MODELLING STOCK PRICE VOLATILITY OF AGRO-ALLIED COMPANIES IN NIGERIA[4]

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ABSTRACT

Empirical work on modelling stock price volatility in the agro-allied sub-sector of the Nigerian Stock Exchange is scarce despite the importance of agriculture to the Nigerian economy, the need to encourage investment in the sector and the importance of volatility patterns to investment decision. This study modelled conditional variances (volatility) of specific but well-known agro-allied companies in Nigeria using daily closing prices from 1st September, 2015 to 31st August, 2016. The study adopted both the symmetric and the asymmetric modifications of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to model the series' volatilities. The results showed no evidence of leverage effects on stock prices except in the case of two firms and therefore based on the appropriate model selection criteria, the symmetric models appeared to be superior to the asymmetric models. It was concluded that investors needed to consider the nature and characteristics of stock price behaviour when taking investment decisions. In addition, policy makers should be careful not to make statements with potential to generate bad news for the capital market. The regulatory agencies should continue to strengthen measures to develop the capital market in order for it to be resilient and able to cope better with bad news when they occur. Finally, more research, based on a wide variety of alternative models is called for to produce more empirical evidence on volatility especially in the agro-allied sector of the Nigerian capital market.

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1. INTRODUCTION

The stock market is the market where shares of publicly held companies are issued and traded either through exchanges or over-the-counter. It is one of the important features of a free market economy and it provides companies with opportunities to access capital from investors who receive part-ownership in return. It also provides opportunity for investors to make profit from their initial investment. Thus, the stock market plays a major role in the reallocation of funds to multiple sectors of an economy.

The flow of information is necessary for the market to perform its price discovery function. As against what obtained in the past, recent developments in information and communication technology (ICT) have led to a sharp drop in both the time and cost of information, and have effectively reduced barriers in communication between financial markets in different geographical locations (Kadongo &Ojah, 2012).

The logic of the random walk is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow's price change will reflect only tomorrow's news and will be independent of the price changes today and the prices will be random. The Efficient Market Hypothesis (EMH), in its strong form, posits that stock prices fully reflect all available information about the value of the firm. In other words, changes in stock prices are completely random. Thus any trading activity based on available information cannot lead to abnormal profit.

Agro-allied industries are very important in stimulating agricultural development, improving food self-reliance and contribute significantly to the growth of an economy. Despite these, the performance of such companies has not been spectacular. In the early 2000's the poor performance of most agro-allied industries in Nigeriahad been attributed to gross capacity underutilization, inefficient pricing policies, inappropriate pattern of investment decisions, inability to generate adequate working capital and maintain existing investments, and high level of indebtedness (Olomola, 2001). These have led to sales of shares to generate capital by some of the companies in order to meet up with their often urgent and critical financial demands.Fluctuations in prices of a company's stock represents uncertainty to the companyand high risk to potential investors especially those who buy and sell shares frequently.

Volatility is the risk or uncertainty in stock prices, which can be measured using a number of approaches, including the use of annualized standard deviation of daily changes in securities prices (Chen &Hsu, 2012). According to Malkiel &Xu (1999), it is the fluctuations, rather than unidirectional changes, in stock prices that is termed "volatility". Volatility of stock price is a form of reaction to the incomplete information in the market (i.e. uncertainty). Volatility guides investors in their decision making because they are not only interested in returns but also in the risk and uncertainty involved. Policies aimed at reforming the financial market may not be effective if proper attention is not paid to the issue of volatility. According to Porteba (2000), consumer confidence is usually reduced by stock market volatility. Osazevbaru (2014) posited that volatility in stock market may cause a rise in the cost of capital, and as a consequence, could harm economic growth.

A lot of research work has been carried out in the area of modelling stock price volatility in Nigeria. These include Arowolo (2013), Egbeonu &Isidore (2016), Ekong & Onye (2017), Asemota &Ekejiuba (2017) among others. No attention has been given to modelling agro-allied companies' stock price volatility in Nigeria. In addition, some authors such as Arowolo (2013), andEgbeonu & Isidore (2016) actually imposed particular volatility model structures to analyze time series. The issue of giving little or no emphasis to the appropriate model selection criteria as suggested by Engle (1982) to select the most appropriate volatility model and to validate the chosen model among other competing models is common in volatility research. Furthermore, stock price volatility is mostly time varying and by implication, the choice of appropriate volatility model may change over time (Salisu & Fasanya, 2012). Therefore, the application of a particular model over a long period may give misleading results.

Since Engle's (1982) paper on Autoregressive Conditional Heteroskedasticity (ARCH), researches involving financial time series have been dominated by the use of various versions of the ARCH models. In recent time, numerous research papers which focus on volatility have evolved including the GARCH and its various extensions such as Generalized Autoregressive Conditional Heteroscedasticity in Mean (GARCH-M), Power GARCH, Threshold GARCH, Integrated GARCH and Exponential GARCH. These have been adjudged to outperform others as far as high frequency financial time series is concerned. The ARCH model which was the starting point of these techniques assumes that the conditional variance is a deterministic linear function of past squared innovations and past conditional variances. Recent empirical research involving stock price volatility goes further to investigate other important characteristics of the market such as the issue of tail distribution, asymmetry, mean reversion and volatility clustering (Eminike &Aleke, 2012; and Osazevbaru, 2014).

Stock market modelling has become very prominent in the field of economics, finance, accounting and financial econometrics, with various modifications revealing further information on the appropriate framework for stock price volatility modelling. This study therefore contributes to the existing literature by estimating different models with a view to describing the nature of the stock price volatility of the Agro-allied sub-sector in the Nigerian Stock Exchange.

2. DATA AND METHODOLOGY

In modelling financial time seriesusing stock returns(r_t), this paper begins with an AR (k) process which involves performing ARCH LM test on model (1) to detect the existence of volatility in a series.

$$r_t = \eta + \sum_{i=1}^{k} \delta_i r_{t-i} + \varepsilon_t \ ; \quad i = 1, \dots, k; \ \ t = 1, \dots, T; \varepsilon_t \sim \mathrm{IID}(0, \sigma^2) \ ; \ |\delta_i| < 1 \qquad (1)$$

Wherer_t, stock returns, is measured as:

$$r_t = 100 * [\Delta \log(SP_t)] \qquad (2)$$

r_{t-i} captures the autoregressive components of the financial series, δ_i represents autoregressive parameters and ε_t is the error term measuring the difference between the *ex-ante* and *ex post* rate of returns.

Having conducted the pre-tests to ascertain the existence of volatility in the stock returns using the ARCH Lagrangian Multiplier (LM) test proposed by Engle (1982), the study proceeded to the second phase which involved the estimation of $\mathrm{ARCH}\ (p)$ and $\mathrm{GARCH}\ (p, q)$models and their extensions through the specification of both the symmetric and the asymmetric models. In this paper, two symmetric and two asymmetric volatility models were considered.

2.1 Symmetric Volatility Models

2.1.1 GARCH Model

Bollerslev (1986) extended Engle's framework by developing a technique that allows the conditional variance to be an ARMA process. Given that $\varepsilon_t = \sigma_t e_t$and $e_t \sim (0,1)$, $the variance equation for the$GARCH (p,q) therefore has the following form:

$$\sigma_t^2 = \varpi + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2 \qquad (3)$$

Where

$$p \geq 0, \quad q > 0; \ \varpi > 0, \beta_j \geq 0, \quad \gamma_i \geq 0, \quad j = 1, \dots, q \text{and } i = 1, \dots, p.$$

and$\sum_{j=1}^{\max(p,q)} (\beta_j + \gamma_j) < 1$

Equation (3) is the GARCH (*p,q*) model where p and q denote maximum numbers of the significant lagged terms of the conditional variance and the squared error term respectively. The ARCH effect is denoted by $\sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2$ and the GARCH effect $\sum_{i=1}^{p} \gamma_i \sigma_{t-i}^2$.

2.1.2 GARCH-M Model

Other important extensions also considered in the modelling of volatility in stock returns were the ARCH- in- mean (ARCH-M) and the GARCH-in-mean (GARCH-M) models, which capture the effects of the conditional variance in explaining the behaviour of stock price returns. For the ARCH-M, equation (1) is modified as:

$$r_t = \eta_t + \sum_{i=1}^{k} \delta_i r_{t-i} + \varepsilon_t \ ; \quad i = 1, \dots, k \qquad (4)$$

Thus;

$$\eta_t = \lambda + \theta \sigma_t^2 \qquad (5)$$

Where $\sigma_t^2$is as defined in the ARCH − M as:

$$\text{var}(\varepsilon_t | \pi_{t-1}) = \beta_0 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \text{ since } \mathrm{E}(\varepsilon_t^2 | \pi_{t-1}) = 1$$

The standard deviation of the conditional variance can also be used. For the GARCH-M, the only difference is that conditional variance (σ_t^2) follows equation (3) instead.

2.2 Asymmetric Volatility Models

In practice, GARCH models have gained popularity because they often give a reasonable fit to financial data and can explain some of the stylized facts. Nevertheless, the model encounters the same weaknesses like the ARCH model. For instance, like the ARCH model, the positive and negative shocks are symmetric. In addition, recent empirical studies on high frequency financial time series indicate that the tail behavior of GARCH models remains too short even with standardized Student-t innovations.

2.2.1 Exponential GARCH (EGARCH) Model

To overcome some weaknesses of the GARCH model in handling financial time series, Nelson (1991) proposes the Exponential GARCH (EGARCH) model, in particular, to allow for asymmetric effects between positive and negative asset returns. Conditional variance in this case is described as the following process:

$$\mathrm{Log}(\sigma_t^2) = \varpi + [1-\tau(L)]^{-1}[1+\beta(L)]f(\varepsilon_{t-1}/\sigma_{t-1}) \qquad (6)$$

EGARCH (1,1) Model is given as:

$$\ln(\sigma_t^2) = \varpi + \tau\left|\sqrt{\varepsilon_{t-1}^2/\sigma_{t-1}^2}\right| + \emptyset\sqrt{\varepsilon_{t-1}^2/\sigma_{t-1}^2} + \psi\ln(\sigma_{t-1}^2) \qquad (7)$$

Unlike the ARCH and GARCH models, equation (6) shows that, in the EGARCH model, the log of the conditional variance is a function of the lagged error terms. The asymmetric effect is captured by the parameter $\emptyset$ in equation (7) (i.e. the function $f(\varepsilon_{t-1}/\sigma_{t-1})$). There is evidence of the asymmetry effect if$\emptyset$is less (greater) than zero, implying that negative (positive) shocks increase volatility more than positive(negative) shocks of the same magnitude. If, however,$\emptyset = 0$, there is no asymmetry effect.

2.2.1 Threshold GARCH (TGARCH) Model

The Threshold GARCH model by Glosten, Jagannathan and Runkle (1993) also known as GJR-GARCH models asymmetric consequences of positive and negative innovations in the GARCH process. This model modifies equation (3) to include a dummy (as an indicator) variable I_{t-j}.

$$\sigma_t^2 = \varpi + \sum_{j=1}^{q}\beta_j\varepsilon_{t-j}^2 + \sum_{i=1}^{p}\gamma_i\sigma_{t-i}^2 + \sum_{j=1}^{q}\varphi_j\varepsilon_{t-j}^2 I_{t-j} \qquad (8)$$

where $I_{t-j} = 1$ if $\varepsilon_{t-j} > 0$ (positive shocks) and $I_{t-j} = 0$ otherwise. Therefore, there is evidence of asymmetric effects if φ_j is less (greater) than zero, which implies that positive (negative) shocks reduce the volatility of r_t by more than negative (positive) shocks of the same magnitude and vice versa. However, in some standard econometric packages like *GARCH* program and Eviews, the reverse is the case for the definition of I_{t-j}. That is, $I_{t-j} = 1$ if $\varepsilon_{t-j} < 0$ (negative shocks) and $I_{t-j} = 0$ otherwise. Thus, there is evidence of asymmetric effect if $\varphi_j >(<)0$ which implies that negative (positive) shocks increase the volatility of r_t by more than positive (negative) shocks of the same magnitude.

2.3 Data and Sources

Daily stock price (SP) data utilized in this study were collected from the Nigerian Stock Exchange (NSE) over the period 09/01/2015–08/31/2016. The study focussed on eight well known agro-allied companies in Nigeria, which were very active on the platform of the Nigerian Stock Exchange: Cadbury Plc (CAD), Dangote Flour Mill Plc (DFM), Dangote Sugar Refinery Plc (DSR), Flour Mills Plc (FML), Honeywell Flour Plc (HWF), Livestock Feeds Plc (LVST), Nestle Foods Plc (NST) and Okomu Oil Plc (OKM).

2.4 Estimation Procedure

In this section, the analyses were carried out in three phases, following Engle (2001) and Kočenda and Valachy (2006). The first phase dealt with some pre-tests to ascertain the existence of volatility in the stock price returns. The ARCH Lagrangian Multiplier (LM) test proposed by Engle (1982) was used in this regard. The second phase proceeded to the estimation of different volatility models involving $\text{ARCH}\,(p)\,\text{to}\,\text{GARCH}\,(p,q)$ type of models including their extensions. Model selection criteria such as Schwartz Information Criterion (SIC), Akaike Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQC) were used to determine the model with the best fit. The third phase provided some post-estimation analyses using the same ARCH LM test to validate the selected volatility models.

3. RESULTS

3.1 Preliminary Analysis

The pre-estimation analysis was done in two-folds: the first provides descriptive statistics for stock price and its returns and the second involved performing ARCH LM test. In empirical analyses, the usual *F* test or the statistic computed by multiplying the number of observations (n) by the coefficient of determination (R^2) were used. The latter statistic (nR^2) follows chi-squared distribution (χ_p) with p degrees of freedom which equal the number of autoregressive terms.

Table 1 below shows the descriptive statistics for stock price (SP_t) and stockreturns (r_t) covering the sample period. Thestatistics showed an equal representation of the eight companies under study, with four companies having positive and the other four having negative values of skewness. The negative skewness for SP_t included DFM, DSR, FML and NST implying left tail were particularly extreme. However, positive skewness was evident for CAD, HWF, LVST and OKM suggesting that the right tails were particularly extreme in these instance. In relation to kurtosis, the SP_t was platykurtic for all the companies under study indicating thinner tails than the normal distribution except OKM which was leptokurtic (i.e. indicating fat tail).

Similarly in relation to stock price returns (r_t), the largest positiver_t as well as the highest standard deviation was recorded for DFM. However, minimal value of r_t was experienced under DSR. Ther_t was negatively skewed for all the companies except DFM, HWF and NST. All the companies were leptokurtic (i.e. evidence of fat tail) except HWF and LVST which showed sign of thin tail. In addition, the JB test revealed that $r_t$were not normally distributed except for CAD, HWF and LVST and, therefore, the alternative inferential statistics that follow non-normal distributions were appropriate in this case (see for example, Salisu and Fasanya, 2013). The available alternatives include the Student-*t* distribution, the generalized error distribution (GED), Student-*t* distribution with fixed degree of freedom and GED with fixed parameter. All these alternatives were considered in the estimation of each volatility model and the Schwartz Information Criterion (SIC), Akaike Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQC) were used to determine the model with the best fit. Based on the empirical analyses, the skewed Student-*t* distribution performed well compared with any other skewed and leptokurtic error distribution and were consequently reported.

Figure 1 represents the behaviour of stock price returns (r_t) and stock price for the different companies under study. The notable spikes were evidences of significant unsteady patterns of stock returns. The graph also clearly showed evidence of volatility clustering where periods of high volatility were followed by periods of high volatility and low volatility were followed by low volatility. Overall, very few points on the graphs hover around zero which further reinforced the observations in table 1 and figure 1 with the trends in r_t showing some evidences of variability in SP_t. It is easy to trace these spikes in r_t to the periods they represent. The behaviour of prices and returns was clearly unsteady and dynamics of returns gives an evidence of volatility clustering.

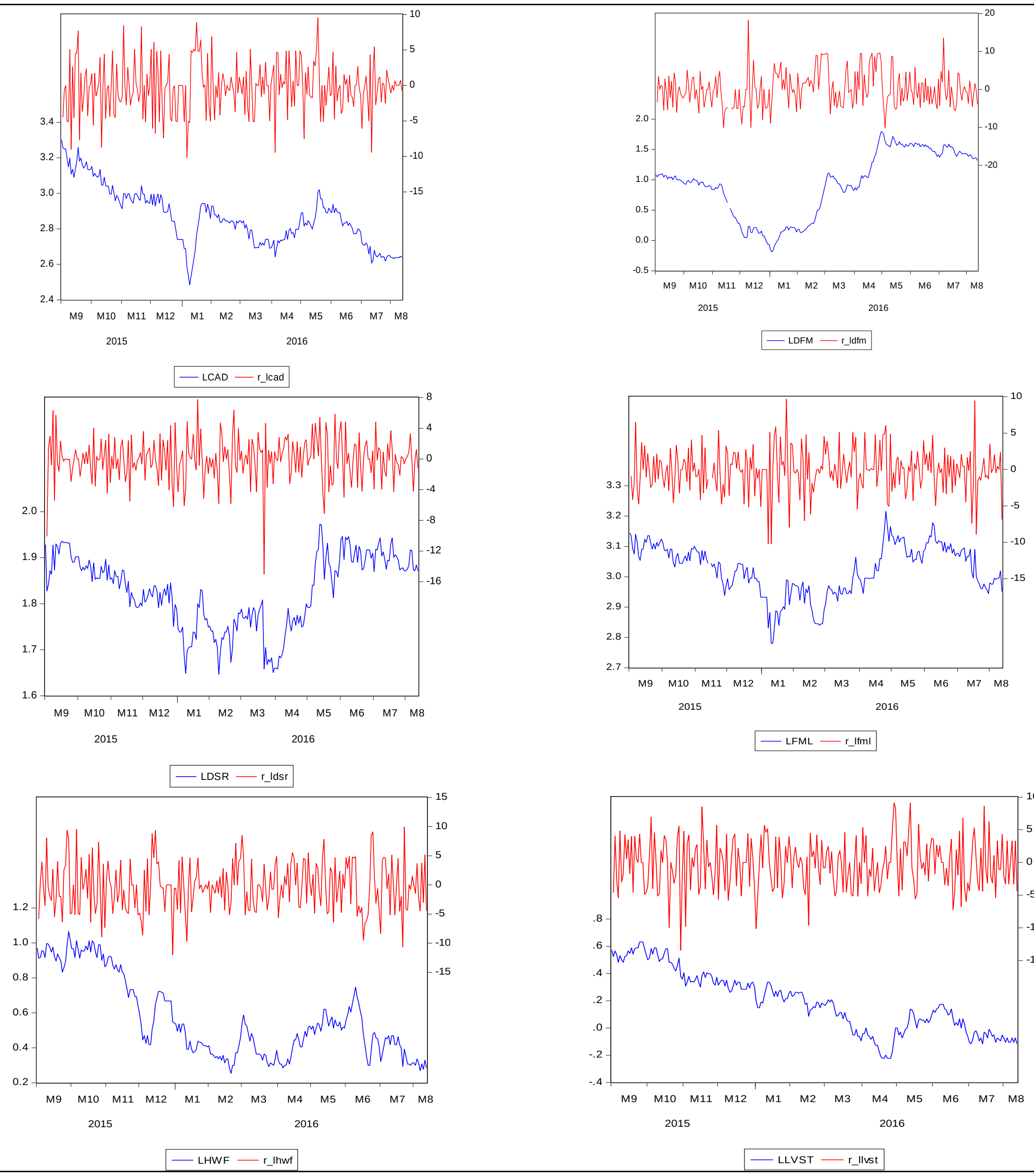
In Table 2, r_t showed evidence of ARCH effects as judged by the results of the *F-test* and nR^2 up to 10 lags for all the agro-allied companies under study. The test statistics at all the chosen lags were statistically significant at various significance levels except for DFM and DSR, perhaps, due to imperfection of the market, thus resoundingly rejecting the "no ARCH" hypothesis for stock prices. This is consistent with the results described under the summary statistics in table 1 and figure 1 and 2 depicting the existence of large movements in stock prices.

Table 1: Summary Statistics

Statistics	CAD		DFM		DSR		FML	
	SP_t	r_t	SP_t	r_t	SP_t	r_t	SP_t	r_t
Mean	2.864	-0.267	0.920	0.135	1.826	-0.023	3.022	-0.079
Median	2.844	0.00	0.974	0.00	1.840	0.00	3.039	0.00
Maximum	3.301	9.545	1.790	18.23	1.972	7.729	3.215	9.656
Minimum	2.484	-10.14	-0.186	-10.18	1.646	-15.00	2.780	-10.19
Std. Dev.	0.160	3.555	0.540	4.579	0.078	2.867	0.081	3.027
Skewness	0.354	-0.037	-0.337	0.596	-0.395	-0.693	-0.471	-0.187
Kurtosis	2.701	3.132	1.898	3.534	2.209	5.830	2.800	4.114
Jarque-Bera	6.12	0.238	17.17	17.45	12.91	102.29	9.57	14.13
	248		248		248		248	

Statistics	HWF		LVST		NST		OKM	
	SP_t	r_t	SP_t	r_t	SP_t	r_t	SP_t	r_t
Mean	0.566	-0.277	0.188	-0.278	6.644	0.001	3.404	0.0006
Median	0.494	-0.36	0.182	0.00	6.685	0.00	3.401	0.00
Maximum	1.064	9.937	0.631	9.097	6.768	9.765	3.610	0.146
Minimum	0.254	-11.97	-0.223	-13.43	6.396	-7.618	3.167	-0.252

Std. Dev.	0.228	4.216	0.222	3.833	0.092	2.088	0.091	0.038
Skewness	0.652	0.127	0.174	-0.102	-0.778	0.268	0.137	-0.839
Kurtosis	2.074	2.630	2.048	2.929	2.493	6.034	3.063	10.680
Jarque-Bera	26.46	2.069	10.61	0.483	27.71	97.73	0.819	636.05
Obs	248		248		248		248	



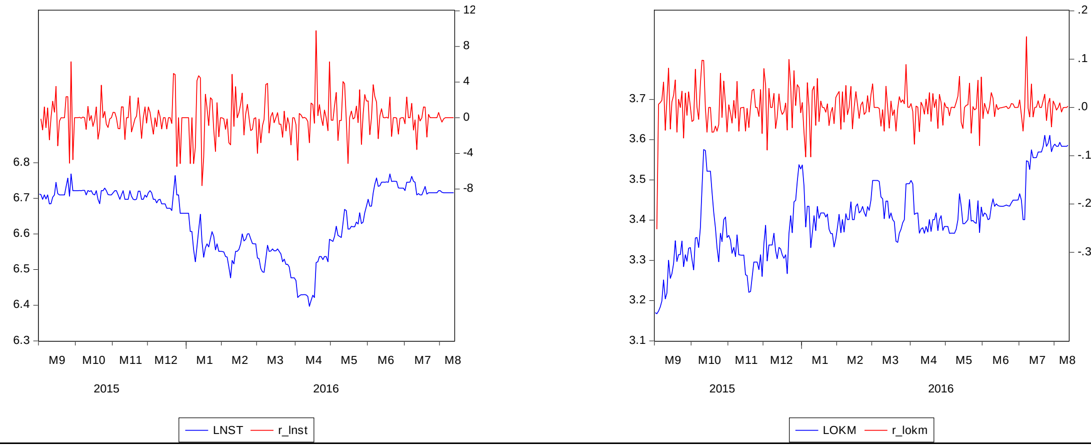


Fig. 1: Daily price of stock and daily returns of stocks - September 1, 2015 to August 31, 2016.

Table 2: ARCH TEST

Variables	p=1		p=6		p=10	
	F-test	$n\ R^2$	F-test	$n\ R^2$	F-test	$n\ R^2$
CAD (Cadbury Plc)	8.182*	7.980*	2.520**	14.629**	1.966**	18.966**
DFM (Dangote Flour Mill)	0.201	0.202	1.346	8.040	0.898	9.059
DSR (Dangote Sugar Refinery)	0.016	0.016	0.126	0.781	0.113	1.186
FML (Flour Mill Plc)	2.199***	2.198***	6.833*	35.915*	5.183*	44.189*
HWF (Honeywell Flour)	2.913***	2.902***	1.544***	9.180***	1.753***	17.061***
LVST (Livestock Feeds)	2.238**	2.236**	1.209***	7.247***	1.989**	19.170**
NST (Nestle Foods Plc)	10.260*	9.925*	2.438**	14.179**	3.007*	27.823*
OKM (Okomu Oil Plc)	2.941***	2.930***	0.935	5.644	0.757	7.688

Note: *, **, ***→ 1%, 5%, 10% levels of significance respectively

3.2 Estimation and Interpretation of Results

Given the evidence of ARCH effects inr_t, the study began the volatility modelling by first estimating equation (1) with GARCH(p, q) effects where $p, q = 1$ followed by the various extensions. The ARCH(q) was not estimated based on the theoretical assumption that GARCH(p, q) model with lower values of p and q provide a better fit than an ARCH(q) with a high value of q (see Salisu and Fasanya, 2012; Salisu and Fasanya, 2013).

Table 3 shows the results of the estimated GARCH (1,1) model for all the companies considered. Both the ARCH and GARCH effects were statistically significant for all the companies except for DFM, DSR and HWF, and, therefore, the evidence of volatility initially reported in table 2 appears to have been captured. The insignificance of the ARCH and GARCH effects in these companies especially DFM and DSR, were well captured in table 2 which shows no sign of ARCH effects, hence, estimating a volatility model becomes irrelevant. Also, the sums of the coefficients for the ARCH and GARCH effects were less than one (i.e. $\beta_j + \gamma_i$<1), which is required to have a mean reverting variance process. However, all the sums were close to one indicating that the variance process for each period reverts slowly. This slow mean reverting process is a sign of evidence of high level of persistence in the volatility of stock price although the degree of persistence may vary across companies. This trend further substantiated the evidence obtained in tables 1 and 2 and also suggested high level of persistence in the stock price volatility in the companies.

Table 3: GARCH(1,1) model estimation

Dependent Variable: Stock returns (r_t)								
Variable	**Coefficients**							
	CAD	**DFM**	**DSR**	**FML**	**HWF**	**LVST**	**NST**	**OKM**
Mean equations								
η	-0.469 (-2.335)**	0.050 (0.176)	-0.049 (-0.262)	-0.140 (-0.785)	-0.235 (-0.835)	-0.145 (-0.575)	-0.013 (-0.106)	0.001 (0.803)

δ_1	-0.211 (-2.737)*	0.328 (4.871)*	-0.252 (-3.551)*	-0.275 (-3.420)*	-0.005 (-0.082)	-0.141 (-2.227)**	-0.140 (-1.767)***	-0.248 (-3.860)*
Variance equations								
ϖ	4.947 (1.878)***	2.400 (0.756)	0.988 (0.656)	2.751 (1.681)***	4.259 (0.831)	28.352 (9.585)*	1.822 (3.021)*	0.0001 (2.590)*
β_1	0.273 (2.450)*	0.057 (0.883)	0.041 (0.922)	0.149 (2.080)**	0.096 (1.139)	0.081 (2.580)*	0.252 (2.496)*	0.294 (3.497)*
γ_1	0.334 (1.249)	0.812 (3.942)*	0.824 (3.589)*	0.524 (2.324)**	0.664 (1.951)***	-0.980 (-30.483)*	0.330 (1.881)***	0.579 (5.732)*
Observations	246	246	246	246	246	246	246	246
Diagnostics								
AIC	5.326	5.775	4.867	4.979	5.735	5.520	4.239	-3.922
SIC	5.397	5.846	4.938	5.050	5.806	5.591	4.310	-3.851
HQC	5.354	5.804	4.896	5.007	5.764	5.549	4.268	-3.893
ARCH LM test (10)								
F-test	0.651	0.350	0.098	1.265	1.028	0.790	1.436	0.316
nR^2	6.641	3.620	1.030	12.564	10.316	8.010	14.162	3.278

Note: *, **, ***→ 1%, 5%, 10% levels of significance respectively.

In this study, the GARCH(1,1) model was compared with the GARCH-M(1,1) model. The results of the latter were presented in table 4. Based on the results obtained for all the companies under study, the GARCH-M (1,1) does not seem to improve the GARCH (1, 1) model for stock price returns as the coefficients on (θ)included in the conditional mean equation was statistically insignificant, and, therefore, did not add any useful information as to the volatility of stock price. Nevertheless, there was still evidence of long memory volatility in stock price returns. The ranking of the degree of persistence in volatility in stock price was the same as the GARCH(1,1) model. In terms of the comparative performance of the two models, the GARCH(1,1) model gave a better fit over the GARCH-M(1,1) model for the symmetric case for all the companies using the SIC value. This is not surprising as the inclusion of the coefficients on the standard deviation of the price returns i.e., θ, in the conditional mean equation, was statistically insignificant and, therefore, did not add any useful information as to the volatility of all the companies.

The asymmetric GARCH models were also estimated to examine the probable existence of leverage effects. TGARCH model and the EGARCH model have become prominent in this regard. Tables 5 and 6 show the results obtained from estimating the two asymmetric models.

Table 4: CE

Dependent Variable: Stock Price returns (r_t)								
Variable	**Coefficient**							
	CAD	**DFM**	**DSR**	**FML**	**HWF**	**LVST**	**NST**	**OKM**
Mean equation								
η	-0.819 (-0.573)	-0.087 (-0.022)	-7.992 (-0.630)	0.427 (0.335)	-3.005 (-0.778)	1.392 (0.735)	0.192 (0.276)	$-4.25*10^{-5}$ (-0.004)
δ_1	-0.211 (-2.672)*	0.327 (4.409)*	-0.218 (-2.904)*	-0.271 (-3.362)*	-0.018 (-0.254)	-0.127 (-1.945)***	-0.137 (-1.568)	-0.248 (-3.883)*
θ	0.109 (0.250)	0.032 (0.035)	2.974 (0.625)	-0.204 (-0.461)	0.667 (0.704)	-0.404 (-0.798)	-0.108 (-0.299)	0.054 (0.175)
Variance equation								
ϖ	5.049 (1.828)***	2.408 (0.754)	4.588 (1.185)	2.649 (1.624)	8.330 (1.266)	27.508 (9.609)*	1.832 (3.060)*	0.0002 (2.594)*
β_1	0.267 (2.355)**	0.058 (0.883)	0.037 (0.579)	0.143 (2.076)**	0.135 (1.193)	0.089 (2.768)*	0.253 (2.480)*	0.299 (3.509)*
γ_1	0.330 (1.180)	0.811 (3.912)*	0.332 (0.616)	0.541 (2.430)**	0.394 (0.961)	-0.964 (-24.978)*	0.326 (1.868)***	0.573 (5.681)*
Observations	246	246	246	246	246	246	246	246
Diagnostics								
AIC	5.333	5.783	4.869	4.986	5.741	5.526	4.247	-3.914
SIC	5.419	5.869	4.954	5.072	5.826	5.611	4.332	-3.829
HQC	5.368	5.818	4.903	5.020	5.775	5.560	4.281	-3.880
ARCH LM test (10)								
F-test	0.671	0.351	0.127	1.116	1.145	0.572	1.387	0.308
nR^2	6.838	3.626	1.328	11.159	11.430	5.857	13.710	3.187

Note: *, **, ***→ 1%, 5%, 10% levels of significance respectively. $\theta = \sqrt{(\text{GARCH 1})}$ (M)

The results obtained from the TGARCH (1,1) model revealed evidence of leverage effects for the stock price of only two agro-allied companies (DFM and DSR). These effects indicated that positive shocks reduced the volatility of stock price by more than negative shocks of the same magnitude for most of the companies except HWF, LVST and OKM which showed that negative shocks reduce the volatility of stock price return more than positive shocks of the same magnitude. Notably, the leverage effects were dominant in DFM and DSR. Thus, good news in the stock market has the potential of increasing volatility in the stock price than bad news (but in the case of HWF, LVST and OKM, bad news in the stock market has the potential of increasing volatility in the stock price than good news.

Interestingly, the belief behind the results of the EGARCH (1, 1) model is not different from the TGARCH model. Similarly, for all companies, the coefficient $\emptyset$ is positive which is the equivalent interpretation for the negative sign of the coefficients of asymmetry in the TGARCH (1,1) model especially for the significant ones (in this case, DFM was the only significant company) and negative for those that were positive under TGARCH. This further validated the conclusion that positive shocks have the tendency of reducing volatility more than negative shocks, thereby suggesting asymmetric effects on the volatility of agro allied stock price. In the same vein, based on the SIC values, the TGARCH (1,1) model appeared to provide a better fit over EGARCH (1,1) model for the asymmetric case with the exception of CAD and DSR where EGARCH model seemed to perform better. In general, the GARCH (1,1) model (symmetric model) seemed better to the TGARCH (1,1) model (asymmetric) when modelling agro allied stock price volatility.

The post-estimation ARCH test was carried out using both the *F*-test and chi-square distributed nR^2 test. The results obtained for all the companies as presented under the diagnostics section of all the volatility models did not reject the null hypothesis of no ARCH effects. Most of the values were statistically insignificant. Thus, this study further authenticated the theoretical literature that ARCH/GARCH models are the most suitable for dealing with volatility in stock market except in few isolated cases.

Table 7 provides a cursory look at the preferred volatility models based on the lowest SIC value. It reveals that the stock price patterns were inconsistent over the sub-sector. On the average however, there is no evidence of leverage effects and therefore the symmetric models out-performed the asymmetric models, except for three companies (DFM, DSR, OKM) which showed evidence of leverage effects and gave an indication that investors in the stock market evidently reacted to bad news.

4. CONCLUSION

A measure of volatility in stock price provides useful information to profit maximizing investors and policy makers in the market particularly about uncertainty or risk in the market. To model volatility, Four GARCH-related models were used to model returns of stock prices of different well known agro-allied companies with the aim of examining whether or not shocks have asymmetric effects on stock price volatility and also to correct the notion of "one-model-fits-all" approach for stock price volatility which will yield misleading and invalid policy prescriptions. The paper provided empirical supports for the arguments that stock price of Agro-Allied companies may give substantially different volatility trends and may affect the choice of modelling framework for such volatility. One interesting innovation of the study was to use specific companies' stock prices data rather than the market index or aggregated index of a segment of the stock market. This was aimed at arriving at more specific and precise outcome.

The study found inconsistent patterns in the performance of the volatility models over the different agro-allied companies. There was no sign of leverage effects on stock prices (except in the case of DFM and DSR) and therefore the symmetric models appeared superior to the asymmetric models in most cases, hence supporting the earlier claim of Emenike and Aleke (2012). It follows that profit maximizing investors and government need to consider the nature and characteristics of stock price behaviour of agro-allied companies in investment decision and financial/stock market policy formulation and pronouncements respectively relating to agriculture and agro-allied companies.Finally, the use of one particular approach for stock price volatility will yield misleading and invalid policy prescriptions.

Table 5: TGARCH(1,1) model estimation

Dependent Variable: Stock Price returns (r_t)								
Variable	Coefficient							
	CAD	DFM	DSR	FML	HWF	LVST	NST	OKM
Mean equation								
η	-0.378 (-1.776)***	0.055 (0.195)	0.005 (0.034)	-0.101 (-0.548)	-0.268 (-0.964)	-0.153 (-0.614)	0.014 (0.114)	0.001 (0.502)
δ_1	-0.201 (-2.728)*	0.342 (5.515)	-0.308 (-6.148)*	-0.282 (-3.387)*	0.003 0.047	-0.137 (-2.122)**	-0.138 (-1.701)***	-0.241 (-3.716)*
Variance equation								
ϖ	6.541 (2.541)*	8.195 (2.260)**	1.813 (2.420)**	3.017 (1.741)***	4.557 (0.892)	28.167 (9.539)*	1.878 (3.338)*	0.0002 (2.421)**
β_1	0.436 (2.335)**	0.135 (0.982)	0.183 (2.026)**	0.209 (1.566)	0.062 (0.659)	0.073 (1.686)***	0.360 (1.925)***	0.236 (2.269)**
γ_1	0.200 (0.806)	0.560 (2.178)**	0.696 (6.552)*	0.480 (1.956)**	0.643 (1.846)***	-0.975 (-30.948)*	0.314 (1.867)***	0.574 (5.319)*
φ_1	-0.328 (-1.567)	-0.312 (-2.084)**	-0.216 (-2.238)**	-0.092 (-0.669)	0.081 (0.565)	0.020 (0.459)	-0.213 (-1.129)	0.125 (1.005)
Obs.	246	246	246	246	246	246	246	246
Diagnostics								
AIC	5.329	5.758	4.836	4.984	5.741	5.528	4.240	-3.917
SIC	5.428	5.843	4.921	5.070	5.826	5.613	4.325	-3.831
HQC	5.369	5.792	4.870	5.019	5.775	5.562	4.274	-3.883
ARCH LM test (10)								
F-test	0.690	0.607	0.298	1.324**	1.030	0.729	0.965	0.364
nR^2	7.025	6.208	3.087	13.119**	10.333	7.414	9.709	3.761

Source: Computed by the Authors

Note: *, **, *** → 1%, 5%, 10% levels of significance respectively. φ_1 **= ASYMETRY Coefficient**

Table 6: EGARCH(1,1) model estimation

Dependent Variable: Stock Price returns (r_t)								
Variable	Coefficient							
	CAD	DFM	DSR	FML	HWF	LVST	NST	OKM
Mean equation								
η	-0.312 (0.112)	0.015 (0.053)	0.167 (NA)	-0.146 (-0.784)	-0.330 (-1.165)	-0.233 (-0.993)	0.046 (0.373)	0.0005 (0.285)
δ_1	-0.209	0.333 (5.173)*	-0.287 (NA)	-0.272 (-3.489)*	-0.002 (-0.037)	-0.093 (-1.388)	-0.132	-0.260 (-4.203)*

	(-2.812)*						(-1.759)***	
Variance equation								
ϖ	0.636 (1.225)	1.585 (2.151)**	3.611 (NA)	0.720 (1.377)	0.315 (0.672)	4.435 (6.548)*	-0.072 (-0.842)	-1.701 (-5.110)*
τ	0.418 (2.656)*	-0.081 (-0.547)	0.118 (NA)	0.237 (2.250)**	0.154 (1.546)	0.234 (1.566)	0.388 (4.946)*	0.672 (6.805)*
$\emptyset$	0.086 (0.960)	0.221 (1.822)***	-0.098 (NA)	0.079 (0.940)	-0.040 (-0.523)	-0.048 (-0.557)	-0.024 (-0.381)	-0.063 (-0.980)
Ψ	0.608 (2.677)*	0.472 (1.683)***	-0.988 (NA)	0.573 (2.157)**	0.846 (4.763)*	-0.740 (-3.491)*	0.859 (17.739)*	0.822 (18.006)*
Observations	246	246	246	246	246	246	246	246
Diagnostics								
AIC	5.326	5.771	4.734	5.005	5.737	5.537	4.233	-3.950
SIC	5.411	5.857	4.820	5.091	5.823	5.623	4.318	-3.865
HQC	5.360	5.806	4.769	5.040	5.772	5.572	4.267	-3.916
ARCH LM test (10)								
F-test	0.817	0.850	0.997	2.086**	0.900	0.778	0.965	0.616
nR^2	8.276	8.597	10.022	20.029**	9.086	7.897	9.709	6.293

Note: *, **, ***→ 1%, 5%, 10% levels of significance respectively.

Table 7: Cursory of Model With Best Fit

	CAD	DFM	DSR	FML	HWF	LVST	NST	OKM
Stock Price (SP)	GARCH	T-GARCH	E-GARCH	GARCH	GARCH	GARCH	GARCH	E-GARCH

REFERENCES

Arowolo, W.B. (2013). "Predicting stock prices returns using GARCH model". *The international journal of engineering and sciences,* 2(5):32-37.

Asemota, O.J. & Ekejiuba, U.C. (2017). "An application of asymmetric GARCH model on volatility of bank equity in the Nigeria stock market". *CBN Journal of applied statistics,*8(1): 73-99.

Bollerslev, T. (1986)."Generalized autoregressive conditional heteroscedasticity". *Journal of econometrics*, 31, 307-327.

Chen, S. S. & Hsu, K. W. (2012). "Reverse globalization: Does high oil price volatility discourage international trade?".*Energy economics*, 34, 1634-1643.

Ekong C.E. & Onye K.U. (2017). "Application of GARCH model to estimate and predict financial volatility of daily stock returns in Nigeria". *International journal of management studies and research.* 5(8),18-34.

Egbeonu O.C. & Isidore, I.I. (2016). "Finametric analysis of Nigeria stock market and volatility of returns". *International journal of accounting research, 2(10),*14- 27.

Emenike K.O. & Aleke, S.F. (2012). "Modeling asymmetric volatility in the Nigerian Stock Exchange". *European journal of business and management,* 4(12), 52-60.

Engle, R. F. (1982). "Autoregressive conditional heteroscedasticity with estimates of the variance of U.K. inflation".*Econometrica,* 50 pp 987-1008.

Glosten, L., Jagannathan, R. & Runkle, D. (1993)."On the relation between the expected value and the volatility of the nominal excess return on stocks". *Journal of finance*, 48, 1779-1801.

Kodongo, O. & Ojah, K. (2012). "A comparative examination of currency risk pricing and market integration in the stock markets of Nigeria and South Africa".*Review of development finance,* 2, 118–129.

Malkiel, B. G., & Xu, Y. (1999). "The structure of stock market volatility". Working paper, *Princeton University.*

Nelson, D. (1991)."Conditional heteroscedasticity in asset returns: A new approach". *Econometrica*, *59*, 347-370.

Olomola, A. S. (2001). "Strategies and impact of agro-allied parastatals reform in Nigeria". *Agricultural economics*,24(2), 221-228.

Osazevbaru, H.O. (2014).**"**Measuring Nigerian stock market volatility". Singaporean *journal of business economics and management studies,* 2(8), 1-14.

Porteba, J. M. (2000). "Stock market wealth and consumption", *Journal of economic perspectives,* 14 (2), 99-118.

Salisu, A.A. & Fasanya, I.O. (2013)."Modelling oil price volatility with structural breaks".*Energy policy*, *52*, 554-562.

Salisu, A.A. & Fasanya, I.O. (2012). "Comparative performance of volatility models for oil price".*International journal of energy economics and policy*, 2(3), 167-183.