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Modelling the Impact of the COVID-19 Pandemic on Some Nigerian Sectorial Stocks: Evidence from GARCH Models with Structural Breaks

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Abstract: This study provides evidence of the impact of COVID-19 on five (5) Nigerian Stock Exchange (NSE) sectorial stocks (NSE Insurance, NSE Banking, NSE Oil and Gas, NSE Food and Beverages, and NSE Consumer Goods). To achieve the goal of this paper, daily stock prices were obtained from a secondary source ranging from 2 January 2020 to 25 March 2021. Because of the importance of incorporating structural breaks in modelling stock returns, the Zivot–Andrews unit root test revealed 20 January 2021, 26 March 2020, 27 July 2020, 23 March 2020 and 23 March 2020 as potential break points for NSE Insurance, NSE Food, Beverages and Tobacco, NSE Oil and Gas, NSE Banking, and NSE Consumer Goods, respectively. This study investigates the volatility in daily stock returns for the five (5) Nigerian Stock Exchange (NSE) sectorial stocks using nine versions of GARCH models (sGARCH, girGARCH, eGARCH, iGARCH, aPARCH, TGARCH, NGARCH, NAGARCH, and AVGARCH); in addition, the half-life and persistence values were obtained. The study used the Student *t*- and skewed Student *t*-distributions. The results from the GARCH models revealed a negative impact of COVID-19 on the NSE Insurance, NSE Food, Beverages and Tobacco, NSE Banking, and NSE Consumer Goods stock returns; however, the NSE Oil and Gas returns showed a positive correlation with the COVID-19 pandemic. This study recommends that the shareholders, investors, and policy players in the Nigerian Stock Exchange markets should be adequately prepared in the form of diversification of investment in stocks that can withstand future possible crises in the market.

Keywords: COVID-19; NSE; GARCH; structural breaks; persistence; half-life

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1. Introduction

The COVID-19 virus was first reported in Wuhan city of China in December 2019 [1], while in Africa, the first COVID-19 case was recorded in Egypt on 14 February 2020 [2]; however, for Nigeria, the first COVID-19 case was recorded on 27 February 2020 [3,4]. COVID-19 impacted both developed economies such as USA, Germany, UK, etc., and developing economies such as Nigeria, Egypt, Morocco, etc. [5]. The impact of COVID-19 on any economy cannot be overemphasized: world economies are expected to have a negative growth of 4.4% in 2020 [6], while developing economies would record a negative growth of 5.6% in the year 2020 [7].

Due to the impact of COVID-19, many economies were in lockdown, leading to a loss in Gross Domestic Product (GDP), of which the financial market was not left out.

In the past, world stock markets have suffered from global financial crises and now, the market is been plague by the COVID-19 pandemic of which developed, developing, and underdeveloped economies and markets are not left out. The stock market can be viewed as a major component in the financial sector of most developing countries such as Nigeria, which can serve as a pivotal role in the development of and contribution to economic growth, through the potential diversification and possible pooling of savings from different investors and making such funds available to companies for optimal utilization. The Nigeria financial market as a case in this study becomes necessary because the study of [5] considered Nigeria as one of the four emerging markets in Africa.

Some previous studies such as ref. [8] used primary data to study the impact of COVID-19 on Nigeria's financial market performance; ref. [3] studied the impact of COVID-19 on the aggregate financial market in Nigeria; while ref. [9] studied the impact of COVID-19 and the economic crisis on the performance of the Nigerian stock market. These studies focused on the impact of COVID-19 on the aggregate Nigerian stock market, but in this present study, we focused on the Nigerian sectorial stock market using some family GARCH models. The major contributions of this study include the following:

i. Contribution to the literature of GARCH models with an exogenous variable (in this case, COVID-19).
ii. In-depth study of each sector stock market of Nigeria's financial market to see how each fared during the COVID-19 pandemic.

Recent works on the impact of COVID-19 on Nigeria's stock market and economy are as follows:

Ref. [8] looked at the impact of COVID-19 on the Nigerian financial market using primary data. The study applied descriptive statistics and chi-square analysis, while the study concluded that COVID-19 had a significant impact on both the financial market performance and the stock market returns in Nigeria. Ref. [8] study did not really study the returns of the stock market, but was only based on opinion derived from the responses to a survey.

The work of [10] investigated the impact of COVID-19 on the global economy and the study revealed that the Nigerian stock market suffered negatively from the COVID-19 pandemic. This study reported the impact of COVID-19 on the overall Nigeria stock market. The work of [11] focused on the implication of COVID-19 on the Nigerian economy; the study unveiled that the COVID-19 pandemic in Nigeria led to the disruption of economic activities, which led to economy instability during the pandemic period in Nigeria. The work of [3] studied the effects of the COVID-19 outbreak on the overall Nigerian Stock Exchange performance using Quadratic and Exponential GARCH Models without paying attention to each sector of the Nigeria Stock Market. Ref. [12] noted that the impact of COVID-19 has severely distorted the real economy, resulting in a loss in the trade, tourism, and transport industry, generating local food shortages. The work of [13] examined the impact of COVID-19 on developed financial markets (China and USA) using a simple regression model on data spanning from 1 March 2020 to 25 March 2020 in China and USA. The findings revealed a positive significant relationship between confirmed cases of COVID-19 and the financial markets. A similar study by [5] examined how the risk spillovers emanating from the United States affect developing African economics during the COVID-19 pandemic. The study employed Value-at-Risk and Conditional Value-at-Risk to measure the down risk exposure of African financial markets as compared with those of the United States. The study concluded that the United States is a main transmitter of risk spillovers, while Nigeria, South Africa, Egypt, and Morocco are the main recipients. Along this line, Ref. [14] examined the impact of COVID-19 infections and deaths on the yields of bonds and stock returns of both developing and developed markets using daily data from 1 July 2019 to 30 June 2020. The study implemented regression analysis, regression with GMM estimation, and the multivariate GARCH-BEKK model. The study finds that COVID-19 infection and lockdowns negatively affect stock returns while volatility becomes more produced during COVID-19 for developed markets. In another work relating to the news and sentiment of COVID-19 impact on the financial market, Ref. [15] examined the relationship between the sentiment towards COVID-19-related news and the volatility of the equity markets. The study revealed that panic generated by the news outlets regarding COVID-19 is associated with increasing volatility in the equity markets. The study of [16] considered the financial markets under the impact of COVID-19 using daily data up to 27 March 2020 for certain countries. The study implemented the volatility analysis, correlation analysis, and minimum spanning tree. Their work confirmed that market risks have increased substantially in response to the pandemic: individual stock market reactions are linked to the severity of the outbreak of the pandemic. Ref. [17] investigated the impact of COVID-19 pandemic uncertainty on financial market volatility, with an interest in new infection cases and the fatality ratio reported at the global level and in the US. The study employed a three-month realized volatility index of S&P 500 as a proxy for the US financial markets' volatility, while the test of simple Ordinary Least Squares (OLS) and the stepwise procedure were implemented. The study concluded that the US financial markets were affected by the persistence of the COVID-19 crisis. The work of [18] investigated the impact of COVID-19 on the volatility of stock prices in India (Nifty and Sensex Daily closing prices of stock indices from 3 September 2019 to 10 July 2020) using the GARCH model. Further, the study made comparisons of the stock price return in the pre-COVID-19 and COVID-19 periods. The findings revealed that the stock market in India has experienced volatility during the pandemic period. In addition, the study found that the return on the indices is higher in the pre-COVID-19 period than in the period of COVID-19. Ref. [19] considered the impact of the COVID-19 pandemic and inflation on the All Share Index (ASI) in Nigeria using the GARCH and GJR-GARCH models. The study shows that the COVID-19 pandemic increased volatility and distorted the possible positive relationship between inflation and stock market returns in Nigeria. Ref. [19] considered ASI, whereas our study focuses on sectorial stock returns to see the effect on each sector of the Nigeria Stock Exchange (NSE).

Other previous studies include the following: Ref. [20] investigated the economic impact of government interventions during the COVID-19 pandemic in relation to international evidence from financial markets; Ref. [21] studied the effect of the COVID-19 pandemic on the transmission of monetary policy to financial markets. In Nigeria, other studies include [9,22].

From the foregoing, much of the work had not paid attention to the sectorial stocks of the Nigerian Stock Exchange. Hence, this study investigates the impact of COVID-19 on five (5) Nigerian Stock Exchange (NSE) sectorial stocks, namely, NSE Insurance, NSE Banking, NSE Oil and Gas, NSE Food and Beverages, and NSE Consumer Goods, using some family GARCH models (sGARCH, girGARCH, eGARCH, iGARCH, aPARCH, TGARCH, NGARCH, NAGARCH, and AVGARCH); in addition, the values of the half-life and persistence were obtained.

2. Methodology

2.1. Variants of GARCH Models

2.1.1. The Standard GARCH(p,q) Model

The general form of the standard GARCH(p,q) model (also known as the GARCH model) is a combination of ARCH and GARCH parameters, and is given as

$$a_t = \sigma_t \varepsilon_t, \quad \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{1}$$

where $a_t = r_t - \mu_t$ (r_t is obtained as the continuous compounding log return series), $\varepsilon_t \sim N(0,1)$ *iid*, α_i is the ARCH parameter and β_j is the GARCH parameter, and $\omega > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, and $\sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_j) < 1$, which means that the GARCH model is stable and suitable for forecasting [23–26].

For instance, the condition on ARCH and GARCH parameters (α_i, β_j) suggests that the volatility (a_i) is finite in nature while the conditional standard deviation (σ_i) increases as well. We observe that if q = 0, then the GARCH model parameter (β_j) becomes extinct and what is left is called the ARCH(p) model.

Suppose $p = 1$ and $q = 1$, then the GARCH(1,1) model can be presented as

$$a_t = \sigma_t \varepsilon_t, \quad \sigma_t^2 = \omega + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{2}$$

The GARCH (1,1) model is popular in modelling financial returns such as in the works of [27,28].

2.1.2. The Asymmetric Power ARCH

The asymmetric power ARCH model is another interesting GARCH model that was proposed by Ding, Engle, and Granger in 1993 [23]. The asymmetric power ARCH model can be stated as

$$\begin{aligned} r = \quad & \mu + a_t, \\ & \varepsilon_t = \sigma_t \varepsilon_t, \\ & \varepsilon_t \sim N(0,1) \\ \sigma_t^\delta = \quad & \omega + \textstyle\sum_{i=1}^{p} \alpha_i (|a_{t-i}| - \gamma_i a_{t-i})^\delta + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta \end{aligned} \tag{3}$$

where

$$\begin{aligned} \omega > \quad & 0,\ \delta \geq 0 \\ & \alpha_i \geq 0 \quad i = 1,\ 2, \cdots,\ p \\ & -1 < \gamma_i < 1 \quad i = 1,\ 2, \cdots,\ p \\ & \beta_j > 0 \quad j = 1,\ 2,\ \cdots,\ q \end{aligned}$$

The asymmetric power ARCH model utilizes a Box–Cox transformation of the conditional standard deviation process and the asymmetric absolute residuals. The leverage effect in the asymmetric power ARCH is the asymmetric response of volatility relating to both positive and negative shocks.

2.1.3. GJR-GARCH(p,q) Model

The GARCH model that attempts to address volatility clustering in the innovation process is called the Glosten–Jagannathan–Runkle GARCH (GJR-GARCH) model. The GJR-GARCH model is obtained by letting $\delta = 2$.

When $\delta = 2$ and $0 \leq \gamma_i < 1$,

$$\begin{aligned} \sigma_t^2 &= \omega + \textstyle\sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \\ &= \omega + \textstyle\sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-i}|^2 + \gamma_i^2 \varepsilon_{t-i}^2 - 2\gamma_i |\varepsilon_{t-i}| \varepsilon_{t-i} \right) + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \\ \sigma_t^2 &= \begin{cases} \omega + \sum_{i=1}^{p} \alpha_i^2 (1+\gamma_i)^2 \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, & \varepsilon_{t-i} < 0 \\ \\ \omega + \sum_{i=1}^{p} \alpha_i^2 (1-\gamma_i)^2 \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, & \varepsilon_{t-i} > 0 \end{cases} \end{aligned} \tag{4}$$

That is,

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i (1-\gamma_i)^2 \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \alpha_i \left\{ (1+\gamma_i)^2 - (1-\gamma_i)^2 \right\} S_i^- \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

$$\sigma_t^2 = \omega + \textstyle\sum_{i=1}^{p} \alpha_i (1-\gamma_i)^2 \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} 4\alpha_i \gamma_i S_i^- \varepsilon_{t-i}^2$$

where

$$S_i^- = \begin{cases} 1 & if\ \varepsilon_{t-i} < 0 \\ 0 & if\ \varepsilon_{t-i} \geq 0 \end{cases}$$

Now, we define

$$\alpha_i^* = \alpha_i (1-\gamma_i)^2 \text{ and } \gamma_i^* = 4\alpha_i \gamma_i$$

then

$$\sigma_t^2 = \omega + \textstyle\sum_{i=1}^{p} \alpha_i (1-\gamma_i)^2 \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \gamma_i^* S_i^- \varepsilon_{t-i}^2 \tag{5}$$

The Equation (5) above is the GJR-GARCH model [23].

However, when $-1 \le \gamma_i < 0$, recall Equation (4):

$$\begin{aligned}\sigma_t^2 &= \omega + \sum_{i=1}^{p} \alpha_i(|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i})^2 + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2 \\ &= \omega + \sum_{i=1}^{p} \alpha_i\Big(|\varepsilon_{t-i}|^2 + \gamma_i^2\varepsilon_{t-i}^2 - 2\gamma_i|\varepsilon_{t-i}|\varepsilon_{t-i}\Big) + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2\end{aligned}$$

$$\sigma_t^2 = \begin{cases} \omega + \sum_{i=1}^{p} \alpha_i^2(1-\gamma_i)^2\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2, & \varepsilon_{t-i} > 0 \\ \omega + \sum_{i=1}^{p} \alpha_i^2(1+\gamma_i)^2\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2, & \varepsilon_{t-i} < 0 \end{cases}$$

$$\begin{aligned}\sigma_t^2 &= \omega + \sum_{i=1}^{p} \alpha_i(1+\gamma_i)^2\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i\Big\{(1+\gamma_i)^2 - (1-\gamma_i)^2\Big\}S_i^+\varepsilon_{t-i}^2 \\ &= \omega + \sum_{i=1}^{p} \alpha_i(1+\gamma_i)^2\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i\{1+\gamma_i^2 - 2\gamma_i - 1 - \gamma_i^2 - 2\gamma_i\}S_i^+\varepsilon_{t-i}^2\end{aligned}$$

where

$$S_i^+ = \begin{cases} 1 & if\ \varepsilon_{t-i} > 0 \\ 0 & if\ \varepsilon_{t-i} \le 0 \end{cases}$$

Define

$$\alpha_i^* = \alpha_i(1+\gamma_i)^2 \text{ and } \gamma_i^* = -4\alpha_i\gamma_i$$

then

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i^*\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j\sigma_{t-j}^2 + \sum_{i=1}^{p} \gamma_i^* S_i^+\varepsilon_{t-i}^2 \tag{6}$$

The Equation (6) obtained above allows the positive shocks to have a stronger effect on volatility than the negative shocks [23]. Lastly, when $p = q = 1$, we can write the GJR-GARCH(1,1) model as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_t^2 + \gamma S_i\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

2.1.4. Integrated GARCH(1,1) Model

The unit-root GARCH models are referred to as the Integrated GARCH (IGARCH) models [26]. The IGARCH(1,1) model can be specified as

$$\begin{aligned} a_t &= \sigma_t\varepsilon_t; \\ \sigma_t^2 &= \alpha_0 + \beta_1\sigma_{t-1}^2 + (1-\beta_1)a_{t-1}^2 \end{aligned} \tag{8}$$

where

$\varepsilon_t \sim N(0,1)$ iid, and $0 < \beta_1 < 1$.

It can be noted that α_i can be used to denote $1 - \beta_i$ [29]. The model also used an exponential smoothing model for the series $\{a_t^2\}$. Then, the model can be rewritten as

$$\begin{aligned}\sigma_t^2 = &\ (1-\beta_1)a_{t-1}^2 + \beta_1\sigma_{t-1}^2 \\ &= (1-\beta_1)a_{t-1}^2 + \beta_1\big[(1-\beta_1)a_{t-2}^2 + \beta_1\sigma_{t-1}^2\big] \\ &= (1-\beta_1)a_{t-1}^2 + (1-\beta_1)\beta_1 a_{t-2}^2 + \beta_1^2\sigma_{t-2}^2\end{aligned} \tag{9}$$

By repeated substitution, we obtain

$$\sigma_t^2 = (1-\beta_1)\Big(a_{t-1}^2 + \beta_1 a_{t-1}^2 + \beta_1^2 a_{t-3}^3 + \cdots\Big) \tag{10}$$

which, in the financial model literature, is a well-known exponential smoothing formation in which β_1 is regarded as the discounting factor [26].

2.1.5. Threshold GARCH(p,q) Model

The advantage of the threshold GARCH model is the capacity to handle leverage effects in financial time series. The TGARCH(1,1) model can be specified as follows:

$$\sigma_t^2 = \omega + (\alpha + \gamma N_{t-1})a_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{11}$$

where N_{t-i} refers to an indicator for negative a_{t-i}, which can further be specified in detail as follows,

$$N_{t-i} = \begin{cases} 1 \text{ if } a_{t-i} < 0, \\ 0 \text{ if } a_{t-i} \geq 0, \end{cases}$$

where α_i, γ_i, and β_j refer to nonnegative parameters that follow conditions similar to those of family GARCH models [26]. Suppose $p = 1,\ q = 1$, then the TGARCH(1,1) model will become as shown in Equation (12) below:

$$\sigma_t^2 = \omega + (\alpha + \gamma N_{t-1})a_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{12}$$

2.1.6. Nonlinear GARCH(p,q) Model

The nonlinear GARCH model has been explored in various ways in the literature by the following scholars: [30–33]. The NGARCH(p,q) model can be shown as follows:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{13}$$

where h_t is known as the conditional variance, while ω, β, and α should satisfy $\omega > 0$, $\beta \geq 0$, and $\alpha \geq 0$.

Finally, the NGARCH(p,q) can then be written as

$$\sigma_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma_i \varepsilon_{t-i} + \sum_{j=1}^{p} \beta_j \sigma_{t-j} \tag{14}$$

2.1.7. EGARCH Model

The exponential GARCH (EGARCH) model is an important model that was proposed around 1991 [34] for the purpose of overcoming some challenges inherent in the GARCH model when handling financial time series [35]. Particularly, the EGARCH model allows for asymmetric effects between positive and negative asset returns. Consider the weighted innovation as shown in Equation (15) below:

$$g(\varepsilon_t) = \theta\varepsilon_t + \gamma[|\varepsilon_t| - \mathrm{E}(|\varepsilon_t|)] \tag{15}$$

where θ and γ can be seen as real constants. Both ε_t and $|\varepsilon_t| - \mathrm{E}(|\varepsilon_t|)$ are zero-mean iid sequences that follow continuous distributions. Therefore, $E[g(\varepsilon_t)] = 0$, then the asymmetry of $g(\varepsilon_t)$ can be rewritten as

$$g(\varepsilon_t) = \begin{cases} (\theta + \gamma)\varepsilon_t - \gamma E(|\varepsilon_t|)\ if\ \varepsilon_t \geq 0, \\ (\theta - \gamma)\varepsilon_t - \gamma E(|\varepsilon_t|)\ if\ \varepsilon_t < 0. \end{cases} \tag{16}$$

An EGARCH(p,q) model, according to [24,26,29,36,37] can be written as

$$\begin{aligned} & a_t = \sigma_t\varepsilon_t, \\ & \ln\left(\sigma_t^2\right) = \omega + \sum_{i=1}^{p} \alpha_i \frac{|a_{t-i}| + \theta_i a_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} \beta_j \ln\left(\sigma_{t-i}^2\right) \end{aligned} \tag{17}$$

The EGARCH(1,1) can then be written as

$$\begin{aligned} & a_t = \sigma_t\varepsilon_t \\ & \ln\left(\sigma_t^2\right) = \omega + \alpha([|a_{t-1}| - \mathrm{E}(|a_{t-1}|)]) + \theta a_{t-1} + \beta\ln\left(\sigma_{t-1}^2\right) \end{aligned} \tag{18}$$

where $|a_{t-1}| - \mathrm{E}(|a_{t-1}|)$ is an iid with zero mean. The EGARCH model with a Gaussian distribution error term, $\mathrm{E}(|\varepsilon_t|) = \sqrt{2/\pi}$, can be specified as:

$$\ln\left(\sigma_t^2\right) = \omega + \alpha\left(\left[|a_{t-1}| - \sqrt{2/\pi}\right]\right) + \theta a_{t-1} + \beta \ln\left(\sigma_{t-1}^2\right) \quad (19)$$

2.1.8. Absolute Value GARCH Model

In the work of [29], an asymmetric GARCH (AGARCH) can be written as

$$\begin{aligned} &a_t = \sigma_t \varepsilon_t; \\ &\sigma^2 = \omega + \textstyle\sum_{t=1}^{p} \alpha_i |\varepsilon_{t-i} - b|^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \end{aligned} \quad (20)$$

However, the absolute value GARCH (AVGARCH) model can be written as

$$\begin{aligned} &a_t = \sigma_t \varepsilon_t; \\ &\sigma^2 = \omega + \textstyle\sum_{t=1}^{p} \alpha_i (|\varepsilon_{t-i} + b| - c(\varepsilon_{t-i} + b))^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \end{aligned} \quad (21)$$

2.1.9. Nonlinear Asymmetric GARCH Model

Another interesting GARCH model that plays a key role in option pricing with stochastic volatility is called the nonlinear asymmetric GARCH (NAGARCH). The NAGARCH can be written as

$$\sigma_{t+1}^2 = \omega + \alpha \sigma_t^2 (z_t - \delta)^2 + \beta \sigma_t^2 \quad (22)$$

Suppose that $z_t \sim IIDN(0,1)$, where z_t is independent of σ_t^2. Then, σ_t^2 is now only a function of an infinite number of past-squared returns, which can derive the long run and unconditional variance under the NGARCH model with the assumption of stationarity:

$$\begin{aligned} E\left[\sigma_{t+1}^2\right] &= \overline{\sigma}^2 = \omega + \alpha E\left[\sigma_t^2 (z_t - \delta)^2\right] + \beta E\left[\sigma_t^2\right] E\left[\sigma_{t\_+1}^2\right] = \overline{\sigma}^2 \\ &= \omega + \alpha E\left[\sigma_t^2 (z_t - \delta)^2\right] + \beta E\left[\sigma_t^2\right] \\ &= \omega + \alpha E\left[\sigma_t^2\right] E\left(z_t^2 + \delta^2 - 2\delta z_t\right) + \beta E\left[\sigma_t^2\right] \\ &= \omega + \alpha \overline{\sigma}^2 \left(1 + \delta^2\right) + \beta \overline{\sigma}^2 \end{aligned} \quad (23)$$

where $\overline{\sigma}^2 = E\left[\sigma_t^2\right]$ and $E\left[\sigma_t^2\right] = E\left[\sigma_{t+1}^2\right]$ because of the condition of stationarity. Then

$$\overline{\sigma}^2\left[1 - \alpha\left(1 + \delta^2\right) + \beta\right] = \omega \Rightarrow \overline{\sigma}^2 = \frac{\omega}{1 - \alpha(1 + \delta^2) + \beta} \quad (24)$$

which exists and is positive if, and only if, $\alpha\left(1 + \delta^2\right) + \beta < 1$. The following are the implications:

(i) The persistence index of an NAGARCH(1,1) can be seen as $\alpha\left(1 + \delta^2\right) + \beta$ and not simply $\alpha + \beta$ as is common with other GARCH models; and
(ii) The NAGARCH(1,1) model is stationary if $\alpha\left(1 + \delta^2\right) + \beta < 1$.

Further details on these implications can be seen in [34,38–41].

2.2. Persistence and Half-Life Volatility

The study of persistence and half-life is very important in financial time series modelling. They help to determine if the estimated GARCH model is stable and how long it takes for the mean reversion. The persistence value of a GARCH model can be obtained as the sum of the GARCH (β_1) coefficient and the ARCH (α) coefficient $(\alpha + \beta_1)$. In empirical financial time series, persistence values are often very close to one (1) [28,42]. Persistence can assumed as the following:

(i) When $\alpha + \beta_1 < 1$, the GARCH model is stationary and has a positive conditional variance.
(ii) When $\alpha + \beta_1 = 1$, the model is strictly stationary. In addition, the GARCH model has an exponential decay model which makes the half-life value become infinity.

Lastly, when $\alpha + \beta_1 > 1$, the GARCH model is assumed to be unstable and non-stationary [27,28].

The half-life volatility of a GARCH model is a statistic that measures the mean reverting speed (known as average time) of a stock return under study. The half-life volatility can be written as

$$Half - Life = \frac{\ln(0.5)}{\ln(\alpha_1 + \beta_1)} \tag{25}$$

When the value of $\alpha + \beta_1$ is very close to one (1), we can expect that the volatility shocks of the half-life of the estimated GARCH model will be longer [28].

2.3. Distributions of GARCH Models

The distribution plays a significant role on the performance of the estimated GARCH model for any given financial time series data. This study used two innovations (namely the Student *t*- and skewed Student *t*-distributions); this is because they have the potential to account for the excessive kurtosis and non-normality inherent in financial returns [27,43,44].

The Student *t*-distribution can be written as

$$f(y) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\Gamma\left(\frac{v}{2}\right)}\left(1 + \frac{y^2}{\nu}\right)^{-\frac{(\nu+1)}{2}}; \quad -\infty < y < \infty \tag{26}$$

While, on the other hand, the Skewed Student *t*-distribution can be written as

$$\begin{aligned} &f(y;\ \mu, \sigma, \nu, \lambda) \\ &= \begin{cases} bc\left(1 + \frac{1}{\nu-2}\left(\frac{b\left(\frac{y-\mu}{\sigma}\right)+a}{1-\lambda}\right)^2\right)^{-\frac{v+1}{2}}, \ if\ y < -\frac{a}{b} \\ bc\left(1 + \frac{1}{v-2}\left(\frac{b\left(\frac{y-\mu}{\sigma}\right)+a}{1+\lambda}\right)^2\right)^{-\frac{v+1}{2}}, \ if\ y \geq -\frac{a}{b} \end{cases} \end{aligned} \tag{27}$$

where ν is the shape parameter of the Skewed Student *t*-distribution with $2 < \nu < \infty$, while λ is the skewness parameter with $-1 < \lambda < 1$. a, b and c are constants given as

$$\begin{aligned} a &= 4\lambda c\left(\frac{\nu-2}{\nu-1}\right); \\ b &= 1 + 3(\lambda)^2 - a^2; \\ c &= \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi(v-2)\Gamma\left(\frac{v}{2}\right)}} \end{aligned} \tag{28}$$

In the Skewed Student *t*-distribution above, μ and σ are known as the mean and standard deviation, respectively.

3. Materials and Methods

Daily stock prices were obtained from a secondary source ranging from 2 January 2020 to 25 March 2021. The data covers this range due to the availability of data for all the sectors considered in this study; Nigerian Stock Exchange (NSE) sectorial stocks, namely, NSE Insurance, NSE Banking, NSE Oil and Gas, NSE Food and Beverages, and NSE Consumer Goods were collected from www.investing.com accessed on 25 March 2021. The structural break was coded as 0 for the period before the break and 1 for the period from the break onward.

We calculated the returns using the following formula in (29) below:

$$R_t = \ln P_t - \ln P_{t-1} \tag{29}$$

In the formula in (29), R_t represents the return at time t; the natural logarithm is represented as ln; P_t represents the current daily stock price at time t; while P_{t-1} represents the previous daily stock price at time $t-1$. As mentioned earlier, we employed the Student t-distribution and Skewed Student t-distribution in this study.

4. Results

The rugarch package in the R environment [45] was employed in the analyses of this study.

Figure 1 shows some evidence of volatility; however, there is a sharp drop at data point 261, which is evidence of a break.

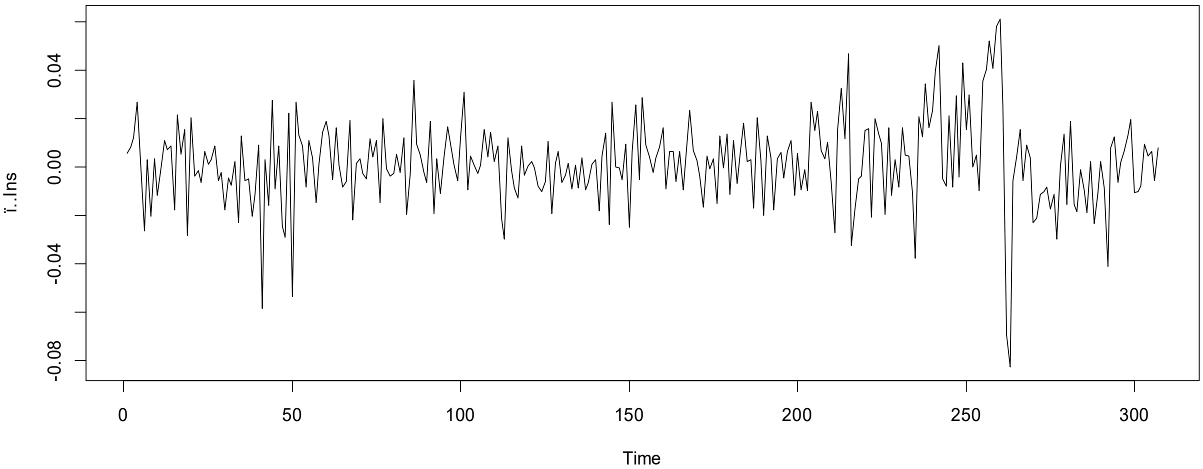

Figure 1. Plot of returns of NSE Insurance.

Figure 2 shows that the return series is stationary with a potential break point at 261 (20 January 2021).

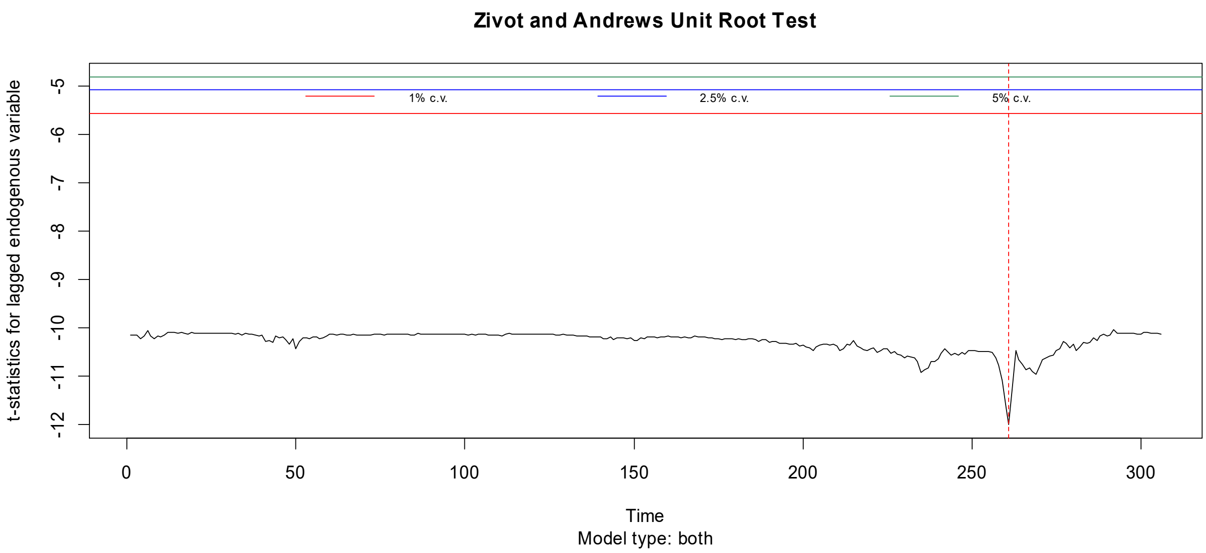

Figure 2. Plot of Zivot and Andrews unit root test of returns of NSE Insurance.

Figure 3 shows some evidence of volatility at the beginning of the return series; however, there is a sharp drop at data point 60, which is evidence of a break.

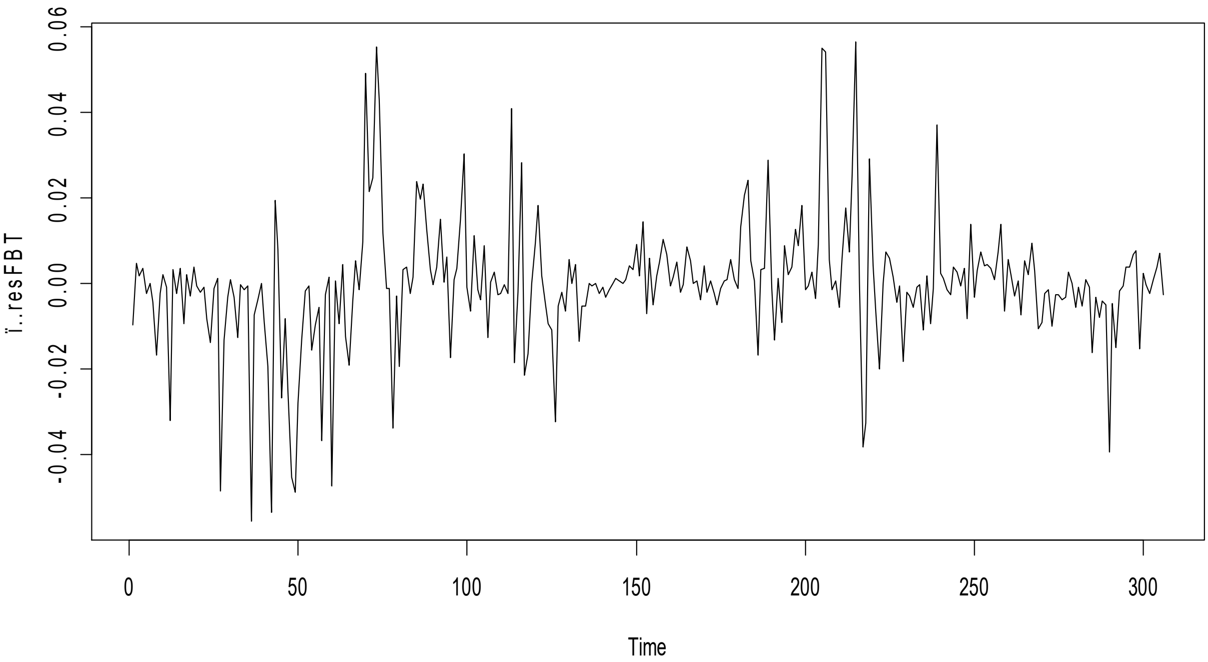

Figure 3. Plot of returns of NSE Food, Beverages and Tobacco.

Figure 4 shows that the return series is stationary with a potential break point at 60 (26 March 2020).

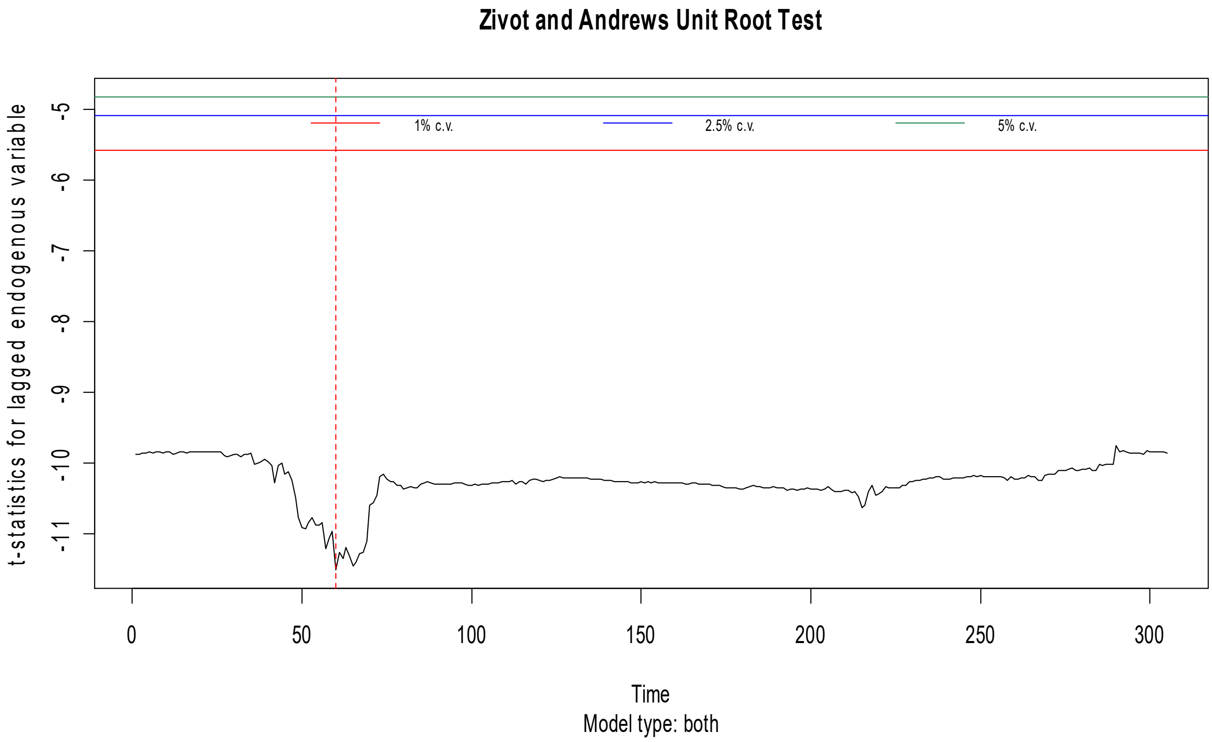

Figure 4. Plot of Zivot and Andrews unit root test of returns of NSE Food, Beverages and Tobacco.

Figure 5 shows some evidence of volatility at the midpoint of the return series; however, there is a sharp drop at data point 142, which is evidence of a break.

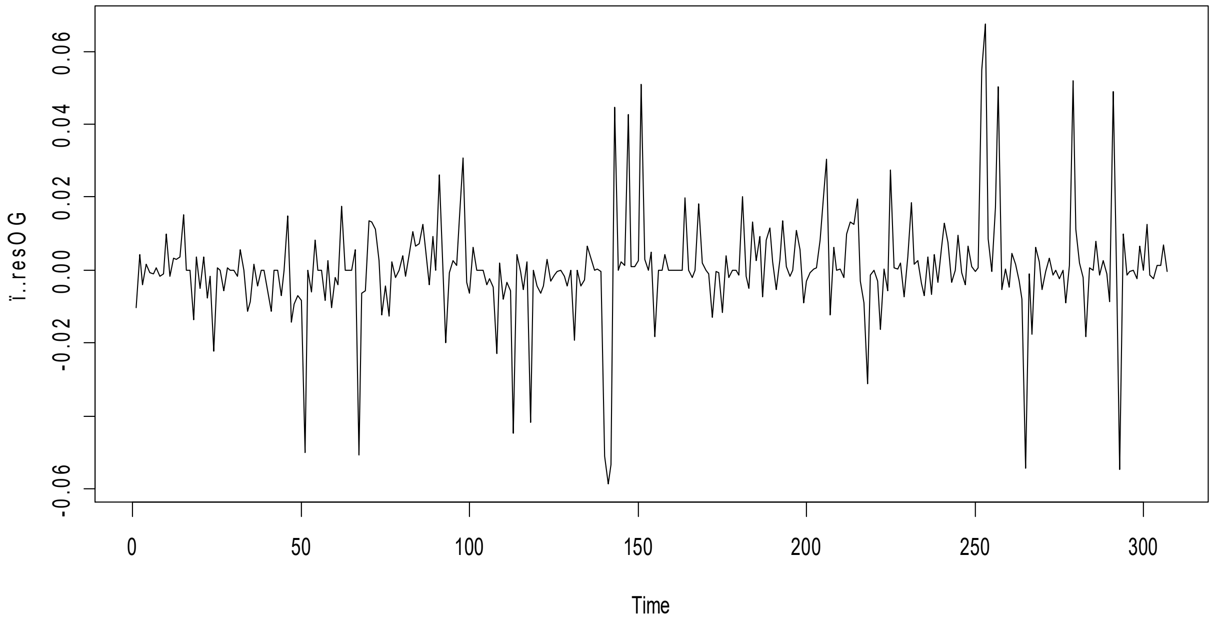

Figure 5. Plot of returns of NSE Oil and Gas.

Figure 6 shows that the return series is stationary with a potential break point at 142 (27 July 2020).

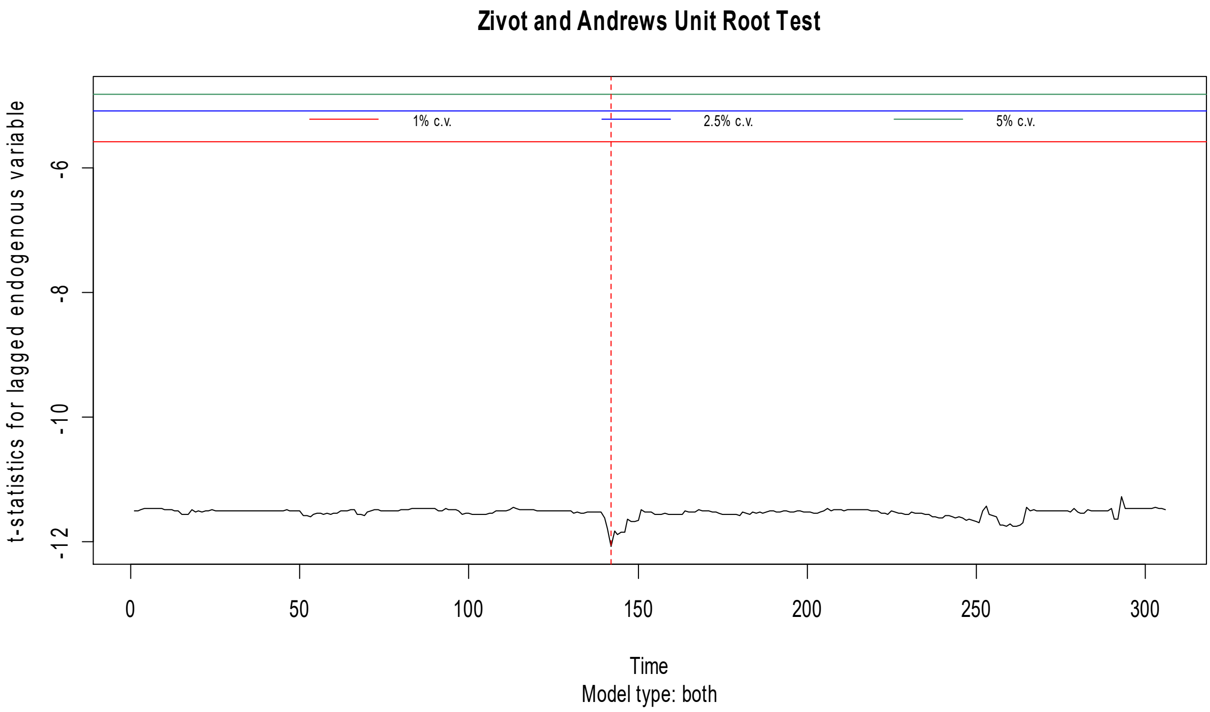

Figure 6. Plot of Zivot and Andrews unit root test of returns of NSE Oil and Gas.

Figure 7 shows some evidence of volatility at the beginning of the return series; however, there is a sharp drop at data point 50, which is evidence of a break.

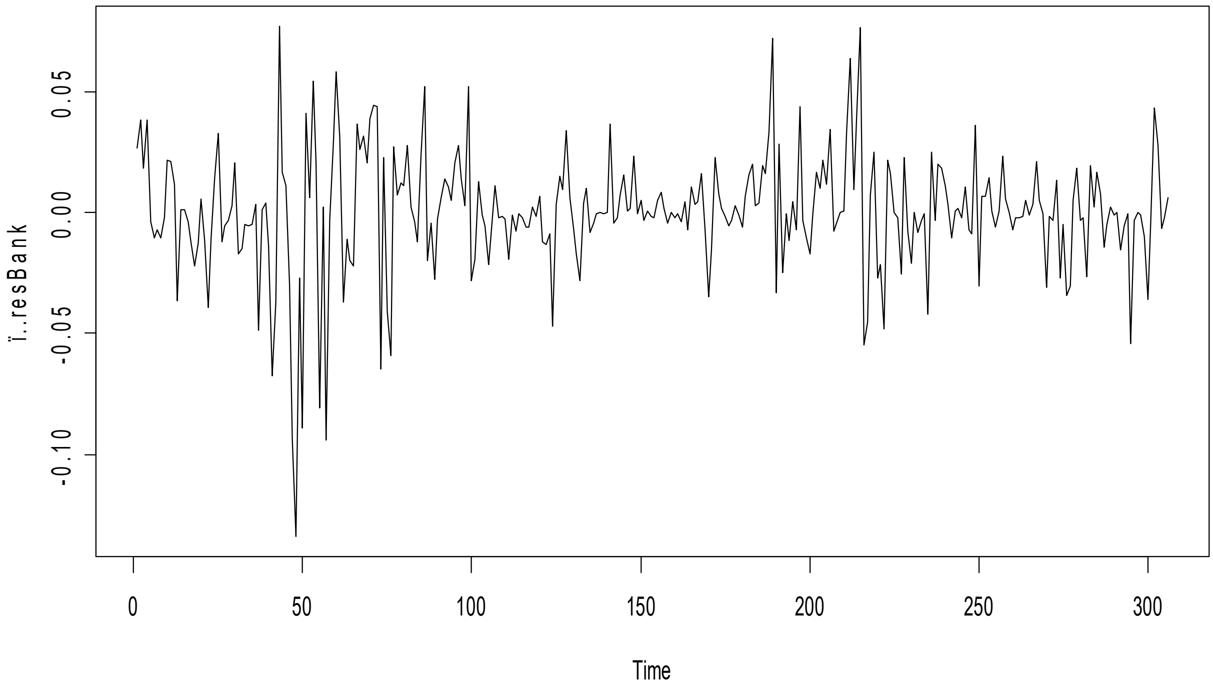

Figure 7. Plot of returns of NSE Banking.

Figure 8 shows that the return series is stationary with a potential break point at 50 (23 March 2020).

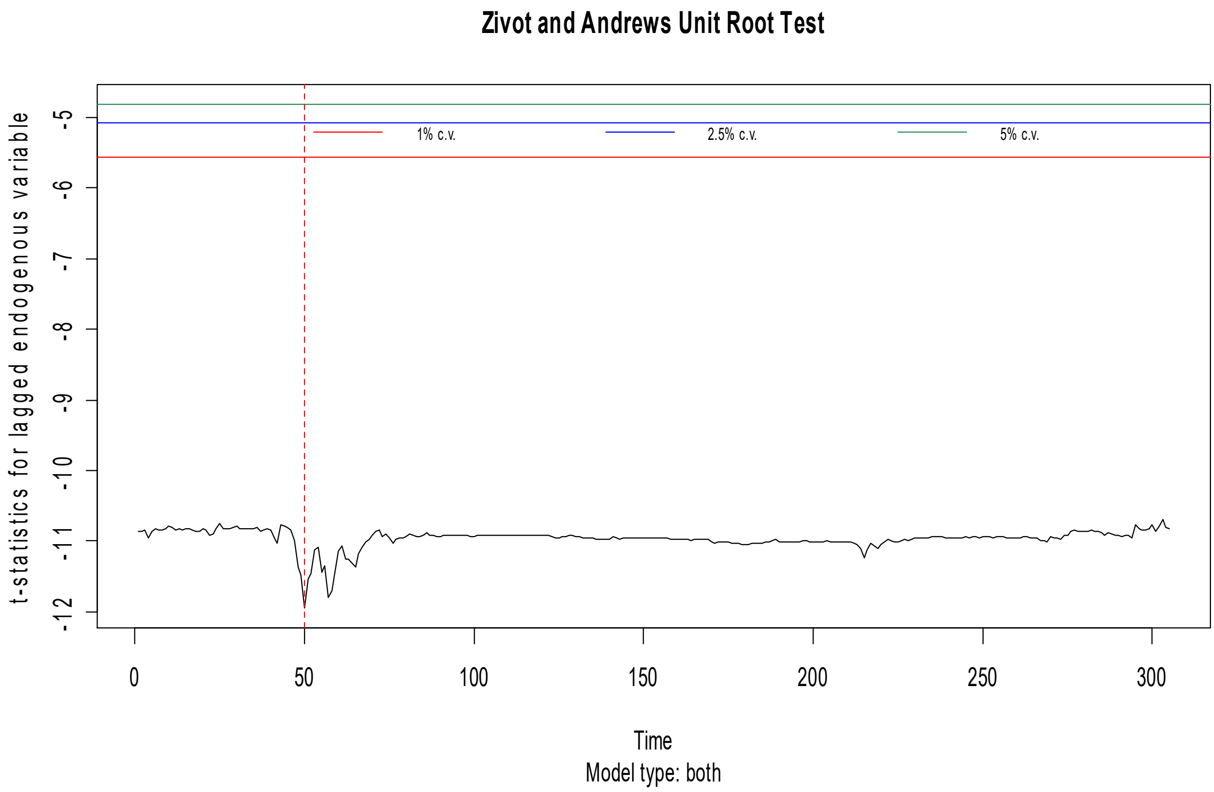

Figure 8. Plot of Zivot and Andrews unit root test of returns of NSE Banking.

Figure 9 shows some evidence of volatility at the beginning of the return series; however, there is a sharp drop at data point 57, which is evidence of a break.

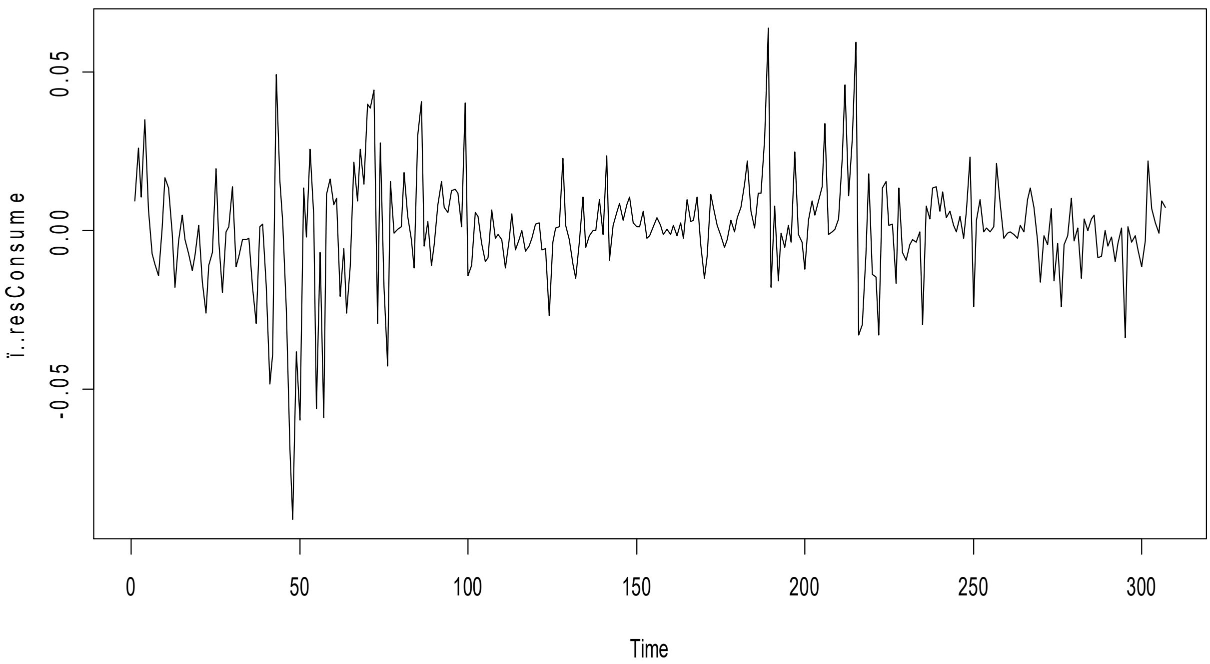

Figure 9. Plot of returns of NSE Consumer Goods.

Figure 10 shows that the return series is stationary with a potential break point at 57 (23 March 2020).

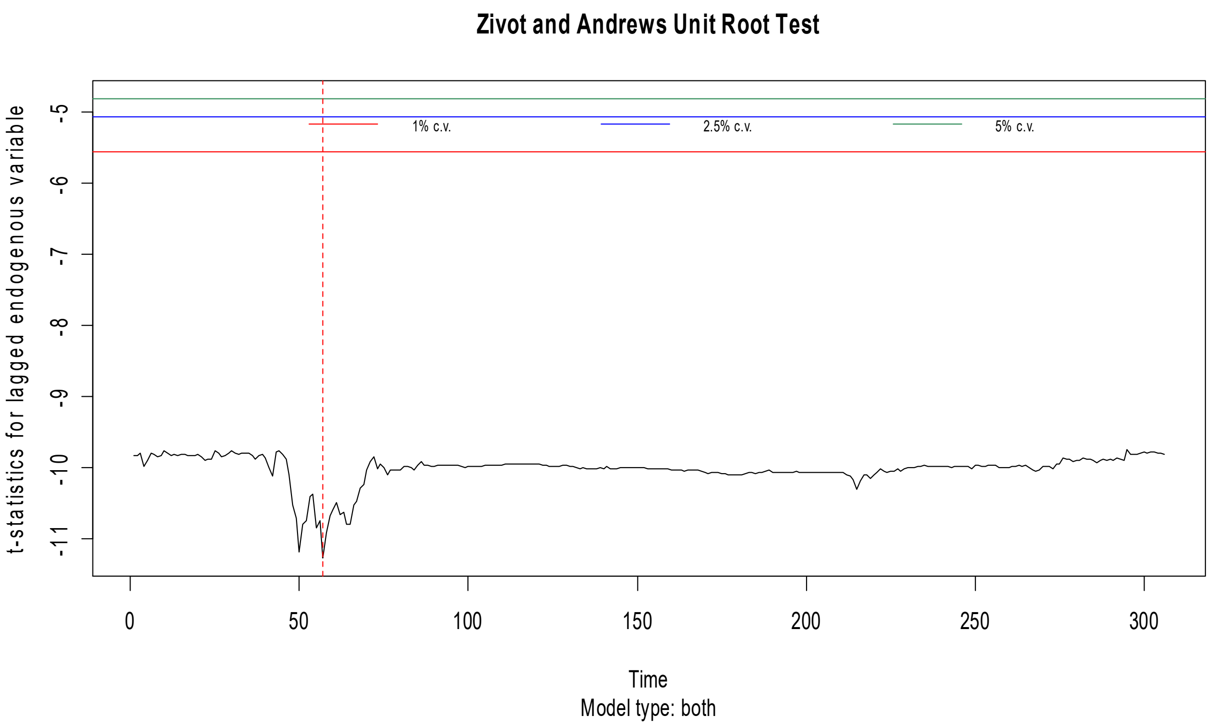

Figure 10. Plot of Zivot and Andrews unit root test of returns of NSE Consumer Goods.

In Table 1 above, the sectorial stock return series are not normally distributed and all the series exhibited evidence of ARCH effects, which shows the appropriateness of the application of GARCH models. The Zivot–Andrews unit root test was applied to the sectorial stock returns, and the results of the unit root test revealed 20 January 2021, 26 March 2020, 27 July 2020, 23 March 2020, and 23 March 2020 as potential break points for NSE Insurance, NSE Food, Beverages and Tobacco, NSE Oil and Gas, NSE Banking, and NSE Consumer Goods, respectively.

Table 1. Descriptive Statistics.

	Insurance	Food and Bevarages	Oil and Gas	Banking	Consumer Goods
min:	−0.0826	−0.0554	−0.0587	−0.1339	−0.0908
max:	0.06104	0.0565	0.06747	0.0769	0.0637
median:	0.00236	−0.0002	0	−0.0003	0.0003
mean:	0.0015	−0.0003	0.0002	4.2941e−05	0.0003
standard-dev	0.0176	0.0148	0.0145	0.0252	0.0172
skewness:	−0.3161	0.0970	−0.0425	−0.8527	−0.6472
kurtosis:	6.135866	7.5910	10.27226	7.4399	8.0291
J-B Test	Chi-squared: 125.2742 p Value: <2.2 × 10^{-16}	Chi-squared: 258.2982 p Value: <2.2 × 10^{-16}	Chi-squared: 651.2702 p Value: <2.2 × 10^{-16}	Chi-squared: 277.7695 p Value: <2.2 × 10^{-16}	Chi-squared: 331.875 p Value: <2.2 × 10^{-16}
Test statistic:	−11.9886	−11.5032	−12.0659	−11.9441	−11.2705
Critical value	−5.08	−5.08	−5.08	−5.08	−5.08
Breakpoint	261 (20 January 2021)	60 (26 March 2020)	142 (27 July 2020)	50 (23 March 2020)	57 (23 March 2020)
Arch Test (lag 15)	χ^2 = 74.761, df = 15, p-value = 6.253 × 10^{-10}	χ^2 = 36.051, df = 15, p-value = 0.001738	χ^2 = 30.743, df = 15, p-value = 0.009507	χ^2 = 88.179, df = 15, p-value = 2.166 × 10^{-12}	χ^2 = 85.276, df = 15, p-value = 7.48 × 10^{-12}

In Table 2 above, the TGARCH(1,1) model has the least AIC value for both Student t and Skewed Student t innovations. The estimated TGARCH model is stable, while the mean reverting takes an average of four days. With the TGARCH(1,1), the effect of COVID-19 is positively correlated, while with EGARCH(1,1), the effect of COVID-19 is negatively related, though it is not significant in both models. For the NSE Insurance returns, all the estimated GARCH models revealed an absence of serial correlation using the weighted Ljung–Box Test. In addition, the ARCH LM test revealed an absence of ARCH effects in the residuals of the estimated GARCH models.

Table 2. Results of NSE Insurance returns.

	Insurance					
	Student *t*-Distribution			**Skewed Student *t*-Distribution**		
Models	**AIC**	**Half-Life**	**Persistence**	**AIC**	**Half-Life**	**Persistence**
sGARCH(1,1)	−5.430249	4.700756	0.8629018	−5.433678	4.685996	0.8625011
gjrGARCH (1,1)	−5.434756	3.320903	0.8116204	−5.440714	3.933909	0.8384519
eGARCH (1,1)	−5.435603	5.540889	0.8824115	−5.443353	6.159152	0.8935622
apARCH(1,1)	−5.438118	3.227181	0.8067156	−5.443518	3.653911	0.8272072
iGARCH(1,1)	−5.423510	−Inf	1.0000000	−5.430062	−Inf	1.0000000
TGARCH(1,1)	−5.443094	3.187461	0.8045593	−5.449578	3.700418	0.8291817
NGARCH(1,1)	−5.415279	7.247415	0.9087906	−5.419009	10.795367	0.9378101
NAGARCH (1,1)	−5.434218	3.419928	0.8165404	−5.440077	4.250878	0.8495404
AVGARCH(1,1)	−5.436992	3.218895	0.8062697	−5.443787	3.908028	0.8374741

In Table 3 above, the EGARCH(1,1) model has the least AIC value for both Student t and Skewed Student t innovations. The estimated EGARCH model is stable, while the mean reverting takes an average of 12 days. The effect of COVID-19 is negatively correlated with the NSE Food, Beverages and Tobacco returns, and significant ($p < 0.05$) for the model with the Student t innovation and not significant with the Skewed Student t innovation.

Table 3. Results of NSE Food, Beverages and Tobacco.

	Food, Beverages and Tobacco					
	Student *t*-Distribution			**Skewed Student *t*-Distribution**		
	AIC	**Half-Life**	**Persistence**	**AIC**	**Half-Life**	**Persistence**
sGARCH(1,1)	−6.187684	−1.736062	1.4907273	−6.181459	−1.711531	1.4992826
gjrGARCH (1,1)	−6.191418	−1.719803	1.4963648	−6.184810	−1.712649	1.4988863
eGARCH (1,1)	−6.204170	11.631495	0.9421486	−6.198026	12.052532	0.9441120
apARCH(1,1)	−6.177988	NA	NA	−6.179059	NA	NA
iGARCH(1,1)	−6.178557	−Inf	1.0000000	−6.172347	−Inf	1.0000000
TGARCH(1,1)	−6.181729	12.360041	0.9454638	−6.175283	12.299470	0.9452027
NGARCH(1,1)	−6.182122	NA	NA	−6.176249	NA	NA
NAGARCH (1,1)	−6.192942	−2.572041	1.3093005	−6.184288	−4.106239	1.1838874
AVGARCH(1,1)	−6.173895	13.416227	0.9496471	−6.174778	13.949783	0.9515255

For the NSE Food, Beverages and Tobacco returns, all the estimated GARCH models revealed an absence of serial correlation using the weighted Ljung–Box Test, while the ARCH LM test revealed an absence of ARCH effects in the residuals of the estimated GARCH models.

In Table 4 above, the EGARCH(1,1) model has the least AIC value for both Student *t* and Skewed Student *t* innovations. The EGARCH model is stable, while the mean reverting takes an average of 20 days. The effect of COVID-19 is positively correlated with the returns and significant ($p < 0.05$).

Table 4. Results of NSE Oil and Gas.

	Oil and Gas					
	Student *t*-Distribution			**Skewed Student *t*-Distribution**		
	AIC	**Half-Life**	**Persistence**	**AIC**	**Half-Life**	**Persistence**
sGARCH(1,1)	−6.407924	19.71041	0.9654446	−6.402832	25.74334	0.9734340
gjrGARCH (1,1)	−6.414883	16.54482	0.9589704	−6.401627	28.62948	0.9760798
eGARCH (1,1)	−6.47725	20.33172	0.9664827	−6.495382	12.72524	0.9469867
apARCH(1,1)	−6.395022	NA	NA	−6.398517	NA	NA
iGARCH(1,1)	−6.401054	−Inf	1.0000000	−6.395362	−Inf	1.0000000
TGARCH(1,1)	−6.400915	13.02266	0.9481655	−6.395914	12.42958	0.9457605
NGARCH(1,1)	−6.411548	NA	NA	−6.401687	NA	NA
NAGARCH (1,1)	NA	NA	NA	−6.401862	23.18114	0.9705413
AVGARCH(1,1)	NA	NA	NA	NA	NA	NA

For the NSE Oil and Gas returns, all the estimated GARCH models revealed an absence of serial correlation using the weighted Ljung–Box Test, while the ARCH LM test revealed an absence of ARCH effects in the residuals of the estimated GARCH models.

In Table 5 above, the iGARCH(1,1) model has the least AIC value for both Student *t* and Skewed Student *t* innovations. However, with EGARCH (1,1), the model is stable, while the mean reverting takes an average of 12 days. The effect of COVID-19 is positively correlated with the returns and not significant using the EGARCH (1,1) model.

Table 5. Results of NSE Banking.

	Banking					
	Student *t*-Distribution			**Skewed Student *t*-Distribution**		
Models	**AIC**	**Half-Life**	**Persistence**	**AIC**	**Half-Life**	**Persistence**
sGARCH(1,1)	−4.953219	−8.225464	1.0879209	−4.946755	−7.966655	1.0909033
gjrGARCH (1,1)	−4.947277	−7.488073	1.0969864	−4.940784	−7.338821	1.0990535
eGARCH (1,1)	−4.949498	11.857763	0.9432206	−4.943097	11.894102	0.9433890
apARCH(1,1)	−4.945765	NA	NA	−4.939431	NA	NA
iGARCH(1,1)	−4.956633	−Inf	1.0000000	−4.950104	−Inf	1.0000000
TGARCH(1,1)	−4.939225	12.750837	0.9470902	−4.932824	12.833706	0.9474227
NGARCH(1,1)	−4.952212	NA	NA	−4.945352	NA	NA
NAGARCH (1,1)	−4.950176	−7.353524	1.0988460	−4.943644	−7.378198	1.0984997
AVGARCH(1,1)	−4.918602	22.477988	0.9696339	−4.912585	24.508573	0.9721144

For the NSE Banking returns, all the estimated GARCH models revealed an absence of serial correlation using the weighted Ljung–Box Test, while the ARCH LM test revealed an absence of ARCH effects in the residuals in the estimated GARCH models.

In Table 6 above, the EGARCH(1,1) model has the least AIC value for both Student *t* and Skewed Student *t* innovations. The EGARCH model is stable, while the mean reverting takes an average of 11 days. The effect of COVID-19 is negatively correlated with the NSE consumer returns and not significant using the EGARCH (1,1) model.

Table 6. Results of NSE Consumer Goods.

	Consumer Goods					
	Student *t*-Distribution			**Student *t*-Distribution**		
Models	**AIC**	**Half-Life**	**Persistence**	**AIC**	**Half-Life**	**Persistence**
sGARCH(1,1)	−5.764543	−14.214268	1.0499727	−5.758081	−14.379034	1.0493862
gjrGARCH (1,1)	−5.758090	−14.067359	1.0505076	−5.751610	−14.259526	1.0498102
eGARCH (1,1)	−5.774400	10.903340	0.9384065	−5.768480	11.137049	0.9396593
apARCH(1,1)	−5.750216	−1.158048	1.8194753	−5.743754	−1.114669	1.8623544
iGARCH(1,1)	−5.769523	−Inf	1.0000000	−5.763061	−Inf	1.0000000
TGARCH(1,1)	−5.753324	14.029914	0.9517956	−5.746889	14.202949	0.9523687
NGARCH(1,1)	−5.756656	−1.625200	1.5318860	−5.749859	−1.291511	1.7103445
NAGARCH (1,1)	−5.759109	−13.832033	1.0513886	−5.752596	−13.716094	1.0518340
AVGARCH(1,1)	−5.746987	18.283307	0.9627982	−5.741949	12.201455	0.9447749

For the NSE Consumer Goods returns, all the estimated GARCH models revealed an absence of serial correlation using the weighted Ljung–Box Test, while the ARCH LM test revealed an absence of ARCH effects in the residuals in the estimated GARCH models.

5. Discussion

In this study, the sectorial return series are not normally distributed, while the return series exhibited evidence of ARCH effects, which shows the appropriateness of the application of GARCH models. The Zivot–Andrews unit root test was applied to the sectorial stock returns and the results of the test revealed 20 January 2021, 26 March 2020, 27 July 2020, 23 March 2020, and 23 March 2020 as potential break points for NSE Insurance, NSE Food, Beverages and Tobacco, NSE Oil and Gas, NSE Banking, and NSE Consumer Goods, respectively. Each of the above dates is associated with some significant economic and financial event. In 20 January 2021, the National Bureau of Statistics (NBS) in Nigeria projected that the economy will grow by 3 percent in 2021, while the World Bank projected that it will grow by 1.7 percent. This was expected to improve the insurance sector in the year 2021 [46].

The Central Bank of Nigeria (CBN) on 16–18 March 2020 announced a set of policy measures to counter the impact of the fast-spreading coronavirus (such policies as interest rate cut, provision of credits to SMEs, injections of USD 3.25 billion into the manufacturing sector, etc.) [47]. This would have caused the structural breaks of 23 and 26 March 2020 in NSE Food, Beverage and Tobacco, NSE Banking, and NSE Consumer Goods, respectively.

Lastly, towards the end of July 2020, OPEC and other non-OPEC producers including Russia and Mexico agreed to extend its record oil production cuts [48]; this would have caused the structural break in NSE Oil and Gas at 27 July 2020 in Nigeria.

For the NSE Insurance returns, the TGARCH(1,1) model has the least AIC value for both Student *t* and Skewed Student *t* innovations. The TGARCH model is stable, while the mean reverting takes an average of four days. With the TGARCH(1,1), the effect of COVID-19 is positively correlated with the returns, while with EGARCH(1,1), the effect of COVID-19 is negatively related with the returns, though it is not significant in both models. This finding is related to the study of [19], whose findings revealed that there are negative effects of COVID-19 on the NSE Insurance returns in Nigeria. This finding is also similar to the study of [18] that studied the Indian stock market.

For NSE Food, Beverages and Tobacco, the EGARCH(1,1) model has the least AIC value for both Student *t* and Skewed Student *t* innovations. The EGARCH model is stable, while the mean reverting takes an average of 12 days. The effect of COVID-19 is negatively correlated with the returns, and significant ($p < 0.05$) for the model with the Student *t* innovation and not significant with the Skewed Student *t* innovation. This finding is related to the study of [19], whose findings revealed that there is a negative impact of COVID-19 on the NSE Food, Beverage and Tobacco returns in Nigeria. Our result is also related to the work of [5] which showed that Nigeria is a net recipient of United States risk spillovers.

For NSE Oil and Gas, the EGARCH(1,1) model has the least AIC value for both Student *t* and Skewed Student *t* innovations. The EGARCH model is stable, while the mean reverting takes an average of 20 days. The effect of COVID-19 is positively correlated with the returns and significant ($p < 0.05$). This shows that the NSE Oil and Gas has higher volatility during the COVID-19 period. This is similar to the result of [18], which showed that the return on the indices is higher in the pre-COVID-19 period than in the period of COVID-19.

For NSE Banking, the iGARCH(1,1) model has the least AIC value for both Student *t* and Skewed Student *t* innovations. However, with EGARCH (1,1), the model is stable, while the mean reverting takes an average of 12 days. The effect of COVID-19 is positively correlated with the returns and not significant using the EGARCH (1,1) model. This shows that the NSE Banking return has higher volatility during the COVID-19 period. This is similar to the result of [18], which showed that the return on the indices is higher in the pre-COVID-19 period than in the period of COVID-19.

For NSE Consumer Goods, the EGARCH(1,1) model has the least AIC value for both Student *t* and Skewed Student *t* innovations. The EGARCH model is stable, while the mean reverting takes an average of 11 days. The effect of COVID-19 is negatively correlated with the NSE Consumer Goods returns and not significant using the EGARCH (1,1) model. This finding is related to the study of [19] whose findings revealed that there is a negative impact of COVID-19 on the NSE Consumer Goods returns in Nigeria. Our result is also related to the work of [5], which showed that Nigeria is a net recipient of United States risk spillovers.

6. Conclusions

This study provides evidence of the impact of COVID-19 on five (5) Nigerian Stock Exchange (NSE) sectorial stocks (NSE Insurance, NSE Banking, NSE Oil and Gas, NSE Food and Beverages, and NSE Consumer Goods). In order to achieve the goal of this paper, daily stock prices were obtained from a secondary source ranging from 2 January 2020 to 25 March 2021. Because of the importance of incorporating structural breaks in modelling stock returns, the Zivot–Andrews unit root test revealed 20 January 2021, 26 March 2020, 27 July 2020, 23 March 2020, and 23 March 2020 as potential break points for NSE Insurance, NSE Food, Beverages and Tobacco, NSE Oil and Gas, NSE Banking, and NSE Consumer Goods, respectively. Each of the above dates is associated with some significant economic and financial event. In 20 January 2021, the National Bureau of Statistics (NBS) in Nigeria projected that the economy will grow by 3 percent in the year 2021 [46], while the Central Bank of Nigeria (CBN) on 16–18 March 2020 announced a set of policy measures to counter the impact of the fast-spreading coronavirus [47]. Lastly, towards the end of July 2020, OPEC and other non-OPEC producers including Russia and Mexico agreed to extend its record oil production cuts [48].

This study investigates the volatility in daily stock returns for the five (5) Nigerian Stock Exchange (NSE) sectorial stocks using nine versions of GARCH models (sGARCH, girGARCH, eGARCH, iGARCH, aPARCH, TGARCH, NGARCH, NAGARCH, and AV-GARCH); in addition, the half-life and persistence values were obtained. The study used the Student *t* and Skewed Student *t* innovations. The estimated GARCH models revealed a negative impact of COVID-19 on the NSE Insurance, NSE Food, Beverages and Tobacco, NSE Banking and NSE Consumer Goods stock returns [3,10,11]; however, the NSE Oil and Gas returns showed a positive correlation with the COVID-19 pandemic. All the estimated GARCH models revealed an absence of serial correlation using the weighted Ljung–Box Test, while the ARCH LM test revealed an absence of ARCH effects in the residuals in the estimated GARCH models.

This study recommends that the shareholders, investors, and policy players in the Nigerian Stock Exchange markets should be adequately prepared in the form of diversification of investment in stocks that can withstand future possible crises in the market.

In our future research, we hope to study the impact of COVID-19 on the Nigeria Stock Market using the GARCH-in-Mean model, Multivariate GARCH model, and Heterogeneous Autoregressive (HAR) model with structural breaks.

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