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COVID-19 AND STOCK MARKET VOLATILITY IN SOUTH AFRICA: A CROSS-SECTOR ANALYSIS

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ABSTRACT

The COVID-19 pandemic has created enormous economic and market uncertainty in the global economy. However, businesses and industries weren't affected homogeneously; whilst others suffered, some blossomed. Equity markets were not spared from the detrimental effects of the pandemic. This study investigates the impact of COVID-19 on stock returns' conditional volatility in different South African stock market sectors using standard symmetrical and asymmetrical GARCH models. The MDCC-GARCH model was employed to understand the dynamics of conditional correlations between the leading indices. The results suggest that COVID-19 has increased return volatility for the majority of the sectors; however, the sectors weren't affected in the same way. The DCC-GARCH model shows significant, high, positive correlations between the major and Small Cap indices, suggesting insignificant diversification benefits during the pandemic. The alternative exchange (ALTX) was found to have declining correlations with the main sectors, indicating an increase in diversification benefits offered by the ALTX following the pandemic shock.

Contribution/Originality: The study examines the impact of COVID-19 at the sector/industry level. This allows investors to appreciate how each sector was differently affected by the pandemic for future asset selection and diversification decisions. In addition, this study adds to the literature by examining the reaction of South Africa's developing economy.

1. INTRODUCTION

There has been remarkable progress in the medical field in researching infectious diseases over the years. However, contagious diseases and epidemics still represent substantial threats to modern societies and financial markets. Specific dimensions of the economic impact of pandemics include direct costs (hospitalizations and medical expenses) and indirect costs (loss of earnings and productivity). Threat to human lives and suffering is the first and most crucial part of any outbreak. Nonetheless, pandemics have significant economic implications through several channels, including, but not limited to, health, finance and insurance, tourism, and transportation sectors through disruption of trade and international supply chains (Delivorias & Scholz, 2020). Stock markets play a significant role in economic development by allocating capital efficiently. The pandemics disrupt the functioning of the capital markets, derailing financial efficiency and economic productivity. Del Giudice and Paltrinieri (2017) reiterated that investors overreact to major adverse events, such as pandemics, thereby withdrawing their savings. This induces shocks and panic in financial markets leading to increased volatility as investors switch positions. On a macro level, Haacker (2004) noted that epidemics diminish government capacities due to increased mortality, slowing domestic revenues during an increase in demand for government services and imposing a significant financial burden on the government and private sector (Haacker, 2004). In this case, it was witnessed as governments spent millions to procure vaccines for the virus, thereby reducing allocation for developmental objectives.

Macroeconomic studies reveal that GDP growth slows in countries with severe epidemics following shrinkage in domestic tax base and domestic government revenue, obscuring the efforts of nations to cope with the amplified demand for services caused by the epidemic. Bloom, Cadarette, and Sevilla (2018) documented that epidemics, fear and panic associated with outbreaks induce numerous economic risks, including overwhelming the health system, limiting an economy's capacity and disrupting and driving down production. Fear of the outbreak's spread reduces trade, travel and tourism to intensely hit regions, and long-running epidemics deter foreign direct investment which compromises growth (Bloom et al., 2018). During the 2013–2014 Ebola outbreak, Liberia suffered a huge 8% decline in GDP (Bloom et al., 2018). Fan, Jamison, and Summers (2018) estimated that the total value of expected losses sustained by the severe global influenza pandemic might reach about 1% of global income ($500 billion) per year. It is argued that another pandemic of the same magnitude as the 1918 influenza pandemic might lead to a 5% reduction in global GDP. The actual impact of the current coronavirus is yet to fully manifest.

However, epidemics do not affect nations and economic sectors equally; some sectors suffer excessively, while others bloom. Pharmaceuticals are arguably among the biggest beneficiaries through the supply of vaccines and antibiotics. Life insurance and health sectors mostly likely bear high costs in the short term as a surge in hospitalization increases operational and administrative expenses (Bloom et al., 2018). Various economic risks resulting from exchange rate movements, market interest rates and trade imbalances are inevitable. The growing body of literature on the impact of COVID-19 mainly focuses on the effects of the pandemic on the aggregate stock market and the economy. However, economic sectors within a market respond differently to shocks due to different industry structures (Albuquerque, Koskinen, Yang, & Zhang, 2020; El Rhadbane & Moudden, 2022). To the best of the researcher's knowledge, none of the previous studies examined how different sectors within a market, specifically in South Africa, responded to the pandemic. This study fills this gap by examining the response of different South African stock market sectors to the COVID-19 shock instead of focusing only on the overall market and economy reactions. It is paramount for investors and policymakers to understand the magnitude and differences in the pandemic's impact on various economic sectors to make informed investment and policy implementation decisions. Stock market volatility acts as a market risk barometer, and it is crucial in gauging uncertainty surrounding investments in financial markets. Volatility knowledge, therefore, helps policymakers and investors to approach the markets with an open mind. Thus, this study sought to shed more light on the impact of the COVID-19 pandemic on the stock price risk in different sectors of the Johannesburg Stock Exchange.

1.1. Overview of COVID-19 and Markets Reaction

The coronavirus pandemic created enormous economic uncertainty across the world. Many nations worldwide were forced to impose drastic measures, including lockdowns, in the process of containing the virus to save lives. Such actions caused detrimental effects on the global economy – business closures, halted production, loss of income, supply chain disruption, decline in global equity markets, and escalated unemployment levels. In reviving the global economy, capital markets' stability will play a central stage as a significant contributor to economic progression. Capital markets are the engine of any economy; they play a fundamental role in assisting firms in raising capital and diversifying their risks and investments, promoting economic growth (Bekiros, Gupta, & Kyei, 2016).

Most of the indices that track firm performance worldwide lost value as hard lockdowns were introduced. Markets recorded significant slumps, which triggered panic selling among investors (Zaremba, Kizys, Aharon, & Demir, 2020). For the first time in history, US oil futures crashed into negative territory amid the pandemic induced supply glut (Albulescu, 2020). As investors globally flocked to safe havens, emerging Forex and equities markets felt the worst sting as trade shocks took hold. The South African Rand nosedived rapidly against the dollar to new historical levels to find some support around R19.35/$, falling from R13.93/$. The COVID-19 wave triggered liquidity constraints; most firms struggled as the capacity to raise funding over the short term became a severe hurdle (Haroon & Rizvi, 2020). The International Monetary Fund (IMF) forecasted a 3% contraction in the global economy's GDP, the worst since the great depression. In South Africa, according to a report released by Statics South Africa, for the first time in 11 years, since the economy contracted by 1.5% in 2009, South Africa's economy shrank by 7% in 2020 as COVID-19 lockdowns negatively affected the economy by disrupting output and trade due to inactivity in industry and commerce. Financial markets have seen the highest rates of uncertainty witnessed in the past 100 years (PwC, 2020). Trading volumes initially spiked due to market panic and sell-offs occurred; trading volumes have remained relatively volatile ever since. The Chicago Board Options Exchange (CBOE) Volatility Index (VIX), a gauge of the volatility in the stock market, recorded the highest closing level on record with volatility rising from 15% in February 2020 to 80% in March 2020. The South African Volatility Index (SAVI) increased from 15% to a peak of 50% (PwC, 2020). To date, neither index has reverted to normal pre-pandemic levels.

2. THE IMPACT OF THE PANDEMIC ON STOCK MARKETS

In financial literature, information on capital markets has a substantial bearing on firms' behavior, financial structure, and the economy (Bilson, Brailsford, & Hooper, 2002). Market volatility in particular poses various implications for financial markets and the economy at large. It reveals risk persistence (Makoko & Muzindutsi, 2018), which brings about volatility clustering, influencing future volatility anticipation in investors. In turn, future volatility affects the behavior of an investor. Therefore, volatility can serve as a risk measurement (Suleman, Gupta, & Balcilar, 2017), and an increase in volatility can be viewed as a negative market indicator. Also, volatility can lead to a spillover effect, or ripple effect, which may increase return volatility in financial markets, discouraging investment and bringing about uncertainty (Miah & Rahman, 2016). Therefore, understanding the drivers of volatility is paramount in investment analysis and for policymakers. In the literature, forecasting the financial markets' movement is enormously challenging because of the stochastic and non-linearity nature of financial markets (Bekiros et al., 2016; Suleman et al., 2017). Despite the importance of forecasting returns and volatility, a wide assortment of predictive models has been used, both non-parametric and non-linear, with various predictors including international and domestic macroeconomic, financial institutional, and behavioral uncertainty. However, there is mixed empirical evidence on the predictability of returns and volatility.

There is limited but growing research in the literature examining the impact of COVID-19 on economies and financial markets. Scholarly empirical evidence on the effects of the current pandemic is still minimal. Goodell (2020) documents that, on a global scale, the coronavirus is triggering an extraordinary level of economic destruction and stipulates that the ultimate impact of the pandemic on the financial sector aspects is yet to fully manifest and encompasses a fertile area for future research. From a global perspective, Zaremba et al. (2020) documented a substantial surge in market volatility in nations where administrations took arduous actions, such as canceling public events, to curb the spread of the virus. Fernandes (2020) projected an asymmetric impact of the coronavirus through sectors subject to the economic structure; nations with deeply service-oriented economies are likely to experience the most significant impact. Gormsen and Koijen (2020) attempted to quantify the expectations of investors concerning policy changes and the evolution of economic growth in response to COVID-19 using US data from the equity market and dividend futures. The study predicted a 2.6% contraction in GDP growth and a 28% decrease in annual dividend growth. Ozili and Arun (2020) documented that more time under lockdown, international travel restrictions, and monetary policy changes have severely impacted economic activity. Yousef (2020) used the GARCH and GJR-GARCH models to examine COVID-19's impact on the volatility of the G7 stock market indices. They found that all indices reached minimum returns during March 2020. Their results revealed that daily new cases increased stock market volatility in the G7 stock markets. Onali (2020) found a significant increase in volatility in the US market following reports of COVID-19 infection cases and deaths in several states. Haroon and Rizvi (2020) identified a significant change in volatility in transportation, energy, travel, leisure, and automobile industries, while other sectors did not exhibit swings in volatility due to media coverage and news sentiment. He, Liu, Wang, and Yu (2020) used non-parametric Mann–Whitney tests and t-tests to investigate the effects and spillovers of COVID-19 and found that coronavirus hurt the stock markets in Asia, Europe, and the US. Ashraf (2020) examined stock markets' reactions to the pandemic and concluded that more confirmed cases corresponded to reductions in growth. Albulescu (2020) examined the impact of COVID-19 on crude oil prices and found that an increase in reported new infections was marginally correlated to decreases in crude oil prices. In the context of developing countries, Hailu and Vural (2021) revealed that COVID-19 had a significant negative impact on stock markets, with the magnitude noted to be different from developed economies and from country to country. Takyi and Bentum-Ennin (2021) found that COVID-19 negatively impacted the stock market performance of 10 out of the 13 African countries analyzed.

Albuquerque et al. (2020) stated a probability of volatility distinction across industries. The majority of studies have analyzed the impact of the COVID-19 pandemic on the entire economy and the broad stock market reaction, the impact of social distancing policies on economic activities and travel bans on the aviation industry, the pandemic's impact on investors' economic growth expectations, the impact on the wellbeing and morale of humans, and the impact on stock returns and crude oil prices. However, there are no studies, to the researchers' best knowledge, that have examined the pandemic's effect on the variability of different stock market sectors, particularly in South Africa. Therefore, this study fills this gap and contributes to the literature by adding to research on stock market reactions to disasters and crises. The study also examines the impact of the novel pandemic on the economy, augmenting scant topical literature on understanding the effects of the COVID-19 pandemic on the volatility of different sectors of the South African stock market. The study's implications will help investors to make informed decisions across various asset classes commensurate with their risk appetite by understanding each sector's response to the pandemic. Policymakers can also respond by making informed policies to save specific industries, stimulate market stability and promote economic growth. Above all, as there may be more pandemics worse than COVID-19 in the future, this study may act as a basis to help policymakers, investors, firms and individuals to plan their responses to future pandemics.

3. EMPIRICAL APPROACH

3.1. Data and the Variables

The study considered daily observation data from all ten sectors of the Johannesburg Stock Exchange (JSE) from March 2020 to December 2021. The ALSHI, Top 40, Alternative Exchange (ALTEX) and the Small Cap indices were also included to capture the response of the broad market. The ten sectors include basic materials, industrials, precious metals & mining, consumer goods, consumer services, oil & gas, health care, financials, telecommunications and technology. The indices' stock return data were obtained from the IRESS database and converted into return series. The study used continuous returns estimated as: $R_t = ln\frac{P_t}{P_{t-1}}$, where R_t is the return at time *t*, and P_t and P_{t-1} are the closing prices at times *t* & *t-1*, respectively. COVID-19 data (daily new infections) were obtained from the South African department of health COVID-19 updates and WHO websites. The study used the daily positive rate (number of positive cases as a ratio of total tests) to capture coronavirus cases.

3.2. Model Specification

Financial time series are characterized by leptokurtic distribution, leverage effects and volatility clustering, which distinguish them from normal time series data and differentiate the analysis of their returns from other assets classes (Yousef, 2020). The asymmetric information of the financial time series is heightened during financial crises and shocks. In such conditions, time-varying volatility models are required as volatility cannot be modelled by standard means. To examine the impact of COVID-19 shocks, following Cermeño and Suleman (2014), we extend the conditional variance equations of the standard symmetric GARCH and non-linear asymmetric (EGARCH & GJR-GARCH) models to include an exogenous variable of COVID-19 infections as a variance regressor. The asymmetric models are designed to allow for asymmetries and capture different impacts of positive and negative shocks in volatility. GARCH models are mostly preferred in finance because they are more parsimonious. They can deal with overfitting and are less likely to breach the non-negativity constraints and effectiveness as they minimize forecasting errors through accounting for errors in prior forecasting, enhancing the accuracy of the forecast (Brooks, 2019). The specific models estimated take the forms outlined in the following section.

3.3. Conventional Linear Symmetrical GARCH Model

Equation 1 depicts the standard GARCH(1,1) model:

$$\sigma_t^2 = \omega_i + \sum_{i=1}^{p} \alpha_i \, \varepsilon^2{}_{t-i} + \sum_{i=1}^{q} \beta_{ij} \, \sigma_{t-j} + \vartheta_1 COVID19_{t-1} \;\; (p, \omega > 0), (q, \alpha_k, \beta_j \geq 0) \tag{1}$$

Where σ_t^2 is the conditional variance; ε_{t-i}^2 & σ_{t-1}^2 *are the ARCH and GARCH terms, respectively;* $\alpha_1, \alpha_2 \ldots \alpha_P$ are ARCH component parameters; $\beta_1,\ \beta_2 \ldots \beta_q$ are the GARCH component parameters; p is the order of the ARCH component; and q is the order of the GARCH component. For the conditional variance (σ_t^2) to be positive and stationary: $w > 0$, $\alpha \geq 0$ and $\beta \geq 0$, where $COVID19_{t-1}$ is an exogenous variable capturing COVID-19 daily infections.

The standard GARCH models overlook the asymmetry found in stock return volatility. The influence of shocks on volatility is asymmetric; they positively and negatively impact lagged residuals. Nelson (1991) proposed the Exponential GARCH (EGARCH) model to overcome these limitations. In addition, Hentschel (1995) proposed a universal form of the GARCH model that nests all asymmetric and symmetric GARCH models governed by the news impact curve shifts and rotations.

3.4. Standard Non-Linear Asymmetrical GARCH Models

The study also employed the non-linear extensions of the GARCH models designed to allow for asymmetries and capture different impacts of positive and negative shocks in volatility.

Equation 2 shows the asymmetric EGARCH(p,q) model proposed by (Nelson, 1991).

$$\ln(\sigma_t^2) = w_0 + \sum_{i=1}^{p} \alpha_i (|\epsilon_{t-1}| + \gamma_i \epsilon_{t-1}) + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) \; + \vartheta_1 COVID19_{t-1}. \quad \epsilon_t \sim P_v(0,1) \tag{2}$$

Where the non-linear function $\gamma_i \epsilon_{t-1}$ captures the asymmetric effect. P_v is the probability distribution function for ϵ_t. The EGARCH process implies that σ_t^2 should always be positive since the model is specified in terms of the log of σ_t^2 and there are no restrictions on model parameter signs (Brooks, 2019).

3.5. The Glosten, Jagannathan, and Runkle (1993) GARCH Model

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-i}^2 d_{t-1} \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \; \vartheta_1 COVID19_{t-1} \tag{3}$$

Where $d_t = 1 \; if \; \varepsilon_t < 0; and \; d_t = 0 \; otherwise.$

Equation 3 presents the GJR-GARCH model proposed by Glosten et al. (1993). Contrary to the exponential form of the EGARCH, in the GJR-GARCH model, the asymmetric effect is expressed in quadratic form (Makoko & Muzindutsi, 2018). To take into effect probable asymmetries, the GJR-GARCH extends the GARCH by including an additional term $\gamma \varepsilon_{t-i}^2 d_{t-1}$ that captures the non-asymmetric component.

Symmetric and non-symmetric models were estimated for each JSE sector and index, the Schwarz criterion (SC) and the Akaike information criterion (AIC) were used to select the best-fitting model (Cermeño & Suleman, 2014). The models that minimize the information criteria (lowest AIC and SC) were identified as the best models.

3.6. Short and Long Memory Volatility Modelling

In addition to the standard GARCH models, the study employed the Baillie, Bollerslev, and Mikkelsen (1996) fractionally integrated GARCH (FIGARCH) model to capture the long memory in volatility. Conventional GARCH models examine conditional variance dynamics over the short run uniquely. However, they cannot capture the effects of long-run dynamics. A slow decay in volatility can cause slight discrepancies between stationarity I(0) and unit root I(1), which is too restrictive.

The FIGARCH permits non-integer integration orders I(d), (0 < d < 1) and thus more subtle reverting behavior in time series (May & Farrell, 2018). The FIGARCH fractional parameter models the long-run dependence, and the ARMA parameter captures the time series' short-run behavior. The FIGARCH model, generally referred to as the FIGARCH(p,d,q), can be specified as shown in Equation 4:

$$h_t^2 = \frac{\omega}{[1-\beta(L)]} + \{1 - \varphi(L)(1-L)^d[1-\beta(L)]^{-1}\}\varepsilon_t^2 \tag{4}$$

The fractional differencing parameter (*d*) shows the decay rate (the speed at which the shock dies out over time). Shocks to the conditional variance die at a slower rate determined by *d*. In the standard GARCH models, $d = 0$.

3.7. Dynamics of JSE Indices' Conditional Correlations During COVID-19

To examine the dynamics of conditional time varying correlations among the JSE's main indices during the COVID-19 pandemic, the study employed the multivariate DCC-GARCH model introduced by Engle (2002).

The multivariate GARCH models aid the examination of temporal dependence of the conditional correlations between variables. In the DCC-GARCH, correlations are allowed to be dynamic and vary over time. The DCC model is premised on the idea that conditional returns are normally distributed with a conditional variance matrix $h_t = E[r_t\, r_t']$ that is generally stated as:

$$H_t = D_t R_t D_t \tag{5}$$

Where D_t is the conditional covariance diagonal matrix, such that $D_t = [diag\ (h_t)]^{1/2}$. The time-varying conditional correlation matrix R_t is specified as:

$$R_t = diag\left(q_{11,t}^{-1/2} \dots q_{NN,t}^{-1/2}\right) Q_t diag\left(q_{11,t}^{-1/2} \dots q_{NN,t}^{-1/2}\right) \tag{6}$$

Such that $Q_t = q_{ij,t}$ is a symmetric positive definite matrix, and the DCC(1,1) model is then expressed as:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon_{t-1} + \beta Q_{t-1} \tag{7}$$

Q_t is the conditional covariance matrix of the error terms; $\bar{Q}$ is the unconditional covariance matrix; $\beta\ and\ \alpha$ are scalar parameters satisfying $\beta + \alpha < 1$. If $\alpha = \beta = 0$, Q_t will be equal to $\bar{Q}$, the CCC model will be suitable for approximating the correlation matrix (Ghorbel & Jeribi, 2021). The main component of interest in this section is R_t, which is given as:

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \tag{8}$$

Equation 8 denotes the conditional correlations between the indices. According to Engle (2002), the DCC model gives computational leverage when estimating huge covariance matrices because estimated parameters in the correlation procedure are independent of the number of series to be calculated.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics

The descriptive statistics shown in Table 1 depict that the energy sector was the top performer with the highest average daily mean return of 0.35% over the sample period. The Basic Materials (0.20%), Precious Metals & Mining (0.17%), Alternative Exchange (0.14%), Consumer Services (0.12%), Small Cap (0.10%), and Top 40 (0.09) indices all outperformed the All-Share Index, which had an average return of 0.08%. Financials (-0.07%), Health Care (-0.04%) and Technology (0.002%) offered the lowest average returns over the sample period. Interestingly, consistent with financial theory, the overall market (All-Share Index) had the lowest risk, as shown by the least standard deviation (1.54%) compared to all market sectors, explaining the essence of diversification. Investing in a market portfolio minimizes risks without an equivalent reduction in returns (Chopra & Ziemba, 1993). Over the sample period, the returns of the energy, telecommunications, precious metals and basic materials sectors depicted the highest risk as shown by the high standard deviations of 5.06%, 2.58%, 2.43% and 2.31%, respectively. Over the sample period, the daily average COVID-19 cases reported in South Africa were the highest rates for all African countries (WHO).

Table 1. Descriptive statistics.

	Sector/Index	Mean	Std. Dev.	Median	Maximum	Minimum	Observations
Index daily returns (%)	FTSE/JSE_ All Share	0.08%	1.54%	0.18%	7.26%	-10.23%	678
	FTSE/JSE_ Top 40	0.09%	1.58%	0.19%	7.91%	-10.45%	678
	FTSE/JSE_ Altx	0.14%	1.64%	0.12%	4.65%	-3.52%	678
	FTSE/JSE_ SmallCap	0.10%	1.55%	0.09%	10.29%	-11.30%	678
	FTSE/JSE_Basic Materials	0.20%	2.31%	0.18%	12.09%	-15.66%	678
	FTSE/JSE_Consumer Discretionary	0.08%	1.58%	0.11%	5.98%	-9.31%	678
	FTSE/JSE_Consumer Services	0.12%	1.53%	0.08%	7.24%	-10.04%	678
	FTSE/JSE_ Energy	0.35%	5.06%	0.00%	32.70%	-30.17%	678
	FTSE/JSE_ Financials	-0.07%	2.23%	0.03%	7.49%	-13.10%	678
	FTSE/JSE_ HealthCare	-0.04%	1.85%	-0.07%	5.46%	-11.11%	678
	FTSE/JSE_ Industrials	0.01%	1.95%	-0.01%	7.64%	-9.72%	678
	FTSE/JSE_ Precious Metals & Mining	0.17%	2.43%	0.09%	13.46%	-15.89%	678
	FTSE/JSE_ Technology	0.002%	2.12%	0.05%	8.23%	-8.96%	678
	FTSE/JSE_ Telecommunications	0.07%	2.58%	0.08%	10.46%	-11.74%	678
COVID-19	New_Cases	4368	5159	2024	26485	0	678
	Positive rate	11.73%	8.34%	8.80%	32.60%	0.00%	678
	New_Deaths	130	146	85	844	0	678

4.2. Pre-Estimation Diagnostic Tests

Before estimating the models, diagnostic tests of the residuals were performed. The Engle (1982) Lagrange multiplier (LM) test was applied to detect ARCH effects. The p-values of the ARCH effect test results for heteroscedasticity shown in Table 2 are less than 5% for all sectors. Thus, the null hypothesis for homoskedasticity is rejected, implying that the indices are heteroskedastic. The ARCH/GARCH models can be estimated in the presence of the ARCH effects (Engle & Bollerslev, 1986). A panel of the augmented Dickey–Fuller (ADF) (Dickey & Fuller, 1979) Phillips–Perron (PP) and KPSS tests were used to test for unit root. As shown in Table 1, the p-values for the ADF and PP tests are all less than 5% and above 5% for the KPSS for all indices; hence, the null hypothesis for the presence of unit root is rejected. Thus, all the return series are stationary at level and can therefore be represented by the GARCH models (Wooldridge, 2003). The residuals plots (not presented here) evidence volatility clustering, indicating that the error terms are conditionally heteroskedastic and, therefore, they can be represented by the ARCH/GARCH models (Miah & Rahman, 2016).

Table 2. Unit root tests and ARCH effects.

Variable	Augmented Dickey–Fuller (ADF)		Phillips–Perron (PP)		KPSS		Heteroskedasticity	
	t-stat	Prob.	t-stat	Prob.	t-stat	Prob.	F-stat	P (Chi-Sq)
FTSE/JSE_ All Share	-5.78	0.0000	-18.95	0.0000	0.4958	0.6203	41.37	0.0095
FTSE/JSE_ Top 40	-16.90	0.0000	-17.55	0.0000	1.2318	0.2186	36.73	0.0000
FTSE/JSE_ Altx	-16.14	0.0000	-15.85	0.0000	2.7665	0.0059	41.61	0.0000
FTSE/JSE_Small Cap	-7.15	0.0000	-15.09	0.0000	1.4634	0.1440	48.33	0.0000
FTSE/JSE_Basic Materials	-7.97	0.0000	-19.04	0.0000	0.7186	0.4729	32.89	0.0014
FTSE/JSE_ Consumer Discretionary	-17.74	0.0000	-17.76	0.0000	0.0471	0.9625	18.66	0.0000
FTSE/JSE_ Consumer Services	-10.99	0.0000	-19.42	0.0000	0.3644	0.7158	32.72	0.0390
FTSE/JSE_ Energy	-19.09	0.0000	-19.09	0.0000	1.2927	0.1972	34.04	0.0000
FTSE/JSE_ Financials	-17.19	0.0000	-17.29	0.0000	-0.4831	0.6294	15.20	0.0001
FTSE/JSE_ HealthCare	-18.04	0.0000	-18.04	0.0000	-1.0052	0.9200	63.33	0.0304
FTSE/JSE_ Industrials	-18.67	0.0000	-18.65	0.0000	-0.2818	0.7783	68.59	0.0000
FTSE/JSE_ Precious Metals & Mining	-19.07	0.0000	-19.01	0.0000	0.6918	0.4895	27.99	0.0063
FTSE/JSE_ Technology	-17.23	0.0000	-17.22	0.0000	0.0670	0.3876	8.81	0.0032
FTSE/JSE_ Telecommunications	-19.24	0.0003	-19.16	0.0000	0.1966	0.8467	19.57	0.0000

4.3. Volatility and Internal/Own Shocks

Plain GARCH models were first estimated to understand the nature of the volatility of the JSE sectors. The results are presented in Table 3, which shows the estimations of the conditional variance equation of the plain GARCH(1,1) models for the 14 JSE indices. The parameters of the ARCH $(\varepsilon^2{}_{t-1})$ $and\ GARCH\ (h_{t-1})$ components α and β are positive and statistically significant for all the sectors except for the Alternative Exchange, which shows the ARCH effect only. The highly significant α and β provide evidence of volatility clustering (May & Farrell, 2018), implying that internal/own shocks drive volatility for the JSE sectors. The concept of volatility clustering implies that such shocks will be felt for some time into the future; thus, investors can expect more prolonged periods of market volatility. Investors and portfolio and risk managers can use this information for efficient portfolio selection, sector rotation, and risk management strategies targeted at hedging and diversification to survive the implied prolonged volatility spell. Market timing strategies can also be adopted to capitalize on any market shifts. These results are consistent with Yousef (2020) and Onali (2020), who found GARCH and ARCH effects in a sample of G7 and several other countries, respectively.

Table 3. Plain GARCH(1,1).

Index	ALSHI	SMLCap	Top40	ALTX	TeleCO	Tech	PMM	IND	BM	CD	CS	Energy	FIN	HC
Coefficient/Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
α	0.34***	0.29***	0.33***	0.81***	0.04**	0.33***	0.23***	0.35***	0.22***	0.14***	0.20***	0.56***	0.49***	0.50***
	0.000	0.000	0.000	0.001	0.016	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
β	0.61***	0.68***	0.61***	0.08	0.95***	0.53***	0.68***	0.59***	0.69***	0.81***	0.79***	0.32***	0.46***	0.20***
	0.000	0.000	0.000	0.281	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
α + β	0.949	0.967	0.944	0.893	0.991	0.854	0.913	0.948	0.921	0.953	0.991	0.879	0.951	0.706
Llik	1516	1580	1493	1571	1216	1258	1235	1345	1275	1407	1453	854	1324	1335
AIC	-6.12	-6.38	-6.03	-6.34	-4.90	-5.08	-4.98	-5.43	-5.14	-5.68	-5.86	-3.59	-5.35	-5.39
SC	-6.09	-6.35	-6.00	-6.30	-4.86	-5.04	-4.94	-5.39	-5.10	-5.65	-5.82	-3.56	-5.31	-5.35
HQC	-6.21	-6.37	-6.02	-6.35	-4.89	-5.06	-4.96	-5.42	-5.12	-5.67	-5.84	-3.58	-5.33	-5.38
Diagnostics: (A) Arch Test														
F-Statistics	0.06	1.76	0.03	1.60	1.91	0.11	2.03	1.18	2.07	4.89	0.25	0.08	2.09	0.01
Prob. Chi-Sq	0.81	0.19	0.87	0.21	0.17	0.74	0.15	0.28	0.15	0.03	0.62	0.77	0.15	0.91
(B) Sign bias test														
t-stat (joint bias)	2.27	2.38	0.91	3.39	3.79	0.29	2.56	0.22	2.79	7.03	0.81	2.04	4.09	2.77
P-value	0.52	0.50	0.82	0.34	0.29	0.96	0.47	0.97	0.43	0.07	0.85	0.56	0.25	0.43
© Nyblom's Parameter Stability Test														
Joint Statistic	1.06	1.16	1.06	1.95	1.18	0.81	1.66	1.56	1.32	0.94	1.33	2.31	1.85	1.81
1% Crit. (Hansen)	1.60	1.60	1.60	1.88	1.88	1.86	1.88	1.60	1.88	1.96	1.88	2.60	1.96	1.86

Note: α & β are ARCH and GARCH coefficients; **and *** represent significance at the 10%, 5% and 1% levels, respectively; ALSHI represents the JSE All-Share Index; SMLCap is the Small Cap Index; ALTX is the Alternative Index; TeleCO is the telecommunications sector; Tech is the technology sector; PMM is the precious metals & mining sector; IND is the industrials sector; BM is the basic materials sector; CD is the consumer discretionary sector; CS is the consumer services sector; Fin is the financials sector; and HC is the health care sector.

Moreover, the large GARCH coefficients for all indices (except the health care and financials indices) connote that shocks to conditional variance are taking long to die; thus, volatility is persistent (May & Farrell, 2018). Therefore, investors should expect a long spell of unstable returns during such market shocks. Engle and Bollerslev (1986) illustrates that the persistence of shocks in Volatility depends on the sum of $\alpha + \beta$ parameters. The results in the table show that the summation of the parameters $\alpha + \beta$ is statistically less than unity and approaching one in all the 14 indices, implying that the shocks in Volatility persist for long periods and the shock effects decay over time. Risk-averse investors should diversify their investments in low risk and stable assets during market turbulence as equities provide poor protection against market volatility. However, for risk-takers, such volatile conditions can provide valuable opportunities for higher returns by purchasing stocks during their historic lows and profit by exiting the positions as markets eventually come out of the shock. The sum of α & β parameters are lower for the health, technology and energy sectors, providing evidence of low persistence in Volatility in these sectors compared to the other 11 during the COVID-19 pandemic.

It is commonly observed that downturns of markets are followed by higher volatility than that which occurs after an upturn of similar magnitude (Yousef, 2020). The GJR-GARCH and EGARCH models were estimated to capture the asymmetric features of the market return series. For the GJR-GARCH models shown in Table 4, the coefficient of γ (asymmetric behaviour) is positive and significant for all the indices (except the HC, FIN, Tech, PMM), suggesting an asymmetric effect in these indices. The implication of these findings is there is a strong reaction to negative news compared to positive news. Implying that negative shocks such as the COVID-19 increased Volatility more than positive shocks for most of the JSE sectors. Investors should expect a higher magnitude of losses in the value of their equity holdings following adverse conditions such as pandemics compared to gains associated with positive market developments. This is consistent with the idea that Brooks (2019) who documents that Volatility rises more in a negative shock than a positive shock of the same magnitude. The magnitude of negative shocks is measured by $\alpha + \gamma$ (May & Farrell, 2018). The ALTX, TeleCO, SMLCap exhibits a higher impact of negative news as shown by the higher and significant coefficients of $\alpha + \gamma$. This suggests that investors in these sectors should expect more losses resulting from negative information during such market shocks thus should demand a higher return from such investments to compensate for the higher risk.

The insignificant coefficient of the asymmetric term for the HC, FIN, Tech, PMM indices suggests the nonexistence of differences between negative and positive Volatility in these sectors. For the HC, this could be due to its importance during the pandemics, hence less affected by negative news. The PMM could be its ability to store value, and for the tech, it could be due to its increased use during lockdowns when people worked from home hence less affected by negative news. These could be better targets for sector rotation during pandemics and other negative market shocks for investors. Consistent with the GJR-GARCH, using the EGARCH model, a negative and statistically significant asymmetric term γ across the indices (except for Energy, Tech and Fin) is evidence of a leverage effect with expectations since positive shocks tend to have smaller impacts. Consistent with May and Farrell (2018) the EGARCH Models shown in Table 5 have higher $\alpha + \beta$ values significantly above 1, corroborating Engle and Ng (1993) findings that EGARCH models lead to too high conditional variance more volatile than the GJR-GARCH.

Table 4. GJR-GARCH(1,1).

Index	ALSHI	SMLCap	Top40	ALTX	TeleCO	Tech	PMM	IND	BM	CD	CS	Energy	FIN	HC
Coefficient/Model	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]
α	0.27***	0.21***	0.19***	0.63***	0.34***	0.38***	0.22***	0.23***	0.22***	0.14***	0.05***	0.22***	0.44***	0.39***
	0.002	0.000	0.005	0.000	0.000	0.000	0.005	0.000	0.005	0.000	0.000	0.000	0.000	0.002
β	0.62***	0.65**	0.72***	0.04	0.56***	0.42***	0.70***	0.73***	0.70***	0.81***	0.93***	0.61***	0.45***	0.17***
	0.000	0.045	0.000	0.560	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.045
γ	0.10**	0.22***	0.05**	0.31*	0.36*	0.08	0.02	0.10**	0.05**	0.02*	0.04**	0.09*	0.11	0.36
	0.028	0.009	0.025	0.065	0.066	0.508	0.998	0.025	0.049	0.070	0.011	0.055	0.415	0.152
α + β	0.894	0.86	0.907	0.669	0.90	0.800	0.917	0.957	0.919	0.952	0.978	0.83	0.893	0.563
α + γ	0.367	0.43	0.240	0.94	0.70	0.460	0.241	0.330	0.267	0.154	0.085	0.310	0.551	0.753
Llik	1517	1689	1515	1549	1273	1258	1234	1481	1275	1407	1434	868	1325	1347
AIC	-6.12	-6.81	-6.12	-6.25	-5.13	-5.07	-4.98	-5.97	-5.14	-5.68	-5.79	-3.64	-5.34	-5.43
SC	-6.08	-6.76	-6.07	-6.21	-5.08	-5.03	-4.93	-5.92	-5.09	-5.63	-5.74	-3.59	-5.30	-5.38
HQC	-6.03	-6.79	-6.10	-6.24	-5.11	-5.06	-4.96	-5.95	-5.12	-5.66	-5.77	-3.62	-5.33	-5.41
Diagnostics: (A) Arch Test														
F-Statistics	0.17	0.66	0.18	0.11	0.00	0.12	2.54	4.22	2.22	4.99	4.25	1.83	2.67	0.01
Prob. Chi-Sq	0.68	0.42	0.67	0.74	1.00	0.73	0.11	0.04	0.14	0.26	0.40	0.18	0.10	0.93
(B) Sign bias test														
t-stat (joint bias)	1.78	0.07	4.66	1.12	1.21	0.39	2.97	0.65	2.95	7.21	6.16	1.19	3.25	1.61
p-value	0.62	1.00	0.20	0.77	0.75	0.94	0.40	0.88	0.40	0.07	0.11	0.75	0.36	0.66
© Nyblom's Parameter Stability Test														
Joint Statistic	1.24	2.60	1.24	1.05	2.86	1.04	1.72	0.95	1.44	1.01	0.88	1.84	1.90	2.26
1% Crit. (Hansen)	1.88	2.82	2.12	1.88	2.96	1.88	1.88	2.12	2.12	1.88	1.88	2.12	2.05	2.56

Note: α & β are the ARCH and GARCH coefficients; *, **and *** represent significance at the 10%, 5% and 1% levels, respectively, ALSHI represents the JSE All-Share Index; SMLCap is the Small Cap Index; ALTX is the Alternative Index; TeleCO is the telecommunications sector; Tech is the technology sector; PMM is the precious metals & mining sector; IND is the industrials sector; BM is the basic materials sector; CD is the consumer discretionary sector; CS is the consumer services sector; Fin is the financials sector; and HC is the health care sector.

Table 5. Plain EGARCH(1,1).

Index	ALSHI	SMLCap	Top40	ALTX	TeleCO	Tech	PMM	IND	BM	CD	CS	Energy	FIN	HC
Coefficient/Model	**[29]**	**[30]**	**[31]**	**[32]**	**[33]**	**[34]**	**[35]**	**[36]**	**[37]**	**[38]**	**[39]**	**[40]**	**[41]**	**[42]**
	0.51***	0.22***	0.59***	0.72***	0.90***	0.50***	0.09***	0.55***	0.11***	0.62***	0.34***	0.84***	0.68***	0.77***
α	0.000	0.000	0.001	0.000	0.000	0.000	0.005	0.000	0.009	0.000	0.000	0.000	0.000	0.000
	0.92***	0.98***	0.89***	0.28***	0.43***	0.82***	0.99***	0.90***	0.99***	0.76***	0.95***	0.48***	0.86***	0.52***
β	0.000	0.000	0.000	0.009	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-0.05***	-0.04*	-0.02*	0.12*	-0.15**	0.03	-0.01**	0.01*	-0.02***	0.05***	0.05***	-0.08	-0.04	-0.19**
γ	0.002	0.059	0.071	0.059	0.034	0.558	0.034	0.087	0.003	0.004	0.003	0.300	0.415	0.027
$\alpha + \beta$	1.428	1.204	1.488	1.001	1.324	1.318	1.077	1.444	1.094	1.382	1.294	1.310	1.548	1.289
Llik	1513	1596	1490	1550	1278	1252	1238	1342	1272	1413	1456	853	1320	1345
AIC	-6.10	-6.45	-6.01	-6.26	-5.15	-5.05	-5.00	-5.41	-5.13	-5.70	-5.87	-3.58	-5.33	-5.42
SC	-6.05	-6.40	-5.96	-6.21	-5.10	-5.00	-4.95	-5.37	-5.08	-5.64	-5.82	-3.53	-5.28	-5.37
HQC	-6.02	-6.43	-5.99	-6.24	-5.13	-5.03	-4.98	-5.40	-5.11	-5.68	-5.85	-3.56	-5.31	-5.40
Diagnostics: (A) Arch Test														
F-Statistics	1.33	5.27	0.13	0.22	0.16	0.37	13.48	1.94	16.38	0.08	0.22	0.07	3.72	0.10
Prob. Chi-Sq	0.25	0.02	0.71	0.64	0.69	0.54	0.00	0.16	0.00	0.77	0.64	0.79	0.05	0.75
(B) Sign bias test														
t-stat (joint bias)	2.01	6.89	0.75	1.77	0.13	0.79	13.64	1.01	14.60	1.40	1.98	0.81	5.51	1.78
p-value	0.57	0.08	0.86	0.62	0.99	0.85	0.00	0.80	0.00	0.71	0.58	0.85	0.14	0.62
© Nyblom's Parameter Stability Test														
Joint Statistic	1.53	1.66	2.17	1.21	2.93	1.36	1.43	1.81	0.85	2.14	1.41	2.47	2.23	2.94
1% Crit. (Hansen)	1.88	2.12	2.12	1.88	2.12	2.12	2.12	1.88	2.12	2.12	2.12	2.12	1.88	2.12

Note: α & β are the ARCH and GARCH coefficients; *, **and *** represent significance at the 10%, 5% and 1% levels, respectively, ALSHI represents the JSE All-Share Index; SMLCap is the Small Cap Index; ALTX is the Alternative Index; TeleCO is the telecommunications sector; Tech is the technology sector; PMM is the precious metals & mining sector; IND is the industrials sector; BM is the basic materials sector; CD is the consumer discretionary sector; CS is the consumer services sector; Fin is the financials sector; and HC is the health care sector.

Table 6. FIGARCH(1,1,1).

INDEX	ALSHI	SMLCap	Top40	ALTX	TeleCO	Tech	PMM	IND	BM	CD	CS	Energy	FIN	HC
Coefficient/Model	**[43]**	**[44]**	**[45]**	**[46]**	**[47]**	**[48]**	**[49]**	**[50]**	**[51]**	**[52]**	**[53]**	**[54]**	**[55]**	**[56]**
α	0.23***	0.38***	0.45***	0.47***	0.43**	0.43***	0.34**	0.50**	0.19**	0.24***	0.29**	0.40***	0.56***	0.35**
	0.000	0.000	0.000	0.000	0.050	0.000	0.040	0.037	0.020	0.001	0.049	0.006	0.002	0.049
β	0.44**	0.61*	0.52***	0.06	0.15**	0.51***	0.64***	0.37*	0.08***	0.09***	0.14*	0.01***	0.39*	0.04**
	0.019	0.066	0.000	0.407	0.042	0.000	0.000	0.075	0.000	0.000	0.069	0.000	0.010	0.048
d	0.67***	0.11**	0.54***	0.07**	0.30**	0.01*	0.57***	0.32**	0.52**	0.22**	0.20**	0.37*	0.32*	0.26**
	0.000	0.010	0.000	0.019	0.015	0.057	0.000	0.019	0.011	0.018	0.036	0.087	0.062	0.018
α + β	0.66	0.99	0.97	0.53	0.58	0.94	0.98	0.87	0.12	0.15	0.42	0.41	0.95	0.40
Llik	1519	1686	1501	1549	1294	1258	1247	1372	1272	1414	1545	874	1349	1351
AIC	-6.13	-6.80	-6.05	-6.25	-5.21	-5.07	-5.03	-5.54	-5.13	-5.70	-6.23	-3.67	-5.45	-5.46
SC	-6.09	-6.75	-6.00	-6.21	-5.15	-5.01	-4.98	-5.49	-5.09	-5.65	-6.18	-3.62	-5.40	-5.40
HQC	-6.19	-6.78	-6.03	-6.23	-5.19	-5.05	-5.01	-5.52	-5.11	-5.68	-6.21	-3.65	-5.43	-5.44
Diagnostics: (A) Arch Test														
F-Statistics	0.49	0.39	0.93	0.24	0.09	0.01	0.09	0.44	0.50	0.86	0.07	0.59	0.32	0.41
Prob. Chi-Sq	0.48	0.53	0.33	0.62	0.77	0.92	0.77	0.50	0.48	0.35	0.79	0.44	0.57	0.52
(B) Sign bias test														
t-stat (joint bias)	3.30	5.10	2.45	1.53	2.83	0.31	0.92	1.00	0.70	2.62	0.65	3.54	1.28	0.91
p-value	0.35	0.17	0.48	0.67	0.42	0.96	0.82	0.80	0.87	0.45	0.88	0.32	0.73	0.82
© Nyblom's Parameter Stability Test														
Joint Statistic	0.64	2.12	1.31	1.33	2.35	1.35	1.54	1.40	1.88	2.80	1.99	2.11	1.65	1.17
1% Crit. (Hansen)	1.88	3.28	2.12	1.88	3.43	2.35	2.12	2.12	2.51	2.12	2.12	3.51	2.12	2.12

Note: α & β are the ARCH and GARCH coefficients; *, **and *** represent significance at the 10%, 5% and 1% levels, respectively, ALSHI represents the JSE All-Share Index; SMLCap is the Small Cap Index; ALTX is the Alternative Index; TeleCO is the telecommunications sector; Tech is the technology sector; PMM is the precious metals & mining sector; IND is the industrials sector; BM is the basic materials sector; CD is the consumer discretionary sector; CS is the consumer services sector; Fin is the financials sector; and HC is the health care sector.

4.4. Long Memory GARCH Model Estimation Results (FIGARCH)

The traditional GARCH models are exceptional in modelling short-run dynamics in conditional variance. However, they cannot model long-run dynamics. The FIGARCH model allows for modelling of the long-run dependence of return series. The results are presented in Table 6. The GARCH terms give the short-term dynamics, and the long-term dynamics and speed at which shocks die out over time (rate of decay) is provided by the fractional integration parameter (d). For all the indices, the long memory parameter (*d) FIGARCH* is statistically significant, which confirms long-run dependence behavior evident in financial assets' nominal prices (May & Farrell, 2018). For all the indices, only the ALSHI, Top 40 and the PMM have higher fractional parameters (d) (0.67, 0.54 and 0.57, respectively), indicating a fast process of mean reversion. Thus, investments in the ALSHI, Top 40 and PMM revert to their average values more quickly than other sub-sectors of the JSE. The rest of the indices have lower fractional parameters; this can be due to turbulence in the financial markets induced by the COVID-19 pandemic. As shown in the table compared to the traditional GARCH models, the arch terms have increased from zero, and the GARCH terms have decreased from one for the majority of the indices.

4.5. Covid-19 and Market Volatility

In examining the impact of the pandemic on the return volatility of JSE sectors, a COVID-19 variable was added as a conditional variance regressor, which analyses the effect of the pandemic on index volatility. Table 7 shows the estimation results of the best models for each sector selected based on the lowest AIC and SC and the highest log-likelihood. The lag of the ALSHI index return (market return) was used as an explanatory variable for the mean equation. The results show a significant positive relationship between the market index return and all the JSE sub-indices, implying that the increase in returns for the market index positively transmits to the other sectors resulting in improved returns. Similarly, the reduction in the market index returns results in a decrease in returns for the sub-sectors.

For the conditional variance equations, the results presented in Table 7 reveal a positive and significant coefficient of the COVID-19 variable (positive rate) for all the JSE sectors and indices except those for technology, health care and precious metals & mining. Therefore, COVID-19 increased the return volatility of the majority of the JSE sectors and indices. The results suggest that COVID-19 shocks negatively transmitted to the volatility of returns in the ALSHI, SmallCap, ALTX, Top40, TeleCO, BM, CD, CS, IND and Energy sectors leading to higher conditional volatility. The returns of these sectors are more responsive to the pandemic's adverse effects. Thus, investors should reduce or diversify their holdings in these sectors during pandemics and adverse market shocks. For the Tech, HC and PMM sectors, we did not find evidence of change in volatility following a COVID-19 shock based on the selected models, suggesting the possible provision of stability in returns during pandemics. The size of the coefficient of the COVID-19 variable is largest for the SmallCap, ALTX, IND, CS and CD indices, indicating that the pandemic hit these sectors the most, implying that holdings in such sectors can increase investors' active risk, or such sectors can be used to increase investors' aggressiveness in portfolio construction. Tech, TeleCO, BM, HC, PMM, and Fin have the smallest coefficients, suggesting a lesser impact of COVID-19 on return volatility. The results are consistent with Yousef (2020), who found a negative relationship between COVID-19 and return volatility of major indices in the G7 countries.

Table 7. Covid-19 and stock market volatility.

Index	**ALSHI**	**SMLCap**	**Top40**	**ALTX**	**TeleCO**	**Tech**	**PMM**	**IND**	**BM**	**CD**	**CS**	**Energy**	**Fin**	**HC**
Model	**[57]**	**[58]**	**[59]**	**[60]**	**[61]**	**[62]**	**[63]**	**[64]**	**[65]**	**[66]**	**[67]**	**[68]**	**[69]**	**[70]**
Selected Model	**GJR-G**	**GJR-G**	**GJR-G**	**E-G**	**E-G**	**GARCH**	**GARCH**	**GJR-G**	**GARCH**	**GJR-G**	**E-G**	**E-G**	**GARCH**	**GARCH**
Mean Equation														
ALSHI(-1)	0.45***	0.26***	0.39***	0.09***	0.26***	0.07***	0.33***	0.38***	1.37***	0.31***	0.26***	0.41***	0.42***	0.28***
Variance equation	0.000	0.000	0.000	0.001	0.000	0.209	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
α	0.37*** 0.000	0.43*** 0.000	0.39*** 0.000	0.15*** 0.000	0.15*** 0.000	0.35*** 0.000	0.20*** 0.000	0.43*** 0.000	0.23*** 0.000	0.30*** 0.000	0.17*** 0.000	0.23*** 0.001	0.49*** 0.000	0.66*** 0.000
β	0.58*** 0.000	0.50*** 0.000	0.52*** 0.000	0.60*** 0.000	0.60*** 0.000	0.50*** 0.000	0.72*** 0.000	0.48*** 0.000	0.69*** 0.004	0.55*** 0.000	0.61*** 0.000	0.72*** 0.000	0.45*** 0.000	0.14*** 0.002
γ	0.07** 0.032	0.05*** 0.003	0.21** 0.024	-0.15** 0.034	-0.12** 0.026	- -		0.015* 0.050	- -	0.07** 0.012	-0.09* 0.053	0.15** 0.043	- -	- -
COVID19	0.03** 0.031	0.52*** 0.008	0.21*** 0.000	0.46*** 0.000	0.03*** 0.000	0.015 0.874	0.024 0.392	0.40*** 0.008	0.03*** 0.010	0.38*** 0.000	0.4*** 0.000	0.09** 0.025	0.05*** 0.000	0.02 0.122
Llik	1518	1600	1521	1506	1204	1258	1242	1364	1567	1421	1442	877	1349	1346
AIC	-6.13	-6.47	-6.14	-6.09	-4.85	-5.07	-5.01	-5.51	-6.32	-5.74	-5.82	-3.68	-5.45	-5.44
SC	-6.08	-6.42	-6.09	-6.04	-4.79	-5.01	-4.95	-5.46	-6.27	-5.69	-5.77	-3.62	-5.39	-5.39
Diagnostics: (A) Arch Test														
F-Statistics	0.02	0.15	0.12	0.38	0.86	0.01	1.93	0.04	0.23	0.56	1.75	0.27	0.01	0.50
Prob. Chi-Sq	0.90	0.70	0.73	0.54	0.35	0.93	0.16	0.84	0.35	0.11	0.19	0.60	0.91	0.48
(B) Sign bias test														
t-stat (joint bias)	1.67	0.51	2.57	3.44	5.32	0.32	2.05	1.04	3.06	0.57	4.69	1.82	1.43	1.55
p-value	0.64	0.92	0.46	0.33	0.15	0.96	0.56	0.79	0.38	0.90	0.20	0.61	0.70	0.67
© Nyblom's Parameter Stability Test														
Joint Statistic	1.32	1.96	1.41	2.02	2.13	1.15	1.67	2.05	1.29	1.86	1.86	2.35	1.87	1.74
1% Crit. (Hansen)	1.88	2.12	2.12	5.05	3.51	2.35	2.35	2.12	2.12	2.12	2.12	4.24	2.31	2.12

Note: α & β are ARCH and GARCH coefficients; *, **and *** represent significance at the 10%, 5% and 1% levels, respectively. ALSHI represents the JSE All-Share index; SMLCap is the Small Cap index; ALTX is the alternative index; TeleCO is the telecommunications sector; Tech is the technology sector; PMM is the precious metals & mining sector; IND is the industrials sector, BM is the basic materials sector; CD is the consumer discretionary sector; CS is the consumer services sector; Fin is the financials sector; and HC is the health care sector. GJR-G is the GJR-GARCH, and E-G is the E-GARCH.

The coronavirus pandemic is causing severe economic and non-economic disruptions, increasing uncertainty leading to lower valuations and higher volatility across the JSE sectors. The nation reduced its economic activities, thereby decreasing the production of goods and services to limit the spread of the virus. Lockdown measures have led to extraordinary shocks and extreme disruptions in supply chains, eventually slowing down global economic growth. The actual extent and ultimate impact of COVID-19 are challenging to pin down at present, and given the uncertainty surrounding the cure and vaccines, countries are in and out of lockdowns to control the spread of the virus; thus, the situation poses severe risks for stock markets and economies. Although the findings of this analysis provide evidence of a negative impact of the pandemic on the stock market, going forward, it remains to be seen how severely the broader financial system has been affected.

4.6. Post-Estimation Diagnostics

The estimates of the GARCH models are consistent if the residuals do not exhibit heteroscedasticity and serial correlation. For all the models (Tables 3 to 7), the ARCH tests are reported below the GARCH estimates (Diagnostic A). The high p-values indicate non-existent ARCH effects in the residuals. Also, no serial correlation in the residuals was detected. The Nyblom test was used to test for model parameter stability. The results in Tables 3 to 7 show that the joint NH test statistics are below the Hansen 5% critical values; thus, the null hypothesis of parameter stability cannot be rejected (Hansen, 1992; Nyblom, 1989) as they indicate the joint stability of our model parameters. The sign bias test was also implemented to detect potential misspecification of the conditional variance equations. In the results reported in Tables 3 to 7 (Diagnostic B), the p-values are high (greater than 5%), indicating that the models are specified correctly.

4.7. Conditional Correlations of Major JSE Indices During the COVID-19 Pandemic

Pairwise dynamic time-variant conditional correlations between JSE major indices (ALSHI, ALTX, Small Cap and Top 40) were examined, and the results are presented in Figure 1. Figure 1 shows that for the ALSHI & Small Cap indices, and the Small Cap & Top 40 indices, there are significant, persistent, high, positive correlations oscillating between 0.6 and 0.9. The high positive correlations between these indices suggest that, holding all else equal, the Small Cap index provided minimal diversification benefits and hedging abilities to the JSE All-Share and Top 40 indices during the pandemic. However, there is noticeably more stability in these correlations, although the correlations are high. The correlation between the Top 40 and the ALSHI is almost perfectly positive over the sample period, indicating a perfect co-movement between these indices and non-existent diversification and hedging abilities between the two. Thus, investors can use the Top 40 as a benchmark for the JSE ALSHI. On the other hand, the correlations between the ALTX and other indices (Top 40, Small Cap and ALSHI) were high at the start of the pandemic (around +0.8) and declined since then to around +0.4 with the Small Cap, and +0.5 and +0.6 with the Top 40 and ALSHI, respectively. They are, however, more volatile (ranging between 0.9 and 0.2) and are declining over time. In the first quarter of 2021, the correlation of the ALTX and other indices recorded a sharp decline to below 0.2 with the ALSHI and the Top 40 and just above 0.2 with the Small Cap. The lower and declining correlations between the ALTX and other indices indicate that holding shares in the ALTX can provide better diversification benefits than holdings in the ALSHI, Top 40 and Small Cap indices. This implies that investing in the ALTX increases diversification benefits during extreme market shocks like the COVID-19 pandemic.

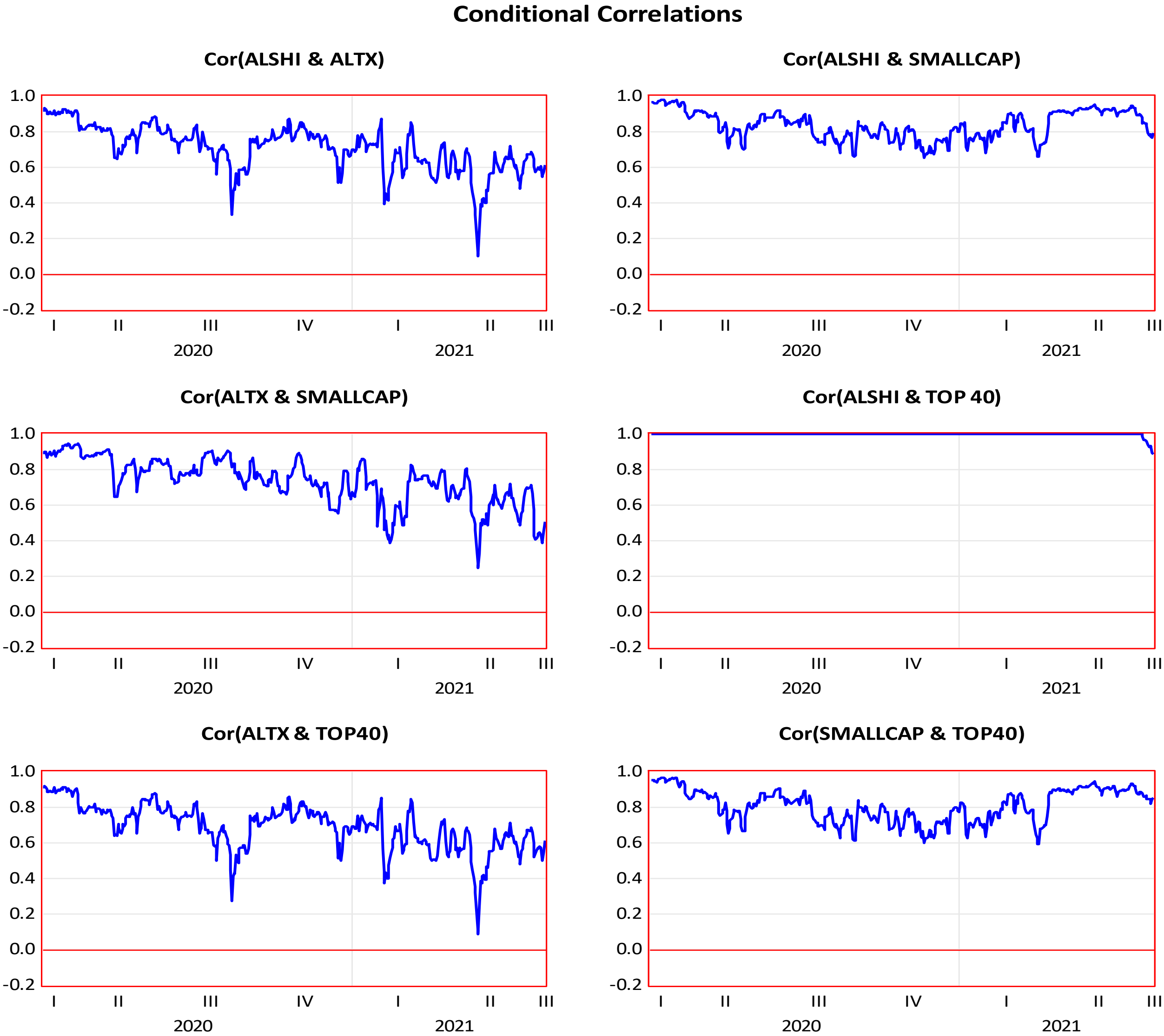

Figure 1. Conditional correlations of JSE major indices.

5. SUMMARY AND CONCLUSION

This study aimed to analyze the impact of the novel coronavirus on the stock market return volatility of different South African stock market sectors using the GARCH family models. The results of the different GARCH models suggest a significant positive relationship between COVID-19 and the return volatility of all the JSE sectors (except Technology, Health, and Precious Metals & Mining). The results imply that the coronavirus has increased market return volatility for the majority of the JSE sectors. These sectors (ALSHI, SmallCap, ALTX, Top40, Telecommunications, Basic Materials, Consumer Discretionary, Consumer Services, Industrials and Energy) were found to be more responsive to the adverse effects caused by the pandemic. The implication is that investments in such sectors can increase investors' active risks. Portfolio managers and investors should reduce or diversify their holdings in these sectors to hedge positions from fluctuations during pandemics. However, these sectors can be used to increase investors' aggressiveness in portfolio construction. The study did not find a change in volatility for the Tech, HC and PMM sectors following the coronavirus shock, which advocates a possible provision of return stability in these sectors during the pandemic. These sectors could be targets for diversification and hedging for investors during market shocks such as the coronavirus pandemic.

The ARCH and GARCH parameters were found to be positive and statistically significant for all the sectors (except for the Alternative Exchange, which showed the ARCH effect only), providing evidence of volatility clustering, implying that internal/own shocks drive volatility for JSE sectors. All the JSE sectors exhibited large GARCH coefficients for all the indices, indicating that shocks to conditional variance are taking longer to die (long memory). Also, the volatility shocks were highly persistent during the COVID-19 pandemic. The results imply that the COVID-19 shock will take effect for a long time into the future, and prolonged market volatility periods are expected. To survive the prolonged market volatility spell, portfolio managers and investors can use this information to implement market timing strategies (to capitalize on market shifts), sector rotation, efficient portfolio selection and adaptive risk management strategies. Diversification in stable and low-risk assets should be considered for risk-averse investors as equities provide poor protection against market volatility during market turbulence. Risk takers can profit by investing in stocks during historic lows and exiting the positions as markets eventually emerge from the shock. For the Health, Technology and Energy sectors, the study found evidence of low persistence in volatility compared to the other sectors.

The asymmetric models indicate the existence of asymmetric effect for all the sectors (except the Health, Finance, Technology and Precious Metals & Mining) during the pandemic. The finding implies a strong reaction to negative news such as a surge in COVID-19 cases, increasing volatility more than good news for the majority of the JSE sectors. Thus, investors should expect their equity holdings in these sectors to lose more following adverse developments in the pandemic compared to positive market development gains. The Telecommunications and Small Cap indices exhibited a higher impact of negative news from all sectors, indicating that holdings in these sectors suffered more significant losses resulting from negative information during such market shocks. Investors should demand a higher return from such sectors during market shocks to compensate for the higher risk. The asymmetric term for the Health, Finance, Technology, and Precious Metals & Mining sectors suggests the non-existence of differences between negative and positive volatility in these sectors. For investors, these sectors could be better targets for sector rotation during such market shocks. The FIGARCH model indicates that the ALSHI, Top 40 and PMM had a fast process of mean reversion during the sample period, showing that investments in these sectors revert to their mean values quicker than other sectors of the JSE after a shock.

Regarding conditional correlations from the DCC-GARCH models on the major JSE indices (ALSHI, Top 40, ALTX and the Small Cap), we found significant high positive correlations between the ALSHI and the Top 40, with the ALSHI and Small Cap suggesting fewer diversification benefits between these indices during a pandemic. The ALTX was found to have lower and declining correlations with the other indices, indicating an increase in diversification benefits offered by the ALTX to other indices following the COVID-19 pandemic shock.

Concerning financial implications, our findings show the presence of volatility clustering for the majority of the JSE indices. Following the COVID-19 pandemic shock, there was a significant increase in volatility, and the phenomenon of volatility clustering implies that this shock will be felt for some time into the future. Hence, investors and portfolio and risk managers should use this knowledge to adjust their value at risk (VaR) estimates, adjust their capital, and take advanced measures to ensure that their institutions and portfolios can bear the additional risk in high shock periods. The knowledge of the impact of COVID-19 on return volatility also helps investors in making informed investment decisions when choosing appropriate investments based on the different effects of the pandemic on various sectors of the stock market. Understanding the nature and degree of market volatility helps policymakers to set in motion the necessary steps to alleviate any potential market burst and economic fallout from the virus through necessary intervention policies, especially for the most affected industries and sectors. For instance, targeted fiscal stimulus assures businesses that they will get the required policy and financial support to uphold the functioning of the stock markets, the means through which firms raise finances to support economic growth. The more capital markets nosedive, the more difficult it will be to recover from the devastating effects of this pandemic.

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REFERENCES

Albulescu, C. (2020). Coronavirus and financial volatility: 40 days of fasting and fear. *arXiv preprint arXiv:2003.04005*.Available at: https://doi.org/10.2139/ssrn.3550630.

Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of environmental and social stocks: An analysis of the exogenous COVID-19 market crash. *The Review of Corporate Finance Studies, 9*(3), 593-621.Available at: https://doi.org/10.1093/rcfs/cfaa011.

Ashraf, B. N. (2020). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance, 54*, 101249.Available at: https://doi.org/10.1016/j.ribaf.2020.101249.

Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 74*(1), 3-30.Available at: https://doi.org/10.1016/s0304-4076(95)01749-6.

Bekiros, S., Gupta, R., & Kyei, C. (2016). On economic uncertainty, stock market predictability and nonlinear spillover effects. *The North American Journal of Economics and Finance, 36*, 184-191.Available at: https://doi.org/10.1016/j.najef.2016.01.003.

Bilson, C. M., Brailsford, T. J., & Hooper, V. C. (2002). The explanatory power of political risk in emerging markets. *International Review of Financial Analysis, 11*(1), 1-27.Available at: https://doi.org/10.1016/s1057-5219(01)00067-9.

Bloom, D. E., Cadarette, D., & Sevilla, J. P. (2018). Epidemics and economics. *Finance & Development, 55*(2), 64.Available at: https://doi.org/10.5089/9781484357415.022.

Brooks, C. (2019). *Introductory econometrics for finance*: Cambridge University Press.

Cermeño, R., & Suleman, M. (2014). *Country risk and volatility of stock returns: Panel-GARCH evidence for the Latin Americas major five*. Unpublished Thesis, Victoria University of Wellington, Wellington.

Chopra, V. K., & Ziemba, W. T. (1993). The effect of errors in means, variances, and covariances on optimal Portfolio choice. *The Journal of Portfolio Management, 19*(2), 6-11.Available at: https://doi.org/10.3905/jpm.1993.409440.

Del Giudice, A., & Paltrinieri, A. (2017). The impact of the Arab Spring and the Ebola outbreak on African equity mutual fund investor decisions. *Research in International Business and Finance, 41*, 600-612.Available at: https://doi.org/10.1016/j.ribaf.2017.05.004.

Delivorias, A., & Scholz, N. (2020). Economic impact of epidemics and pandemics, EPRS: European Parliamentary Research Service. Retrieved from: https://policycommons.net/artifacts/1337306/economic-impact-of-epidemics-and-pandemics/1945029/. [Accessed 08 May 2022].

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*(366a), 427-431.Available at: https://doi.org/10.2307/2286348.

El Rhadbane, A. B., & Moudden, A. E. (2022). COVID-19 pandemic, real effective exchange rate and foreign direct investment inflows: Evidence from Morocco, Turkey and Egypt. *International Journal of Applied Economics, Finance and Accounting, 12*(2), 38–51.Available at: https://doi.org/10.33094/ijaefa.v12i2.543.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics, 20*(3), 339-350.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987-1007.Available at: https://doi.org/10.2307/1912773.

Engle, R. F., & Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The Journal of Finance, 48*(5), 1749-1778.

Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric Reviews, 5*(1), 1-50.Available at: https://doi.org/10.1080/07474938608800095.

Fan, V. Y., Jamison, D. T., & Summers, L. H. (2018). Pandemic risk: How large are the expected losses? *Bulletin of the World Health Organization, 96*(2), 129-134.Available at: https://doi.org/10.2471/blt.17.199588.

Fernandes, N. (2020). Economic effects of Coronavirus outbreak (COVID-19) on the world economy (March 22, 2020). IESE Business School Working Paper No. WP-1240-E, Available at SSRN: https://ssrn.com/abstract=3557504 or http://dx.doi.org/10.2139/ssrn.3557504.

Ghorbel, A., & Jeribi, A. (2021). Investigating the relationship between volatilities of cryptocurrencies and other financial assets. *Decisions in Economics and Finance, 44*(2), 817-843.Available at: https://doi.org/10.1007/s10203-020-00312-9.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779-1801.Available at: https://doi.org/10.1111/j.1540-6261.1993.tb05128.x.

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters, 35*, 101512.Available at: https://doi.org/10.1016/j.frl.2020.101512.

Gormsen, N. J., & Koijen, R. S. (2020). Coronavirus: Impact on stock prices and growth expectations. *The Review of Asset Pricing Studies, 10*(4), 574-597.Available at: https://doi.org/10.1093/rapstu/raaa013.

Haacker, M. (2004). The impact of HIV/AIDS on government finance and public services. The macroeconomics of HIV/AIDS, 198. International Monetary Fund. Retrieved from: https://books.google.co.za/books?id=cNoIsYZYObYC.

Hailu, S. M., & Vural, G. (2021). The impact of COVID-19 pandemic on financial markets: Evidence from developed and developing countriesstock markets indexes. *European Journal of Business and Management Research, 6*(4), 372-377.

Hansen, B. E. (1992). Testing for parameter instability in linear models. *Journal of Policy Modeling, 14*(4), 517-533.Available at: https://doi.org/10.1016/0161-8938(92)90019-9.

Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance, 27*, 100343.Available at: https://doi.org/10.1016/j.jbef.2020.100343.

He, Q., Liu, J., Wang, S., & Yu, J. (2020). The impact of COVID-19 on stock markets. *Economic and Political Studies, 8*(3), 275-288.

Hentschel, L. (1995). All in the family nesting symmetric and asymmetric garch models. *Journal of Financial Economics, 39*(1), 71-104.Available at: https://doi.org/10.1016/0304-405x(94)00821-h.

Makoko, K., & Muzindutsi, P.-F. (2018). Modelling return volatility in the main board and the alternative exchange of the Johannesburg stock exchange: Application of GARCH models. *EuroEconomica, 3*(37), 66-76.

May, C., & Farrell, G. (2018). Modelling exchange rate volatility dynamics: Empirical evidence from South Africa. *Studies in Economics and Econometrics, 42*(3), 71-113.Available at: https://doi.org/10.1080/10800379.2018.12097339.

Miah, M., & Rahman, A. (2016). Modelling volatility of daily stock returns: Is GARCH (1, 1) enough? *American Academic Scientific Research Journal for Engineering, Technology, and Sciences, 18*(1), 29-39.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*(2), 347-370.Available at: https://doi.org/10.2307/2938260.

Nyblom, J. (1989). Testing for the constancy of parameters over time. *Journal of the American Statistical Association, 84*(405), 223-230.Available at: https://doi.org/10.1080/01621459.1989.10478759.

Onali, E. (2020). Covid-19 and stock market volatility. *Available at SSRN 3571453*.Available at: https://doi.org/10.2139/ssrn.3571453.

Ozili, P., & Arun, T. (2020). *Spillover of COVID-19: Impact on the global economy*. Germany: University Library of Munich.

PwC. (2020). Learning from the impacts of COVID-19 and leading the recovery. Retrieved from https://www.pwc.com/gx/en/issues/crisis-solutions/covid-19.html.

Suleman, T., Gupta, R., & Balcilar, M. (2017). Does country risks predict stock returns and volatility? Evidence from a nonparametric approach. *Research in International Business and Finance, 42*, 1173-1195.Available at: https://doi.org/10.1016/j.ribaf.2017.07.055.

Takyi, P. O., & Bentum-Ennin, I. (2021). The impact of COVID-19 on stock market performance in Africa: A Bayesian structural time series approach. *Journal of Economics and Business, 115*, 105968.Available at: https://doi.org/10.1016/j.jeconbus.2020.105968.

Wooldridge, J. M. (2003). Further results on instrumental variables estimation of average treatment effects in the correlated random coefficient model. *Economics Letters, 79*(2), 185-191.Available at: https://doi.org/10.1016/s0165-1765(02)00318-x.

Yousef, I. (2020). Spillover of COVID-19: Impact on stock market volatility. *International Journal of Psychosocial Rehabilitation*, *24*(6), 18069-18081.

Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020). Infected markets: Novel coronavirus, government interventions, and stock return volatility around the globe. *Finance Research Letters*, *35*, 101597.Available at: https://doi.org/10.1016/j.frl.2020.101597.