STATISTICS IN TRANSITION new series, March 2023
Vol. 24, No. 2, pp. 17–37, DOI 10.59170/stattrans-2023-018
Received – 01.01.2021; accepted – 04.08.2022

Modelling the volatility of African capital markets in the presence of the Covid-19 pandemic: evidence from five emerging economies in Africa

Nureni Olawale Adeboye[1], **Sakinat Oluwabukonla Folorunso**[2], **Olawale Victor Abimbola**[3], **Rasaki Yinka Akinbo**[4]

Abstract

The growing concern over the global effects of the COVID-19 pandemic on every aspect of human endeavour has necessitated a continuous modelling of its impact on socio-economic phenomena, allowing the formulation of policies aimed at sustaining future economic growth and mitigating the looming recession. The study employed Exponential Generalised Autoregressive Conditional Heteroscedasticity (EGARCH) procedures to develop stock volatility models for the pre- and COVID-19 era. The Fixed-Effects Two Stage Least Square (TSLS) technique was utilised to establish an empirical relationship between capital market volatility and the COVID-19 occurrence based on equity market indices and COVID-19 reported cases of five emerging African economies: Nigeria, Egypt, South Africa, Gabon and Tanzania. The stock series was made stationary at the first order differencing and the model results indicated that the stock volatility of all the countries responded sharply to the outbreak of COVID-19 with the average stock returns of Nigeria and Gabon suffering the most shocks. The forecast values indicated a constant trend of volatility shocks for all the countries in the continuous presence of the COVID-19 pandemic. Additionally, the confirmed and death cases of COVID-19 were found to increase stock prices while recovered cases bring about a reduction in the stock prices in the studied periods.

Key words: African countries, capital market, COVID-19, volatility, GARCH model.

1. Introduction

Capital market is one of the major pilots of fiscal growth and economic development, of which its activities have been a daily occurrence save for non-working

[1] Deartment of Statistics, Osun State University, Osogbo, Nigeria. E-mail: nureni.adeboye@uniosun.edu.ng. https://orcid.org/0000-0002-8023-221X
[2] Department of Mathematical Sciences, Olabisi Onabanjo University, Ago Iwoye, Nigeria. E-mail: sakinat.folorunso@oouagoiwoye.edu.ng.
[3] Data Science Nigeria, Nigeria. E-mail: olawale@datasciencenigeria.ai.
[4] Department of Mathematical Sciences Federal Polytechnic Ilaro, Nigeria. E-mail: rasaki.akinbo@federalpolyilaro.edu.ng.

days (Adeboye and Fagoyinbo, 2017; Olowe, 2009). Globally, there is an increasing reliance on stock trading data as a fundamental tool for making reliable investment decisions and the Africa case is not an exception. Therefore, it is a fundamental reality that the capital market constitutes one of the major pitfalls of the Covid-19 outbreak. The capital market can be an extremely volatile place with broad day-to-day swings that present a significant investment risk. In modelling stock market time series data, the presence of long memory is very obvious. The behaviours of the investors are influenced, which can make their decisions based on different investment horizons. Stock market data were found to exhibit characteristics that are more consistent with long memory (Baillie, 1996). However, national and regional economic factors like interest rate policies, inflation trends, tax etc. have been found to substantially contribute to the directional change of the market, thus portend greater potentials to influence volatility. Capital market volatility is a statistical evaluation of the variation in returns for a given stock or market index. According to Chiang and Dong (2001), a higher level of volatility appears to be associated with higher average returns in most cases, however, unexpected volatility that is adverse could spell doom for would-be investors. This has been a contentious issue in wealth creation across the globe with a surfeit of literature on how to mitigate its effect and its impact on investment drives and economic activities of every nation (Ser-Huang and Taylor, 1992; Pramod and Puja, 2015). However, according to Ayinde et al. (2020) and Oyelola et al. (2020), the global occurrence of coronavirus with its antecedent daily upsurge in the count of confirmed cases around the globe is becoming alarming, and according to the NSE (2020) report, one can say it has nearly shut down the capital market with almost all the known bullish stocks experiencing a worsening rate of volatility. Weltman (2020) opined that risk experts in financial matters have made significant efforts to rearrange their market appraisal in light of the unprecedented economic challenges posed by the Covid-19 crisis that has put nearly all the globe in virtual lockdown. In the same Euromoney report, M. Nicolas Firzli refers to the Covid-19 effect on the financial market as the peak of all financial crisis and opined that it is bringing to the fore many repressed financial and geopolitical disorders. As highlighted by the Financial Times Stock Exchange and Dow Jones Industrial Average reports, 100 companies listed on the London stock exchange with the highest market capitalization dropped beyond three percent as COVID-19 outbreak worsened and spread beyond China. On February 27th 2020, due to persistent concerns posed by the coronavirus outbreak, most United States capital market indices indicated the sharpest declines since 2008. On the overall, capital markets declined beyond 30% as at March 2020 implied volatilities of equities have spiked to crisis levels; credit spreads on non-investment grade debt have widened sharply as investors attempt to reduce risks (Barron's, 2020). This uncertainty in global financial markets is occurring despite the elaborate financial reforms conceptualized by

G-20 financial authorities in the post-crisis era. According to OECD (2020) interim economic outlook highlighted in early March 2020, Covid-19 had already worsened China economic growth, and subsequent outbreaks in other continents were eroding prospects for economic growth. Hitherto, governments of countries have introduced unprecedented measures to contain the epidemic. While it is of necessity to contain the virus, it is of note that measures involved have led to both socio and economic quagmire in the countries mostly affected. Thus, the shutdowns could lead to high declination in the level of economic development, thereby causing most consumers' expenditure to be adversely affected. The magnitude of these occurrences would far outweigh the economic recession experienced during the global financial meltdown if the situations persist for too long.

Presently, COVID-19 remains the most traumatic pandemic threatening the entire globe. According to Adebayo et al., 2020, the first COVID-19 confirmed case in Africa was reported on 14th February 2020 in Egypt, which has been chosen to represent the North Africa region in this research. Since then, the number of reported cases has experienced geometric increases. The United States Embassy in Egypt gave the statistics as 90,413 confirmed cases with 4,480 deaths as of July 23rd, 2020. Nigeria's first case was reported on 27th February 2020, when an Italian citizen in Lagos tested positive for the virus (NCDC, 2020; MacLean et al. 2020). Ayinde et al. (2020) gave the statistics of Nigeria coronavirus as 1,932 confirmed cases, 319 discharged cases, and 58 deaths as of 30th April 2020. These records have experienced daily increase with the total number of confirmed cases in Nigeria now stood at 41,180, of which 860 deaths have been recorded as of 28th July 2020 according to WHO (2020) coronavirus global updates. The WHO reports for African regional office also confirmed South Africa to be the epicentre of the COVID-19 outbreak in Africa region with 45,9761 positive cases identified and 7,257 recorded deaths as of 28th July 2020. South Africa is presently ranked fifth in the whole world. Gabon and Tanzania were confirmed to have recorded their first COVID-19 pandemic in March 2020. Up to 5,087 COVID-19 cases were reported in Gabon as of June 24 with a death toll of 40. As for Tanzania, government authorities ceased all attempts of reporting COVID cases in May 2020 after President John Magufuli alleged that laboratories were giving out fake results of confirmed cases.

WHO records on Covid-19 as of 30th July 2020 indicated 17,039,160 confirmed cases and 667,084 deaths globally. The spread of the disease is so alarming to the extent that the United States of America have recorded 4,427,493 confirmed cases and 150,716 deaths as of date, despite the existence of a well-structured medical system in place. These statistics is closely followed by South America with 2,983,227 confirmed cases, 108,432 deaths, and 2,002,553 recoveries; Europe was reported to have 1,596,917 confirmed cases and 578,319 deaths according to ECDC and CDC (2020) report. Although African continent still has the least records of 625,562 confirmed cases, 13,763 deaths, and 193,481 recoveries according to NBS (2020) report accessed on July 17th, 2020, the socio-economic effect of the pandemic had been so alarming and has further worsened the living standard of the citizenry in Africa (Adhikari et al., 2020). Though the Covid-19 pandemic has been widely acclaimed to have originated from Wuhan city, Hubei China (Giordano et al., 2020; Nadeem, 2020; Huang et al., 2020; Adegboye et al., 2020; Guo et al., 2019). However, in their study, Adegboye et al. (2020) emphasized that the risk of importing the pandemic from Europe to Africa exceeded that of importation from China. Martinez-Alvarez et al. (2020) compared early transmission of the pandemic in selected countries and observed a more rapid spread of the virus in some West African countries than in Europe. Gilbert et al., (2020); Vladimir and Vasily (2020) opined that situation in African countries could be more fatal than what is being reported, as most of African countries are unprepared and not sufficiently capable in the management of disease outbreak. Thus, the need to model capital market volatility as occasioned by the pandemic, to serve as the impetus to project new normal for capital market businesses in the African region and the world at large.

This study investigates the capital market volatility for the pre-COVID-19 era and compared with the activities during the Covid-19 pandemic using equity market indices and Covid-19 reported cases of five (5) emerging economies in Africa. One prominent and economically endowed country was chosen from each of the regions in the African continent. These countries are Nigeria (West Africa), South Africa, Egypt (North Africa), Tanzania (East Africa), and Gabon (Central Africa). We use Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) to model the stock volatility for each of the African countries in the two periods. Fixed-Effects Two Stage Least Square (TSLS) is then employed to model the coronavirus impact on the market activities. EGARCH and TSLS models would be capable of providing forecasts to predict the market volatility in the continuous presence of the pandemic. Currently, most literature on stock market volatility adopted regional and national economic factors approaches for its modelling. For instance, see Ser-Huang & Taylor (1992); Theodore & Lewis (1992); Blinder & Merges (2001); Chiang & Diong (2001); Grundy & Kim (2002); Pramod & Puja (2015). The contribution of this paper is the modelling of the Covid-19 trajectory in the day-to-day volatility of stock market affairs in the African continent.

2. Materials and Methods

The data set used for this research is for the selected countries from the major sub regions of African continent. Stock updates for the five countries under consideration were sourced from Yahoo Finance while COVID-19 data were sourced from different legitimate sources such as World Health Organization (WHO), European Centre for Disease Prevention and Control (ECDC), Nigeria Center for Disease Control (NCDC), Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE), UNICEF and US embassy in African countries. The time series observations of daily returns of stock exchange closing prices between 2019–10–01 to 2020–02–28 (pre-COVID era) and 2020–03–02 to 2021–04–30 (during COVID-19) for the five selected African countries under study, utilized for this research are available as supplementary data shared on GitHub repository link https://bit.ly/37LqPkw. This supplementary data also includes information of the reported Covid-19 cases for the regions. However, some of the observations were no longer available after being subjected to differencing in order to attain stationarity. As a result of these omitted lagged data points, data imputation techniques as suggested by Olalekan et al. (2020) were employed to obtain the missing observation so as to be able to fit the EGARCH model on the data set.

2.1. Volatility Model (Exponential Generalized Autoregressive Conditional Heteroscedasticity)

E-GARCH is a family of the GARCH model. The E-GARCH model was proposed by Nelson (1991) to overcome the challenges of volatility clustering in the handling of GARCH for modelling financial time series.

Let ε_t denote the error term of a time series $\{X_t\}$. If the typical size of ε_t is characterized by stochastic piece u_t and time-dependent standard deviation σ_t, then

$$\varepsilon_t = u_t \, \sigma_t \tag{1}$$

where the stochastic piece u_t is a strong white noise process and the time-dependent variance can be expressed as

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \qquad , \alpha_0 > 0 \tag{2}$$

$$\sigma_t^2 = \alpha_i + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \qquad \alpha_i > 0, i > 0 \tag{3}$$

where p is the length of ARCH lags.

Considering the Autoregressive Moving Average Model $\left[ARMA_{(pq)}\right]$ given as

$$X_t - \alpha_1 X_{t-1} - \cdots - \alpha_p X_{t-p} = \in_t - \beta_1 \in_{t-1} - \cdots - \beta_q \in_{t-q} \tag{4}$$

If equation (4) is assumed for the error variance, then we have

$$X_t = X'_{t-p} \, b + \in_t \tag{5}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \tag{6}$$

Thus, equation (3) can be written for $ARMA_{(pq)}$ as

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{7}$$

$$ln \, \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i (|\epsilon_{t-1}| - \mathrm{E}|\epsilon_{t-1}|) + \gamma_i \epsilon_{t-1} \sum_{j=1}^{q} \beta_j ln \, \sigma_{t-j}^2 \tag{8}$$

Equation (7) is the generalized autoregressive conditional heteroskedasticity $\left[\boldsymbol{GARCH}_{(\boldsymbol{pq})}\right]$ model while equation (8) is the $\boldsymbol{EGARCH}_{(\boldsymbol{pq})}$ where p is the order of the ARCH component; q is the order of the GARCH component; $\boldsymbol{\sigma_t}$ is the volatility at time $\boldsymbol{t}$; $\boldsymbol{\omega}$ ***is the intercept***, $\boldsymbol{\alpha_1}, \cdots, \boldsymbol{\alpha_p}$ are the parameters of the ARCH component; $\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \cdots, \boldsymbol{\beta_q}$ are the parameters of the GARCH component model; $\boldsymbol{\gamma}$ is the magnitude of the shock and $\in_t$ is a zero mean white noise as. It is pertinent to note that there are no sign restrictions for the EGARCH parameters since $\boldsymbol{ln\,\sigma_t^2}$ can be negative. All the parameters $(\boldsymbol{\mu}, \boldsymbol{\omega}, \boldsymbol{\alpha}, \boldsymbol{\gamma}, \boldsymbol{\beta})$ **are estimated** simultaneously by maximizing the log likelihood, where **μ is the expected shares return.**

2.2. Model Specification

The time-series econometric model specified for this research is given as

$$Stock_{it} = \ f(Confirmed_{1.it}, Recovered_{2.it}, Death_{3.it}) + \varepsilon_{it} \tag{9}$$

When this model is written explicitly, it becomes

$$Stock_{it} = \ \beta_0 + \beta_1(Confirmed)_{1.it} \ + \beta_2(Recovered)_{2.it} \ \ - \beta_3(Death)_{3.it} \tag{10}$$

The instrumental variables specified for this model are confirmed, death and recovered variables. The lagged cases variables, i.e. d_confirmed, d_death and d_recovered were excluded from the list of instruments since they are endogenous variables and thus correlated with the residuals.

2.3. Fixed-Effects Two Stage Least Square (TSLS)

TSLS is a fixed effect model which is a special case of instrumental variables regression. In this model, there are two distinct stages of which the first stage involves finding the portions of the endogenous and exogenous variables that can be attributed to the instruments. The stage involves estimating an OLS regression of each variable in the model on the set of instruments while the second stage is a regression of the original equation, with all of the variables replaced by the fitted values from the first-stage regressions. The coefficients of this regression are the TSLS estimates.
By denoting Z as the matrix of instruments, y and X as the dependent and explanatory variables respectively, the computed coefficients and its covariance matrices are given by the equations

$$b_{TSLS} = (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'y \tag{11}$$

$$\hat{\Sigma}_{TSLS} = s^2(X'Z(Z'Z)'Z'X)^{-1} \tag{12}$$

where S^2 is the estimated residual variance.

The strategy for estimation involved taking deviations of the group means to have

$$y_{it} - \bar{y}_i = (x_{1it} - \bar{x}_{1i})'\beta_1 + (x_{2it} - \bar{x}_{2i})'\beta_2 + \varepsilon_{it} - \bar{\varepsilon}_i. \quad (13)$$

3. Results and Discussion

All the indices used for the E-Garch modelling were pulled from the share returns of five (5) African countries considered in this research, for pre and post COVID-19 era. Furthermore, the share returns of all the countries were merged with the daily cases, recoveries and deaths due to COVID-19.

3.1. Descriptive Statistics

Table 1: Descriptive Statistics of Stock Returns of the Considered Countries before Covid-19

Index	Nigeria	South Africa	Tanzania	Gabon	Egypt
Mean	-0.00120	-0.00049	-0.0039	-0.00112	0.00040
Median	-0.00159	0.00117	0.0000	0.00000	0.00000
Minimum	-0.06580	-0.05855	-0.1923	-0.03396	-0.08898
Maximum	0.04702	0.03027	0.1569	0.02290	0.09483
Standard Dev	0.01448	0.01467	0.0375	0.00896	0.02690
Skewness	-0.44	-1.1	-1.2	-0.62	0.41
Kurtosis	7.3	5.5	14	4.8	5.1

Table 1 indicates the descriptive statistics of stock returns before COVID-19. The result shows that Tanzania has the highest volatility in the daily returns of the series, for the periods of average negative share returns for the countries except Egypt. In addition to this, the daily stock returns of Nigeria, South Africa, Tanzania, and Gabon show traces of series that are negatively skewed while the daily stock returns of Egypt are positively skewed. Furthermore, the kurtosis values for the five countries are greater than three (3), which explains that the data set has abnormal peaked than a normal distribution.

According to Table 2 below, Nigeria has the highest mean stock returns of 0.0024 with Egypt having the highest deviation out of all the other four countries. Looking closely, there exist negative skewness for Nigeria and South Africa, while Tanzania, Gabon and Egypt are positively skewed. The series are equally peaked (leptokurtic) for the countries save for that of Egypt which is platykurtic.

Table 2: Descriptive Statistics of Stock Returns of the Considered Countries During Covid-19

Index	Nigeria	South Africa	Tanzania	Gabon	Egypt
Mean	0.00022	0.00013	0.0015	0.0019	0.0024
Median	0.00051	0.00269	0.0000	0.0000	0.000
Minimum	-0.05063	-0.14823	-0.1525	-0.14407	-0.1965
Maximum	0.04251	0.10090	0.3111	0.13333	0.3235
Standard Dev	0.01013	0.02868	0.0513	0.02527	0.0585
Skewness	-0.859	-1.066	1.35	0.382	1.222
Kurtosis	8.58	9.38	9.86	13.92	10.00

The trend of the stock returns time series before and during the COVID-19 periods is presented in Figures 1 and 2 below. The figures captured the different types of shocks observed by daily stock returns in the two periods.

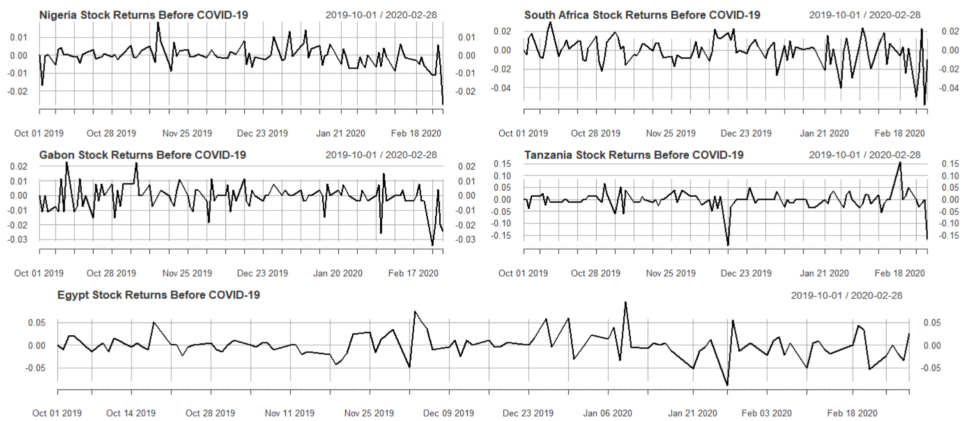

Figure 1: Stock Returns Plot of the Countries Before Covid-19

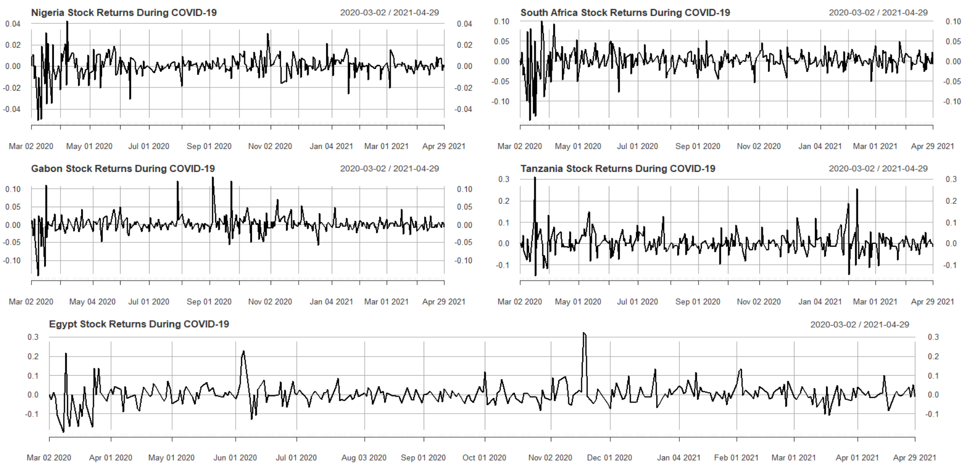

Figure 2: Stock Returns Plot of the Countries During Covid-19

The above plots revealed that each of the stock returns were not stationary at the initial stage and this leads to differencing and each of the data was made stationary

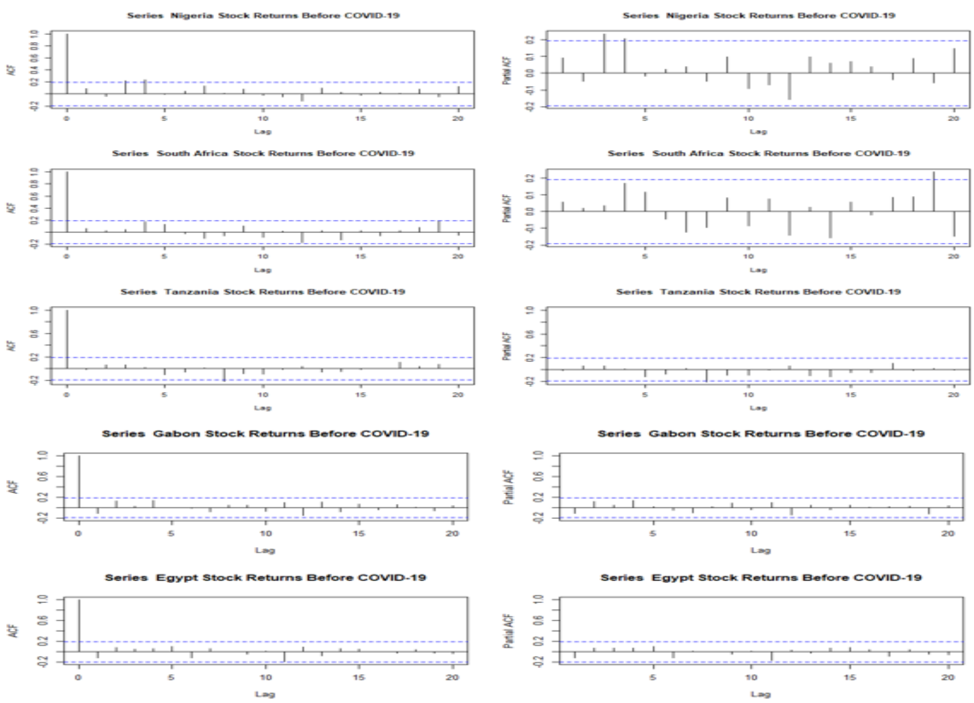

Figure 3: ACF and PACF plots Before COVID-19 for Countries

at the first-order difference, in compliance with the results of the Augmented Dickey Fuller (ADF) test which shows the presence of unit root. The results of ADF are as presented in Table 3 below. The table contains the summary of the results at the level and at the first differencing, which is also a confirmation that the series is stationary at the first order differencing. The small p-values < $\alpha = 0.05$ significance level showed that the series is stationary at the first difference.

Table 3: ADF Results for Unit root Test During COVID-19 for Countries

Country	Test	Lag order	P-value 5%	Test Statistic
Nigeria	*@Level*	4	0.2	-3
	@1stDifference	5	0.01	-6
South Africa	*@Level*	4	0.2	-3
	@1stDifference	5	0.01	-6
Tanzania	*@Level*	4	0.2	-4
	@1stDifference	5	0.01	-5
Gabon	*@Level*	4	0.2	-3
	@1stDifference	4	0.04	-4
Egypt	*@Level*	4	0.06	-3
	@1stDifference	5	0.01	-5

A precise order of differencing was determined by the plots of ACF and PACF. A cross-examination of the ACF showed the presence of long memory structure, and the two plots provided significant spikes at lag 1 in both cases as shown in Figure 3 and Figure 4 for Nigeria returns. Achieving this stationarity condition is highly essential for modelling the adopted volatility technique.

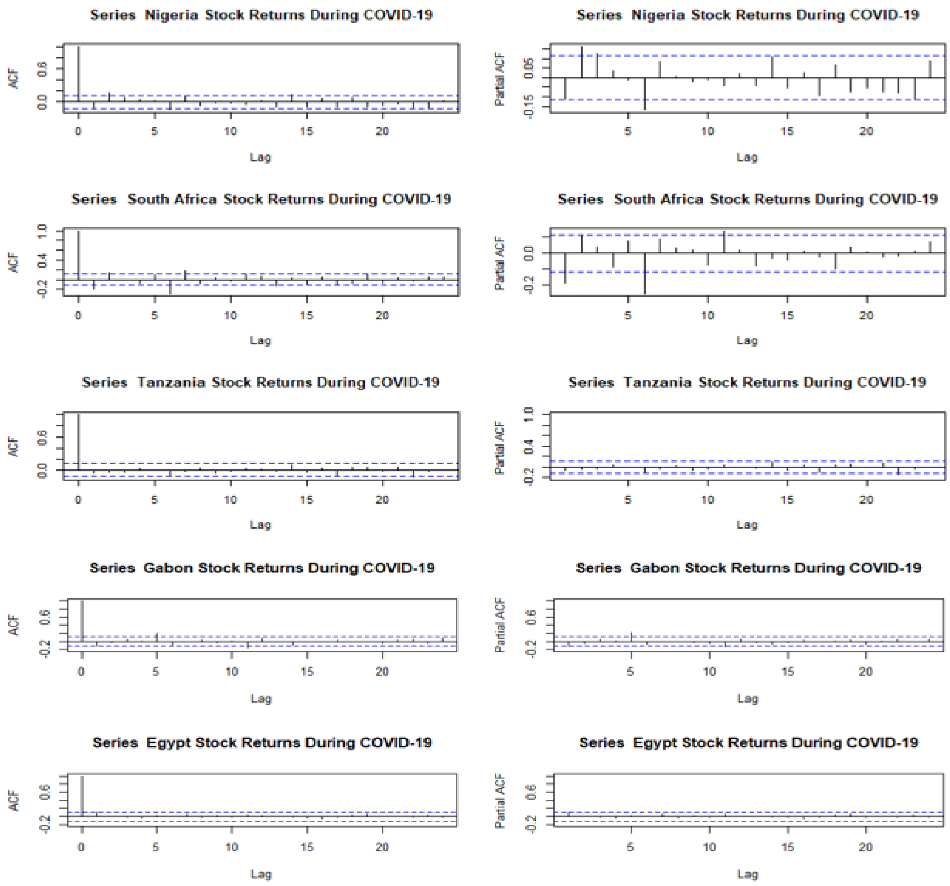

Figure 4: ACF and PACF plots During COVID-19 for Countries

3.2. Summary of Findings: Country by Country Volatility Rates for Pre and Covid-19 Periods

This research adopted a model order of $p = 1$ *and* $q = 1$ because it has the lowest values of Akaike, Bayes, Shibata and Hanan-Quinn information criteria. More so, it has been established as the best order that fits financial time series excellently (Tsay, 2005).

Table 4: Results of Egarch (1,1) Modelling of Stock Returns Volatility Before COVID-19

Parameters	Nigeria	South Africa	Tanzania	Gabon	Egypt
μ	-0.00605 (0.1198)	-0.00378 (0.1185)	0.00370 (0.4231)	0.00001 (0.9464)	-0.00250 (0.4688)
ω	-5.13609 (0.0011)**	-1.24177 (0.1357)	-2.70244 (0.0007)**	-4.56987 (0.0019)**	-2.21648 (0.0037)**

Table 4: Results of Egarch (1,1) Modelling of Stock Returns Volatility Before COVID-19 (cont.)

Parameters	Nigeria	South Africa	Tanzania	Gabon	Egypt
α	-0.04821 (0.7585)	-0.32487 (0.0720)	0.11536 (0.4359)	0.06709 (0.5249)	-0.11993 (0.4566)
β	0.15536 (0.5428)	0.81935 (0.0000)**	0.47592 (0.0012)**	0.41317 (0.0272)*	0.62058 (0.0000)**
γ	0.96837 (0.0000)**	0.66643 (0.0017)**	1.17323 (0.0000)**	1.03121 (0.0000)**	1.26898 (0.0000)**

*Note: P-Values are in parenthesis and *, ** statistically significant at the 5% and 1% significant level.*

Table 4 shows the results of EGARCH (1,1) models for the considered countries before the occurrence of Covid-19 in Africa with the following models specified respectively.

$$log(\sigma_t^2) = -5.136 + 0.155log(\sigma_{t-1}^2) - 0.048\frac{e_{t-1}}{\sigma_{t-1}} + 0.968\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (14)$$

$$log(\sigma_t^2) = -1.241 + 0.819log(\sigma_{t-1}^2) - 0.324\frac{e_{t-1}}{\sigma_{t-1}} + 0.666\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (15)$$

$$log(\sigma_t^2) = -2.702 + 0.465log(\sigma_{t-1}^2) - 0.115\frac{e_{t-1}}{\sigma_{t-1}} + 1.173\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (16)$$

$$log(\sigma_t^2) = -4.569 + 0.413log(\sigma_{t-1}^2) + 0.067\frac{e_{t-1}}{\sigma_{t-1}} + 1.031\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (17)$$

$$log(\sigma_t^2) = -2.216 + 0.620log(\sigma_{t-1}^2) - 0.119\frac{e_{t-1}}{\sigma_{t-1}} + 1.268\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (18)$$

Examining the models (14) – (18), the leverage effect α was negative and at the same time not significant for Nigeria, South Africa, and Egypt's daily stocks. This shows the presence of high risk in stock returns due to the increased leverage induced by negative shocks in the aforementioned countries. On the other hand, there exist no leverage effect on the stock returns of Tanzania and Gabon due to the positive values of their α values. This implies that volatility responds better to favorable news than it does to unsavory news of equal magnitude, as a pointer to the fact that there exists little or no risk in the stock returns of Tanzania and Gabon before the pandemic, especially with the positive average returns of 0.00370 and 0.0001estimated respectively for the countries compared to that of Nigeria, South Africa and Egypt.

The results for β show that only the coefficient of South Africa is close to one (1) and this implies high persistence of volatility shocks for the country while countries like Nigeria, Tanzania, Gabon, and South Africa have experienced a low persistence of volatility shock.

The γ parameter shows the extent at which the magnitude of the shock to the variance affects the future volatility in the daily returns of each country's stock and also the spillover. The estimated γ results are positive estimates for all the countries, and this implies that the magnitude of the spillover effect of the volatility is positively related and significant at both 1% and 5% levels. This shows that the changes in the behaviour of the daily stock prices of each country will influence changes in subsequent behaviours of the prices.

Table 5: Results of Egarch (1,1) Modelling of Stock Returns During COVID-19

Parameters	Nigeria	South Africa	Tanzania	Gabon	Egypt
μ	-0.00044 (0.35501)	-0.00154 (0.34770)**	0.0017 (0.54)	-0.0008 (0.4827)	0.0040 (0.0569)
ω	-3.03575 (0.000442)**	-1.40256 (0.02342)*	-2.7806 (0.0000)**	-4.4548 (0.0000)**	-2.0429 (0.0000)**
α	-0.016552 (0.848044)	-0.12288 (0.2391)	0.0430 (0.5940)	-0.0007 (0.9926)	0.0851 (0.2318)
β	0.652116 (0.0000)**	0.79215 (0.0000)**	0.4897 (0.0000)**	0.36050 (0.0002)***	0.60816 (0.0000)**
γ	1.06462 (0.0000)**	0.69089 (0.0093)**	0.91140 (0.0000)**	0.99653 (0.0000)**	0.78343 (0.0000)**

*Note: P-Values are in parenthesis and *, ** statistically significant at the 5% and 1% significant level.*

Table 5 shows the results of the EGARCH (1,1) models for the considered countries during Covid-19 in Africa with the following models specified in the equations below.

$$log(\sigma_t^2) = -3.035 + 1.064log(\sigma_{t-1}^2) - 0.016\frac{e_{t-1}}{\sigma_{t-1}} + 0.652\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (19)$$

$$log(\sigma_t^2) = -1.402 + 0.690log(\sigma_{t-1}^2) - 0.122\frac{e_{t-1}}{\sigma_{t-1}} + 0.792\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (20)$$

$$log(\sigma_t^2) = -2.780 + 0.911log(\sigma_{t-1}^2) + 0.043\frac{e_{t-1}}{\sigma_{t-1}} + 0.489\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (21)$$

$$log(\sigma_t^2) = -4.454 + 0.996log(\sigma_{t-1}^2) - 0.0007\frac{e_{t-1}}{\sigma_{t-1}} + 0.360\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (22)$$

$$log(\sigma_t^2) = -2.042 + 0.783log(\sigma_{t-1}^2) + 0.0851\frac{e_{t-1}}{\sigma_{t-1}} + 0.608\left|\frac{e_{t-1}}{\sigma_{t-1}}\right| \quad (23)$$

Equations (19), (20), (21), (22), and (23) are the respective Egarch (1,1) models' specification for daily stock prices in Nigeria, South Africa, Tanzania, Gabon, and Egypt during the COVID19 period.

For the Covid-19 period, the average stock returns for the countries are -0.00044, -0.00154, 0.0017, -0.0008 and 0.0040 respectively for Nigeria, South Africa, Tanzania, Gabon and Egypt. These results clearly shown that only Nigeria, South Africa and Gabon average stock returns have suffered significantly from the pandemic effects, compared to the pre-Covid-19 periods. We noticed that there exists no leverage effect on the stock returns of Nigeria, Tanzania, Gabon and Egypt and this implies that volatility in these countries responded well to the Pandemic more than they did in the previous era. These countries, however, experienced no leverage effect due to the fact that α is either positive or negative and which at the same time was not significant. The results for β show that the coefficient values for Nigeria, South Africa and Egypt are close to one. These values imply high persistence of volatility shocks for these countries during the Covid-19 pandemic and, on the other hand, we noticed that the β coefficient for Tanzania and Gabon is relatively low. The γ parameter shows the extent at which the magnitude of the shock to the variance affects the future volatility in the daily returns of each country's stock and also the spillover. These estimated γ shows that there is a positive estimate for Nigeria, South Africa, Tanzania, Gabon and Egypt. This means that the magnitude or the spillover of the volatility is positively related and significant at 1% level. This shows that the changes in the behaviour of the daily stock prices of each of the countries will influence changes in subsequent behaviours of the prices.

The graphs in Figure 5 below presented the impact of Covid-19 on the volatility of stock returns for the five countries. Based on the graphs, the stock volatility of all the countries responded sharply to the outbreak of COVID-19. With the exception of Gabon, the returns for the countries nosedived and remained constant for most of the periods ε_{t-1}.

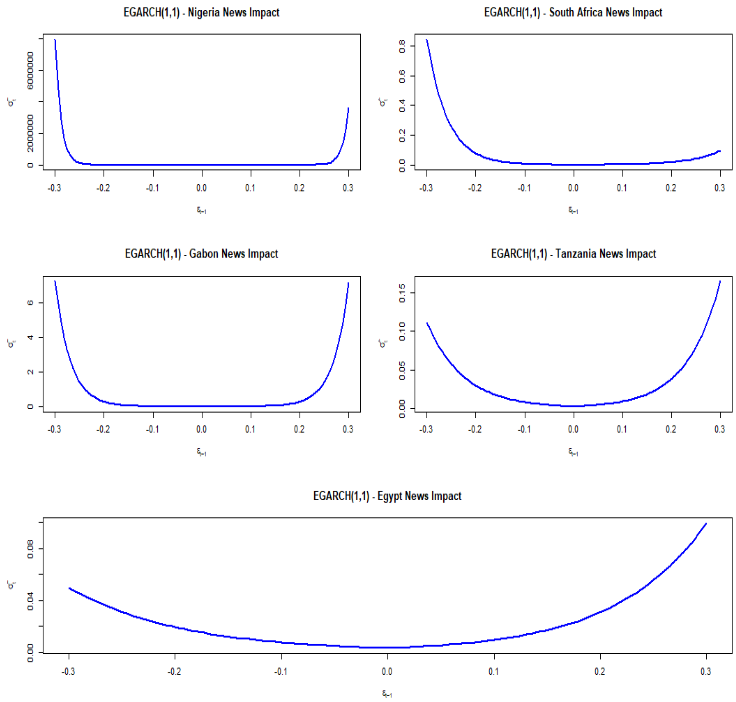

Figure 5: COVID-19 Impact on the Stock Returns of Nigeria, South Africa, Tanzania, Gabon and Egypt

3.3. Consolidated Effects of Covid-19 Trajectory on Stock Volatility

The results of 2SLS estimated to model the effect of Covid-19 on the countries' stock returns are presented in Table 6 while its validity statistic are given in Table 7 below.

Table 6: Results of Instrumental Variable (2sls)

Specification	coefficient	std. error	t-ratio	p-value
Const	-47.01110362	16.01185123	-2.936019262	0.0033**
Confirmed	0.006351376	0.001401122	4.533065161	6.14E-06**
Deaths	0.036818759	0.008865751	4.152920586	3.41E-05**
Recovered	-0.008172232	0.001820635	-4.488672282	7.55E-06**

*Note: P-Values are in *, ** are statistically significant at the 5% and 1% significant level.*

Table 7: Model Diagnostic of IV (2sls)

Mean dependent var	22.502	S.D. dependent var	38.0
Sum squared residual	86709876.35	S.E. of regression	202.6
R-squared	0.019968308	Adjusted R-squared	0.018
F(3, 2111)	7.157	P-value(F)	8.82E-05
Log-likelihood	-46703.4761	Akaike criterion	93414.9
Hausman test	911.00	p-value	3.97E-200

The Instrumental variable model which was specified from Table 6 above is shown below:

$$Stock_{it} = -47.011 + 0.0063(Confirmed)_{1.it} - 0.008(Recovered)_{2.it} + 0.036(Death)_{3.it} \tag{27}$$

Equation (27) specified the direct impact of Covid-19 cases (i.e. confirmed, deaths and recoveries) on the stock returns of all the countries pooled together and the individual parameters are significant based on their p-values provided in Table 7. The model provided overall goodness of fit as reflected in its F-value of 7.157 with P-value of 0.0000882. More so, the results of the estimated coefficients aligned with the a priori. That is, confirmed and death cases increase price volatility while recovered cases will bring about reduction in the stock prices. Based on the results shown in Table 7, this instrument can be considered as exogenous given that the null hypothesis is not rejected at both 1% and 5% levels as measured by the Hausman test statistic.

3.4. Forecast

Predicted values of the fitted EGARCH (1,1) were studied using the test data after adequacy check of the models was done. An unconditional sigma forecast was made for the days in the month of October, November and December 2021. The forecast values exhibited a constant trend of volatility shocks for all the countries in the continuous presence of the Covid-19 pandemic. However, Nigeria volatility experienced a significant spike during the few days of October before maintaining a constant trend. The extreme coloured ends of the graphs presented in Figure 6 (a - e) depicted the forecasts.

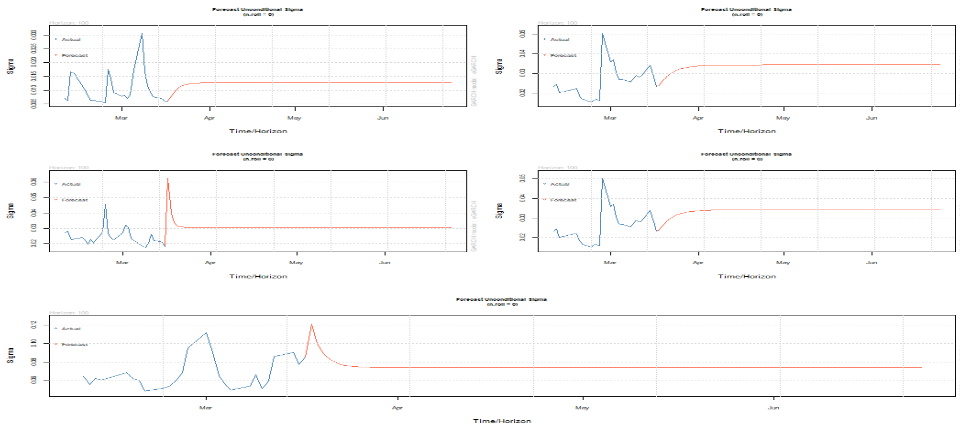

Figure 6: Volatility Forecasts in the Continuous Presence of COVID-19

3. Conclusions

This article has exemplified and emphasized through empirical analysis, the impact of Covid-19 on the volatility of stock markets within the African continent. Stock volatility during COVID-19 compared well with that of the pre-COVID-19 period and it has been well established that the stock volatility of all the countries responded sharply to the outbreak of COVID-19 with the average stock returns of Nigeria and Gabon suffering the most shocks from the pandemic effects. The stock returns of the five countries equally exhibited a long memory as the autocorrelation function of the series showed persistence characteristic with exponential decay towards zero, which is one of the features of a long memory process. The results thus implied high persistence of volatility shocks for all the countries during the Covid-19 pandemic and that the magnitude or the spillover effect of the volatility is positively related and highly significant. The positive feat achieved in terms of average returns by South Africa, Tanzania and Egypt during the pandemic may be attributed to smart investors' bargain, their bullish attitudes gingered by the release of positive year-end financial results of several quoted companies, coupled with improved dividend declaration. The study has also established that confirmed and death cases increase stock price volatility while recovered cases will bring about reduction in stock prices for all the countries considered in this research. Also, the forecast values exhibited a constant trend of volatility shocks for all the countries in the continuous presence of the Covid-19 pandemic. The implication of this trend is such that many investors will not be willing to stake their funds in the capital markets as long as the Covid-19 pandemic persists. Thus, stock prices might remain unchanged for a long period due to the inactive capital market.

The above deduction is in line with the submission of Jeremy Schneider, a personal financial expert at Personal Finance Club, on the effect of the ongoing war on the stock market of Ukraine. He posited that the war has introduced new uncertainty to a stock market that has already had a shaky start to the year, and that the S&P 500 saw its most dramatic one-day drop since May 2020, amid a war with no end in sight. With hundreds of civilians dead, including children, and more than half a million refugees having fled Ukraine, the most important consequence is clearly the human cost, rather than anything having to do with people's investments. As the war continues, so does the unpredictability of the consequences beyond the borders of Ukraine, according to Vaughn (2022). This conclusion is also in tune with the earlier work of Scott *et al.* (2016), where the authors were of the opinion that uncertainty caused by irregular variation such as the ongoing war between Russia and Ukraine is associated with greater stock price volatility and reduced investment.

Acknowledgement

The authors wish to acknowledge the online data producers through which the data for this research were sourced.

References

Adebayo A. O., Esther O. O., Kafilat A. B., Mayowa J. F., (2020). Preliminary Evaluation of COVID-19 Disease Outcomes, Test Capacities and Management Approaches among African Countries. *Cold Spring Harbor Laboratory*.

Adeboye, N. O., Fagoyinbo, I. S., (2017). Fitting of Seasonal Autoregressive Integrated Moving Average to the Nigerian Stock Exchange Trading Activities. *Edited Proceedings of 1st International Conference, Professional Statistical Society of Nigeria,* vol. 1, pp. 12–16.

Adegboye, O., Adekunle, A., Pak, A., Gayawan, E., Leung, D., Rojas, D., Elfaki, F., Mcbryd, E., Eisen, D., (2020). Change in outbreak epicenter and its impact on the importation risks of COVID-19 progression: A modelling study. *medRxiv 2020.*

Adhikari S. P., Shameng S, Wu Y., Mao Y., Ye R., Wang Q., Sun C., Sylvia S., Rozelle S., Raat H, Zhou H., (2020). Epidemiology, causes, clinical manifestation and diagnosis, prevention and control of coronavirus disease (COVID-19) during the early outbreak period: a scoping review. Infectious Diseases of Poverty 2020, vol. 9, issue 1, pp. 29. doi:10.1186/s40249-020-00646-x.

Arellano, M., Bond. S., (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies,* vol.58, issue 2, pp. 277–297.

Ayinde, K., Adewale,F. L., Rauf, I. R., Alabi, O. O., Okon, C. E., Ayinde, E. O., (2020). Modeling Nigerian Covid-19 cases: A comparative analysis of models and estimators. *Chaos, Solitons and Fractals*, vol. 138 (2020) 109911. https://doi.org/10.1016/j.chaos.2020.109911, 0960-0779/© *Elsevier*.

Baillie, R., (1996). Long Memory Processes and Fractional Integration in Econometrics. vol. 73, issue 1, pp. 5–59.

Baker, S. R., Bloom, N., Davis, S. J., (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4), pp. 1593–1636.

Barron's (2020). The Dow Is Down 700 Points as the Coronavirus Strikes in Europe. https://www.barrons.com/articles. Accessed July 28.

Blinder, J. J., Merges, M. J., (2001). Stock Market Volatility and Economic Factors. *Review of Quantitative Finance and Accounting*, vol. 17, pp. 5–26.

CDC, (2020). Centre for Disease Control. Available at https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/cases-in-us.html. Accessed July 20.

Chiang, T. C., Doong, S., (2001). Empirical Analysis of Stock Returns and Volatility: Evidence from Seven Asian Stock Markets Based on TAR-GARCH Model. *Review of Quantitative Finance and Accounting,* vol. 17, pp. 301–318 https://doi.org/10.1023/A:1012296727217.

ECDC, (2020) European Centre for Disease Prevention and Control. Available at https://www.ecdc.europa.eu/en/covid-19-pandemic. Accessed July 20.

Giordano G, Blanchini F, Bruno R, Colaner P, Filippo A. D., Matteo Ad, Colaneri M., (2020). Nat Med 2020: 1–32. doi:10.1038/s41591-020-0883-7.

Gilbert, M., Pullano, G., Pinotti, F., Valdano, E., Poletto, C. Boëlle, P. Y., D'Ortenzio, E., Yazdanpanah, Y., Eholie, S. P., Altmann, M., (2020). Preparedness and vulnerability of African countries against importations of COVID-19: a modelling study, *Lancet,* vol. 395, pp. 871–877.

Grundy, B. D., Kim, Y., (2002). Stock Market Volatility in a Heterogeneous Information Economy. *Journal of Financial and Quantitative Analysis,* vol. 37, issue 1, pp.1–27. https://doi.org/10.2307/3594993.

Guo Y, Cao Q, Hong Zhong-Si, Yan Y., (2019). The origin, transmission and clinical therapies on coronavirus disease 2019 (COVID-19) outbreak – an update on the status. *Military Medical Research,* vol. 7, issue 1, doi:10.1186/s40779-020-00240-0.

GitHub, (2020). *olawale0254/Dataset-of-daily-stock-prices-and-Covid-19-Reported-Cases-in-Selected-African-Countries.* A Data Repository for an Econometric Modelling for Stock and Covid-19, https://bit.ly/37LqPkw.

Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y., (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet 2020,* vol. 395, pp. 497–506, doi:10.1016/S0140-6736(20)30183-5.

JHU CSSE, (2020). An Interactive Web-based dashboard to track COVID-19 in real time, https://www.arcgis.com/apps/opsdashboard/index.html#/bda7594740fd4029942346 7b48e9ecf6.

Maclean, O.A., Orton, R., Singer, J. B., Robertson, D. L., (2020). Response to *On the origin and continuing evolution of SARS-CoV-2*, http://virological.org/t/ response-to-on-the-origin–and-continuing-evolution-of-sars-cov-2/418.

Olowe, R. A., (2009). Modelling Naira/Dollar Exchange Rate Volatility: Application of Garch and Asymmetric Models. *International Review of Business Research Papers*, vol. 5, issue 3, pp. 377–398.

NCDC, (2020). http://covid19.ncdc.gov.ng. Accessed July 16.

Nigerian Stock Exchange Weekly Market Report, (2020). https://www.nse.com.ng. Accessed July 18.

Martinez-Alvarez, M., Jarde, A.; Usuf, E., Brotherton, H., Bittaye, M., Samateh, A. L., Antonio, M., Vives-Tomas, J., D'alessandro, U., Roca, A., (2020). COVID-19 Pandemic in west Africa. *Lancet Glob. Health.*

NBS, (2020). Covid-19 Impact Monitoring, Round 2, Nigeria COVID-19, National Longitudinal Phone survey with support from the World Bank, https://www.nigerianstat.gov.ng. Accessed July 17.

Nelson, D. B., (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica*, 59(2), pp. 347–370, doi: 10.2307/2938260, https://www.jstor.org/stable/2938260.

Nadeem S., (2020). Coronavirus COVID-19: Available Free Literature Provided by Various Companies. Journals and Organizations around the World. *J Ong Chem Res 2020,* vol. 5, issue 1. pp. 7–13. Document ID: 2020JOCR37, doi: 10.5281/zenodo.3722904.

OECD, (2020). Global financial markets policy responses to COVID-19. http://www.oecd.org/coronavirus/policy-responses/global. Accessed July 28.

Olalekan J. Akintande., Olusanya E. Olubusoye., Adeola F. Adenikinju., Busayo T. Olanrewaju, (2020). Modeling the determinants of renewable energy consumption: Evidence from the five most populous nations in Africa. *Energy,* 206(2020) 117992, https://doi.org/10.1016/j.energy.2020.117992, 0360-5442/© 2020 Elsevier.

Oyelola A. A., Adeshina I. A., Ezra G., (2020). Early Transmission Dynamics of Novel Coronavirus (COVID-19) in Nigeria. *International Journal of Environmental Research and Public Health,* vol. 17, pp. 3054, doi: 10.3390/ijerph17093054.

Pramod, K. N., Puja, P., (2015). Stock Market Volatility and Equity Trading Volume: Empirical Examination from Brazil, Russia, India and China (BRIC). Global Business Review, 16(5), https://doi.org/10.1177/0972150915601235.

Ser-Huang, P., Taylor, S. J., (1992). Stock returns and volatility: An empirical study of the UK stock market. *Journal of Banking and Finance*, 16(1), pp. 37–59, https://doi.org/10.1016/0378-4266(92)90077-DGet rights and content.

Scott R. B., Nicholas B., Steven J. D., (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, 131(4), pp. 1593–1636, https://doi.org/10.1093/qje/qjw024.

Tsay, R. S., (2005). Analysis of Financial Time Series – 2nd Ed. Wiley-Interscience.

Theodore, F. D., Lewis, M., (1992). Stock market volatility and the information content of stock index options. *Journal of Econometrics,* vol. 52, issue 1–2, pp. 267–287.

UNICEF, (2020). UNICEF Gabon Covid-19 Report, https://www.africanews.com/2020/06/28/coronavirus, Accessed July 28, 2020.

U.S. Embassy in Egypt, (2020). Covid-19 Information. https://eg.usembassy.gov/u-s-citizen-services/covid-19-informatio, Accessed July 28.

Vladimir R. C., Vasily V. L., (2020). Ribonucleocapsid Assembly/packaging Signals in the Genomics of the Coronaviruses SARS-CoV and SARS-CoV-2; Detection, Comparison and implications for Therapeutic Targeting. *Journal of Biomolecular Structure and Dynamics*.

Vaughn H., (2020). War in Ukraine Means Fresh Volatility for the Stock Market. That Shouldn't Change Your Investing Strategy, https://time.com/nextadvisor/investing/stock-market-rattled-by-russia-ukraine/ Accessed May 10, 2022.

Weltman, J., (2020). ECR risk experts contemplate another financial crisis. *Euromoney*, https://www.euromoney.com/article. Accessed July 28.

WHO, (2020). Africa report COVID-19 case, https://www.afro.who.int/health-topics/coronavirus-covid-19. Accessed July 28.

WHO, (2020). Global Covid-19 updates, https://covid19.who.int. Accessed July 28.

Yahoo Finance, (2020). Stock Market Live Quotes, Business & Finance News. https://finance.yahoo.com/.

Yi Hu, Dongmei G., Ying D., and Shouyang W., (2014). *Estimation of NonlinearDynamic Panel Data Models with Individual Effects.* Mathematical Problems in Engineering, Article ID 672610, http://dx.doi.org/10.1155/2014/672610.