Modeling Volatility of Agricultural Commodity Food Price Index in Nigeria using ARMA-GARCH Models

David Adugh Kuhe

Lecturer, Department of Mathematics/Statistics/Computer Science, College of Science, Federal University of Agriculture, Makurdi-Nigeria.
Email: davidkuhe@gmail.com

Article Received: 30 August 2018  Article Accepted: 29 December 2018  Article Published: 05 March 2019

ABSTRACT

This study searches for optimal Autoregressive Moving Average and Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) models that best describe the log returns price volatility of selected Agricultural commodity food products in Nigeria. The study utilizes monthly time series data on Commodity Food Price Index from January 1991 to January 2017 and employs ARMA-GARCH, ARMA-EGARCH and ARMA-TGARCH models with varying error distributions to evaluate variance persistence, mean reversion rates and leverage effect while estimating conditional volatility. Results showed that ARMA (2,1)-GARCH (1,1) and ARMA (2,1)-EGARCH (1,1) models with student-t innovations were appropriate in describing the symmetric and asymmetric behaviours of the log returns. Price volatility was found to be quite persistence and mean reverting in all the estimated GARCH models indicating that past volatility was important in forecasting future volatility. The study also found evidence of asymmetry with leverage effect in the log returns suggesting that negative shocks have more impact on volatility than positive shocks of the same magnitude. Volatility half-life was found to be 10 months for basic ARMA (2,1)-GARCH (1,1) model and 15 months for ARMA (2,1)-EGARCH (1,1) model indicating that no matter how high or low the commodity food prices in Nigerian market shall move, they will eventually revert to a long-run average level. The evidence provided by this study shows that the best fitted models are not necessarily the best forecast performance models. The study provides some food price policy recommendations.

Keywords: Food Price, GARCH Models, Mean Reverting, Shock Persistence, Volatility, Nigeria.

1. INTRODUCTION

Commodity food price fluctuations have been attracting increasing attention in recent economic and financial literature and have been recognized as one of the most important economic phenomena. Commodity food price volatility (fluctuations) was found by [1] to reduce welfare and competition by increasing consumer costs. Apergis and Rezitis [2] found that commodity food price volatility increases the risk and uncertainty of both producers and consumers. Thus volatility of commodity food prices has been studied to some extent in recent times. Agricultural commodity prices are generally known for their continuously volatile nature [3]. The findings of [4] revealed that price volatility in the markets of major cereals crops remains high in Ethiopia. Literature on agricultural food price volatility remained an area in which little empirical attention has been paid in Nigeria. Hence it appears worthwhile to devote effort to modeling agricultural commodity food prices using ARMA-GARCH models. Investigating the pattern of domestic food price volatility is important in mitigating food price instability and risks, food insecurity, food policy decisions and strategic planning, granting of licenses for private firms to import or export food etc. Since similar effects of domestic food price instability can occur at production levels, investment and income stability of consumers, whole sellers, producers as well as at the macro level of the country. This study will be found significant in contributing to identify the pattern of domestic food price volatility for the purpose of making more informed food policy decisions and in regulating food prices.

It will also assist in identifying the underlying forces on domestic food price fluctuations in the agricultural commodity market for the purpose of setting monetary policy in a price stabilization–targeting regime. The result of this study will be used as a basis to other researchers for further investigations. Modelling the temporal behaviour of stock market volatility has been investigated by many scholars, a large body of literature relating to such studies focuses on the estimation of stock returns volatility and the persistence of volatility shocks. See for example [5, 6, 7, 8 & 9].

Since Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models represent short memory features and are inadequate in modeling the long memory in volatility, Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) introduced by [10] and extended by [11 & 12] becomes the most widely used models in studying the volatility of financial return series. The common characteristics found in financial time series such as fat tails, volatility clustering, volatility persistence and leverage effect are easily captured by the GARCH family models. The basic ARCH and GARCH models capture the symmetric properties of return series while their extensions such as EGARCH, TGARCH, APARCH, GJR-GARCH, etc., capture the asymmetry and leverage effects in the return series. In recent times, several empirical evidences in the financial literature found support for the GARCH-type models.

Al-Najjar [13] examined the volatility characteristics on Jordan’s capital market using ARCH, GARCH and EGARCH models to investigate the behaviour of stock return volatility for Amman Stock Exchange (ASE) covering the period from January 2005 to December 2014. The symmetric ARCH/GARCH models showed evidence for both volatility clustering and leptokurtosis, while the asymmetric EGARCH model showed no evidence for the existence of leverage effect in the stock returns at Amman Stock Exchange. Harrison and Paton [14] employed stock markets data from Romania and the Czech Republic to identify the correct GARCH specification under varying distributional assumptions and found that when log returns are characterized by heavy tails or kurtosis the use of GARCH-type model with student-t innovation specification is appropriate. Tudor [15] conducted a study on the Romanian stock market to investigate the Risk-Return Tradeoff using basic GARCH, GARCH-in-Mean and EGARCH models. He found that EGARCH model outperformed the other GARCH models in the Bucharest Stock Exchange composite index volatility in terms of sample-fit. In studying the volatility of Chinese stock returns during the crisis and pre-crisis period from 2000 to 2010, [16] found that EGARCH model fits the sample data better than basic GARCH model. He also found long term volatility to be more volatile during the crisis period and that leverage effect was present in the Chinese stock market during the crisis.

Regarding the effectiveness of basic ARCH and GARCH models in capturing volatility of financial returns, empirical findings by independent researchers such as [17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28 & 29] among others; found similar conclusions that basic GARCH (1,1) is sufficiently adequate in capturing all volatility in financial returns. They also confirm the ability of asymmetric GARCH models in capturing asymmetry and leverage effects in stock return volatility. In comparing between various asymmetric GARCH models such as EGARCH, GJR-GARCH, PGARCH, TGARCH and GARCH-M, empirical findings of [16, 21, 30 & 31] among
others; found that EGARCH model exhibit more fitness accuracy in estimation of volatility in comparison to other types in the asymmetric GARCH family models.

In this paper we attempt to model and examine the conditional variance effects of selected agricultural commodity food price log returns in Nigeria using ARMA-GARCH models. The ARMA models are specified in the mean equation while the GARCH-type models are specified in the variance equation.

2 MATERIALS AND METHODS

2.1 Data source and Integration

The data used in this paper are the monthly Commodity Food Price Index (CFPI) which includes Cereals, Vegetable Oils, Meat, Seafood, Sugar, Bananas, and Orange price indices. The prices are in Nigeria naira. The data spanned from January, 1991 to January, 2017 and is obtained as secondary data from http://www.indexmundi.com/commodities/?commodity=food-price-index&months=360. The monthly return of commodity food price index is computed from the following formula:

\[ r_t = 100 \times \ln \left( \frac{P_t}{P_{t-1}} \right) \]  

(2.1)

where \( P_t \) is the monthly closing price index at time \( t \) for \( t = 1, 2, 3, \ldots, T \) where \( T \) is the total number of observations and the variance of return is referred as the volatility of \( r_t \).

2.2 Methods of Data Analysis

The following statistical tools are utilized in analyzing data in this study using Eviews version 8.0 econometrics software.

2.2.1 Dickey-Fuller Generalized Least Squares (DF GLS) Unit Root Test

To investigate the unit root property and order of integration of food commodity price index in Nigeria, we employ Dickey-Fuller Generalized Least Squares (DF GLS) unit root test. The DFGLS test involves estimating the standard ADF test equation:

\[ \Delta Y_t = \alpha Y_{t-1} + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \cdots + \beta_p \Delta Y_{t-p} + v_t \]  

(2.2)

After substituting the DFGLS detrended \( Y^d_t \) for the original \( Y_t \), we have

\[ \Delta Y^d_t = \alpha Y^d_{t-1} + \beta_1 \Delta Y^d_{t-1} + \cdots + \beta_p \Delta Y^d_{t-p} + v_t \]  

(2.3)

Note that we do not include the \( X_t \) in the DFGLS test equation. As with the ADF test, we consider the t-ratio for \( \hat{\alpha} \) from this test equation and evaluate

\[ t_\alpha = \frac{\hat{\alpha}}{se(\hat{\alpha})} \]  

(2.4)
Where $\hat{\alpha}$ is the estimate of $\alpha$, and $se(\hat{\alpha})$ is the coefficient standard error. The null and alternative hypotheses may be written as: $H_0: \alpha = 0$ against $H_1: \alpha < 0$. The test rejects the null hypothesis of unit root if the DFGLS test statistic is less than the test critical values at the designated test sizes. While the DFGLS t-ratio follows a Dickey-Fuller distribution in the constant only case, the asymptotic distribution differs when you include both a constant and trend [32]. Since the DFGLS unit root test has severe size distortions and low power, we employ KPSS stationarity test which has higher power as a confirmatory test to DFGLS unit root test. Details of this test are provided by [33].

2.3 Models Specifications

2.3.1 Autoregressive Moving Average (ARMA) Model

To specify an ARMA model, we first specify an Autoregressive (AR) and a Moving Average (MA) models which are integral part of ARMA model. An autoregressive model of order $p$ denoted AR ($p$) is given by:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t$$

(2.5)

Suppose that \{\varepsilon_t\} is a white noise process with mean zero and variance $\sigma^2$, then the process $Y_t$ is said to be a moving average model of order $q$ denoted MA ($q$) if:

$$Y_t = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \cdots + \beta_q \varepsilon_{t-q}$$

(2.6)

A stochastic process resulting from the combination of autoregressive and moving average models is called an Autoregressive Moving Average (ARMA) model. An ARMA model of order $p,q$ written ARMA ($p,q$) is specified as:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \cdots + \beta_q \varepsilon_{t-q}$$

(2.7)

Where $\phi_i$ are the autoregressive parameters, $\beta_i$ are the moving average parameters, $p$ and $q$ are the orders of autoregressive and moving average parameters respectively.

2.3.2 The Autoregressive Conditional Heteroskedasticity (ARCH) Model

The Autoregressive Conditional Heteroskedasticity model of order $q$, ARCH ($q$) proposed by [10] is given by:

$$r_t = \mu + \varepsilon_t$$

(2.8)

$$\varepsilon_t = \sigma_t \varepsilon_t; \quad e_t \sim N(0,1)$$

(2.9)

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

(2.10)

where $\varepsilon_t$ is the shock at day $t$ and it follows heteroskedastic error process, $\sigma_t^2$ is the volatility at day $t$, $\varepsilon_{t-i}^2$ is the squared innovation at day $t - i$ and $\omega$ is a constant term
2.3.3 The Generalized ARCH (GARCH) Model

The ARCH model was generalized to GARCH model by [11]. A Generalized Autoregressive Conditional Heteroskedasticity process is said to be a GARCH (p, q) process if:

\[ \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \]  

(2.11)

Where \( \varepsilon_t^2 \) is the ARCH term, \( \sigma_t^2 \) is the GARCH term. The above model is variance and covariance stationary if the following necessary conditions are satisfied: \( \omega > 0; \alpha_i > 0, i = 1, 2, ..., q; \beta_i > 0, i = 1, 2, ..., p \) and \( \sum \alpha_i + \sum \beta_i < 1 \). This summation indicates the persistence of volatility shock. Bollerslev et al. [34] showed that basic GARCH (1,1) model is sufficient in capturing all the volatility in any financial time series. The basic GARCH (1,1) is expressed as:

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

(2.12)

In many empirical applications using high frequency financial time series data, extreme persistence in the conditional variance can be observed, so that in the basic GARCH (1,1) model the sum of ARCH and GARCH parameters is close to unity.

2.3.4 The Exponential GARCH (EGARCH) Model

The EGARCH was the first asymmetric GARCH model proposed by [12] to allow for asymmetric effects between positive and negative asset returns. EGARCH (1,1) can be expressed as:

\[ \ln \sigma_t^2 = \omega + \beta_1 \ln \sigma_{t-1}^2 + \alpha_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \]  

(2.13)

Where \( \alpha_1 \) represents the symmetric effect of the model, \( \beta_1 \) measures the persistence in conditional volatility shock. Large value of \( \beta_1 \) implies that volatility will take a long time to die out following a crisis in the market [35]. If \( \gamma < 0 \), then leverage effect exists and negative shocks (bad news) generate more volatility than positive shocks (good news) of the same magnitude and when \( \gamma > 0 \), it implies that positive shocks generate more volatility than negative shocks of the same modulus. The volatility shock is asymmetric when \( \gamma \neq 0 \). If on the other hand \( \gamma = 0 \), then the model is symmetric (positive and negative shocks of the same magnitude have the same effect on volatility).

2.3.5 The Threshold GARCH (TGARCH) Model

The Threshold GARCH (TGARCH) model was introduced independently by [36 & 37]. This model allows for asymmetric shocks to volatility. The conditional variance for the simple TGARCH (1,1) model is defined by:

\[ \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 \delta_{t-1} \]  

(2.14)
Where $d_t = 1$ if $\varepsilon_t$ is negative and 0 otherwise. In the TGARCH (1,1) model, volatility tends to increase with bad news ($\varepsilon_{t-1} < 0$) and decreases with good news ($\varepsilon_{t-1} > 0$). Good news has an impact of $\alpha_1$ whereas bad news has an impact of $\alpha_4 + \gamma$. If leverage effect parameter $\gamma > 0$ and statistically significant then the leverage effect exists. If $\gamma \neq 0$, the shock is asymmetric, and if $\gamma = 0$, the shock is symmetric. The persistence of shocks to volatility is measured by $\alpha_1 + \beta_1 + \gamma/2$.

2.4 Estimation of ARMA-GARCH Models and Innovation densities

In modelling the returns series for high frequency financial time series, we obtain the estimates of ARMA-GARCH process by maximizing the likelihood function:

$$L_\theta = - \frac{1}{2} \sum_{t=1}^{T} \left( \ln 2\pi + \ln \sigma_t^2 + \frac{\varepsilon_t^2}{\sigma_t^2} \right)$$  \hspace{1cm} (2.15)

(1) The Normal (Gaussian) Distribution is given by:

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}, -\infty < z < \infty$$  \hspace{1cm} (2.16)

(2) The Student-t distribution is defined as:

$$f(z) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{\pi} \Gamma\left(\frac{v}{2}\right)} \left(1 + \frac{z^2}{v}\right)^{-\frac{v+1}{2}}, -\infty < z < \infty$$  \hspace{1cm} (2.17)

where $v$ denotes the number of degrees of freedom and $\Gamma$ denotes the Gamma function. The degree of freedom $v > 2$ controls the tail behaviour. The $t-$distribution approaches the normal distribution as $v \rightarrow \infty$.

(3) The Generalized Error Distribution (GED) is given as:

$$f(z, \mu, \sigma, v) = \frac{\sigma^{-1} \nu e^{-\left(-\frac{\sqrt{\nu} \left|\frac{z-\mu}{\sigma}\right|}{\sqrt{\nu}} \right)^\nu}}{\lambda 2^{(1+1/v)} \Gamma\left(\frac{1}{v}\right)}, 1 < z < \infty$$  \hspace{1cm} (2.18)

$v > 0$ is the degrees of freedom or tail -thickness parameter and $\lambda = \sqrt{2^{(-2/v)} \Gamma\left(\frac{1}{v}\right) / \Gamma\left(\frac{3}{v}\right)}$

If $v = 2$, the GED yields the normal distribution. If $v < 1$, the density function has thicker tails than the normal density function, whereas for $v > 2$ it has thinner tails.

2.5 Model Selection Criteria

To select the best fitting GARCH model, Akaike Information Criteria (AIC) due to [38], Schwarz Information Criterion (SIC) due to [39] and Hannan-Quinn Information Criterion (HQC) due to [40] and Log likelihood are the most commonly used model selection criteria. These criteria were used in this study and are computed as follows:
\[ AIC(K) = -2 \log L + 2K \]  
\[ SIC(K) = -2 \log L + K \log T \]  
\[ HQC(K) = 2 \log[\log T] K - 2 \log L \]

where \( K \) is the number of independently estimated parameters in the model, \( T \) is the number of observations; \( L \) is the maximized value of the Log-Likelihood for the estimated model. Thus given a set of estimated ARMA-GARCH models for a given set of data, the preferred model is the one with the minimum information criteria and larger log likelihood value.

### 2.6 Volatility Forecasts Evaluation

We compare volatility forecasts performance of different ARMA-GARCH models using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). These accuracy measures are defined as follows:

\[
\text{Root Mean Squared Error (RMSE)} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (\hat{\sigma}_t - \sigma_t)^2}
\]  
\[
\text{Mean Absolute Error (MAE)} = \frac{1}{T} \sum_{t=1}^{T} |\hat{\sigma}_t - \sigma_t|
\]  
\[
\text{Mean Absolute Percentage Error (MAPE)} = \frac{1}{T} \sum_{t=1}^{T} \left| \frac{\hat{\sigma}_t - \sigma_t}{\sigma_t} \right|
\]

Where \( T \) is the number of out-of-sample observations, \( \sigma_t \) is the actual volatility at forecasting period \( t \) measured as the square daily return, and \( \hat{\sigma}_t \) is the forecast volatility at period \( t \). Note that these three forecast error statistics depend on the scale of the dependent variable and should be used as relative measures to compare forecasts for the same series across different models; the smaller the error, the better the forecasting ability of that model according to that criterion.

### 3. RESULTS AND DISCUSSION

#### 3.1 Summary Statistics

For better understanding of the nature and distributional properties of the log returns series, we compute summary statistics such as daily mean returns, maximum and minimum returns, standard deviations, skewness, kurtosis, and Jarque-Bera statistics for the commodity food price index. The result is presented in Table 1.
Table 1: Summary Statistics of Log Returns of Commodity Food Prices in Nigeria

<table>
<thead>
<tr>
<th>N</th>
<th>Mean</th>
<th>Median</th>
<th>Max.</th>
<th>Min.</th>
<th>SD</th>
<th>Skew.</th>
<th>Kurt.</th>
<th>JB</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>313</td>
<td>0.1191</td>
<td>0.2315</td>
<td>9.0266</td>
<td>-17.195</td>
<td>2.8732</td>
<td>-0.5967</td>
<td>6.8668</td>
<td>212.89</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

The summary statistics reported in Table 1 shows that the average monthly log return of commodity food price index in Nigeria is 0.1191% with a monthly standard deviation of 2.8732%. This reflects high level of dispersion from the average returns in the market over the period under review. The wide gap between the maximum and minimum log returns gives supportive evidence to the high level of variability of price changes in the market over the study period. The high kurtosis value of 6.8668% suggests that big shocks of either signs are more likely to be present in the series and that the returns series are clearly leptokurtic. The skewness coefficient of -0.5967 indicates asymmetry in the log returns series. The negative skewness value indicates that the distribution have fat left tails, meaning that large negative movements of stock prices are not likely to be followed by equally large positive movements.

The null hypotheses of zero skewness and kurtosis coefficient of 3 are rejected at 1% significance level suggesting that the monthly log returns series of commodity food price index do not follow a normal distribution. This rejection of normality in the log returns series is confirmed by Jarque-Bera test as its associated p-value is far below 1% marginal significance level.

3.2 Graphical Properties of the Level and Return Series

The first step in analyzing time series data is to plot the original series in level against time and observe its graphical properties. This help in understanding the trend as well as pattern of movement of the original series. Here we plot the original series of commodity food price index and its returns in Nigeria as function of time. The time plots are presented in Figure 1.

Figure 1: Time Plot of Monthly Price Movement and Monthly Returns of Commodity Food Price Index in Nigeria

From the time plot of monthly price movement, it is clearly seen that the trend movement in the plot is not smooth. This indicates that the mean and variance are heteroskedastic and the series seems to be non-stationary. We therefore transform the daily commodity food price index \( \{ Y_t \} \) to natural log returns \( \{ r_t \} \). The time plot of log returns indicates that some periods are more risky than others. There is also some degree of autocorrelation in the riskiness of the log returns. The amplitudes of the returns vary over time as large changes in returns tend to be
followed by large changes and small changes are followed by small changes. This phenomenon was first noted by [41] and described by [42] as volatility clustering, and is one of the stylized facts of the financial time series. The volatility clustering in the series indicates that the log returns are being driven by market forces. Periods of high volatility clustering implies frequent changes in the commodity food prices in the market while periods of low volatility clustering entails either persistence of constant prices over time or persistence of shocks in the market. Thus both volatility clustering and persistence of shocks are evidenced in the log returns.

3.3 Autocorrelation and Partial Autocorrelation Functions

We also examine the autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of log returns to see the degree of correlation in the data points of the series. The ACF and PACF plots are reported in Figure 2.

The result of the ACF and PACF plot reported in Figure 2 for the log returns of commodity food prices shows that the log returns are serially correlated. This is evidenced in the observed similarities between log returns as functions of the time lags between them. This means that there is substantial dependence in the volatility of the returns series and the present levels of volatility have effects on its future values.

![ACF and PACF Plot](image)

**Figure 2:** ACF and PACF Plot of Monthly Log Returns of Commodity Food Price Index in Nigeria

3.4 Unit Root and Stationarity Test Results

To examine the unit root and stationarity characteristics of the monthly commodity food price index and its log returns in Nigeria, we employ the Dickey-Fuller Generalized least squares (DF GLS) unit root test and KPSS Lagrange Multiplier stationarity test. The tests are conducted for constant only and constant and linear trend. The results of the DF GLS and KPSS tests are reported in Tables 2.

**Table 2:** DF GLS Unit Root KPSS Stationarity Test Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Option</th>
<th>DF GLS test statistic</th>
<th>5% Critical value</th>
<th>KPSS test statistic</th>
<th>5% Critical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Y_t )</td>
<td>Constant only</td>
<td>-1.2592</td>
<td>-1.9418</td>
<td>1.4117</td>
<td>0.4630</td>
</tr>
</tbody>
</table>
Table 2: ARMA Model Order Selection

<table>
<thead>
<tr>
<th>Model</th>
<th>LogL</th>
<th>AIC</th>
<th>SIC</th>
<th>HQC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARMA(0,1)</td>
<td>-745</td>
<td>4.7905</td>
<td>4.8245</td>
<td>4.8308</td>
</tr>
<tr>
<td>ARMA(1,0)</td>
<td>-740</td>
<td>4.7693</td>
<td>4.7933</td>
<td>4.7789</td>
</tr>
<tr>
<td>ARMA(1,1)</td>
<td>-739</td>
<td>4.7743</td>
<td>4.8204</td>
<td>4.7887</td>
</tr>
<tr>
<td>ARMA(1,2)</td>
<td>-738</td>
<td>4.7730</td>
<td>4.8211</td>
<td>4.7922</td>
</tr>
<tr>
<td>ARMA(1,3)</td>
<td>-738</td>
<td>4.7781</td>
<td>4.8382</td>
<td>4.8021</td>
</tr>
<tr>
<td>ARMA(2,1)</td>
<td>-733</td>
<td>4.7681</td>
<td>4.8163</td>
<td>4.7874</td>
</tr>
<tr>
<td>ARMA(2,2)</td>
<td>-734</td>
<td>4.7739</td>
<td>4.8341</td>
<td>4.7980</td>
</tr>
<tr>
<td>ARMA(2,3)</td>
<td>-734</td>
<td>4.7789</td>
<td>4.8512</td>
<td>4.8078</td>
</tr>
<tr>
<td>ARMA(3,1)</td>
<td>-737</td>
<td>4.7803</td>
<td>4.8524</td>
<td>4.8091</td>
</tr>
<tr>
<td>ARMA(3,2)</td>
<td>-735</td>
<td>4.7738</td>
<td>4.8579</td>
<td>4.8074</td>
</tr>
<tr>
<td>ARMA(3,3)</td>
<td>-737</td>
<td>4.7852</td>
<td>4.8698</td>
<td>4.8191</td>
</tr>
</tbody>
</table>

From the result of ARMA model order selection presented in Table 3, it is clearly seen that ARMA (2,1) is the best model specification for modeling the commodity food price log returns in Nigeria. This is because it presents the
minimum values of information criteria and maximum value of log likelihood. The estimates of the ARMA (2,1) model together with heteroskedasticity test result are presented in Table 4.

Table 4: Parameter Estimates of ARMA (2,1) Model and Heteroskedasticity Test Result

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi_0$</td>
<td>0.169768</td>
<td>0.183181</td>
<td>0.926777</td>
<td>0.3548</td>
</tr>
<tr>
<td>AR(1) $\phi_1$</td>
<td>1.261577</td>
<td>0.144780</td>
<td>8.713763</td>
<td>0.0000</td>
</tr>
<tr>
<td>AR(2) $\phi_2$</td>
<td>-0.400418</td>
<td>0.065361</td>
<td>-6.126224</td>
<td>0.0000</td>
</tr>
<tr>
<td>MA(1) $\theta_1$</td>
<td>-0.831735</td>
<td>0.145709</td>
<td>-5.708187</td>
<td>0.0000</td>
</tr>
<tr>
<td>F-statistic</td>
<td>23.63976</td>
<td>Q(12)-statistic</td>
<td>17.1442</td>
<td>Durbin Watson</td>
</tr>
<tr>
<td>P-value</td>
<td>0.000000</td>
<td>P-value</td>
<td>0.1448</td>
<td>2.010635</td>
</tr>
</tbody>
</table>

Heteroskedasticity Test Result

<table>
<thead>
<tr>
<th>Lags</th>
<th>F-statistic</th>
<th>P-value</th>
<th>nR$^2$</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.004312</td>
<td>0.0035</td>
<td>0.005012</td>
<td>0.0032</td>
</tr>
<tr>
<td>28</td>
<td>0.008803</td>
<td>0.0043</td>
<td>0.007224</td>
<td>0.0051</td>
</tr>
</tbody>
</table>

The parameters of ARMA (2,1) model are estimated using maximum likelihood method. Apart from the constant term ($\phi_0$), all other parameters of the model are statistically significant at 1% marginal significance level. The F-statistic which measures the overall fitness of the model is highly statistically significant with a p-value of 0.0000. The Ljung-Box Q-statistics of standardized residuals at lag 12 showed a p-value of 0.1448 > 0.05 indicating that the null hypothesis of no autocorrelation in the residuals of the estimated model is accepted at 5% significance level. The Durbin Watson statistic value of 2.010635 also shows the absence of autocorrelation in the residuals and that the model is non-spurious. As a result the ARMA (2,1) model appears to be adequate, valid and a good fit.

To test for the presence of ARCH effects in the log returns, we use Engle's (1982) Lagrange Multiplier (LM) test procedure which is applied to the residuals of the estimated ARMA (2,1) model. The test procedure is to regress the squared residuals on a constant and q lagged values of the squared residuals. The result which is presented in the lower panel of Table 4 provide a strong evidence against the null hypothesis of no ARCH effect for all lags at 1% marginal significance level, implying the presence of heteroskedasticity effect in the residuals of mean equation of the log returns series. Only ARCH or GARCH related models can sufficiently capture volatility of log returns in this scenario since the conditional variance is non-constant.
3.6 Model Order Selection for ARMA-GARCH Models

To select optimal symmetric and asymmetric GARCH-type models that will best fit the log returns series under investigation; we use the log-likelihoods in conjunction with some selected information criteria. The best fitting model is one with highest log-likelihood and least information criteria. This study applies GARCH (1, 1) consistent with many previous studies such as [18, 21]. The result is reported in Table 5.

**Table 5: Model Order Selection for ARMA-GARCH Models using Information Criteria**

<table>
<thead>
<tr>
<th>Model</th>
<th>Distribution</th>
<th>LogL</th>
<th>AIC</th>
<th>SIC</th>
<th>HQC</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARMA(2,1) - GARCH(1,1)</td>
<td>ND</td>
<td>-727</td>
<td>4.7378</td>
<td>4.8222</td>
<td>4.7715</td>
</tr>
<tr>
<td>ARMA(2,1) - GARCH(1,1)*</td>
<td>STD</td>
<td>-724</td>
<td><strong>4.7143</strong></td>
<td>4.8108</td>
<td><strong>4.7529</strong></td>
</tr>
<tr>
<td>ARMA(2,1) - GARCH(1,1)</td>
<td>GED</td>
<td>-725</td>
<td>4.7340</td>
<td>4.8204</td>
<td>4.7625</td>
</tr>
<tr>
<td>ARMA(2,1) - EGARCH(1,1)</td>
<td>ND</td>
<td>-721</td>
<td>4.7023</td>
<td>4.7987</td>
<td>4.7409</td>
</tr>
<tr>
<td>ARMA(2,1) - EGARCH(1,1)*</td>
<td>STD</td>
<td>-718</td>
<td><strong>4.6902</strong></td>
<td>4.7986</td>
<td><strong>4.7335</strong></td>
</tr>
<tr>
<td>ARMA(2,1) - EGARCH(1,1)</td>
<td>GED</td>
<td>-720</td>
<td>4.7023</td>
<td>4.8108</td>
<td>4.7457</td>
</tr>
<tr>
<td>ARMA(2,1) - TGARCH(1,1)</td>
<td>ND</td>
<td>-726</td>
<td>4.7337</td>
<td>4.8301</td>
<td>4.7722</td>
</tr>
<tr>
<td>ARMA(2,1) - TGARCH(1,1)</td>
<td>STD</td>
<td>-724</td>
<td>4.7288</td>
<td>4.8373</td>
<td>4.7722</td>
</tr>
<tr>
<td>ARMA(2,1) - TGARCH(1,1)</td>
<td>GED</td>
<td>-723</td>
<td>4.7232</td>
<td>4.8316</td>
<td>4.7665</td>
</tr>
</tbody>
</table>

From the result of Table 5, we observe that the log likelihood and information criteria select ARMA(2,1)-GARCH(1,1) and ARMA(2,1)-EGARCH(1,1) models as the best fitting symmetric and asymmetric models that best describe the volatility of log returns of commodity food price index in Nigeria. The parameter estimates of symmetric ARMA (2,1)-GARCH(1,1) is presented in Table 6.

**Table 6: Parameter Estimates of ARMA (2,1) - GARCH (1,1) Model with Student-t**

<table>
<thead>
<tr>
<th>Mean Equation</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi_0$</td>
<td>0.169075</td>
<td>0.173726</td>
<td>0.973231</td>
<td>0.3304</td>
</tr>
<tr>
<td>AR(1) $\phi_1$</td>
<td>1.144534</td>
<td>0.145693</td>
<td>7.855783</td>
<td>0.0000</td>
</tr>
<tr>
<td>AR(2) $\phi_2$</td>
<td>-0.347738</td>
<td>0.063508</td>
<td>-5.475458</td>
<td>0.0000</td>
</tr>
<tr>
<td>MA(1) $\theta_1$</td>
<td>-0.751042</td>
<td>0.145796</td>
<td>-5.151319</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Variance Equation
From the result of the upper panel of Table 6, the estimated ARMA (2,1) model is represented in equation (3.1):

\[ Y_t = 0.169075 + 1.144534Y_{t-1} - 0.347738Y_{t-2} + \varepsilon_t - 0.751042\varepsilon_{t-1} \] (3.1)

The result of equation (3.1) shows that the intercept (\(\phi_0\)) is positively related with log returns although not statistically significant. This implies that the predicted value of log returns will be approximately 0.17% if all other explanatory variables are kept constant. The AR and MA slope coefficients of the model are all statistically significant at 1% marginal significant levels. The estimated model has also satisfied the stationarity condition since the sum of AR and MA terms is less than unity. That is \(\phi_1 + \phi_2 + \theta_1 = 1.144534 - 0.347738 - 0.751042 = 0.045754 < 1\). This shows that the estimated ARMA (2,1) model is stationary.

The middle panel of Table 6 shows the parameter estimates of GARCH (1,1) model with all parameters being statistically significant. The conditional variance equation of the basic GARCH (1,1) model is presented as:

\[ \sigma_t^2 = 0.435197 + 0.02703\varepsilon_{t-1}^2 + 0.907853\sigma_{t-1}^2 \] (3.2)

From the model equation, the value of the ARCH term \(\alpha_1\) is 0.02703 and the value of the GARCH term \(\beta_1\) is 0.907853. Large value of the GARCH term (\(\beta_1 = 0.907853\)) shows that the effect of volatility shocks to the conditional variance takes a very long time to die out (long memory process), and the volatility is quite persistent. Low value of ARCH term (\(\alpha_1 = 0.02703\)) suggests that large market surprises induce relatively small reversion in future volatility. The sum of the ARCH and GARCH parameters \(\alpha_1 + \beta_1 = 0.934883\) shows that the stationarity condition of \(\alpha_1 + \beta_1 < 1\) is satisfied. This also shows that the conditional variance process of the log returns series is stable and predictable. When GARCH models are estimated using student’s t-distribution, the t-distribution degree of freedom parameter, (\(v\)) need to be greater than 2 for the distribution to be fat-tailed. From our estimates \(v = 8.91958\) indicating that the log returns series under review are fat-tailed. The ARCH LM test reported in the lower panel of Table 6 showed the ability of the estimated ARMA(2,1)-GARCH(1,1) model in capturing all the ARCH effects in the residuals of log returns as the associated p-values for F-statistic and nR\(^2\) tests are strictly greater than 0.05.
The time plots of the actual, fitted and residual of the series are presented in Figure 3. The trend of the fitted values move in sympathy with the actual series and the residuals are stationary. This indicates that our model is a good fit.

![Figure 3: Plot of Residual, Actual and Fitted ARMA(2,1)-GARCH(1,1) Model](image)

3.7 Testing for Asymmetry and Leverage Effect in the Log Returns

To investigate the presence of asymmetry and leverage effects in the monthly log returns series of commodity food price index in Nigeria, we estimate simultaneously ARMA (2,1)-EGARCH (1,1) model and the result is reported in Table 7.

**Table 7: Parameter Estimates of ARMA (2,1) - EGARCH (1,1) Model with Student-t Innovation**

<table>
<thead>
<tr>
<th>Mean Equation</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\phi_0$</td>
<td>0.218211</td>
<td>0.111559</td>
<td>1.956010</td>
<td>0.0505</td>
</tr>
<tr>
<td>AR(1) $\phi_1$</td>
<td>1.214466</td>
<td>0.094728</td>
<td>12.8206</td>
<td>0.0000</td>
</tr>
<tr>
<td>AR(2) $\phi_2$</td>
<td>-0.338003</td>
<td>0.054728</td>
<td>-6.176051</td>
<td>0.0000</td>
</tr>
<tr>
<td>MA(1) $\theta_1$</td>
<td>-0.852067</td>
<td>0.073906</td>
<td>-11.52905</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variance Equation</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\omega$</td>
<td>0.155947</td>
<td>0.041700</td>
<td>3.739726</td>
<td>0.0002</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.031222</td>
<td>0.024559</td>
<td>2.752339</td>
<td>0.0059</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.922337</td>
<td>0.007201</td>
<td>133.9522</td>
<td>0.0000</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>-0.110814</td>
<td>0.040621</td>
<td>-2.727980</td>
<td>0.0064</td>
</tr>
<tr>
<td>$\nu$</td>
<td>16.52597</td>
<td>13.85486</td>
<td>1.192792</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Shock persistence ($\beta_1$) = $\alpha_1 + \beta_1$ = 0.953559

ARCH Test  
F-statistic: 0.02207 [0.8820]  
$\nu^2$: 0.02222 [0.8815]
The ARMA (2,1) model result shown in the upper panel of Table 7 shows the mean equation of the simultaneous estimated model. The result reveals that all parameters of the model are statistically significant and satisfied the stationarity requirement of the model.

In the variance equation, the estimated EGARCH (1,1) model is presented in equation (3.3) below.

\[
\ln \sigma_t^2 = 0.155947 + 0.922337 \ln \sigma_{t-1}^2 + 0.031222 \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - 0.110814 \frac{\varepsilon_{t-1}}{\sigma_{t-1}}
\]

We observe that all parameters of the EGARCH (1,1) model are significant and the shock persistence parameter ($\beta_1 = 0.922337$) is very close to unity implying that the conditional variance has long memory and volatility shock is quite persistence in Nigerian market. The practical explanation is that historical events such as economic recession have a long and lasting effect. The EGARCH (1,1) model also shows that the leverage effect parameter ($\gamma = -0.110814$) is negative and statistically significant suggesting that past negative shocks have greater impact on subsequent volatility than positive shocks of similar magnitude. This confirms that asymmetric effects are indeed present in Nigerian consumer market. This means that positive and negative shocks of the same magnitude have different impacts on volatility in Nigerian consumer market.

The time plots of the actual, fitted and residual of the estimated ARMA (2,1)-EGARCH (1,1) are presented in Figure 4. The trend of the fitted values move in sympathy with the actual series and the residuals seems to be stationary indicating that our model is a good fit.

![Figure 4: Plot of Residual, Actual and Fitted ARMA(2,1)-EGARCH(1,1) Model](image)

3.8 Volatility Mean Reversion and Half-Life

When a given series is stationary, it is mean reverting and volatility will eventually reverts to its long run average. We can test for volatility mean reversion in the monthly log returns using GARCH models. In a stationary GARCH (1,1) model, volatility mean reversion rate is given by the sum $\alpha_1 + \beta_1$ which is generally close to unity for most financial data. The half life of volatility shock measures the average number of time periods it takes the volatility to revert to its long run level. In our estimated models the mean reverting rates $|\alpha_1 + \beta_1|$ which controls the speed of mean reversion are given in Table 8.
Table 8: Volatility Mean Reversion and Half-life

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean reversion rate</th>
<th>Volatility half-life (in month)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARMA(2,1)-GARCH(1,1)</td>
<td>$\alpha_1 + \beta_1 = 0.934883$</td>
<td>10</td>
</tr>
<tr>
<td>ARMA(2,1)-EGARCH(1,1)</td>
<td>$\alpha_1 + \beta_1 = 0.953559$</td>
<td>15</td>
</tr>
</tbody>
</table>

The half life of a volatility shock measures the average time it takes for $|\epsilon_t^2 - \sigma^2|$ to decrease by one half. The closer the value of $\alpha_1 + \beta_1$ is to 1, the longer the half life of a volatility shock. In our models the volatility half life is 10 months (approximately one year) for basic ARMA(2,1)-GARCH (1,1) model 15 months for ARMA(2,1)-EGARCH (1,1). Thus we conclude that the series under investigation is stationary and mean reverting indicating that no matter how high or low the commodity food prices in Nigerian market shall move, they will eventually revert to a long-run average level.

3.9 Model Diagnosis

We conduct model adequacy checks in the standardized residuals of the estimated models according to [43 & 44]. These models are ARMA (2,1)-GARCH(1,1) and ARMA (2,1)-EGARCH(1,1) and the results are presented in Table 9.

Table 9: Model Adequacy Checking of Standardized Residuals

<table>
<thead>
<tr>
<th></th>
<th>ARMA(2,1)-GARCH(1,1)</th>
<th>ARMA(2,1)-EGARCH(1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skewness</td>
<td>-0.416506</td>
<td>-0.412331</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>6.104845</td>
<td>6.055474</td>
</tr>
<tr>
<td>Jarque-Bera statistic</td>
<td>133.4805</td>
<td>129.3732</td>
</tr>
<tr>
<td>Q(1)-statistic</td>
<td>0.1858 [0.6661]</td>
<td>0.0224 [0.8815]</td>
</tr>
<tr>
<td>Q(8)-statistic</td>
<td>6.9584 [0.5423]</td>
<td>4.0744 [0.8502]</td>
</tr>
<tr>
<td>Q(15)-statistic</td>
<td>9.9116 [0.6983]</td>
<td>6.5539 [0.9387]</td>
</tr>
</tbody>
</table>

Note: values in [ ] are p-values

The model adequacy test result presented in Table 9 indicates that the coefficients of skewness and kurtosis measures slightly reduces in absolute values for ARMA(2,1)-GARCH(1,1) and ARMA(2,1)-EGARCH(1,1) estimated models when compared with the summary statistics of the original log returns series reported in Table 1. The diagnostic checks which are based on the distribution of standardized residuals indicates the ability of GARCH-type models to capture the asymmetry and fat tailed characteristics in residual distribution as well as the squared return autocorrelation in the selected Nigerian commodity food price index. Although, the GARCH-type models can capture the non-normality characteristics of log return series to some extent, the excess skewness and
kurtosis characteristics are still exposed. The Ljung-Box Q-statistics of the standardized residuals of the estimated models shown in Table 9 are highly statistically insignificant indicating the absence of autocorrelation in the standardized residuals of the estimated models.

3.10 Forecast Performance Evaluation of the Models

We employ three model accuracy measures, namely: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) to select the best forecast performance model among the three competing GARCH models for the monthly stock returns. The results are presented in Table 10. The smaller the accuracy measure, the better the forecast performance according to our criterion, ARMA (2,1)-GARCH (1,1) with student-t innovation produced better forecasts in the monthly log returns of the food commodity price index in Nigeria for symmetric GARCH while ARMA (2,1)-TGARCH (1,1) with normal distribution provides the better forecast in the log returns in terms of asymmetric GARCH. It is important to mention that in terms of comparing the best fitting GARCH model and the best forecast performance GARCH model, the evidence provided by this study shows that the best fitted models are not necessarily the best forecast performance models.

Table 10: Forecast Performance Evaluation of Estimated GARCH-type Models

<table>
<thead>
<tr>
<th>Model</th>
<th>Distribution</th>
<th>RMSE</th>
<th>MAE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARMA(2,1) - GARCH(1,1)</td>
<td>ND</td>
<td>2.8582</td>
<td>2.1349</td>
<td>109.9451</td>
</tr>
<tr>
<td>ARMA(2,1) - GARCH(1,1)*</td>
<td>STD</td>
<td>2.8579</td>
<td>2.1338</td>
<td>107.9386</td>
</tr>
<tr>
<td>ARMA(2,1) - GARCH(1,1)</td>
<td>GED</td>
<td>2.8582</td>
<td>2.1356</td>
<td>111.6953</td>
</tr>
<tr>
<td>ARMA(2,1) - EGARCH(1,1)</td>
<td>ND</td>
<td>2.8641</td>
<td>2.1463</td>
<td>115.0361</td>
</tr>
<tr>
<td>ARMA(2,1) - EGARCH(1,1)</td>
<td>STD</td>
<td>2.8615</td>
<td>2.1395</td>
<td>118.6180</td>
</tr>
<tr>
<td>ARMA(2,1) - EGARCH(1,1)</td>
<td>GED</td>
<td>2.8609</td>
<td>2.1394</td>
<td>115.3026</td>
</tr>
<tr>
<td>ARMA(2,1) - TGARCH(1,1)*</td>
<td>ND</td>
<td>2.8579</td>
<td>2.1336</td>
<td>109.4802</td>
</tr>
<tr>
<td>ARMA(2,1) - TGARCH(1,1)</td>
<td>STD</td>
<td>2.8639</td>
<td>2.1461</td>
<td>114.1571</td>
</tr>
<tr>
<td>ARMA(2,1) - TGARCH(1,1)</td>
<td>GED</td>
<td>2.8579</td>
<td>2.1342</td>
<td>111.3366</td>
</tr>
</tbody>
</table>

Note: * denotes the best forecasting model selected by the criteria.

4. CONCLUDING REMARKS

This study have attempted to search for optimal ARMA-GARCH models that best fit and forecast the log returns price volatility of selected Agricultural commodity food products in Nigeria. The study utilized monthly time series data on Commodity Food Price Index from January 1991 to January 2017 and employed ARMA-GARCH, ARMA-EGARCH and ARMA-TGARCH models with different innovation densities such as normal, student-t and...
Generalized Error Distributions to evaluate variance persistence, mean reversion rates and leverage effect while estimating conditional volatility. The best fitting symmetric and asymmetric ARMA-GARCH models were assessed through log likelihoods and information criteria such as AIC, SIC and HQC while the forecast performances of these ARMA-GARCH models were evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Results showed that ARMA (2,1) model was the best fitted model in the mean equation for the log returns, whereas in the variance equation, basic GARCH (1,1) and EGARCH (1,1) models with student-t innovations were appropriate in describing the symmetric and asymmetric behaviours of the log returns respectively. Price volatility was found to be quite persistence and mean reverting in all the estimated GARCH models indicating that past volatility is important in forecasting future volatility. The study also found evidence of asymmetry and leverage effect in the log returns suggesting that negative shocks have more impact on volatility than positive shocks of the same magnitude. Volatility half life was found to be 10 months for basic GARCH (1,1) model and 15 months for EGARCH (1,1) model. This suggests that no matter how high or low the commodity food prices in Nigerian commodity market shall move, they will eventually revert to a long-run average level. In terms of forecast evaluation, this study found ARMA (2,1)-GARCH (1,1) with student-t innovation to produced better forecasts in the monthly log returns of the food commodity price index in Nigeria for symmetric GARCH while ARMA (2,1)-TGARCH (1,1) with normal distribution provides better forecast in the log returns in terms of asymmetric GARCH. The evidence provided by this study shows that the best fitted models are not necessarily the best forecast performance models.

4.1 RECOMMENDATIONS

The empirical findings of this study have provided many important insights into the volatility of prices of some selected agricultural products in Nigeria. An in-depth understanding of domestic price volatility is essential for the country as well as policy makers; policy makers should address the importance of considering the sub-national factors in formulating the national commodity prices. The analysis in this study showed that the student-t distribution outperformed the normal distribution, indicating evidence of leptokurtosis in the volatility of food commodity prices in Nigeria. This result implies that if such leptokurtic behaviour is not taken into account when estimating the conditional volatility, the standard option pricing formula of Black and Scholes, which depends on the expected volatility parameter, could lead to unreliable results when pricing the future option contracts in the commodity markets.

REFERENCES


