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Econometric Analysis of the Effect of Price Dynamics of Selected Food Crops on Food Security in Nigeria

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Abstract **Original Research Article**

This study analyzed the dynamics and volatility of selected staple food crop prices and their effect on food security in Nigeria using monthly data from January 1980 to November 2025. The study focused on three major staple crops—maize, rice, and cowpea—due to their importance in household consumption and national food security. The Augmented Dickey-Fuller Test (ADF)and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model were employed to examine stationarity and volatility dynamics of the selected crop prices. The ADF test results revealed that all price series were non-stationary at level but became stationary after first differencing, indicating integration of order one, I (1). The ARCH-LM tests confirmed the presence of ARCH effects in all crop prices, justifying the use of the GARCH (1,1) model. The empirical findings revealed significant differences in volatility persistence among the selected crops. Maize prices exhibited the highest volatility persistence with a persistence parameter (α + β) of 0.9605 and a volatility half-life of approximately 17.2 months, indicating prolonged effects of market shocks. Cowpea prices also displayed high volatility persistence with a persistence coefficient of 0.9057 and a half-life of about 7 months, suggesting strong responsiveness to short-run shocks. Rice prices, however, showed relatively moderate volatility persistence with a persistence parameter of 0.5887 and a shorter half-life of 1.3 months, indicating faster market adjustment and greater stability. Diagnostic tests confirmed the adequacy and robustness of the estimated models, as no residual ARCH effects or serial correlation were detected. The study concludes that staple food price volatility constitutes a major threat to food security in Nigeria, particularly for maize and cowpea whose prices are highly sensitive to economic, climatic, and structural shocks. The study recommends strengthening strategic grain reserves, improving rural infrastructure, promoting climate-smart agriculture, ensuring macroeconomic stability, and enhancing market information systems to reduce food price volatility and improve food security outcomes in Nigeria.

Keywords: Food price volatility, Food security, GARCH model, Maize, Rice, Cowpea, Nigeria.

1.0 Introduction

Food security continues to be a major developmental concern in developing countries, especially within sub-Saharan Africa. In Nigeria, the challenge is particularly severe because of ongoing fluctuations in the prices of staple foods, increasing inflation, and structural weaknesses in agricultural production systems (FAO, 2025).

The Food and Agriculture Organization defines food security as a condition in which all individuals, at all times, have physical and economic access to adequate, safe, and nutritious food. Nevertheless, this condition is becoming increasingly difficult to maintain in Nigeria due to unstable food prices, which significantly impact household welfare and overall national food stability (FAO, 2023).

Staple crops such as maize, rice, and cowpea are vital components of Nigeria's food system, providing major sources of calories and protein for much of the population. In addition to their nutritional value, they also represent important sources of livelihood for rural households. However, the prices of these crops have shown considerable fluctuations over time due to both internal and external factors, including climate variability, exchange rate instability, insecurity in major food-producing areas, and increasing costs of inputs such as fertilizer, transportation, and Labor (World Bank, 2023; Adeyemi et al., 2024).

Volatility in agricultural commodity prices has significant consequences for food security. Rapid increases in food prices weaken the purchasing power of consumers, especially low-income households, leading to greater risks of hunger and malnutrition. For producers, unstable prices create uncertainty, which can discourage agricultural investment and lower productivity (Minot, 2014). In Nigeria, recurring surges in food prices, particularly since 2016 and after the COVID-19 pandemic, have intensified poverty and weakened efforts toward achieving national food security objectives (National Bureau of Statistics [NBS], 2024).

Understanding the behavior of food prices is essential for developing effective agricultural and food policies. Conventional econometric methods typically assume constant variance in time series data, but agricultural prices often display volatility clustering, where periods of high fluctuations are followed by similar periods, while stable periods tend to persist. This characteristic makes advanced techniques such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model more appropriate, as it is designed to capture changing volatility patterns in financial and commodity price data (Bollerslev, 1986).

The application of GARCH models in agricultural economics has gained prominence due to their ability to model and forecast volatility patterns effectively. Several empirical studies have applied GARCH-type models to analyze food price volatility in developing countries, revealing significant persistence and asymmetric effects in price movements (Gilbert & Morgan, 2010; Abdulai, 2022). In Nigeria, however, there remains limited comprehensive analysis focusing specifically on staple crops such as maize, rice, and cowpea using volatility modeling techniques, particularly in relation to food security outcomes.

Furthermore, Nigeria's agricultural sector is undergoing structural transformation amidst policy interventions such as the Anchor Borrowers' Programme, border closures (2019–2020), and recent subsidy reforms. While these policies aim to stabilize food supply and prices, their actual effects on price dynamics and volatility remain unclear. Given the importance of stable food prices in achieving food security, there is a need for empirical investigation into how price volatility in key staple crops evolves over time and how it impacts food security.

This study therefore seeks to analyze the dynamics of selected staple food crop prices—maize, rice, and cowpea—in Nigeria using the GARCH modeling framework. By examining volatility patterns and persistence, the study provides insights into the stability of food prices and their implications for food security. The findings are expected to inform policymakers on strategies to mitigate price volatility and enhance food system resilience in Nigeria.

1.1 Problem Statement

Despite numerous agricultural policies and interventions implemented by the Nigerian government, food insecurity remains widespread and persistent. Nigeria is currently ranked among countries facing significant food insecurity challenges, with millions of households unable to meet their daily nutritional requirements (FAO, 2023; World Bank, 2024). One of the key drivers of this problem is the continuous fluctuation and instability in staple food prices.

In recent years, the prices of major staple crops—maize, rice, and cowpea—have exhibited pronounced volatility. These fluctuations are influenced by multiple factors including climate shocks, insecurity in agricultural regions, exchange rate depreciation, and rising production costs. The unpredictability of these price movements poses serious challenges for both producers and consumers. For consumers, especially low-income households, rising and unstable prices reduce access to food, thereby worsening food insecurity. For producers, price uncertainty affects production planning and investment decisions, ultimately reducing agricultural output. While several studies have examined food price trends and determinants in Nigeria, most have relied on traditional econometric methods that do not adequately capture the dynamic and volatile nature of agricultural prices. As a result, there is limited understanding of the persistence, clustering, and transmission of volatility in staple food prices. Moreover, existing studies often focus on individual commodities or aggregate food price indices, with little attention given to a comparative analysis of key staples such as maize, rice, and cowpea.

Another critical gap lies in the linkage between price volatility and food security outcomes. Although it is widely acknowledged that price instability affects food access and availability, empirical evidence quantifying this relationship in Nigeria remains insufficient. Without a clear understanding of how price volatility impacts food security, policy responses may be ineffective or misdirected. Given these challenges, there is a need for a comprehensive analysis that captures the dynamic behavior of staple food prices using appropriate econometric tools such as the GARCH model. Such an analysis will not only enhance understanding of price volatility patterns but also provide evidence on their implications for food security in Nigeria. Addressing this gap is essential for designing policies aimed at stabilizing food prices and improving the welfare of households.

1.2 Objectives of the Study

The main objective of this study was to carry out Econometric analysis of the Effect of Price Dynamics of selected Food Crops on Food Security in Nigeria.

The specific objectives are to:

1. To determine the persistence and effects of price volatility of these staple crops on food security.
2. Provide policy recommendations aimed at stabilizing food prices and improving food security outcomes.

2.0 Literature Review

2.1 Concept of Food Price Volatility and Food Security

Food price volatility is a major concern in both developed and developing economies because it affects welfare, macroeconomic stability, and food security. It describes how much prices fluctuate over time in terms of both frequency and size. In agricultural markets, these fluctuations are commonly caused by supply shocks, changes in demand, policy shifts, and broader macroeconomic instability. The problem is often more severe in developing countries like Nigeria, where structural weaknesses and external shocks intensify price instability (Tolulope, 2022).

Food security refers to the availability, access, utilization, and stability of food. Price volatility mainly affects access and stability by reducing purchasing power and making food supply less predictable. Research shows that unstable and rising food prices disproportionately harm low-income households, increasing poverty, malnutrition, and food insecurity (Ajibade et al., 2020). In Nigeria, where households spend a large share of income on food, even small price increases can have serious welfare effects.

Empirical studies also show that food price shocks significantly drive inflation. Research supported by the Central Bank of Nigeria indicates that food price changes strongly increase overall inflation, with price rises having a greater effect than price falls

(Bello & Rafindadi, 2023). This asymmetric transmission worsens household vulnerability and reinforces inflationary pressure. Overall, evidence suggests that food price volatility, influenced by macroeconomic factors and external shocks, contributes significantly to persistent inflation and welfare losses in developing economies like Nigeria (Bello & Rafindadi, 2023).

Recent empirical studies using advanced econometric methods provide deeper understanding of food price volatility. Essien et al. (2024), using GARCH models, found that food prices in Nigeria show strong volatility clustering and persistence, meaning shocks such as fuel price increases or exchange rate depreciation can have long-lasting effects and worsen food insecurity if not addressed. Similarly, Udeaja and Isah (2024), applying a GARCH-MIDAS approach, showed that insecurity—especially terrorism—plays a major role in driving food price volatility in Nigeria, outweighing traditional factors like climate variability. This highlights the growing importance of conflict-related disruptions in food price dynamics.

Cross-country evidence also reinforces these findings. Ng'ombe (2025), using a GARCH-X model, found that including external factors such as exchange rates, fertilizer prices, and global commodity prices improves the explanation of maize price volatility in African countries, including Nigeria, emphasizing strong global-local market linkages in import-dependent economies. In a broader global context, Dai et al. (2024) showed that geopolitical risks significantly affect the volatility of staple crops like maize, rice, and wheat, with shocks transmitting quickly into domestic markets, especially where market integration is weak.

Other studies emphasize structural and institutional weaknesses. Poor infrastructure, weak storage systems, and inefficient supply chains increase volatility by raising costs and reducing market efficiency, while macroeconomic instability—particularly exchange rate depreciation and rising energy prices—further worsens food price fluctuations in Nigeria and similar economies. Finally, Zimboh et al. (2024) highlight those broader macroeconomic shocks, including currency fluctuations and global crises, strongly influence volatility in Nigeria's consumer staple markets. Although focused on financial markets, their findings are relevant to food commodities due to strong macroeconomic linkages.

Recent studies show that food price volatility has significant implications for food security outcomes. Persistent fluctuations reduce household purchasing power, heighten uncertainty, and discourage agricultural investment, thereby worsening livelihood stability. In Nigeria, where households allocate a large share of income to food, these effects are particularly severe. Empirical evidence further shows that food price volatility negatively affects food access and dietary quality, as households often substitute toward cheaper, less nutritious foods during periods of price increases (Amolegbe et al., 2021; Tolulope, 2022; Masters, 2022). However, gaps remain in the literature. Many studies using advanced GARCH-type models focus on overall food price indices rather than key staples like maize, rice, and cowpea. There is also limited integration of volatility analysis with food security indicators using recent data, particularly reflecting post-COVID-19 and subsidy reform periods. In addition, comparative studies across different staple crops using models such as GARCH-MIDAS and GARCH-X are still limited.

To address these gaps, this study applies the GARCH model to examine volatility in maize, rice, and cowpea prices and their implications for food security in Nigeria. It incorporates recent economic developments to provide updated and policy-relevant insights into staple food price behaviour.

2.2 Theoretical and Empirical Approaches to Price Volatility Modelling

The analysis of price volatility has evolved significantly with the development of econometric models capable of capturing time-varying variance. Traditional linear models assume constant variance, which is unrealistic for agricultural price series characterized by volatility clustering. To address this limitation, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was introduced as an extension of ARCH models, allowing for dynamic modelling of conditional variance (Engle, 1982; Bollerslev, 1986).

GARCH models are widely used in financial and agricultural studies because they effectively capture volatility clustering and persistence. Evidence shows that food prices are highly persistent, meaning shocks have long-lasting effects. For instance, Fasanya et al. (2018) found that macroeconomic factors such as exchange rates, inflation, and oil prices significantly affect food price volatility in Nigeria using multivariate GARCH models.

Similarly, Udeaja and Isah (2024), using a GARCH-MIDAS approach, showed that insecurity and terrorism are key drivers of food price volatility in Nigeria, even more influential than climate-related factors. This is especially important given rising security challenges in major agricultural regions. Globally, advanced GARCH-type models such as GJR-GARCH and EGARCH are used to capture asymmetry and nonlinear behavior in price movements. Evidence shows that agricultural commodity prices commonly display volatility clustering and persistence, where shocks affect both short- and long-term market stability (Dai et al., 2024). In addition, newer methods using high-frequency and range-based estimators suggest that volatility can act as an early warning signal of market stress, especially in fragile and conflict-affected regions (Andrée, 2026).

2.3 Empirical Evidence on Staple Food Price Volatility in Nigeria

Empirical evidence from Nigeria shows persistent volatility in staple food prices, especially for maize, rice, and other cereals. Tolulope (2022) found clear evidence of volatility clustering in food prices from 2000–2012, indicating alternating periods of high and low instability, which suggests that price shocks follow predictable patterns rather than occurring randomly. Focusing on maize, Sani and Orefi (2022) used ARCH and GARCH models and found that maize prices are highly volatile, driven by both market forces and policy changes. They also observed asymmetry, where positive shocks (such as good harvests or supportive policies) reduce volatility more strongly than negative shocks increase it.

Similarly, Ajibade et al. (2020) identified exchange rate fluctuations, inflation, and agricultural production disruptions as key drivers of food price volatility in Nigeria, noting that macroeconomic instability worsens food insecurity. More recent developments reinforce these findings, as persistent food inflation—driven by currency depreciation, rising fuel costs, and climate shocks—has significantly increased staple food prices and reduced household purchasing power, especially among vulnerable groups.

2.4 Link Between Food Price Volatility and Food Security

The link between food price volatility and food security is well established in the literature. Price instability disrupts food access and availability, making it harder for households to maintain stable consumption patterns. Unpredictable and high prices reduce real income and force coping strategies such as reducing meal frequency or switching to cheaper, less nutritious foods (FAO, IFAD, UNICEF, WFP, & WHO, 2023; Headey & Martin, 2016).

Evidence from Nigeria shows that food price volatility negatively affects food security, leading to lower food consumption and increased poverty, particularly among rural and urban poor households (Ajibade et al., 2020; Amolegbe et al., 2021). It also increases uncertainty in agricultural markets, discouraging investment and reducing productivity, which further constrains food supply (Headey & Martin, 2016).

Recent studies further emphasize that structural and institutional weaknesses—such as poor infrastructure, weak market integration, and ineffective policy responses—intensify these effects (Timmer, 2010; Bellemare, 2015). In addition, insecurity and climate change have increased the frequency and severity of food price shocks, deepening vulnerability in

Nigeria's food system (FAO et al., 2023; IFPRI, 2022).

3.0 Methodology

3.1 The Study Area

Nigeria is a West African country located along the Gulf of Guinea, positioned between latitudes 4°N–14°N and longitudes 2°–15°E, covering approximately 923,768 km². It shares borders with Benin, Niger, Chad, and Cameroon (Wikipedia, 2024). The country has a rapidly growing population, increasing at over 2% annually, with life expectancy estimated in the mid-50s (World Bank, 2024; Britannica, 2026).

Nigeria is also ecologically diverse, with vegetation zones that support extensive agricultural and livestock production. It has an estimated surface water capacity of about 267.7 billion m³ and groundwater resources of about 57.9 billion m³. The country spans several ecological zones, including the Sudan/Sahel, Guinea and Derived Savanna, and Forest/Mangrove belts, where variations in rainfall and ecological conditions strongly influence farming systems and resource use (Erragheore, 2011).

Agriculture remains central to Nigeria's economy, with major cash crops such as cocoa, oil palm, and rubber. Key staple crops include rice, cassava, yam, maize, sorghum, and millet. Livestock production (goats, sheep, cattle, and poultry) and artisanal fisheries also contribute significantly to food supply and rural livelihoods (Hussfarm, 2024).

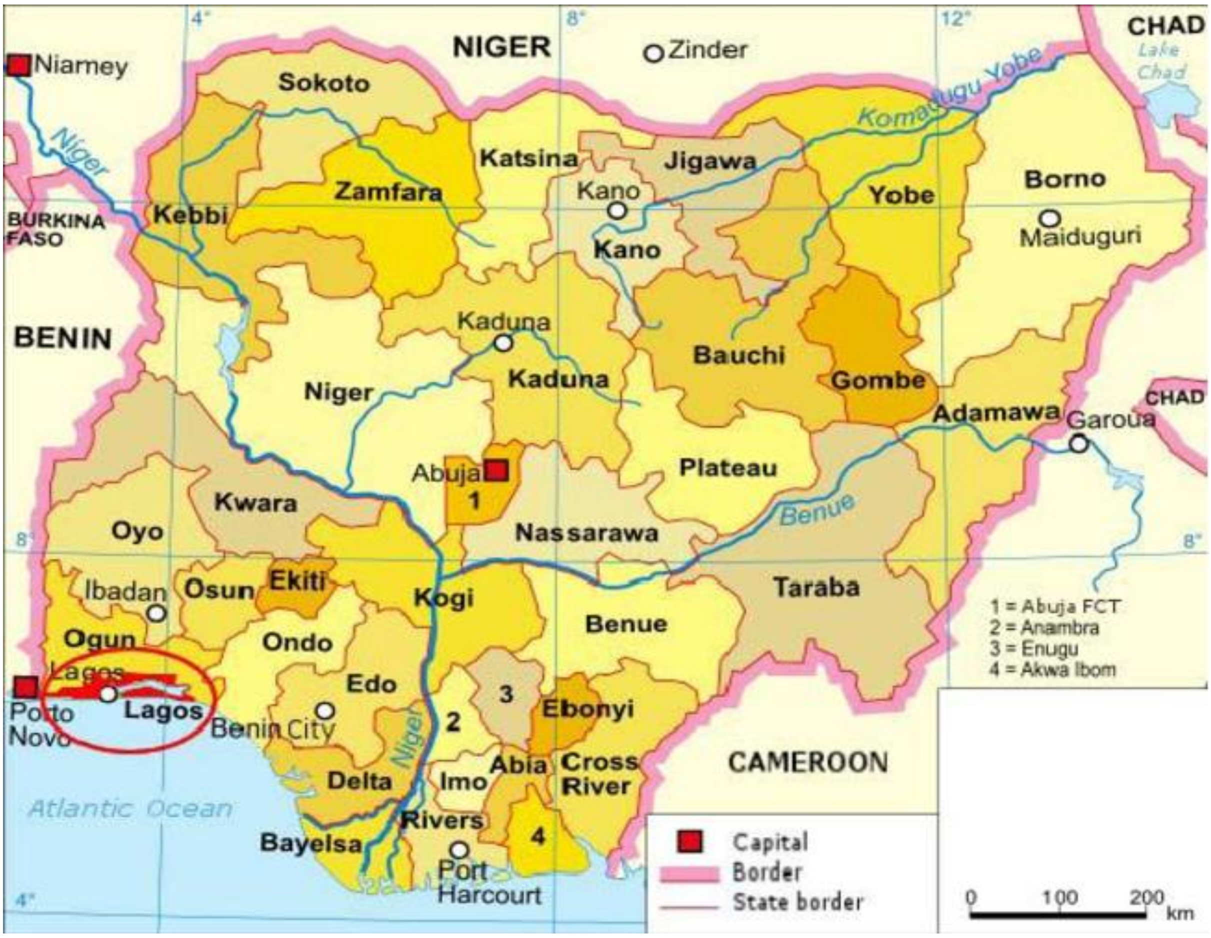

Figure 1: Map of Nigeria showing the 36 States and the federal Capital Territory (FCT).
Source: www.researchgate.net

3.2 Data Source

The study used secondary data. Time series data were collected from multiple sources including the Central Bank of Nigeria (CBN) and Nigeria Bureau Statistics (NBS) Statistical Bulletins respectively (2019, 2020, and 2022). The dataset covered the period from 1981 to 2022.

3.3 Method of Data Analysis

The secondary data used in this study were analyzed using the Generalized Autoregressive Conditional Heteroskedascity (GARCH).

3.4 Model Specification/Estimation Techniques

3.4.1 Stationarity Test

Most time series data need to be tested initially to establish the integration order of the variables, mainly to prevent spurious regression outcomes (Granger & Newbold, 1974; Gujarati & Porter, 2009; Enders, 2015). Accordingly, the presence of unit roots in the variables was examined using the Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1981).

The ADF test is based on the following regression given in equation 3.1.

$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} \sum_{i=0}^{n} \lambda i \, \Delta Y_{t-1} + \varepsilon_t$ …. (3.1)

Where:

$\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2})$ represent the difference of the variable at time t.

Y = coefficient of the lagged level of the variable

$\beta_{1=}$ coefficient on the time trend (indicating how series changeover time).

δ = coefficient on the lagged difference of the series

ε_t = pure white noise error term and

The number of lagged difference terms to include is often determined empirically. The ADF test that the series is not stationary is shown by the null hypothesis (Ho: $\beta = 0$) whereas the alternative hypothesis (H_1: $\beta < 0$) shows that the series is stationary. The rule is that if the computed ADF statistics is greater than the critical at the specified level of significance, then the hull hypothesis of unit root is accepted otherwise it is rejected.

3.4.2 Test for ARCH Effect

Time-series econometric models are commonly used to analyze price volatility, with Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) being standard tools for measuring conditional volatility (Engle, 1982; Bollerslev, 1986). Extensions such as Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH) capture asymmetries, where positive and negative shocks affect volatility differently (Iheanacho & Edike, 2020). Volatility often clusters and persists, meaning shocks can have prolonged effects.

Before applying a GARCH model, it is necessary to test for ARCH effects to confirm that volatility exists, as non-volatile series are unsuitable for such models; this is typically done using a univariate framework. The ARCH effect is typically assessed using a univariate model.

$\lambda_t = \varphi + \sum_{i=1}^{k} \psi_I \lambda_{t-1} + \varepsilon_{t;}$ i=1, k ……… (3.1)

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

Where:

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

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 test for ARCH effects, a three-step procedure based on Robert F. Engle (1982) was used. First, Equation (3.1) was estimated with Ordinary Least Squares (OLS) to obtain residuals. Then, the squared residuals were regressed on a constant and their lagged values, as shown in Equation (3.2).

$\varepsilon_t^2 = \zeta_0 + \zeta_1 \varepsilon^2_{t-1} + \zeta_2 \varepsilon^2_{t-2} + \ldots + \zeta_k \varepsilon^2_{t-k} + \mu_t$ (3.2)

The final step involves applying the ARCH-LM test to determine the presence of ARCH effects in the model. The null hypothesis of the test is stated as follows:

$H_o: \xi_1 = \xi_2 = \ldots = \xi_k = 0$

The presence of ARCH effects is evaluated using the F-statistic or the Chi-square (χ^2) test, computed as the product of the sample size (n) and the coefficient of determination (R^2) from Equation (3.2). A p-value below the chosen significance level leads to rejection of the no-ARCH hypothesis, indicating volatility and suitability for GARCH modelling.

4.4 GARCH (p, q) Model.

To achieve the study objective of evaluating price volatility and persistence in selected staple food crops in Nigeria, the GARCH (p, q) model was employed. The model assumes an underlying first-order autoregressive [AR (1)] process. The Autoregressive Conditional Heteroskedasticity model of order q, ARCH(q), introduced by Engle (1982), is specified as follows:

$r_t = \mu_t + \mathcal{E}_t$ ……………… (3.3)

$\mathcal{E}t = \sigma_t e_t$; $e_t \sim N(0,1)$ ……………… (3.4)

$= \text{Ꞷ} + \alpha_1 \varepsilon^2 t_{t-1} + \alpha_2 \varepsilon^2_{t-2} + \text{-----} + \alpha_q \varepsilon^2_{t-q} = \text{Ꞷ} + \sum \alpha_1 \varepsilon^2_{t-1}$ …………………………. (3.5)

Where $\mathcal{E}_t$ is the shock at time t and it follows heteroskedastic error process, $\sigma^2\ t$ is the volatility at time t, ε^2_{t-1} is the squared error term at time t-1 and Ꞷ is a constant term. The ARCH model was generalized to GARCH model by (Bollerslev, 1986). A Generalized Autoregressive Conditional Heteroskedasticity process is said to be a GARCH (p, q) process if;

$\delta^2_t = \text{Ꞷ} + \sum \alpha_1 \varepsilon^2_{t-1} + \sum \beta_1 \sigma^2_{t-1}$ ………… (3.6)

Where; $\sigma^2\ t$ is the Conditional variance, Ꞷ is a constant term. Equation (3.6) implies that the conditional variance of the error term which is a proxy of farm price volatility at period 't' was explained by the past shocks or square of the error term (ARCH i.e. ε^2_{t-1}) and past variance or volatility term (the GARCH term i.e. σ^2_{t-1}). It is presumed that, for equations 3.6 to be stationary,$0 < \alpha 1 < 1$; $0 < \beta 1 < 1$ and $\alpha 1 + \beta 1 < 1$ must be met. Bollerslev (1986) stated that as the sum of α and β becomes close to unity, volatility becomes much more persistent.

4.0 RESULTS AND DISCUSSION

4.1 Augmented Dickey-Fuller (ADF) test

The result of the unit root test is presented in Table 1. The test revealed that the variable became stationary and at first difference. That is, the variable is integrated of order I (1).

Table 1: Augmented Dickey-Fuller Unit Root Test Result for Stationarity- Monthly Prices Selected Food Crops (JAN.1980- DEC.2025)

Variable	Order of stationarity	ADF Calculated	ADF Critical Value	Prob.	Order of integration	Decision
PCOWPEA	Level	-0.206009	-3.975367	0.9928	I(0)	NS
	1st Dif.	-7.058700	-3.418274	0.0000	I(1)	S
PMAIZE	Level	-0.211022	-3.418290	0.9927	I(0)	NS

	1^{st} Dif.	-6.55033	-3.418306	0.0000	I(1)	S
PRICE	Level	-1.716692	-3.418274	0.7428	I(0)	NS
	1^{st} Dif.	-6.151856	-3.418274	0.0000	I(1)	S

Source: Output from (E-views 10)

4.2 Test for ARCH effects for Maize Price

The ARCH-LM test was used to examine volatility in maize prices, with results presented in Table 2. The significant p-values for both the F-statistic and observed R^2 confirm the presence of ARCH effects, indicating that maize prices are volatile. Since the p-value (0.0002) is below standard significance levels (0.01, 0.05, 0.10), the null hypothesis of no ARCH effects is rejected (Engle, 1982; Brooks, 2019). This suggests that maize price volatility is time-varying, thereby justifying the application of a GARCH model.

Table 2: ARCH-LM Test

Variable	Coefficient	Probability
F-Statistics	14.21521	Prob. F (0.0002)
Observed R2	13.90581	Prob. Chi-Square (0.0002)

Source: output form EViews

4.2.1 Volatility Dynamics of Maize Prices in Nigeria: GARCH (1,1)

Understanding maize price volatility is essential for food security, as unstable prices can disrupt access to food, consumption patterns, and agricultural investment (FAO, 2023; World Bank, 2025). The GARCH (1,1) results for monthly maize prices (1980–2025), presented in Table 3, capture time-varying volatility driven by past shocks and previous volatility (Engle, 1982; Bollerslev, 1986).

The lagged maize price coefficient (0.9847) is highly significant, indicating strong persistence. This suggests that price shocks tend to last over time, making market outcomes and household planning more uncertain (Minot, 2014; Gilbert & Morgan, 2010). The ARCH coefficient ($\alpha = 0.9553$) is large and significant, showing that recent shocks strongly and immediately affect maize price volatility. This confirms that volatility is highly responsive to new information such as policy changes, supply disruptions, and market shocks.

The GARCH coefficient ($\beta = 0.0052$), although significant, is relatively small, implying that volatility is influenced more by recent shocks than by past volatility. The sum ($\alpha + \beta = 0.9605$) is less than 1, indicating a stable and mean-reverting process. However, the dominance of the ARCH term suggests that maize price volatility in Nigeria is largely shock-driven rather than persistent. This pattern aligns with evidence that food price volatility in developing countries is mainly influenced by external factors such as climate variability, exchange rate fluctuations, and policy shocks (Arezki & Brückner, 2011; Siciliano et al., 2019).

High sensitivity to shocks implies that events like weather changes, insecurity, or policy shifts can significantly destabilize maize prices. Given maize's importance in Nigeria, this increases risks for low-income households and may lead to reduced food access, unstable production costs, and lower agricultural investment (Nwosu et al., 2021). The findings suggest the need for shockmitigating measures such as grain reserves, price stabilization policies, sound macroeconomic management, and climate-resilient agricultural investments (FAO, 2023; World Bank, 2025).

Overall, the GARCH (1,1) results show that maize price volatility in Nigeria is stable but primarily driven by short-term shocks rather than long-term persistence. This shock-driven volatility poses significant risks to food security and economic stability.

Table 3: Maize Price GARCH estimates

Variable	Coefficient	Std. Error	Z-Statistic	Prob.
C	0.045387	0.002877	15.77648	0.0000
MPRETURNS (-1)	0.984662	0.001328	741.3493	0.0000
		Variance Equation		
C ((ω)	0.000615	3.36E-05	18.30329	0.0000
RESID (-1) ^2	0.955274	0.113143	8.443090	0.0000
GARCH (-1)	0.005185	0.008342	0.621531	0.0343
R-squared	0.797274	Mean dependent var		1.526120
Adjusted R-squared	0.797269	S.D. dependent var		0.931321
S.E. of regression	2.048671	Akaike info criterion		3.611309
Sum squared resid	1.298113	Schwarz criterion		3.572128
Log likelihood	998.1100	Hannan-Quinn criter.		3.595998
Durbin-Watson stat	1.911095			

Source: output from EViews

4.2.3 Post Estimation Tests for Maize Price ARCH Effect

To confirm the robustness of the GARCH estimates, an ARCH effect diagnostic test was performed. The heteroskedasticity test results reveal that the probability values for both the F-statistic and R² suggest the absence of ARCH effects as presented in Table 4. Because the p-values associated with the F-statistic (0.7354) and the Chi-square statistic (0.7348) are higher than standard significance thresholds (0.01, 0.05, and 0.10), the null hypothesis of no ARCH (1) effects was accepted, indicating that ARCH effects are not present.

Table 4: Heteroskedasticity Test: ARCH

F-statistic	0.114344	Prob. F (1,547)	0.7354
Obs*R-squared	0.114738	Prob. Chi-Square (1)	0.7348

Source: Authors computation from EViews

4.2.4 Post Estimation Tests for Serial Correlation Test

The post estimation test for serial correlation as shown in table 5 below reveals that the probability of Q-Stat for the AC and PAC are all not significant. This implies that there is no serial correlation.

Table 5: Serial Correlation Test

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.051	0.051	1.4352	0.231
.|. |	.|. |	2	-0.035	-0.038	2.1216	0.346
.|. |	.|. |	3	-0.019	-0.016	2.3283	0.507
.|. |	.|. |	4	-0.019	-0.018	2.5244	0.640
.|. |	.|. |	5	-0.033	-0.033	3.1388	0.679
.|. |	.|. |	6	-0.023	-0.021	3.4233	0.754
.|. |	.|. |	7	-0.012	-0.013	3.5084	0.834
.|. |	.|. |	8	-0.003	-0.004	3.5123	0.898
.|. |	.|. |	9	-0.023	-0.026	3.8213	0.923
.|. |	.|. |	10	0.027	0.027	4.2163	0.937
.|. |	.|. |	11	-0.011	-0.017	4.2803	0.961
.|. |	.|. |	12	0.046	0.047	5.4691	0.940
.|. |	.|. |	13	-0.016	-0.023	5.6187	0.959
.|. |	.|. |	14	-0.008	-0.004	5.6522	0.975
.|. |	.|. |	15	0.002	0.003	5.6543	0.985
.|. |	.|. |	16	-0.004	-0.004	5.6647	0.991
.|. |	.|. |	17	-0.002	0.001	5.6661	0.995
.|. |	.|. |	18	-0.039	-0.040	6.5182	0.994
.|. |	.|. |	19	0.017	0.023	6.6928	0.996
.|. |	.|. |	20	-0.000	-0.008	6.6928	0.998

Source: output from EViews

4.2.5 Post Estimation Tests for Serial Correlation of Squared Residuals

The post estimation of serial correlation of Squared Residuals as presented in table 6 below reveals that non of the probability of Q-Stat for the AC and PAC is significant. This implies the absence of serial correlation of squared residuals.

Table 6: Test for Serial Correlation of Squared Residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.051	0.051	1.4352	0.231
.|. |	.|. |	2	-0.035	-0.038	2.1216	0.346
.|. |	.|. |	3	-0.019	-0.016	2.3283	0.507
.|. |	.|. |	4	-0.019	-0.018	2.5244	0.640
.|. |	.|. |	5	-0.033	-0.033	3.1388	0.679
.|. |	.|. |	6	-0.023	-0.021	3.4233	0.754
.|. |	.|. |	7	-0.012	-0.013	3.5084	0.834
.|. |	.|. |	8	-0.003	-0.004	3.5123	0.898
.|. |	.|. |	9	-0.023	-0.026	3.8213	0.923
.|. |	.|. |	10	0.027	0.027	4.2163	0.937
.|. |	.|. |	11	-0.011	-0.017	4.2803	0.961

.|. |	.|. |	12	0.046	0.047	5.4691	0.940
.|. |	.|. |	13	-0.016	-0.023	5.6187	0.959
.|. |	.|. |	14	-0.008	-0.004	5.6522	0.975
.|. |	.|. |	15	0.002	0.003	5.6543	0.985
.|. |	.|. |	16	-0.004	-0.004	5.6647	0.991
.|. |	.|. |	17	-0.002	0.001	5.6661	0.995
.|. |	.|. |	18	-0.039	-0.040	6.5182	0.994
.|. |	.|. |	19	0.017	0.023	6.6928	0.996
.|. |	.|. |	20	-0.000	-0.008	6.6928	0.998

Source: output from EViews

4.3. Test for ARCH effects for Rice Price

The ARCH-LM results presented in Table 7 reveal significant ARCH effects in rice prices, as the p-values for both the F-statistic and the observed R^2 are 0.0000, far below the 0.05 threshold. This provides strong evidence to reject the null hypothesis of no ARCH (1) effects, confirming the existence of volatility. The finding indicates that maize price volatility changes over time, supporting the appropriateness of applying a GARCH model.

Table 7: Heteroskedasticity Test: ARCH

F-statistic	18.12226	Prob. F (1,547)	0.0000
Obs*R-squared	17.60526	Prob. Chi-Square (1)	0.0000

Source: output from EViews

4.3.1 Volatility Dynamics of Rice Prices in Nigeria: GARCH (1,1)

Rice price volatility in Nigeria was examined using a GARCH (1,1) model with monthly data from 1980–2025 presented in Table 8. The lagged price coefficient (0.9912) is positive and highly significant, indicating strong persistence—current prices are largely driven by past values, and shocks dissipate slowly, reflecting rigid market structures (Gilbert & Morgan, 2010; Minot, 2014; FAO, 2023). The ARCH coefficient ($\alpha = 0.0071$) is positive, significant, but small, suggesting that recent shocks have limited short-term effects on volatility. By contrast, the GARCH coefficient ($\beta = 0.5816$) is larger and significant, indicating that past volatility has a stronger influence, resulting in moderate persistence and volatility clustering over time (Bollerslev, 1986; World Bank, 2022).

Since $\alpha + \beta < 1$, volatility is stable and mean-reverting, implying that shocks are temporary and fade over time. Compared to maize, rice prices exhibit lower persistence and a more stable volatility structure. The insignificant variance constant further indicates that volatility is driven mainly by past shocks and past volatility rather than long-term structural factors. Overall, rice price volatility is moderate—fluctuations occur but are not permanent—allowing for more effective policy intervention and suggesting lower food security risk relative to maize. However, the persistence of volatility implies that macroeconomic shocks can still influence prices over time (Headey & Fan, 2008; FAO, 2023).

In summary, rice prices in Nigeria display moderate, mean-reverting volatility with limited short-term shock effects. Although more stable than maize, sustained policy attention is required to maintain price stability and safeguard household welfare.

Table 8: Rice Price GARCH estimates

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.023449	0.008357	2.805921	0.0050
RPRETURNS (-1)	0.991236	0.004392	225.6736	0.0000
	Variance Equation			
C	0.001900	0.002127	0.893475	0.3716
RESID (-1) ^2	0.007093	0.000197	36.03575	0.0000
GARCH (-1)	0.581601	0.469666	1.238330	0.0156
R-squared	0.796183	Mean dependent var		2.058115
Adjusted R-squared	0.796176	S.D. dependent var		0.897471
S.E. of regression	2.055497	Akaike info criterion		2.876697
Sum squared resid	1.687807	Schwarz criterion		2.837516
Log likelihood	796.0918	Hannan-Quinn criter.		2.861386
Durbin-Watson stat	1.928244			

Source: output from EViews

4.3.2 Post Estimation Tests for Rice Price ARCH Effect

Check for ARCH Effects: To validate the GARCH results, an ARCH effect test was performed and result is presented in Table 9. The p-values for both the F-statistic (0.5941) and Chi-square (0.5933) exceed standard significance levels (0.01, 0.05, 0.10), indicating no ARCH effects. Thus, the null hypothesis of no ARCH (1) effect is accepted, confirming the absence of heteroskedasticity.

Table 9: Heteroskedasticity Test: ARCH

F-statistic	0.284292	Prob. F	0.5941
Obs*R-squared	0.285184	Prob. Chi-Square	0.5933

Source: output from Eviews

4.3.4 Post Estimation Tests for Serial Correlation Test

The post estimation test for serial correlation as shown in table 10 below reveals that the probability of Q-Stat for the AC and PAC are all not significant. This implies that there is no serial correlation.

Table 10: Serial Correlation Test

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|* |	.|* |	1	-0.002	-0.002	0.0001	0.990
.|* |	.|* |	2	-0.029	-0.029	0.0423	0.979
.|. |	*|. |	3	-0.030	-0.030	0.0868	0.993
*|. |	*|. |	4	-0.031	-0.032	0.1358	0.998
*|. |	*|. |	5	-0.032	-0.034	0.1904	0.999
*|. |	*|. |	6	-0.033	-0.036	0.2495	1.000
*|. |	*|. |	7	-0.033	-0.038	0.3119	1.000
*|. |	*|. |	8	-0.034	-0.040	0.3775	1.000
.|. |	.|. |	9	-0.034	-0.042	0.4471	1.000
.|. |	.|. |	10	-0.034	-0.044	0.5180	1.000
.|* |	.|* |	11	-0.036	-0.048	0.5994	1.000
.|. |	.|* |	12	-0.036	-0.050	0.6838	1.000
.|* |	.|* |	13	-0.039	-0.055	0.7842	1.000
.|* |	.|. |	14	-0.038	-0.057	0.8828	1.000
.|. |	.|. |	15	-0.040	-0.063	0.9944	1.000
*|. |	.|. |	16	-0.007	-0.032	0.9975	1.000
*|. |	*|. |	17	-0.007	-0.035	1.0009	1.000
*|. |	.|. |	18	-0.005	-0.034	1.0030	1.000
*|. |	.|. |	19	-0.005	-0.035	1.0053	1.000
*|. |	.|. |	20	-0.005	-0.035	1.0072	1.000

Source: output from EViews

4.3.5 Post Estimation Tests for Serial Correlation of Squared Residuals

The post estimation of serial correlation of Squared Residuals as presented in table 11 below reveals that non of the probability of Q-Stat for the AC and PAC is significant. This implies the absence of serial correlation of squared residuals.

Table 11: Test for Serial Correlation of Squared Residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.023	0.023	0.2873	0.592
.|. |	.|. |	2	-0.004	-0.004	0.2958	0.863
.|. |	.|. |	3	-0.003	-0.003	0.3017	0.960
.|. |	.|. |	4	-0.005	-0.005	0.3176	0.989
.|. |	.|. |	5	-0.006	-0.006	0.3407	0.997
.|. |	.|. |	6	-0.008	-0.008	0.3758	0.999
.|. |	.|. |	7	-0.006	-0.006	0.3959	1.000
.|. |	.|. |	8	-0.006	-0.006	0.4168	1.000
.|. |	.|. |	9	-0.005	-0.005	0.4316	1.000
.|. |	.|. |	10	-0.005	-0.005	0.4454	1.000
.|. |	.|. |	11	-0.006	-0.006	0.4665	1.000

.|. |	.|. |	12	0.001	0.001	0.4670	1.000
.|. |	.|. |	13	-0.006	-0.007	0.4909	1.000
.|. |	.|. |	14	-0.005	-0.005	0.5028	1.000
.|. |	.|. |	15	-0.004	-0.004	0.5128	1.000
.|. |	.|. |	16	-0.004	-0.004	0.5227	1.000
.|. |	.|. |	17	-0.002	-0.002	0.5253	1.000
.|. |	.|. |	18	-0.006	-0.006	0.5435	1.000
.|. |	.|. |	19	0.004	0.004	0.5544	1.000
.|. |	.|. |	20	-0.005	-0.006	0.5715	1.000

Source: output from EViews

4.4 Test for ARCH effects for Cowpea Price

The ARCH-LM test in Table 12 shows an F-statistic p-value of 0.0000, well below 0.05, leading to rejection of the no ARCH (1) effects hypothesis. This confirms the presence of ARCH effects and indicates volatility in cowpea prices, justifying the use of a GARCH model. It also suggests that price volatility is time-varying and suitable for GARCH analysis.

Table 12: Heteroskedasticity Test: ARCH

F-statistic	25.78032	Prob. F	0.0000
Obs*R-squared	24.70999	Prob. Chi-Square	0.0000

Source: output from EViews

4.4.1 Volatility Dynamics of Cowpea Price in Nigeria: GARCH (1,1) Results

A GARCH (1,1) model was used to examine cowpea price volatility in Nigeria, the result is presented in Table 13. The positive and significant constant (0.047840) indicates a long-run upward price trend driven by supply constraints, inflation, and climate shocks (Adenegan & Olagunju, 2012). The lagged price coefficient (0.981800) is close to one, showing strong dependence on past prices and slow adjustment to shocks, consistent with market inefficiencies (Nyangena & Mutai, 2008; Balchin & Hossein, 2018). The significant variance constant reflects a stable baseline level of volatility linked to seasonal and production risks (Ayinde & Adebayo, 2019).

The high ARCH coefficient (α = 0.779572) indicates that recent shocks strongly influence volatility, while the smaller but significant GARCH coefficient (β = 0.126164) shows that past volatility plays a lesser role, meaning short-term shocks dominate price movements (Oluwole & Adejumo, 2021; Zerihun & Shimelis, 2020). Since $\alpha + \beta = 0.906$ (<1), volatility is stable and mean-reverting, though shocks persist for some time (Balchin & Hossein, 2018; Ngeiywa et al., 2021). Overall, cowpea prices are highly responsive to shocks with moderate persistence. As a key protein source, this volatility has welfare implications—raising vulnerability to climate and market disruptions and affecting food access for low-income households (Adenegan & Olagunju, 2012; Headey & Fan, 2008; FAO, 2023). These findings highlight the need for policies that stabilize markets and strengthen food security.

Table 13: GARCH estimates for Price Volatility

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.047840	0.003406	14.04399	0.0000
CPRETURNS (-1)	0.981800	0.001519	646.5041	0.0000
	Variance Equation			
C	0.000291	4.13E-05	7.036759	0.0000
RESID (-1) ^2	0.779572	0.115815	6.731195	0.0000
GARCH (-1)	0.126164	0.047932	2.632147	0.0085
R-squared	0.797565	Mean dependent var		1.786705
Adjusted R-squared	0.797560	S.D. dependent var		0.960558
S.E. of regression	0.047443	Akaike info criterion		3.669045
Sum squared resid	1.233479	Schwarz criterion		3.629863
Log likelihood	101.9872	Hannan-Quinn criter.		3.653733
Durbin-Watson stat	1.28114			

Source: Output from EViews

4.4.3 Post Estimation Tests for Cowpea Price ARCH Effect

To confirm the reliability of the GARCH results, an ARCH effect test was conducted. The heteroskedasticity test results presented in Table 14 show that both the F-statistic and R^2 probabilities (F = 0.7328; Chi-square = 0.7322) are above conventional significance levels (0.01, 0.05, 0.10). Therefore, the null hypothesis of no ARCH effects is accepted, indicating no evidence of ARCH (1) effects and confirming the absence of heteroskedasticity.

Table 14: Heteroskedasticity Test: ARCH

F-statistic	0.116690	Prob. F	0.7328
Obs*R-squared	0.117092	Prob. Chi-Square	0.7322

Source: output from EViews

4.4.4 Post Estimation Tests for Serial Correlation Test

The post estimation test for serial correlation as shown in table 15 below reveals that the probability of Q-Stat for the AC and PAC are all not significant. This implies that there is no serial correlation.

Table 15: Serial Correlation Test

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.043	-0.040	18.487	0.618
.|. |	.|. |	2	0.048	0.039	19.805	0.595
.|. |	.|. |	3	0.017	0.009	19.977	0.643
.|. |	.|. |	4	0.037	0.032	20.777	0.652
.|. |	.|. |	5	0.023	0.019	21.070	0.689
.|. |	.|. |	6	-0.002	-0.000	21.072	0.738
.|. |	.|. |	7	-0.045	-0.049	22.257	0.724
.|. |	.|. |	8	-0.025	-0.010	22.618	0.752
.|. |	.|. |	9	-0.014	-0.000	22.734	0.789
.|. |	.|. |	10	-0.038	-0.042	23.566	0.791
.|. |	.|. |	11	-0.046	-0.056	24.823	0.776
.|. |	.|. |	12	-0.031	-0.035	25.372	0.791
.|. |	.|. |	13	-0.042	-0.051	26.389	0.786
.|. |	.|. |	14	-0.019	-0.042	26.606	0.813
.|. |	.|. |	15	0.007	-0.010	26.636	0.844
.|. |	.|. |	16	0.026	0.007	27.048	0.859
.|. |	.|. |	17	0.037	0.020	27.865	0.861
.|. |	.|. |	18	-0.018	-0.036	28.067	0.881
.|. |	.|. |	19	-0.027	-0.019	28.490	0.893
.|. |	.|. |	20	-0.037	-0.030	29.297	0.894

Source: output from EViews

4.4.5 Post Estimation Tests for Serial Correlation of Squared Residuals

The post estimation of serial correlation of Squared Residuals as presented in table 16 below reveals that non of the probability of Q-Stat for the AC and PAC is significant. This implies the absence of serial correlation of squared residuals.

Table 16: Test for Serial Correlation of Squared Residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.014	-0.014	0.1156	0.734
.|. |	.|. |	2	-0.021	-0.021	0.3497	0.840
.|. |	.|. |	3	-0.014	-0.014	0.4526	0.929
.|. |	.|. |	4	-0.031	-0.031	0.9718	0.914
.|. |	.|. |	5	-0.055	-0.056	2.6403	0.755
.|. |	.|. |	6	-0.033	-0.037	3.2504	0.777
.|. |	.|. |	7	-0.038	-0.043	4.0584	0.773
.|. |	.|. |	8	0.023	0.018	4.3617	0.823
.|. |	.|. |	9	-0.037	-0.044	5.1488	0.821
.|. |	.|. |	10	0.007	-0.001	5.1729	0.879
.|. |	.|. |	11	0.048	0.041	6.4868	0.839
.|* |	.|* |	12	0.086	0.083	10.700	0.555
.|. |	.|. |	13	0.018	0.021	10.887	0.620
.|. |	.|. |	14	0.011	0.013	10.950	0.690

.|. |	.|. |	15	-0.004	0.003	10.959	0.755
.|. |	.|. |	16	-0.020	-0.012	11.191	0.798
.|. |	.|. |	17	-0.047	-0.033	12.463	0.771
.|. |	.|. |	18	-0.030	-0.023	12.961	0.794
.|* |	.|* |	19	0.080	0.085	16.611	0.616
.|. |	.|. |	20	-0.038	-0.037	17.446	0.624

Source: output from EViews

4.5 Comparative Volatility Analysis of Maize, Rice and Cowpea in Nigeria

This section synthesizes the volatility dynamics of maize, rice, and cowpea prices using GARCH (1,1) models. The aim is to compare the nature, persistence, and food security implications of price volatility across these key staples in Nigeria. Table 17 reveals that across all three commodities, the lagged price term in the conditional mean equations is positive and highly significant, indicating strong price persistence:

Table 17: Comparative Volatility

crop	**Coefficient**	**Persistence**
Maize MPR_{t-1}	0.984662	Highly significant
Rice RPR_{t-1}	0.921236	Highly significant
Cowpea CPR_{t-1}	0,981800	Highly significant

Source: Output from EViews

All coefficients are less than one, indicating stable autoregressive processes, but they differ in degree. Cowpea and maize exhibit greater persistence than rice, meaning that shocks to their prices take longer to dissipate. In rice markets, although persistence is still strong, prices adjust more quickly than in maize and cowpea. This pattern is consistent with empirical findings for African staple markets where structural rigidities such as limited storage, fragmented markets, and transport bottlenecks contribute to slow adjustment processes (Nyangena & Mutai, 2008; Balchin & Hossein, 2018).

A look at the Volatility Structure and Persistence for each crop as presented in Table 4.18 reveals that Maize has ARCH ($\alpha = 0.9553$), GARCH ($\beta \approx 0.0052$) and persistence ($\alpha + \beta \approx 0.9605$). This result implies that maize price volatility is heavily driven by recent shocks rather than past volatility. A very large ARCH term indicates maize prices react sharply to new disturbances (e.g., seasonal harvest failures, fuel price changes, security disruptions). The high persistence (close to 1) indicates shocks dissipate slowly. This is consistent with results for maize price volatility in West Africa, where maize markets often show strong reaction to exogenous shocks (Zerihun & Shimelis, 2020; Oluwole & Adejumo, 2021).

Rice Price Volatility reveals that ARCH effect is small but significant ($\alpha = 0.0071$), GARCH effect is moderate ($\beta = 0.5816$), while Persistence ($\alpha + \beta \approx 0.5887$). This implies that

Rice price volatility is driven more by past volatility than by recent shocks. Past variance plays a larger role than immediate shocks and volatility clustering is present but moderate with the volatility process stable and mean-reverting. This finding suggests that rice price shocks do not produce persistent instability and tend to dissipate faster compared to maize and cowpea. This behavior may reflect the influence of import policies and market interventions (e.g., import tariff adjustments, buffer stocks) that moderate short-run volatility in rice markets (Odusola & Akinlo, 2017; FAO, 2023).

Cowpea Price Volatility shows strong ARCH effect ($\alpha = 0.7796$), smaller GARCH effect ($\beta = 0.1262$), Persistence ($\alpha + \beta \approx 0.9057$). The result suggests that cowpea price volatility is shock-driven like maize but shows high immediate sensitivity to shocks (large ARCH) with moderate persistence of volatility ($\alpha + \beta \approx 0.91$). This implies that cowpea markets react strongly to new information (e.g., weather shocks, local supply constraints) and such shocks have a moderately persistent effect. This is consistent with volatility patterns documented in African legume markets, which are often characterized by high responsiveness to short-run production risks due to climatic variability (Ayinde & Adebayo, 2019).

Volatility persistence ($\alpha + \beta$) indicates how long shocks remain influential: Maize**:** ~0.96 (very high persistence), Cowpea: ~0.91 (high persistence) and Rice: ~0.59 (moderate persistence). Since all $\alpha + \beta < 1$, the volatility processes for all crops are stationary and mean-reverting, meaning that price volatility shocks eventually dissipate. However, the degree and speed of mean reversion differ across crops: Rice returns to its long-run volatility faster while Maize and cowpea retain volatility for longer periods. Similar patterns have been documented in African cereal markets, where maize and other cereals display stronger volatility persistence than imported staples like rice (Minot, 2014; Balchin & Hossein, 2018). Table 19 is a table showing comprehensive summary of the comparative findings.

Table 18: GARCH (1,1) Variance Parameters

Crop	**ARCH (α)**	**GARCH (β)**	**α + β**
Maize	0.955274	0.005185	0.960459
Rice	0.007093	0.581601	0.588694
Cowpea	0.779572	0.126164	0.905736

Source: output from EViews

4.5.1 Economic Interpretation and Food Security Implications

Maize shows high volatility persistence means that shock episodes (e.g., drought, fuel price hikes, insecurity) generate long-lasting uncertainty. This can undermine food access and household welfare since maize is a primary staple in many Nigerian diets.

Rice shows moderate volatility persistence suggests that although price fluctuations occur, they are less disruptive over time. The import component of rice may cushion short-run shocks but expose prices to exchange rate fluctuations.

Cowpea shows intense short-run volatility (high ARCH) exposes consumers to sharp price fluctuations. Since cowpea is a key source of protein, volatility may adversely affect nutritional security beyond caloric access. Overall, persistent volatility in staple prices increases: Food insecurity risks**,** Consumption smoothing difficulty for poor households**,** Market uncertainty for producers and traders. This confirms the broader literature that staple food price instability is a major threat to food security in Nigeria and sub-Saharan Africa (Headey & Fan, 2008; FAO, 2023; World Bank, 2022).

Table 19: Summary of Comparative Findings

Crop	Price Persistence	ARCH Effect	GARCH Effect	α + β (Persistence)	Volatility Nature
Maize	Very strong	Very high	Very low	~0.96	Shock-driven, persistent
Rice	Strong	Low	Moderate	~0.59	Past volatility-driven
Cowpea	Very strong	High	Moderate	~0.91	Shock-dominant, persistent

Source: output from EViews

4.5.2 Volatility Shock Half-Life Computation

For Maize, from Table 20, volatility shock Half-Life Computation reveals the half-life for maize at Half-life ≈ 17.2 Months. The half-life measures the number of periods (months, in this case) required for a volatility shock to decay by 50%. A volatility shock in maize prices takes approximately 17.2 months to reduce by half. This indicates very slow volatility decay, High structural persistence and prolonged market instability following shocks. This confirms that maize price volatility in Nigeria is highly persistent and potentially destabilizing for food security during the period studied.

For Rice, Table 20 shows rice has a Half-life of approximately 1.3 months. This implies that Rice volatility shocks decay very quickly. A shock reduces by half in approximately 1.3 months. This indicates, Strong mean reversion, Lower persistence, Faster market stabilization. Rice markets appear comparatively more stable than maize and cowpea.

For Cowpea, table 20 result indicated a half-life of approximately 7.0 Months indicating that it takes cowpea volatility shocks approximately 7 months to reduce by half. It is an Indication of moderate to high persistence, strong short- run shock sensitivity and medium-term instability in protein markets.

The half-life results reveal substantial heterogeneity in volatility persistence across staple crops in Nigeria:

- Maize exhibits extremely persistent volatility, implying that shocks (e.g., insecurity, climate events, fuel price changes) can destabilize the market for over a year.
- Cowpea displays moderate persistence, with volatility effects lasting about half a year.
- Rice volatility dissipates rapidly, suggesting stronger adjustment mechanisms or policy cushioning.

These findings imply that maize poses the greatest long-term volatility risk to food security, followed by cowpea, while rice appears relatively more stable.

Table 20: Half-Life Comparative Summary

Crop	α + β	Half-Life (Months)	Volatility Nature
Maize	0.9605	17.2 months	Very highly persistent
Cowpea	0.9057	7.0 months	Moderately persistent
Rice	0.5887	1.3 months	Low persistence

Source: Output from EViews

5.0 Summary, Conclusion and Recommendations

5.1 Summary of the Study

This study examined the volatility dynamics of maize, rice, and cowpea prices in Nigeria using monthly data from January 1980 to December 2025. The Augmented Dickey-Fuller (ADF) test and GARCH (1,1) model were applied to assess stationarity, volatility persistence, and price shocks. Results showed that all price series were non-stationary at levels but became stationary after first differencing, confirming they were integrated of order one, I (1). ARCH-LM tests further confirmed the presence of heteroskedasticity and time-varying volatility, justifying the use of the GARCH model.

The findings revealed varying levels of volatility persistence across the crops. Maize exhibited the highest volatility persistence, with shocks dissipating slowly and remaining influential for about 17 months, making it the most unstable crop and the greatest threat to food security. Rice showed relatively low volatility persistence and faster market adjustment, with shocks fading within about 1 month, indicating greater stability. Cowpea displayed strong short-run volatility with moderate persistence, as shocks lasted about 7 months before returning to equilibrium. Diagnostic tests confirmed the reliability and adequacy of the estimated GARCH models. Overall, the study established that staple food price volatility poses serious risks to food security, household welfare, and market stability in Nigeria, particularly for maize and cowpea.

5.2 Conclusion

The study concluded that food crop prices in Nigeria are characterized by significant but varying volatility patterns. Maize and cowpea prices are highly sensitive to shocks such as insecurity, climate variability, exchange rate movements, transportation costs, and policy inconsistencies, while rice prices are relatively more stable due to stronger market adjustment and policy interventions. Although volatility is mean-reverting in the long run, slow adjustment—especially for maize and cowpea—creates uncertainty for producers, traders, and consumers, discourages investment, and weakens food security outcomes.

5.3 Recommendations

Based on these findings, the study recommends strengthening strategic grain reserves, improving rural infrastructure and storage systems, promoting climate-smart agriculture, ensuring macroeconomic stability, addressing insecurity in food-producing regions, improving market information systems, and expanding social protection programmes for vulnerable households. It also suggests further research using advanced volatility models such as EGARCH, TGARCH, and GARCH-MIDAS with additional macroeconomic and structural variables. These measures would help reduce staple food price volatility, improve market stability, and enhance food security in Nigeria.

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