Nature, Trends and Drivers of Food Price Volatility in Nigeria

Tolulope R. Jerumeh

ABSTRACT

The volatility of food prices is an important risk factor which constitutes serious threat to the welfare of millions of people around the world, particularly in developing countries like Nigeria. The study therefore investigated the pattern and drivers of food price volatility in Nigeria using annual and monthly time series data from January, 2000 to December, 2020. Data analysis was done using descriptive statistics, Coefficient of Variation, Auto-Regressive Conditional Heteroscedasticity (ARCH) model, Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) model, and Exponential GARCH (EGARCH). The study reveal volatility clustering between time period 2000 and 2012 but afterwards, the fluctuation observed in food prices was almost muted. Prices of most food items witnessed a forward leap between the periods 2000-2006 and 2007-2012, with the price of rice almost experiencing a threefold rise. Beyond this period, food prices have remained high, clearly surpassing their initial levels in 2013-2020. Returns on consumer price index, lending rates, exchange rate, and food price rate are important drivers of food price volatility in Nigeria. The study therefore recommends the need for an effective and sustainable price stabilization mechanism which involves holding strategic or buffer stock to protect the interest of producers against unstable prices.

Keywords: food prices, price volatility, price stabilization, risk factor.

I. INTRODUCTION

The significant changes in the prices of food over the last decade have continued to draw the attentions of both national governments and international agencies, even before the outbreak of COVID-19. Prior to the 2007, food prices have remained at historic lows for years, after which the international and domestic food prices soared multiple times and remained volatile ever since. Nigeria, like most developing countries, is experiencing staggering levels of food prices. For example, NBS [1] report reveals that food inflation increased from 14.5% in January 2020 to about 17.4% in October 2020. The report also shows that food price index rose from 95.8 points in 2009 to 109.9 points in 2010, averaged 148.9 points (10%) between 2011 to 2015 and up by 15% in 2016 (base period 2009=100). The most remarkable increase in food prices was recorded in 2017 where composite food price index rose by almost 20% over that of the year 2016. However, 2018 witnessed significant improvement in CPI as it decreased by 14%, a change which persisted till 2019. More recently, the index increased by 20.57% in January 2021 compared to an increase of 19.56% in December, 2020 [2].

Available evidence shows that food prices have increased continuously over the years. Apparently, food prices have remained high without corresponding increase in disposable personal income, the growth of which has stagnated at less than 1% since 2009 [1], or adequate protective policies or subsidies to shield the producers. The foregoing situation therefore exert a second round effects on malnutrition, poverty and food security. However, an important short-term policy response to price volatility is the use of publicly-held food reserves which is expected to provide the needed food supply intervention for vulnerable households. Presently, the National Strategic Food Reserves, which has a storage capacity of 1.3 million metric tons, is almost empty or put to other uses. Covid-19 pandemic has also dealt a heavy blow to Nigeria’s grain reserve which is currently in deficit of 5,000 metric tons as a result of the grains borrowed from the food stock of the Economic Community of West African States (ECOWAS). While Nigeria is still being disconcerted by the prevailing situation, some countries are already taking actions to tackle the surging domestic food prices. Recent FAO report reveal that while grain consuming giant China is stockpiling supplies, Russia is restricting the exports of Barley, Wheat and Maize through the imposition of taxes and Argentina recently lifted the ban on maize export to replace it with a temporary 30,000 tons daily cap on foreign sales [3]. The situation is of particular concern for China who is stockpiling, at historically high level, food and other calculated items gathered from different countries. FAO specifically warns of a sharp fall in stock and signaled concern about the extremely large import demands from China [3]. Stockpiling of supplies and trade restrictions can export inflation to the rest of the world while creating local shortages during periods of threats [4].

Stripping the foregoing to its essentials, the fact that food price volatility is likely to persist [5],[6] with the possibility of inducing risk adverse behavior impeding effective investment decisions, Nigeria may be at the brink of a serious food crisis if actions are not urgently taken. High and volatile
prices may lower the total food supply in Nigeria even in the face of high price incentives. Slow or non-response of supply to unstable prices, may tighten food supply alongside the welfare gains of net producers [7]. Against this backdrop, the study intends to assess the nature and trend of food price volatility as well as identify the factors influencing food price volatility in Nigeria.

II. EFFECTS OF VOLATILE AND EXTREME FOOD PRICES

Food price volatility, whose manifestation is demonstrated in the type of price hikes experienced in poor countries, is generating considerable anxiety in these countries where storage capacity and price integration across different regions are limited [8]. A reconnaissance of literature reveal scores of the associated consequences of food price volatility. Food price volatility arising from increase in international food prices affects the macroeconomic policy actions of countries around the world, particularly food import dependent countries, leading to high lending rates, inflationary pressures and volatile exchange rate [9].

Although the population of the world poor has decreased significantly, more than 40% of the Sub-Saharan population still live in extreme poverty. Existing indices in Nigeria, for example reveal high and disturbing levels of extreme poverty. Hikes in food prices have serious consequences for people in this category because the increases worsen their precarious economic situation by lowering their purchasing power and food security [10]. Repeated episodes of high food volatility and prices are major threats to food security, particularly in developing countries [5]. Amolegbe et al. [11], in their study of the effect of price volatility on food security in Nigeria found that upward volatility in the price of imported rice have negative implications for food security and the impact on household food share was higher for poor households than the rich ones. Okeke-Agulu and Aogejo [12] also reported similar result where food price volatility was shown significantly reduce food security of households in Jos-North Local government area of Plateau state, Nigeria.

As earlier mentioned food price volatility has different implications for producers and consumers. For net consumers, high and sustained food prices negatively impact their consumption pattern given that food share in the total consumption basket is substantively high. This may therefore result in decreased caloric intake and dietary diversity which ultimately intensifies household food insecurity. Akerele [13] showed that about 3.99 million Nigerians transitioned into hunger and calorific undernutrition due to spikes in food prices. Ikuemonisan et al. [14] pointed out that due to high food inflation, households had to forgo an average of 12% of their food consumption and 13% of their transportation expenditure to ensure continued household food stability. High food prices is of serious concern particularly for already malnourished preschool age children as the impact on them is irreversible even after periods of price decline or stabilization [5]. For producers, although high prices may seem favorable initially, but when coupled with increased volatility, supply may reduce even in the face of remarkable price incentives due to the associated production risks [15]. With dawdling and minimal response to high and volatile prices, changes in food supply along with the welfare gains of producers may remain inappreciable [7].

Substantial variations in food prices can also lead to political and market overreaction expressed in terms of export restriction [16]. Trade restrictions have been shown to negatively impact global food security as it creates local scarcities of food while exporting inflation to the rest of the world. In extreme cases, excessive price volatility and price spikes can have severe consequences on social and political stability [8],[16]–[18]. For example, 2007–2008 food crisis saw 33 countries experience violent riots and social unrest and similarly the widespread riots in 2011 have also been linked to 2010/2011 food price spikes [8]. Other negative consequences of food price volatility are losses in economic efficiency, more malnutrition and negative impacts on trade balance of the affected countries [17],[18].

III. METHODOLOGY

The study employed both monthly and annual time series data from reliable secondary sources which include World Bank, CBN FAOSTAT, NBS, IMF, FEWSNET among others. The study considered series data on food commodity prices, Gross domestic product, consumer price index, crude oil prices, maximum lending rate and exchange rate data. The selection of the data set was based on literature review and data availability. Due to the data paucity and the problem of missing data, the study selected variables that contains at least 90%, if not all the observations between 2000 and 2020.

A. Method of Data Analysis

The analytical techniques used in the study include descriptive statistics, coefficient of variation, Augmented Dickey Fuller Test, (ARCH) model, Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) model and EGARCH. It is important to conduct the diagnostic tests before conducting time series analysis because most of the series, according to Myers [19], have unit root and share the tendency to co-move (i.e having long run relationship with each other).

B. Coefficient of Variation

The coefficient of variation is expressed as the ratio of the standard deviation of a given resource or variable to its mean [20].

\[ C = \frac{\sqrt{V}}{\mu} \]  

(1)

Where:

\( \sqrt{V} \) –the standard deviation and

\( \mu \) – the mean.

By extension, the coefficient of variation was used to derive food price volatility calculated as the ratio of the standard deviation of monthly food prices to the mean of the prices over the period 2000–2020. Volatility in food prices was further analyzed using a forward looking or conditional volatility measure called GARCH model which provides a graphical representation and the nature of food price volatility in Nigeria. This is discussed in details in section on GARCH.
C. Unit Root

A common problem with time series model is the presence of non-stationary data series which when used without first correcting for non-stationary will lead to spurious regression as it generates biased estimates with high R² [21]. The common approach is to differentiate the non-stationary series until it becomes stationary. To establish whether or not each series employed in the study has unit root, the Augmented Dickey-Fuller (ADF) Test will be conducted. The test equation is generally represented as [22]:

\[ \Delta H_t = \sigma_0 + \sigma_1 t + \rho H_{t-1} + \epsilon_t \]  

(2)

where, 
- \( \Delta \) represents the first difference operator,
- \( H \) – time series data,
- \( \sigma_0 \) – the coefficient and
- \( \sigma_1 \) – the coefficient of the trend series,
- \( \rho \) – the lagged order of the autoregressive process,
- \( H_{t-1} \) – the data series in time t-1 and \( \mu \) is the error term.

A series that is stationary without any differencing is depicted as I (0) or integrated of order zero while those that are stationary at first difference or second difference are designated as I (1) and I (2), respectively. In sum, the number of differencing done to make a series stationary is represented by the value in parenthesis.

D. Autoregressive Conditional Heteroskedasticity (ARCH) Model

After testing for stationarity and determining the order of integration, the study used ARCH model to test for the presence of heteroscedasticity before analyzing the determinants of food price volatility. The ARCH model as developed by Engle [23] is specified using two equations: Mean equation and the variance equation

Mean Equation

\[ Y_t = \alpha + \epsilon_t \]  

(3)

\[ \epsilon_t = \alpha_t Z_{it}, \epsilon_t \sim iid N(0, \sigma_t) \]  

(4)

where:
- \( Y_t \) – the time series with a mean
- \( \alpha \) and \( \epsilon_t \) are – error term which is independently and normally distributed with mean zero and a unit variance \( \sigma_t \).

Variance Equation

\[ \sigma_t^2 = \delta_0 + \sum_{i=1}^m \delta_i \epsilon_{t-i}^2 + \sum_{j=1}^n \varphi_i \sigma_{t-j}^2 \]  

(5)

The variance equation is specified such that \( \delta_0 > 0, \delta_i \geq 0 \) and i>0. Tsay [24] documented that the error term \( \epsilon_t \) in equation (5) is normally distributed and follows a generalized error or student-t test distribution.

E. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

Following the result of the ARCH test, evidence of heteroscedasticity in the time series data requires the application of the GARCH model or the use of the Autoregressive Moving Average (ARMA) model if the result is otherwise [25]. The GARCH model was developed by Bollerslev [26] and it has been proven to be very useful in predicting conditional variances. It asserts that the best predictor of a variance in the coming period is a weighted average of the current period’s variance, long run mean variance and the squared residual of the current period.

The GARCH model is quite similar to the ARCH model with the only difference in the variance equation. The variance equation for the GARCH (m,n) model is thus written as:

\[ \sigma_t^2 = \delta_0 + \sum_{i=1}^m \delta_i \epsilon_{t-i}^2 + \sum_{j=1}^n \varphi_i \sigma_{t-j}^2 + \alpha \ln \left( \frac{V_{t-1}}{V_t} \right) \]  

(6)

For the variance equation, the model is specified such that the value of the variance scaling parameter \( V_t \) is influenced:

\[ \sigma_t^2 = \delta_0 + \sum_{i=1}^m \delta_i \epsilon_{t-i}^2 + \sum_{j=1}^n \varphi_i \sigma_{t-j}^2 + \alpha \ln \left( \frac{V_{t-1}}{V_t} \right) \]  

(7)

where:
- \( \delta_0 \) – the constant term and
- \( \delta_i, \varphi_i \) – the coefficient estimates.

The return series are RCPI, REOP, RLI and EXR and they represent monthly data on consumer price index (index points), crude oil prices (Bonny Light) (US Dollars/barrel), maximum lending rate (%) and exchange rate (%), respectively. The study computed the returns on these series because the use of returns, according to Belasri and Ellaila [27], produces series that are stationary and allows comparisons across different markets without need for a unit or scale. The monthly returns on the time series were calculated using the formula below:

\[ R_t = \log \left( \frac{P_t}{P_{t-1}} \right) \]  

(8)

where:
- \( R_t \) – the return on prices,
- \( P_t \) and \( P_{t-1} \) – prices in period t and t-1, respectively.

F. The E-GARCH Model

The ARCH and GARCH models specified above do not include leverage or asymmetric effects of shocks on the time-varying conditional variance, this study therefore includes the estimation of the Exponential GARCH (E-GARCH) Model developed by Nelson [28]. The EGARCH model is an improvement over the GARCH which has a restrictive condition that requires that all explanatory variables included in the model be positive [29]. As was with GARCH model, the only difference between the E-GARCH model and GARCH model is in the variance equation which is expressed as:

\[ \ln \sigma_t^2 = \delta_0 + \delta_1 \left( \frac{\epsilon_{t-i}^2}{V_{t-1}} \right) + \varphi_i \left( \frac{\epsilon_{t-j}^2}{V_{t-1}} \right) + \alpha \ln \left( \frac{V_{t-2}}{V_{t-1}} \right) \]  

(9)

where:
- \( \varphi \) is the asymmetric effect parameter which is absent when it is equal to zero and present when its value is greater than or less than zero. With the presence of asymmetric effect, negative values (\( \varphi < 0 \)) increases volatility more than positive values of the same magnitude and vice versa. The mean equation, as adopted by this study, is similar to that specified in equation (10) above.
IV. RESULTS AND DISCUSSION

A. The Nature and Extent of Food Price Volatility in Nigeria

High and volatile prices have been shown to increase production risks which ultimately lowers the total food supply. Instability in food prices is an important risk factor and constitute serious threat to food security, nutritional status and overall wellbeing of people. This section therefore attempts to determine the extent of food price volatility in Nigeria in the period 2000-2020 using monthly price data of maize, millet, rice and sorghum. The food commodities were both past volatility (shock) and lagged squared error term. However, for this study, the mean equation for the GARCH Model is simply represented as follows:

B. Review of Selected Food Commodity Prices

As shown in Table I below, apart from millet, the prices of all the food items witnessed a forward leap in 2007–2012, with the price of rice almost experiencing a threefold rise. This result is not surprising given that the period 2007–2012 represents a time period when the world experienced the twin crisis of the 2007/2008 food crisis and a resurge in 2011/2012. The period 2007–2008, in similitude of the historic 1974 food price crisis, together with the 2011 episode, saw the prices of virtually all food items increase significantly than they were at the beginning of the year 2000 [30]. Beyond the period 2007–2012, prices of these food items remained high, clearly surpassing their initial levels including the price of millet which initially decreased but went up by over 250% in the subsequent period (2013–2020). The prices of most food items continued to rise even after 2008 due to demand pressures from surrounding countries (some of whom have earlier experienced food riots), increase in global oil prices and substitution effect arising from 2008 crisis itself [31]. Conceivably, the food price index more than doubled through the time periods. This result is further confirmed by the trends in food commodity prices shown in Fig. 1 below.

C. Distribution of Food Price Volatility in Nigeria

To measure the extent of variations in food prices, the study estimated the coefficient of volatility which is expressed as the ratio of the standard deviation of the price of a resource to its mean over a given period of time. This result is not surprising given that the period 2007–2012 was probably due to inadequate access of farmers to improved seeds and rising insecurity in the Northern part of Nigeria, particularly in Borno State which is a major millet producing state. Consequently, AVISA [32] further revealed that several campaigns have been put in place to increase millet production in Nigeria. These include prioritizing millet as a choice crop in the achievement of food and nutrition security, especially in achieving the SDG Goals 2,3,12 and 13, promoting iron-biofortified pear millet, enlightenment and sensitization of farmers, among others. Despite all the several interventions for the development and adoption of high yielding varieties, production of millet, as shown by Statista [33], has not been able to resume its peak value of 9,064 metric tons in 2008, only averaging about 1,593 metric tons from 2011–2021. Therefore, the variations in production volumes accounts to a reasonable extent for the high volatility of millet prices. It should also be noted that, unlike the volatility of other food commodities prices whose strength fluctuated, the price volatility of rice was observed to increase steadily through time.

In general, food price volatility has been decreasing, with the highest volatility of roughly 6% recorded in the first sub period, a value higher than that of the overall period (4.6%). This results suggests that food price volatility in Nigeria has been generally weak, with the highest volatility record being 6%. This finding sits well with that of Minot [34] who refuted the widely held claim that food prices have become more volatile in Sub-Saharan Africa ever since the 2007/2008 food crisis. Going by the forgone, high level of food prices (Table I) rather than food price volatility may represent a more immediate problem in Nigeria.

TABLE I: FOOD PRICE INDEX AND AVERAGE PRICES OF SELECTED FOOD COMMODITIES, 2000–2020

<table>
<thead>
<tr>
<th>Food item</th>
<th>Average Price (₦)</th>
<th>Price Change</th>
<th>Average Price (₦)</th>
<th>Price Change</th>
<th>Average Price (₦)</th>
<th>Price Change</th>
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<tbody>
<tr>
<td><strong>2000–2006</strong></td>
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<tr>
<td>Maize (100Kg)</td>
<td>4,002.108</td>
<td>20.00</td>
<td>3,542.63</td>
<td>118.99</td>
<td>7,655.07</td>
<td>-13.08</td>
</tr>
<tr>
<td>Millet (100Kg)</td>
<td>1,672.62</td>
<td>92.78</td>
<td>1,268</td>
<td>-75.25</td>
<td>4,849</td>
<td>215.42</td>
</tr>
<tr>
<td>Rice(kg)</td>
<td>332.66</td>
<td>15.90</td>
<td>813.03</td>
<td>746.22</td>
<td>6,210.45</td>
<td>95.58</td>
</tr>
<tr>
<td>Sorghum(kg)</td>
<td>138.93</td>
<td>-26.53</td>
<td>150.23</td>
<td>74.98</td>
<td>171.92</td>
<td>-20.63</td>
</tr>
<tr>
<td>Food Price Index</td>
<td>50.63</td>
<td>1.28</td>
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<td>88.88</td>
<td>238.21</td>
<td>1.50</td>
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<td><strong>2007–2012</strong></td>
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<td></td>
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<td>1.50</td>
</tr>
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Note: Average nominal prices in Naira and price change measured in percentage: *Price data for computing CV only available from year 2002 for all food commodities; **price data not available in years 2003 and 2004.

TABLE II: PRICE VOLATILITY OF SELECTED FOOD COMMODITIES, 2000–2020

<table>
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<tbody>
<tr>
<td>Coefficient of Variation</td>
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</tr>
<tr>
<td>Maize</td>
<td>0.148</td>
<td>0.132</td>
<td>0.249</td>
<td>0.187</td>
</tr>
<tr>
<td>Millet</td>
<td>0.466</td>
<td>0.656</td>
<td>0.311</td>
<td>0.461</td>
</tr>
<tr>
<td>Rice</td>
<td>0.118</td>
<td>0.189</td>
<td>0.247</td>
<td>0.199</td>
</tr>
<tr>
<td>Sorghum</td>
<td>0.201</td>
<td>0.092</td>
<td>0.170</td>
<td>0.151</td>
</tr>
<tr>
<td>Food Price Index</td>
<td>0.059</td>
<td>0.044</td>
<td>0.038</td>
<td>0.046</td>
</tr>
</tbody>
</table>

*Price data for computing CV only available from year 2002 for all food commodities; **price data not available in years 2003 and 2004, respectively.
As earlier pointed out, the GARCH model was used for the graphical test of volatility in food prices. In addition, spikes and trends (estimated using the Hodrick-Prescott time-series filter) of food prices, were provided. Fig. 1 and 2 present the result of spikes, trends, and volatility of the prices of maize and rice as well as that of food price index. The price spikes analysis shows that price spikes were more evident in rice than in maize and in both cases, the negative price spikes were not pronounced. Exceptionally high prices were recorded for rice in 2008, 2011, 2013 and 2018 with the first two periods representing periods of significant food crisis in the world. Although significant price increases in maize were only observed in periods 2017 and 2019, the pattern of the price spikes of these cereals established that during the crises periods, high global food prices were transmitted to Nigeria, just like other domestic markets. The fact that Nigeria did not experience significant price spikes in maize prices during these periods may be largely due to the inclusion of maize in the import prohibition list, an import ban placed on selected commodities between January 2004 to October 2008. Also, Fig. 1 shows that volatility in the price of rice was stable up to 2007, clustered in 2008, punctuated by relative calm between 2009 and 2011 and became more frequent and pronounced afterwards, particularly in periods 2018–2020. Sustained volatility clustering was however noticed for both maize and rice in recent times. With volatility clustering, sustained high (low) period of volatility is closely followed by another high (low) period of volatility. The overall trend pattern for maize and rice is similar as seen in a stationary or horizontal trend observed in their plots. This trend is also linear, as the series data seemingly appears to cluster around a straight line.

The jagged peaks of the food price index in the first half of the distribution are explained by volatility clustering between period 2000 and 2012 and beyond this period, volatility was observed to be almost muted (Fig. 2). The sustained period of volatility between periods 2000 and 2012 clearly shows periods of high volatility being followed by periods of low volatility. Based on the plot of food price index with emphasis on pattern observed in the last one decade, price volatility in subsequent periods may follow similar pattern of remaining relatively stable. The trend in Food price index was fairly unstable between periods January 2000 and April 2013, after which it started declining reaching a record low of 7.79 points in December 2017. Beyond this period, prices have been increasing reaching an all-time high of 23.68 points in December 2021. The overall trend for food price index, just as was the case for the selected food commodities, is both stationary and linear. In addition, the price spike analysis reveals a period of repeated and alternated positive and negative spikes between the period 2000 and 2010. In all, positive and negative spikes were observed to be more pronounced between the periods 2000 and 2010.

D. Determinants of Food Price Volatility

Before determining the factors influencing food price volatility, there is a need to report stylized facts about the return series to be included in the analysis. Results in Table III, Table IV and Table V show the preconditions for estimating an ARCH/GARCH model.
Coefficient of Variation

The least was noticed in crude oil price. The Jarque Bera test which was significant in all the series (p<0.001) implies that the null hypothesis of normal distribution should be rejected and as expected this result is consistent with those of Kurtosis and skewness. The result reveals a non-symmetric distribution for all the return series - exchange rate, food price index and consumer price index were negatively skewed while oil price, and lending rate had positive skewness. The negative and positive skewness suggests that the series have long left tail and long right tail, respectively. With a Kurtosis value greater than 3, all the return series can be described as leptokurtic i.e., they all have a distinct peak and many observations near the mean with a relatively heavy tail. The result on the return series in Table III shows that the ADF was reported unit roots in return series. Following Belasri and Ellaia [37], the results of the stationarity test in Table VI shows that the ADF was statistically significant at 1% for all the series. This suggests that the null hypothesis of unit root is rejected, and the return series are stationary at their levels.

E. Descriptive statistics of the Return Series

The result on the return series in Table V shows that the consumer price index has the highest mean value (0.987) and the least was noticed in crude oil price. The highest fluctuation in prices was noticed in crude oil market given a standard deviation of 11.92. For a standard normal distribution, the kurtosis must be close to three (3) and the skewness zero (0) [35]. The result reveals a non-symmetric distribution for all the return series - exchange rate, food price index and consumer price index were negatively skewed while oil price, and lending rate had positive skewness. The negative and positive skewness suggests that the series have long left tail and long right tail, respectively. With a Kurtosis value greater than 3, all the return series can be described as being leptokurtic i.e., they all have a distinct peak and many observations near the mean with a relatively heavy tail. The kurtosis values ranged from 5.89 in real food price to 30.79 in crude oil price. The Jarque Bera test which was significant in all the series (p<0.001) implies that the null hypothesis of normal distribution should be rejected and as expected this result is consistent with those of Kurtosis and skewness. The above properties of the series underscore the suitability of the ARCH/GARCH model employed in the study.

F. Test for Stationarity

The result on the return series in Table V shows that the consumer price index has the highest mean value (0.987) and the least was noticed in crude oil price. The Jarque Bera test which was significant in all the series (p<0.001) implies that the null hypothesis of normal distribution should be rejected and as expected this result is consistent with those of Kurtosis and skewness. The above properties of the series underscore the suitability of the ARCH/GARCH model employed in the study.

The study employed the Augmented Dickey Fuller Test to check for stationarity of the monthly return series which were calculated as log of the ratio of the series in periods t and t-1. Although, Belasri and Ellaia [27] documented that the use of returns produces series that are stationary, the study still conducted the stationary test for confirmation as Apergis and Apergis [36] and Ayele et al. [37] reported unit roots in return series. Following Belasri and Ellaia [27], the results of the stationarity test in Table VI shows that the ADF was statistically significant at 1% for all the series. This suggests that the null hypothesis of unit root is rejected, and the return series are stationary at their levels.

G. ARCH LM Test

The applicability of the GARCH model or otherwise depends on the resulting outcome of the ARCH LM test. This is done by testing the residuals of the return series for evidence of heteroscedasticity. Findings from Table V show that the null hypothesis of no arch effect was rejected at the last two lags of the residuals at 1% while the first lag was found to be significant at 10%. The presence of heteroscedasticity in the ARCH LM test therefore suggests the need to estimate a GARCH model, the results of which are discussed in the next section.

### Table III: Summary Statistics of the Return Series

<table>
<thead>
<tr>
<th></th>
<th>Exchange rate</th>
<th>Real Oil price</th>
<th>Real food price</th>
<th>Consumer Price index</th>
<th>Lending rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.531</td>
<td>-0.726</td>
<td>4.901</td>
<td>0.987</td>
<td>0.049</td>
</tr>
<tr>
<td>Maximum</td>
<td>23.981</td>
<td>65.815</td>
<td>-23.918</td>
<td>7.163</td>
<td>26.371</td>
</tr>
<tr>
<td>Minimum</td>
<td>-6.579</td>
<td>-82.606</td>
<td>-23.918</td>
<td>-3.490</td>
<td>-12.373</td>
</tr>
<tr>
<td>STD. DEV</td>
<td>2.803</td>
<td>11.922</td>
<td>1.860</td>
<td>1.297</td>
<td>3.448</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.543</td>
<td>2.943</td>
<td>-0.113</td>
<td>-0.070</td>
<td>1.238</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>13.139</td>
<td>30.794</td>
<td>5.891</td>
<td>5.961</td>
<td>9.897</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>1083.114</td>
<td>8407.822</td>
<td>87.586</td>
<td>91.525</td>
<td>559.41</td>
</tr>
<tr>
<td>No of obs.</td>
<td>0.000</td>
<td>0.0000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>
H. Estimating the Determinants of Food Price Volatility using GARCH and EGARCH Models

The study used the GARCH MODEL and EGARCH model to capture the symmetric and asymmetric responses of volatility in the series following the detection of heteroscedasticity in the ARCH LM test. Results in Table VI present the parameter estimates of GARCH and EGARCH models. For the GARCH model, all the parameter estimates of the variance equations are statistically significant at 1% and this shows that news about past volatility in food prices strongly influence volatility in the current period. Since the summation of $\alpha_1$ and $\beta_1$ (1.89) exceeds 1, the conditional variance in the variance equation is unpredictable and unstable and it progresses through a non-stationary process. This explains the Nigerian food market, which in addition to the seasonal and reoccurring fluctuations, experiences external and internal shocks which have serious implication for production decisions and investments. Although producers benefit from high prices by taking advantage of the associated profit, which eventually improves future physical availability, significant, frequent, and unexpected changes in food prices according to Global Panel [6], put producers at risk of making investment and production decisions because of uncertainty surrounding future prices. Therefore, a mix of high and volatile prices discourages farmers from making important production decisions even in the face of high prices.

Similarly, results from the asymmetric EGARCH model shows that all the estimated parameters in the variance equation are significant at 1% with only $\gamma$ of the model being significant at 10%. The summation of $\alpha_1$ and $\beta_1$ was also shown to be greater than 1. The presence of asymmetric response in the monthly return series is confirmed by the leverage effect and non-zero asymmetric $\gamma$ parameter (-0.0623). The negative and significant leverage effect parameter indicates that positive shocks generate greater volatility than negative shocks of the same magnitude.

Since the GARCH model only assumes that both positive and negative shocks have symmetric effects on volatility, the study only relies on the results of EGARCH for the parameter estimates of the mean equation. The result shows that return on consumer price index (RCPI), Return on lending rates (RLI), Return on exchange rate and the lagged values of food price index (FPI_1) and RLI (RLR_1) have significant effect on food price volatility. The coefficient estimate of RCPI was shown to have a positive and significant effect (p<0.0001) on food price volatility. This result is consistent with the findings of Pasanya and Olawepo [9] who revealed that information shocks arising from consumer price index market have a direct effect on the current conditional volatility in food market. Ukoha [38] explained that the prices of most food commodities and the price deflator for agriculture seemingly exhibit a similar trend or pattern with inflation rate. Variations in food prices resulting from inflation disincentivize farmers from making optimal production decisions. Inadequate market information can moderate resource use efficiency as investors do not have access to prices that can guide their production decisions [39].

RLI was statistically significant at 1%. A unit increase in RLI increases food price volatility by 0.95%. This result is based on the reasoning that price volatility of food items can result if changes in interest rate are expected to be long-running. As earlier shown by the $\beta_1$ parameter, significant and positive sign of the lagged value of food price index indicates that a 1% increase in the food price index in the previous year increases food price volatility by 4.2%. The fact that agricultural production has a delayed supply response makes the decision to adjust production to a change in price not to be instantaneous for farmers, particularly the poor ones. An increase in price in a particular year can result in further increase or decrease in production the next depending on whether farmers believe the increase will persist or not, particularly when the price change does not result from the usual seasonal fluctuations. In other words, production level may remain unchanged or even reduced in the face of a price incentive [15]. A percentage change in the lagged value of lending rate (RLR_1) was also noticed to increase the likelihood of food price volatility by 0.73%.

V. CONCLUSION AND RECOMMENDATION

Instability in food prices is an important risk factor threatening the welfare of millions of people around the world, particularly in developing countries. To this end, the study therefore investigated the nature and determinants of food price volatility in Nigeria using annual and monthly time series data from January,2000 to December 2020. Volatility clustering in food prices was observed between periods 2000 and 2012 after which volatility was almost muted.

---

**TABLE IV: TEST FOR STATIONARITY**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Level</th>
<th>Trend</th>
<th>Intercept</th>
<th>Order of Integration</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCPI</td>
<td>-13.558***</td>
<td>-13.554***</td>
<td>1 (0)</td>
<td></td>
</tr>
<tr>
<td>REOP</td>
<td>-12.0716***</td>
<td>-12.0775***</td>
<td>1 (0)</td>
<td></td>
</tr>
<tr>
<td>REXR</td>
<td>-10.9445***</td>
<td>-11.0075***</td>
<td>1 (0)</td>
<td></td>
</tr>
<tr>
<td>RFPI</td>
<td>-25.3681***</td>
<td>-25.25134***</td>
<td>1 (0)</td>
<td></td>
</tr>
<tr>
<td>RLR</td>
<td>-17.3410***</td>
<td>-17.3931***</td>
<td>1 (0)</td>
<td></td>
</tr>
</tbody>
</table>

**TABLE V: LM TEST FOR ARCH EFFECT**

<table>
<thead>
<tr>
<th>Lags(p)</th>
<th>Chi squared statistic ($\chi^2$)</th>
<th>DF</th>
<th>Prob&gt;chi2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.814</td>
<td>1</td>
<td>0.0508</td>
</tr>
<tr>
<td>2</td>
<td>10.485</td>
<td>2</td>
<td>0.0053</td>
</tr>
<tr>
<td>3</td>
<td>13.747</td>
<td>3</td>
<td>0.0033</td>
</tr>
</tbody>
</table>

**REFERENCES**


DOI: http://dx.doi.org/10.24018/ejfood.2022.4.6.619
However, prices of most food items witnessed a forward leap between the periods 2000–2006 and 2007–2012 with the price of rice almost experiencing a threefold rise. Beyond this period, food prices have remained high, clearly surpassing their initial levels in 2013–2020. Further, the main determinants of food price volatility are returns on consumer price index, lending rates, exchange rate, and the lagged values of food price index.

Given that food price index more than doubled through the time periods considered in the study and food price volatility has been relatively stable in recent times, high level of food prices rather than food price volatility may represent a more immediate problem in Nigeria. The study therefore recommends a need to shift policy focus from input support to sustained price stabilization mechanism which involves holding strategic or buffer stock to protect the interest of producers against unstable prices. This may include the rebirth of deficit and new marketing boards who were saddled with the responsibility of offering guaranteed minimum price to producers for their commodities all year round. Policy focus can also take the form of stabilizing exchange rate and providing more credit access to farmers so as to increase and diversify domestic food production, particularly that of high value food commodities.

**CONFLICT OF INTEREST**

There is no conflict of interest.

**REFERENCES**


[10] HLPE. Price volatility and food security. A report by the high-level panel of experts on food security and nutrition of the committee on world food security, Rome 2011.


<table>
<thead>
<tr>
<th>Variables</th>
<th>GARCH (1)</th>
<th>E-GARCH (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCPI, αₘ</td>
<td>1.032***</td>
<td>1.089***</td>
</tr>
<tr>
<td>REOPG₄</td>
<td>0.001</td>
<td>0.001***</td>
</tr>
<tr>
<td>RLI</td>
<td>0.011***</td>
<td>0.013***</td>
</tr>
<tr>
<td>REXX</td>
<td>-0.009</td>
<td>-0.014</td>
</tr>
<tr>
<td>FPI</td>
<td>0.096***</td>
<td>0.016</td>
</tr>
<tr>
<td>R (Resi,1/2)²GARCH (1)²</td>
<td>0.160***</td>
<td>0.172</td>
</tr>
<tr>
<td>(ln)GARCH (1)²</td>
<td>0.290***</td>
<td>0.959</td>
</tr>
<tr>
<td>Variance Equation</td>
<td>0.017***</td>
<td>0.666*</td>
</tr>
<tr>
<td>Constant</td>
<td>0.1892</td>
<td>2.188</td>
</tr>
</tbody>
</table>

R-Squared 0.6599 0.6619
Adjusted R-Squared 0.6544 0.6565
Log likelihood -202.0677 -203.7221
Sum Squared Residual 286.0847 284.3256
Durbin-Watson 1.7695 1.7272
AIC 1.6739 1.6950

**Table VI: Determinants of Food Price Volatility**


Minot N. Food price volatility in sub-Saharan Africa: has it really increased? *Food Policy* 2014, 45:45–56.

