WHEN POLICY SHOCKS RESET THE CLOCK: STRUCTURAL-BREAK SARIMA-GARCH MODELING AND FORECASTING OF NIGERIAN INFLATION DYNAMICS

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ABSTRACT

Nigeria's inflation has been among the most volatile and policy-sensitive in sub-Saharan Africa, buffeted by a long string of domestic and external shocks. This study examines monthly headline inflation from January 2003 to January 2026 using a time series approach that combines structural break detection, seasonal ARIMA modelling, GARCH volatility estimation and out-of-sample forecasting. Three-unit root tests all point to the series being integrated of order one. The Bai-Perron test, which is more suitable than the Zivot-Andrews single-break test, identifies seven breaks associated with the 2005 CBN banking consolidation, 2008 global financial crisis, 2012 monetary tightening, 2016 recession and devaluation of the naira, 2018 foreign exchange restrictions, 2020 COVID-19 shock and the June 2023 fuel subsidy removal and naira floatation, the largest shock in the 23-year period. The best fit is the SARIMA (1,1,0) $(1,0,2)_{[12]}$ model, which accounts for the 12-month seasonal inflation pattern of Nigeria. The GARCH (1,1)-t estimates suggest persistent volatility, with $\alpha + \beta = 0.999$ and heavy-tailed conditional distributions. All actual values in the holdout period are within the 95% forecast intervals supporting directional accuracy. The 12-month forecast points to continued disinflation to about 10.2% by June 2026, followed by a seasonal rise to 15.55% by January 2027. The findings have implications for CBN monetary policy calibration, federal budget planning and food security interventions.

1. INTRODUCTION

Inflation has never been a quiet problem in Nigeria. Price instability has been a factor that has shaped the way households budget, businesses plan and policymakers respond, often reactively and sometimes too late, for decades. Nigeria is Africa's most populous country and largest economy (World Bank, 2024) and thus, inflation in Nigeria is difficult to manage and an important subject of study as inflation is at the nexus of monetary policy, oil dependence, structural supply weaknesses and political economy.

The sample window of this study, 2003–2026, is a particularly instructive chapter in the macroeconomic history of Nigeria. It began with the National Economic Empowerment and Development Strategy (NEEDS) under the Obasanjo administration that introduced fiscal discipline, monetary targeting and banking sector reform under the then CBN Governor Charles Soludo (Soludo, 2004). The dynamics of inflation over the next two decades were influenced by a sequence of shocks. The 2008 global financial crisis was transmitted through oil price volatility and reversal of capital flows (Raifu & Afolabi, 2024). The 2016 economic recession was explained by the decline in crude oil prices and the CBN's foreign exchange restrictions (World Bank, 2017). The COVID-19 pandemic in 2020 resulted in a reduction in aggregate demand and supply chain disruptions (Aniemeke, 2024). The policy shock of subsidy removal and naira floatation in June 2023 jointly pushed up the 12-month headline inflation rate from about 22% to a high of 34.8% (NBS, 2025), the highest since the early 2000s.

The human cost is not an abstraction. Food and non-alcoholic beverages represent the biggest component of Nigeria's CPI basket (NBS, 2024), meaning rising prices fall hardest where ordinary Nigerians spend most of their money. For the 128 million plus people below the poverty line (Aniemeke, 2024), this means less food and less money. In addition to social welfare, persistent inflation affects investment planning, credit markets and foreign exchange management (Eregha & Ndoricimpa, 2022) and thus, undermines long run growth. Thus, understanding how inflation evolves, what forces drive its regime shifts and where it is headed is therefore a practical necessity for anyone serious about governing the Nigerian economy.

The existing literature on Nigerian inflation is sizeable but has not kept pace with recent events. Akpanta and Okorie (2015), Otu et al. (2014) and Doguwa and Alade (2013) established important methodological foundations but all draw on data that predates the 2023 reform shock. Beyond the data gap, most studies fit ARIMA or SARIMA models without formally testing for structural breaks, a significant omission in a series that has gone through several distinct regimes. Where unit root tests ignore structural breaks, the results are known to be biased (Perron, 1989). In addition, despite the attention to volatility clustering in the literature on the Nigerian exchange rate and oil price (Nzeh et al., 2023), its application to the inflation series is underexplored, despite its importance to monetary policy uncertainty and interval forecasting.

This study uses 277 monthly observations from January 2003 to January 2026 to address the gaps. The objectives are: (i) to test for integration using ADF, PP and KPSS unit root tests; (ii) to detect structural breaks endogenously using Zivot-Andrews (1992) and Bai-Perron (2003) procedures; (iii) to select and estimate the optimal SARIMA specification; and (iv) to model conditional volatility using GARCH(1,1)-t and produce a validated 12-month ahead forecast. The study is motivated by the need for inflation analysis that covers the full post-2023 reform cycle, a period existing studies do not reach, and one whose findings have implications for CBN monetary policy, federal budget planning and social protection design. **Section 2** reviews the relevant literature, **Section 3** describes the methodology, **Section 4** presents the results, and **Section 5** concludes with policy implications.

2. LITERATURE REVIEW

The modelling of inflation as a univariate time series draws on two broad frameworks. The macroeconomic foundation is anchored on the quantity theory of money which postulates that persistent inflation is caused by the money supply growing faster than the growth in real output and other co-determinants in oil dependent economies such as Nigeria include oil price dynamics and exchange rate pass-through (Bawa et al., 2021). This is operationalized by autoregressive and moving average components of the Box-Jenkins (1976) framework, the dominant forecasting tool in developing economies. However, the assumption of time-invariant variance limits its ability to capture episodic volatility. This is solved by the GARCH framework of Bollerslev (1986), which extends Engle's (1982) ARCH model by modeling time varying conditional variance, where policy shocks create bursts of price volatility.

Studies of Nigeria inflation series using ARIMA and SARIMA models have produced useful but increasingly out of date results. Akpanta and Okorie (2015) found SARIMA $(1,2,1)(0,0,1)_{[12]}$ to be the best fitting model on data of 1996 to 2013 confirming Nigeria's inflation is non-stationary with a 12-month seasonal cycle. Ekpenyong and Patrick (2016) found seasonal specifications to be superior to their non-seasonal counterparts in out of sample validation, but their sample predates the structural disruptions of 2016, 2020 and 2023. Doguwa and Alade (2013) recommended SARIMAX as the CBN's preferred forecasting tool, yet this was based on data that predates the most turbulent decade in recent Nigerian inflation history. Most recently, Guobadia et al. (2023) modeled inflation for 1981-2020 and could not capture the post-2023 reform trajectory. Typically, these studies do not formally test for the presence of structural breaks and this can lead to models that can fit one regime but not the other.

The treatment of structural breaks in inflation modelling has grown in importance following Perron (1989), who showed that ignoring breaks biases unit root tests, and Bai and Perron (2003), who developed a framework for detecting multiple breaks simultaneously. Clemente et al. (2017) applied Bai-Perron on G7 inflation series and found that breaks substantially change inferences about long run price behavior, which is particularly pertinent given Nigeria's eventful inflation history. Göktaş and Dişbudak (2014) utilized Bai-Perron with GARCH on Turkish CPI data and determined that omitting breaks from the mean equation led to an overestimation of volatility persistence, which raises significant questions about the current Nigerian GARCH inflation research.

Omotosho and Doguwa (2012) modeled the volatility of inflation in Nigeria using GARCH and found significant time varying conditional variance, but without accounting for structural breaks which, as Göktaş and Dişbudak (2014) show, may overstate persistence. Eregha and Ndoricimpa (2022) using BEKK GARCH-M model found that inflation uncertainty is an independent drag on output growth in Nigeria. The finding is consistent with the Cukierman-Meltzer hypothesis (Cukierman & Meltzer, 1986). Similar results were found in another study for Nigeria using other GARCH specifications (Nzeh et al., 2023), which also detected the food inflation persistence near the unit root. But they do not allow for structural breaks that could overstate persistence.

Raifu and Afolabi (2024) used dynamic ARDL to study the inflationary effect of the fuel subsidy removal shock in the 2023 reform and found persistent price effect. These authors, however, did not formally define the event as an endogenous structural break. Yahaya (2025) using the ARDL-VECM model, found the removal of the fuel subsidy to be associated with naira depreciation and persistent cost push inflation using data from January 2018 to December 2024. Nevertheless, the study did not include break detection with volatility modelling nor extend the sample to capture the subsequent disinflation. These studies leave three important gaps unaddressed.

First, no existing study covers Nigeria's full headline inflation cycle through the post-2023 reform peak and the disinflation to January 2026. Second, the Bai-Perron framework has not been applied to Nigeria's headline inflation series in a way that traces each break to its specific economic or policy context. Third, as Göktaş and Dişbudak (2014) note, GARCH studies of Nigerian inflation have not accounted for structural breaks, which can lead to overstated persistence estimates. This study addresses all three gaps by combining Zivot-Andrews (1992) and Bai-Perron (2003) break tests, SARIMA modelling and GARCH(1,1)-t estimation on the longest and most current monthly Nigerian inflation dataset available, with findings that have implications for how policymakers, researchers and forecasters understand Nigeria's evolving inflation dynamics.

3. MATERIALS AND METHODS

3.1 Data Source and Description

This study uses monthly data on Nigeria's headline inflation rate measured as the year-on-year percent change in the All-Items Consumer Price Index (CPI) from the Central Bank of Nigeria statistical database (CBN, 2026). The data run from January 2003 to January 2026, giving 277 monthly observations. The year 2003 marks the start of the NEEDS reform programme (NPC, 2004) and what many regard as the beginning of modern macroeconomic management in post-military Nigeria, while January 2026 covers the full period after the June 2023 fuel subsidy removal and the disinflation that followed. Headline inflation was chosen over core or food inflation because it is what the CBN and the Federal Government watch most closely, and it covers the full consumer price basket, including food and energy, which took the biggest hit from the 2023 policy changes.

3.2 Preliminary Analysis

Prior to formal modelling, descriptive statistics including the mean, median, minimum, maximum, standard deviation, skewness, kurtosis, and the Jarque-Bera normality test (Jarque & Bera, 1987) were computed and the inflation series was plotted. The Jarque-Bera test is particularly relevant as rejection of normality directly informs the choice of error distribution in the GARCH specification.

3.3 Unit Root Tests

Three complementary unit root tests were performed, at level and at first difference, to investigate the order of integration. The augmented Dickey-Fuller test (ADF; Dickey & Fuller, 1979) is based on the following regression:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta y_{t-i} + \varepsilon_t \qquad (1)$$

where y_t is the inflation series, Δ is the first difference operator, α is a constant, βt is a deterministic trend, γ is the coefficient tested under the null hypothesis $H_0\colon \gamma = 0$ implying a unit root, p is the number of lagged differences selected by AIC, and ε_t is a white noise error term.

The Phillips-Perron test (PP; Phillips & Perron, 1988) uses a simpler base regression:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \varepsilon_t \qquad (2)$$

Unlike the ADF test, the PP test does not augment with lagged differences but instead applies a non-parametric correction to the standard errors of γ using a long-run variance estimator, making it more robust to serial correlation and heteroscedasticity.

The Kwiatkowski-Phillips-Schmidt-Shin test (KPSS; Kwiatkowski et al., 1992) reverses the null hypothesis by testing the null of stationarity against the alternative of a unit root. The series is decomposed as:

$$y_t = \xi t + r_t + \varepsilon_t, \qquad r_t = r_{t-1} + u_t, \qquad u_t \sim i.i.d.(0, \sigma_u^2) \qquad (3)$$

where r_t is a random walk and ε_t is a stationary error. The null hypothesis $H_0\colon \sigma_u^2 = 0$ implies stationarity. The test statistic is:

$$KPSS - \frac{1}{T^2} \frac{\sum_{t=1}^{T} S_t^2}{\hat{\sigma}^2} \qquad (4)$$

where $S_t = \sum_{i=1}^{t} \hat{\varepsilon}_i$ is the partial sum of residuals and $\hat{\sigma}^2$ is a consistent estimate of the long-run variance. The order of integration was accepted only if all three tests provided a consistent result.

3.4 Structural Break Tests

Given that the 2003–2026 sample spans several major economic shocks, the possibility that Nigeria's inflation series contains structural breaks in its mean was formally investigated.

When breaks like these are ignored, unit root tests tend to give misleading results and models can end up misspecified (Perron, 1989).

The Zivot-Andrews (1992) test adjusts the standard ADF framework to allow for a single break of unknown timing in both the intercept and trend. The most general specification is:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \theta DU_t(\lambda) + \psi DT_t(\lambda) + \sum_{i=1}^{k} d_i \, \Delta y_{t-i} + \varepsilon_t \qquad (5)$$

where $DU_t(\lambda) = 1$ if $t > T\lambda$ and zero otherwise is a level shift dummy, $DT_t(\lambda) = t - T\lambda$ if $t > T\lambda$ and zero otherwise is a trend shift dummy, λ is the relative break point and T is the sample size. The break date is chosen as the value of λ that minimizes the ADF t-statistic on γ, that is, the date at which the evidence against the unit root null is strongest.

The Bai-Perron (2003) test extends this by allowing for m structural breaks at unknown dates $T_1, T_2, \dots, T_m$ in the following pure mean-shift model:

$$y_t = \mu_j + \varepsilon_t, \qquad t = T_{j-1} + 1, \dots, T_j, \qquad j = 1, \dots, m + 1 \qquad (6)$$

where μ_j is the mean inflation level in segment j. The break dates are estimated by minimising the global sum of squared residuals:

$$\{\hat{T}_1, \dots, \hat{T}_m\} = \arg\min_{T_1,\dots,T_m} \sum_{j-1}^{m+1} \sum_{t-T_{j-1}+1}^{T_j} (y_t - u_j)^2 \qquad (7)$$

The optimal number of breaks is selected by minimizing the BIC across all candidate partitions from zero to a specified maximum. A minimum segment length of $h = 0.10$, roughly 28 months, was required between breaks to ensure that detected breaks are economically meaningful rather than driven by statistical noise. The test was applied to the pure mean-shift model and 95% confidence intervals were computed for all detected break dates.

3.5 ARIMA/SARIMA Model Selection

Integration was confirmed at first difference, $I(1)$, and the Box-Jenkins (1976) methodology was used for model identification, estimation and diagnostic checking. The general ARIMA(p,d,q) model was specified as

$$\Delta^d Inflation_t = \mu + \sum_{i=1}^{p} \varphi_i \Delta^d Inflation_{t-i} + \sum_{i=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (8)$$

where Δ^d denotes the d-th order difference operator, φ_i are the autoregressive parameters, θ_j are the moving average parameters, μ is a constant and ε_t is white noise. Given that the series is $I(1)$, $d = 1$ throughout.

Since the ACF of the differenced series showed significant spikes at seasonal lags 12 and 24, a SARIMA(p,1,q)(P,0,Q)$_{[12]}$ specification was also considered to account for Nigeria's documented 12-month inflationary cycle driven by agricultural harvest patterns and recurring festive demand (Mbah et al., 2022; Sakanko et al., 2025). The SARIMA model is specified as

$$\Phi_P(B^{12})\phi_p(B)\Delta\Delta_{12}^D Inflation_t = \Theta_Q(B^{12})\theta_q(B)\varepsilon_t \quad (9)$$

where B is the backshift operator such that $B^k y_t = y_{t-k}$, $\phi_p(B)$ and $\Phi_P(B^{12})$ are the non-seasonal and seasonal autoregressive polynomials respectively, $\theta_q(B)$ and $\Theta_Q(B^{12})$ are the non-seasonal and seasonal moving average polynomials respectively, and $\Delta_{12}^D = (1 - B^{12})^D$ is the seasonal differencing operator.

Ten candidate models were estimated together with the auto.arima exhaustive search algorithm (Hyndman & Khandakar, 2008). Final selection was based on BIC, preferred to AIC for its heavier complexity penalty, with model adequacy assessed via the Ljung-Box portmanteau test (Ljung & Box, 1978) on the residuals. The selected SARIMA model was further benchmarked against an Exponential Smoothing State Space model (ETS; Hyndman et al., 2008) on the holdout period to provide a comparative assessment of out-of-sample forecast accuracy.

The Bai-Perron test for structural change found seven breaks in the series but the intervention variables for these breaks were not directly included in the SARIMA model for forecasting. This choice was deliberate, as the main objective of the SARIMA model in this study is to provide a parsimonious representation of the inflation data generating process that is capable of producing reliable out-of-sample forecasts and incorporating seven break dummies into the mean equation would risk overfitting the model to historical regime shifts and reducing forecast generalizability. Instead the structural breaks are viewed as contextual evidence that helps to interpret the results and justify the complementary GARCH volatility analysis in line with the sequential approach of Omotosho and Doguwa (2012).

3.6 GARCH(1,1) Volatility Model

The ARCH-LM test of Engle (1982) was applied to the SARIMA residuals with 12 lags to formally test for volatility clustering. Given confirmation of ARCH effects, the GARCH(1,1) model of Bollerslev (1986) was used to model the conditional variance of the inflation series. The model is specified as

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (10)$$

where h_t is the conditional variance, ε_{t-1}^2 is the squared error capturing the impact of the past shocks on current volatility, h_{t-1} is the lagged conditional variance capturing persistence and ω is a constant. The sum of $\alpha_1 + \beta_1$ measures overall volatility persistence, subject to the stationarity constraint $\alpha_1 + \beta_1 < 1$, with values close to unity implying that shocks to inflation uncertainty dissipate very slowly.

The model was estimated under both normal and Student-t error distributions, with final selection based on AIC, BIC, log-likelihood and the Pearson goodness-of-fit test. The Nyblom (1989) parameter stability test was also applied to assess whether the estimated parameters remain stable across the full sample period. Where the persistence sum $\alpha_1 + \beta_1$ approaches unity, this raises the question of whether the series follows an Integrated GARCH process in which shocks to variance are permanent, a possibility that is examined in the context of the structural breaks identified in **Section 3.4**. The structural break dummies were not incorporated directly into the GARCH variance equation, for the same reasons outlined in **Section 3.5**, and the two analyses are therefore conducted as complementary sequential steps rather than a fully integrated framework.

3.7 Forecast Evaluation and Projection

The forecasting analysis was conducted in three stages. In the first stage, the last 12 months of the sample (February 2025 to January 2026) were held out as a validation set and the SARIMA model was re-estimated on the training period only. Forecast accuracy was assessed using three standard metrics. The Mean Absolute Error is defined as

$$MAE = \frac{1}{h}\sum_{t=1}^{h}|y_t - \hat{y}_t| \quad (11)$$

The Root Mean Squared Error (RMSE) is defined as

$$RMSE = \sqrt{\frac{1}{h}\sum_{t=1}^{h}(y_t - \hat{y}_t)^2} \tag{12}$$

The Mean Absolute Percentage Error (MAPE) is defined as

$$MAPE = \frac{1}{h}\sum_{t=1}^{h}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100 \tag{13}$$

where y_t is the actual inflation value, $\hat{y}_t$ is the forecast value and h is the forecast horizon. The proportion of actual observations falling within the 95% prediction intervals was also assessed as a calibration check.

In the second stage, a rolling origin evaluation was implemented via an expanding window with a minimum training size of 240 observations so that a more comprehensive assessment of forecast robustness could be performed across multiple origins and horizons. The method is a generalization of the single holdout evaluation. Instead of a single fixed period, it evaluates the performance of the model over multiple training windows.

In the third stage, the model was re-estimated on the complete 277-observation sample to produce a 12-month ahead forecast for February 2026 through January 2027, with 80% and 95% prediction intervals. It should be noted that the prediction intervals are derived from the SARIMA model under the assumption of constant variance. The GARCH results are reported separately to characterize the conditional volatility process rather than to adjust the forecast intervals.

3.8 Software and Estimation

All analyses were carried out in R (version 4.3+). The unit root and Zivot-Andrews tests used the urca package (Pfaff, 2008); Bai-Perron structural break tests used strucchange (Zeileis et al., 2002); ARIMA and SARIMA estimation and forecasting used forecast (Hyndman & Khandakar, 2008); the ARCH-LM test used FinTS (Boshnakov, 2007); and GARCH(1,1) estimation used rugarch (Galanos, 2026).

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics

Table 1 shows the descriptive statistics of the headline inflation rate in Nigeria for the period January 2003 to January 2026. The positive skewness of 1.14 and the right tail of the distribution as a result of the spike following the 2023 reforms are consistent with the mean of 14.49% being greater than the median of 12.80%. The maximum of 34.80% reflects the peak of the shock from the removal of the fuel subsidy and the high standard deviation of 6.63 percentage points highlights the large variability across periods which motivates the volatility modelling. The kurtosis of 4.06 exceeds the normal benchmark of 3 and the Jarque-Bera statistic of 72.93 ($p = 0.000$) formally rejects normality, thus supporting the Student-t GARCH specification adopted in **Section 4.6.**

Table 1: Descriptive Statistics of Nigeria Monthly Headline Inflation Rate (2003–2026)

Statistic	Mean	Median	Min	Max	Std Dev	Skewness	Kurtosis	JB Stat	JB p-value
Value	14.492	12.800	3.000	34.800	6.634	1.140	4.057	72.935	0.000

Note: All values are in percentage points. JB = Jarque-Bera normality test. Source: Authors' computation from CBN data.

4.2 Time Series Plot

Figure 1 shows a time plot of the monthly headline inflation rate in Nigeria from January 2003 to January 2026. The series is clearly non-stationary with observable regime changes that correspond with important domestic and global economic events. A rapid decline is observed from high levels in the mid-2000s following CBN banking sector reforms, with the global financial crisis of 2008 providing a second observable disruption (Didigu et al., 2022). The long low-inflation regime of 2013–2015 was followed by the 2016 recession and devaluation of the naira (Ozili, 2024). Most dramatically, the post-June 2023 fuel subsidy removal episode pushed inflation to its highest level in the sample, approximately 34.8%, before a gradual but uneven decline through early 2026. These visual regularities motivate the formal tests for structural breaks undertaken in **Section 4.5.**

Figure 1: Nigeria Monthly Headline Inflation Rate (2003-2026)

4.3 Unit Root Test

Table 2 reports the results of three unit root tests. The Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were applied at both level and first difference. At the level, all three tests unanimously indicate non-stationarity: the ADF statistic of -2.77 and PP statistic of -2.81 both fail to exceed their respective 5% critical values (-3.42 and -3.43), while the KPSS statistic of 0.51 far exceeds even the 1% critical value of 0.22. Upon first differencing, all three tests unanimously indicate stationarity: the ADF and PP statistics of -10.32 and -13.69 respectively are far below the 1% critical values, and the KPSS statistic of 0.04 is comfortably below all critical values. The series is therefore integrated of order one, I(1), a finding consistent with previous empirical literature (Doguwa & Alade, 2012; Otu et al., 2014).

Table 2: Unit Root Test Results

Test	Level	Test Statistic	CV 1%	CV 5%	CV 10%	Decision
ADF	Level	-2.766	-3.980	-3.420	-3.130	Non-Stationary
ADF	1st Difference	-10.322	-3.440	-2.870	-2.570	Stationary ***
PP	Level	-2.809	-3.995	-3.426	-3.137	Non-Stationary
PP	1st Difference	-13.687	-3.456	-2.872	-2.572	Stationary ***
KPSS	Level	0.513	0.216	0.146	0.119	Non-Stationary
KPSS	1st Difference	0.039	0.739	0.463	0.347	Stationary ***

*Note: *** significant at 1%. ADF and PP null hypothesis: series has a unit root. KPSS null hypothesis: series is stationary. All tests confirm the series is I(1).*

4.4 ACF and PACF

Figure 2 presents the ACF and PACF of the first-differenced inflation series. The ACF drops sharply after lag 1, with significant spikes at lags 12 and 24, pointing to a seasonal MA component at lag 12. The PACF exhibits a peak at lag 1 while peaks are also seen at 12 and 15 consistent with an AR(1) and seasonal autoregressive structure. These patterns pointed to a SARIMA specification, consistent with Nigeria's 12-month inflation cycle associated with harvest seasons and festive demand (Mbah et al., 2022; Sakanko et al., 2025).

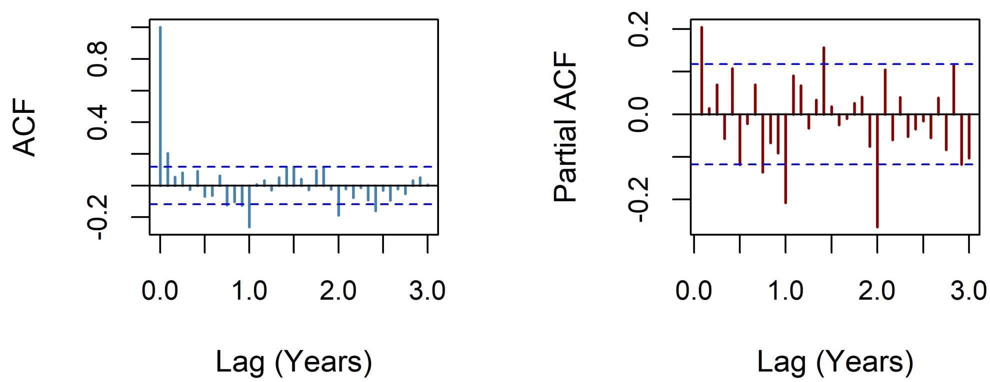


Figure 2: ACF and PACF of First Differenced Inflation Series

4.5 Structural Break

Table 3 presents the Zivot-Andrews (1992) test allowing for a single endogenous structural break in both intercept and trend. The test statistic of -3.83 does not exceed the 5% critical value of -5.08, indicating that the null of a unit root cannot be rejected even when a single break is accommodated. The identified break at August 2005 coincides with the early phase of CBN banking sector consolidation (Soludo, 2004). This result does not contradict the I(1) finding from **Section 4.3** but rather indicates that the unit root persists even with a single break accounted for, directly motivating the Bai-Perron multiple break approach of Bai and Perron (2003).

Table 3: Zivot-Andrews Unit Root Test with Structural Break

	Model	Test Stat	CV 1%	CV 5%	CV 10%	Break Date	Decision
Zivot-Andrews	Both	-3.8345	-5.57	-5.08	-4.82	Aug 2005	Fail to Reject H_0

Note: Source: Zivot and Andrews (1992). Computed using urca package in R.

The Bai-Perron results are presented in **Figure 3** and **Table 4**. The BIC (BIC = 1528) selected the 7-break (8-segment) partition as optimal, with all seven breaks precisely estimated and 95% confidence intervals narrow, between 1 and 3 months. The detected breaks are statistically associated with well-documented economic and policy events in Nigeria's recent history (CBN, 2026): December 2005 with the CBN banking sector consolidation and NEEDS monetary reforms (Soludo, 2004); May 2008 with the global financial crisis and commodity price shocks; December 2012 with post-crisis monetary tightening and relative price stability; January 2016 with Nigeria's economic recession and the naira devaluation (World Bank, 2017); April 2018 with continued CBN foreign exchange restrictions (CBN 2026); November 2020 with the COVID-19 supply chain and demand shock (Aniemeke, 2024); and most crucially, June 2023 with the fuel subsidy removal and naira floatation, which pushed inflation from around 22% to a peak of nearly 35% within 12 months (Raifu & Afolabi, 2024; Yahaya, 2025). The last break produces the maximum upward shift in the segmented mean, thus suggesting it is the dominant structural event in the sample. These results are consistent with Hall et al. (2025) and Cavallo and García Zavaleta (2026), who show that major economic and policy shocks are endogenously detectable structural breaks in inflation series. This is also supported by Sakanko et al. (2025) who confirm Nigeria's inflation after the 2023 reforms was the highest in 28 years.

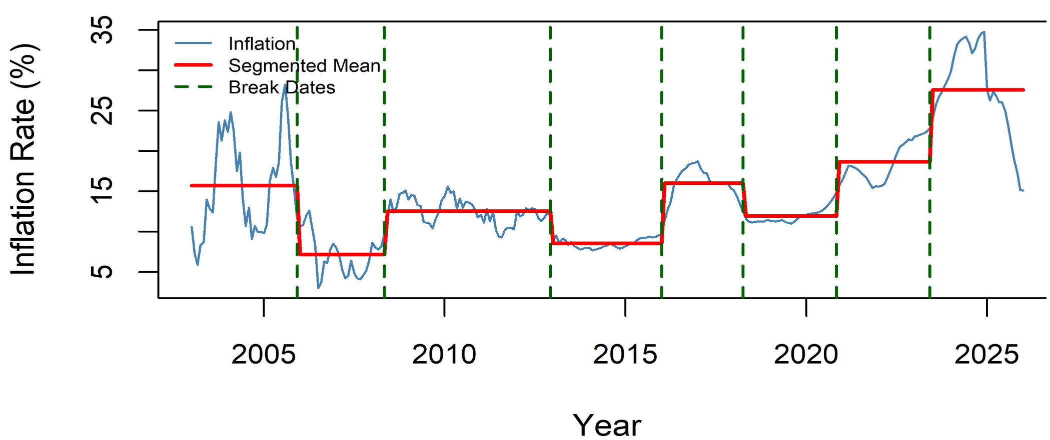


Figure 3: Bai-Perron Multiple Structural Breaks (m = 7)

Table 4: Bai-Perron Multiple Structural Break Results (m = 7, Optimal)

Break	Break Date	95% CI Lower	95% CI Upper
Break 1	December 2005	November 2005	June 2006
Break 2	May 2008	April 2008	August 2008
Break 3	December 2012	November 2012	February 2013
Break 4	January 2016	December 2015	February 2016
Break 5	April 2018	March 2018	July 2018
Break 6	November 2020	September 2020	December 2020
Break 7	June 2023	January 2023	July 2023

Note: BIC selected m = 7 as optimal (BIC = 1528). 95% confidence intervals reported. Source: Bai and Perron (2003). Computed using strucchange package in R.

4.6 ARIMA/SARIMA Model Estimation

The model selection results for 11 candidate ARIMA and SARIMA specifications are presented in **Table 5**. The auto.arima model SARIMA(1,1,0)(1,0,2)$_{[12]}$ with AIC = 944.57 and BIC = 962.67 was selected as the best model among all the manually specified alternatives by the BIC criterion. The better performance of seasonal specifications relative to pure ARIMA models is consistent with Nigeria's 12-month inflation cycle driven by harvest seasons, festive demand and school resumption periods (Ekpenyong and Patrick, 2016; Mbah et al., 2022; Sakanko et al., 2025). The Ljung-Box test statistic was computed as 24.59 ($p = 0.217$) and since $p > 0.05$, the null hypothesis of no autocorrelation in the residuals is not rejected.

Table 5: ARIMA/SARIMA Model Selection Criteria

Rank	Model	AIC	BIC
1	SARIMA(1,1,0)(1,0,2)$_{[12]}$ *	944.57	962.67
2	SARIMA(0,1,1)(0,0,1)$_{[12]}$	963.48	974.34
3	SARIMA(1,1,1)(1,0,1)$_{[12]}$	957.18	975.28
4	SARIMA(1,1,1)(0,0,1)$_{[12]}$	964.27	978.75
5	SARIMA(0,1,1)(1,0,0)$_{[12]}$	1000.00	1010.86
6	SARIMA(1,1,1)(1,0,0)$_{[12]}$	1001.59	1016.07
7	ARIMA(1,1,0)	1020.92	1028.16
8	ARIMA(0,1,1)	1021.36	1028.60
9	ARIMA(1,1,1)	1022.78	1033.64
10	ARIMA(2,1,1)	1020.93	1035.41
11	ARIMA(1,1,2)	1024.45	1038.93

*Note: * Selected model. Lower BIC preferred. Auto.arima exhaustive search via forecast package in R. All models estimated with d=1 (I(1) series).*

As a second benchmark, **Table 6** compares the out-of-sample forecast accuracy of the selected SARIMA(1,1,0)(1,0,2)$_{[12]}$ model to an ETS (A,N,N) model for the February 2025 to

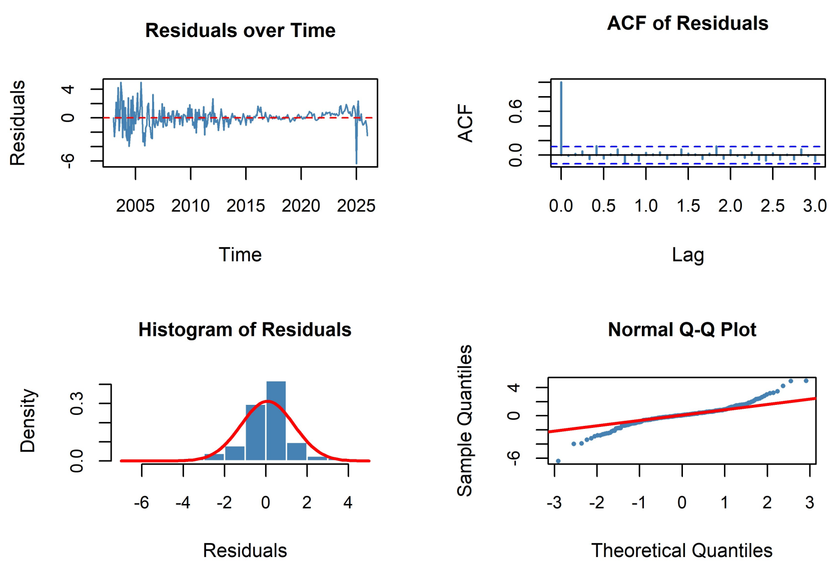
January 2026 holdout period. The SARIMA model outperforms the ETS benchmark on all three accuracy measures, with a MAE of 2.81 versus 5.26, RMSE of 3.17 versus 6.90 and MAPE of 12.22% versus 29.38%. This result further supports the seasonal SARIMA specification and is consistent with the finding in the ARIMA/SARIMA literature that models accounting for seasonal structure tend to outperform simpler smoothing approaches for monthly macroeconomic series (Hyndman and Khandakar, 2008).

Table 6: SARIMA vs ETS Benchmark (Out-of-Sample Forecast Accuracy)

Model	MAE	RMSE	MAPE (%)
SARIMA(1,1,0)(1,0,2)$_{[12]}$	2.81	3.17	12.22
ETS(A,N,N)	5.26	6.90	29.38

Note: MAE and RMSE in percentage points. MAPE in percent. Holdout period: February 2025 to January 2026. ETS model automatically selected as ETS(A,N,N). Source: Authors' computation using forecast package in R.

Figure 4 presents the residual diagnostics. The residuals are centered at zero over the entire sample but the top panel shows visibly larger swings in 2003-2007 and after 2023 relative to the calm 2014-2021 period, classic volatility clustering. The ACF lags of all residuals are within 95% confidence intervals indicating linear adequacy. In line with the Jarque-Bera rejection of normality, the residual histogram shows leptokurtosis, in agreement with the Student-t GARCH extension of **Section 4.7** (Omotosho & Doguwa, 2012; Nzeh et al., 2023).



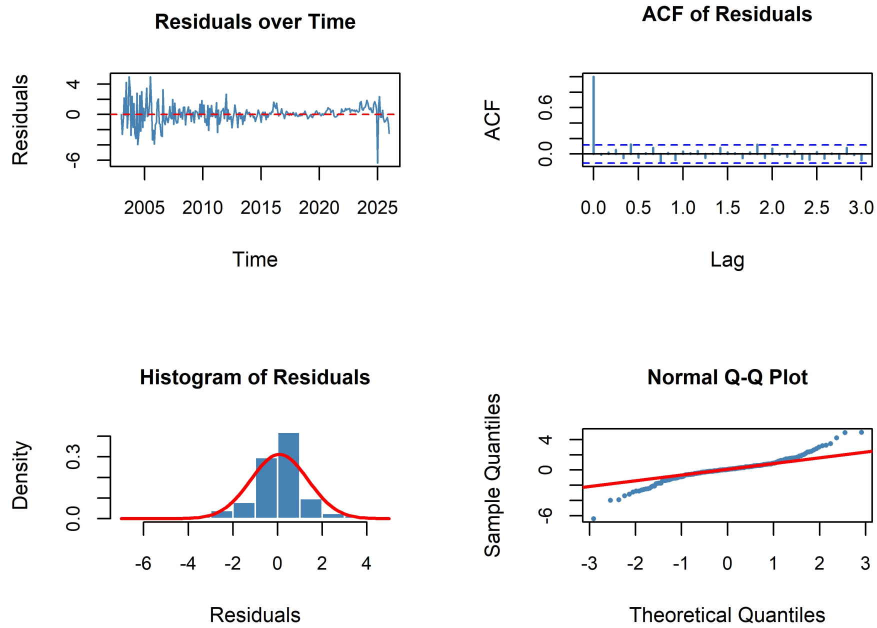


Figure 4: Residual Diagnostics of the SARIMA(1,1,0)(1,0,2)$_{[12]}$ Model

4.7 Volatility Analysis

Table 7 shows the result of the ARCH-LM test. The chi-squared statistic of 60.26 ($p = 2.02\times10^{-8}$) strongly rejects the null of no ARCH effects at the 1% level, indicating the existence of periods of high inflation volatility followed by further volatility, consistent with the visual evidence from **Figure 4** and with Nzeh et al. (2023). The GARCH (1,1) was then estimated using the normal and the student-t error distributions. The student-t distribution was found to be better than the normal distribution on all criteria of lower AIC (2.53 vs 3.00), lower BIC (2.61 vs 3.06), higher log-likelihood (-343.67 vs -408.55) and Pearson goodness-of-fit p-values all greater than 0.34 as against all less than 0.05 for the normal distribution, consistent with Ajijola and Jeje (2025) who also found that the student-t distribution outperforms the normal distribution on all AIC, BIC and log-likelihood criteria in modelling Nigerian market volatility.

Table 7: ARCH-LM Test

Test	Chi-Sq Stat	df	p-value	Decision
ARCH-LM	60.263	12	2.022e-08	Reject H_0

*Note: *** significant at 1%. H_0: no ARCH effects. Source: Authors' computation using FinTS package in R.*

Table 8 shows the final GARCH(1,1)-t estimates. Both ARCH coefficient ($\alpha_1 = 0.271$, $p < 0.001$) and GARCH coefficient ($\beta_1 = 0.728$, $p < 0.001$) are highly significant, suggesting that past shocks and past conditional variance together drive current volatility. The persistence measure of $\alpha + \beta = 0.999$ is close to one suggesting that shocks to Nigeria's inflation uncertainty dissipate very slowly, consistent with Nzeh et al. (2023) and Eregha and Ndoricimpa (2022). The shape parameter of 4.1966 ($p < 0.001$) is evidence of heavy tails in the conditional distribution, which is why the Student-t was preferred over the normal.

Table 8: GARCH(1,1)-t Estimation Results

Parameter	Estimate	Std. Error	t-value	p-value	Sig.
μ (mu)	0.1078	0.0442	2.438	0.0148	**
AR(1)	0.5322	0.0630	8.453	0.0000	***
ω (omega)	0.0059	0.0037	1.573	0.1157	ns
α_1 (ARCH)	0.2710	0.0603	4.493	0.0000	***
β_1 (GARCH)	0.7280	0.0495	14.695	0.0000	***
shape (t d.f.)	4.1966	0.6384	6.573	0.0000	***
$\alpha + \beta$	**0.9990**				**Near unit-root**

*Note: *** p<0.01, ** p<0.05, ns = not significant. AIC = 2.5339, BIC = 2.6126, Log-likelihood = −343.672. Distribution: Student-t. Source: Authors' computation using rugarch package in R.*

The Nyblom joint stability statistic of 4.67 in **Table 9** is greater than the 1% critical value of 2.12, indicating parameter instability over the full sample, consistent with the seven structural breaks identified in **Section 4.5**. Similar results are shown by Chung et al. (2025) and Göktaş and Dişbudak (2014), who find that GARCH models without structural breaks tend to overestimate volatility persistence. The near-unity persistence of $\alpha + \beta = 0.999$, interpreted together with the Nyblom instability result, reflects the unresolved structural uncertainty from the successive policy shocks isolated by the Bai-Perron test, especially the 2023 reforms, rather than an inherent long-memory in the inflation process itself. The distinction is important: while Göktaş and Dişbudak (2014) and Chung et al. (2025) find that GARCH models with fully integrated breaks tend to produce lower estimates of persistence in general, the high persistence estimates obtained in this paper are an important contribution in their own right, implying that inflation uncertainty in Nigeria remains structurally high in the post-reform era.

Table 9: Nyblom Parameter Stability Test

Test	Joint Statistic	CV 10%	CV 5%	CV 1%	Decision
Nyblom	4.6699	1.49	1.68	2.12	Reject stability at 1%

Note: Null hypothesis: parameter stability. Source: Authors' computation using rugarch package in R.

Figure 5 shows the standardized residuals and squared standardized residuals of the GARCH(1,1)-t model. In panel (a), the standardized residuals are distributed around zero and the majority of the observations lie within the ±2 bands, indicating adequate model specification. The two conspicuous spikes around 2015 and 2025 capture isolated extreme shocks related to the devaluation of the naira and the post-subsidy removal episodes. Panel (b) illustrates that the squared standardized residuals are close to zero for most of the sample. The same two spikes can be observed but there is no systematic pattern of remaining volatility clustering. This is consistent with the weighted ARCH-LM diagnostic tests reported in the GARCH output which show no remaining ARCH effects after estimation.

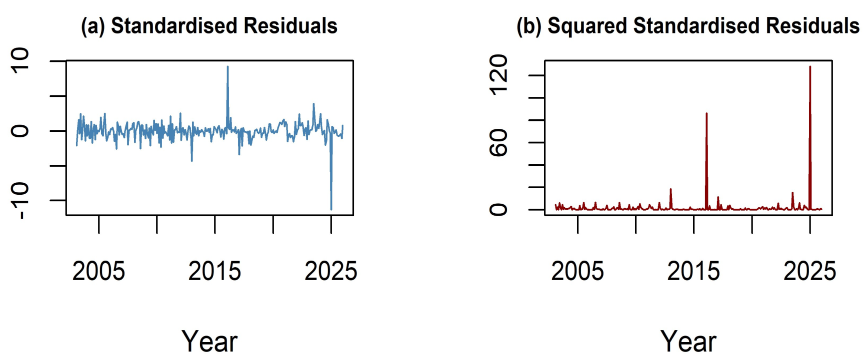


Figure 5: Standardized Residuals and Squared Standardized Residuals from the GARCH(1,1)-t Model

Figure 6 plots the conditional standard deviation from the GARCH(1,1)-t model against the absolute values of the first-differenced inflation series. Three distinct volatility regimes are visible. High and erratic volatility from 2003 to 2007, a prolonged calm from 2014 to 2022, and a sharp spike from late 2023 through 2025 associated with the fuel subsidy removal and naira floatation (Raifu & Afolabi, 2024; Yahaya, 2025). The fact that conditional volatility remains elevated even as the point inflation rate declines through 2024 and 2025 is consistent with the persistence estimate of $\alpha + \beta = 0.999$ in **Table 8**, and is consistent with the wide prediction intervals reported in **Section 4.8**, which are derived from the SARIMA model rather than directly from the GARCH conditional variance estimates.

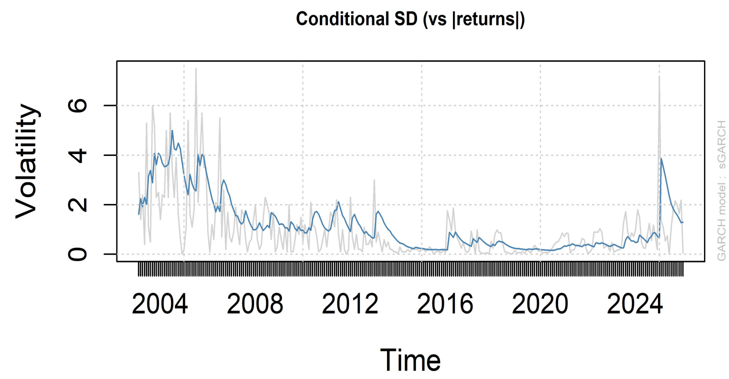


Figure 6: Conditional Volatility from the GARCH(1,1)-t Model, Nigeria Headline Inflation (2003–2026)

4.8 Forecast Evaluation and 12-Month Ahead Forecast

The forecasting analysis was performed in three stages. In the first stage, the last 12 months of the sample (February 2025 to January 2026) were held out as a validation set to assess the out-of-sample forecast accuracy. The results are reported in **Table 10**. The model achieved a MAE of 2.81 percentage points, RMSE of 3.17 and MAPE of 12.22%. All 12 actual values were within the 95% prediction intervals, supporting the model's calibration and directional reliability.

Table 10: Out-of-Sample Forecast Evaluation of SARIMA(1,1,0)(1,0,2)$_{[12]}$, Nigeria Headline Inflation (February 2025 to January 2026)

Month	Actual (%)	Forecast (%)	95% CI Lower	95% CI Upper	Error	Abs. Error
Feb 2025	26.270	24.918	22.383	27.453	1.352	1.352
Mar 2025	27.350	23.289	19.302	27.277	4.061	4.061
Apr 2025	26.820	22.499	17.390	27.607	4.322	4.322
May 2025	26.060	22.032	15.993	28.070	4.029	4.029
Jun 2025	26.060	21.475	14.630	28.320	4.585	4.585
Jul 2025	24.940	20.778	13.211	28.344	4.162	4.162
Aug 2025	23.140	20.067	11.841	28.292	3.073	3.073
Sep 2025	20.980	18.979	10.144	27.815	2.001	2.001
Oct 2025	18.970	17.740	8.334	27.145	1.230	1.230
Nov 2025	17.330	16.585	6.642	26.528	0.745	0.745
Dec 2025	15.150	15.668	5.215	26.122	−0.518	0.518
Jan 2026	15.100	18.697	7.757	29.637	−3.597	3.597

Note: MAE = 2.810, RMSE = 3.170, MAPE = 12.22%. All 12 actual values fall within the 95% prediction intervals supporting model calibration. Negative errors indicate overestimation. Model: SARIMA(1,1,0)(1,0,2)$_{[12]}$ re-estimated on January 2003 to January 2025. Source: Authors' computation.

Figure 7 compares the out-of-sample forecasts to the actual inflation values. The model systematically underpredicts inflation in the first half of the validation period (February to July 2025) by about 4 to 5 percentage points. Two factors are likely to have contributed to this: first, the lingering post-reform inflationary pressures which are beyond what historical parameters would have predicted (Raifu and Afolabi, 2024); and second, the NBS CPI methodological rebasing in early 2025 which caused an upward level shift in the reported series that a model trained on pre-rebase data could not have anticipated (NBS, 2025). From August 2025, forecasts and actual values converge rapidly, with December 2025 yielding an error of only ~0.52 percentage points.

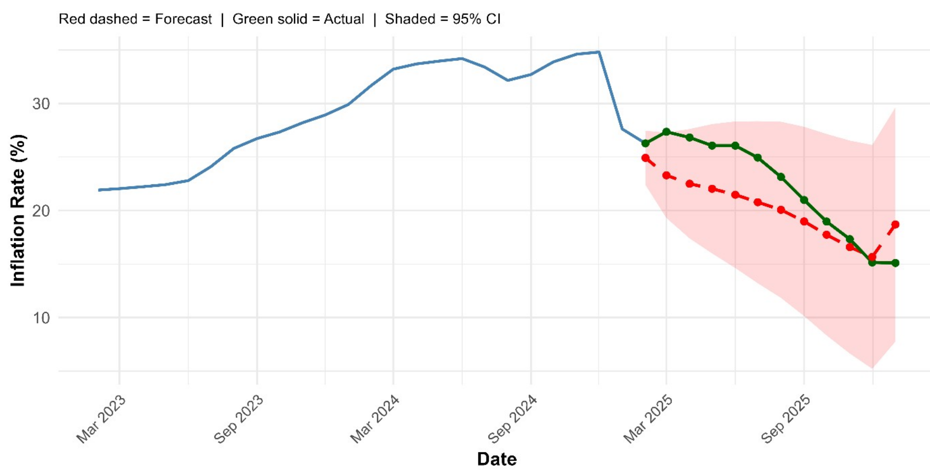


Figure 7: Out-of-Sample Forecast Evaluation (Feb 2025 to Jan 2026)

In the second stage, a rolling origin evaluation was conducted using an expanding window with a minimum training size of 240 observations, generating 378 forecasts across 37 origins and horizons of 1 to 12 months ahead. **Table 11** compares the two evaluation methods. The rolling window produces an overall MAE of 5.54 percentage points, RMSE of 7.06 and MAPE of 19.79%, compared with MAE = 2.81, RMSE = 3.17 and MAPE = 12.22% from the single holdout. The higher rolling window errors are attributable to the inclusion of forecast origins from the pre-2023 period, where the model generates forecasts across the fuel subsidy removal and naira floatation episode from training windows that predate the shock, thereby inflating the aggregate error metrics. While the rolling window provides a broader assessment of model performance across multiple origins, the single holdout period is treated as the primary evaluation because it specifically assesses model accuracy in the post-2023 structural regime that is the focus of this study. Both evaluation approaches indicate that the model performs reliably at short to medium term horizons.

Table 11: Single Holdout and Rolling Window Forecast Accuracy Comparison

Evaluation Method	MAE	RMSE	MAPE (%)
Single Holdout (Feb 2025 – Jan 2026)	2.806	3.166	12.22
Rolling Window (Overall)	5.542	7.062	19.79

Note: Single holdout: February 2025 to January 2026. Rolling window: expanding origin from observation 240. MAE and RMSE in percentage points. MAPE in percent. Source: Authors' computation.

In the third stage, the model was re-estimated on the full 277-observation sample to generate a 12-month ahead forecast for February 2026 through January 2027, with results reported in **Table 12** and **Figure 8**. The central forecast indicates that the disinflation process will continue until approximately June 2026, reaching around 10.2% before rising to about 15.55% in January 2027, in line with Nigeria's well-known January seasonal price increase associated with post-harvest demand and the effects of school resumption (Akpanta & Okorie, 2015). The 95% forecast interval for January 2027 spans 4.70% to 26.40%, derived from the SARIMA model prediction intervals, with the width consistent with the elevated volatility environment documented in **Section 4.7**. The widening confidence limits suggest that scenario-based planning would be more appropriate than reliance on a single point estimate for fiscal and monetary decisions over the 2026 to 2027 period.

Table 12: 12-Month Ahead Forecast of Nigeria Headline Inflation (February 2026 to January 2027)

Month	Point Forecast (%)	80% CI Lower	80% CI Upper	95% CI Lower	95% CI Upper
Feb 2026	13.720	12.070	15.380	11.190	16.250
Mar 2026	11.720	9.120	14.310	7.750	15.690
Apr 2026	11.140	7.820	14.460	6.060	16.220
May 2026	10.940	7.010	14.860	4.940	16.930
Jun 2026	10.210	5.760	14.650	3.410	17.010
Jul 2026	10.460	5.550	15.370	2.950	17.970
Aug 2026	11.180	5.840	16.520	3.020	19.350
Sep 2026	11.380	5.650	17.120	2.610	20.150
Oct 2026	11.080	4.980	17.190	1.750	20.420
Nov 2026	10.800	4.350	17.250	0.930	20.660
Dec 2026	11.280	4.490	18.060	0.900	21.650
Jan 2027	15.550	8.450	22.650	4.700	26.400

Note: Model: SARIMA(1,1,0)(1,0,2)$_{[12]}$ estimated on full sample January 2003 to January 2026. Confidence intervals reported at 80% and 95% levels. Widening intervals reflect high volatility persistence ($\alpha + \beta = 0.999$) from Section 4.7. Source: Authors' computation.

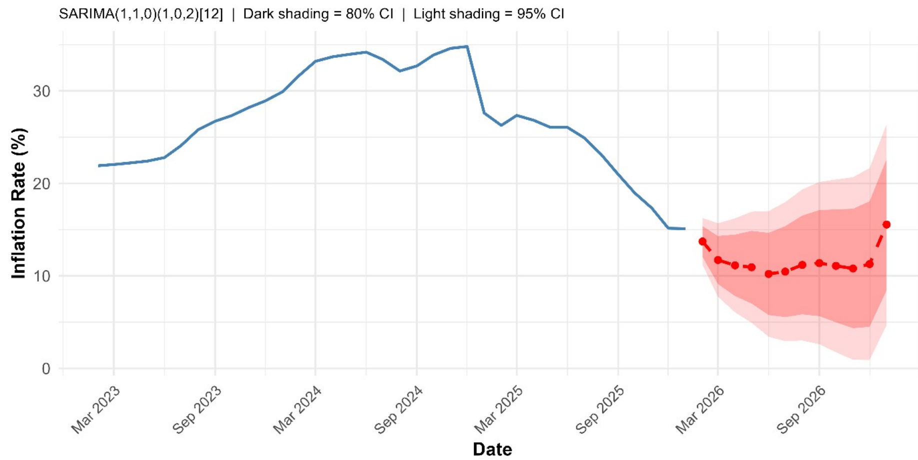


Figure 8: 12-Month Ahead Forecast of Nigeria Headline Inflation (February 2026 to January 2027)

4. CONCLUSION AND POLICY RECOMMENDATIONS

This study investigated the dynamics of monthly headline inflation in Nigeria for the period January 2003 to January 2026. The time series framework employed included unit root testing, multiple structural break detection, SARIMA modelling, GARCH volatility estimation and validated forecasting. The major findings are as follows.

All three tests (ADF, PP, and KPSS) identified the series as I(1). The Zivot-Andrews test failed to support a single break, directly motivating the use of the Bai-Perron multiple break test, which detected seven significant structural breaks statistically associated with 2005 CBN banking consolidation and NEEDS reform, 2008 global financial crisis, 2012 post-crisis monetary tightening, 2016 economic recession and naira devaluation, 2018 CBN FX restrictions, 2020 COVID-19 shock, and most notably the June 2023 fuel subsidy removal and naira floatation, the dominant structural event in the 23-year sample. The optimal SARIMA (1,1,0)(1,0,2)$_{[12]}$ model is consistent Nigeria's 12-month inflationary seasonality, passing all residual diagnostic tests. The selected model also outperformed an ETS benchmark across all accuracy metrics, with a MAPE of 12.22% against 29.38% for the ETS (A,N,N) model over the holdout period, providing additional support for the seasonal SARIMA specification. GARCH (1,1)-t estimates imply volatility persistence near a unit root ($\alpha + \beta = 0.999$) and heavy-tailed conditional distributions, with a sharp increase in conditional volatility after 2023, tapering through 2025. The 12-month forecast is for more disinflation toward 10.2% in June 2026 and a seasonal rise to 15.55% in January 2027.

Several policy implications follow from these findings. First, the CBN should treat the June 2023 break as a permanent regime shift in Nigeria's inflation-generating process, rather than a transitory shock. The CBN's tightening cycle had pushed the MPR from 18.75% in September 2023 to a peak of

27.5% by 2024, before a modest reduction to 26.5% in February 2026 (CBN, 2026), which illustrates the difficulty of bringing post-reform inflation under control. The near-unit-root volatility persistence documented in this study suggests that premature monetary easing may reignite inflationary pressures before the post-reform adjustment is complete. Bello and Isah (2025) also find that the CBN's monetary targeting framework has limited and lagged pass-through of changes in interest rates on inflation, lending further credence to the need for proactive instead of reactive monetary policy adjustments in Nigeria. Second, considering the 95% forecast interval for January 2027 is between 4.70% and 26.40%, the Federal Ministry of Finance should consider scenario-based rather than single point estimate planning for its 2026-27 budget frame. Third, considering the documented 12-month seasonal pattern in Nigeria's inflation, the timing of food security and social protection programs should be planned in anticipation of the mid-year lean season and the January price surge (Akpanta & Okorie, 2015; Sakanko et al., 2025). Fourth, the Nyblom parameter instability finding implies that Nigeria's inflation forecasting models will need to be updated from time to time, as each new structural break will change the underlying inflation-generating process.

This study has three limitations. First, the univariate framework does not model the determinants of inflation. The absence of relevant macroeconomic variables such as the exchange rate, oil prices, money supply, interest rates and food prices implies that the model cannot differentiate between demand-pull and cost-push drivers of inflation and also cannot trace the direct transmission of external shocks to domestic prices. The forecasts should be interpreted with this caveat in mind, and the results should be seen as descriptive of inflation dynamics rather than causal explanations of price movements. Second, the 2025 NBS CPI rebasing introduced a methodological discontinuity which, although detected endogenously by the Bai-Perron test, may affect the precision of medium-term forecasts. Third, the structural break dummies identified by the Bai-Perron test were not directly incorporated into the GARCH variance equation. Future research should estimate a fully integrated break-adjusted GARCH model to assess whether the near-unity persistence documented here reflects genuine volatility persistence or unaccounted structural shifts in the variance process, and should explore regime-specific SARIMA-GARCH models estimated separately for each Bai-Perron segment to test whether Nigeria's inflation data-generating process has fundamentally changed in the post-reform era.

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