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Application of GARCH models in the volatility of food inflation in Nigeria

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Abstract

This paper aimed to investigate the behavior of the current food inflation volatility arising from the recent past behavior and to know if this volatility is persistent over time in Nigeria. The study covered the period from 2003M1 to 2021M9 under both the asymmetric and the symmetric GARCH models. The findings of the study revealed that one period lag of food inflation had a positive and significant impact on the current value of food inflation. Furthermore, it was found that in all the selected models, volatility in food inflation is persistent and bad news had an impact on food volatility in two of the models, while good news had an impact in one model. However, the asymmetric coefficient in all the asymmetric models is not significant. Consequently, the study contends that policymakers should factor in the impact of recent past values of inflation when framing policies meant to tame food inflation in Nigeria.

Keywords: Asymmetric models, GARCH models, inflation, volatility;

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1. Introduction

Rising food prices have become a major issue that calls for concern by the government of most developing countries. In a country like Nigeria where the poverty rate is high, the rising cost of food aggravates the poverty situation in the country. As observed by Egwuma et al., (2017*),* rising volatility in food prices reduces the purchasing power of households which reduce their real per capita income. This contention found support in Sekhar et al., (2017) who noted that food inflation has a strong impact on the welfare of the people, especially that of the poorer section of society. In Nigeria, so many factors have been identified as the causes of rising food prices over the years. Since the discovery of oil in commercial quantity, the agricultural sector has witnessed years of neglect. The huge revenues accruing from the oil boom displaced the development of the agricultural sector as the political leaders are only interested in quick revenues coming from the oil sector. As observed by Emediegwu and Okeke (2017), in 1962 crude oil contributed less than one percent of Nigeria's gross domestic product (GDP) and the figure rose to 36 percent in 1985. However, in 1962 the agricultural sector contributed 62 percent to the GDP but in 1985 the figure dropped to 33 percent and reduced further to 24.14 and 23.36 percent in 2020 and 2021, respectively. In terms of export, the study noted that crude oil export which constituted less than three percent of total exports in the early sixties rose to 98.7 percent in 2000 which further rose to 96.5 percent in 2010. The neglect of the agricultural sector manifests in many forms such as lack of the development of the rural areas where farming activities usually take place. This neglect results in rural-urban migration, especially among the youths. To make matters worse, agricultural practice in the country is still non-mechanized and its drudgery nature is among the factors why many people find it uninteresting.

It should be noted that on a regional basis, the northern part of Nigeria produces a larger part of the food needs of the country compared to the southern part (Nwuneli et al., 2014). In a survey undertaken by Sasu (2022), crop farming was 83.6% in the North East, 82.9% in the North West and 75.8% in the North Central. However, in the southern part of the country the figure for the South East was 72.8%, while that of the South South and the South West were 68.9% and 39.5%, respectively. Therefore, food price disparity occurs on a regional basis with the prices low in the northern part, while the southern part experiences rising prices. To tap into the high demand in the south, producers in the northern part and other middlemen move their commodities to the south regularly. However, the mode of transporting the commodities is a major factor that leads to volatility in the prices in the southern part. These commodities are transported using diesel-powered trucks, so with the high cost of diesel in the country, sellers of agricultural commodities pass the increasing cost of transport onto the consumers. In another dimension, the depreciating value of the domestic currency (naira) is another factor that causes food inflation in Nigeria. With the high population in the country, although with a limited supply of locally produced goods, food importation becomes necessary to augment the local supply. However, the naira depreciation has made it expensive to import food items from abroad and this is made worse by the ban placed on the importation of some essential food items.

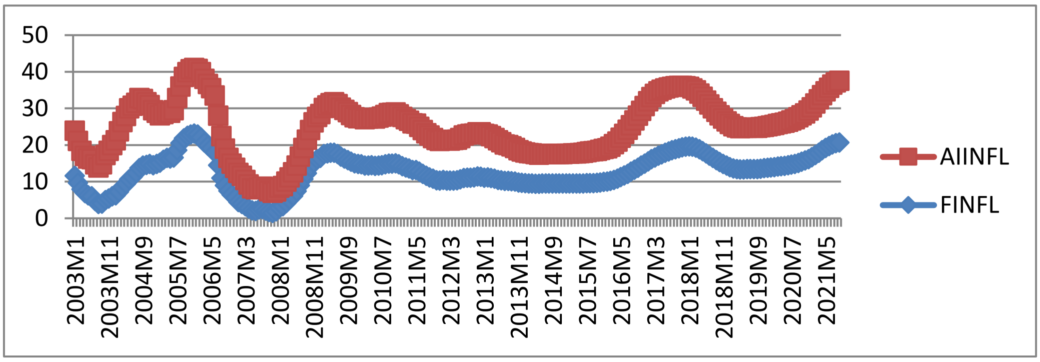
1.1. Purpose of study

The focus of this paper is to investigate the volatility in food inflation in Nigeria to identify the behavior of current food prices concerning recent past prices. Furthermore, the aim is to examine the role of news on the volatility of food inflation as it has been observed that food prices are sometimes influenced by the news of the happenings in the economy. This study is a departure from previous studies that investigated the impact of multiple factors that influence food inflation. The study is of the view that while investigating the impact of these factors is necessary, there is a need to observe the impact of the recent past value of food inflation on the current value so that policymakers will equally use the current value to predict future values. Thus, apart from the current policy formulation using past values of food inflation, the current value can equally serve as a compass for future policymaking. The study also contributes to the literature by including different error distributions in the GARCH estimation to obtain unbiased and optimal results. Bearing in mind that one volatility model cannot be adequate to capture food volatility in Nigeria; this study included both the symmetric and asymmetric GARCH models under various error distributions and the optimal models were selected using model selection criterion.

1.2. Conceptual background

In this sub-section, we provide trend analyses of some variables. Figure 1 reveals that both all-item inflation and food inflation exhibited fluctuations within the sample period. It should equally be noted that both variables exhibited a similar pattern of movement in each period. Evidence shows that in October 2005, both variables trended high but descended to a trough in April 2007. However, from 2008, the two variables began to trend up, but, from 2011 to 2015, they trended very low. In May 2017, they reached a peak, descended from December 2017, and began to rise in 2019. What this implies is that the composition of food inflation to the all-item inflation in Nigeria is very high such that it influences general inflation in the country. This viewpoint of ours finds support in some empirical works in Nigeria such as Babalola and Salman (2016) that found a positive link between general inflation and food price inflation.

Figure 1. The trend of inflation in Nigeria

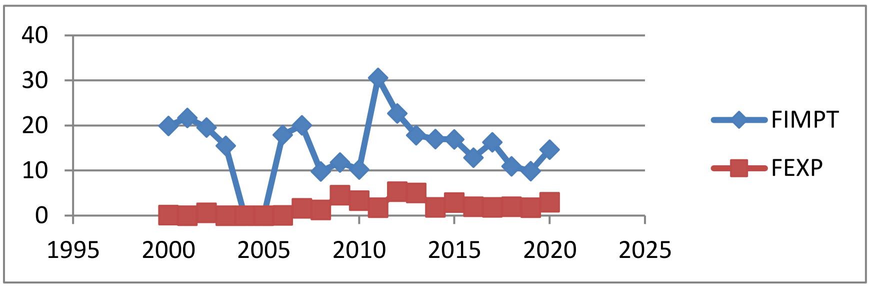


Source: Authors' compilation

Note: AIINFL = all commodity inflation, FINFL = food inflation

We did trend analyses of some variables that we think could influence food inflation in Nigeria. The trend in food import and export was evaluated because food import dependency is a major feature in Nigeria, while the volume of food export is small relative to food export. This point is found elucidation in Figure 2 where food import trended very high, while food export trended very low within the sample period. The trend of food export was almost flat in all the periods, except in some months between 2009 and 2012, while food import assumed its peak in 2011. To prove further the fact that the import composition of food is high in Nigeria, evidence in Figure 2 shows that most of the time when food import was high, food inflation reduced, and vice versa. For instance, in 2004, when food import was very low, food inflation trended high. In 2007, when the import of food was high, food inflation was very low, and a similar phenomenon occurred in 2011 when food import attained a peak, and food inflation was very low. This link means that any shock arising from food importation could transmit to food inflation in Nigeria. To prove this, the recent ban on the importation of some essential commodities as well as the depreciation in the exchange rate of the domestic currency (naira) have been pointed out as responsible for the current high food inflation in Nigeria. However, empirical evidence by Egwuma et al., (2017) showed that food import impacted positively food price inflation in the long run in Nigeria and we believe that this could occur through the rising cost of food import as a result of the depreciating value of the domestic currency.

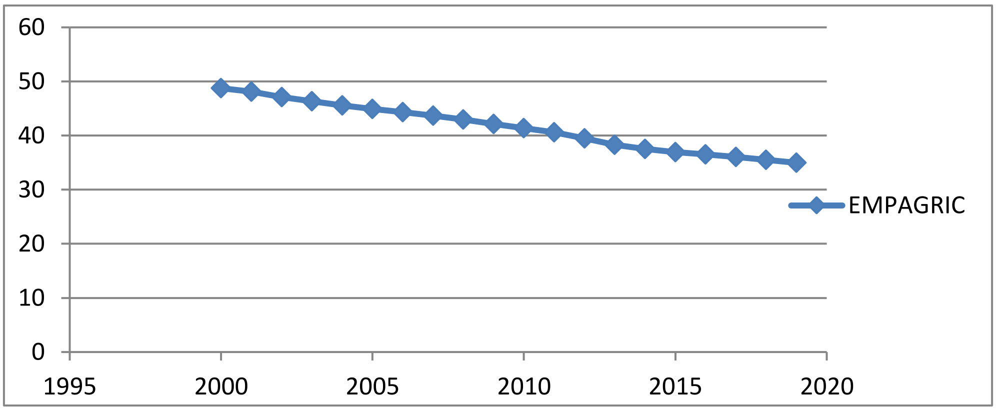
Figure 2. Trends in food import and export



Source: Authors' compilation
Note: FIMPT = food imports measured as a percentage of merchandise imports
FEXP= food export measured as a percentage of merchandise exports

The agricultural sector is essential in reducing fluctuations in food prices. On the grounds of this, we did a trend analysis of some factors that could impact agriculture. We first considered employment in the agricultural sector. Evidence in Figure 3 indicates that the trend in employment in agriculture descended all through the study period. What this portends is that fewer people are productively engaged in the production of food to cater to the teeming population of the country. To worsen matters, agricultural production in the country is mainly done at a subsistence level with very low mechanization.

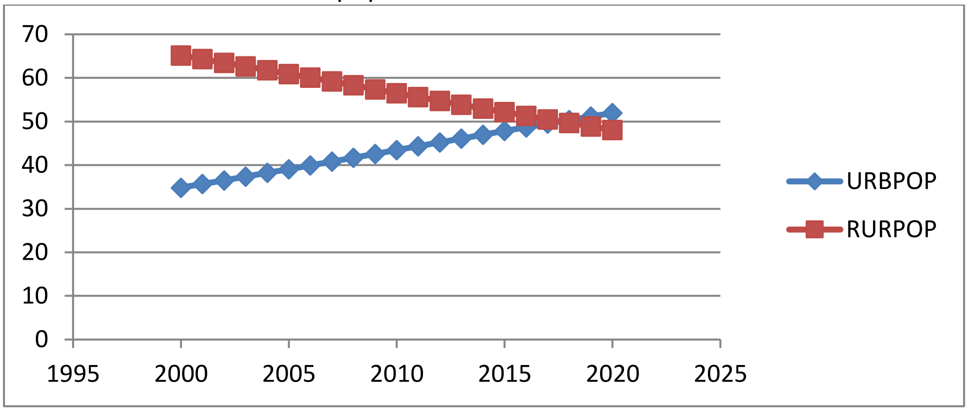
Figure 3. The trend of employment in agriculture



Source: Authors' compilation
Note: EMPAGRIC = Employment in agriculture measured as a percentage of total employment

One of the major factors identified to be responsible for low productivity in agriculture in Nigeria is rural-urban migration, especially among the youth. Figure 4 shows that in all the sample periods, while the trend for the urban population was high, the trend for the rural population was low. With a high urban population, the implication is a continuous rise in demand for food about low supply as old and weak people are left in the rural areas to produce what will cater to the high demand. This accounts for the need for the country to import food to argue the shortfall in the domestic supply.

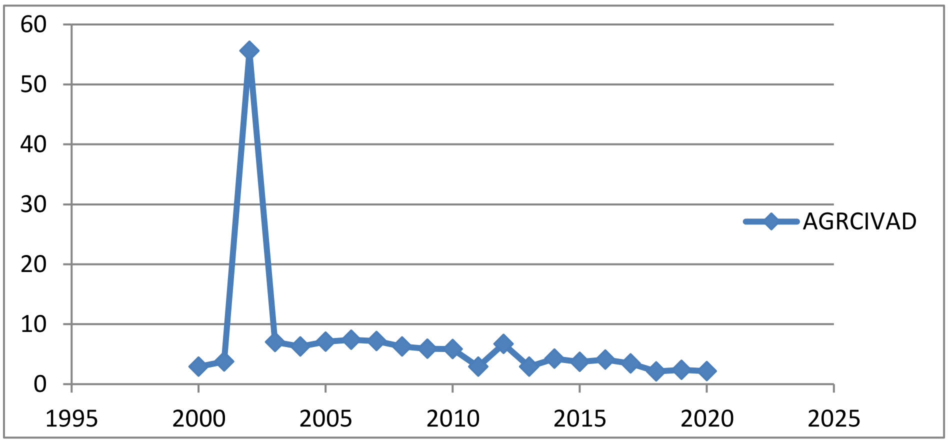
Figure 4. The trend in urban and rural population



Source: Authors' compilation
Note: URBPOP = urban population, RURPOP = rural population. All measured as a percentage of the total population

To further show that the level of agricultural productivity is very low in Nigeria, the trend analysis of the agricultural value added as a percentage of gross domestic product (GDP) in Figure 5 indicates that except for 2002 when the trend was high, the trend for other years was almost flat. Hence, apart from not adequately catering to the high population in the country, the agricultural sector also does not contribute much to the country's GDP.

Figure 5. The trend in agriculture, forestry, and fishing, value added



Source: Authors' compilation

Note: AGRICVAD = Agriculture, forestry, and fishing, value added (annual % growth)

1.3. Literature

The hydra-headed nature of inflation and its implications in the economy in general and food, in particular, has made any study that involves it a worthy venture. Across different countries and regions, studies have been carried out to investigate the determinants of food inflation with findings showing diverse results (Dastgerdi, 2020; Shahani & Taneja, 2022; Kartal & Depren, 2023; Shiferaw, 2023; Urak & Bilgic, 2023). In Nigeria, Effiong and Eze (2010) used a histogram and price index number to prove that the cause of food price inflation was a continuous hike in petroleum product prices in addition to poor agricultural sector performance. In another study examining the effects of macroeconomic variables on food inflation in Nigeria, Akinbode et al., (2021) used the autoregressive distributed lag (ARDL) model to reveal that in the short run, exchange rate, crude oil prices, money supply, and food production significantly impacted food inflation, while in the long run, only food production did not have a significant impact on food inflation. Furthermore, Egwuma et al., (2017) used the VECM in an annual study covering the period from 1988 to 2017 to reveal that food import, real GDP, and crude oil prices impacted food price inflation positively in the long run in Nigeria.

For studies involving countries other than Nigeria, Rehman and Khan (2015) used the VECM and dataset ranging from 1990 to 2013 in a study for Pakistan to reveal that, while food exports and indirect taxes positively and significantly impacted food price inflation, GDP and subsidy by the government had a negative link with food price inflation. In their analyses of factors that influenced food price inflation in Pakistan, Qayyum and Sultana (2018) used data over the period from 1970 to 2017 to show that food exports, taxes, GDP, and food imports fuelled food inflation, while money supply led to its decline. In another study for Pakistan, Afzal and Mian (2020) used the OLS to indicate that agricultural value addition significantly and negatively influenced food inflation, while food imports affected food inflation significantly and positively. The result of the positive impact of food export on food price inflation by Rehman and Khan (2015) found consistency in the finding by Qayyum and Sultana (2018). In a study for India, Sasmal (2015) found that food price inflation kept pace with rising per capita income and that productivity in agriculture has not been able to curb this phenomenon. Another study for India by Sekhar *et al.* (2017) found that supply and demand for food items were the main drivers in food inflation volatility and that there was no uniformity in the level of high inflation among the commodities.

In Ethiopia, Hilegebrial (2015) used the ordinary least squares (OLS) to reveal that food price was influenced by money supply and expectation as well as output and world food price. In sub-Saharan Africa (SSA) countries, Alper et al. (2015**)** found evidence that from 2009, food inflation became less persistent due to improvements in monetary policy frameworks. Furthermore, the finding indicated that high food inflation was mainly driven by non-tradable food. Using the Nonlinear ARDL method in a study for Malaysia, Hasan and Mashi (2018) showed that the nexus between food price and the exchange rate was symmetric in the long run, while the short-run result indicated the nexus to be asymmetric. In Indonesia, Ismaya and Anugrah (2018) used the generalized moments of method (GMM) to reveal that productivity in agriculture, food import, credit to the agricultural sector, the output of the agricultural sector, seasonal events, and demand level were the dominant determinants for food inflation.

2. Materials and Methods

2.1. Analytical Framework

The analytical framework that guided this study is the adaptive expectation hypothesis introduced by Cagan (1956). The choice of this framework is predicated on the effect of past values of inflation rate in predicting future inflation rates in Nigeria as empirically observed by Udoh et al. (2018). Such a link can be extended to food inflation due to the direct link between general inflation and food inflation. In Nigeria, news of events such as the government ban on some staple foods and the occurrence of natural disasters such as flooding in farming communities, affect food prices. On grounds of this news, food suppliers/sellers will adjust the prices of food items to reflect the recent past prices occasioned by similar events. To the consumers, buying behavior could be tied to the recent past prices which were caused by recent past events, leading at times to panic buying.

The adaptive expectation is a theoretical proposition that concentrates on the formulation of future expectations on the grounds of recent past events and experiences. This theoretical view highlights the fact that economic agents form their expectations concerning past behavior. That is to say that, an individual will alter his expectation of any variable should there exists a difference between the last period expectation of a variable and the actual value of such variable last period. For instance, if the rate of inflation was higher in the recent past, economic agents will expect that the current year's rate will be higher. Suppose economic agents expected the inflation rate to be 10% in the previous year and the actual rate for the reference year settled at 10%, adaptive expectation concludes that economic agents will hardly change their expectation of the inflation rate in the current period. Thus, suggesting that economic agents will still expect the rate of inflation to be 10% in the current period. On the contrary, suppose the inflation rate for the previous year was higher than 10%, say 12%, the adaptive expectations hypothesis suggests that economic agents will alter their expectation of the rate for the current period. Economic agents may raise their expectations of the current period inflation by more than 10%. The algebraic expression of the adaptive expectation hypothesis using past price level to predict the current price level is stated as follows:

$$P_t^e - P_{t-1}^e = \psi\left(P_{t-1} - P_{t-1}^e\right) \quad (1)$$

Were

P_{t-1} = last period's actual price level

P_{t-1}^e = last period's expected price level

P_t^e = current period expected price level

ψ = expectations parameter $0 < \psi < 1$

The interpretation of equation 1 is that past expectations of the price level can be used to predict the current price level and by extension, future price level. The gap between the actual level and the previous period's price level expectation determines whether the current expectation about the level will be raised or lowered. In the equation, ψ is the error-adjustment parameter. It should be noted that the price level adjusts sluggishly when a difference exists between the actual value of the variable and the expected value of that variable. The determinant of the adjustment is thus the parameter ψ that differs in value across economic agents. Equation (1) above can be expressed as follows:

$$P_t^e = \psi P_{t-1}^e + (1-\psi)P_{t-1}^e \quad (2)$$

Equation 2 above provides a link between the current period's expected price level, the previous period's expected price level, and the actual last period's price level. If we include the second-period price level, we have the following expression:

$$P_{t-1}^e = \psi P_{t-2}^e + (1-\psi)P_{t-2}^e \quad (3)$$

were

P_{t-2} = last two periods' actual price level

P_{t-2}^e = last two periods expected price level

2.2. Data

This study used monthly data that span the period from 2003M1 to 2021M9 and the data were sourced from the Central Bank of Nigeria Statistical Bulletin. Three estimation phases are carried out in this study. First, is the determination of the statistical properties of food inflation, and this is done using the Augmented Dickey–Fuller (ADF), Phillip–Perron (PP), and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests. Next to that, we tested for the ARCH effect to ascertain the volatile nature of the variable and this is done using the ARCH-LM test. The study used both the symmetric and asymmetric models in the analysis. After estimating the models, model selection was conducted using the Schwarz Information Criterion (SIC). From the estimated models also, the new impact of food inflation was identified. Post-estimation tests were conducted to ensure that there is no remaining ARCH effect in the model and that the model does not have a serial correlation.

2.3. Analysis

2.3.1. The Test for ARCH Effect

In the estimation of the GARCH models, it is proper to first carry out a pre-test to identify if the variable exhibits the ARCH effect that is to ascertain if the variable is volatile. It should be noted that the non-volatility of a variable is an indication that such a variable cannot be included in the GARCH estimation because the GARCH model is specifically meant for volatile series. The ARCH effect can be estimated using the following univariate model:

$$\lambda_t = \phi + \sum_{i=1}^{k} \psi_i \lambda_{t-1} + \varepsilon_t ; i = 1,...k \text{..}(4)$$

$$t = 1; \varepsilon_t \approx IID(0, \delta^2); |\psi| \prec 1$$

were

λ_t = food inflation which depends on its past value λ_{t-1} and captures the autoregressive part of food inflation

ψ_i = the coefficient of the autoregressive term

ε_t = the error terms

ε_t is expected to be independently and identically distributed (IID) with zero mean and constant variance

To examine the existence of the ARCH effect, three stages are followed. As proposed by Engle (1982), the first stage is to estimate equation (4) using the ordinary least squares (OLS) approach to obtain the fitted residuals. The next stage is to regress the square of the fitted residuals on the constant and lagged values of the squared residuals, as shown in Equation 5 below:

$$\hat{\varepsilon}_t^{\,2} = \zeta_0 + \zeta_1 \hat{\varepsilon}^2_{t-1} + \zeta_2 \hat{\varepsilon}^2_{t-2} + ... + \zeta_k \hat{\varepsilon}^2_{t-k} + \mu_t \text{..}(5)$$

The final stage is to apply the ARCH-LM test to identify the existence of the ARCH effect in the model. The null hypothesis for the ARCH-IM test is stated as follows:

$$H_0 : \xi_1 = \xi_2 = ... = \xi_k = 0$$

The empirical test for the presence of the ARCH effect requires the evaluation of either the F-test or the Chi-square distribution (X^2) and this involves multiplying the number of observations (n) by the coefficient of determination (R^2) which was obtained from equation 5. If p-value of the test statistics is less than the chosen level of significance, this implies the rejection of the null hypothesis of no ARCH effect. It thus means that the variable is volatile and as such can be estimated with the GARCH models.

2.3.2. The ARCH Model

Having provided an insight into how the ARCH effect is tested, the study went further to specify the ARCH (Autoregressive conditional heteroskedasticity)/model. The specification of the ARCH model requires two procedures, namely, the specification of the conditional mean and the specification of the conditional variance. The conditional mean is specified as follows:

$$\omega_t = \vartheta_0 + \sum_{i=1}^{p} \gamma_1 \varpi_{t-1} + \varepsilon_t \text{..}(6)$$

were

ω_t = the variable of interest

γ = the coefficient of the variable of interest

ϖ_{t-1} = the lag of the variable of interest

ε_t = the error term which is expected to have a zero mean and constant variance

The conditional variance is specified as follows:

$$\delta^2 = v_0 + \sum_{i=1}^{p} v_1 \varepsilon_{t-1}^2 ,,,\ldots\ldots,,,,,,,,,,,,,, (7)$$

were

ε_{t-1}^2 = ARCH term

$0 < \sum_{i=1}^{p} v_1 < 1$ = stationarity series

If $\sum_{i=1}^{p} v_1 \to 1$, it indicates that the variable exhibits slow mean-reverting

If $\sum_{i=1}^{p} v_1 \to 0$, it shows that the variable exhibits fast mean-reverting

2.3.3. GARCH (1,1) Model

The ARCH models do not allow for appropriate lag length selection and such shortcomings led to the introduction of the GARCH model by Bollerslev (1986) and Taylor (1986). The GARCH model ensures that the conditional variance depends on the previous lags. The GARCH model is specified as follows:

$$\delta^2 = v_0 + \sum_{i=1}^{p} v_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \Phi_j \delta_{t-j}^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

were

$0 \le \sum_{i=1}^{p} v_i + \sum_{j=1}^{q} \Phi_j < 1$ = mean-reverting-process.

If $0 \le \sum_{i=1}^{p} v_i + \sum_{j=1}^{q} \Phi_j \to 1$ = slow mean-reverting.

If $0 \le \sum_{i=1}^{p} v_i + \sum_{j=1}^{q} \Phi_j \to 0$ = fast mean-reverting.

2.3.4. GARCH-in-Mean (GARCH-M) Model

The GARCH-M model is specified in a way that the conditional mean depends on its conditional variance. Engle et al., (1987) noted that the GARCH-M model is derived by the introduction of the conditional variance or standard deviation into the mean equation as follows:

$$\theta_t = \varsigma_0 + \sum_{i-1}^{p} \Gamma \theta_{t-1} + \varepsilon_t + \tau \delta_t^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

In equation 6, the null hypothesis is given as $H_{0:} = 0$, while the alternative hypothesis is given as $H_{1:} \neq 0$. If the null hypothesis (H_0) is rejected, it implies that the GARCH-M model provides valid information for the volatility in the variable.

The need for asymmetric models arose due to the realization that a shock to a variable can produce both positive and negative consequences and such a possibility cannot be handled by the ARCH and GARCH models. Consequently, several asymmetric GARCH models were introduced to handle the leverage effect arising from shocks to a variable. In this study, three such asymmetric models were used to determine the new impact of food inflation in Nigeria. The asymmetric GARCH models used are the threshold GARCH (TGARCH) model, the Exponential GARCH (EGARCH), and the Power GARCH (PGARCH) model. The TGARCH was independently developed by Zakoian (1994) and Glosten et al, (1993). To capture asymmetries in the model, the variance equation contains a multiplicative dummy variable.

2.3.5 TGARCH Model

The TGARCH model is specified as follows:

$$\delta^2 = \vartheta_0 + \sum_{j=1}^{p} \vartheta_j \,\delta_{t-j}^2 + \sum_{i=1}^{q} \lambda_1 \eta_{t-1}\, \varepsilon_{t-1}^2 + \sum_{k=1}^{q} \chi\, \varepsilon_{t-1}^2 d_{t-1} \quad \text{...(10)}$$

were

η_{t-1} = 1 if $\delta^2 < 0$ and 0 otherwise

If $\delta^2 > 0$, it implies that good news produced the shock in the variable

If $\delta^2 < 0$, it implies that bad news produced the shock in the variable

It should be noted that the two shocks have differential effects on conditional variance. Concerning impact, good news has an impact ϑ_j but bad news has an impact $\vartheta_j + \lambda_1$. If $\lambda_1 > 0$, it indicates that volatility increases bad news, implying the existence of a leverage effect. However, if $\lambda_1 \neq 0$, it means that there is an asymmetry in the news impact.

2.3.6 The EGARCH Model

The EGARCH model introduced by Nelson (1991) is another asymmetric model considered in this study. The EGARCH model was improved by replacing the lagged squared autoregressive component ε_{t-i}^2 that features in the standard GARCH model with a standard normal variable. The EGARCH model is specified as follows:

$$\log(\delta_t^{\,2}) = \Omega_0 + \Omega_t \sqrt{\frac{\varepsilon_{t-1}^2}{\delta_{t-1}^2}} + \Phi_1 \sqrt{\frac{\varepsilon_{t-1}^2}{\delta_{t-1}^2}} + \Gamma_i \log(\delta_{t-1}^2) \quad \text{...(11)}$$

If $\delta_t^{\,2} > 0$, good news produced a shock in the variable

If $\delta_t^{\,2} < 0$, bad news produced a shock in the variable

The sum effect of the two shocks is given as follows:

$(1+\Gamma_i)\left|\varepsilon_{t-i}^2\right|$ and $(1-\Phi_i)\left|\varepsilon_{t-1}^2\right|$, respectively

Bad news exerts more impact on volatility if $\Phi_i < 0$

2.3.7. The Power GARCH (PGARCH) Model

Ding et al. (1993) proposed a variant to asymmetric GARCH models and provided power GARCH (PGARCH) models. Unlike the GARCH family, we can model both the conditional standard deviation as well as conditional variance. The PGARCH (were) specification is expressed as follows:

$$\delta_t^d = \lambda_0 + \sum_{i=1}^{p} \lambda_i + \left(|\mu_{t-1}| + \eta_i \mu_{t-i}\right)^d + \sum_{j=1}^{q} \varpi_j \left(\delta_{t-j}^d\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(12)$$

were

$d > 0$

$|\eta| < 1$ 1 establishes the presence of leverage effects. The symmetric model sets $\eta < 0$ = for all *i*. The first order PGARCH (1, d, 1) is expressed as:

$$\delta_t^d = \lambda_0 + \varpi_1 \left(|\mu_{t-1}| + \eta_1 \mu_{t-1}\right)^d + \lambda_1 \left(\delta_{t-1}^d\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(13)$$

If the null hypothesis $\eta_1 = 0$ is rejected, then the leverage effect is present

3. Results

The stationarity tests were carried out to ascertain the order of integration of the variable. As noted earlier, we used the ADF, PP, and the KPSS unit root tests to investigate the order of integration of the variable, and the results were evaluated at the 5% and the 10% level of significance. In Table 1, except for the ADF under which the variable achieved stationarity at the level *I (0)*, the results for PP and KPSS indicated that the variable did not achieve stationarity (has unit root).

Table 1. *Unit Root Result at Level*

Variable	ADF t-stat	PP t-stat	KPSS t-stat	ADF critical value	PP critical value	KPSS critical value	Order of integration
FINFL	-2.87	-2.87	0.46	0.00	0.13	0.29	

Note: asterisks (**) indicate the rejection of the null hypothesis at the 5% level.

The results in Table 2 revealed that as the variable was first differenced, stationarity was achieved at the 5% level under all the tests, except under the ADF where stationarity was attained at the 10% level. Results in Table 2, therefore, indicated that the variable became *I (1)* after the first differencing. These results, it implies that the variable has passed the first pre-diagnostic test, indicating that the problem of running a spurious result will not occur in the study.

Table 2. *Unit Root Result at First Difference*

Variable	ADF t-stat	PP t-stat	KPSS t-stat	ADF critical value	PP critical value	KPSS critical value	Order of integration
ΔFINFL	-2.57	-2.87	0.46	0.06	0.00	0.05	

Note: asterisks (**) indicate the rejection of the null hypothesis at the 5% level.

Having ascertained that the variable is stationary, the next pre-diagnostic test we carried out is a test on the volatility of the variable, that is, to investigate the existence of the ARCH effect in the variable. The essence of the volatility test is to determine if the GARCH models are suitable for the estimation of the result. If the variable is not volatile or exhibited no ARCH effect, then the GARCH models are not appropriate for the study.

The result in Table 3 revealed that p-values of both the F-test and the Obs*R^2 are less than the 5% level of significance, thus suggesting that we have to reject the null hypothesis of no ARCH effect. By implication, the variable exhibits volatility and this finds support in the plot of the residual in Appendix 7.

Table 3. *Results of the ARCH Effect*

Variable	Test	
FINFL	F-Test/p-value	198.14(0.00)
	Obs*R2/p-value	105.42(0.00)

Since the variable exhibited the ARCH effect, the study went ahead to investigate the volatility in the variable under different GARCH models with emphasis on three different error distributions. The reason for considering the various error distributions is to avoid the possibility of model misspecification. To guide the optimal model selection, the study used the SIC. Under each model, the error distribution with the least SIC is considered the optimal model, and the SIC for each model was extracted from Table 5 below. In Table 4, findings show that in all the models, the student's *t*-distribution has the least SIC, thus suggesting that it is the best error distribution to capture volatility in food inflation under each of the GARCH models.

Table 4. *Optimal Model Selection*

First-Order GARCH Models	Schwarz Information Criterion (SIC)		
	Normal Distribution	Student's t-Distribution	Generalized Error Distribution
GARCH (1,1)	0.98	0.80*	0.93
GARCH-M	1.00	0.79*	0.95
TGARCH (1,1)	0.99	0.80*	0.95
EGARCH (1,1)	0.99	0.93*	0.97
PARCH (1,1)	0.98	0.71*	0.94

With the results of the model selection showing that the student's *t*-distribution provides the best model fit, it is obvious that contrary to the usual norm, the normal error distribution cannot provide a better specification to capture volatility in food inflation in Nigeria. The results of Student's *t*-distribution in all the GARCH models displayed in Table 5 are therefore considered for interpretation. The result of the mean equation in all the models shows that one period lag of food inflation had a significant and positive impact on the current value of food inflation. This shows that the recent past value of food inflation influenced the current value positively, meaning that a rise in food inflation in the recent past leads to a rise in the current period. It is also found that the ARCH coefficient is significant in all the models which support the earlier finding of the existence of the ARCH effect. Furthermore, findings indicated that the in all the models, the sum of ARCH and GARCH coefficients is greater than unity. This result implies that volatility in food inflation is not mean-reverting, thus revealing that the shocks to food inflation in Nigeria are permanent. It can therefore be convenient to state that food inflation in Nigeria is upward sticky. This result aligns with the price phenomenon in Nigeria as whenever the prices of food items go up; it is difficult for the prices to fall irrespective of subsequent policy measures to address the cause of the rising prices.

Table 5 Results of Estimated Volatility of Food Inflation

Models	Equations	Model Parameters	Normal Distribution			Student's t-Distribution			Generalized Error Distribution		
			Coefficients	P-value	SIC	Coefficients	P-value	SIC	Coefficients	P-value	SIC
GARCH(1.1)	Mean	Intercept	-0.02	0.65	0.98	-0.23	0.00	0.80	-0.24	0.00	0.93
		FINL(-1)	1.00	0.00		1.02	0.00		1.02	0.00	
	Variance	ARCH	0.84	0.00		2.35	0.00		1.07	0.00	

		GARCH	0.41	0.00		0.14	0.00		0.37	0.00	
GARCH-M	Mean	Intercept	-0.03	0.50		-0.23	0.00		-0.24	0.00	
		FINL(-1)	1.00	0.00	1.00	1.02	0.00	0.79	1.02	0.00	0.95
	Variance	ARCH	0.81	0.00		2.97	0.00		1.04	0.00	
		GARCH	0.42	0.00		0.08	0.00		0.38	0.00	
		@SQRT(GARCH	-0.070347	0.24		0.00	0.86		-0.03	0.50	
T-GARCH(1,1)	Mean	Intercept	-0.02	0.60		-0.23	0.00		-0.24	0.00	
		FINL(-1)	1.00	0.00		1.02	0.00		1.02	0.00	
	Variance	ARCH	0.98	0.00		2.47	0.00		1.05	0.01	
		GARCH	0.42	0.00	0.99	0.10	0.00	0.80	0.37	0.00	
		ASYMETRIC	-0.34	0.12		1.19	0.22		0.03	0.94	0.95
EGARCH(1,1)	Mean	Intercept	-0.08	0.02		-0.20	0.00		-0.20	0.00	
		FINFL(-1)	1.01	0.00		1.02	0.00		1.02	0.00	
	Variance	ARCH	1.06	0.00	0.99	1.31	0.00		1.26	0.00	
		GARCH	0.02	0.00		0.92	0.00	0.93	0.92	0.00	0.97
		ASYMETRIC	0.06	0.36		-0.03	0.73		-0.04	0.66	
PARCH(1,1)	Mean	Intercept	-0.06	0.20		-0.23	0.00		-0.24	0.00	
		FINFL(-1)	1.01	0.00		1.02	0.00		1.02	0.00	
	Variance	ARCH	1.04	0.14		1.14	0.00		2.25	0.51	
		GARCH	0.19	0.60	0.98	0.34	0.00	0.71	0.11	0.71	0.94
		ASYMETRIC	-0.12	0.07		0.01	0.88		0.04	0.58	

Source: Authors' estimation.

The news impact of the volatility in food inflation under the asymmetric models is shown in Tables 6-8 below.

Table 6. *News Impact Under the TGARCH (1,1)*

Error Distribution	**Student's t-Distribution**
Good News	2.47
Bad News	3.67

Table 7. *News Impact Under the EGARCH (1,1)*

Error Distribution	**Student's t-Distribution**
Good News	1.31
Bad News	1.09

Table 8. *News Impact Under the PARCH (1,1)*

Error Distribution	**Student's t-Distribution**
Good News	1.14
Bad News	1.16

The impact of good news is evaluated by the ARCH coefficient, while the impact of bad news is evaluated by the sum of the ARCH coefficient and the asymmetric coefficient. If the value of the ARCH coefficient is greater than the value of the sum of the ARCH coefficient and asymmetric coefficient, this implies that good news dominates bad news. By extension, good news leads to volatility more than bad news. However, the reverse is the case if the sum of the ARCH coefficient and asymmetric coefficient is greater than the ARCH coefficient. In Tables 6 and 8 under both TGARCH and PARCH, evidence showed that bad news dominated good news as the sum of the ARCH coefficients and the asymmetric coefficients (3.67) and (1.16) is greater than the ARCH coefficients in the two models, that is, 2.47 and 1.14, even though the asymmetric coefficients are not significant.

What this reveal is that bad news influences food price volatility more than good news. A typical scenario is the effect of the menace of herdsmen's activities on farming communities in Nigeria. The herdsmen parade their cattle around these communities to graze on the farmlands. Any resistance arising from the farmers will be visited with hostilities by the herdsmen. Hence, any time news of the hostile activities of the herdsmen filters out, prices of food items will climb. In Table 7, however, evidence shows that good news dominated bad news under the EGARCH, though with an insignificant asymmetric coefficient. This reveals that good news can as well influence food inflation in Nigeria.

We used two post-estimation tests to ensure the validity of the models used in the study, namely, the ARCH effect test and the serial correlation test. The ARCH effect test was conducted to ensure that there is no remaining ARCH effect in the model and this was evaluated using the ARCH-LM test. In Appendix 1 below, findings indicated that we do not have any reason to reject the null hypothesis of no remaining ARCH effect in the models because p-values of the ARCH-LM test for all the models were greater than the 5% level of significance. The results of the serial correlation test evaluated using the probability values of the Q statistics as shown in Appendixes 2-6 revealed that in each of the lags, there was no evidence of serial correlation in the residuals at the 5% level of significance.

4. Discussion

Food inflation in Nigeria has remained a phenomenon that needs serious attention from the government and policymakers. Without reining in this ugly development, whatever gains achieved concerning poverty alleviation will continue to be eroded by rising food prices. In this study, three key findings are very germane as they have policy implications.

The first of the findings is that in the mean equation, the past value of food inflation led to a rise in the current value of food inflation. This finding implies that past values of food inflation in Nigeria can be used to predict current and even future values. Consequently, the monetary authorities should factor in the effect of recent past values of food inflation when formulating current policies to tame inflation.

The second finding is that in all the models, volatility in food inflation exhibited non-mean-reverting, implying that once food price has risen, it remains permanent as the value of the inflation does not bounce back to its original level. This suggests that volatility in food inflation in Nigeria is upwardly sticky. Then what consequences does this have on the poor and those on a fixed income as their income level hardly matches the rising food prices?

The third finding is that, even though the coefficients of the asymmetric models are not significant, bad news plays more roles in causing volatility in food inflation than good news. Around 2012, flooding took place in many agricultural-producing states in Nigeria. The impact of such negative news led to rising food prices across the country.

5. Conclusion

The news impact of the recent ban on some essential commodities as well as the activities of herdsmen in the farming communities cannot be over-emphasized. The findings of the study revealed that one period lag of food inflation had a positive and significant impact on the current value of food inflation. Furthermore, it was found that in all the selected models, volatility in food inflation is persistent and bad news had an impact on food volatility in two of the models, while good news had an impact in one model.

On the grounds of the aforementioned, the study concludes that past values of food inflation contain much information concerning the present value and as such, monetary authorities should not overlook this fact. On a general note, the study recommends the engagement of both fiscal and monetary measures to achieve food security in Nigeria.

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Appendix 1. ARCH LM test

Models	**Error Distribution**
	Student's *t*-Distribution
GARCH (1,1)	
F-test/P-value	0.00(0.94)
nR^2/P-value	0.00(0.95)
GARCH-M	
F-test/P-value	0.00(0.94)
nR^2/P-value	0.00(0.94)
TGARCH (1,1)	

F-test/P-value	0.00(0.94)
nR^2/P-value	0.00(0.94)
EGARCH (1,1)	
F-test/P-value	0.20(0.65)
nR^2/p-value	0.20(0.65)
PARCH (1,1)	
F-test/P-value	0.00(0.94)
nR^2/P-value	0.00(0.94)

Appendix 2. Serial Correlation of GARCH (1,1) Model

Lag	AC	PAC	Q-stat.	Prob*
Student's *t*-Distribution				
1	−0.00	−0.00	0.00	0.94
2	−0.00	−0.00	0.00	0.99
3	−0.00	−0.00	0.01	1.00
4	−0.00	−0.00	0.01	1.00
5	−0.00	−0.00	0.02	1.00
6	−0.00	−0.00	0.02	1.00
7	−0.00	−0.00	0.03	1.00
8	−0.00	−0.00	0.03	1.00
9	−0.00	−0.00	0.04	1.00
10	−0.00	−0.00	0.04	1.00

Appendix 3. Serial Correlation of GARCH-M Model

Lag	AC	PAC	Q-stat.	Prob*
Student's t-Distribution				

1	−0.00	−0.00	0.00	0.94
2	−0.00	−0.00	0.00	0.99
3	−0.00	−0.00	0.01	1.00
4	−0.00	−0.00	0.01	1.00
5	−0.00	−0.00	0.02	1.00
6	−0.00	−0.00	0.02	1.00
7	−0.00	−0.00	0.03	1.00
8	−0.00	−0.00	0.03	1.00
9	−0.00	−0.00	0.04	1.00
10	−0.00	−0.00	0.04	1.00

Appendix 4. Serial Correlation of TGARCH (1,1) Model

Lag	AC	PAC	Q-stat.	Prob*
Student's t-Distribution				
1	−0.0	−0.0	0.00	0.95
2	−0.00	−0.00	0.00	0.99
3	−0.00	−0.00	0.01	1.00
4	−0.00	−0.00	0.02	1.00
5	−0.00	−0.00	0.02	1.00
6	−0.00	−0.00	0.03	1.00
7	−0.00	−0.00	0.03	1.00
8	−0.00	−0.00	0.04	1.00
9	−0.00	−0.00	0.04	1.00
10	−0.00	−0.00	0.05	1.00

Appendix 5. Serial Correlation of EGARCH (1,1) Model

Lag	AC	PAC	Q-stat.	Prob*

	Student's t-Distribution			
1	−0.03	−0.03	0.21	0.64
2	−0.04	−0.05	0.76	0.68
3	−0.05	−0.05	1.36	0.72
4	0.04	0.03	1.74	0.78
5	−0.02	−0.02	1.83	0.87
6	−0.01	−0.01	1.85	0.93
7	0.08	0.09	3.50	0.84
8	−0.00	−0.00	3.52	0.89
9	−0.07	−0.06	4.74	0.86
10	−0.04	−0.04	5.14	0.88

Appendix 6. Serial Correlation of PARCH (1,1) Model

Lag	AC	PAC	Q-stat.	Prob*
	Student's *t*-Distribution			
1	−0.00	−0.00	0.00	0.94
2	−0.00	−0.00	0.00	0.99
3	−0.00	−0.00	0.01	1.00
4	−0.00	−0.00	0.01	1.00
5	−0.00	−0.00	0.02	1.00
6	−0.00	−0.00	0.02	1.00
7	−0.00	−0.00	0.03	1.00
8	−0.00	−0.00	0.03	1.00
9	−0.00	−0.00	0.04	1.00
10	−0.00	−0.00	0.04	1.00

Appendix 7 Plot of the Residual