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MODELLING THE ASYMMETRIC AND SYMMETRIC CONDITIONAL VOLATILITY AND THEIR PERFORMANCE IN THE NIGERIAN CAPITAL MARKETS

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Abstract
Nigerian capital market has an essential role in stimulating economic growth by mobilizing domestic savings and encouraging static financial resources to be allocated to more productive activities. Considering this pivotal role of the capital market, this study explores the behavior of the Nigerian capital market excess stock return via the asymmetric and symmetric conditional volatility over the period January 2, 2001, to November 8, 2018. By assessing the comparison among various conditional volatility models, the results are i) there is strong persistence volatility in the stock returns, that is, the presence of ARCH and GARCH, ii) no evidence of asymmetric in the volatility, and iii) no risk premium from the best-fitted models. The study, therefore, concludes that there is no linear relationship between risk and returns as the coefficient is insignificant and that there are no differential effects between positive and negative shocks in the Nigerian capital market. This study offers some insight into the portfolio management strategy and contributes to the growing stock conditional volatility literature in portfolio optimization.

Keywords: Risk-return, information criteria, trade-off, volatility and stock prices
JEL Classification: C58 G11 G1

1. Introduction

In finance, volatility is an essential element in estimating the riskiness of an asset. The assessment of any asset requires the valuation of the risks on the potential payments from the asset. The ability to predict volatility is based on available information from pricing stocks, options, and securitization pricing (Yalaman and Saleem, 2017). Volatility modeling and volatility forecasting have continued to play a significant role in finance, especially in asset pricing (Hull and White 1987), asset allocation, and risk measurement (Aizenman and Marionm 1999), given the increasing shorter horizons of data over time. The volatility of equity markets affects economic growth and development by affecting investors' confidence and risk capacity (Baker and Wurgler 2007). Studies have shown that the volatility of stock markets will affect the stock market. Increased stock market volatility, for example, can lead to a rise in equity investment risk and thus a shift of the

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equity funds into less volatile asset classes, i.e., debt. This change may result in a rise in the cost of capital to companies, so new firms may abide by this impact as investors buy superior stock from well-known firms. As stock markets exhibit higher volatility, it induces investment fear and sadistically decreases the value of overall stock portfolios, Wagner (2007). It is clear that stock markets follow an economic cycle that booms, followed by recession and crashes, then markets reorganize and start to build trust in investors and become part of the recovery and boom process.

On the empirical front, the volatility behavior of stock prices exhibits signs of a leptokurtic trend and fat tails compared with a normal distribution (Kim and Singal, 2000; Fama, 1965). Given that it is a practical tool for allocating resources to its highest value players, stock markets help enhance investments and savings that are imperative for economic growth. Reisman (1999) has argued that stock prices are directly influenced by the rise in money supply, as this rise in money supply is only channeled into the stock market and not invested elsewhere in the economy. When such an increase in the supply of capital is directed through the economy and causes the price level to rise, the effect on the stock market is different. By implication, inflation is expected to have a massive impact on capital creation, thereby making the capital market riskier.

However, this study is unique because i) few studies have also examined volatility behavior and their performance in the African markets with particular attention to Nigeria (see Emenike, 2018; Mekoya, 2013; Osazevbaru, 2014). ii) Most of the studies conducted are in line with the evidence from the developed market; iii) There is no consensus on the uniqueness of a particular technique (Mostafa, Dillon & Chang, 2017). iv) The controversy on the presence of the "leverage effect" in the existing literature in the Nigerian stock market is yet to be resolved (Figlewskie6952 & Wang, 2000).

2.0 Literature review

Considerable attention has accorded to this area of study in understanding the level of stock return volatility and its effect on the smooth working of any stock market (Wu, 2001; Kao, Chuang and Ku, 2019; Nihat Solakoglu and Demir, 2014). A portion of these investigations have analyzed the consequences of stock return volatility on economic growth and its effect on the certainty and risk-taking capacity of speculators (see Aljandali and Tatahi, 2018; Guptha, and Rao, 2018; Lama et al., 2015; Ali et al., 2019; Ghufran et al., 2016). More recent analysts have stretched out to distinguish the degree of stock volatility in the stock market (Elshareif and Kabir, 2017a, b; Ali et al., 2019; Ghufran et al., 2016). The debate among researchers is centered on the presence of fat tails, volatility clustering, leverage impacts, long memory and co-movement in volatility, and a risk-return relationship of assets in the capital market (see, for example, Coffie, 2018; Mostafa, Dillon and Chang, 2017; Aljandali and Tatahi, 2018; Lin, 2018; Tah, 2013; Karmakar, 2007; Chen, 2015).

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Another strand of literature on stock market volatility lies at the heart of two opposing debates: fundamentalist and technical analysis. To Mallikarjuna and Rao (2019), fundamentalists employ financial reports of firms to forecast stock prices and the Technical analysts, on the other hand, apply previous data to forecast future prices on the premise that market forces drive stock prices and that past performance or movement do reoccur in predictable patterns in the future. The fundamentalists believed that a rational investor must rigorously evaluate fundamental financial facts relating to assets so that their intrinsic prices can be calculated as a prelude to finding mispriced assets on the market (Ogbulu, 2015). The second school of thought is the random walk hypothesis, known as an Efficient Market Hypothesis (EMH). To Fama (1970), an efficient market assumed that stock prices reflect entirely the information and changes in security prices of securities available and that they are random, not systematic, as advocated by technicians (Mallikarjuna and Rao, 2019; Almudhaf, 2018).

Empirical studies have supported the above claim by proposing different techniques for modeling conditional volatility of stock returns. Engle (1982) proposed the ARCH model to ascertain the time-varying conditional volatility using the past stochastic error term information. However, the technique suffers some defects due to over-parameterization and the inability to capture the conditional variance dynamics. Bollerslev (1986) broadened Engle's (1982) study by summing up the ARCH model, popularly known as the GARCH model. The GRACH model accounts for the time-varying volatility of both past innovation and past variances.

Meanwhile, financial time series or stock prices can respond differently to any economic news in asymmetric or leverage effects that the conventional ARCH and GARCH cannot capture (Black 1976). In this line of argument, Nelson (1991); Glosten et al. (1993) found that a significant negative return may expand volatility more than the positive returns to a similar extent. Similarly, negative innovation could be more transparent than positive innovation of a similar size. The implication is that the stock returns are asymmetrically linked to volatility over time (Wang et al., 2018; Cai et al., 2017).

In case of Morocco and Bourse Régionale des Valeurs Mobilières (BVRM) stock markets, Coffie (2017) reported that EGARCH had a negative shock that has a greater impact on future volatility, than a positive leverage shock of the same magnitude. Meanwhile, the GJR forecasts in both markets suggest that positive rather than negative shocks will have a higher conditional variance for the next period. A similar finding has been reported by Coffie (2018), who investigated the stock market returns from Botswana and Namibia and concluded that the existing conditional variance shocks would less impact future market volatility. In both financial markets investigated, the news effect is asymmetrically contributing to the leverage effect. All markets demonstrate reverse asymmetry of volatility, contrasting with the widely accepted theory of volatility asymmetry. In the case of predictive powers of the models, the study showed clear evidence of symmetric GARCH model and fatter-tail distributions as a better sampling forecast for both stock markets. Jayawardena et al. (2020) explored volatility forecasting in the Tokyo Stock

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Exchange (TSE) using high-frequency data from Nikkei 225 and Topix. The study introduced a heterogeneous autoregressive model to identify an optimal approach to forecasting daily volatility by incorporating intraday volatility metrics based on after-hour news. The study found that the overnight non-trading period can be linked to forecasting purposes.

Aliyev et al. (2020) employed EGARCH and GJR-GARCH to investigate the volatility of non-financial, innovative, and hi-tech focused stock index over a period of 2000 to 2019. The study documents evidence of returns persistence and leverage effect. Comparatively, the study concludes that the impact of positive shocks is higher than the negative shocks of the NASDAQ-100. Balaban (2018) tested the volatility persistence and asymmetry in the volatility of Bourse Istanbul using the TGARCH-M model for the period from 1995 to 2015. The study further analyses the interday and intraday distribution of stock returns and shows that volatility is more pronounced in the second session of Monday and Thursday except for Friday. Kenourgios, Asteriou, and Samitas (2013) tested for the presence of asymmetric during the Asian crisis by applying the asymmetric generalized conditional correlation (AG-DCC) model. The study focused on asset markets, equity, and foreign exchange markets and found asymmetric dynamic correlation patterns in series.

In Nigeria, Emenogu et al. (2020) investigated the volatility in the daily returns for total Nigeria Plc using the GARCH extension for 2001 to 2017. The estimation showed the presence of volatility persistence among the GARCH models except for IGARCH and EGARCH. Emenike (2018) conducted a comparative analysis of market history, forecasting market risk, and the market sentiment of selected African stock markets using the GARCH extensions. Since the global financial crisis, the research showed signs of clustering volatility, the persistence of uncertainty, and asymmetric returns in Africa. Lama et al. (2015) compared the Indian domestic oil prices and the international index on oil prices on the predictive efficiency by employing a monthly set of data from April 1982 to March 2012. Using the ARIMA model with GARCH and EGARCH, the study established that the AR(2)-GARCH(1,1) in local and global oil prices provide the most predictive efficiency.

Further, Mekoya (2013) used the GARCH-type model on the NSE 20 Share Index return. The study recorded the following results: The stock market is inefficient in its weak form; leptokurtosis and skewed to the left and not normally distributed. It also exhibited a serial correlation. The unit root test showed that daily returns are non-stationary at order one; the variance of the performances was not constant — the presence of volatility persistence and clustering effect, leverage effect, and asymmetric response to external shocks. Further, the market is not efficient in pricing risk.

When evaluating symmetric and asymmetric estimates, Ali et al. (2019) integrated oil assets to analyze the reaction of different shocks and asset variance and covariance series. Researchers found that previous news and lagged volatility significantly affected G7 stock markets' present conditional volatility. Their findings show that **FIGARCH** and

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FIEGARCH demonstrate some degree of continued volatility among the G7 stock markets. In a similar study, Banumathy and Azhagaiah (2015) employed the non-linear GARCH models to examine the volatility using a daily stock price from 2003 to 2012 on the two sets of market indexes, namely the S&P and CNX Nifty Indexes. With the information criteria GARCH-MEAN, EGARCH, and TGARCH, the study documents a positive and insignificant risk premium in the model and asymmetric effect (leverage) and negative shocks in the model conditional volatility. Fousekis (2020) investigated the relationship between stock returns and time-varying volatility using data from four stock pairs (EU, USA, Australia, Chinese market), implied volatility indices, and the non-parametric local regression approach. The results show that the association between these variables is negative and asymmetric concerning the sign and the size of stock returns.

The generalized autoregressive conditional heteroskedasticity (GARCH) model was used by Ortiz and Arjona (2001) for different countries. The analysis found no evidence of heteroskedasticity and autocorrelation in major Latin American stock exchanges, suggesting high volatility time-dependent. In a related study, Mallikarjuna and Rao (2019) analyzed the predictive performance of linear, nonlinear, artificial intelligence, frequency domain, and hybrid models to find the correct model for forecasting different stock returns for 2000-2018. Interestingly, the findings showed that modern techniques were outperformed by conventional linear and not linear models for accurate predictions. Osazevbaru (2014) applied the TGARCH (11) using day-to-day and month-to-month portfolio data from the Nigerian stock market from 1995 to 2011. The result showed that news does not have asymmetries and that the effect of bad news is no more significant than good news for volatility. The response was robust and symptomatic of relatively slow dissipating shocks from the test. The analysis suggests that old information plays a more significant role than new information in returns.

In a study relating volatility and dynamic linkages on variables, Ogbulu (2018) analyzed the effect of Nigeria's market prices of crude oil, and currency exchange rates move from January 1985 to August 2017. Using the ECM technique, Granger causality tests, variance decomposition, and GARCH (1,1) model. Regarding the GARCH model, they showed that ARCH-GARCH volatility analysis indicates that NSE stock market prices exhibit an ARCH effect with a large and optimistic first-order ARCH term. The author claimed that these results provide essential knowledge signals to policymakers, fund managers/advisors, and the investing public to achieve optimum asset and fund profiles

From the above discussion, this study therefore explores the conditional volatility and its performance in the Nigerian Stock Exchange market using various GARCH model over the period from January 2nd, 2001 to November 8, 2018 for the All-Share index. First, the study will examine the volatility clustering, shock persistence, fat-tails distribution, presence of ARCH and GARCH, and leverage effects as they provide essential information on the behavior of any stock market. Second, this study explores the extent

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past news and lagged volatility affect the current conditional volatility of stock markets (in this case the study assesses the performance of the models).

From the above discussions the following hypotheses are tested:

H_1: Stock market volatility and returns are positively correlated;

H_2: Stock market returns have equal volatility and persistence over time;

H_3: Stock market returns have ARCH effects;

H_4: Stock market returns have GARCH effects;

H_5: Stock market returns observe asymmetric effect

3.0 Method

Definition of variables and data description

To measure the daily returns of the Nigerian Securities Exchange, the daily index of the stock market, and the ASI share index, were employed. The financial time series data for this study was generated from the daily stock exchange. The index helps determine the performance of the Nigeria stock exchange (NSE) by measuring the general price movement in the shares of listed firms on the stock exchange. The daily share index was obtained from NSE covering January 2nd, 2001, to November 8, 2018. This period coincides with the stock market crashes and economic crunch in the Nigerian financial system.

Empirical model and estimation method

Engle, 1982; Bollerslev, 1986 suggested GARCH model for estimating stock volatility. Based on their suggestion, scholars like (Enders, 2004; Nelson, 1991; Glosten, Jagannathan, & Runkle, 1993; Taylor, 1986; and Schwert, 1989) proposed different GARCH method for instance; ARCH, GARCH, TGARCH, EGARCH, and PGARCH. Therefore, this study is anchored on the works of (Banumathy and Azhagaiah, 2015; Emenike, 2018; Osazevbaru, 2014).

The following steps are followed based on (Emenike, 2018) recommendations;

The first step is to generate the return series from the ASI. The daily returns, were calculated with the following formula formula $R_t = \ln(\frac{P_t}{P_{t-1}})$ Given that$P_t$will be observed as the daily ASI share index and P_{t-1} is the past value of the ASI. In our study, Rt represents the daily return of a market index, and, followed by the unit root test. The third step is to test for ARCH effect and volatility clustering generated from the simple OLS. Finally, is the estimation of the coefficients through various GARCH model and evaluation of the model.

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Model specifications

ARCH (q) model explains variation in conditional volatility using its own past innovation. (a) The reasoning behind the ARCH model is that the present value of a variable is dictated by its past value(s).

$$\mathbf{y = \lambda_0 + \lambda_1 y_{t-1} + \mu_t} \quad \textbf{(1)}$$

$$\mathbf{h_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2} \quad \textbf{(2)}$$

Equation (1) & (2) represent the conditional mean and variance respectively. The "q" represents the order for the past conditional variance. The "p" is the order for the past error term, while the "q" remains the order for the prior conditional variance.

Conditional Variance Equation

The GARCH model is shown below

$$\varepsilon_t|\Omega_{t-1} \sim N(0, h_{t-j}^2) \quad (3)$$

$$h_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{i-2}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2 \quad (4)$$

$\omega > 0, \alpha_i, \beta_j \geq 0, \rightarrow h_t^2 \geq 0$,$i = 1, \ldots \ldots p$, and $j = 1, \ldots . q$

where $\Omega_{t-1}$is the arrangement of all data available at time $t - 1$. The conditional variance of the GARCH model characterized in equation 4 is a component of three terms. The principal term is the mean of yesterday's forecast, ω. The second term is the lagged of the squared residuals got from the mean condition, ε_{i-2}^2, or the ARCH expressions. The ARCH expressions stand for the news (data) about volatility from the past period that has a weighted impact, which decays steadily, while failing to reach zero, on the current conditional volatility. The third term is the GARCH expression, h_{t-j}^2, estimating the impact of last period's forecast variance. Note that these three parameters (ω, α_i's, and β_j's) are limited to be non-negative to guarantee positive qualities for the conditional variance or $h_t^2 \geq 0$.

Decision rule:

The size of the parameters αi and βj decides the short-run elements of the volatility of the information, and the total of the evaluated α_i and β_j decides the persistence of volatility

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to a particular shock. A large positive estimation of α_i shows high volatility clustering is available in the time series data. A large estimation of β_j demonstrates that the impact of the shock to the conditional volatility goes on for quite a while before vanishing, so volatility is persistent.

Garch-in-Mean

GARCH-M captures risk premium and conditional volatility of returns relationship. It is designed to explore security market and accept that risk can be estimated by a measure of variance of returns on securities (Enders, 2004). In GARCH-in-mean, return of the security may rely upon its volatility or conditional variance. The condition of GARCH-M (1,1) model can be composed as follows:

$$r_t = \boldsymbol{\lambda_0} + \lambda\sigma t_t^2 + \varepsilon_t \tag{5}$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta\, \sigma_{t-1}^2 + \sum_{j=1}^{q} \alpha\, \varepsilon_{t-1}^2 \tag{6}$$

Decision rule:

In equation (5) λ stands for the risk premium. A positive λ shows a rise in mean return is as a result of an increase in conditional variance as a represented by an increased risk.

Asymmetric measurement

Symmetric GRACH has been criticized by previous scholars due its inability to respond asymmetrically to fluctuation in the stock returns. Therefore, other models have been introduced to handle such issues and are called asymmetric models viz., EGARCH, TGARCH and PGARCH.

A. EGARCH Model

As proposed by Nelson (1991) EGARCH model is shown as thus:

$$\ln(\sigma_t^2|\Omega_{t-1}) = \omega + \sum_{j=1}^{q} \gamma_j\big[|z_{t-j}| - E|z_{t-j}|\big] + \sum_{j=1}^{q} \theta_j z_{t-j} + \sum_{i=1}^{p} \Delta_i \ln(\sigma_{t-i}^2|\Omega_{t-i-1}) \tag{7}$$

The presents of natural logarithm in equation 7 ensure that the conditional variance remains non-negative and to allow for the persistence of shocks to the conditional variance. Evidence of innovation and its sizes are captured by θ' and 'γ' respectively.

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B. Threshold-GARCH Model

Glosten, Jagannathan, & Runkle (1993) introduced the asymmetric effect by a dummy variable to reflect negative returns. This can help to mimic good and bad news on the conditional volatility considering the variation between negative and positive shock (Enders, 2004).

Considering the TGARCH process:

$$\sigma_t^2 = \boldsymbol{\omega} + \sum_{j=1}^{q} \alpha\, \epsilon_{t-j}^2 + \sum_{j=1}^{q} \vartheta\, D_{t-1}\epsilon_{t-j}^2 + \sum_{j=1}^{q} \beta\, h_{t-j} \quad (8)$$

Where: $\sigma_t^2 -$ the conditional variance at time t

$\alpha_1 -$ the coefficient for the ARCH(1)process

$D_{t-j} = 1$ whenever $\epsilon_{t-j} < 0$

$\beta -$ the coefficent for the GARCH(1) process

We expect$\epsilon_{t-j} < 0$, such the effect of ϵ_{t-1}on h_t would be $(\alpha_1 + \vartheta)\epsilon_{t-j}^2$ and therefore, if $\epsilon_{t-j} \geq 0$ then ϵ_{t-j} is $\alpha_1\epsilon_{t-j}^2$.

The positive and statistical significant of ϑ indicates that bad news or negative shocks impact greatly on current volatility than good news.

Decision rule:

'ϑ' = captures 'the asymmetric volatility. The study concludes that if the presence of positive shocks generates more volatility than negative shocks when $'\vartheta'$ positive and statistically significant.

C. Power ARCH (PARCH) Model

Taylor (1986) and Schwert (1989) proposed the PGARCH which also be used to model nonlinear volatility of asymmetric volatility. It is shown as thus

$$\sigma_t^2 = w_0 + \sum_{j=1}^{q} \alpha_j \left[\left| \varepsilon_{t-j} \right| - \gamma_i \left| \varepsilon_{t-j} \right|^d \right] + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^d \quad (9)$$

when d = 2, then the PGARCH can be collapse into conventional GARCH model with a leverage effect. However, when d = 1, the standard deviation is modeled.

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Model selection and diagnostic test

Akaike Information Criteria (AIC) developed by Akaike (1977), and Schwartz Information Criteria (SIC) developed by Schwarz (1978) were applied using minimum criterion. After which the criteria for the remaining ARCH effect and serial correlation using ARCH-LM test are performed at 5% level of significance.

4. Results

Pre-testing

Table 1 depicts the results of the normality test and the descriptive statistics for the daily returns. Under assumptions of normality, skewness and kurtosis the series have asymptotic distributions.

Table 1: Summary of Descriptive statistics of the Nigerian Stock Returns

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
DLASI	0.000309	0.010285	0.119109	11.95844	14793.84	0.000000

Source: Author’s computation

The regular return distributions are substantially different from the normal distribution. The standard deviation is low, which means that portfolio output variations are low. The signs of positive skewing (Skw=0.119109) suggest that their returns increase rather than decrease, indicating renewed share interest. The coefficient for Kurtosis was positive because the return sequence was a fairly high value (Kurt = 11.95844) which showed that the return distribution was leptocurtic and fat-tailed. The null hypothesis of normality was dismissed by applying D'Agostino et al. (1990) in order to check the mutual importance of skewness and kurtosis.

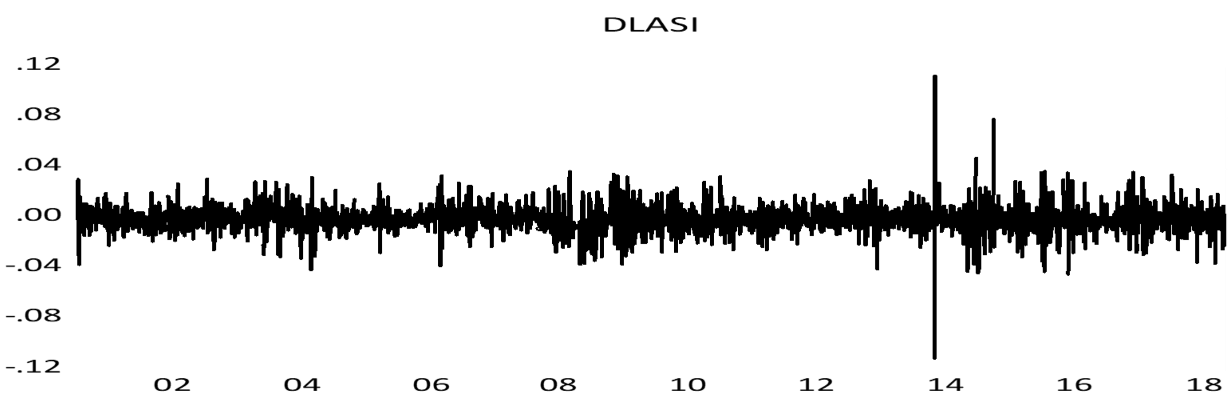

Figure 1: Time series plots of ASI (stock return series)

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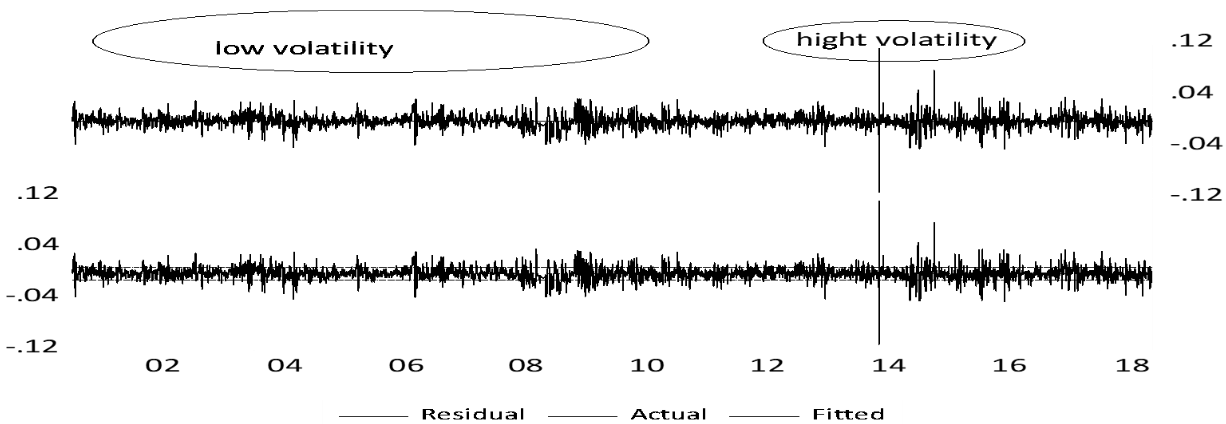

Figure 2: Volatility clustering of daily returns series over the mean

The graphical portrayal of the securities market is shown in Figures 1 and 2. Visual review of the plots demonstrates that the return series fluctuates around the mean, implying that the data is mean-returning. In the series, volatility was low over a continued period, and this period is trailed by another time of high volatility. The series also display clustering behavior, which is another common fact that can be represented by applying a conditional volatility model. In this manner, the degree of peakedness, non-normality, ARCH Effect, and volatility of the daily stock returns justify the utilization of the GARCH extension to account for symmetric and asymmetric conditional volatility.

Stationary test

The ASI was logged to lessen the difference and was changed into a persistently aggravated every day stock returns. The arrival arrangement was tried to decide the request for mix utilizing ADF, and the outcome in table 2 shows that the arrangement is stationary at level.

Table 2:

Unit Root Test for ASI (Return series)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-41.94291	0.0000
Test critical values:	1% level	-3.431646	
	5% level	-2.861998	
	10% level	-2.567057	

Source: extract from eviews

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Tables 2 and 3 indicate the presence and heteroscedasticity of the unit root in the series tested using ADF-testing. ADF's p values are below 5 percent point, leading to the assumption that time series data for the entire study period is stationary. The ADF-test statistics in Table 2 reject the 1 percent point hypothesis for the ADF-tests in the return sequence with a critical value of –3.431646.

Table 3:

ARCH effect

F-statistic	1277.179	Prob. F(1,4418)	0.0000
Obs*R-squared	991.2121	Prob. Chi-Square(1)	0.0000

Source: Extract from eviews

Estimation and model selection

Table 4:

ARCH/GARCH estimates for the return series

Parameter	**ARCH**	**P-value**	**GARCH(1,1)**	**P-value**	**GARCH-M(1,1)**	**P-value**
Constant (c)	0.000256	0.0383	0.00017	0.1844	-0.000137	0.4900
Risk premium (ʎ) β_0	-	-	-	-	3.780468	0.0713
Intercept	5.09E-05	0.0000	2.31E-05	0.0000	2.30E-05	0.0000
ARCH term β_1	0.542134	0.0000	0.389125	0.0000	0.384204	0.0000
GARCH term α_1	-	-	0.400046	0.0000	0.403806	0.0000
$\beta_1 + \alpha_1$			0.789171		0.78801	
log L	14537.82		14618.16		14619.94	
AIC	-6.57535		-6.611248		-6.611599	
SC	-6.57102		-6.605463		-6.604367	
Observations	4421		4421		4421	

Source: Extract from eviews

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Table 4 presents results from three different models. The coefficient of ARCH suggests that the square lagged error terms have a positive and significant effect on the current volatility of stock returns indicating that the rate of response of stock volatility to the market activities are high. The parameter in the GARCH (1, 1) model shows that variance coefficients are positively significant at a 5% level, suggesting that past period volatility significantly affects the conditional volatility at the present time frame. The ARCH coefficient revealed that the last error terms have a positive and significant effect on current period volatility, and the degree is highly persistent. The total volatility for the evaluated models are high, and shocks on these returns cease to exist gradually. As expected, persistence of volatility is highest with $\beta_1 + \alpha_1$= 0.78917, suggesting that it represents volatility persistence, and the persistence ceases to exist gradually.

The GARCH-M (1, 1) model is evaluated by permitting the mean condition of the return series to rely upon an element of the conditional variance. The constant in the mean equation is not significant, demonstrating that there is a normal return for the market. From table 4, it is inferred that the coefficient of conditional variance (λ) in the mean equation value is positive and statistically insignificant, which suggests that there is no conditional volatility effect on the expected return. This shows an absence of risk-return trade-off within the time horizon. In the variance equation of GARCH-M (1,1), the parameters viz., α, β_0, and β_1 are exceptionally high and statistically significant at a 1% level. The entirety of α and β is 0.78801, which shows that shocks will endure later on the period.

The model selection is based on the performance of the model through the information criteria. All the estimates have been estimated and assessed to produce AIC and SIC results. As referenced in the last passage, the inclination ought to be given to the model that gives the least information criteria. The GARCH-M model beats the other conventional models ARCH and symmetric GARCH models.

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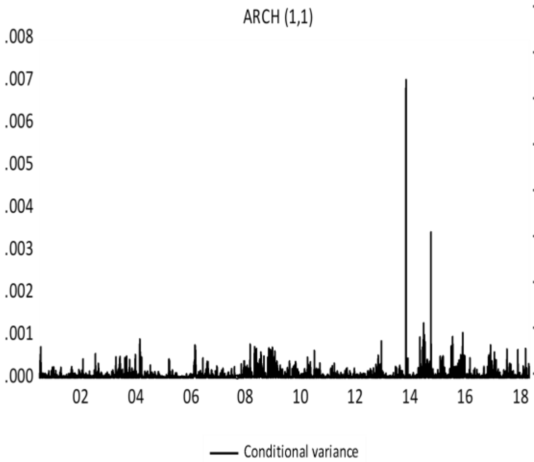
Figures 3a to 3c: Graphical Representation of Conditional Variance of Stock Market Returns



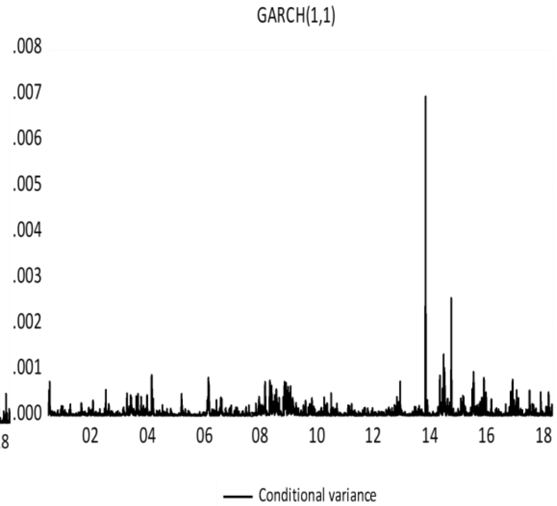


Figure 3a Figure 3b

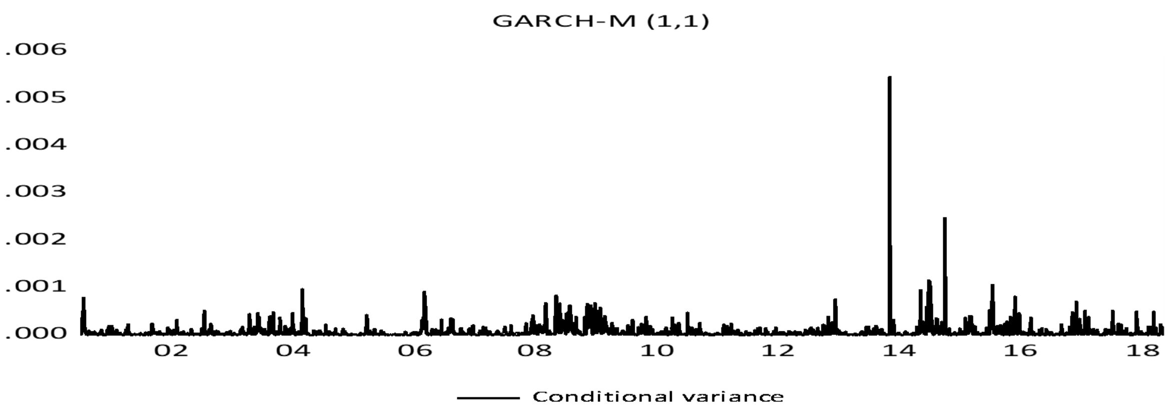


Figure 3c

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Asymmetric measurement (estimation)

Table 5:

Parameter Estimate for Asymmetric ARCH/GARCH Model for Return series

	Estimates					
Parameter	**TGARCH**	**P-value**	**EGARCH(1, 1)**	**P-value**	**PGARCH(1, 1)**	**P-value**
Constant (c)	0.000175	0.1925	0.000203	0.1039	0.000217	0.0608
Intercept	2.30E-05	0.0000	-2.694893	0.0000	0.002581	0.0000
ARCH term α_1	0.394615	0.0000	0.538236	0.0000	0.342404	0.0000
Asymmetric effect ϒ β_1	-0.01319	0.7041	0.00789	0.5251	-0.005328	0.8254
GARCH term	0.401182	0.0000	0.756274	0.0000	0.468308	0.0000
$\alpha_1 + \beta_2$	0.795797		1.29451		0.810712	
<u>Model Selection</u>						
log L	14618.22		14602.76		14616.31	
AIC	-6.61082		-6.603826		-6.609957	
SC	-6.60359		-6.596594		-6.602726	
Observations	4421		4421		4421	

Source: Extract from eviews

This section summarizes the asymmetric effect in the model. Three models were used: Threshold GARCH (1,1), Exponential GARCH (1, 1), and Power GARCH (1, 1) to identify the asymmetric effect. As shown in Table 5, the intercept and ARCH term of TGARCH is positive and statistically significant at the 5% level. The squared lagged error term significantly impacts the current period volatility, and the speed of response of volatility to market innovation is high. The GARCH component is positive and statistically significant at a 5% level. The significance of the GARCH expression infers that past period volatility has a substantial impact on conditional volatility in the current period and the future. The

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leverage coefficient is not statistically significant at a 5% level suggesting the non-appearance of the leverage effect, which repudiates the adoption of the common fact in stock volatility that the same magnitude of bad news has an unequal impact on the volatility of stock returns.

The intercept and ARCH term in the EGARCH model is statistically significant, indicating the squared lagged error impacts the current time volatility with a coefficient of 0.538236. The GARCH coefficient maintained the expected sign and was significant. This suggests that past period volatility significantly impacts the conditional volatility in the current period. However, the leverage effect is insignificant, indicating the absence of the leverage effect. This condition shows that a negative shock does not produce volatility more than the equivalent size of a positive shock.

The estimated volatility model using power GARCH is relatively similar to that obtained from the previous model, which affirms that the assessed ARCH (0.342404) and GARCH (0.468308) parameters are highly significant. The ARCH parameter estimates show that the squared lagged error has a positive and significant effect on the current period volatility of ASI returns, and the speed of response of volatility to market shock is high. Likewise, the GARCH coefficient shows that the past period variance of ASI returns significantly affects the conditional volatility, and it additionally indicates that volatility persistence is low. The outcome further revealed that the asymmetric coefficient is negative and not significant, affirming the absence of the leverage effect.

The model selection is based on the performance of the model through the information criteria**.** The best-equipped models are selected based on the lowest AIC and SIC value and the highest log-likelihood value, both in symmetric and asymmetric effects. Comparatively, the AIC value (–6.6115;–6.60436) is small, and the log probability value (14619.94) is high for GARCH-M (1, 1) relative to its alternative symmetric model, called (A) GARCH (1, 1). The GARCH-M (1, 1) model is the best-suited model. TGARCH models dominate other asymmetric GARCH models.

The conditional volatility of stock market returns is shown in Figures 3d to 3f.

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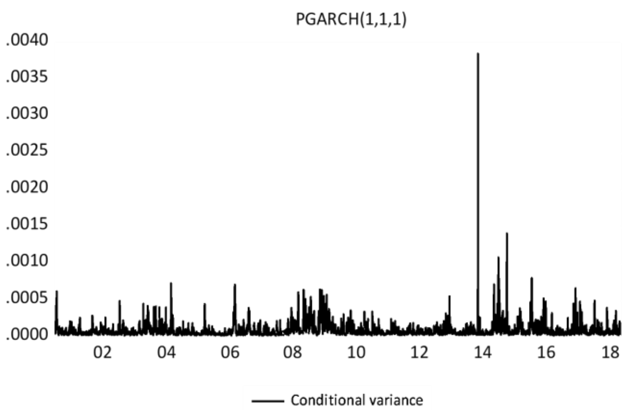

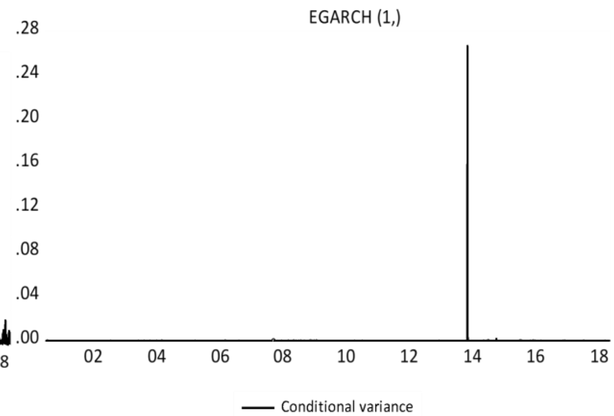

Figure 3d Figure 3e

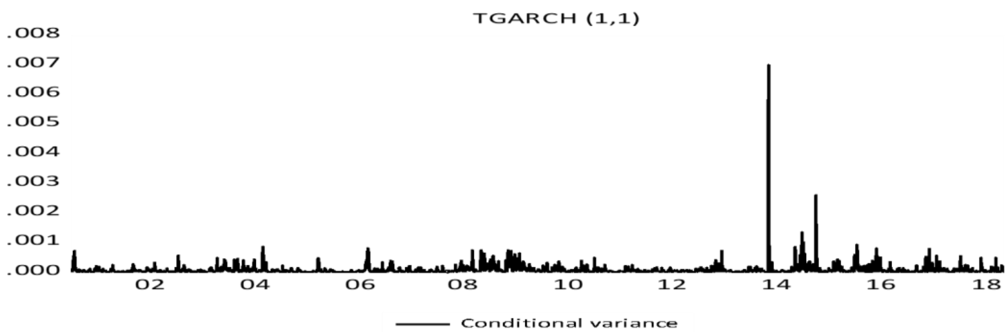

Figure 3f: Volatility clustering for the various models

Diagnostic test

Table: 6

Test for the best fitted GARCH models

Hetroscedasticity Test:				
ARCH		**Lag 1**	**Lag 5**	**Lag 10**
GARCH-M (1,1)	F-statistic	0.0602	0.1252	0.0911
	Obs*R-squared	0.0602	0.6269	0.9131
	Prob. F(1,4418)	0.8062	0.9868	0.9999
	Prob. Chi-Square(1)	0.8061	0.9867	0.9999
TGARCH (1,1)	F-statistic	0.1591	0.1593	0.1095
	Obs*R-squared	0.1591	0.7978	1.0978
	Prob. F(1,4418)	0.6900	0.9772	0.9997
	Prob. Chi-Square(1)	0.6899	0.9772	0.9997

Sources: Extract from eviews

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A diagnostic test was presented to test the presence of the remaining ARCH effect in the model. At a 5% level of significance, as indicated in Table 6, the null hypothesis of no ARCH effect cannot be rejected. This shows evidence of a good volatility model, and indeed ARCH effect has been appropriately established.

Discussion

The pre-test examination showed that the daily returns do not follow a normal distribution and give indications of the ARCH effect in the financial data. Further, volatility clustering was seen in the daily returns. Likewise, the conventional GARCH return shows time-varying volatility heteroscedasticity and leptokurtosis. These findings validate the already documented evidence on stylized facts on stock return volatility for the ASI stock. It also demonstrates volatility clustering with the summation of ARCH and GARCH parameters.

At last, there is a bit of clear proof that the effect of present shock persists (stays) in the forecast of variance for some periods later on. Previous studies upheld these findings (see Banumathy and Azhagaiah, 2015). It was discovered that the daily return showed an ARCH effect and non-normality. To distinguish the wellsprings of volatility, we looked at the different GARCH models created for the period under investigation. It was seen that the fluctuation or volatility in 2004, 2006, 2014, and 2015 are higher among volatilities in different periods. Further examination uncovered that these times of high volatility are the period following financial liberalization, as seen in the recapitalization of banks, stock brokerage firms, and insurance agencies. Financial liberalization and monetary policy choices are the main sources of volatility in the Nigerian financial system. The clarification of the reasons for the return volatility by this examination is additionally bolstered by past research on the effectiveness of the Nigerian financial market by Okpara (2010), who found high volatility during the period following financial liberalization as in the case of recapitalization of banks, stock brokerage firms, and insurance agencies

From the empirical analysis in GARCH (1,1) model, the coefficient ($\alpha + \beta$) is 0.78917, which infers that the volatility is generally high and persistent. That is, news about volatility from the past periods has an informative force on current volatility. With this outcome, the volatility of the Nigerian securities market found by this investigation can be credited to examples of speculators' behavior. That means speculators in the Nigerian financial capital market are driven more by some behavioral factors (sociological and mental elements) than crucial elements attributed to the organizations. Data propagation, consequently, leads financial speculators to overreact to both good and bad news. In the case of Nigeria, it is common to see speculators submitting general direction to institutional financial speculators and insider trading activities (Emenike, 2018).

In the GARCH-M, risk premium (α) is positive and insignificant, meaning that higher market risks from conditional variance do not automatically drive high returns or that the expected return does not depend on the variance. In other words, it revealed the lack of trade-offs in risk and returns, and investors can still hold these assets because it is less

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risky. This will allow policymakers and market participants to understand these assets and evaluate the securities hedging strategy and portfolio management.

Given the best model judging from the asymmetric impact. The TGARCH (β) is negative and insignificant at 5%, indicating the absence of leverage effect. This means that either negative or positive shocks may not have a more significant impact on the conditional volatility of stocks. Theoretically, Figlewski and Wang (2000) clarified that a phenomenon might be called the 'Down Market Effect'. The general conclusion on this outcome implied that both negative and positive shocks have a similar impact on return volatility. There are also no asymmetries in the news, and the market does not differentiate between lousy news (negative shock). This finding confirms the situation in the Nigerian Stock Exchange as reported also by Osazevbaru (2014).

5. Conclusion

Nigerian capital markets play significant roles in stimulating economic growth through the mobilization of domestic savings and by encouraging the allocation of static financial resources to more productive activities. This study accessed conditional volatility and its performance in the Nigerian capital markets. The ASI daily closing prices for eighteen (18) years (comprising a sample size of 4,421) were collected and modeled using five distinctive GARCH models capturing the volatility clustering and leverage effect for the study time frame, i.e., from January 2, 2001, to November 8, 2018. In the analysis, the results are as follows: i) the selected models that outperformed the rest of the models are GARCH-in mean and TGARCH ii) the presence of ARCH effect and volatility clustering. iii) The predicted sign of the coefficient in GARCH-M is negative and insignificant. iii) TGARCH model is negative and insignificant, indicating that daily news asymmetries were not established.

Our results contradict Karmakar (2007) research findings in which the risk premium is significant in India. From the performance of the selected models (GARCH-M and TARCH), this analysis concludes that increased risk did not increase returns as the coefficient is insignificant for the research duration. It points to the fact that the Nigerian stock market is not informationally effective because it defines all kinds of news on the market to be the same. Potential consequences of these findings are: The Nigerian stock market is underdeveloped and cannot differentiate between good news, negative shock, and positive shock. Secondly, since good news and bad news can be predicted similarly, it may deter business financing and entrepreneurs. This perhaps corroborates that Osaze (2000) and others found the money market as a source of business finance in Nigeria more attractive than the capital market. Therefore, this study recommends that policymakers and market participants consider various resource means in evaluating multiple assets, portfolio management, and hedging strategies. The policymakers should also improve the information divulgation system for the explicit propagation of information.

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