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Volatility Modelling of Stock Returns in the Petroleum Marketing Sector of the Nigerian Stock Exchange

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ABSTRACT

Introduction: Financial markets play key role in the growth and sustainability of the economy. However, high levels of volatility in the markets may adversely affect the financial system and weaken the economy.

Purpose: This paper examined the presence of volatility in the stock returns of the petroleum marketing sector of the Nigerian Stock Exchange using ten petroleum marketing firms quoted on the Nigerian Stock Exchange for a period of twenty-four months that is from January 2017 to December 2018.

Methodology: The study adopted empirical research design using time series data where ordinary least squares was employed to run the analysis through the use of ARCH/GARCH models.

Findings: Among other results, it was seen that a unit increase in volatility (VLT) will lead to 0.006916 decrease in stock returns (STR). Also, the result of R-squared implies that about eight per cent (8%) of the changes in stock returns (STR) is captured by volatility (VLT) while the remaining ninety-two per cent (92%) of the variation in the model is captured by the error term. The ARCH effect observed is statistically significant. The coefficient of the GARCH effect which is significantly positive at 5% shows that past volatility of stock market return is significant and has effect on current volatility.

Unique Contribution to theory, Practice and Policy: The implication of this is that an increase in volatility is linked to a significant increase of returns, which is an expected result and thus conforms to economic theory. The results of static and dynamic forecasting of GARCH volatility showed that the volatility is stable. As a result, investors can hold the stock. Among other things, the author recommends that Government should make sufficient regulatory effort that will improve efficiency of stocks performance and reduce volatility aimed at boosting investors' confidence in the petroleum marketing sector and since the various ARCH and GARCH models showed volatility movement in stock returns, Nigerian government should look for new ways to diversify the economy from dependence on oil and explore other sectors like manufacturing sector and agricultural sector to reduce volatility in the economy and the overall effect on it.

Keywords: Nigeria Stock Exchange (NSE), Jumps, Volatility, Stock returns, ARCH/GARCH



1. Introduction

The financial market is the major driving force behind the growth, development and sustainability of any economy. In most developing economies, the major financial market is the stock market where the major transactions undertaken include trading in the stocks of quoted companies. Financial markets provide the necessary facilities for the creation of financial assets and obligations. Among other functions, it is involved in the setting of fair prices for stocks. By providing markets such as the Nigeria Stock Exchange, similar stocks are traded at one location and participants get to know the true market price of the stock at any point in time.

The stock price is a highly volatile variable in the stock market. The unstable property and other considerable factors such as liquidity on stock return call for concern on the part of investors, since the sudden change in share prices occurs randomly and frequently. Researchers are therefore propelled to look into the behavior of the unstable market variable so as to advise investors and owners of cooperation who are looking for convenient ways to raise money by issuing shares of stocks in their corporation (Adeosun, Edeki & Ugbebor, 2014).

Investors are interested in the fairness of stock prices and level of their predictability in the stock market because they desire and require an adequate return on their investment. Stock returns usually consists of dividends and capital gain. However, as a result of fluctuations in the stock market, the expected returns from a stock could fall below the expectation of an investor. These fluctuations are a result of the volatility in price changes and jumps experienced in the financial markets (Bedowska-Sojka, 2015).

Financial markets sometimes generate significant discontinuities, so-called jumps, in financial variables (Wikipedia). Empirical and theoretical studies in the field of finance have validated the presence of jumps and their subsequent impact on the financial market. In spite of the breakthroughs in the development of various models and their inference techniques, researchers have discovered that jumps are empirically cumbersome to identify, because only discrete data are available from continuous-time models, in which most of the aforementioned applications were studied (Lee & Mykland, 2006). In Merton's (1976) model, the asset return follows a Brownian motion with drift punctuated by jumps arriving according to a compound Poisson process with constant intensity and with normally distributed jump sizes. (Merton, 1994)

In finance, volatility (σ) is the degree of variation a trading price series experiences over time as measured by the standard deviation of logarithmic returns. Historic volatility quantifies a time series of previous market prices. Implied volatility is futuristic as it looks forward in time. This is caused by its derivation from the market price of a market-traded derivative (Wikipedia). It is at the discretion of the financial analyst to advice which stocks to be traded in order to achieve maximum returns, however, stocks with high volatility are more favorable because while they are prone to having higher negative returns than less volatile stocks, they also promise higher yields.

In Nigeria, one market which experiences these "significant discontinuities" is the Petroleum Market. As a member of the Organization of Petroleum Exporting Countries



(OPEC), it is subject to the rules and regulations governing the body. Also, being the mainstay of the economy, it is easily susceptible to fluctuations as a result of government regulations and policies, and sanctions placed on it by the body in charge of all petroleum exploration, production and marketing, the Nigeria National Petroleum Corporation (NNPC). These regulations combined with the instabilities in the political terrain and the adjustments made to production of by -products causes the industry to be a highly volatile one.

In recent times, modelling volatility of returns has been an increasingly interesting area for researchers both in academia and in the practical world. Modelling volatility is an important element in pricing equity, risk management and portfolio management (Emenike, 2010). Number of studies have shown that, among other outcomes, jumps in asset prices have significant implications for derivative pricing, risk management, and portfolio allocation. In particular, the empirical literature on jumps has substantially improved our understanding of return properties of various financial assets, such as interest rates, exchange rates, and equity market indexes (Jiang & Yao, 2008). This gave rise to the search of models that will adequately capture these peculiarities of the financial market and as pointed out by Merton (1994), much of the applied financial research on the use of mathematical models takes place within financial institutions. Since the 1980s a number of models have been developed that are especially suited to estimate the conditional volatility of financial assets. Well-known and frequently applied models of this type are the (generalized) conditional heteroscedastic models (Abdalla & Winker, 2012).

These models are saddled with the task of examining the behavior of volatility in return series, based on historical information and possibly predict same in future return series. An accurate prediction and estimation of this could have policy implications on security valuation, portfolio selection, asset pricing, risk management and most importantly, an efficient financial market and system. It is therefore expedient to model the volatility inherent in the stock returns of the Petroleum Marketing sector of the Nigerian Stock Exchange.

2. Literature Review

2.1. Overview of Concepts

2.1.1 Jumps

Jump process is a type of stochastic process that has little and not too noticeable movements, called jumps, with random arrival times, rather than continuous movement. In finance, various stochastic models are used to model the price movements of financial instruments;

A price jump is understood as an abrupt price change over a very short time that is related to a broad range of market phenomena that cannot be connected to a noisy Gaussian distribution (Hanousek et al, 2013). The presence of jumps has dire repercussions for financial risk management and pricing.

Jumps are defined by high magnitudes of some market factors such as volume of trade and transactions, and volatility. Various factors ranging from macroeconomic information to



the advent of new market policies can trigger jumps. Market jumps are facts of every investor's lives. They represent great opportunities, but more importantly, great risks. (Ramos et al, 2016).

A number of recent theoretical and empirical studies have proven the importance of jumps in financial markets. (Bedowska-Sojka, 2015). The existence of jumps has an impact on financial management (Piazzesi 2005), jumps are said to have different implications for risk management (Duffie & Pan, 2004), they are also important for asset allocation and valuation (Jarow & Rosenfeld,1984). Taking into account the distribution and causes of jumps improves asset pricing models (Huang & Tauchen, 2005). Jumps allow us to quantify and take into account the risk of strong stock price movements over short time intervals (Tankov & Voltchkova, 2007)

The empirical literature on jumps has substantially improved the understanding of return properties of various financial assets, such as interest rates, exchange rates, and equity market indexes (Jiang & Yao, 2008). Adequate knowledge and analysis of jump trends in the financial market helps in predicting stock returns. Jump clarity predicts future stock returns volatility. As such, large jumps in national stock indices should be accompanied by news influencing future returns or discount rates. (Baker et al, 2019).

2.1.2 Volatility

Volatility σ is originally defined as the annualized standard deviation of logarithmic stock returns (Tankov & Voltchkova, 2007). Researchers are still in doubt about the major causes of stock market volatility but there is a general agreement that volatility is caused by the arrival of fresh and unanticipated information in the market which modifies and changes expected stock returns. What this assumes is that fluctuations in market volatility is an aftermath of fluctuations in the economic terrain. Other causes of volatility are changes in trading volume, practices or patterns which are driven by modification in macroeconomic policies, shift in investors' tolerance of risk and increased uncertainty. Thus, the degree of stock market volatility can help researchers to predict the path of an economy's growth. (Shittu et al, 2008).

Heston model developed by Steve Heston shows the stochastic volatility process of a stock, it is shown as;

$$dS_{t} = \mu S_{t}d_{t} + \sqrt{V_{t} S_{t}}dW_{t1}$$
(1)

$$dV_{t} = K (\theta - V_{t})dt + \sigma \sqrt{V_{t} dW_{t2}}$$
(2)

$$E^{P}[dW_{t1} dW_{t2}] = pdt$$
(3)



Where μ is the drift process of the given stock

 $\theta > 0$ the mean reversion level of the variance of the stock

K > 0 the mean reversion rate of the variance

 $\sigma > 0$ the volatility of the variance;

P E [-1, I) the correlation between the two shown Brownian motions W_{t1} and W_{t2}

 λ = the price of the risk

In a real world, the variance of a stock price return is

$$PU^{2} + (1-p)d^{2} - (pu + (1-p)d]^{2}$$
(4)

While in a risk neutral world, it is

$$PU^{2} + (1-p)d^{2} - [pu + (1-pd]^{2} = [e^{r}\Delta t(u+d) - ud - e^{2r}\Delta t]$$
(5)

Volatility is associated with unpredictability, uncertainty and has implications for market risk (Peiris, 2011). The relationship between risk and returns plays an important role in the asset pricing literature. It has long been recognized that both expected return and volatility change over time (Wei and Zhang (2006). Variations in the volatility of stock returns can expectedly have negative impacts on investors who are risk averse and, on the economy, therefore many researchers have studied the nature, movements and pattern of stock market volatility and its effect on the economy.

Modelling volatility aids in calculating value at risk of a stock and for quantifying the risk in the stock return. It also plays an important role in asset allocation under the meanvariance framework. Modelling time series volatility can also improve efficiency in parameter estimation and accuracy of interval forecast. (Shittu et al, 2008)

2.1.3 Nigerian Stock Exchange (NSE)

The NSE is the principal institution that facilities transactions in the Stock Market. The NSE evolved from the Lagos Stock Exchange that commenced business in 1961 with 19 securities. It became the NSE in 1977. NSE is regulated by the Securities and Exchange Commission (SEC) but its transactions are subject to regulations by the NSE as a self-regulatory body. According to Owoloko and Okeke, as at 1998, there were 264 securities listed on the NSE, made up of 186 equity securities listed on the NSE, and 78 debt securities. By 2006, the number had increased to 288 securities, made up of 202 equity securities and 86 debt securities. The major activity of the NSE is to provide facilities for the mobilization of private and public savings and making such funds available for productive uses. The NSE also provides operational facilities for trading in new and



existing securities. The NSE has trading floors in Lagos, Abuja, Port Harcourt, Kaduna, Ibadan, Kano, Benin, Abeokuta, Ilorin, Bauchi, Uyo and Onitsha.

2.1.4 Petroleum Marketing Sector

The petroleum industry in Nigeria is the largest in Africa and the sixth largest in the world. Many multinationals and firms have licenses to explore oil but are under the leadership of the Nigerian National Petroleum Corporation (NNPC). NNPC oversees all commercial activities relating to the sector and has the power to enforce rules and regulations governing it. The government has the power to import petrol via NNPC and to fix prices. They're involved in Upstream Ventures which covers exploration, production and marketing; Midstream Ventures which covers refining, transportation and importation; and Downstream Ventures which covers retail, distribution, research, investment and development. There is no gainsaying that Petroleum products marketing and exports has contributed immensely to the development of the economy. Oil revenue accounted for 71% of the total federally collected revenue which rose by 82% to N13.3 trillion in 2018 from N7.3 trillion in 2017 (Babajide & Akpan, 2019).

2.2 The (Generalized) Autoregressive Conditional Heteroscedastic (ARCH/GARCH) Model (ARCH/GARCH) Model

The (generalized) autoregressive conditional heteroskedasticity [(G)ARCH] process is an econometric term developed in 1982 by Robert F. Engle, an economist and 2003 winner of the Nobel Memorial Prize for Economics, to describe an approach to estimate volatility in financial markets.

GARCH process incorporates historical market data to construct a specific volatility pattern. GARCH model captures the effects of the real-world applications volatility. GARCH models parameters which should be estimated which means that it has more degrees of freedom and should be more flexiblea priori (it should adapt faster to changing market conditions) (Wikipedia).

The (G)ARCH model, models conditional variance as a function of its lagged values as well as squared lagged values of the disturbance term.

An ARCH model is given by

$$Var(X(t)) = \sigma^{2}(t) = \sigma^{2}(t-1) + 1$$

(6)

and the time series is given as

$$X(t) = w(t)\sigma(t) = w(t) \ (\sigma^2(t-)+1)$$

(7)

Where w(t) is white noise

The process follows an ARCH model if



$$E_{t-1}\left[\varepsilon_t\left(\theta_0\right)\right] = 0 \quad t = 1, 2...$$

(8)

and the conditional variance

$$\sigma_t^2(\theta_0) = V_{art-1}[E_t(\theta_0)] = E_{t-2}[E_t^2(\theta_0)] = 1,2...$$

(9)

And it depends on the $\,\sigma\,$ field generated by past observations

$$\{E_{t-1}\theta_0\}E_{t-2}(\theta_0)\dots]$$

(10)

(11)

Let $\{y_t(\theta_0)\}$ denote the stochastic process of interest with conditional mean

$$\mu_t(\theta_0) \equiv E_{t-1}(y_t) \quad t = 1, 2...$$

The process $(E_t(\theta_0))$ is defined as

$$E_t(\theta_o) \equiv y_t - U_t(\theta_o)$$

(12)

 Z_t has a standardized process and it is given as

$$Z_t(\theta_0) \equiv E_t(\theta_0) \sigma_t^2(\theta_0)^{-\frac{1}{2}}$$

(13)

When modeling asset returns as a linear function of past squared disturbances, it can be given as

$$\sigma_t^2 = w + \sum_{i=1}^q aiE_{t-i}^2$$
(14)

The unconditional variance is given as

$$E(E_t^2) = w/(1-a1-..aq)$$
(15)

For a GARCH model, when a series follows the GARCH process, the conditional distribution of the series is written as



$$\begin{array}{c} y_t / \psi_{t-1} \sim N(O, ht) \\ (16) \end{array}$$

Where Ψ_{t-1} denotes all available information at timed t-1.

The conditional variance ht will be given by

$$h_{t} = wt \sum_{i=1}^{q} aiy_{t}^{2} - 1 + \sum_{j=1}^{p} y_{j} h_{t-j}$$

(17)

Where $p \ge O, q > O$

$$w. > O, ai \ge O, y_j = \ge O$$

The GARCH regression model is given as

$$y_t = X_t^1 \beta + E_t$$

(18)

Where $E_t = \sqrt{h_t e_t}$ and

$$h_{t} = w_{t} \sum_{i=1}^{q} ai E_{t}^{2} - 1 + \sum_{j=1}^{p} Y_{j} h_{t-j}$$

Where $e_t \sim IN(O, 1)$

In this model, the conditional variance is represented as a linear function of a long term mean of the variance, its own lags and the previous realized variance. The simplest model specification of the ARCH/GARCH (1,1) model:

Mean equation $\gamma_t = \mu + \varepsilon_t$, (19)

Variance equation $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ (20)

where $\omega > 0$, $\alpha_1 \ge 0$ and $\beta_1 \ge 0$, and :

 $\gamma_t =$ return of the asset at time t, $\mu =$ average return, $\varepsilon_t =$ residual returns, defined as: $\varepsilon_t = \sigma_t Z_t$



Where: σt is the conditional variance

zt is the standardized residual variance

GARCH model is used to measure the unconditional variance of the shocks or innovations in the financial market (Kumari, 2018). It is used to explain why large residuals tend to clump together, by regressing squared residual series on its lag(s). The GARCH reduces the number of estimated parameters from an infinite number to just a few (Emenike, 2010).

2.3. Empirical Review

There is quite an extensive literature on stock returns, jumps and volatility and the use of various ARCH/GARCH models in estimating stock market volatility. Emenike (2010) discovered modelling volatility is an important element in pricing equity, risk management and portfolio management. Overall results from his study provide evidence to show volatility persistence, fat-tail distribution, and leverage effects for the Nigeria stock returns data.

Thanh Nam Vu (2018) explored the connection between international oil indices and Southeast Asian stock markets. In the study, besides using EGARCH model, the GARCHjump models were employed to capture the movement of stock returns. The findings confirmed the significant impacts of oil price fluctuations on stock markets, especially for six markets investigated. In overall, the outcomes of research suggest the significant interaction between the Southeast Asian stock markets and the global oil indices. Besides confirming the oil-stock markets relationship, the study indicated the negative influences of oil volatility shocks on stock market returns in Southeast Asian countries. The results of empirical analysis could be utilized in improving the prediction of stock price movements, forming a proper investment decision. Adesina (2013) examined the volatility of returns on the Nigerian Stock Exchange. The preliminary analysis of data used reveals the stationarity, non-normal distribution and strong evidence of ARCH effects in NSE return series.

Abdalla and Winker (2012) modeled and estimated stock return volatility in two African markets; the Sudanese stock market (Khartoum Stock Exchange, KSE), and the Egyptian stock market (Cairo and Alexandria Stock Exchange, CASE). The researchers found strong evidence that daily returns could be characterized by the above-mentioned models for the two markets, KSE and CASE data showed a significant departure from normality and the existence of heteroscedasticity in the residuals series. Second, the parameter estimates of the GARCH (1,1) models indicate that the conditional volatility of stock returns on the Khartoum Stock Exchange is an explosive process, while it is quite persistent for the CASE index returns series. Third, the parameter describing the conditional variance in the mean equation, measuring the risk premium effect for GARCH-M(1,1), is statistically significant in the two markets, and the sign of the risk premium parameter is positive. The implication is that an increase in volatility is linked to an increase of returns, which is an expected result. Fourth, based on asymmetrical EGARCH (1,1) and TGARCH (1,1) estimation, the results showed a significant evidence for the existence of the leverage effects in the two markets, the same result is confirmed only for the CASE by using the PGARCH (1,1) model.



Dritsaki (2017) used daily stock returns from the Stockholm Stock Exchange in order to examine their volatility. The findings revealed that negative shocks have a large impact than positive shocks in this market. Also, indices for the return of forecasting have shown that the ARIMA - EGARCH model with t-student provide more precise forecasting on volatilities and expected returns of the Stockholm Stock exchange. Osarumwense (2015) comprehensively assessed the day-of-the-week in the Nigeria stock exchange (NSE-30) in returns and volatility. It was revealed that the day-of-the-week in the Nigeria stock exchange in the Nigeria stock exchange (NSE-30) in returns and volatility is sensitive to distributional assumptions and its anomalies vary depending on the assumption made on returns and variance.

Shittu, Yaya and Oguntade (2008) examined the presence and of volatility in the return on stock of the banking sector of the Nigerian stock market with a view to building models that provides the optimum forecast for future stocks using the ARCH and GARCH models. The data on stock of five major banks in Nigeria showed varying degree of persistence in volatility. Peiris and Peiris, (2011) examined the volatility of different sectors in CSE and how macroeconomic factors affect volatility by fitting Autoregressive Conditional Heteroskedasticity (ARCH) and the Generalized ARCH (GARCH) models for the composite index of the volatile sectors. Asemota and Ekejiuba (2017) investigated equity returns volatility for six banks in the Nigeria's stock exchange. Their study recommends that, given the level of risk associated with portfolio investment, financial analysts, investors, and empirical work should consider variants of GARCH models with alternative error distributions for robustness of results. They also recommend for adequate regulatory effort by the CBN over commercial banks operations that will enhance efficiency of their stocks performance and reduce volatility aimed at boosting investors' confidence in the banking sector.

Maqsood, Safdar, Shafi, and Lelit, (2017) presented an empirical study to model the Nairobi securities exchange (NSE) using the family of GARCH models. The presence of volatility clustering and leverage effects were strongly confined from all the estimated models as they obtained the significant estimates corresponding to ARCH effect and GARCH effect parameters. Kumari (2018) investigated volatility clustering of the Bombay Stock Exchange (BSE) returns series through using various ARCH FAMILY models. Various ARCH and GARCH models showed volatility movement in stock returns. Adesina, Oyewole and Adekola (2017) considered the performance of GARCH models in modelling Nigeria foreign exchange returns. The datasets consisted of the foreign exchange of Naira for the periods before recession and during recession. It was observed that volatility is higher during recession than when there was no recession.

Taruvinga, Kang and Nikitopoulos (2018) showed that the inclusion of asset-volatility jumps has a significant impact on the free boundaries, especially near expiry. Bibinger and Winkelmann (2018) introduced a statistical test for simultaneous jumps in the price of a financial asset and its volatility process. A simulation study and an empirical example with NASDAQ order book data demonstrate the practicability of the proposed methods and highlight the important role played by price volatility co-jumps. Yaya, Bada and Atoi (2016) estimated volatility in the Nigerian Stock Market using the recently proposed jumps robust volatility models which account for jumps and asymmetry inherent in financial



returns with the view to comparing the estimated models with the choice of IGARCH-t model for ASI series and recommending the most appropriate model for financial Analysts and portfolio managers in the financial market.

3. Methodology

Monthly Index was obtained from the NSE and used to model the volatility in Nigerian Stock Exchange. The study period covers 18 months starting from January, 2017 to December, 2018. The population of this study consists of 10 Petroleum firms quoted on the Nigerian Stock Exchange. The financial time series data for the exchange will be generated from the observed index on a monthly basis. This study made use of secondary data. These data were sourced from the Nigerian Stock Exchange (NSE) fact book. These sources of data are considered reliable and dependable. Specifically, the study will make use of monthly data which ranged from January 2017 to December 2018 for 10 Petroleum firms, summing up to 240 sample observations.

3.1.Model Specification

In measuring volatility, Engle's (1982) autoregressive conditional heteroscedasticity (ARCH), and its extension generalized ARCH (GARCH) are commonly used. The generalized autoregressive conditional heteroskedasticity (GARCH) process is an econometric term developed in 1982 by Robert F. Engle, an economist and 2003 winner of the Nobel Memorial Prize for Economics, to describe an approach to estimate volatility in financial markets.

GARCH process incorporates historical market data to construct a specific volatility pattern. GARCH model captures the effects of the real world applications volatility. GARCH models parameters which should be estimated which means that it has more degrees of freedom and should be more flexible apriori (it should adapt faster to changing market conditions) (Wikipedia)

To measure the conditional variance, the GARCH (1, 1) model is used. The conditional variance, σ^2 t, can be stated as follows:

 $\sigma^2_t = \omega + \alpha \varepsilon^2_{t-1} + \beta \sigma^2_{t-1}$

Where, ω *is a constant term,* $\alpha \varepsilon^2_{t-1}$ *is the ARCH term and* $\beta \sigma^2_{t-1}$ *is the GARCH term.*

In this model, the conditional variance is represented as a linear function of a long term mean of the variance, its own lags and the previous realized variance. The simplest model specification is the GARCH (1,1) model:

Mean equation
(1)
Variance equation
(12)

$$\gamma_t = \mu + \varepsilon_t,$$

 $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

where $\omega > 0, \alpha_1 \ge 0$ and $\beta_1 \ge 0$, and :



 γ_t = return of the asset at time t,

 μ = average return,

 ε_t = residual returns, defined as:

 $\varepsilon_t = \sigma_t Z_t$

Where: σt is the conditional variance

zt is the standardised residual variance

3.2. Apriori Expectations of the Result

The estimation of the return series with the jump and volatility models are expected to have significant effects on the stock returns.

4. Data and Empirical Results

The data extracted from Nigerian Stock Exchange (NSE) fact book was properly arranged in excel spreadsheet and exported to Econometric Views (E-Views) 9.0 statistical software for proper analysis. Furthermore, the data analysis involved the application of unit root test and the ARCH-GARCH (1,1) model to test for volatility effect from changes in oil price and stock returns.

- **a.** Unit Root Test: The aim of conducting the unit root test is to avoid spurious regression which comes from regressing one non-stationary variable upon another non-stationary variable. Thus, this test was conducted to determine if a time series variable is non-stationary and possesses a unit root.
- **b.** The ARCH-GARCH Test: This was used to capture the effect of serially correlation of volatility in time series data according to which the ARCH model expresses conditional variance.

4.1. Descriptive Statistical Analysis

The section presents the result of descriptive analysis as follows:

Table 4.1: Descriptive Statistics of Stock Returns (STR) and oil and Gas Prices (OGP)

STR	OGP
0.92125	57.04188
1.00000	5.995000
3.62000	299.0000
-1.910000	0.050000
0.437067	86.18533
	STR 0.92125 1.00000 3.62000 -1.910000 0.437067



Skewness	-0.922132	1.388250
Kurtosis	19.41716	3.506684
Jarque-Bera	2729. 244	79.65683
Probability	0.000000	0.000000
Sum	221.1000	13690.05
Sum Sq. Dev.	45.65563	1775271
Observations	240	240

Source: E-view Results, 2019.

Table 4.1 presents the descriptive statistics of stock returns (STR) and oil and gas prices (OGP) monthly series over the period of 2017 to 2018 for ten quoted petroleum firms on the Nigerian Stock Exchange. As can be observed, the stock returns (STR) recorded a mean average of 0.92125 with a maximum of 3.62000 and minimum of -1.91000 per annum. The computed Jarque-Bera is 2729. 244 with probability value of 0.000000. Since the probability-value of the Jarque-Bera is smaller than 0.05, it can be concluded at 95% confidence interval that the distributed population of the return series are not normal (not normally distributed). Also, the negative skewness -0.922132 implies that the distribution of the variable (stock returns) has a long-left tail (mean < median < mode). In other words, the distribution is negatively skewed to the normal distribution. The kurtosis 19.41716 indicates that the distribution is peaked (leptokurtic) relative to kurtosis 3.

Furthermore, the oil and gas prices (OGP) recorded a mean average of 57.04188 with a maximum of 299.0000 and minimum of 0.050000 per annum. The computed Jarque-Bera is 79.65683 with probability value of 0.000000. Since the probability-value of the Jarque-Bera is smaller than 0.05, it can be concluded at 95% confidence interval that the distributed population of the return series are not normal (not normally distributed). Also, the positive skewness 1.388250 implies that the distribution of the variable (stock returns) has a long right tail. In other words, the distribution is positively skewed. The kurtosis 3.506684 indicates that the distribution is peaked (leptokurtic) relative to kurtosis.



4.2 Trend Analysis



Source: E-Views 8.0 Output

Figure 4.1 shows the pattern of stock returns (STR) monthly series over the period of 2017 to 2018 for ten quoted petroleum firms on the Nigerian Stock Exchange. As can be observed, there are inconsistent upward and downward movements in the graph throughout the research period.





Source: E-Views 8.0 Output

Figure 4.2 shows the pattern of oil and gas prices (OGP) monthly series over the period of 2017 to 2018 for ten quoted petroleum firms on the Nigerian Stock Exchange. As can be observed, there are inconsistent upward and downward movements in the graph throughout the research period.

4.3 Ordinary Least Squares Analysis

Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	0.862495	0.154822	5.570900	0.0000
VLT	0.006916	0.001500	4.610167	0.0000
R-squared	0.081980	Mean dependent var		1.257000
Adjusted R-squared	0.078123	S.D. dependent var		2.081792
S.E. of regression	1.998821	Akaike info criterion		4.231290
Sum squared resid	950.8779	Schwarz criterion		4.260296
Log likelihood	-505.7549	Hannan-Quinn criter.		4.242977

Table 4.2: Results of Ordinary Least Squares Analysis



F-statistic	21.25364	Durbin-Watson stat	2.061124
Prob(F-statistic)	0.000007		

Source: E-Views 9.0 Output 1. Interpretation of the Regression Coefficient:

There is a positive relationship between volatility (VLT) and stock returns (STR). This is because the coefficient of volatility (VLT) is positive with 0.006916. This means that a unit increase in volatility (VLT) will lead to 0.006916 increase in stock returns (STR) while a unit decrease in volatility (VLT) will lead to 0.006916 decrease in stock returns (STR).

2. Interpretation of R-Squared

The value of R-squared from the regression result in table 4.2 is 0.081980. The result of R-squared implies that about eight per cent (8%) of the changes in stock returns (STR) is captured by volatility (VLT) while the remaining ninety-two per cent (92%) of the variation in the model is captured by the error term (unknown variables factors outside the model.

3. Interpretation of Adjusted R-Squared

The adjusted R-squared obtained from the empirical results of the regression analysis is 0.078123. This shows that, if the coefficient of determination is adjusted, approximately eight per cent (8%) of the changes in stock returns (STR) are attributable to changes in volatility (VLT) while the remaining ninety two per cent (92%) of the variation in the model is captured by the error term (unknown variables factors outside the model).

4. Interpretation of T-statistics (Prob. values)

This measures the statistical significance of the coefficient of the explanatory variables in the specified model at 5% level of significance. To determine this, we compare the P-value of individual parameter with the alpha value of 0.05. From the regression result, the P-value for money supply is 0.0000 while the alpha value is 0.05. However, since the P-value is less than the alpha value (i.e. 0.0000 < 0.05), we therefore conclude that volatility (VLT) is statistically significant.

5. Interpretation of F-statistics (Prob. values)

This tests overall significance of the explanatory variables in the specified model at 5% level of significance. In other words, it tests the joint significant impact of the independent variables on the dependent variable. To determine this, we compare the prob (F-statistic value) with the alpha value of 0.05. From the regression result, prob (F-statistic value) is 0.000000 while the alpha value is 0.05. However, since the prob(F-statistic) value is less than the alpha value (i.e, 0.000000 < 0.05), we therefore conclude that the model estimated is statistically significant. This also means that volatility (VLT) has significant effect on stock returns (STR).





4.4 Stability Cusum Tests

Figure 4.3: Stability Cusum Tests

Source: E-Views 9.0 Output

The figure above shows the stability test diagram. The stability Cusum test assesses the stability of coefficient (β) in the model. The cusum series which is in between the upper and lower critical line (dotted lines) indicates that the model is stable.

4.5 Breusch-Godfrey Serial Correlation LM Test

The results of Breusch-Godfrey serial correlation LM test are presented in table 4.3 below:

Table 4.3: Breusch-Godfrey Serial Correlation LM Test

F-statistic	0.035991	Prob. F (2,235)	0.9647
Obs*R-squared	0.073185	Prob. Chi-Square (2)	0.9641

Source: Eviews 9.0 Output

Table 4.3 presents the results of Breusch-Godfrey serial correlation LM test. The null hypothesis of the test states that there is no serial correlation in the residuals. However, since the Prob. Chi-Square(2) value is greater than 0.05, the hypothesis of no serial



correlation is therefore accepted and we conclude that there is an absence of serial correlation in the model. This indicates that the series are not serially correlated.

4.6 Unit Root Test Result

Unit root was conducted using Augmented Dickey Fuller (ADF) test which was used to test for the stationarity of the variables at 1%, 5% and 10 % critical values. However, the results of the Unit root test are presented in table 4.4 below:

Table 4.4: Results of Stationary Test

Null Hypothesis: D(STOCK_RETURNS) has a unit root				
Exogenous: Constant				
Lag Length: 10 (Automatic	- based on SIC, maxlag=14)			
		t-Statistic	Prob.*	
Augmented Dickey-Fuller t	est statistic	-12.92039	0.0000	
Test critical values:	1% level	-3.458973		
	5% level	-2.874029		
	10% level	-2.573502		

*MacKinnon (1996) one-sided p-values.

Source: Eviews 9.0 Output

From table 4.4 above, After comparing the test statistic value against the Mackinnon critical value at 5% level of significance, it was noticed that the stock returns in the test employed (that is, ADF) is stationary at first difference (i.e. integrated of order I(1) and is significant at 1%, 5% and 10%.

4.7 Testing for ARCH Effects

In order to estimate GARCH-type model, it is very vital to first identify whether there is sufficient statistical evidence of heteroskedasticity (ARCH effects), which determine whether or not it is necessary to apply the ARCH estimation methods. In order to test for the presence or absence of ARCH effects in the return series, this study employed Lagrange Multiplier Test method to check the correlation in residuals. However, the results of Heteroskedasticity Test are presented in table 4.5 below:



F-statistic	11.267314	Prob. F(1,236)		0.0000
Obs*R-squared	12.269275	Prob. Chi-Square(1)	0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
С	0.197904	0.054785	3.612383	0.0004
RESID^2(-1)	0.033648	0.065080	5.517025	0.0000
R-squared	0.001131	Mean dependent v	/ar	0.191539
Adjusted R-squared	-0.003101	S.D. dependent va	r	0.822287
S.E. of regression	0.823561	Akaike info criter	ion	2.458011
Sum squared resid	160.0678	Schwarz criterion		2.487189
Log likelihood	-290.5033	Hannan-Quinn cri	ter.	2.469770
F-statistic	0.267314	Durbin-Watson sta	at	2.002351
Prob(F-statistic)	0.605623			

Table 4.5: Results of Heteroskedasticity Test: Arch

Source: Eviews 9.0 Output

The hypothesis involved is stated as:

H₀: There is no ARCH effect.

H_A: There is ARCH effect.

Decision Rule:

- Reject the null hypothesis (H₀) at 5% level of significance if the *p*-value is less than 0.05 (*p*-value < 0.05).
- Accept the null hypothesis (H₀) at 5% level of significance if the *p*-value is greater than 0.05 (*p*-value > 0.05).

From the results above, LM statistic is 12.269275 while *p*-value is 0.0000. However, since the *p*-value is less than 0.05 at 5% level of significance i.e. 0.0000 < 0.05, we therefore reject the null hypothesis (H₀) and conclude that ARCH effect is present and there is therefore sufficient statistical evidence to estimate ARCH model for better result.



4.8 Estimation of ARCH (1) Model

Since there is presence of ARCH effect, the next procedure is to estimate the ARCH model by maximum likelihood method. Thus, the results of estimation of ARCH (1) model are presented in this section as follows:

Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	0.936169	0.028172	33.22998	0.0000
STOCK_RETURNS(-1)	0.006526	0.020777	3.814087	0.0000
	Variance	Equation		
С	0.168711	0.004562	36.98243	0.0000
RESID(-1)^2	0.020880	0.006381	3.272049	0.0011
R-squared	-0.000908	Mean dependent	var	0.920711
Adjusted R-squared	-0.005132	S.D. dependent v	ar	0.437905
S.E. of regression	0.439027	Akaike info crite	rion	1.188824
Sum squared resid	45.68044	Schwarz criterior	1	1.247007
Log likelihood	-138.0644	Hannan-Quinn cr	iter.	1.212270
Durbin-Watson stat	1.911728			

1 and 1 . \mathbf

Source: Eviews 9.0 Output

From the results above, the upper part is the main equation gives the outcome of the main equation while the lower part gives the outcome of the variance equation. However, b_0 given by the (C) is the main value of the stock returns which is 0.936169. Also, the variance equation gives the results of the ARCH model. Thus, the time-varying volatility includes a constant (0.936169) plus a component which is dependent on the past errors (0.020880U²_{t-1}). However, the z-statistic of the 1st order coefficient (3.272049) with a p-value of 0.0011



which is less than 0.05 suggest a significant ARCH (1) coefficient. Based on these findings, there is sufficient statistical evidence to conclude that ARCH effect is statistically significant.

4.9 Estimation of GARCH (1,1) Model

Table 4.7: Results of Garch (1,1) Model Estimation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
С	0.967918	0.033991	28.47542	0.0000
	Variance	Equation		
С	0.094671	0.093672	1.010658	0.3122
RESID(-1) [^] 2	0.127029	0.011896	9.789978	0.0000
GARCH(-1)	0.866183	0.010123	95.44280	0.0000
R-squared	0.011449	Mean dependent var		0.921250
Adjusted R-squared	0.011449	S.D. dependent var		0.437067
S.E. of regression	0.439562	Akaike info criterion	l	1.141849
Sum squared resid	46.17832	Schwarz criterion		1.199860
Log likelihood	-133.0219	Hannan-Quinn criter		1.165223
Durbin-Watson stat	1.903042			

Source: Eviews 9.0 Output

The results of the estimates of the GARCH (1, 1) model are shown in the table above. The coefficient (0.866183) of the GARCH effect is significantly positive at 5% which shows that past volatility of stock market return is significant and has effect on current volatility and exhibits the expected sign in the market. The sum of ARCH and GARCH parameters or coefficients (0.127029 + 0.866183) which is close to 1 means that shocks to conditional variance will be highly persistent and is expected to have a mean reverting variance process, indicating that volatility shocks are quite persistent but not explosive. Lastly, since the GARCH parameter is significant, large excess return value, either positive or negative, will lead future forecasts of variance to be high for a prolonged period of time. This means



that GARCH model will be a better forecasting model than the ARCH model in the period of high volatility.



4.10 Dynamic Forecasting of GARCH Volatility

Forecast: STOCK_RETUF	
Actual: STOCK_RETURNS	
Forecast sample: 1 240	
Included observations: 240	
Root Mean Squared Error	0.438645
Mean Absolute Error	0.189087
Mean Abs. Percent Error	143.4567
Theil Inequality Coefficient	0.220735
Bias Proportion	0.011319
Variance Proportion	NA
Covariance Proportion	NA

Source: Eviews 9.0 Output

Figure 4.4: Dynamic Forecasting of Garch Volatility

From the results, the time series plot of the conditional variance does not change over time. Based on the results above, it can be concluded that volatility is stable. This is because it lies within the standard error bands. As a result, investors can hold the asset/stock.







Forecast: STOCK_RETUF Actual: STOCK RETURNS	
Forecast sample: 1 240	
Included observations: 240	
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Bias Proportion	0.011319
Variance Proportion	NA
Covariance Proportion	NA

Source: Eviews 9.0 Output

Figure 4.5: Static Forecasting of Garch Volatility

From the results, the time series plot of the conditional variance does not change over time. Based on the results above, it can be concluded that volatility is stable. This is because it lies within the standard error bands. As a result, investors can hold the asset/stock.

4.2 Discussion of Findings

The study modeled the jumps and volatility in stock returns of the petroleum marketing sector of the Nigerian Stock Exchange by employing different GARCH models. The quoted petroleum firms covered include: Oando PLC, Conoil PLC, Total PLC, Mobil (11 PLC), Eterna Oil & Gas PLC, Forte Oil PLC, Rak Unity Pet. PLC, Capital Oil PLC, Japaul Oil & Marine Services Plc and MRS PLC.

The results of the study show that Heteroscedasticity Test showed that ARCH effect is present and there is therefore sufficient statistical evidence to estimate ARCH model for better result and that the ARCH effect observed is statistically significant. The coefficient of the GARCH effect which is significantly positive at 5% shows that past volatility of stock market return is significant and has effect on current volatility. The implication of



this is that an increase in volatility is linked to a significant increase of returns, which is an expected result and thus conforms to economic theory. The results of static and dynamic forecasting of GARCH volatility showed that the volatility is stable. As a result, investors can hold the asset/stock.

5.1 Summary of Findings

The study modeled volatility in stock returns of the petroleum marketing sector of the Nigerian Stock Exchange by employing different GARCH models. Specifically, the study examined the impact of jumps on stock returns and investigated the effects of volatility on stock returns. The related literature was conceptually, theoretically and empirically reviewed. Also, the research design adopted for this study is empirical research design. The study made use of monthly time series data that covered the period of January 2017 to December 2018 for ten quoted petroleum firms on the Nigerian Stock Exchange.

The quoted petroleum firms covered include: Oando PLC, Conoil PLC, Total PLC, Mobil (11 PLC), Eterna Oil & Gas PLC, Forte Oil PLC, Rak Unity Pet. PLC, Capital Oil PLC, Japaul Oil & Marine Services Plc and MRS PLC. A range of GARCH family models was used to test the presence of volatility. The findings emanating from the data analysis are hereby summarized as follow:

- 1. There is a positive and significant relationship between volatility and stock returns.
- 2. About eight per cent (8%) of the changes in stock returns (STR) is captured by volatility.
- 3. The cusum series which is in between the upper and lower critical line (dotted lines) indicates that the estimated model is stable.
- 4. There is an absence of serial correlation in the estimated model.
- 5. The stock returns is stationary at first difference (i.e. integrated of order I(1) and is significant at 1%, 5% and 10%.
- 6. The results of Heteroskedasticity Test showed that ARCH effect is present and there is therefore sufficient statistical evidence to estimate ARCH model for better result.
- 7. The ARCH effect observed is statistically significant.
- 8. The coefficient of the GARCH effect which is significantly positive at 5% shows that past volatility of stock market return is significant and has effect on current volatility. The implication of this is that an increase in volatility is linked to a significant increase of returns, which is an expected result and thus conforms to economic theory.
- 9. The results of static and dynamic forecasting of GARCH volatility showed that the volatility is stable. As a result, investors can hold the asset/stock.

5.2 Conclusion and Recommendations

The study modeled volatility in stock returns of the petroleum marketing sector of the Nigerian Stock Exchange by employing different GARCH models. Overall results from this study provided evidence to show volatility persistence in the Nigerian stock returns data while it is also evident that oil and gas prices contribute significantly to the volatility of the stock returns in Nigeria. Also, the parameter estimates of the GARCH (1,1) models indicate that the conditional volatility of stock returns on the stable and persistent. Based



on the findings the study concludes that volatility has a positive and significant effect on the stock returns in the petroleum marketing sector of the Nigerian Stock Exchange.

Based on the findings of this study, the researcher proffers the following recommendations:

- 1. Government should make sufficient regulatory effort that will improve efficiency of stocks performance and reduce volatility aimed at boosting investors' confidence in the petroleum marketing sector.
- 2. Since the various ARCH and GARCH models showed volatility movement in stock returns, Nigerian government should look for new ways to diversify the economy from dependence on oil and explore other sectors like manufacturing sector and agricultural sector to reduce volatility in the economy and the overall effect on it.
- 3. Investors in the Nigerian stock market should wisely make use of important information emanating from the international oil market as well as the Nigerian foreign exchange market in their investment decision process.
- 4. Nigerian policy makers should design and sustain investment-friendly policies that can aid boosting of oil production and enabling environment stock exchange market to thrive.

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