the market was becoming more fearful as a result of the uncertainty caused by the virus. By mid-2023, it had slumped to nearly 20 as infection and death rates dropped and market confidence improved. The chart also shows the adjusted closing price for the JSE main index shown in Rands. When the pandemic started, the market experienced slightly lower returns which became more erratic and volatile as the pandemic spread.

3.5 Summary statistics

The summary statistics of the data are shown in Table 1 below.

Table 1. Summary statistics

	SAVI	JSER	New cases	New deaths
Mean	15.278	0.000	3080.585	77.606
Median	19.455	0.000	1187.429	21.857
Maximum	49.040	0.026	23437.140	577.571
Minimum	14.300	-0.040	0.000	0.000
Standard Deviation	11.116	0.006	4589.761	116.293
Skewness	-0.284	-0.277	1.972	2.015
Kurtosis	2.097	8.554	6.366	6.870
Jarque-Bera	62.772***	1715.709***	1481.849***	1719.374***
Sum	20197.810	-0.033	4072533.000	102595.000
Observations	1322	1322	1322	1322

Notes: *** Implies that the variable is significant at the 1 percent significance level.
Source: Authors' calculations

There were 1322 observations from the data set in total. Table 1 shows that the financial data, being the SAVI, had an average of 15.278 index points which is low compared to a maximum of 49.04 caused by elevated uncertainty due to the virus. JSER seems to be constant with average returns remaining at 0 for the period under review. The SAVI and the JSER have negative skews implying that there are tails on the left side. New cases and new deaths are positively skewed implying that the data is distributed mostly on the right side of the mean. When considering kurtosis one can infer that the SAVI is platykurtic while the rest of the variables are leptokurtic.

4. RESULTS

The first results presented in Table 4 are the VAR system results for the two systems under analysis, the model is a VAR(1) type with only one lag.

Table 2. VAR Systems Results

System 1	SAVI	New cases	New deaths
1. SAVI{1}	0.722***	0.674	-0.013
	(0.019)	(0.505)	(0.015)
2. New cases {1}	0.001**	1.015***	0.001***
	(0.000)	(0.003)	(0.001)
3. New deaths {1}	0.008*	-0.844***	0.975***
	(0.004)	(0.106)	(0.003)
F-Test		F-Statistics	
SAVI	1435.790***	1.777	0.833
New cases	5.780**	143134.663***	87.102***
New deaths	3.751*	63.866***	100885.260***
System 2	JSER	New cases	New deaths
1. JSER{1}	-0.073***	-416.362	77.714*
	(0.028)	(1429.942)	(41.513)
2. New cases{1}	0.000	1.015***	0.001***
	(0.000)	(0.003)	(0.000)
3. New deaths{1}	0.000	-0.825***	0.975***
	(0.000)	(0.105)	(0.003)
F-Test		F-Statistics	
JSER	6.978***	0.085	3.505
New cases	0.155	146971.825***	87.134
New deaths	0.087	62.044	102852.663***

Note: *** are variables that are significant at the 1% level and ** are significant at the 5% level, while * is significant at the 10% level. The numbers in brackets are standard errors for the coefficients.
Source: Authors' calculations

From Table 2 above, the one-day lagged SAVI index is positively significant at the 1% level on itself. This means that if the SAVI value of yesterday increased by 1%, then the same index of today will grow by 0.72% exhibiting volatility clustering. COVID-19 New cases with a one-day lag are positively significant at the 5% level in determining volatility, measured using the SAVI. New deaths on the other hand were positively significant at the 10% level with the volatility index. The one-day lagged JSER is negatively significant at the 1% level in explaining the current returns of the JSE main index.

After looking at the VAR model and getting a clear picture, one can analyse the variance decomposition results which are the BEKK and DCC GARCH-type models. The M-GARCH results are shown next.

Table 3. SAVI M-GARCH model

	BEKK			DCC		
Variable	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
	Mean Model(SAVI)					
Constant	10.906***	0.573	19.046	12.758***	0.263	48.561
SAVI{1}	0.324***	0.026	12.549	0.194***	0.014	14.209
New cases{1}	0.000	0.000	-0.325	0.000**	0.000	2.078
New deaths{1}	-0.005	0.003	-1.482	-0.006***	0.002	-2.730
	Mean Model(New cases)					
Constant	-0.001***	0.000	-6.109	-21.876***	8.118	-2.695
SAVI{1}	0.000***	0.000	9.298	0.434	0.390	1.114
New cases{1}	0.911***	0.001	978.242	1.041***	0.001	1027.670
New deaths{1}	0.856***	0.015	56.518	-0.962***	0.048	-20.220
	Mean Model(New deaths)					
Constant	0.000	0.000	-0.000	0.001***	0.000	3.380
SAVI{1}	0.000	0.000	0.000	0.000	0.000	0.107
New cases{1}	0.000	0.000	0.258	0.002***	0.001	30.006
New deaths{1}	0.985***	0.004	256.291	0.977***	0.001	981.850
	Variance					
C(1,1)	8.735***	0.611	14.300	52.819***	2.423	21.795
C(2,2)	0.000	0.001	0.000	5162.744***	323.536	15.957
C(3,3)	0.000	0.000	0.000	0.000	0.000	0.384
A(1)	0.054*	0.031	1.755	0.417***	0.017	24.559
A(2)	2.488***	0.091	27.325	0.234***	0.003	81.681
A(3)	0.615***	0.020	31.154	0.587***	0.007	78.510
B(1)	-0.471***	0.111	-4.236	0.255***	0.024	10.841
B(2)	0.236***	0.040	5.910	0.462***	0.004	105.333
B(3)	0.921***	0.001	1615.123	0.575***	0.008	72.360
D(1)	-0.338***	0.064	-5.316	-0.193***	0.026	-7.521
D(2)	1.265***	0.449	2.816	0.340***	0.007	51.940
D(3)	-0.165	0.103	-1.604	0.694***	0.015	47.907
M(2,1),DCC(A)	0.001	0.001	0.930	0.010***	0.000	28.641
M(3,1),DCC(B)	0.000	0.000	0.000	0.524***	0.008	66.951
M(3,2)	0.000	0.000	0.000			
Observation		1321			1321	
Log-likelihood		-14437.598			-16022.219	

Note: *** are variables that are significant at the 1% level and ** are significant at the 5% level, while * is significant at the 10% level.
Source: Authors' calculations

The spillover effect of COVID-19 on SAVI is shown in Table 5 above with the mean equations of the VAR(1) system in the first three rows, while the conditional covariance results are shown in the fourth row. In the table, both the results for the BEKK and DCC models are presented.

In the conditional covariance section of the results in row four, the news effect in A(1) which is the SAVI is weakly and positively significant at the 10% level, indicating that the news effect has a spillover effect on the current conditional covariance. New infection cases A(2) and new deaths A(3) also had a news spillover effect on the conditional covariance. This means that COVID-19 had a short-term volatility spillover effect on investor sentiment. In the case of the BEKK model concerning volatility persistence, one can observe that the SAVI represented by B(1) is negatively significant at 1% in explaining the conditional covariance, implying that in the long run, the SAVI reduced volatility in the system. In the case of the DCC model, the persistence was positively significant at the 1% level indicating a conflict within the results. However, the authors of this study chose the BEKK results as the log-likelihood is higher than that of the DCC. The COVID-19 proxy of new cases, B(2) and new deaths, B(3) are positively significant. Consequently, since these two factors positively contribute to the growth in conditional covariance, they are ultimately accountable for the persistence of volatility. The results are consistent for both the BEKK and DCC models.

The SAVI index represented by D(1) shows that the coefficient is negatively significant at the 1% level in explaining conditional covariance. This means that positive news about the index reduces volatility and market fear. New-cases of infections as shown by D(2), have a positive and significant asymmetric effect at 1% in increasing conditional covariance. It makes sense that negative news, especially about rising infection rates, should have a larger negative effect on volatility and investor sentiment than good news has.

Lastly, based on the DCC(A) and DCC(B) results, it can be concluded that both the long- and short-term dynamic correlations are positively significant at the 1% level. This suggests that volatility clustering can occur when there is a positive correlation between the three variables, which in turn influences the dynamic correlation over the course of the two periods.

The next results to be presented represent how COVID-19 spilled over to returns, these are shown in Table 6 below.

Table 4. JSER M-GARCH model

	BEKK			DCC		
Variable	Coeff	Std Error	T-Stat	Coeff	Std Error	T-Stat
			Mean Model(JSER)			
Constant	-0.000**	0.000	-2.108	-0.001	0.000	-0.308
JSER{1}	-0.118***	0.028	-4.251	-0.0862***	0.026	-3.261
New cases{1}	0.000*	0.000	1.746	0.000	0.000	1.032
New deaths{1}	0.000	0.000	-1.571	0.000	0.000	-1.066
			Mean Model(New cases)			
Constant	-12.329***	3.537	-3.485	-30.286***	6.334	-4.781
JSER{1}	-1865.253***	542.641	-3.437	1956.339*	1173.850	1.667
New cases{1}	1.014***	0.002	695.572	1.036***	0.001	796.869
New deaths{1}	-0.984***	0.055	-17.780	-0.928***	0.051	-18.269
			Mean Model(New deaths)			
Constant	-0.005	0.014	-0.368	0.119***	0.021	5.821
JSER{1}	3.378	3.182	1.062	-5.792	4.454	-1.304
New cases{1}	0.001***	0.000	40.081	0.001***	0.000	25.581
New deaths{1}	0.969***	0.001	820.094	0.965***	0.002	531.716
			Variance			
C(1,1)	0.004***	0.000	81.308	0.001***	0.000	30.944
C(2,2)	62.734***	2.277	27.548	2785.425***	448.675	6.208
C(3,3)	-0.026***	0.009	-3.017	-0.007	0.018	-0.390
A(1)	0.193***	0.020	9.861	0.231***	0.008	28.27
A(2)	0.687***	0.007	95.514	0.259***	0.006	41.555
A(3)	0.468***	0.037	12.662	0.540***	0.009	61.598
B(1)	0.699***	0.008	85.919	0.484***	0.011	43.168
B(2)	0.716***	0.004	170.543	0.563***	0.019	29.714
B(3)	0.901***	0.006	152.350	0.743***	0.011	66.616
D(1)	-0.037	0.069	-0.536	-0.196***	0.020	-9.782
D(2)	0.226***	0.044	5.094	0.353***	0.007	51.062
D(3)	-0.612***	0.059	-10.447	0.401***	0.033	12.297
M(2,1),DCC(A)	-1.451	2.902	-0.500	0.046***	0.004	12.347
M(3,1),DCC(B)	0.009	0.009	1.003	0.543***	0.010	57.255
M(3,2)	-0.044***	0.011	-4.077			
Observations		1321			1321	
Log-likelihood		-7114.266			-7294.734	

Note: *** are variables that are significant at the 1% level and ** are significant at the 5% level, while * is significant at the 10% level.

Source: Authors' calculations

Table 4 above shows that A(1), A(2) and A(3), which represent the short-run volatility spillover impact from the news effect of returns, new infections, and new deaths, respectively, are all positively significant at the 1% level. The results confirm that the three variables all influenced the system's volatility. B(1), B(2) and B(3) represent the long-run volatility spillover effect of the three variables in the same order. All three coefficients linked to the variables are positively significant at the 1% level, implying a persistent effect of the volatility spillover in the long run.

For the BEKK model D(2) is positively significant at the 1% level, implying that new infections had an asymmetric spillover effect on the system. D(3) is negatively significant at the 1% level, meaning that new deaths had an asymmetric spillover effect on volatility. The negative effect, though, implies that good news about the reduction in new deaths had a more positive effect in reducing conditional covariance. DCC(A) and DCC(B) are all positively significant. Therefore, for both the short-run and the long-run, an increase in correlation between the three variables will lead to further correlation the following day causing volatility clustering.

It is evident from the models that COVID-19 had a net positive spillover effect on investor sentiment. The results are empirically definitive in explaining how the virus spread to investor emotions via sentiment. In most cases, the COVID-19 representations had a positive asymmetric effect, meaning that bad or negative news has a higher magnitudinal spillover impact than positive news on the conditional covariance and overall volatility regarding investor sentiment. The results further show that the BEKK model is best suited for forecasting the JSE during pandemics as the log-likelihood for the model is always higher than for the DCC.

5. CONCLUSIONS

Understanding how investors react to certain conditions in the market is very important for policymakers and practitioners. One such market condition has been increased market volatility due to COVID-19 globally. The pandemic brought with it great uncertainty about future prospects with financial markets not being spared. Although much work has been done to understand the impact of the virus on financial markets, little has been done to understand how it affected investor behaviour during that period. This study looked at how the pandemic affected investor behaviour, especially looking at investor sentiment in terms of fear and overconfidence. The 7-day rolling smoothed COVID-19 data for new cases and new deaths was used to investigate whether there was a spillover effect between the virus and market fear/confidence. Using two multivariate GARCH approaches, the BEKK and DCC methods, this study empirically shows that there was a positive spillover effect between COVID-19 and investor sentiment in the JSE. This spillover was asymmetric, and negative news was more impactful than positive news most of the time. Also, investors seem to pay more attention to news concerning new cases rather than new deaths because they react more to new cases as evidenced by 1 percent significance compared to 5 percent significance from new deaths. Furthermore, there is evidence to suggest that COVID-19 is persistent in both short-run and long-run and that there is a dynamic conditional correlation in those time frames.

To investors and practitioners, these results have certain implications, being that during periods of pandemics, they should trade more cautiously and not sell in panic or buy in panic. This is because if they want to gain maximum utility from their portfolio investment they should hold their positions until market conditions return to equilibrium. Also, smart investors can take advantage of speculative trading opportunities created by conditions such as COVID-19 by taking advantage of strategies such as short selling and option trading. Still, when looking at options trading, some investors can hedge some of their positions effectively by factoring in the short- and long-term dynamic correlations of the virus and returns. Since the short-term and long-term dynamic correlations vary over time in the JSE, practitioners can time these changes in correlations to hedge against potential excessive correlated assets which might increase portfolio risk and reduce returns.

The study recommends that during pandemics investors should trade cautiously to avoid considering the heightened volatility and that policymakers need to minimise contagion from the virus to financial markets by calming down the markets or even halting trading temporarily.

For policymakers, the results are important to understand how the current and future dynamics will affect the behaviour of investors participating in the market. The results of this research are vital in that they can be used in the South African context to understand how pandemics affect investor wealth. This is essential in future when similar situations erupt to make markets more stable by learning from past events and how they propagated volatility. Finally, policymakers and investors can use the BEKK framework to forecast investor sentiment and returns for the JSE. Future work that can be done is to delve deep and understand how the spillover differed from each major sector in the JSE.

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Conflict of interests

The authors declare there is no conflict of interest.

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ЕФЕКАТ ПРЕЛИВАЊА ВОЛАТИЛНОСТИ ПАНДЕМИЈЕ ИЗАЗВАНЕ ВИРУСОМ КОРОНА НА РАСПОЛОЖЕЊЕ ИНВЕСТИТОРА НА ЈОХАНЕСБУРШКОЈ БЕРЗИ

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САЖЕТАК

Ова студија истражује ефекат преливања волатилности пандемије изазване вирусом корона на расположење инвеститора на Јоханесбуршкој берзи. Студија анализира како су нови случајеви и смрти утицали на расположење учесника на берзи током пандемије. Студија користи јужноафрички индекс волатилности као главну мјеру тржишног расположења и приноса главног индекса јоханесбуршке берзе. Дневни подаци о пандемији од 03. 01. 2020. до 19. 03. 2023. добијени су од Свјетске здравствене организације, док су остали финансијски подаци добијени са странице Yahoo Finance. Коришћене методе су баба, енгле, крафт и кронер и динамичка условна корелација, мултиваријантни GARCH са средњим једначинама као троваријантним векторским ауто-регресивним системом. Резултати показују да је пандемија имала ефекат преливања на расположење инвеститора. Ово преливање је било асиметрично, што имплицира да су негативне вијести имале више ефекта него позитивне вијести. Штавише, нови случајеви имали су више ефеката преливања на расположење инвеститора него нови смртни случајеви. Студија препоручује да инвеститори треба да тргују опрезно током пандемије с обзиром на повећану волатилност и да креатори политике морају да минимизирају преношење ефеката вируса на финансијска тржишта тако што ће смирити тржишта, или чак привремено зауставити трговање.

Кључне ријечи: *КОВИД 19, преливање волатилности, BEKK garch, DCC garch, расположење инвеститора*.