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Econometric Estimation of Rice Price Volatility in Nigeria (1981 – 2021): Application of GARCH and ARCH Models

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Abstract

Objective: Given the recent unprecedented magnitude of food price volatility, this study aims to determine the level of rice price volatility in Nigeria.

Methods: The GARCH and ARCH models are employed to examine the presence of price volatility, while the ARDL model is used to identify the drivers of rice price volatility in Nigeria.

Results: Empirical evidence indicates that inflation and the real exchange rate positively influence rice price volatility at the 10% and 5% significance levels, respectively. Conversely, rice production, the first lag of rice price, and government expenditure on agriculture have negative effects on rice price volatility. In the short run, the first lag of rice price and total foreign direct investment in agriculture are negatively associated with volatility at the 1% and 5% significance levels, respectively. Furthermore, forecast of a food commodity (rice price) can be relatively explained by the past price volatility of the same commodity and that of others.

Conclusion: ARCH and GARCH techniques show that rice prices in Nigeria are highly volatile. Given the relatively stronger impact of unexpected shocks compared to seasonal fluctuations, the findings suggest that policymakers should exercise caution when formulating policies that affect imported rice prices—particularly protectionist trade and exchange rate policies that may intensify price volatility.

Keywords: Price volatility, rice, GARCH and ARCH, inflation

التقدير الاقتصادي القياسي لتقلب أسعار الأرز في نيجيريا (1981 - 2021): تطبيق نماذج GARCH وARCH

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الأهداف :نظرًا لأن أسعار المواد الغذائية قد شهدت مؤخرًا حجمًا غير مسبوق من التقلبات، فقد سعت هذه الدراسة إلى تحديد مستوى تقلب أسعار الأرز في نيجيريا.

المنهجية :تم استخدام نموذجي GARCH و ARCHلتحديد وجود أو عدم وجود تقلبات الأسعار في حين تم استخدام ARDLللتنبؤ بمحركات تقلب الأسعار في أسواق الأرز.

النتائج :تشير نتائج الدراسة إلى أن التضخم وسعر الصرف الحقيقي يؤثران بشكل إيجابي على تقلبات أسعار الأرز عند مستويات دلالة 10% و5% على التوالي. وعلى العكس، فإن إنتاج الأرز، التباطؤ الأول في متغير سعر الأرز، وإنفاق الحكومة على الزراعة لها تأثيرات سلبية على تقلبات أسعار الأرز. في الأجل القصير، يرتبط التباطؤ الأول في سعر الأرز وإجمالي الاستثمار الأجنبي المباشر في الزراعة ارتباطًا سلبيًا مع التقلبات عند مستويات دلالة 1% و 5% على التوالي. .علاوة على ذلك، يمكن تفسير توقعات سلعة غذائية (سعر الأرز) نسبيًا من خلال تقلبات الأسعار السابقة لنفس السلعة وتقلبات أسعار السلع الأخرى.

الخلاصة :تشير نتائج ARCHو GARCH إلى أن أسعار الأرز في نيجيريا شديدة التقلب .علاوة على ذلك، ونظراً للتأثير الكبير نسبياً لتقلبات الأسعار غير المتوقعة مقارنة بتقلبات الأسعار الموسمية، تشير النتائج إلى أنه ينبغي لواضعي السياسات توخي الحذر عند سن سياسات قد تؤثر على أسعار الأرز المستورد، بما في ذلك سياسات التجارة الحمائية وسياسات سعر الصرف التي يمكن أن تزيد أسعار الأرز.

الكلمات الدالة: تقلب الأسعار، الأرز، نماذج GARCH وARCH، التضخم.

INTRODUCTION

While the debate over the impact of food and energy prices on the economy of developing countries has continued to attract global reactions, their destabilizing effects have reached a peak following unacceptably high inflation and poverty rates, income disequilibrium, as well as the distorted and eroded purchasing power of money (IMF, 2023; UNCTAD, 2023). However, in terms of inflation, income, and poverty distribution in these countries, high food prices have been reported to be of more concern (IMF, 2023; UNCTAD, 2023; World Bank, 2023), although policy efforts and responses toward high food prices have been scuttled by growing oil prices, which are responsible for imbalances in fiscal and monetary payments. The alarm bells are being sounded globally, with the UN recently warning against food riots emanating from the upward spiraling prices of staples, especially rice, wheat, and corn (Kemmerling et al., 2021).

Behind the sprinting food prices is a global fall in food production (FAO, 2023), coupled with the depletion of economic buffers which were put in place to weather the impact of oil price shocks and initial food price rises in the last two decades. This situation is more devastating for economies like Nigeria that are predominantly dependent on oil and agriculture as their major sources of foreign exchange, economic growth, development, employment, and livelihood (Ikechukwu & Nwani, 2020; Natalia, 2020; Agwu et al., 2022). With food prices having moved steadily higher into unprecedented levels, Nigerian farmers are confronted with volatile prices and therefore depend on them to make decisions about planting since anticipated profits depend on anticipated prices of planted crops, thus making price an important tool in analyzing markets (FAO, 2023; World Bank, 2023; IMF, 2023; UNCTAD, 2023; OECD, 2023).

The effects of all these are felt by producers and consumers alike. Since the effects of food price volatility are long-term, household welfare, livelihood, and food security are heavily threatened; thus, food price volatility issues are strong sources of risk. On the producers' side, food price volatility is a major source of output risk which limits efficient resource allocation, investment decisions, resilience to shocks, as well as increases farmers' vulnerability to international market price shocks and instabilities which are inadvertently transmitted to local markets (Badgley, 2023). This resultant effect is economic hardship, especially in low-income earning countries like Nigeria, where food price volatility is a major concern (World Bank, 2023; FAO, 2023; Green et al., 2013).

While a holistic solution to food price volatility may not be provided by this study, it has also become imperative to develop strategies that enhance individual households' access to affordable food. This cannot be possible without first establishing the volatile nature of food prices in a country like Nigeria, where other macroeconomic variables like exchange rate and inflation are also experiencing unacceptably high volatilities. Rice has been selected as the crop of interest because it is the most consumed staple in Nigeria. It also tops the list of imported food and commands a huge influence in the international market. The following are the research objectives as examined in this research.

i. determine the trend of rice prices and some selected macroeconomic variables in Nigeria from 1991-2021
ii. examine the response of rice prices to some selected macroeconomic variables from 1991-2021
iii. determine the drivers of rice prices from 1991-2021

LITERATURE REVIEW

Price volatility in agricultural markets, particularly in staple commodities like rice, has been a central topic of economic research due to its implications for food security, income stability, and economic planning. In Nigeria, rice is a major staple food, and its price volatility directly affects a large segment of the population, including consumers, producers, and policymakers. Understanding and forecasting rice price volatility is crucial for devising appropriate agricultural and economic policies.

The Autoregressive Conditional Heteroskedasticity (ARCH) model, introduced by Robert Engle (1982), and its generalization, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, developed by Bollerslev (1986), have become fundamental tools in the econometric analysis of financial time series volatility. These models have been extensively applied to analyze the volatility of commodity prices, including agricultural products.

ARCH models capture the clustering of volatility—periods of high volatility followed by high volatility and periods of low volatility followed by low volatility. The GARCH model extends this by allowing past variances to affect current volatility, providing a more flexible framework for modeling time-varying volatility.

Numerous studies have applied ARCH and GARCH models to examine price volatility in agricultural commodities. For instance, Yang et al. (2001) employed a GARCH model to analyze the agricultural liberalization policy and commodity price volatility. Their study highlighted the persistence of volatility and the impact of external shocks on price movements. Similarly, Rezitis and Stavropoulos (2010) used GARCH models to investigate price volatility and rational expectations in a sectoral framework commodity model, confirming the presence of significant volatility clustering.

In the context of developing economies, including Nigeria, these models have been used to analyze the volatility of staple food prices, though literature specifically focusing on rice in Nigeria remains limited. Studies like Oyinbo and Rekwot (2014) have applied GARCH models to study the nexus of exchange rate deregulation and the agricultural share of Gross Domestic Product in Nigeria, providing a basis for similar analysis in the rice sector.

Rice price volatility in Nigeria is influenced by several factors, including domestic production levels, import dependency, exchange rate fluctuations, and government policies. The period from 1981 to 2021 has witnessed significant changes in these factors, making it a rich period for analyzing price volatility.

However, most studies in this area have utilized basic econometric techniques like OLS regression or ARIMA models, which may not adequately capture the complexity of rice price volatility. The application of ARCH and GARCH models offers a more robust framework for understanding the time-varying nature of this volatility and its persistence.

While specific literature on the application of ARCH/GARCH models to rice prices in Nigeria is limited, related studies provide valuable insights. For example, Ajao and Igbekoyi (2013) applied GARCH models to investigate the determinants of real exchange rate volatility in Nigeria. Similarly, Lawal et al. (2016) utilized GARCH models to analyze the volatility of agricultural product prices in Nigeria. The following null hypotheses are proposed for this study:

H_1: The volatility in the price of rice is not time varying, that is, there are no ARCH effects

H_2: Rice price volatility is directly related to inflation and real exchange rate and negatively related to rice production, rice price and government expenditure on agriculture.

RESEARCH METHODOLOGY

Study area

The study was carried out in Nigeria, located in West Africa on the Gulf of Guinea. Nigeria shares land borders with the Republic of Benin to the west, Chad and Cameroon to the east, and Niger to the north, covering a total area of 923,768 km² (356,669 sq mi). The population is growing rapidly, rising from 88.9 million in 1991 to 140 million in 2006, and 198.4 million in 2019 (NPC, 2019). Nigeria is one of the worst-hit countries by the falling crude oil prices resulting from the oil price wars and the COVID-19 pandemic. The heavy reliance on oil has put the country in a precarious position during these unprecedented times, leading to substantial borrowing for sustenance.

Data collection and analyses

This study relied on available annual data spanning 1981–2021. Data were sourced from the Food and Agriculture Organization (FAO) statistical database of the United Nations, the Central Bank of Nigeria, the World Bank, and the World Development Indicators database. The collected data were analyzed using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, the exponential trend model, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Autoregressive Conditional Heteroskedasticity (ARCH) regression models, as well as the Autoregressive Distributed Lag (ARDL) model.

Augmented Dickey-Fuller (ADF) test for stationarity

The ADF test consist of estimating the following regression

$$\Delta Y_t = \beta_0 + \beta_1 + \delta Y_{t-1} + \alpha_i \Delta Y_{t-1} + e_t \qquad (1)$$

Where,

Yt = Rice price; Y_{t-1} = Lag of rice prices; Δ = Difference operator; β_0 and β_1 = coefficients to be estimated; e_t = error term

It is a one tail test whose null hypothesis is $\delta = 0$ versus $\delta<0$ (thus expansive negative estimations of the test measurements prompts the dismissal of the invalid) and Δ is the difference operator. Under the alternative, Yt is as of now stationary and no difference is required (Dickey & Fuller, 1981).

Trend model

$$\ln Y = a + b_t + f_t^2 + u_t \qquad (2)$$

Where

ln = natural logarithm; Y = rice prices; t = time trend variable measure in years; β_0 and β_1 = Parameters to be estimated; u_t =error term. A positive significant value of *f* indicates acceleration while a negative value implies a deceleration. A non-significant value shows stagnation in the growth process.

Autoregressive conditional heteroskedasticity (GARCH) model

The GARCH model of the form GARCH $(p, q)_t$ for which p, q = 1 was specified and used to generate variability in the variables of interest (rice price, government expenditure on agriculture, inflation rate, interest rate, real exchange rate, total foreign direct investment in agriculture, rice area, rice production and rice yield. The variables were subjected to an initial first-order autoregressive (AR) (1) process as follows;

$$\Delta \log(Y_t) = \theta_0 + \theta_1 \Delta \log(Y_{t-1}) + \varepsilon_1 \qquad (3)$$

Where $\varepsilon \sim iid\ (0,1)$

Where;

$Y_t =$ variables of interest; $\varepsilon =$ is the stochastic disturbance term.

Since the assumption of no serial correlation is not violated, the GARCH process was derived and specified as:

$$Vari_t = \delta + \propto \sum \varepsilon_{t-1}^2 + \beta \sum h_{t-1} \qquad (4)$$

Where,

$Vari_t$ at period 't' = past variations or square of error term (ARCH term i.e. ε_{t-1}) as describe in equation (3) and past variance or variability term (the GARCH term i.e. h_{t-1}). For equation (4) to be stationary, $\delta > 0,\ \propto \geq 0,\ \beta \geq 0$ and the persistent of variability (price) shocks (α +β) should be less than 1. As the sum of α and β becomes close to unity, price shocks become much more persistent.

Autoregressive Distributed Lags (ARDL) bounds testing approach

To analyze long run and short run effect of rice outpout and some selected macroeconomic variables on rice price, ARDL bounds testing approach developed by Pesaran *et al.* (2001) was employed. This approach is used when dealing with large set of variables with varying levels of integration, that is, purely I(0), purely I(1) or mixture of both (Duasa, 2006; Onwusiribe et al., 2017). The ARDL approach to cointegration (Pesaran et al., 2001) also deals with the estimation of the conditional error correction (EC) version of the ARDL model. The null hypothesis of no cointegration is that H_0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = \delta_7 = \delta_8 = 0$ against the alternative hypothesis H_1: $\delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq \delta_5 \neq \delta_6 \neq \delta_7 \neq \delta_8 \neq 0$.

To establish a cointegrating relationship among the variables, the F-statistic is used. Following the critical bounds tabulated by Pesaran et al. (2001), two bounds exist—the upper critical bound (UCB) and the lower critical bound (LCB)—based on the assumption that all series are I(1) and I(0), respectively. There are three possible outcomes: (i) the null hypothesis of no cointegration is accepted if the UCB is lower than the calculated F-statistic; (ii) the null hypothesis of no cointegration is rejected if the LCB is higher than the F-statistic; and (iii) an inconclusive outcome exists if the F-statistic lies between the UCB and LCB. In the case of an inconclusive outcome, a negative and statistically significant coefficient of the lagged error correction term is used to establish a long-run relationship. The orders of the lags in the specification (equation 5) are selected by the Schwarz Bayesian Criterion (SBC), which chooses the lag length that minimizes the SBC. The ARDL is specified in logarithmic form as:

$$\text{Rprice}(t) = \delta_0 + \delta_1 Ln\text{GEA}_t + \delta_2\text{LnINF}_t + \delta_3\text{LnINTR}_t + \delta_4\text{LnREXR}_t + \delta_5\text{TFDIA}_t + \delta_6\text{LnRA}_t + \delta_7\text{LnRP}_t + \delta_8\text{LnRY}_t + U_t \quad (5)$$

Where, (t) is the food crop price volatility,

GEA = Government expenditure on agriculture (Naira)

INF = Inflation

INTR = Interest rate

REXR = Real exchange rate

TFDIA = Total foreign direct investment in agriculture

RA = Rice area cultivated (Hectares)

RP = Rice production/output (Tonnes)

RY = Rice yield (Output per total area cultivated)

U_t - error term, Ut ~ (0, δ $2u$).

The ARDL representation of the price and macroeconomic relationships of variables in (equation 5) can be represented since a dynamic Error Correction Model (ECM) will be derived from the ARDL model through a simple linear reparameterization. The version of ARDL approach is given by:

$$\Delta\text{LnRprice}_t = \delta_0 + \delta_1\text{LnRprice}_{t-1} + \delta_2 Ln\text{GEA}_{t-1} + \delta_3\text{LnINF}_{t-1} + \delta_4\text{LnINTR}_{t-1} + \delta_5\text{LnREXR}_{t-1} + \delta_6\text{TFDIA}_{t-1} + \delta_7\text{LnRA}_{t-1} + \delta_8\text{LnRP}_{t-1} + \delta_9\text{LnRY}_{t-1} + \sum_{i=0}^{p}\omega_1\Delta\text{LnRprice}_{t-i} + \sum_{i=0}^{p}\omega_2\Delta Ln\text{GEA}_{t-i} + \sum_{i=0}^{p}\omega_3\Delta\text{LnINF}_{t-i} + \sum_{i=0}^{p}\omega_4\Delta\text{LnINTR}_{t-i} + \sum_{i=0}^{p}\omega_5\Delta\text{LnREXR}_{t-i} + \sum_{i=0}^{p}\omega_6\Delta\text{TFDIA}_{t-i} + \sum_{i=0}^{p}\omega_7\Delta\text{LnRA}_{t-i} + \sum_{i=0}^{p}\omega_8\Delta\text{LnRP}_{t-i} + \sum_{i=0}^{p}\omega_9\Delta\text{LnRY}_{t-i} + U_t \quad (6)$$

Δ = the first-difference operator,

λ's and ω's = Long run and short run coefficients, respectively.

Ln= Stands for natural logarithm,

t-1 = a period lag of the variables,

t-i = i^{th} number of lags required for each variable for a best fit, and

If a long run relationship exists, the ARDL representation of equation (6) is formulated as follows:

$$\Delta \text{LnRprice}_t = \omega_0 + \sum_{i=0}^{p} \omega_1 \Delta \text{LnRprice}_{t-i} + \sum_{i=0}^{p} \omega_2 \Delta Ln\text{GEA}_{t-i} + \sum_{i=0}^{p} \omega_3 \Delta \text{LnINF}_{t-i} + \sum_{i=0}^{p} \omega_4 \Delta \text{LnINTR}_{t-i} + \sum_{i=0}^{p} \omega_5 \Delta \text{LnREXR}_{t-i} + \sum_{i=0}^{p} \omega_6 \Delta \text{TFDIA}_{t-i} + \sum_{i=0}^{p} \omega_7 \Delta \text{LnRA}_{t-i} + \sum_{i=0}^{p} \omega_8 \Delta \text{LnRP}_{t-i} + \sum_{i=0}^{p} \omega_9 \Delta \text{LnRY}_{t-i} + U_t \quad (7)$$

The ARDL specification of short run dynamics will be investigated using ECM version of ARDL model of the following form:

$$\Delta \text{LnRprice}_t = \omega_0 + \sum_{i=0}^{p} \omega_1 \Delta \text{LnRprice}_{t-i} + \sum_{i=0}^{p} \omega_2 \Delta Ln\text{GEA}_{t-i} + \sum_{i=0}^{p} \omega_3 \Delta \text{LnINF}_{t-i} + \sum_{i=0}^{p} \omega_4 \Delta \text{LnINTR}_{t-i} + \sum_{i=0}^{p} \omega_5 \Delta \text{LnREXR}_{t-i} + \sum_{i=0}^{p} \omega_6 \Delta \text{TFDIA}_{t-i} + \sum_{i=0}^{p} \omega_7 \Delta \text{LnRA}_{t-i} + \sum_{i=0}^{p} \omega_8 \Delta \text{LnRP}_{t-i} + \sum_{i=0}^{p} \omega_9 \Delta \text{LnRY}_{t-i} + \eta \text{ECM}_{t-1} + U_t \quad (8)$$

ECM_{t-1} = Error Correction term lagged by one period,

η = coefficient of the correction term,

All other variables as previously defined

The goodness of fit for ARDL model will be checked through stability tests such as cumulative sum of recursive residuals (CUSUM) and cumulative sum of squares of recursive residuals (CUSUMSQ).

RESULTS AND DISCUSSION

Unit root test of the variables

Prior to using the time series data for analysis, the variables were subjected to stationarity tests using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to confirm stationarity and ascertain the order of integration of the variables. The ADF and PP test statistics were compared with their respective critical values at the 5% significance level; thus, variables found to be significant at this level were selected for further analysis. The ADF and PP results are presented in Table 1.

Table 1: Unit root test of the variables

Variable	Augmented Dickey – Fuller (ADF)				Phillips-Perron (PP)				Decision
	Level	5%	1st diff	5%	Level	5%	1st diff	5%	
Crude Oil	-1.496	-2.964	-4.962	-2.968	-1.531	-2.964	-4.929	-2.968	I(1)
GEA	-2.802	-2.964	-5.898	-2.972	-2.802	-2.964	-8.339	-2.968	I(1)
Inflation	-4.101	-2.976	-4.441	-2.972	-2.378	-2.964	-5.752	-2.968	I(0)
Interest Rate	-2.784	-2.964	-4.558	-2.976	-2.730	-2.964	-12.293	-2.968	I(1)
Real ER	-3.591	-2.964	-4.720	-2.968	-4.047	-2.964	-4.694	-2.968	I(0)
Rice Price	-2.677	-2.964	-6.747	-2.972	-2.533	-2.964	-10.426	-2.968	I(1)
Total FDIA	-1.790	-2.964	-5.555	-2.968	-1.762	-2.964	-5.554	-2.968	I(1)
Rice Area	-1.909	-2.964	-4.672	-2.968	-1.857	-2.964	-4.735	-2.968	I(1)
Rice Prod.	-1.676	-2.964	-5.426	-2.968	-1.530	-2.964	-5.833	-2.968	I(1)
Rice Yield	-2.882	-2.964	-6.338	-2.968	-2.813	-2.964	-6.529	-2.968	I(1)

The ADF and PP results are similar, with insignificant differences. The results showed that government expenditure on agriculture, interest rate, rice price, total foreign direct investment in agriculture, rice area, rice production, and rice yield were all significant at first difference, while inflation and the real exchange rate were stationary at level. Given that all variables were stationary either at level or at first difference, the data are suitable for further estimation. This ensures the data will provide stable, non-spurious, and unbiased estimates.

If two or more series are individually integrated (in the time series sense), typically they are first-order integrated (I(1)), but some cointegrating vector of coefficients exists that forms a stationary linear combination of them. The series may drift apart in the short run, then follow a common trend that permits a stable long-run relationship. Since the variables are integrated of different orders, a cointegration test is necessary. This implies that some linear combinations of the series are expected to be cointegrated, such that even though individual series may be integrated of order I(0), I(1), or non-integrated (NI), the series would not drift apart in the short run and would follow a common trend permitting a stable long-run relationship.

At levels, the absolute values of the variables were less than the critical values at the 5% level. This implies that some variables had unit roots at level [I(0)]. This finding aligns with Awe (2013) and Anwana and Affia (2018). Under this scenario, some variables were deemed stationary at level, while others became stationary only after first differencing [I(1)], as indicated by absolute values greater than the critical values at the 5% level. This decision is consistent with Aminu (2020) and Afolabi et al. (2021). The models were further guided by the nature of the trends observed in their line graphs, as stipulated by Gujarati (2003).

Exponential Trend Analysis of the Variables

The exponential trend analysis equation was estimated for all variables in this study to test for stagnation, acceleration, or deceleration. As a rule of thumb, variables with positive and statistically significant coefficients are considered to be accelerating; those with negative and statistically significant coefficients are considered to be decelerating, while those with non-significant coefficients are considered to be stagnating. The results are presented in Table 2.

Table 2: Exponential trend for variable.

Variable	T^2	DW	R^2	Decision
Government expenditure on agric.	-6.259^{***}	0.045	-14.663	Decelerating
Inflation	-3.760^{***}	0.135	-3.916	Decelerating
Interest rate	0.469	1.193	0.215	Stagnated
Real exchange rate	-7.175^{***}	0.078	-0.802	Decelerating
Rice area	-1.375	0.553	0.337	Stagnated
Rice price	-6.017^{***}	1.917	0.706	Decelerating
Rice production	-1.406	0.479	0.366	Stagnated
Rice yield	-4.451^{***}	0.134	-7.171	Decelerating
Total FDI in agriculture	-5.425^{***}	0.239	-1.206	Decelerating

The results show that the price of rice, exchange rate, and production are accelerating. As expected, the rising prices are a result of inflation and exchange rate fluctuations, which are also accelerating. This is consistent with findings in developing countries, where commodity prices and inflation tend to continuously increase (Sokol, 2009; Harry et al., 2007). Production was also found to be accelerating despite the rising prices, indicating high demand for these commodities. For instance, rice is the most consumed cereal in Nigeria. According to Nur and Zaki (2019), production behavior in Muslim restaurants was affected by the rise in prices of basic commodities. However, the increase in prices did not hinder the acceleration of production, further indicating strong demand.

The area cultivated, however, was declining, probably due to urbanization, which has led to the destruction of farmlands. Additionally, land pollution in oil-producing areas and insurgencies in many parts of the country have forced farmers out of their farms. These findings align with those of Thomas et al. (2009) and Eric et al. (2011).

Conditional Variance (Volatility) Analysis

ARCH-LM tests

The ARCH-LM test result shows that all variables' price returns rejected the null hypothesis of no ARCH effects at 1% significant level, in favour of the presence of ARCH effect. The result is presented in Table 3.

Table 3: Heteroskedasticity Test: ARCH

F-statistic	4.733774	Prob. F(1,27)	0.002
Obs*R-squared	7.767275	Prob. Chi-Square(1)	0.001

The confirmation of the presence of ARCH effect in these cases indicates that the volatility in the prices of these variables are time varying. The LM statistic of 7.77 was significant, indicating the presence of ARCH. This is rejected since the Obs*R-squared is not significant, so we conclude that the model has passed the heteroskedasticity test, that is, there is no heteroskedasticity.

Diagnostics of the model

To test the stability of the ARCH model, certain tests were performed.

Residual test

The null hypothesis is that of the presence of residuals. The result is presented in Table 4.

Table 4: Heteroskedasticity Test: ARCH

F-statistic	0.4316	Prob. F(1,27)	0.401
Obs*R-squared	0.4635	Prob. Chi-Square(1)	0.707

The results showed that the statistics were significant at the 1% level; therefore, the null hypothesis is rejected, and we conclude that the model has passed the residual test, indicating no autocorrelation in the residuals.

Rice Price Conditional Volatility Forecasting

A forecast analysis was conducted using the GARCH model. The sample was divided into two periods: the full sample (1991–2021) and a reduced sample (2019–2021). The results are presented in the following sections.

Full sample forecast

The result is presented in Group of Figures, 1.

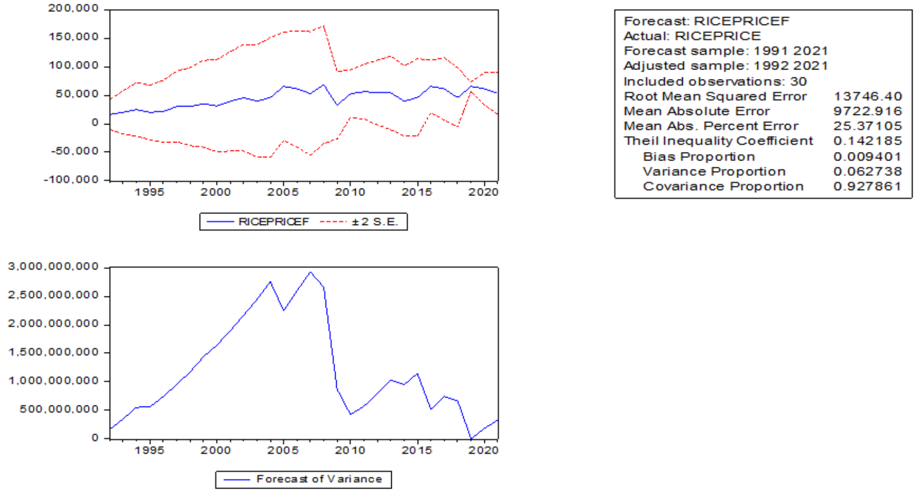


Figure 1: Rice price full sample forecast

The results show that the rice price was stable from 1995 to 2004, with volatility increasing significantly from around 2012 until 2020. This finding is consistent with Joseph et al. (2021) and Harold et al. (2016).

Reduced sample forecast

The result is presented in Group of Figures, 2.

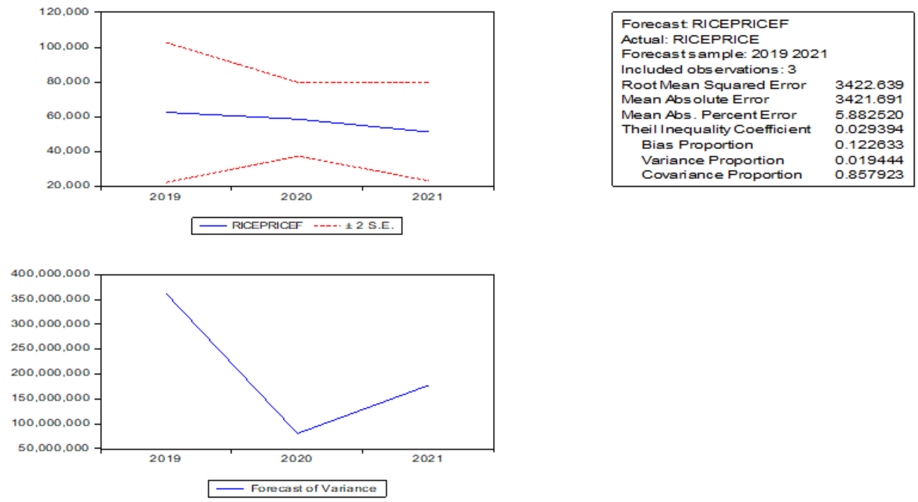


Figure 2: Rice price reduced sample forecast

The results show that the rice price was stable from 2019 to 2021, with volatility being almost absent. Farmers and investors are concerned not only with price levels but also with the risks involved in production investment. Volatility forecasting provides a measure of this investment risk. Findings from this study indicate that rice prices were relatively stable overall but experienced volatility in some years. This finding aligns with Andreosso et al. (2010), who observed that volatility in agricultural markets, including rice, is not uncommon, although overall volatility in recent decades has been lower than in the past.

3.4 Drivers of Food Prices Volatility

To estimate the drivers of food prices, the Auto-regressive distributive lag was employed

Bounds test analysis

After estimating the autoregressive distributed lag (ARDL) model, the bound testing approach was applied to examine the presence of a cointegration (long-run) relationship among the study variables. Ordinary Least Squares (OLS) estimation was used to determine whether cointegration exists. Subsequently, an F-test was conducted to test the null hypothesis of no cointegration between the variables.

To assess the existence of a long-run relationship, the F-statistic is compared to the critical bounds. If the F-statistic exceeds the upper bound critical value, the null hypothesis of no cointegration is rejected. If the F-statistic falls within the critical bounds, the result is inconclusive. Finally, if the F-statistic is below the lower bound critical value, the null hypothesis is accepted. The results of the bounds test are presented in Table 5.

Table 5: Co-integration Bounds test

Test Statistic	Value	k
F-statistic	5.414596	9
Critical Value Bounds		
Significance	I0 Bound	I1 Bound
10%	1.88	2.99
5%	2.14	3.3
2.5%	2.37	3.6
1%	2.65	3.97

The results clearly indicate that the calculated F-statistic value (5.415) is greater than both the upper bound (3.3) and lower bound (2.14) values at the 5% level of significance, implying the existence of a long-run relationship among the variables. This finding is consistent with Olusi et al. (2015) and Drama et al. (2018).

Long-run (LR) and short-run (SR) ARDL estimates

Serial correlation

Since the F-statistic values for both the long-run and short-run equations of the ARDL model were found to be statistically insignificant, the null hypothesis of no serial correlation is retained, as presented in Table 6.

Table 6. Breusch-Godfrey Serial Correlation LM Test: long and short run ARDL estimates

	Short run equation			Long run equation		
F-statistic	1.031	Prob. F(2,16)	0.124	1.492	Prob. F(1,16)	0.215
Obs*R-squared	14.848	Prob. χ^2 (2)	0.0006	8.082	Prob. χ^2 (1)	0.005

From the long- and short-term results of the autoregressive distributed lag (ARDL) model in this study, it was found that a long-term cointegration relationship exists among the study variables. The findings showed that the R-squared values were 0.70 and 0.62 for the long and short run, respectively, implying that 70% and 62% of the variation in rice price volatility was explained by the independent variables in the model during these periods. The F-tests were statistically significant at the 1% level for both periods, indicating a good fit of the regression model. The long- and short-term results of the ARDL approach are reported in Table 7.

Table 7: Long-run (LR) and short-run (SR) ARDL estimates

Variable	Coefficient	Std. Error	t-Statistic
Constant	30741.31	34440.00	0.892605
Rice price1(-1)	-0.436052	0.182840	-2.384884**
Govt. expenditure on agric(-1)	-8458.498	3832.471	-2.207061**
Inflation(-1)	2250.181	1210.52	1.858885*
Interest rate1(-1)	-199.7842	296.6003	-0.673581
Real exchange rate(-1)	12195.00	4555.00	2.677277**
Total foreign direct investment in agric.(-1)	-4483.752	5792.926	-0.774005
Rice area(-1)	0.026623	0.021830	1.219564
Rice production(-1)	-0.113999	0.015153	-7.523196***
Rice yield(-1)	-6.747066	3.671798	-1.837537*
R-squared	0.704343	F-statistic = 12.990	
Adjusted R-squared	0.195873	Prob(F-statistic) = 0.0032	

Short-run estimates

Variable	Coefficient	Std. Error	t-Statistic
Constant	143.0209	4555.458	0.031396
Rice price1(-1)	-0.578057	0.178641	-3.235867***
Govt. expenditure on agric(-1)	-7579.045	6925.427	-1.094379
Inflation(-1)	-9903.429	20960.12	-0.472489
Interest rate1(-1)	-102.1515	302.9732	-0.337163
Real exchange rate(-1)	-18854.09	49338.15	-0.382140
Total FDI in agric.(-1)	-7739.380	3754.585	-2.061314**
Rice area(-1)	0.026190	0.026264	0.997182
Rice production(-1)	-0.012201	0.016308	-0.748170
Rice yield(-1)	6.457808	4.356097	1.482476

R-squared = 0.618563 F-statistic = 3.24336

Adjusted R-squared = 0.42784 Prob(F-statistic) = 0.016097

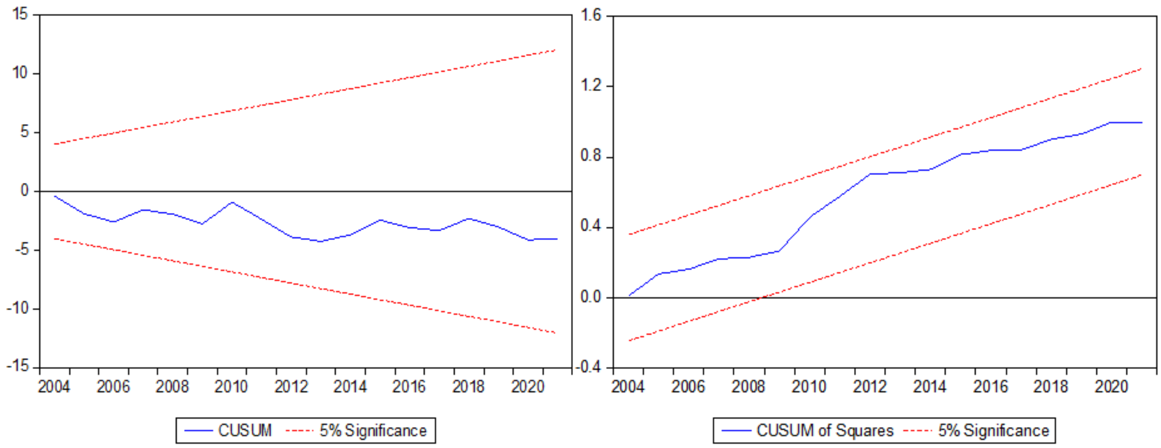
The results showed that inflation and the real exchange rate had positive effects on rice price volatility at the 10% and 5% levels of significance, respectively, while rice production, the first lag of rice price, and government expenditure on agriculture (GEA) had negative impacts on rice price volatility. In the short run, the first lag of rice price and total foreign direct investment in agriculture (TFDIA) were negatively associated with rice price volatility at the 1% and 5% levels of significance, respectively.

The positive coefficient of the real exchange rate implies that as this variable increases, volatility also increases. With the dollar gaining significant strength over the naira in recent years, local production has been greatly affected since most production inputs are imported. Given that farmers lack access to credit facilities, they are vulnerable to volatile exchange rates, which further influence rice prices. This finding aligns with Deyshappriya et al. (2023), who indicated that an increase in the exchange rate (depreciation of the domestic currency) raises the prices of imports, thereby discouraging production processes reliant on imported inputs. Consequently, economic growth is adversely affected by the increased exchange rate. This suggests that many industries produce their products with inadequate local content, making them more vulnerable to exchange rate shocks compared to industries where the country has a comparative advantage (Almisshal & Emir, 2021). The same holds true for inflation.

Government expenditure on agriculture (GEA) was negatively signed, implying that increased government investment in agriculture leads to higher production and thus greater price stability. There is a long-run positive relationship between GEA and agricultural productivity (Megbowon et al., 2019). Eric et al. (1994) also noted that instability in GEA deters agricultural output growth. This also explains why rice production had a negative coefficient: higher output helps balance demand-supply gaps and reduces the likelihood of rice price volatility.

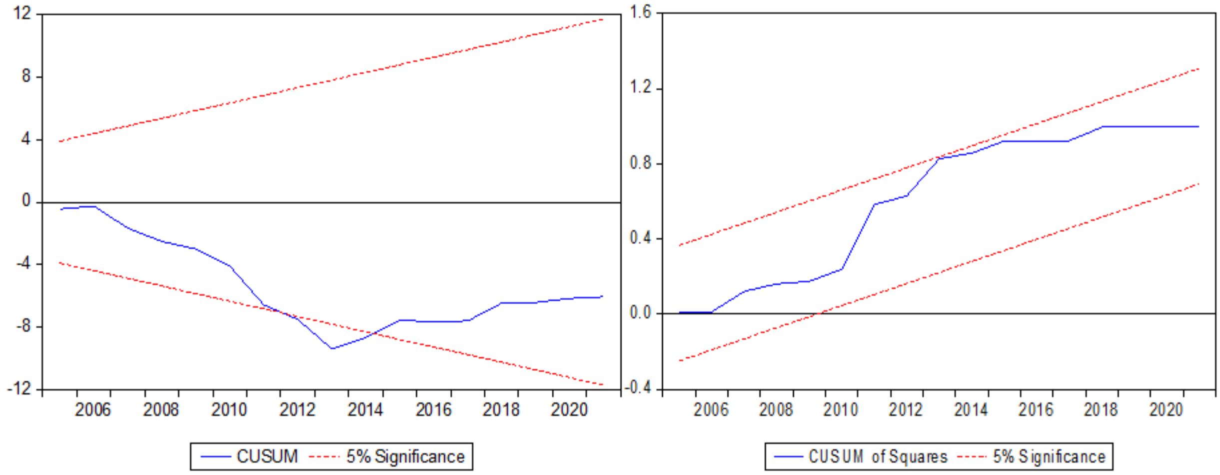
Test of model stability

The goodness of fit for ARDL model was checked using the cumulative sum of recursive residuals (CUSUM) and cumulative sum of squares of recursive residuals (CUSUMSQ) as shown in Figures 3,4 and 5,6.



Figures 3,4: CUSUM and CUSUMQ for short run ARDL estimates

Figures 3 and 4, as well as Figures 5 and 6, all show that the data are stable, since the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMQ) graphs remain within the 5% significance limits.



Figures 5,6: CUSUM and CUSUMQ for long run ARDL estimates

CONCLUSION AND POLICY RECOMMENDATIONS

Our study applied the GARCH and ARCH models to predict the volatile nature of rice prices in Nigeria from 1981 to 2021. The exponential trend analysis showed that rice price, exchange rate, and production were all accelerating. As expected, the rising prices are driven by inflation and exchange rate fluctuations, which are also accelerating. Meanwhile, the area cultivated for rice has been declining, likely due to urbanization, which has led to the destruction of farmland. The ARCH-LM test results indicate that the price returns of all variables rejected the null hypothesis of no ARCH effects at the 1% significance level, confirming the presence of ARCH effects. A forecast analysis using GARCH was conducted with the sample divided into two periods: the full sample (1981–2021) and a reduced sample (2019–2021). Both samples indicated the presence of rice price volatility. The country should focus more on sectors where it has a comparative advantage, such as agriculture and food exports, since these sectors show no significant long-run response to exchange rate volatility. Additionally, the government should provide local farmers with credit to boost rice production, which would help stabilize demand-induced price fluctuations. These credits should be channeled directly to farmers to prevent diversion by politically connected individuals.

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