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# Modeling Retail Price Volatility of Selected Food Items in Cross River State, Nigeria Using GARCH Models

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**Abstract:** Food inflation presents a significant challenge in Nigeria. This study examines the volatility of four primary food items—tomatoes, yam, yellow garri, and imported rice—in Cross River State, Nigeria, utilizing data on monthly retail prices per kilogram from January 1997 to November 2023, sourced from the National Bureau of Statistics (NBS). Three asymmetric volatility models were employed: Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH), Threshold Autoregressive Conditional Heteroscedasticity (TARCH), and Power Autoregressive Conditional Heteroscedasticity (PARCH). The parameters of these models were estimated using three distributions of error innovations: Normal, Student's t-distribution, and Generalized Error Distribution (GED). The performance of the models was assessed based on log-likelihood for fitness and Root Mean Square Error (RMSE) for forecasting accuracy. The results indicated that non-Gaussian error innovations outperformed the normal distribution. Notably, higher persistence in volatility was observed for yam and tomatoes compared to yellow garri and imported rice. Tomatoes exhibited the highest volatility persistence among the food items analyzed. Significant Generalized Autoregressive Conditional Heteroscedasticity (GARCH) terms for tomatoes and yam suggested that past volatility has a significant positive impact on their current volatility, whereas this effect was not significant for yellow garri and imported rice ($p<0.05$). The leverage effect was found to be insignificant, indicating that positive and negative shocks in volatility exert similar effects on the volatility of these food items. These findings underscore the urgent need for incentives and adequate security measures to ensure food sufficiency in Cross River State and Nigeria at large.

**Keywords:** Volatility modelling; Asymmetric; Error innovation; Heteroscedasticity

## 1 Introduction

Human beings, irrespective of age, nationality, and social status, must necessarily eat food to survive. Unfortunately, for several months now, the price of food items in Nigeria has been on the rise. Food price volatility is the fluctuation or variation in the prices of food items. Food price volatility is one of the indices that can be used to assess agricultural production and food sufficiency. When the volatility in prices of food items is high, it is an indication that there is a sharp change in agricultural production, which may result in food insufficiency if not addressed on time. Food price volatility has been observed to be one of the major indices of economic development [1]. No wonder food price volatility has generated serious concern for policymakers and other stakeholders in the food market chain. Food price volatility plays a significant role in enhancing macroeconomic stability as well as food production. Its effect on the survival of human beings and the economy cannot be overemphasized [1].

The issue of high volatility in the prices of food items has brought untold hardship to Nigerians. At present, in Nigeria, common food items such as garri and beans, which are usually within reach of the lower socioeconomic class, have suddenly become food for the upper class. This development has forced many Nigerians to go into farming. Because of the effect that high volatility in the prices of food items could have on the survival of human beings, the issue globally has generated research attention [2]. Rashid [3] noted that the prices of food, especially agricultural commodities in general, are highly volatile. In this vein, the volatility of edible oil in India was examined by Lama et al. [4], while Wang [5] modeled Ontario agricultural commodity price volatility with mixtures of GARCH processes, but in Nigeria, not much has been done even now that the prices of agricultural commodities have been reported to be on the increase almost every day. It is also important to note that the majority of studies that have been carried out, especially in Nigeria, focused more on the volatility of assets or financial indicators with little or no attention to agricultural commodities, which are necessary for human survival as no one can do without food. Therefore, given this, it is important to model the volatility of some agricultural commodity prices in Cross River State, Nigeria. This study is limited to four food items, namely, tomatoes, yam, yellow garri, and imported rice. The study also focused on three volatility models, namely the EGARCH model [6], the TARCH model [7], and the PARCH model [8]. Also, only three different distributions of error innovations are applied in the study, namely: the normal distribution, the Student-t distribution, and the GED.

The objective of this study is therefore to examine the volatility of four food items majorly consumed in Nigeria (yam, yellow garri, and imported rice) with the hope that this could provide policy direction and an intervention strategy that would help address the problem of food shortage in Cross River State and Nigeria at large. Our major contribution to knowledge lies in the use of asymmetric GARCH models to model the volatility dynamics of food items in the study area, which, to the best of the researchers' knowledge, has not been done even despite the issue of food shortages remaining a major problem in Cross River State and Nigeria at large.

## 2 Review of Literature

Several models for studying volatility have been proposed by researchers in the field of financial time series. The ARCH model developed by Engle [9] expressed volatility in terms of past squared residuals. Although the ARCH model was proven to be efficient in modeling volatility, its major limitation was that a higher order of ARCH was required to capture volatility. Hence, Bollerslev [10] provided a way out of this by proposing the GARCH, which expresses the volatility as a function of the past squared residual and the past lagged volatility. The GARCH model, though able to overcome the lack of parsimony observed in the ARCH model, also has its limitations because it was unable to account for the leverage effect, which is one of the stylized facts of financial series. This therefore necessitates asymmetric volatility models like the EGARCH model by Nelson, the TARCH model by Zakonian, and the PARCH model by Ding, Granger, and Engle, among others.

Several studies have been carried out on the volatility of food items. To determine the impact of news on volatility, Zheng et al. [1] investigated the impact of news on the volatility of 45 retail food prices in the United States. The data used in the study covered 25 years, and two volatility models (GARCH and EGARCH) were considered. Findings showed that news has a significant impact on the volatility of 16 food items, with asymmetric volatility effects and large impacts from high price news for 10 items, leading to amplified price volatility. Lama et al. [4] used the Autoregressive Integrated Moving Average (ARIMA) model, the GARCH model, and the EGARCH model in the modeling and forecasting of three price series. It was found that these series exhibited asymmetric volatility patterns and that the EGARCH model outperformed the ARIMA and GARCH models in forecasting the international cotton price series.

In Italy, Onour and Sergi [11] examined the volatility of six food items (wheat, beef, coffee, rice, sugar, and groundnut). The study employed two error distributions, namely the Student's t-distribution and the normal distribution, and it was found that the Student's t distribution outperformed the normal error innovation. The study established that the volatility of these items was characterized by both immediate and short memory behavior, implying that the volatility of these food items is mean-reverting. Similarly, the volatility of farm commodities in Nigeria was examined in the study [12], who found that the Autoregressive Moving Average (ARMA) model is the most appropriate for food items in the Nigerian agricultural commodity markets. The spot prices of eighteen commodities traded by most Sub-Saharan African countries were examined in the study [13] using the random walk, simple regression, and five models from the ARCH family. It was found that the non-ARCH family models performed better than the ARCH family models.

In the same way, Nwoko et al. [14] looked at how volatile five foods were in Nigeria from 2000 to 2013 using the GARCH(1, 1), VAR model, and Johansen co-integration test. The foods were maize, rice, sorghum, soy beans, and wheat. The study found no long-run relationship between oil price and any of the individual price volatility as indicated by the Johansen co-integration test. The study also established that, in the short run, there is a positive and significant effect of oil prices on maize and soy beans. The findings of this study also showed that agricultural commodity prices have some degree of inherent volatility and therefore recommended intervention to reduce their price variability to their natural level in a way that it will not become a problem for farmers and hence food security in the country.

The volatility and co-movement of food commodity prices in Nigeria for five food items: rice, maize, sorghum, cassava, and yam, for the period of 1966 to 2013, was investigated using a vector autoregressive model and GARCH regression [15]. The results revealed high volatility and persistence in the prices of these commodities. The study also found that the Nigerian food commodity price experienced high fluctuations over the period, which therefore necessitated the need for proper storage facilities and infrastructure for the food distribution corporations in Nigeria.

Sukuta [16] investigated the price volatility of maize in Swaziland using ARCH and GARCH models. The data used in the study was obtained between February 1998 and September 2013, for a total of 188 data points. Results revealed evidence of very high volatility in the past years, indicating that the price of maize has not been stabilized in the past years, as revealed by the GARCH term.

The volatility of seven items in Indonesia was examined by the study [17]. These items include arabica coffee, crude palm oil, natural rubber TSR20, Robusta coffee, cocoa, black pepper, and white pepper, using weekly data that spanned from January 1, 2005, to June 30, 2011. The weekly spot price in this study is the closing price of the immediate cash price on the last trading day of each week. Five volatility models (ARCH, GARCH, GARCH, EGACRH, and TGARCH) were considered. The findings showed differences in the volatility models for each commodity. To the best of the researchers' knowledge, only very few studies have been carried out on the volatility of food items in Nigeria, even though the issue of food price volatility remains a major problem in Nigeria as food price inflation in Nigeria now remains the highest in the history of Nigeria. Therefore, there is an urgent need for empirical evidence on food price inflation that would give insights on this issue in the hope that it would help stimulate policy decisions that would help alleviate the problem of food crises bedeviling Nigeria. The skyrocketing prices of food items in Cross River State, Nigeria, also emphasize the need for a model and forecast of the volatility of food items in Cross River State, Nigeria.

## 3 Methodology

The data used in this study consist of the average monthly retail price per kilogram of tomatoes, yam, yellow garri, and imported rice in Cross River State between January 1997 and November 2023, obtained from the NBS. The retail price of these food items was obtained from the NBS, Cross River State office.

### 3.1 Computation of Monthly Returns from Monthly Price

The monthly return of these agricultural commodities were computed using the formula shown below:

$$M_r = \ln\left(\frac{p_t}{p_{t-1}}\right) \qquad r = 2, \ldots, n \tag{1}$$

where, $p_t$ is the current price of the item at time $t$ and $p_{t-1}$ is the previous price as at $t-1$ and $n$ is the number of observations.

### 3.2 Test of Normality of the Price Return Series

The normality of the price returns series was determined using as Jarque-Bera test are given by:

$$J = \frac{n}{6}\left[k + \frac{(\lambda-3)^2}{4}\right] \tag{2}$$

which is approximately $\chi_2^2$, $k$ is the skewness and $\lambda$ is the kurtosis.

The decision rule is to Reject Ho: if $J$ statistic exceeds the corresponding critical value or if the $p$-value is less than 0.05.

### 3.3 Test of Stationarity

To test for the stationarity of the series, the Phillips-Perron (PP) Test was used. The Phillips-Perron Test is used in time series analysis to test the null hypothesis that a time series is integrated of order 1. The Phillips-Perron statistic corrects for serial correlation and heteroscedasticity in the error non-parametrically by upgrading the Dickey Fuller test statistics. The test regression for Phillips-Perron (PP) test is the AR(1) process:

$$\Delta X_t = \alpha_0 + \alpha_1 X_{t-1} + \varepsilon_t \tag{3}$$

$\mathrm{H}_0 : \alpha_1 = 0$ (the series contains unit root)
$\mathrm{H}_1 : \alpha_1 < 0$ (the series is stationary)
The test statistic is

$$\begin{gathered} T = \left(\frac{\chi_0}{f_0}\right)^{\frac{1}{2}} - \frac{T\,(f_0 - \chi_0)\, S_e(\widehat{\beta})}{2 f_0^{\frac{1}{2}} s} \\ T = \left(\frac{T-K}{T}\right) S^2 \end{gathered} \tag{4}$$

where, $\hat{\beta}$ is the parameter estimate. $t_\beta$ is the t - ratio of $\beta, S_e(\widehat{\beta})$ is the standard error of $\beta$, $S$ is the standard error of the last regression, $\chi_0$ is the consistent estimate of error variance, $f_0$ is the estimator of the residual spectrum at frequency zero, $T$ is the number of observation and $K$ is the number of parameter.

The decision rule is to reject $\mathrm{H}_0$ if $t_{\hat{\beta}}$ is less than the asymptotic critical value or $(\mathrm{p} < 0.05)$.

### 3.4 Volatility Model

To model the returns of these food items, the Autoregressive Moving Average (ARMA) model was used and the specification of each of the heteroscedasticity models is presented below.

The Exponential Generalized Autoregressive Conditional Heteroscedasticity EGARCH(p,q) is given by;

$$
\begin{aligned}
&r_t = a_0 + a_1 r_{t-1} + \varepsilon_t + b_1 \varepsilon_{t-1}, \varepsilon_t = \sigma_t z_t, \varepsilon_t \sim N(0,1) \\
&\ln\left(\sigma_r^2\right) = \beta_0 + \sum_{i=1}^{p} \beta_i \left[ w\varepsilon_{i-1} + w\left(|\varepsilon_{i-1}| - \sqrt{\frac{2}{\Pi}}\right)\right] + \sum_{j=1}^{q} \gamma_j \ln\left(\sigma_{r-j}^2\right)
\end{aligned}
\tag{5}
$$

where, $r_t$ the mean equation which is ARMA(1,1), $\beta_0, \beta_i, w, \gamma_i$ are the parameters of the Exponential Generalized Autoregressive Conditional Heteroscedasticity model EGARCH(p,q). If $\varepsilon_{i-1} > 0$ implies good news while $\varepsilon_{i-1} < 0$ implies bad news.

The TARCH(p,q) is given by:

$$
\begin{aligned}
&r_t = a_0 + a_1 r_{t-1} + \varepsilon_t + b_1 \varepsilon_{t-1}, \varepsilon_t = \sigma_t z_t, \varepsilon_t \sim N(0,1) \\
&\sigma_r^2 = \beta_0 + \sum_{i=1}^{p} \beta_i \left(\varepsilon_{i-1}\right) + w d_{i-1} \varepsilon_{i-1}^2 + \sum_{j=1}^{q} \gamma_j \ln\left(\sigma_{r-j}^2\right) \\
&\begin{cases} d_{i-1} = 1, \varepsilon_{i-1} < 0 \\ 0, \varepsilon_{i-1} > 0 \end{cases}
\end{aligned}
\tag{6}
$$

where, $r_t$ is the mean equation which is ARMA(1,1). $\beta_0, \beta_i, w, \gamma_j$ are the parameters of the model. If $\varepsilon_{t-1}^2 > 0$ implies good news while $\varepsilon_{t-1}^2 < 0$ implies bad news.

The general Power ARCH model introduced by Ding et al. [8] is specified as:

$$
\begin{aligned}
&r_t = a_0 + a_1 r_{t-1} + \varepsilon_t + b_1 \varepsilon_{t-1}, \varepsilon_t = \sigma_t z_t, \varepsilon_t \sim N(0,1) \\
&\sigma_t^\delta = \beta_0 + \sum_{i=1}^{p} \left(|\varepsilon_{i-1}| + w\varepsilon_{i-1}\right)^\delta + \sum_{j=1}^{q} \gamma_j \sigma_{t-1}^\delta
\end{aligned}
\tag{7}
$$

where, $r_t$ is the mean equation which is $\mathrm{ARMA}(1,1), \beta_0$ is the constant term, $\beta_1 =$ ARCH term, $w =$ GARCH term, and $y_j =$ leverage term, $\beta_0 > 0, w_i \geq 0, \gamma_j \geq 0, 0 \leq \sum_{i=1}^{p} w_i + \sum_{j=1}^{q} \gamma_j \leq 1$.

3.4.1 Distribution of error innovation

The parameters of these asymmetric volatility models were estimated based on three distributions of error innovations namely: Normal, Student-t-distribution and Generalized Error Distribution (GED).

The density function of the standardized normal distribution is

$$
f(w) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{w^2}{2}\right), -\infty < w < \infty \tag{8}
$$

with log-likelihood function defined as

$$
L_N = \frac{-n}{2} \ln(2\Pi) - \frac{1}{2} \sum_{i=1}^{n} w_i^2 \tag{9}
$$

The standardized Student-t distribution was proposed to circumvent the problem of non-normality of innovation of Heteroscedasticity model. The standardized student t distribution is given below.

$$
f\left(w_t / v\right) = \frac{\Gamma((v+1)/2)}{\Gamma(v/2)\sqrt{\pi(v-2)}} \left[1 + \frac{w_t^2}{v-2}\right]^{-\left(\frac{v+1}{2}\right)} \tag{10}
$$

where, gamma function is $\Gamma(v/2)$ and degree of freedom $V > 2$.

The Log-likelihood function for the standardized t-distribution is:

$$
L_{st} = -\frac{1}{2}\left[N \log\left(\frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma((v+1)/2)^2}\right) + \sum_{r=1}^{N} \log \sigma_r^2 + (v+1) \sum_{r=1}^{N} \log\left[1 + \frac{\varepsilon_r^2}{\sigma_r^2(v-1)}\right]\right] \tag{11}
$$

In 1991, Nelson [6] proposed another distribution which is referred to as the Generalized Error Distribution (GED) which has the density function.

$$f\left(w_t v\right) = v \cdot \exp\left[\frac{\left(-\ 0.5\left|w_t\right|\lambda\right|^{v})}{\lambda.2^{(1+v^{-1})\Gamma(v^{-1})}}\right] \tag{12}$$

with $v > 0$, and $v$ is tail fitness parameter defined by

$$\lambda = \sqrt{\frac{2^{-\frac{2}{v}}\Gamma\left(v^{-1}\right)}{\Gamma\left(3v^{-1}\right)}}$$

where, $\lambda$ is the skewness parameter.

The Log-likelihood of each of the distribution of the GED is given as:

$$L_{GED} = -\frac{1}{2}\left[N\log\left(\frac{\Gamma\left(v^{-1}\right)^3}{\Gamma\left(3v^{-1}\right)\left(v/2\right)^2}\right) + \sum_{r=1}^{N}\log\sigma_r^2 + (v+1)\sum_{r=1}^{N}\left(\frac{\Gamma\left(3v^{-1}\right)\varepsilon_r^2}{\sigma_r^2\Gamma\left(v^{-1}\right)}\right)\right] \tag{13}$$

### 3.5 Root Mean Square Error

This is the root of the mean of the squared error. It is mostly used to measure the differences between values predicted by a model and the actual value observed.

$$RMSE = \sqrt{\frac{\sum_{t=2}^{n}\left(\sigma_t^2 - \hat{\sigma}_t^2\right)^2}{n}} \tag{14}$$

where, $\sum =$ Sum of all values; $\sigma_t^2$ is the actual volatility at the period $t$ and $\hat{\sigma}_t^2$ is the estimated volatility for the same period. $n =$ is the number of observation.

## 4 Results and Discussion of the Findings

A test of stationarity was performed using the Philips-Perron test, and the results presented in Table 1 reveals p-values of 0.000, indicating that a p-value of 0.0001 was obtained for tomatoes and 0.0001, 0.0000, and 0.00001 were obtained for yam, yellow gari, and imported rice, respectively. This result implies that the series were stationary, hence there is no need for differencing.

**Table 1.** Test of Stationarity of the series using Philips-Perron test

| Food Items | Test Statistic | Test Critical Values | P-Value | Remarks |
|---|---|---|---|---|
| Tomatoes | -28.609 | -2.87 | 0.0000 | Stationary at level |
| Yam | -47.159 | -2.87 | 0.0001 | Stationary at level |
| Yellow garri | -21.557 | -2.87 | 0.0000 | Stationary at level |
| Imported rice | -88.294 | -2.87 | 0.0001 | Stationary at level |

The forecasting models are as follows:

**Tomatoes:** From Table 2, the ARMA(1,1)/TARCH(1,1)- GED model for tomatoes is given as:

$$\sigma_t^2 = 0.000115 + 0.063393\varepsilon_{t-1}^2 + 0.890522\sigma_{t-1}^2 + 0.101080d_{i-1}\varepsilon_{t-1}^2 \tag{15}$$

**Yam:** The ARMA(1,1)/TARCH(1,1)- Student-t for yam obtained from Table 3 is:

$$\sigma_t^2 = 0.0000684 + 0.093717\varepsilon_{t-1}^2 + 0.834398\sigma_{t-1}^2 + 0.087899d_{i-1}\varepsilon_{t-1}^2 \tag{16}$$

**Yellow garri:** ARMA(1,1)/PARCH(1,1) with GED for yellow garri obtained from Table 4 is given as:

$$\sigma_t^{0.491222} = 0.067323 + 0.533371\left(\left|\varepsilon_{i-1}\right| - 0.460261\varepsilon_{i-1}\right)^{0.491222} - 0.010225\sigma_{t-1}^{1.60281} \tag{17}$$

**Imported rice:** For imported rice, the fitted ARMA(1,1)/TARCH(1,1)-Student-t obtained from Table 5 is:

$$\sigma_t^2 = 0.378969 + 2815.329\varepsilon_{t-1}^2 + 0.041633\sigma_{t-1}^2 - 767.3076d_{i-1}\varepsilon_{t-1}^2 \tag{18}$$

In Eqs. (15)–(18), $\begin{cases} d_{i-1} = 1, \varepsilon_{i-1} < 0 \\ 0, \varepsilon_{i-1} > 0 \end{cases}$

The results in Tables 2–5 reveal that the ARCH and GARCH terms were statistically significant ($p<0.05$) in some of the models, which implies that large changes in volatility tend to go with large changes in volatility. This also shows the volatility persistence of these food prices. The results presented in Tables 2–5 also reveal that in some of the models, the leverage was significant ($p<0.05$), which means that rising prices of these food items are accompanied by declining volatility in the prices of tomatoes. The results presented in Tables 6–9 show that ARMA(1,1)/TARCH(1,1) with GED, ARMA(1,1)/TARCH(1,1) with Student's t-distribution, ARMA(1,1)/Parch(1,1) with GED, and ARMA(1,1) /TARCH(1,1) with Student-t distribution were the best models for tomatoes, yam, yellow garri, and imported rice, respectively.

**Table 2.** Parameter estimate for the mean equation based on ARMA(1,1) and heteroscedastic models for tomatoes

| **Models** | | **Mean Equation Parameter** | | | **Heteroscadastic Model Parameters** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $\alpha_0$ (p-value) | $\alpha_1$ (p-value) | $\beta_1$ (p-value) | $B_0$ (p-value) | $B_1$(p-value) | $\gamma_1$( p-value ) | $W_1$ (p-value ) | $\delta$ (p-value) |
| ARMA(1,1)-EGARCH(1,1) | Normal | 0.003280** | 0.640012** | -0.952996** | -0.598255** | 0.499905** | 0.95559** | 0.011007 | - |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0002) | (0.0000) | (0.0000) | (0.8376) | |
| | Student-t | 0.003389* | 0.604056** | -0.829858** | -0.386241 | 0.313105 | 0.961097 | -0.00531 | - |
| | | (0.0159) | (0.0000) | (0.0000) | (0.0399) | (0.0143) | (0.0000) | (0.9499) | |
| | GED | 0.001021 | 0.624939** | -0.660973** | -0.645206 | 0.319104 | -0.103124 | 0.908127** | - |
| | | (0.2915) | (0.0097) | (0.0036) | (0.1152) | (0.0534) | (0.3920) | (0.000) | |
| ARMA(1,1)-TARCH(1,1) | Normal | 0.003232** | 0.650288 | -0.957944 | 0.000595 | 0.319682** | 0.745637** | 0.008413 | - |
| | | (0.0000) | (0.0000) | (0.0000) | (0.2487) | (0.0001) | (0.0000) | (0.9422) | |
| | Student-t | 0.006805 | -0.001806 | -0.450527** | 0.012748 | 1.204369 | 0.060378 | -0.663938 | - |
| | | (0.1437) | (0.9918) | (0.0008) | (0.0948) | (0.2236) | (0.7249) | (0.4526) | |
| | GED | 0.002875** | 0.819485** | -0.886938** | 0.000115 | 0.063393 | 0.890522** | 0.101080* | - |
| | | (0.0061) | (0.0000) | (0.0000) | (0.3737) | (0.3825) | (0.0000) | (0.0456) | |
| ARMA(1,1)-PARCH(1,1) | Normal | 0.002604** | 0.500004 | -0.876574** | 0.018585 | 0.195394** | 0.79442** | -0.071000 | 0.326722 |
| | | (0.0010) | (0.0000) | (0.0000) | (0.3716) | (0.0027) | (0.0000) | (0.6155) | (0.3976) |
| | Student-t | 0.003480* | 0.628599** | -0.833323** | 0.003060 | 0.147598* | 0.883373 | -0.047882 | 0.884422 |
| | | (0.0262) | (0.0000) | (0.0000) | (0.7232) | (0.0496) | (0.0000) | (0.8899) | (0.4003) |
| | GED | 0.002021 | 0.676102** | 0.773497** | 0.002688 | 0.150336* | 0.87300** | 0.130949 | 0.969280 |
| | | (0.1560) | (0.0000) | (0.0000) | (0.6341) | (0.0458) | (0.0000) | (0.7404) | (0.1631) |

**p<0.01 means significant at 1% level, *p<0.05 means significant at 5% level.

**Table 3.** Parameter estimate for the mean equation based on ARMA(1,1) and heteroscedastic models for yam

| **Models** | | **Mean Equation Parameter** | | | **Heteroscadastic Model Parameters** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $\alpha_0$ (p-value) | $\alpha_1$ (p-value) | $\beta_1$ (p-value) | $B_0$ (p-value) | $B_1$(p-value) | $\gamma_1$( p-value ) | $W_1$ (p-value ) | $\delta$ (p-value) |
| ARMA(1,1)-EGARCH(1,1) | Normal | 0.004212** | 0.513266 | -0.999952** | -1.453937 | 0.237186* | 0.035161 | 0.734639 | - |
| | | (0.000) | (0.0000) | (0.000) | (0.0763) | (0.0485) | () | (0.0000) | |
| | Student-t | 0.003879** | 0.480965** | -0.893959** | -0.512661 | 0.489434 | 0.956558** | -0.095929 | - |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0012) | (0.0006) | (0.0000) | (0.1961) | |
| | GED | 0.004057** | 0.643855** | -0.993315** | -0.460217 | 0.369812** | 0.958564 | -0.029089 | - |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0206) | (0.0004) | (0.0000) | (0.7098) | |
| ARMA(1,1)-TARCH(1,1) | Normal | 0.004280** | 0.473993 | -0.999917** | 0.000601* | 0.034425 | 0.841406 | 0.071512 | - |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0449) | (0.0756) | (0.0000) | (0.1839) | |
| | Student-t | 0.003919** | 0.506383 | -0.991037 | 0.0000684 | 0.093717 | 0.834398 | 0.087899 | - |
| | | (0.000) | (0.0000) | (0.000) | (0.0779) | (0.0062) | (0.0000) | (0.1683) | |
| | GED | 0.004039** | 0.638228 | -0.994122** | 0.0000067 | 0.134654 | 0.849149** | 0.075096 | - |
| | | (0.0000) | (0.0000) | (0.0000) | (0.3786) | (0.1340) | (0.0000) | (0.5810) | |
| ARMA(1,1)-PARCH(1,1) | Normal | 0.004262** | 0.498085** | -0.999973** | 0.008499 | 0.128455 | 0.765465** | -0.033043 | 1.177044 |
| | | (0.0000) | (0.0000) | (0.0000) | (0.6393) | (0.0491) | (0.000) | (0.9176) | (0.0770) |
| | Student-t | 0.003902** | 0.469425** | -0.892709** | 0.001015 | 0.338845 | 0.117550 | 0.787320** | 1.425490 |
| | | (0.0000) | (0.0000) | (0.0000) | (0.5662) | (0.0570) | (0.5191) | (0.000) | (0.0057) |
| | GED | 0.003220** | 0.066147 | -0.429624** | 0.003024 | 0.224103** | 0.816335 | 0.000266 | 1.043048* |
| | | (0.0000) | (0.4839) | (0.0000) | (0.5781) | (0.0073) | (0.0000) | (0.9994) | (0.0253) |

**p<0.01 means significant at 1% level, *p<0.05 means significant at 5% level.

The result also shows that among the four food items, tomatoes have the highest volatility, followed by yam, and then imported rice and garri, respectively. The study area likely produces yellow garri, the commodity with the lowest volatility. In terms of volatility clustering, tomatoes and yam were the two major commodities with the highest volatility clustering, while yellow garri had the lowest value. This indicates that periods of high volatility followed by periods of low volatility were more pronounced in tomatoes and yam compared to yellow garri and imported rice.

This finding agrees with that of the finding in the study [18] on the estimation of the GARCH model for the Nigerian exchange rate under non-Gaussian innovations, where the GED and Student-t distributions were found to be superior to the normal distribution. Similarly, this finding is in line with that of the finding in the study [19] in Ghana, which also established a significant positive GARCH effect on the price of food items in Ghana.

**Table 4.** Parameter estimate for the mean equation based on ARMA(1,1) and heteroscedastic models for yellow garri

| Models | | Mean Equation Parameter | | | Heteroscadastic Model Parameters | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $\alpha_0$ (p-value) | $\alpha_1$ (p-value) | $\beta_1$ (p-value) | $B_0$ (p-value) | $B_1$(p-value) | $\gamma_1$( p-value ) | $W_1$ (p-value ) | $\delta$ (p-value) |
| ARMA(1,1)-EGARCH(1,1) | Normal | 0.002963 | 0.317692* | -0.549101** | -8.608765 | 0.609228 | -0.468458 | 0.084840 | - |
| | | (0.1901) | (0.0311) | (0.0000) | (0.0000) | (0.0000) | (0.0001) | (0.2505) | |
| | Student-t | 0.001610 | 0.121546 | -0.331305* | -0.936652 | 7.486265 | 0.718516 | 0.499914 | - |
| | | (0.2913) | (0.4722) | (0.0297) | (0.1673) | (0.4230) | (0.0000) | (0.6110) | |
| | GED | 0.000000025 | 0.343574 | -0.343574 | -1.513482* | 0.935769 | 0.779284 | 0.045785 | - |
| | | (0.9924) | (0.0842) | (0.0842) | (0.0237) | (0.0037) | (0.0000) | (0.8299) | |
| ARMA(1,1)-TARCH(1,1) | Normal | 0.000961 | 0.313611 | -0.537574** | 0.005140 | 0.125155 | -0.427044* | 0.097879 | - |
| | | (0.7135) | (0.0967) | (0.0003) | (0.0000) | (0.1106) | (0.0385) | (0.3916) | |
| | Student-t | 0.000851 | 0.018859 | -0.294507 | 0.053587 | 1438.853 | 0.279371** | 369.4389 | - |
| | | (0.3093) | (0.9233) | (0.0966) | (0.9980) | (0.9981) | (0.0000) | (0.9981) | |
| | GED | 0.001008** | 0.613759 | -0.662198** | 0.000941* | 1.745385 | 0.325728 | 0.193267 | - |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0358) | (0.1663) | (0.0257) | (0.9110) | |
| ARMA(1,1)-PARCH(1,1) | Normal | 0.003584 | 0.166426 | -0.503226** | 0.000236 | 0.059805 | 0.856884** | 0.190377 | 2.121232* |
| | | (0.2293) | (0.3931) | (0.0042) | (0.7028) | (0.0765) | (0.0000) | (0.3985) | (0.0124) |
| | Student-t | 0.000980 | 0.194930 | -0.418870** | 0.040778 | 2.091722 | 0.405448** | 0.049203 | 0.724244* |
| | | (0.1085) | (0.1448) | (0.0003) | (0.5134) | (0.5462) | (0.0000) | (0.7367) | (0.0191) |
| | GED | 0.000587** | 0.636770** | -0.670367** | 0.067323 | 0.533371 | 0.460261** | 0.010225 | 0.491222 |
| | | (0.0000) | (0.0000) | (0.0000) | (0.3487) | (0.1098) | (0.0015) | (0.9768) | (0.1685) |

**p<0.01 means significant at 1% level, *p<0.05 means significant at 5% level.

**Table 5.** Parameter estimate for the mean equation based on ARMA(1,1) and heteroscedastic models for imported rice

| Models | | Mean Equation Parameter | | | Heteroscadastic Model Parameters | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $\alpha_0$ (p-value) | $\alpha_1$ (p-value) | $\beta_1$ (p-value) | $B_0$ (p-value) | $B_1$(p-value) | $\gamma_1$( p-value ) | $W_1$ (p-value ) | $\delta$ (p-value) |
| ARMA(1,1)-EGARCH(1,1) | Normal | 0.003961 | 0.409426 | -0.983516 | -1.384202** | 0.728692** | 0.819156 | 0.391202** | - |
| | | (0.0000) | (0.0000) | (0.0000) | (0.0021) | (0.0000) | (0.0000) | (0.0003) | |
| | Student-t | 0.001638 | -0.130356 | -0.116378 | -2.500707 | 2.749631 | 0.456886** | -0.797301 | - |
| | | (0.1693) | (0.4109) | (0.4757) | (0.1693) | (0.5595) | (0.0000) | (0.5815) | |
| | GED | 0.000312 | -0.344419** | 0.318041** | -3.020600** | 1.102933** | 0.507781 | -0.368799 | - |
| | | (0.0857) | (0.0000) | (0.0000) | (0.0002) | (0.0014) | (0.0008) | (0.1516) | |
| ARMA(1,1)-TARCH(1,1) | Normal | 0.002483 | -0.101687 | -0.746658 | 0.003033** | 0.189194 | 0.069658 | 2.197708* | - |
| | | (0.0575) | (0.1943) | (0.000) | (0.0000) | (0.1943) | (0.2580) | (0.0160) | |
| | Student-t | 0.002015 | -0.023570 | -0.238833 | 0.378969 | 2815.329 | 0.041633 | -767.3078 | - |
| | | (0.0885) | (0.8805) | (0.1089) | (0.9991) | (0.9991) | (0.3747) | (0.9991) | |
| | GED | 0.002672 | -0.149068 | -0.014291 | 0.002203** | 1.742897 | 0.043006 | -0.002779 | - |
| | | (0.0000) | (0.0104) | (0.8352) | (0.0002) | (0.2498) | (0.5606) | (0.9988) | |
| ARMA(1,1)-PARCH(1,1) | Normal | 0.003383 | -0.074095 | -0.762002 | 0.0000009 | 1.697460* | -0.000379 | 0.544512** | 4.843244** |
| | | (0.0016) | (0.4848) | (0.0000) | (0.8530) | (0.0413) | (0.7238) | (0.0006) | (0.0096) |
| | Student-t | 0.001869 | -0.177911 | -0.098731 | 0.169010 | 4.481714 | 0.044962 | -0.028738 | 0.879304* |
| | | (0.0752) | (0.1219) | (0.3646) | (0.8528) | (0.8614) | (0.6645) | (0.6645) | (0.0364) |
| | GED | 0.002946** | 0.097714 | -0.130226 | 0.047782 | 0.929843 | 0.130787 | 0.015820 | 0.902325 |
| | | (0.000) | (0.5523) | (0.4261) | (0.4808) | (0.1266) | (0.3688) | (0.9572) | (0.0966) |

**p<0.01 means significant at 1% level, *p<0.05 means significant at 5% level.

The results of the fitness and forecasting performance for each of the asymmetric volatility models are presented in Tables 6–9. Results in Tables 6–9 show that the EGARCH(1,1)-GED outperformed other asymmetric models. This implies that a combination of EGARCH with the GED is the best-fitted model for all four food items considered. But for forecasting performance, TARCH(1,1)-GED gave the least RMSE (RMSE = 0.090116) for tomatoes, TARCH(1,1)-Student-t (RMSE = 0.104556) for yam, PARCH(1,1)-GED (RMSE = 0.067105) for yellow garri, and EGARCH(1,1)-Student-t (RMSE = 0.114221) for imported rice. Therefore, TARCH(1,1)-GED, ARCH(1,1)-Student-t, PARCH(1,1)-GED, and EGARCH(1,1)-Student-t are the best forecasting models for tomatoes, yam, yellow garri, and imported rice, respectively. Based on the forecasting performance, tomatoes have the least RMSE of 0.090116, while yam, yellow gari, and imported rice have the least RMSE of 0.104556, 0.067105, and 0.114221, respectively. Among these food items, yellow garri has the lowest RMSE, while imported rice has the highest RMSE, indicating that yellow garri is the easiest to forecast, while imported rice is the hardest to forecast.

**Table 6.** Fitness and forecasting performance of the different heteroscedasticity model at three distribution of error innovation for tomatoes

| Models | | LL | AIC | P-Value | RMSE |
|---|---|---|---|---|---|
| | Normal | 283.166 | -2.300133 | 0.6698 | 0.090172 |
| EGARCH(1,1) | Student-t | 296.1207 | -2.391043 | 0.7696 | 0.090145 |
| | GED | **299.9943** | **-2.423189** | 0.53160 | 0.090442 |
| | Normal | 281.8653 | -2.281040 | 0.7257 | 0.090167 |
| TARCH(1,1) | Student-t | 295.1096 | -2.382652 | 0.00357 | 0.090120 |
| | GED | 299.1562 | -2.416234 | 0.8750 | **0.090116** |
| | Normal | 282.7517 | -2.280097 | 0.7675 | 0.090204 |
| PARCH(1,1) | Student-t | 296.1376 | -2.382884 | 0.8064 | 0.090142 |
| | GED | 299.4515 | -2.410386 | 0.190226 | 0.090262 |

LL- Log Likelihood, AIC- Akaike Information Criteria, RMSE refers to Root Mean Square Error. The bolded values show the highest log likelihood, and the least RMSE respectively.

**Table 7.** Fitness and forecasting performance of the different heteroscedasticity model at three distribution of error innovation for yam

| Models | | LL | AIC | P-Value | RMSE |
|---|---|---|---|---|---|
| | Normal | 252.0065 | -2.033249 | 0.8012 | 0.104801 |
| EGARCH(1,1) | Student-t | 306.1678 | -2.474422 | 0.7308 | 0.104564 |
| | GED | **307.0414** | **-2.481671** | 0.7787 | 0.104797 |
| | Normal | 252.6618 | -2.038687 | 0.5321 | 0.104848 |
| TARCH(1,1) | Student-t | 303.5399 | -2.444314 | 0.7906 | 0.104704 |
| | GED | 306.8217 | -2.479848 | 0.7748 | 0.104701 |
| | Normal | 253.5036 | -2.037375 | 0.8044 | 0.104840 |
| PARCH(1,1) | Student-t | 306.1426 | -2.465913 | 0.7365 | **0.104556** |
| | GED | 293.0730 | -2.357452 | 0.7783 | 0.104754 |

LL- Log Likelihood, AIC- Akaike Information Criteria, RMSE refers to Root Mean Square Error. The bolded values show the highest log likelihood, and the least RMSE respectively.

**Table 8.** Fitness and Forecasting performance of the different heteroscedasticity model at three distribution of error innovation for yellow garri

| Models | | LL | AIC | F-Value | RMSE |
|---|---|---|---|---|---|
| | Normal | 332.2106 | -2.698843 | 0.468977 | 0.067157 |
| EGARCH(1,1) | Student-t | 381.4199 | -3.098921 | 0.581814 | 0.067220 |
| | GED | **413.7627** | **-3.367326** | 0.473316 | 0.067296 |
| | Normal | 328.1773 | -2.656537 | 0.00003 | 0.067223 |
| TARCH(1,1) | Student-t | 389.5498 | -3.166388 | 0.121041 | 0.067225 |
| | GED | 404.5709 | -3.291045 | 0.5796 | 0.067159 |
| | Normal | 324.3549 | -2.625352 | 0.034309 | 0.067168 |
| PARCH(1,1) | Student-t | 391.2791 | -3.172441 | 0.159716 | 0.067242 |
| | GED | 409.3716 | -3.322586 | 0.4328335 | **0.067105** |

LL- Log Likelihood, AIC- Akaike Information Criteria, RMSE refers to Root Mean Square Error. The bolded values show the highest log likelihood, and the least RMSE respectively.

**Table 9.** Fitness and Forecasting performance of the different heteroscedasticity model at three distribution of error innovation for imported rice

| Models | | LL | AIC | F-Value | RMSE |
|---|---|---|---|---|---|
| | Normal | 271.9379 | -2.198655 | 0.0388 | 0.123257 |
| EGARCH(1,1) | Student-t | 397.3017 | -3.230720 | 0.037506 | 0.123254 |
| | GED | **410.6665** | **-3.341631** | 0.037506 | 0.123260 |
| | Normal | 274.4711 | -2.219677 | 0.043148 | 0.123231 |
| TARCH(1,1) | Student-t | 402.9352 | -3.277470 | 0.02488 | **0.114221** |
| | GED | 401.5056 | -3.265607 | 0.01728 | 0.123246 |
| | Normal | 278.5662 | -2.245336 | 0.0017 | 0.12355 |
| PARCH(1,1) | Student-t | 403.0215 | -3.269888 | 0.0307 | 0.12347 |
| | GED | 407.3662 | -3.305944 | 0.01087 | 0.123283 |

LL- Log Likelihood, AIC- Akaike Information Criteria, RMSE refers to Root Mean Square Error. The bolded values show the highest log likelihood, and the least RMSE respectively.

## 5 Conclusions

In modeling the volatility of the returns price of tomatoes, yam, imported rice, and yellow garri in Cross River State, it is concluded that for enhanced fitness and forecasting performance, ARMA(1,1)/TARCH(1,1)-GED, ARMA(1,1)/TARCH(1,1) with a Normal distribution, and ARMA(1,1)/TARCH(1,1) with a Student's t distribution were the best models for tomatoes, yellow garri, and imported rice respectively. Meanwhile, ARMA(1,1)/PARCH(1,1) with GED should be used when modeling the volatility of yam.

Based on these findings, there is a need for the government to address the security challenges in Nigeria, as many farmers are unable to access their farms due to these issues, particularly in the Northern part of Nigeria where commodities like tomatoes are produced in large quantities. The government should intensify campaigns to encourage people to return to farming. Good storage and packaging facilities for these foodstuffs should be provided to avoid wastage during times of abundance. Additionally, incentives such as modern equipment, improved seeds, and fertilizers should be made available to farmers.

Financial institutions should provide non-interest loans to farmers to enhance food sufficiency. Stakeholders in the marketing chain should use the TARCH(1,1) model to make predictions about volatility in food items. Individuals should plan to engage more in cassava and yam farming in the coming year and consider how best to store these products for future use. This study is a case study, and therefore, similar studies are needed in other states of the federation and in Nigeria as a whole. There is also a need to consider more robust error distributions in the volatility modeling of food prices.

### Data Availability

The data used to support the research findings are available from the corresponding author upon request.

### Conflicts of Interest

The authors declare no conflict of interest.

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