



An Assessment on the Predictive Performance of Arima-Garch and Arimax-Garch Models on Nigerian Inflation Rate

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ABSTRACT

Accurate inflation forecasting is critical for effective economic planning and decision-making in Nigeria, yet it remains challenging due to exchange rate fluctuations, oil price shocks, and shifts in monetary policy. Traditional models such as ARIMA often fail to capture these complex dynamics, particularly during periods of high volatility. This study evaluates the predictive performance of two hybrid time series models, ARIMA-GARCH and ARIMAX-GARCH, using monthly inflation data from 1997 to 2024. While ARIMA-GARCH models the conditional mean and volatility of inflation, ARIMAX-GARCH extends this by incorporating exogenous variables, including the exchange rate, premium motor spirit (PMS) price, and money supply. Stationarity was tested using the Augmented Dickey-Fuller (ADF) test, model selection guided by AIC and BIC, and volatility clustering confirmed with the ARCH-LM test. Forecast accuracy was assessed using RMSE, MAE, and MAPE. Results demonstrate that ARIMAX-GARCH consistently outperforms ARIMA-GARCH, yielding more accurate forecasts. The study recommends ARIMAX-GARCH for inflation forecasting in Nigeria, as it provides robust, reliable predictions that support improved policy and investment strategy.

Keywords: volatility, hybrid model, inflation, exchange rate, PMS price

1.0 INTRODUCTION

Inflation refers to an economic phenomenon in which the money supply exceeds the actual amount of money needed for economic operation in the circulation, resulting in a relative decrease in the purchasing power of money and causing a sustained and widespread rise in price levels for some time (Zhang & Zhou, 2025). Higher inflation reduces asset-value and interest-rate effects, stifling economic growth and mitigating income inequality (Zheng *et al.*, 2020). Hence, accurate inflation forecasting is vital for policymakers to implement effective monetary and fiscal measures aimed at ensuring price stability and fostering sustainable growth. The complexity of Nigeria's inflation is amplified by its tendency to exhibit trend behavior and volatility clustering, largely driven by structural inefficiencies and recurrent external shocks (Adeoye & Saibu, 2020). Factors such as unstable exchange rates, fluctuating oil prices, and inconsistent policy actions complicate inflation forecasting. Traditional time series models like the Autoregressive Integrated Moving Average (ARIMA) assume linearity and constant variance (homoskedasticity), limiting their capacity to model such complexities effectively (Box & Jenkins, 1970).

To address these limitations, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, developed by Bollerslev (1986) as an enhancement of Engle's (1982) ARCH model, offers a

method to model time-varying volatility. GARCH-type models reflect the volatility clustering property whose essence is that the fluctuation in the current will impact on the certain day of fluctuation expected value in the future (Dangal & Gajurel, 2021). The hybrid ARIMA-GARCH model integrates ARIMA for mean estimation and GARCH for volatility modeling, improving forecast reliability (Pahlavani & Roshan, 2015). The ARIMAX-GARCH model extends this by incorporating exogenous variables, thus allowing the model to account for external macroeconomic influences (Wang *et al.*, 2005), such as exchange rates, petroleum prices, and monetary policy changes. Qasim *et al.* (2021), in their paper titled "Forecasting Inflation Applying ARIMA Model with GARCH Innovation: The Case of Pakistan," analyzed the Consumer Price Index (CPI) data from Pakistan, covering the period from January 1962 to December 2019. The study aimed to forecast inflation rates using the ARIMA model for the conditional mean and various GARCH models for the conditional variance. The findings revealed that the GARCH (2,2) model was the best fit for capturing variance in the CPI data, indicating that while asymmetric effects (modeled by EGARCH and TGARCH) were not crucial, considering volatility was essential for accurate forecasting. The ARIMA model with GARCH innovation effectively forecasted the inflation rate, outperforming other models. The study concluded that incorporating both the conditional mean and variance using these models provides a robust



framework for inflation forecasting. It recommended using the ARIMA with GARCH innovation approach for better economic planning and policy-making in Pakistan. Pahlavani and Roshan (2015) studied the forecasting performance of two models, the Autoregressive Integrated Moving Average (ARIMA) and the hybrid ARIMA-GARCH, in the context of Iran's exchange rate against the U.S. Dollar. The researchers utilized daily exchange rate data from March 20, 2014, to June 20, 2015. The study specifically examined the non-stationarity of the exchange rate series, using the Augmented Dickey-Fuller (ADF) test approach. The ADF test results indicated that the time series data achieved stationarity after transformation. The performance of each model was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Theil's Inequality Coefficient (TIC). The findings revealed that the ARIMA(7,2,12)-EGARCH(2,1) model, which captures volatility and leverage effects, was optimal for forecasting exchange rate returns. The study concluded with a recommendation to use hybrid ARIMA-GARCH models for better forecasting accuracy in financial time series, emphasizing their effectiveness in capturing volatility and leverage effects. Aryani *et al.* (2015) studied forecasting inflation in Indonesia. The study provided insights into modeling inflation volatility by utilizing Autoregressive Integrated Moving Average (ARIMA) with exogenous factors and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. The data used in the study were obtained from the Publication of Price Statistics Indonesia (BPS). The specific data used includes monthly inflation data of Indonesia from January 1991 to December 2014, as well as the percentage change in world crude oil prices data from January 1990 to December 2014. Findings indicate that the asymmetric GJR-GARCH model outperformed the symmetric GARCH model in capturing inflation volatility in Indonesia based on evaluation criteria such as Mean Squared Error, Mean Absolute Error, and Mean Absolute Percentage Error. They concluded that the ARIMAX-GJR-GARCH model outperformed symmetric GARCH in capturing inflation volatility in Indonesia, demonstrating superior forecasting accuracy, and recommended that aspiring researchers in this field consider utilizing the ARIMAX-GJR-GARCH model for forecasting inflation volatility due to its superior performance in terms of mean square error, mean absolute error, and mean absolute percentage error metrics. Bunnag (2023) studied the effectiveness of three forecasting models—the Autoregressive Integrated Moving Average (ARIMA), the ARIMA-Generalized

Autoregressive Conditional Heteroscedasticity (ARIMA-GARCH), and the ARIMA-Threshold GARCH (ARIMA-TGARCH)—in predicting gold prices. The research utilized daily gold price data from January 1, 2021, to October 13, 2023, obtained from various financial databases. The study assessed the ability of these models to handle trends and volatility in the gold price series. The ARIMA model effectively captured the trend but struggled with volatility, while the ARIMA-GARCH model improved prediction accuracy by accounting for volatility clustering. The ARIMA-TGARCH model further enhanced forecast precision by addressing asymmetric volatility shocks. The model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Findings indicated that the ARIMA (2,1,3)-GARCH(1,1) model yielded the lowest MAE and RMSE, making it the most accurate for forecasting gold prices. The study concluded with a recommendation for investors to use the ARIMA (2,1,3)-GARCH (1,1) model for more reliable gold price predictions, suggesting that if gold prices exceed 1991 USD per troy ounce, investors should wait for a price adjustment before purchasing or gradually sell to realize profits. Additionally, it encouraged researchers to explore hybrid models further and advised policymakers to consider advanced forecasting models in economic decision-making and policy formulation.

2.1 MATERIALS AND METHOS

2.2 Description and Source of Data

The data employed in this study consist of monthly observations of Nigeria's inflation rate from 1997 to 2024. In addition, key macroeconomic variables, including exchange rate, premium motor spirit (PMS) price, and money supply, were incorporated as exogenous inputs in the ARIMAX-GARCH model. These data were sourced from the Central Bank of Nigeria and the National Bureau of Statistics.

2.3 Method

We briefly present the models specification, information criteria and forecasting performance measure to assess hybrid models performance in forecasting Nigeria's inflation rate volatility. This study analyses the process and volatility of inflation rate by using various models such as: AIRMA, ARIMAX, AIRMA-GARCH and AIRMAX-GARCH. In this study three different criteria, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute percentage Error (MAPE) are used to evaluate the forecasting performance of the various models.

2.3.1 ARIMA-GARCH model

The ARIMA-GARCH model is defined by two main components: the ARIMA model for the mean equation and the GARCH model for the variance equation. The equation (1) represents the ARIMA model given as:

$$\left(1 - \sum_{i=1}^p L^i \phi_i\right) (1-L)^d y_t = \left(\sum_{j=0}^q L^j \theta_j\right) \varepsilon_t \tag{1}$$

where L is the lag operator, ϕ_i are the AR coefficients, θ_j are the MA coefficients, d is the differencing order, ε_t is the residual or error term from the ARIMA model. While the GARCH model in equation (2) is defined as:

$$\varepsilon_t = v_t \sqrt{h_t}$$

In a way that $\sigma_v^2 = 1$ and

$$h_t = \alpha_0 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j h_{t-1} \tag{2}$$

In this condition, one needs to make sure that $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ and $1 - \sum_{i=1}^p \alpha_i + \sum_{j=1}^q \beta_j > 0$ to see the conditional variance positive. Since v_t is a white noise; the key point here is that the conditional variance of ε_t is the following: $E_{t-1} \varepsilon_t = h_t$

2.3.2 ARIMAX-GARCH Model

The ARIMAX-GARCH model is distinguished by two main components: the ARIMAX model for the mean equation and the GARCH model for the variance equation. The equation (3) represents the ARIMAX (p, d, q) model is given as:

$$\left(1 - \sum_{i=1}^p L^i \phi_i\right) (1-L)^d y_t = \left(\sum_{j=0}^q L^j \theta_j\right) \varepsilon_t + \sum_{k=1}^m \beta_k x_{t-k} \tag{3}$$

where: L is the lag operator, ϕ_i are the AR coefficients, θ_j are the MA coefficients, x_{t-k} represents the exogenous variable at time $t-k$, and β_k is the coefficient for the exogenous variable, ε_t is the residual or error term. After modelling the mean with the ARIMAX process, the residuals ε_t are modelled with a GARCH (p, q) process to capture volatility. The conditional variance h_t of the residuals is defined in equation (2).

where h_t is the conditional variance (volatility) at time t , α_0 is a constant, α_i are the ARCH coefficients capturing past squared residuals, β_j are the GARCH coefficients capturing past conditional variances.

2.4 Information Criteria

Model selection for evaluating the predictive performance of ARIMA-GARCH and ARIMAX-GARCH models on Nigeria’s inflation rate was guided by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). These criteria ensure a balance between goodness of fit and model complexity by penalizing overfitting while maintaining adequate data representation. The Akaike information criterion is represented in equation (4) as:

$$AIC = -2 \ln L + 2K \tag{4}$$

where L is the value of the likelihood function, K is the number of estimated parameters, and N is the number of observations. The Bayesian Information Criterion is represented in equation (5) as:

$$BIC = -2 \ln L + k \ln T \tag{5}$$

2.5 Forecast Performance Measures

Forecast performance measures summarize the errors due to prediction. In this research, the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) will be used to determine the best prediction model. MAE and RMSE are among the most popular forecast performance measures for evaluating the forecasting power of a model (Lawal *et al.*, 2015). The equation (6), (7), (8) represent the MAE, MAPE, and RMSE respectively which are defined as follows;



$$MAE = \frac{1}{N} \sum_{t=1}^N |\hat{\sigma}_t - \sigma_t| \tag{6}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (\hat{\sigma}_t - \sigma_t)^2} \tag{7}$$

$$MAPE = \frac{1}{N} \sum_{t=1}^N \frac{|\hat{\sigma}_t - \sigma_t|}{\sigma_t} \tag{8}$$

where σ_t and $\hat{\sigma}_t$ denote the actual and predicted conditional variance at a given time, respectively. When evaluating ARMA-GARCH models, the model with the lowest MSE, RMSE, and MAPE values is considered the most accurate for forecasting.

3.0 RESULT AND DISCUSSION

The analysis was done on ARIMA-GARCH and ARIMAX-GARCH model, using the monthly data set of Nigeria’s inflation rate from 1997 to 2024. These data were obtained from the Central Bank of Nigeria and the National Bureau of Statistics.

3.1 Statistics and Data Analysis

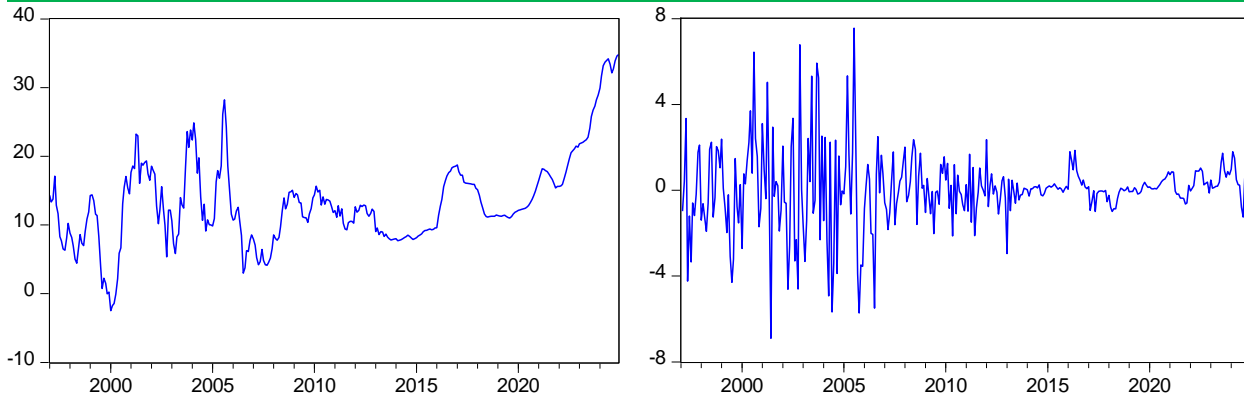
This details the diagnostic checks conducted on the data, the parameter estimations of the respective models, and the model evaluation metrics employed to determine forecasting accuracy.

Table 1: Descriptive Statistics of the Macroeconomic Variables

	Inflation rate	Exchange rate	Money supply (₦B)	PMS price (₦)
Skewness	0.944857	3.590952	-0.003127	3.475877
Kurtosis	4.660937	16.82214	1.795323	16.21921
Jarque-Bera	88.61627	3396.838	20.31801	3123.043
Probability	0.000000	0.000000	0.000039	0.000000
Sum	4493.300	83734.90	2016916	38229.95
Sum Sq. Dev.	14324.47	25132042	1820000	8453700

Table 1 summarizes the key descriptive features of inflation, exchange rate, money supply, and PMS price for the study period. The inflation series shows a positive skewness and high kurtosis, indicating a right-skewed and leptokurtic distribution, which suggest the presence of volatility clustering and fat tails, reinforcing the relevance of volatility-sensitive models such as ARIMA-GARCH for modeling inflation dynamics as observed in prior studies that found Nigeria’s inflation data deviate from normality and exhibit volatility clustering (Olalude et al., 2020). The exchange rate displays very high skewness and kurtosis values, implying persistent fluctuations and heavy tails. Similar findings reveal that exchange rate returns are highly volatile and better captured with GARCH-type models that account for

conditional heteroskedasticity (Arikewuyo, 2024). Money supply appears relatively stable, showing near-symmetric distribution with mild tail behavior. Although less volatile, it remains an important monetary driver influencing exchange rate dynamics and, consequently, inflation (Eniyewu et al., 2024). PMS prices display sharp spikes and extreme values, aligning with recent findings that petroleum-price volatility significantly amplifies domestic inflation (Omodunbi et al., 2025). Overall, the non-normal and volatile nature of these variables justifies the application of hybrid models such as ARIMAX-GARCH, which can accommodate exogenous shocks and volatility persistence within Nigeria’s inflation framework.



Inflation Rate at Level

Inflation Rate at First Differencing

Figure 1: Graph of Inflation Rate at Level and First Differencing

The inflation rate plot at the level (Figure 1, left) shows clear evidence of non-stationarity, marked by persistent fluctuations and a noticeable upward trend after 2020, reflecting structural changes and long-term variability in the inflation process. This behavior suggests that the original series lacks a constant mean and variance, thereby violating the stationarity assumption required by many time-series models, including ARIMA. To correct this, the series was first-differenced, as shown in Figure 1 (right). The transformed series exhibits greater stability, oscillating around a constant mean near zero with relatively constant variance, especially after 2005. This indicates that first differencing successfully removed the trend and mitigated volatility clustering, rendering the inflation series stationary.

Table 2: Augmented Dickey-Fuller test for Stationarity of Variables

Variables	At Level		First Differencing	
	t-statistic	P-value (5% Critical value)	t-statistic	P-value(5% Critical value)
Inflation	-2.011706	0.2818	-15.61149	0.0000
Exchange Rate	3.13946	1.0000	-4.777471	0.0001
Pms Price	2.524905	1.0000	-20.77931	0.0000
Money Supply	0.053664	0.9519	-14.89841	0.0000

The table 2 present the Augmented Dickey-Fuller (ADF) test used to assess the stationarity of Inflation, Exchange Rate, PMS Price, and Money Supply. At their level form, none of the variables were stationary, as the test statistics (Inflation: -2.0117 , Exchange Rate: 3.1395 , PMS Price: 2.5249 , Money Supply: 0.0537) had p-values above 0.05, confirming the presence of unit roots. After first differencing, however, all variables became stationary, with highly negative test statistics (Inflation: -15.6115 , Exchange Rate: -4.7775 , PMS Price: -20.7793 , Money Supply: -14.8984) and p-values ≤ 0.0001 . This indicates that each series is integrated of order one, $I(1)$.

Table 3: Model Selection Criteria Table

Model	AIC*	BIC	HQ
ARIMA (2,1,1)	3.942711	3.999639	3.965407
ARIMA (0,1,1)	3.964509	3.998666	3.978126
ARIMA (1,1,0)	3.964780	3.998937	3.978397
ARIMA (1,1,1)	3.970462	4.016004	3.988619
ARIMA (0,1,2)	3.970467	4.016008	3.988623
ARIMA (2,1,0)	3.970531	4.016073	3.988687
ARIMA (1,1,2)	3.976091	4.033018	3.998786
ARIMA (2,1,2)	3.981223	4.049536	4.008458
ARIMA (0,1,0)	3.982716	4.005487	3.991794



Table 3 presents the model selection criteria used to compare various ARIMA model configurations based on information criteria. Among the models evaluated, the ARIMA (2,1,1) model stands out as the most optimal, as it records the lowest values between the two information criteria, AIC (3.942711) and HIC (3.999639). While the BIC points to ARIMA (0,1,1) as a simpler alternative, the differences are very small. Since ARIMA (2,1,1) performs best in two of the three criteria, it offers a stronger balance between accuracy and efficiency, making it the most reliable choice for the analysis.

3.2.1 Model Estimation

Table 4: Estimation of ARIMA-GARCH Model for Inflation Rate

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Constant	-316.4841	11768.13	-0.026893	0.9785
AR(1)	1.712084	0.006756	253.40180	0.0000
AR(2)	-0.711938	0.010295	-69.15483	0.0000
MA(1)	-0.338479	0.057820	-5.854008	0.0000
Variance Equation				
Constant	0.014784	0.004362	3.388994	0.0007
RESID(-1)^2	0.181084	0.047874	3.782485	0.0002
GARCH(-1)	0.812215	0.038665	21.006300	0.0000
R-squared	0.0626	Mean dependent var		13.3702
Adjusted R-squared	0.0541	S.D. dependent var		6.5585
S.E. of regression	1.8232	Akaike info criterion		3.0321
Sum squared resid	1096.9220	Schwarz criterion		3.1112
Log likelihood	-499.3635	Hannan-Quinn criter.		3.0640
Durbin-Watson stat	1.9986			
Inverted AR Roots	0.69	-0.13		
Inverted MA Roots	0.20			

Table 4 presents the ARIMA-GARCH estimation results for Nigeria's inflation rate. In the mean equation, the constant term is insignificant ($p = 0.9785$), indicating no fixed average once past values and shocks are considered. The autoregressive terms AR(1) and AR(2) are highly significant, with positive AR(1) and negative AR(2) coefficients suggesting a dynamic, oscillatory inflation pattern. The MA(1) term is also significant and negative, reflecting the lasting impact of past shocks on current

inflation. In the variance equation, all components are statistically significant, confirming the model's ability to capture inflation volatility. The ARCH effect (0.181084) shows that past shocks raise current volatility, while the high GARCH(1) coefficient (0.812215) indicates strong persistence, meaning large changes in inflation are likely to be followed by further large changes. This persistence aligns with the structural and policy-related instability of Nigeria's economy. Finally, the Durbin-Watson statistic (1.998575) confirms that the residuals are free from serial correlation, validating the model's adequacy.

Table 5: Estimation of ARIMAX-GARCH using some Determinant of Inflation rate

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.417534	14.74162	-0.028324	0.9774
D(LOG(EXCHANGE_RATE))	1.044927	0.528335	1.977772	0.0480
D(LOG(MONEY_SUPPLY__B_))	-0.119450	0.513893	-0.232441	0.8162
D(LOG(PMS_PRICE))	0.454852	0.195103	2.331348	0.0197
AR(1)	0.205882	0.035952	5.726531	0.0000



IJSGS FUGUSAU VOL.11(3)		WEBSITE: https://fugus-ijsgs.com.ng		
AR(2)	0.811791	0.036684	22.12946	0.0000
MA(1)	0.963327	0.020398	47.22649	0.0000
Variance Equation				
C	0.019792	0.004569	4.332121	0.0000
RESID(-1)^2	0.209951	0.052341	4.011231	0.0001
GARCH(-1)	0.790521	0.038694	20.42986	0.0020
R-squared	0.7573	Mean dependent var		0.064222
Adjusted R-squared	0.7536	S.D. dependent var		1.766376
S.E. of regression	1.8251	Akaike info criterion		3.025644
Sum squared resid	1092.5960	Schwarz criterion		3.128340
Log likelihood	-496.2826	Hannan-Quinn criter.		3.066590
Durbin-Watson stat	2.0001			
Inverted AR Roots	.70			
Inverted MA Roots	.33			

Table 5 reports the ARIMAX-GARCH estimation results, which integrate external macroeconomic variables with volatility dynamics to better explain Nigeria's inflation rate. In the mean equation, the constant term is insignificant ($p = 0.9774$), indicating no fixed baseline for inflation once other factors are considered. The exchange rate ($D(\text{LOG}(\text{EXCHANGERATE}))$) is significant ($p = 0.0480$) with a positive coefficient (1.044927), confirming that Naira depreciation increases inflation. Similarly, PMS price ($\text{LOG}(\text{PMSPRICE})$) is significant ($p = 0.0197$), reinforcing the strong link between fuel price hikes and inflation. By contrast, money supply ($D(\text{LOG}(\text{MONEYSUPPLY}))$) is insignificant ($p = 0.8162$), suggesting its short-term impact is negligible. The autoregressive and moving average terms are highly significant, with large AR(2) (0.811791) and MA(1)

(0.963327) coefficients, indicating persistent effects of past inflation and shocks. In the variance equation, both the ARCH (0.209951) and GARCH(1) (0.790521) terms are significant, showing strong persistence in volatility where past shocks continue to shape future uncertainty. Model performance improved substantially, with $R^2 = 0.757$ and adjusted $R^2 = 0.753$, indicating that over 75% of inflation variation is explained. The Durbin-Watson statistic (2.000121) rules out serial correlation, while the AR and MA roots within the unit circle confirm model stability. Overall, the ARIMAX-GARCH model provides a robust and comprehensive framework for capturing both the determinants and volatility of inflation in Nigeria.

Table 6: Forecasting efficiency of the estimated models

Model	RMSE	MAE	MAPE	Rank
ARIMA(2,1,1)-GARCH(1,1)	1.812235	1.121774	2.962866	2
ARIMAX(2,1,1)-GARCH(1,1)	1.730652	1.107155	2.436751	1

Table 6 compares the forecasting efficiency of the four inflation models using three standard forecast accuracy metrics: RMSE, MAE, and MAPE. Across all three metrics, the ARIMAX(2,1,1)-GARCH(1,1) model demonstrates the best forecasting performance, with the lowest RMSE (1.730652), MAE (1.107155), and MAPE (2.436751). This suggests that the model not only fits the historical data well but also predicts future inflation more accurately than the other models.

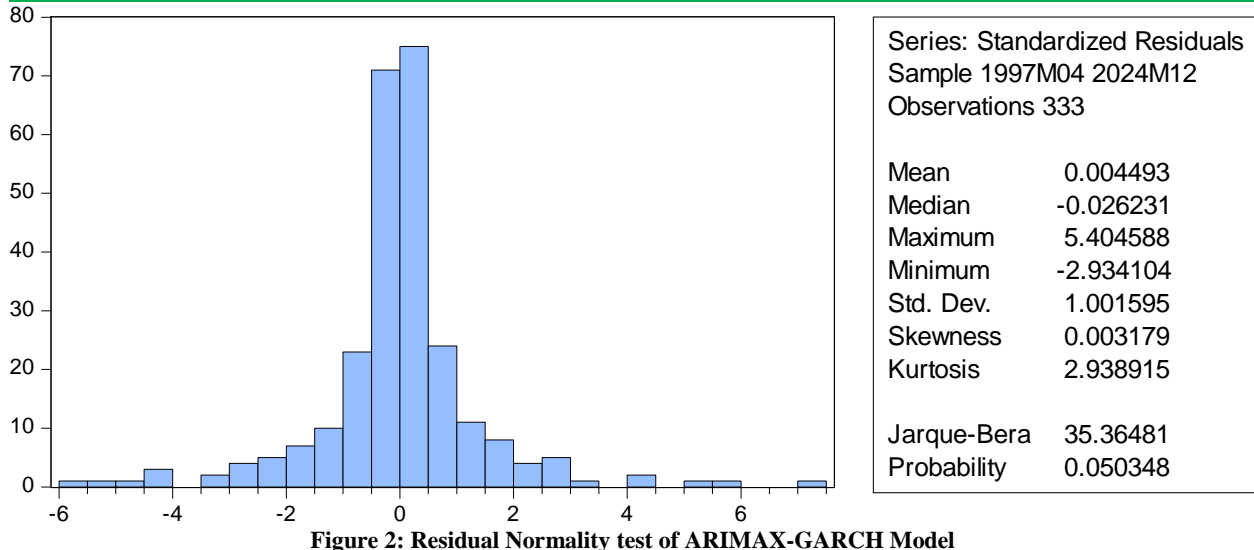


Figure 2: Residual Normality test of ARIMAX-GARCH Model

Figure 2 Shows the Residual Normality Test for the Arimax-garch Model. The Standardized Residuals are Nearly Symmetric and Bell-shaped, with a mean close to zero (0.0045), Standard Deviation Near One (1.0016), Minimal Skewness (0.0032), and Kurtosis (2.94) close to the Normal Benchmark. The Jarque-bera Statistic (35.36, $p = 0.0503$) is slightly above the 5% Threshold, so the Null Hypothesis of Normality cannot be Rejected. Overall, the Residuals Approximate Normality, Indicating Reliable Statistical Inference and Confirming the Adequacy of the Arimax-garch Model for Explaining Nigeria’s Inflation Dynamics.

Table 7: Heteroskedasticity Test: ARCH

F-statistic	0.004819	Prob. F(1,330)	0.9447
Obs*R-squared	0.004848	Prob. Chi-Square(1)	0.9445

Table 7 reports the ARCH test results for the ARIMAX-GARCH model. Both the F-statistic (0.0048, $p = 0.9447$) and the Obs*R-squared statistic (0.0048, $p = 0.9445$) are highly insignificant, confirming the absence of residual ARCH effects. This indicates that the GARCH component has effectively captured the volatility dynamics, validating the model’s specification for handling time-varying variance in Nigeria’s inflation data.

4.0 Conclusion

This study examined the forecasting performance of alternative time series models for Nigeria’s inflation, with emphasis on the ARIMA-GARCH and ARIMAX-GARCH frameworks. Results show that although the ARIMA-GARCH model adequately captures volatility clustering in inflation dynamics, it does not account for the role of external macroeconomic drivers. In contrast, the ARIMAX-GARCH model, which incorporates exogenous factors such as exchange rate and PMS prices, substantially enhances explanatory power and predictive

accuracy. These findings highlight the critical role of integrating relevant macroeconomic indicators in modeling inflation, particularly within an open and import-dependent economy like Nigeria.

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