Journal of Namibian Studies, 35 (2023): 100-124 ISSN: 2197-5523 (online)

Special Issue on Business and Management

Evaluating The Asymmetric Effect And Volatility Persistence In The Nigerian Stock Market

Ndubuisi Udemezue[1], Ebere Ume Kalu[2], Wilfred I. Ukpere*[3]

[1]Alex Ekwueme Federal University,
Ebonyi State, Nigeria, ndubuisi96@yahoo.com
[2] University of Nigeria, Enugu Campus
Enugu State, Nigeria, ebere.kalu@unn.edu.ng
[3] Department of Industrial Psychology and People Management, School of Management, College of Business Economics, University of Johannesburg, wiukpere@uj.ac.za

Abstract

Volatility modelling in Nigeria and sub-Sahara Africa lacks the use of non–Gaussian models for estimating stock market returns series; researchers have been focusing on the Gaussian process. To overcome this deficiency, we used non-Gaussian assumptions alongside normal assumptions. Our major focus here is to investigate the presence of leverage effect and volatility persistence in Nigeria Exchange non-Normal specifications. GARCH models and their asymmetric extensions viz. EGARCH, TGARCH and PGARCH were employed to conduct the analysis with each estimated in Normal, Student's-t and Generalized error distributions. Student-t specification outperformed the other error distribution models. Important outcomes of the study include that the Exchange did not have an evidence of leverage effect; EGARCH, TGARCH and PGARCH models all showed empirical results contrary to the theoretical a priori signs of asymmetry. Secondary, there is high volatility persistence in the market, EGARCH model even indicated an explosive volatility persistence. We conclude that Nigeria Exchange is dominated by uninformed investors with a short-term investment strategy. Additionally, the market is very volatile and has the implication of weakening the investors' confidence.

Keywords: Nigeria Stock Market, Leverage Effect, Volatility Persistence, GARCH Models, Error Distributions.

Introduction

Broadly, volatility is a change that occurs in bunches or pools, it exists when a series of returns or prices display a prolonged oscillation and then calmness illustrating volatility and stability. According to Cutler, Porterba and summers (1989) and Mandelbrot (1963), it is the propensity that security prices may experience huge fluctuations occasioning extended and relatively protracted large price swings. Volatility can mostly be seen in financial datasets including security and currency prices, etc. In the stock market where we situate our investigation, Uyabo, Atoi and Usman (2015) state that stock market volatility is employed to assess the level of risk in the prices of financial assets against its previous values; specifically the fluctuations in stock returns over a defined period. Technically, this indicates an arithmetic estimation of rapid variations in a particular equity prices or even that of an index as it reveals the deviations in prices of financial assets. In fact, it measures the uncertainty of return and the risk of a market. Volatility can be indicative of uncertainty and bad prospect, and its upsurge exposes assets to inevitable harmful speculation. Put differently, rising volatility subjects financial securities to high risk. This has been affirmed by Campbell and Hentschel (1992) when they state that volatility is a measure of risk.

It is important to sustain some degree of volatility in any market but this should be cautiously monitored as unrestricted swings in returns will adversely affect the market development and economic growth (De Long, Schleifer, Summers and Waldmam, 1989; Ferderer, 1993; Ramey and Ramey, 1995; Porteba, 2000; Arestis, Demetriades and Luintel, 2001). At stock market level, presence of excess volatility may weaken the effectiveness of equity prices to perform its important role of serving as a guide for discovery of the real worth of a company (Karolyl, 2001); may lead to investors withdrawal from stock market in preference to other less risky financial assets (Mala and Reddy, 2007), and reduce incentive to save and cut the aggregate investment levels (Mohammed, 2009). At macro-economic level, excess volatility can reduce personal consumption expenditure (Campbell, 1996; Starr McCluer, 1998; Ludvigson and Steindel, 1999; Porteba, 2000; Mala and Reddy, 2007), and also business investments since corporations will find it difficult to raise funds through the exchange (Zuliu, 1995; Opschoor, 2013; Alcorn, 2014). It can expose national markets to high financial risk; this is possible when there is volatility transmission across other sectors like foreign exchange, bond and money markets (Hurditt, 2004). Thus, it can be seen that high volatility can be harmful to the economy.

Particularly, the effects of volatility can be more detrimental to emerging markets due to their vulnerability. As a result of their fledging phase, they are susceptible to domestic and foreign shocks which are quickly transmitted into the system (Osazevbaru, 2014). It can be an impediment to attracting investments. This position has earlier been canvassed by Dabusinskas, Kulikov and Randveer (2012) who have indicated that the negative effects of volatility on growth should be weaker in countries with more developed financial sector.

These negativities notwithstanding, volatility has some positive aspects; volatility can be useful in giving guidance to investors on the risk of holding an asset (portfolio management) and placing of value on an asset (pricing). It also provides reasonable forecasting confidence for investors as it serves to measure the level of the entire financial market susceptibility (Engle, Forcard and Fabozzi, 2005; Okpara, 2011; Onwukwe, Bassey and Isaac, 2011). In other words, it is multi-functional as it helps in other critical financial areas apart from management of portfolio and risks as well as determining the value of derivatives. Therefore it is very helpful to financial analysts who use it to evaluates the riskiness of security markets (Okpara, 2011). Further, the estimates of stock markets volatility can be used to determine the economic health of a nation as well as guide in formulating and implementing monetary and fiscal plans (Onwuekwe, Bassey and Isaac, 2011). This informed the need why local and foreign investors as well as monetary authorities usually maintain a close watch over volatility (Opschoor, 2012).

With the above background it can be seen that volatility occupies a central position in shaping the perception of stock markets, it affects the investment behavior of firms and individuals; hence modelling of stock returns has become very important and will continue to generate fresh interest to researchers. Specifically, it reveals whether there is existence of the stylized facts of stock yields in a particular stock market, which include volatility clustering, fat tails/high kurtosis, volatility persistence, leverage effect and co-movement (when two or more markets are involved).

There is a good number of empirical works on stock market volatility across the developed markets, however in Africa and particularly Nigeria where we situate our investigation; such studies are still very scanty. Even more severe is near absence of non-Gaussian specifications in the studies. Fortunately, there has been glowing interest among Nigerian researchers on the topic since the beginning of this millennium; the empirical results have been mixed regarding the existence of leverage effect and persistence of volatility. With regard to volatility clustering, researchers seem to be in agreement about its existence in the Nigerian Exchange. However, predominant number of these works in Nigeria (see Agwu and Ogbonna, 2020; Kuhe and Ikughur, 2017; Adebayo, 2017; Adeniji, 2015; Osazevbaru, 2014) has only employed Gaussian process for modeling the return series and this is weak in capturing the leptokurtic (Peakedness) and autocorrelation features of the high frequency return series; these studies have ignored the contributions of error distributions. In Nigerian context, there is very few empirical works on the role of error assumptions on modeling of volatility. Non–Gaussian models such as student’s t and Generalized error distributions (GED) which we employed in this study are suitable to produce efficient and reliable results. They produce credible outcomes compared with the results obtained through various methods of Guassian process as they emphasize the importance of skewness and tail-thickness in the conditional distribution of returns, particularly with the developing stock exchanges. These stylized facts are very important for portfolio and risk management and also for pricing of equities.

Additionally, most of the empirical works in Nigeria employed weekly and monthly data in their estimations, but to capture the stylized facts of stock returns accurately; daily data is the appropriate series as low frequency series will no doubt smooth the swings effect of the series. Volatility test needs very high frequency series (that are expanded and of a reasonable large observation which was lacking in almost all the reviewed works (See Adeniji, 2015; Adebayo and Ibraheem, 2017). This is to be able to capture the intraday trading so as to produce robust and credible results (Ngo Thai Hung, 2018; Jebran and Iqbal 2016; Li and Gile 2015). Furthermore, the importance of a long-time daily series can never be over-emphasized; it produces a better credible result as it captures all the ups and downs of the economic situations. Advantageously, we have a large set of data from 2001 to 2020 which reflects all major financial events of the world economy and interestingly Nigeria (recent 2016 and 2018 nigeria’s economic recessions, COVID-19, etc.) in contrast to the existing literatures. In addition to the above features, this study used more recent data as it seeks to extend literature on volatility in Nigerian context. Also, we ensured that autocorrelation is not mistaken with arch effect by adding autoregressive processors in our model, this is virtually absent in our reviewed works. The aim of this paper is therefore to examine whether there is existence of leverage effect and volatility persistence in Nigeria Exchange and to determine the optimal non-gaussian models.

Literature Review

Conceptual Review

The stylized facts of stock returns which represent the characteristic features of stock returns include: fat tails, high kurtosis (Glosten, Tagannathan, Runkel, 1993; Alemeida and Hotta, 2014), leverage effect, volatility clustering, asymmetry and non Gaussianity (Cont, 2001). Others include long memory and co-movement in volatility. Ability to bring out and reveal these stylized facts distinguishes a typical volatility model.

Fat tails simply means that the distributions have excess kurtosis which is densely clustered towards the tail of the series. Stock returns are characterized with Kurtosis whose value is more than 3 hence not appropriate for normality assumption. Volatility clustering implies a situation of high order and rapid changes occurring in bunches suggesting nonlinear movement. Whereas leverage effect basically implies that bad news has greater impact on volatility than good news of the same effect (Black, 1976). Long memory is the ability of volatility to persist for a long time and tending to unity having the likelihood to spillover from one period to the other. Whereas co-movement is existence of correlation between two or more markets with the ability to trigger a response from one market to another. The co-movement can only be possible if two or more stock markets are involved.

Stock market volatility can be ascribed to many factors; according to the Popular Model Theory, sociological and psychological beliefs are the core factors that spur volatility in the market. The theory argues that these factors are of more influence than economic fundamentals. It is of the view that Efficient Market Hypothesis (EMH) cannot totally explain the phenomenon of price movements and the possible explosive volatility in the stock exchange. In fact, it attributes excess volatility to investors' socio–psycho behaviours. According to it, information usually takes some time lag to be reflected in the asset prices which violates one of the principles of EMH, and also that investors can act inappropriately to information received. In this line of argument, Shiller (2000) also corroborates that changes in investors' behaviours can drive volatility. He asserts that these fundamental changes in the investors behaviour are occasioned more by emotions, perceptions as well as social factors which are well encapsulated in behavioral finance model, and therefore less by fundamental variables posited by EMH.

Further, the financial condition of the domestic markets can affect volatility. In a more precise manner, severe financial situations correlate with excess volatilities (Opschoor,2013). This has earlier been canvassed by Black (1976) who argues that in recessions, volatility tend to be higher because in economic downturn companies are adversely exposed to risk if their debt-equity relationship is on the high side. Additionally, volatility also increases consequent on arrival of new information. Anderson, Bollerslev, Diebold and Vega (2007), and Engle and Ng (1993) argue that public information affects volatility. According to them announcement of public information can engender instantaneous variations in security prices. Earlier on this has been somewhat acknowledged by Veronesi (1999) when he stated that in uncertainty situations, anticipation of cash flows also displays speed response to news information and that its news elasticity heightens changes in security prices. Also fluctuations in financial deals and rules arising from modifications in macroeconomic policies and increased uncertainty can also increase stock market volatility (Mala and Reddy, 2007). Likewise, lack of confidence by investors in the economic fundamentals and situations can stimulate volatility. Bittlingmayer (1998) introducing political perspectives believes that political factors play important role in financial volatility arguing that political instabilities can affect economic returns and further help to determine economic productivity.

More, the level of financial development and its co-movement with international markets can trigger volatility. Volatility in stock exchange can be influenced not only by the country specific volatility, but also by the volatility of other markets. The resultant increase in the speed of transmission and assimilation of shocks and crisis in the stock prices can intensify unrestricted price oscillations. Although, Aggarwal, Inclan and Lea (1999) have firmly argued that jumps in volatility of several markets are caused mainly by local and internal shocks.

Volatility in stock market is measured with stock market price. This stock index is a general performance indicator of stock markets development and dynamics of price movements. It specifically captures the changes and activities of the market.

Contextual Review

The contextual base of this work is Nigerian Exchange (NGX). The Exchange's All-Share Index consists of equities only and as at 31st December, 2020 it had recorded 40,270.72 points, the index was formulated in 1984 with 100 points. It should be noted that the exchange has seen some enormous advancements and development in areas of infrastructure, availability of large variety of financial securities, increasing volume and value of daily transactions and growing number of market participants.

Among the infrastructural development the market has witnessed are introduction of CAPNET (for meeting the challenges of internationalization), Central Securities Cleaning System (CSCS), Automated Trading System (ATS), Trade Alert and Remote Trading. All these have elevated the market into global visibility and accorded it competitive advantages and best practices. The exchange opened to foreign investors and operators with the internationalization of the market in 1995 thereby attracting a good measure of portfolio investments.

Empirical Review

The developed markets have got quite a good number of empirical investigations on volatility in stock market, whereas on African continent insufficient amount of research is yet to be undertaken. In Nigeria where we situate our investigation, though there has been rising interest in modeling stock returns volatility since the beginning of this millennium; there is still scarce investigation on it. Even the available scant empirical work has produced mixed results in aspects asymmetric effect and persistence of volatility; however, with regard to volatility clustering, there seems to be an increasing consensus about its existence in the Nigerian Exchange. It should be remarked that out of the empirical evidences, fairly few had examined the leverage information, while only a minute studies had been carried out on volatility persistence.

Unfortunately, just a tiny number of the few empirical works employed non–Gaussian process like General Error Distribution and student's t process; others tend to estimate the stylized realities of market returns ignoring the use of error distribution (see Agwu and Ogbonna, 2020; Kuhe and Ikughur, 2017). Large and predominant number of them applied Gaussian model which is weak in capturing leptokurtic and autocorrelation features of daily asset returns series. Student's t distribution and GED are more suitable to produce efficient and reliable result. The specification and application of proper volatility model to reflect oscillations in stock returns is imperative for sound policy formulations and profitable investments.

Again, most of the empirical studies employed either weekly or monthly data series which can smooth the swing effect of the series (see Emenike, 2010; Okpara; 2011; Adebayo and Ibraheem (2017). Stock markets tends to show swift reaction to fresh news, hence weekly or monthly series will always misrepresent the information. Therefore, daily data is the appropriate frequency series to be able to capture intraday activities as well as the stylized facts of stock returns (Mandelbrot, 1963; Fama, 1965). The very few that employed daily data under error distributions mostly did not use long period of observations in their investigations (see Atoi, 2014); they merely captured single economic crisis and this would not be adequate enough to holistically reflect the inherent realities of stock returns. Our work used 4,954 data points covering 20 years between 2001 to 2020, and to the best of the knowledge of the researchers, this is by far the highest ever employed in the study of volatility with error distributions in Nigeria context. This is very necessary and crucial to capture and reflect all the many economic booms and bursts in Nigeria and globally and hence will produce credible and reliable results. Having a larger dataset will help us to extract more accurate conclusions about volatility. Our work largely contributes in the above mentioned areas amongst others.

Among the studies that investigated and found leverage impact in Nigerian Exchange are Emenike (2010), Ogum (2005), Okpara (2011), Atoi (2014), and Onwukwe (2011). Others include Agwu and Ogbonna (2020), Herbert, Ugwuanyi and Nwaocha (2019) and Omokehinde (2017). Conversely, Emenike (2012), Osazevbaru (2014), Aliyu (2011), Uyabo, Atoi and Usman (2015), and Adebayo and Ibraheem (2017) found no leverage effect. Specifically, Emenike (2010) with GARCH and GJR GARCH found leverage effect. He employed monthly data between 1985 and 2008. Likewise, Okpara (2011) showed leverage effect with monthly data using EGARCH– IN–MEAN framework. Similarly, Onwukwe (2011) selected four big companies from the stock market and used them to represent the Nigerian Exchange and established evidence of asymmetric effect. He employed GARCH, E-GARCH and GJR GARCH with daily data ranging from 2002 to 2006.

Further Atoi (2014) discovered evidence of leverage effect when he used GARCH, TGARCH, EGARCH and PGARCH to model daily series between 2008 and 2013 (five years period). He argued that Gauissian process does not have the capacity for volatility modeling, maintaining that student's t specifications under non Gauissian presents the most appropriate technique. Agwu and Ogbonna (2020) with daily data between 1999 and 2016 and TGRACH model recorded leverage effect. Here the time period is long but they did not used error distributions. Also Herbert, Ugwuanyi and Nwaocha (2019) discovered leverage effect using GARCH and GJR model on daily data spanning 2010 to 2016. Kuhe and Ikughur (2017) employed GARCH, TGARCH and PGARCH on daily returns between 1995 and 2014 and indicated leverage effect. Their study sample was Guinness Nigeria Plc, a quoted company on Nigerian Exchange. Also, here the time frame is long, but they used only Gaussian method and just a single company for the estimate.

A slightly different result from the findings of above studies is Adebayo and Ibraheem (2017) who measured asymmetric information after the melt down, they found leverage effect but with non-significant statistic. Using weekly data ranging from 2010-2016, they questioned the credibility of findings of the earlier studies which have largely depended on Gussian specifications. They argued that EGARCH and TGARCH under T distribution provide the overall best estimates. Likewise, Aliyu (2011) showed weak support for leverage effect (that is, showing insignificant coefficient).

On the other side, Emenike and Aleke (2012) found no leverage effect. They employed EGARCH and GJR GARCH on daily data from 1996 to 2011 time series. In the same vein, Osazevbaru (2014) found a similar result of no leverage effect when he used TGARCH to model time series from 1995 – 2011. Again, Uyaebo, Atoi and Usman (2013) investigating panel data of five counties found no leverage effect on Nigeria Stock market between 2000 and 2013 using TGARCH and EGARCH models. They indicated TGARCH under t–distribution as the best model.

On the persistence of volatility, Olowe (2009), Emenike and Aleke (2012), Herbert, Ugwuanyi and Nwaocha (2019), Ogum, Beer and Nouyrigat (2005), Kuhe and Ikughor (2017) and Okpara (2011) established evidence that there is persistence of return fluctuations on the Exchange. While Emenike and Aleke discovered high persistence, Okpara (2011) found low persistence. However, Agwu and Ogbonna (2020) found no evidence of persistence. These studies employed either GJR GARCH or EGARCH Models.

On investigations for determining the best and most appropriate models for modeling volatility, Atoi (2014) arguing that non error distribution methods are unsuitable for capturing volatility, stated that non-Gaussian alternatives like student's t specification represents an ideal technique. Similarly, Ekum, Owolabi and Alakija (2018) with similar objectives however found that PARCH, EGARCH and TGARCH error distributions are the appropriate and suitable estimation processes. Yaya, Bada and Atoi (2016) argued that Beta–t–EGARCH process has proved a better estimator of security return wild changes relative to IGARCH–t. They contended that Beta–t–EGARCH takes care of jumps and breaks occasioned by economic and political shocks in time series. Omokehinde (2017) concluded that APARCH under GED was the best fitted model.

Beyond Nigeria, in major and emerging markets, there are evidence indicating leverage effect, non-leverage effect and total lack of asymmetric behavior. So, like in Nigerian case, there are also mixed results.

In India for instance, Kaur (2004) found that bad news has greater impact on volatility than good news of the same effect on Bombay Stock Exchange between 1993 to 2003. They conducted the investigation with EGARCH and TGARCH distributions. Similarly, Goudazzi and Ramanara–Yanam (2011) also discovered leverage effect in India with EGARCH and TGARCH. Also in China, Long, Tsui and Zhang (2014) indicated that there was significant leverage effect on the mainland Chinese stock market.

However, Samanta (2010) examining the impact of high volatility return on economic performance of India found that the roles were vague (no definite facts). In some instances, lagged parameters of growth indicators were found to be non-significant whereas in others they showed negative signs. Mun, Sundaram and Yin (2008) evaluated the asymmetric information and effectiveness of Bursa Malaysia through EGARCH on weekly closing prices of the stock market. The findings could not establish evidence of leverage effect. Similarly, Yeh and Lee (2000) on China stock markets used TGARCH model and concluded that there was no leverage effect in the two of Chinese Stock Exchanges (Shanghai and Shenzhen), however, they found evidence of asymmetric impact in Hong Kong and Taiwan Stock Exchanges. Contrary, Jingli and Sheng (2011) discovered leverage effect, volatility clustering and fat tail with ARIMA EGARCH and ARIMA TGARCH models on Shanghai and Shenzhen stock markets from 2003 to 2010. Also, Bekaert and Wu (2000) found no leverage effect when they concurrently analsyed the leverage effect at company and market level in the Nikkei 225 stock market. They showed existence of volatility clustering. Saleem (2007) reported that Karachi Stock Exchange had no leverage effect, however there was volatility persistence.

Richard (1990) noted high swings in market returns in some developing markets. He explained that the rise in volatility is occasioned by the sensitivity of the economic conditions of the developing markets to the foreign investments. Investigating the asset returns volatility across ten selected Asian developing economies, Arora, Das and Jain (2009) found evidence of returns oscillation in the ten stock exchanges, however only four of the countries showed asymmetric effect. Additionally, Okicie (2015) analysed volatility of stock returns across the Central Eastern and South East European stock exchanges and discovered sufficient proof of presence of leverage effect, they applied ARIMA and GARCH models in the study. Sungh and Kisher (2016) employed EGARCH to analyze volatility returns on the stock markets of the four BRIC countries of Brazil, Russia, India and China and indicated the presence of volatility, however their study revealed different degrees of volatility across the BRIC markets. Similarly, Dania and Spillan (2013) investigated the spillover of stock markets volatility between four advanced economies comprising of US, Germany, UK and France, and emerging MENA economies using GARCH and TGARCH with monthly data from 2005 to 2011. The result established evidence of wild changes in asset returns and leverage effect but however revealed differences in stylized facts between the two regions. Guidi (2008) through the family of GARCH models attempted to examine the volatility of returns in German, Swiss and UK stock markets. He found presence of leverage effect.

Materials and Methods

Extended daily time series of Nigerian all share index transformed into market returns covering the period of 2001–2020 is used in the examination. We sourced our data from NGX daily official publications.

Preliminary and diagnostic checks are conducted to confirm the fitness of the models.

Transformation of Data

We employ rate of return over absolute price movements in measuring volatility; this is to smooth the wild fluctuations in price level. Using natural logarithm, the daily observations of Nigeria Exchange All Share Index were converted into daily returns.

$$R_{mt} = LN\,(S_t / S_{t-1})100 \qquad 1$$

Where: R_{mt} = Daily returns for ASI for period (*t*).
S_t = Daily ASI for period (*t*).
St-1 = Daily ASI for period (*t-1*).

This method has been adopted by some authors like Koulakiotis, Papasyriopoulos and Molyneux (2006), Kula, Amoo and Joseph-Raji (2007), Rashid and Ahmad (2008), and Leon (2008).

Methods

ARCH Model is volatility modelling method generally applied on time series data for investigating conditional variance. It was formulated by Engle (1982) and later revised into GARCH model by Bollersler and Taylor (1986). The two models are specially designed to be able to observe the stylized facts in a curvilinear data series (Hsieh, 1989). They have been successful in capturing volatility clustering. According to Bollerslev (2009), ARCH particularly, was first used to model the movements of the inflation rate in UK. However, they are unable to reveal some salient characteristics of financial series. For example, GARCH is based on the assumption that reaction to the shock and volatility is symmetrical; that is there will be always symmetrical reaction to shock. The response must always be positive (non-negativity constraint). There is no differentiation in the responses.

To overcome this limitation and others such as constraint in determination of the appropriate number of lags, developments of asymmetrical models including EGARCH, PGARCH, TGARCH amongst others were introduced. These new models have become imperative to fill the gap of providing suitable specification that could differentiate the impact on volatility arising from positive and negative shocks of the same size. Their importance is to enhance the efficacy of volatility models in capturing the inherent features of return series. Their adequacy to estimate the stock market asymmetries and transmission with a high level of accuracy has been acknowledged by (Paul, 2006; Magnus and Oteny Abayie, 2006). However it should be remarked that their performance is not the same as it depends on the market and period under review.

ARCH Model q

The variance equation of ARCH Model of order q is given as by (Engel 1982)

$$\boldsymbol{\sigma}_t^2 = \omega + \sum_{i=1}^{q} \alpha_1\, \varepsilon_{t-1}^2 + \beta\sigma^2{}_{t-1} \qquad \text{--------------------} \; 2$$

Where $\omega > 0$; $\alpha_i \geq 0$; $i > 0$.

The ARCH effect deals with heteroskedasticity, it always becomes clear when there is pattern in the variance of a variable.

GARCH (p, q) Model.

Bollerslev (1986) and Taylor (1986) introduced this model. the variance equation of this model is:

$$\boldsymbol{\sigma_t^2} = \omega + \sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j\boldsymbol{\sigma_t^2}_{-j} \quad \text{---------------------------------3}$$

Here p indicates the order of the GARCH terms, $\boldsymbol{\sigma}2$, then q represents the order of the ARCH terms, ε^2. $\boldsymbol{\sigma_t^2}$ is volatility whereas ε_t^2 stands for error term. While ω is the intercept, $\alpha_1, \alpha_2, \ldots, \alpha_q$ are the parameters of ARCH processes, whereas $\beta_1, \beta_2, \ldots, \beta_p$, are the parameters of GARCH specifications.

Exponential GARCH (EGARCH) Model.

Nelson (1991) introduced the EGARCH with the following volatility specifications:

$$\log(\boldsymbol{\sigma_t^2}) = \omega + \sum_{j=1}^{q}\beta_j\log(\boldsymbol{\sigma_{t-j}^2}) + \sum_{i=1}^{p}\alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r}\boldsymbol{\gamma}\mathrm{k}\frac{\varepsilon_{t-k}}{\sigma_{t-k}}$$

Where $\boldsymbol{\gamma}_i$ is leverage effect parameter, ω stands foe intercept, ε_{t-1} is the ARCH term and $\boldsymbol{\sigma_{t-1}^2}$ is the GARCH term. At the leftward is the variability of the conditional distributions which suggest that the asymmetry has a rapid and fast impact. To determine if the return series bear evidence of leverage effect, the hypothesis is stated thus: $\boldsymbol{\gamma}_i < 0$, the impact is asymmetric if $\boldsymbol{\gamma}_i \neq 0$. It assumes that the effect of bad news is greater (Tsay 2005). This means that theoretically it is expected that the effect of negative shocks would be larger on conditional variance when $\gamma_i < 0$. Put differently, γ_i will exhibit a negative value if the effect of the negative shock on volatility is bigger. This would indicate that there is asymmetric impact implying that negative shocks affect volatility of stock return more than positive shocks. In EGARCH, one of the upsides is that leverage effect is not subjected to constraints in order to obtain positivity, stationarity and finite kurtosis as against the constrictions required on the coefficients of symmetric models for these features (Rodriguez and Ruiz, 2009).

Power ARCH (PARCH) Model.

This model was initiated by Taylor (1986) and Schwert (1989) for modelling standard deviation instead of variance as in EGARCH. Here this model provides for estimation of the coefficient exponent ẟ of the standard deviation as against imposing it. Again optional γ coefficients are required to accurately obtain asymmetry of up to order r:

$$\boldsymbol{\sigma_t^\delta} = \omega + \sum_{j=1}^{q}\beta_j\boldsymbol{\sigma_{t-j}^\delta} + \sum_{i=1}^{p}\alpha_i(|\varepsilon_{t-1}| - \boldsymbol{\gamma}_i\varepsilon_{t-1}) \qquad \text{------5}$$

$\boldsymbol{\delta}$ = coefficient of the exponential term. The PARCH Model basically builds from GARCH processes. There is evidence existence of leverage impact if r ≠ 0,

The Threshold GARCH (TARCH) Model

It was Zakoian (1994) that originated this asymmetric model with the conditional variance specified as:

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} \beta_j \boldsymbol{\sigma_{t-j}^{\delta}} + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \boldsymbol{\gamma}_k \varepsilon_{t-k}^2 \mathrm{r}_{t-k} \quad \text{----6}$$

ω = intercept, ε_{t-1} is the ARCH term and $\boldsymbol{\sigma_{t-1}^2}$ is the GARCH term. The impact of positive news is α_i, and the impact of negative news = α_i+.γ_i. Here the a priori expectation is that $\gamma_i > 0$, meaning that negative shocks intensifies volatility, this implies that the market has leverage impact. Put differently, it is only when the numerical number of of γ_i is positive that the negative shocks will exert a higher impact on volatility. Here γ stands for the asymmetric effect parameter. According to Tsay (2005), TGARCH is considered to have better capacity to capture the movements of the adverse impact, which have a larger outcome on volatility compared to the favorable impact. But TGARCH has some shortcomings: the coefficients of the model require some slight constriction in order to ensure absence of unit roots as well as an evidence of kurtosis. Besides it can encounter some problems trying to reflect concurrently a leverage effect which holds restricted kurtosis and also high persistence (Rodriguez and Ruiz, 2009). This is because as errors assume heavy peakedness, the leverage effect estimated with TGARCH process becomes lesser which will decrease some of its flexibility.

ERROR DISTRIBUTIONS

Gaussian specification has shown some deficiencies and thus inefficient for estimating high frequency financial time series such as return series. Frequency of large magnitude observations appears far higher than could be forecasted with the Gaussian process (Bartolommeo, 2007; Verhoeven and McAleer, 2003 and Harvey and Siddique, 1999). Mandelbrot (1963) had earlier questioned the adequacy of Gaussian method to capture high incidence of extreme observations in financial time series. It lacks the ability to estimate the extreme events and skewness of return series. Fama (1965) has also stated that non linearity of daily stock index returns will always likely exhibit leptokurtic and fat-tailed distribution which will pose difficulties for normal distribution methods.

Further, Alberg, Shalit and Yosef (2011), Malmsten and Terasvirta (2004), and Bollerslev, Engle and Nelson (1994) have also contested that normal error distribution does not have adequate flexibility for capturing kurtosis and autocorrelation in stock returns. Thus, they suggested an enhancement of Gaussian specification by substituting it with more heavy-tailed error assumption. They further stated that enhancing the kurtosis of the Gaussian specification will strengthen symmetric specifications to be able to detect kurtosis in the series of stock returns.

Specifically, Nelson (1991) advocates for EGARCH specification with generalized error distribution (GED) arguing that GED has capabilities for more heavy-tails over Gaussian assumption. He canvassed that EGARCH will increase the kurtosis and lessen the autocorrelation of squared observation. He also posited that EGARCH specification is stationary if the innovations have GED. For robust modeling of stock returns, all these have led to our use of error distributions to model the distribution of conditional return series. The t and GED distributions are necessary so as to reflect the stylized facts intrinsic in the high frequency series, such as heavy tail. This would accurately account for the kurtosis in returns.

Normal Distribution:

$$l_t = -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log\boldsymbol{\sigma_t^2} - \frac{1}{2}(y_t - X_t'\theta)^2 / \boldsymbol{\sigma_t^2} \quad \text{-----------------}\mathbf{7}$$

Student's T-Distribution:

$$l_t = -\frac{1}{2}\log\left[\frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma((v+1)/2)^2}\right] - \frac{1}{2}\log\sigma_t^2 \frac{(v+1)}{2}\log\left[1+\frac{(y_t - X_t'\theta)^2}{\boldsymbol{\sigma_t^2}\,(\mathbf{v-2})}\right]$$

Here r>2; r is the degree of freedom and it accounts for the tail behavior.

Generalized Error Distribution (GED):

$$l_t = -\frac{1}{2}\log\left[\frac{\Gamma(1/r)^3}{\Gamma(3/r)(r/2)^2}\right] - \frac{1}{2}\log\sigma_t^2 - \left[\frac{\Gamma(3/r)y_t - X_t'\theta)^2}{2a}\right]^{r/2} \quad \text{------------}\mathbf{9}$$

Here v > 0. V is the coefficient that indicates the shape and skewness of returns. The more the value of v the bigger the weight of the tail. GED would return to normal distribution if v = 0.

Results and Analysis

Preliminary Tests

Descriptive Statistics

Table 1: Descriptive Analysis of Nigeria Market Returns.

Mean	Median	Min	Max	Std Dev	Skewness	Kurtosis	JB	P.Value
10.16	**10.17**	**9.00**	**11.10**	**0.41**	**-0.54**	**3.33**	**267.49**	**0.0000**

Source: Author's Eviews computation

Table 1 shows the stock returns distributional properties. The daily mean and median values of 10.16 and 10.17 were obtained respectively. The mean indicates that there were impressive positive returns/gains across the period of the study. The standard deviation with low value of 0.41 shows that the data was clustered around the mean and this implies that trading in the Nigerian stock market is without excess risk. Further the value (2.10) of price fluctuations in the equity transaction calculated as the difference between the highest and lowest returns is not much high thus affirming the figures of the reported standard deviation of the market. A skewness value of 0.54 suggests that the return is moderately negatively skewed and not normal. It further implies that the distribution is asymmetric. Kurtosis of 3.33 means that the series is leptokurtic. A Jarque-Bera (JB) test statistics of 267.49 is significantly large, and its commensurate p-value of 0.0000 is a validation that the null hypothesis of normality would be rejected. We would then proceed to subject the returns series to appropriate volatility models such as EGARCH, TGARCH and PGARCH.

Unit Root Test for LNASI

It is a prerequisite to check for stationarity of the data when modelling the Index return. The Augmented Dickey-Fuller (ADF) test is employed to examine the presence of the unit root in the series.

Table 2: ADF Test Result Summary

Variables	ADF Stat	Critical value @ 1%	Critical value @ 5%	Critical value @ 10%	Order of Integration
LNASI	**-45.16**	**-3.43**	**-2.86**	**-2.56**	**I(1)**

*significant at 5%

Source: Authors' computed result using E-views

It can be seen from Table 2 that the series became stationary at first difference. At this order, the calculated ADF test statistics for the returns series are lower than the critical values at the various conventional significance levels of 1%, 5%, and 10%; therefore, it justifies the rejection of the null hypothesis and concludes that the returns are stationary at order 1(1). The data having satisfied the stationarity condition, estimating the model will not produce spurious results.

Autocorrelation Test

There is need to add autoregressive processors [AR (1 to 2)] in the model before taking decision on autocorrelation in order to ensure that autocorrelation will not be mistaken with arch effect. Autoregressive processor deals with autocorrelation which usually behaves like arch effect; this is a precautionary measure to ensure that any observed changes in bunches will be confidently categorized as arch effect. Arch model will not be suitable for use if there is autocorrelation in the mean.

In the figure 1 below, there is no autocorrelation as it can be seen that the dots are neatly tucked in and are not shooting out across the perpendicular lines.

Figure 1 Correlogram of Residuals

Date: 08/30/21 Time: 09:38
Sample: 1/02/2001 12/31/2020
Included observations: 4954
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.002	-0.002	0.0133	
		2	0.092	0.092	42.399	
		3	-0.003	-0.003	42.446	0.000
		4	-0.013	-0.021	43.240	0.000
		5	-0.005	-0.005	43.385	0.000
		6	0.005	0.008	43.498	0.000
		7	-0.016	-0.016	44.834	0.000
		8	0.003	0.001	44.874	0.000
		9	0.006	0.009	45.041	0.000
		10	0.016	0.016	46.312	0.000
		11	0.010	0.008	46.773	0.000
		12	0.012	0.009	47.462	0.000
		13	0.011	0.010	48.045	0.000
		14	0.011	0.009	48.613	0.000
		15	0.011	0.010	49.213	0.000
		16	0.018	0.017	50.771	0.000
		17	-0.000	-0.001	50.772	0.000
		18	0.018	0.015	52.368	0.000
		19	0.006	0.007	52.541	0.000
		20	0.008	0.005	52.859	0.000
		21	0.012	0.010	53.518	0.000
		22	0.030	0.030	58.057	0.000
		23	0.015	0.014	59.184	0.000
		24	0.019	0.014	61.072	0.000
		25	0.010	0.008	61.585	0.000
		26	0.023	0.021	64.231	0.000
		27	0.041	0.040	72.750	0.000
		28	0.029	0.025	76.888	0.000
		29	0.013	0.006	77.675	0.000
		30	0.009	0.005	78.078	0.000
		31	-0.008	-0.009	78.416	0.000
		32	-0.006	-0.007	78.570	0.000
		33	-0.014	-0.014	79.602	0.000
		34	-0.021	-0.021	81.731	0.000
		35	0.003	0.004	81.777	0.000
		36	0.004	0.005	81.860	0.000

Arch Test:

This is to ascertain the presence of arch effect (that is whether the variance is non constant) on the Nigeria Exchange. Plot of the index daily time series and daily market returns in figures 2 and 3 respectively, and heteroskedasticity test in table 3 were carried for this purpose. Arch effects can be clearly seen in table 3 as the probabilities of 1594.666 F-Statistics and 1206.658 Chi-Square are not significant at 0.0000. Besides, this is evident in figure 2 where there is evidence of volatility clustering, and as well in figure 3 where the market returns fluctuate around the figure zero. All these mean that there are unequal variances of the error term. Therefore, we can confidently adopt non-linear models (arch models) as appropriate for estimation of our data.

Table 3: Heteroskedasticity Test: Arch Effect Test

F-statistic	**1594.666**	**Prob. F(1,4951)**	**0.0000**
Obs*R-squared	**1206.658**	Prob. Chi-Square(1)	0.0000

Source: Extracted from the ARCH effect estimates in EViews

Figure 2: Daily Time Series Plot of Nigeria Stock Market Index

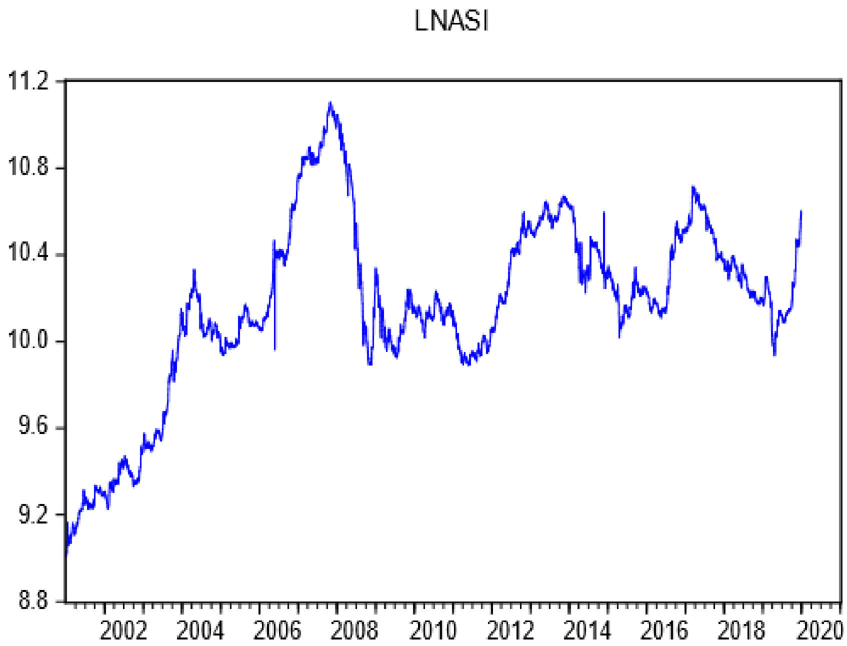
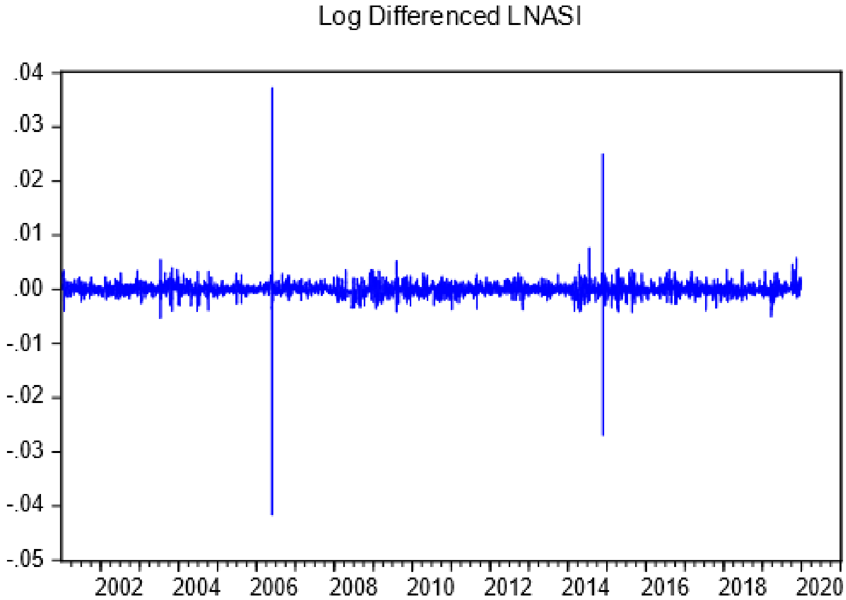


Figure 3: Daily Market Returns of Nigeria Stock Market



Model Selection

In table 4, We applied four volatility models (GARCH, EGARCH, TGARCH, and PGARCH) to estimate stock returns, considering three different distributions (normal, Student's t- and Generalized Error distributions), resulting in a total of twelve ARCH family models. Then we determined the appropriate distribution and best model which have the least information criteria (SIC) for the purpose of finding the leverage and persistent effects in the Nigerian stock market.

Table 4: Stock Returns Estimates Using GARCH Family Models

Models	Equations	Model parameter	Normal distribution			Student's t distribution			Generalised error distribution			Min SIC across error Distr
			Coefffs	P-value	SIC	Coeffs	P-Value	SIC	Coeffs	P-Value	SIC	
GARCH (1, 1)	Mean	Intercept	0.0021	0.4821	-6.3844	0.0079	0.0011	-6.6583	0.0046	0.0208	-6.6393	
		AR	1.0002	0.0000		0.9992	0.0000		0.9995	0.0000		
	Variance	Intercept	9.59E-06	0.0000		1.71E-05	0.0000		1.74E-05	0.0000		
		ARCH	0.4568	0.0000		0.5308	0.0000		0.5297	0.0000		
		GARCH	0.6091	0.0000		0.4148	0.0000		0.4268	0.0000		
EGARCH (1, 1)	Mean	Intercept	0.0055	0.0439	-6.3945	0.0079	0.0010	-6.6489	0.0136	0.0000	-5.9208	
		AR	1.0006	0.0000		0.9992	0.0000		0.9986	0.0000		
	Variance	Intercept	-1.9265	0.0000		-2.2185	0.0000		-0.7131	0.0000		
		ARCH	0.6676	0.0000		0.6017	0.0000		0.0120	0.0000		
		Asymetrc	-0.1071	0.0000		0.0105	0.5235		0.0117	0.0000		
		GARCH	0.8410	0.0000		0.8106	0.0000		0.9253	0.0000		
TGARCH(1 1)	Mean	Intercept	-0.0027	0.3673	-6.3949	0.0080	0.0009	-6.6582	0.0046	0.0198	-6.6389	
		AR	1.0003	0.0000		0.9992	0.0000		0.9995	0.0000		
	Variance	Intercept	1.60E-0	0.0000		1.70E-0	0.0000		1.74E-0	0.0000		
		ARCH	0.4070	0.0000		0.5619	0.0000		0.5273	0.0000		
		Asymetrc	0.3557	0.0000		-0.0678	0.2316		0.0052	0.9338		
		GARCH	0.4774	0.0000		0.4164	0.0000		0.4267	0.0000		
PGARCH (1 1)	Mean	Intercept	-0.0058	0.0346	-6.3996	0.0083	0.0005	-6.6611	0.0043	0.0253	-6.6410	
		AR	1.0006	0.0000		0.9991	0.0000		0.9995	0.0000		
	Variance	Intercept	0.0010	0.0020		0.0004	0.1381		0.0003	0.1964		
		ARCH	0.4308	0.0000		0.4374	0.0000		0.4378	0.0000		

		Asymetrc	0.1597	0.0000		-0.0462	0.1189		-0.0066	0.8397		
		GARCH	0.5573	0.0000		0.5069	0.0000		0.5154	0.0000		

Source: Extract from the models estimates

Table 5: Student's T- Distribution Suitability Validation

GARCH Models	Schwarz Information Criterion			**Performance of Non-Gaussian Process over Gaussian Process (%)**	
	Normal Distribution	Student's t Distribution	Generalized Error Distribution	Student's t Distribution	Generalized Error Distribution
GARCH (1, 1)	-6.3844	**-6.6583**	-6.6393	**27.4**	25.5
EGARCH (1, 1)	-6.3945	**-6.6489**	-5.9208	**25.4**	-47.4
TGARCH (1, 1)	-6.3949	**-6.6582**	-6.6389	**26.3**	24.4
PGARCH (1, 1)	-6.3996	**-6.6611**	-6.6410	**26.2**	24.14

Source: Authors' Computation

In table 4, student's t-distribution produced the minimum information criteria across all the three distributions. This was validated by the computation and comparison of percentage improvements of the two non-Gaussian process over the Gaussian assumption. The student's t-distribution has greater improvement over normal process than the generalized error distribution across the four GARCH models. This has two implications: first, the non-Gaussian process is more appropriate to reflect the volatility characteristics of stock returns in Nigeria Exchange due to the asymmetricity of the data. Second, student's t error processes is a suitable choice and has superior estimating capability. This was specially highlighted in table 5. Consequently, we adopted student's t distribution estimate for the measure and analysis of asymmetric and persistent parameters.

Leverage effect

For the leverage estimation, we determine its existence with the non-gaussian distributions. The null hypothesis (H0) of asymmetric parameter, $\gamma=0$ is estimated at 5% significance level. Not accepting H0 means that there is news effect. Specifically the sign and significance of the asymmetric parameter (γ) indicate the existence or otherwise of leverage effect. And since the best error distribution here is student t- distribution, we considered all the asymmetric GARCH models across it.

It can be noted that news effect is non-existent in Nigerian Stock Exchange within the review period. Results of all the asymmetric specifications are similar. With EGARCH model, the asymmetric coefficient is positive (0.0105) and insignificant (0.5235) as against its a priori expectation of negative sign. Likewise, with TGARCH model, the asymmetric parameter is negative (-0.0678) and insignificant (0.2316) and this does not conform to its theoretical assumption of positive sign. Similarly, under PGARCH model, the negative asymmetric coefficient of (-0.0462) is also contrary to positive sign general assumption, it is as well insignificant (0.1189). In Nigerian Exchange therefore, volatility reacts to positive information in a greater degree compared with its response to negative information of same size. This indicates that investors are increasingly inclined to favorable announcements over unfavorable ones of equivalent degree.

The above results are in conflict with the outcomes of the works of Agwu and Ogbonna (2020), Herbert, Ugwuanyi and Nwaocha (2019), Omokehinde (2017), Atoi (2014), Okpara (2011), Onwukwe (2011), Emenike (2010) and Ogum (2005). Their investigations disclosed presence of leverage in Nigerian Exchange. Nevertheless, the results allied with the evidence from Emenike (2012), Osazevbaru (2014), Aliyu (2011), Uyabo, Atoi and Usman (2015), and Adebayo and Ibraheem (2017) which failed to establish news effect in the market. Note that most of these works adopted Gaussian processes.

Table 6: Persistence Effect

GARCH Models	GARCH	EGARCH	TGARCH	PGARCH
Error Distribution	Student's t	Student's t	Student's t	Student's t
Volatility Persistence	0.9456	1.4123	0.9783	0.9443

Source: Extract from the models estimates

Volatility persistence is captured by Arch and Garch coefficients. Going by the selected error assumption, that is t-distribution, we can see that Nigeria Exchange exhibited explosive volatility persistence. In table 6, most of the persistence parameters are approximately 1, (0.9456, 0.9783 and 0.9443), worse still the parameter under EGARCH is high above 1 (1.4123) which implies that the volatility is protracted and exhibits spillover from one period to other. The consequence of all these is that market shock and disturbance take time to fade away.

Our result supports Emenike and Aleke (2012) who discovered high and prolonged volatility in Nigeria Exchange, however it differs slightly from Okpara (2011) that established low persistence. Further, it is in sharp contradiction to the findings of Agwu and Ogbonna (2020) as they stated no volatility persistence.

Diagnostic Check

Arch LM Test is employed for two purposes here: to investigate if the time-stamped data still has trace of arch effect, that is if the series still shows bits of heteroscedasticity, and also ascertain the GARCH family models validity.

Table 7: Summary of Diagnostic Test Using ARCH LM

	STATISTICS	**VALUE**	**P-VALUE**
GARCH, Student t	F-statistics	0.025441	0.8733
	Observed R^2	0.025451	0.8732
EGARCH, Student t	F-statistics	0.015590	0.9006

	Observed R^2	0.015596	0.9006
TGARCH, Student t	F-statistics	0.022989	0.8795
	Observed R^2	0.022998	0.8795
PGARCH, Student t	F-statistics	0.217308	0.6411
	Observed R^2	0.217387	0.6410

Source: estimates of ARCH LM

We failed to reject the null hypothesis of no residual arch effect in the time-stamped data as shown in Table 7. Note that the results were obtained with student's t specifications.

The probabilities of F-statistics and Observed R2 in all the four GARCH models are greater than 5% significance level. The homoscedasticity has convincingly confirmed the models as good and appropriate for estimating volatility because arch effect has been adequately taken care of.

CONCLUSION

The knowledge of stock market elasticity to news is one of the investors' major consideration for optimal asset portfolio selections. It guides investors to properly evaluate the risk inherent in investing in stock market instruments and help policy makers (particularly, SEC) in their efforts towards capital market reforms. Using more recent and an extended sample of daily data, this work examined the presence of volatility persistence and leverage effect in the Nigerian Exchange. We employed the daily stock prices of Nigerian Exchange ranging from 2001 to 2020 which was transformed into market returns. The series was estimated with various GARCH models such as GARCH, EGARCH, TGARCH and PGARCH through different non gaussian process viz. normal, student-t and GED. Student-t (having outperformed the other assumptions) was selected as the best fit error distribution across the entire four GARCH models through the information criteria. It is important to note that Gaussian distribution is mostly used in the previous studies, our non-Gaussian approach in this paper is rarely used. The finding has shown that the normal and non-normal methods differ remarkably in estimating accuracy with student-t being the best volatility estimator in Nigeria Exchange

The results of the descriptive statistics confirmed the characteristic definition of stock returns series; non-normality, skewness, leptokurtosis, and ARCH effects are displayed. In the estimation, it was found that Nigerian exchange had no asymmetric effect and this simply means that swings in stock returns react favorably to good news than that of bad news of equal size. The empirical results of EGARCH, TGARCH and PGARCH estimates run contrary to their leverage effect theoretical signs, implying that volatility is more responsive to good news compared to bad news. Further the result shows presence of excess volatility persistence in the market in the period under review, and this can create wave of uncertainty in the minds of market participants. The shock is found to be more persistence under EGARCH model with parameter of 1.4123. Afterwards, diagnostic test was conducted where homoscedasticity was established indicating that the right choice was made applying GARCH specifications for the estimation.

The implication of this asymmetric presence is that Nigerian Exchange is largely controlled by individuals and institutions with short-term investment plan. There is no doubt that with this attitude the Nigerian Exchange will hardly grow and develop into medium and long-term investment outlet. In addition, investors in the market are more inclined to investing in equities with good news over those with bad news both of equal size. Further, the finding of wild fluctuations in asset returns in Nigerian exchange is with some mixed consequences: these include increase in the cost of capital and corresponding high return on investment because of the high-risk content of the market. Furthermore, the excess volatility in the market explains why stock prices of Nigerian firms do not reflect market fundamentals because it undermines the efficacy of the asset prices as guide for discovery of the correct and real worth of companies. More, explosive volatility is one of the reasons for intermittent massive withdrawal of investors from stock market in preference to other less risky financial assets. One typical instance in Nigeria is the resultant uncontrolled volatility in 2006 - 07 and massive exodus of investors arising from margin loans in the Exchange.

We recommend that concerted efforts should be made towards moderating the volatility level by promoting market education and improving the investor’s understanding of the market mechanisms. this will help to ensure positive risk taking behaviours. Also, strong institutions are foundation for creating a heathy investment environment; thus continuous improvement of the rule of law, regulatory framework governance and ease of doing business will ease down volatility. Of similar importance is the serious and urgent need to reduce the security risk and tension (banditry, kidnapping, terrorism, etc.) in the country as they are catalyst for investment flight. There must be a consistent effort to instill confidence and trust in the market. Further, the market should be adequately equipped with more variety of securities offered to improve the attractiveness of the Exchange to both local and international investors. All these will help in furthering the market depth and width to achieve market stability.

3. References

Adebayo, A. & Ibraheem, N. (2017). Measuring leverage effect on the Nigerian stock Exchange in the post financial meltdown, TGRACH VS EGARCH. Amity Journal of Finance, 1(2), 1 – 21.

Aggarwal, R., Inclan, C. & Leal, R. (1999). Volatility in emerging stock markets. Journal of Financial and Quantitative Analysis, 34(1), 33 – 55.

Agwu, E. & Ogbonna, G. (2020). Evaluation of volatility persistence and asymmetric effect in Nigerian capital market. IOSR Journal of Economics and Finance, 11(1), 19 – 26.

Alberg, D., Shalit, H. & Yosef, R. (2011). Estimating stock market volatility using asymmetric GARCH models, Applied Financial Economics, 18(15), 1201- 1208.

Alcorn, S. (2014). How stock market volatility could impact the economy. Retrieved form http/www/marketplace.org.

Aliyu, S. (2011). Does inflation have an impact on stock returns and volatility? Evidence from Nigeria and Ghana. 2011 International Conference on Economic and Finance Research, IPEDR, 4, 399 - 405

Almeida, D. & Hotta, L. (2014). The leverage effect and the asymmetry of the error distribution in GARCH based models: the case of Brazilian market-related series. Pesquisa Operational, 34(2), 237 – 250.

Anderson, T. (2007). Real–time price discovery in global stock, bond and foreign exchange markets. Journal of International Economics, 73, 251 –

277.

Arestis, P., Demetriades, P. & Luintel, K. (2001). Financial development and economic growth: the role of stock markets. Journal of Money Credit and Banking, 33(1), 16 – 41.

Arora, R., Das, H. & Jim, K. (2009). Stock returns and volatility: evidence form selected emerging markets. Review of Pacific Basin Financial Markets and Policies, 12(4), 221 – 238.

Atoi, N. (2014). Testing volatility in Nigeria stock market using GARCH Models. Central Bank of Nigeria Journal of Applied Statistics, 5(2), 65 – 93.

Bartolommeo, D. (2007). Fat tails, tale tails and Puppy dog tail. Annual summer seminar – Newport, R1.

Bekaert, G. & Harvey, C. (1997). Emerging market volatility. Journal of Financial Economics.

Bekaert, G. & Wu, G. (2000). Asymmetric volatility in equity markets. The Review of Financial Studies, 13(1), 1 – 42.

Bittlingmayer, G. (1998). Output stock volatility and political uncertainty in a natural experiment: Germany, 1880 – 1940. Journal of Finance, 53(6), 2243 – 2257.

Black, F. (1976). Studies of stock price volatility changes. Business and Economical Statisstics, 177 – 181.

Bollersleo, T. (1986) Generalized Autoregressive Conditional Heteroskedasticity: Journal of Economics; 31, 307 – 327.

Bollerslev, T., Engle, R. & Nelson, D. (1994). ARCH models, in Engel, R & McFadden, D. (eds), Handbook of Econometrics. 4, 2959-3038.

Bollerslev, T. (2009). Volatility and Time Series Econometrics: Essays in honour of Engle, R. London, UK: Oxford University press.

Braun, P., Nelson, D. & Sunier, A. (1995) Good news, bad news, volatility and betas. Journal of Financial, 1(5): 1575 – 1603

Campbell, J. & Hentschel, L. (1992). No news is good news: an asymmetric model of changing volatility in stock returns. Journal of Financial Economics, 31, 281 – 318.

Campbell, J. (1996). Consumption and the stock market: interpreting international experience. NBER Working Paper, 5610.

Charles, A. (2010). The day-of- the week effects on the volatility: the roles of the asymmetry.. European Journal of Operational Research, 202(1), 143 – 152.

Cheng, A., Jahan–Paver, M. & Rothman, P. (2010). An empirical investigation of stock market behavior in the Middle East and North Africa. Journal of Empirical Finance, 17(3), 413 – 427.

Cont, R. (2001). Empirical properties of asset return; stylized facts and statistical issues. Quant Fin., 1, 223 – 236.

Cutler, D., Porterba, J. & Summers, L. (1989). What moves stock prices? Journal of Portfolio management, 15, 4 -11.

Dabusinbkas, A., Kulikuv, D. & Randveer, M. (2012). The impact of volatility on economic growth. Ecsti-pank Working Paper Series, 7/2012, 1 – 21.

Dania, A. & Spillan, E. (2013). Volatility transmission from mature global stock markets to Middle East and North African stock markets. Accounting and Finance Research, 2(1), 19 – 31

Delong, J., Shleifer, A., Summers, L. & Waldmam, R. (1989). The size and incidence of the losses from noise trading. The Journal of Finance, 44, 681 – 696.

Ding, W. & Engle, R. (1993). A long memory property of stock market returns and a new model. Journal of Empirical Finance, 1, 83-106.

Ekum, M., Owolabi, T. & Alakija, T. (2018). Modeling volatility in selected Nigerian stock market. International Journal of Economics and Financial Management, 3(1).

Emenike, K. (2010). Modeling stock returns volatility in Nigeria using GARCH models. Munich Personal REPEC Archive, 22723, 1 – 19.

Emenike, K. & Aleke, S. (2012). Modeling asymmetric volatility in the Nigerian Stock Exchange. European Journal of Business and Management, 4(12).

Engle, R. & Ng, V. (1983). Measuring and testing the impact of news on volatility. Journal of Finance, 48(1), 1749 – 1778.

Engle, R., Forcard, S. & Fabozzi, F. (2005). ARCH/GARCH Models in applied financial econometrics. Journal of Econometrics and Financial, 60(4), 109 – 133.

Fama, E. (1965). The behavior of stock market prices. Journal of Business, 38(1), 34 – 105.

Fama, F. (1970). Efficient capital markets: a review of theory and empirical works. Journal of Finance, 25(2), 383 – 399.

Ferderer, J. (1993). The impact of uncertainty on aggregate spending. Journal of Money, Credit and Banking, 25, 30 – 45.

Floros, C. (2008). Modeling volatility using GARCH models: evidence from Egypt & Israel. Middle Eastern Finance & Economics, 2, 31 – 41.

Francis, P. & McAleer, M. (2002). Financial volatility: an introduction. Journal of Applied Economics, 17, 419 – 424

Glosten, L., Jagannathan, R. & Runkle, D. (1993). On the relation between the expected value and volatility of nominal excess return on stocks. The Journal of Financial, 48(5), 1779 – 1801

Goudarzi, H. & Ramanarayanan, (2011). Modeling asymmetric volatility in the Indian stock market. International Journal of Business and Management, 6(3), 221 – 231.

Guidi, F. (2008). Volatility and long-term relations in equity markets: empirical evidence from Germany, Switzerland, and the UK http.//mpra.ub.unimuenchen (Mumich Personal RePEc Archive) paper, no. 11535.

Harvey, C. & Siddique, A. (1999). Autoregressive conditional skewness. Journal of financial and Quantitative Analysis, 34 (4), 465 – 477.

Herbert, W., Ugwuanyi, G. & Nwaocha, E. (2019). Volatility clustering, leverage effects and risk return trade–off in the Nigerian stock market. Journal of Finance and Economics, 7(1), 1 – 13.

Hsieh, D. (1989). Testing for non-linear dependence in daily foreign exchange rates. Journal of Business, 62, 339 - 368

Hurditt, P. (2004). An assessment of volatility transmission in the Jamaican financial system. Retrieved from http://www.bog.org.jm/publications.

Jayasuriya, S. (2002). Does stock market liberalization affect the volatility of stock returns: evidence form emerging market economics? Georgetown University Discussion Series. Jebran, K. & Iqbal, A. (2016). Examining volatility spillover between Asian countries' stock markets. China Finance and Economic Review, 4(1).

Jingli, X. & Sheng, Z. (2011). Stock market volatility in China: based on the mode of ARIMA–EGARCH–M (1,1) and ARIMA–TARCH–M (1,1). Journal of Management Science & Statistical Decision, 8(1).

Karolyl, G. (2001). Why stock return volatility really matters. Preliminary and incomplete version.

Kaur, H. (2004). Time varying volatility in the Indian stock market. VIKALPA 29(4), 25 – 42.

Koulakiotis, A., Papasyriopoulos, N. and Molyneux, P. (2006). More evidence on the relationship between stock price returns and volatility. Journal of Finance and Economics.

Kuhe, D. & Ikughur, J. (2017). Investigating stylized facts of asset returns in an emerging stock market in the presence of Gaussian errors. Trends in

Science and Technology Journal, 2(113), 537 – 542.

Lee, T. (2000). The interaction and volatility asymmetric of unexpected returns in the greater China stock markets. Global Finance Journal, 11, 129 – 149.

Léon, N. (2007). Stock market returns and volatility in the BRVM. African Journal of Business Management, 15,107-112.

Li, Y. & Giles, D. (2015). Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets. International Journal of Finance and Economics, 20(2), 155-177.

Long, L., Tsui, A. & Zhang, Z. (2014). Conditional heteroskedasticity with leverage effect in stock returns: evidence from the Chinese stock market. Economic Modeling, 37, 89–102.

Ludvigson, S. & Steindel, C. (1999). How important is the stock market effect on consumption? Federal Reserve Bank of New York Economic Policy Review, 5(1), 29 – 51.

Mala, R. & Reddy, M. (2007). Measuring stock market volatility in an emerging economy. International Research Journal of Finance and Economics, 8; 126 – 133.

Magnus, F & Oteng–Abayie, E. (2006). Modeling and forecasting volatility of returns on the Ghana Stock Exchange using GARCH Models. American Journal Applied Sciences, 3(10), 2042 – 2048.

Malnisten, H. & Terasuirta, T. (2004). Stylized facts of financial time series and three popular models of volatility. SSE/EFI Working Paper Series in Economic and Financial Finance, 563, Stockholm School of Economics

Mandelbrot, B. (1963). The variation of certain speculative prices. Journal of Business, 36(4), 394 – 419.

Mele, A. (2008). Understanding stock market volatility: a business cycle perspective. Working Paper Lunder School of Economic, London.

Mohammad, A. & Hasanur, R. (2009). The effect of information technology on stock market trade volume and volatility: case for Dhaka Stock Exchange in Bangledesh. AUJ Journal, 12(14).

Mun, H., Sundaran, H. & Yin, O. (2008). Leverage effect and market efficiency of Kuala Lumpur composite index. International Journal of Business and Management, 3(4), 138 – 144.

Nelson, D. (1991). Conditional Heteroskedasticity in Asset returns: a new approach. Econometrical, 59,347-370.

Ngo Thai Hung (2018). Dynamics of volatility spillover between stock and foreign exchange market: empirical evidence from central and eastern European countries. European Council for modelling and simulations, 27-34

Ogum, G., Beer, F. & Nouyrigat, G. (2005). Emerging equity market volatility: an empirical investigation of markets in Kenya and Nigeria. Journal of African Business, 6(1/2), 139 -154.

Okicie, J. (2015). An empirical analysis of stock returns and volatility: the case of stock market from Central Eastern Europe and South East. European Journals of Economic and Business, 9(1).

Okpara, G. & Nwezeaku, N. (2009). Idiosyncratic risk and the cross–section of expected stock returns: evidence from Nigeria. European Journal of Economics, Finance and Administrative sciences, 17, 1–10.

Okpara, G. (2011). Volatility modeling and the Nigerian Stock return relationship in EGARCH- in-mean framework. International Journal of Current Research, 3(8), 176–185.

Olowe, A. (2009). Stock return, volatility and the global financial crisis in an emerging market: the Nigerian case. International Review of Business Research Papers, 5(4), 426 – 447.

Omokehinde, J., Abata, M., Somoye, R. & Migiro, S. (2017). Asymmetric information and volatility of stock returns in Nigeria. Journal of Economics and Behavioral Studies, 9(3), 220 – 231.

Onwukwe, C., Bassey, B. & Isaac, I. (2011). On modeling the volatility of Nigerian stock returns using GARCH models. Journal of Mathematics Research, 3(4), 31 – 43.

Opschoor, A. (2014). Understanding financial market volatility. Tinbergen Institute, 1 – 189.

Osazevbaru, H. (2014). Modeling Nigerian stock market news using TGARCH model. International Journal of Development and Sustainability, 3(9), 1894 – 1900.

Oskooe, S. & Shamsavari, A. (2011). Asymmetric volatility in emerging stock markets: a case of Iran. International Journal of Economics and Finance, 3 (6); 15 – 24.

Paul, R. (2006). Autoregressive conditional Heteroscedasticity (ARCH) Family of Models for Describing Volatility. New Delhi: New Deihi University Press.

Porterba, J. (2000). Stock market wealth and consumption. Journal of Economic Perspective, 14(2), 99 – 118.

Raju, M. & Ghosh, A. (2004). Stock market volatility: an international comparison. SEC Board of India, Working Paper Series No. 8.

Ramey, G. & Ramey, V. (1995). Cross country evidence on the link between volatility and growth. America Economic Review, 85(5), 1138 – 1151.

Richard, A. (1996). Volatility and predictability in natural market; how do emerging and mature markets differ. International Review of Financial Analysis, 17(1), 27 – 46.

Rodriguez, J. & Ruiz, E. (2009). Garch models with leverage effect: differences and similarities. Working Paper 09-03, Statistics and Econometrics Series 02, 1—35.

Saleem, K. (2007). Modeling time varying volatility and asymmetry of Karachi Stock Exchange (KSE). International Economics & Business Knowledge Society, 1 – 7.

Samanta, G. (2010). Stock market return, volatility and future output growth – some observations relating to Indian economy.

Schwert, W. (1989). Stock volatility and crash of '87. Review of Financial studies, 3, 77-102.

Shiller, R. (2000). Irrational Exuberance. Princeton University's Press.

Starr–McCluer, M. (1998). Stock market wealth and consumer spending. The Federal Reserve System, Finance and Economic Discussion Paper Series, 98/20.

Sungh, P. & Kiosh, N. (2016). Stock return volatility effect: study of BRICS countries. Transactional Corporation Review, Vivekananda Institute of Professional Studies, 6(4), 406 – 418.

Taylor, S. (1986). Modeling financial Tine Series. New York: John Wiley & sons.

Tsay, R. (2005). Analysis of Financial Time Series. New Jersey, USA: John Wiley & Sons.

Uyaebo, S., Atoi, V. & Usman, F. (2015). Nigeria stock market volatility in comparison with some countries: application of asymmetric GARCH models. Central Bank of Nigeria Journal of Applied Statistics, 6(2), 133 – 160.

Verhoeven, P. & McAleer, M. (2003). Fat tails and asymmetry in financial volatility models. CIRJE-F-211 Discussion Paper.

Veronesi, P. (1999). Stock market overreaction to bad news in good times: a rational expectations equilibrium model. The review of financial studies, 12(5), 975 – 1007.

Yaya, O., Bada, A. & Atoi, N. (2016). Volatility in the Nigerian stock market: empirical application of Beta-t-GARCH variants. Central Bank Nigeria Journal of Applied Statistics, 7(2), 27 – 48.

Yeh, Y. & Lee, T. (2000). The interaction and volatility asymmetric of unexpected returns in the greater China stock markets. Global Finance Journal, 11, 129 – 149.

Zakoian, J. (1986). Threshold heteroskedastic models. Journal of Economic Dynamics and Control, 18, 931 – 944.

Zuliu, H. (1995). Stock market volatility and corporate investment. IMf Working Paper, 95/102.