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Full Length Research Article

BAYESIAN SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE: MODELLING TWO DECADES OF INFLATION DYNAMICS IN NIGERIA

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ABSTRACT

There is a growing recognition of the unique characteristics of individual economies, particularly in developing countries. These peculiarities necessitate country-specific studies, as they provide insights tailored to the economic realities and challenges of the nation under examination. This study was motivated by the need to explore these specific dynamics. This study employed Bayesian statistical methods to model and forecast inflationary dynamics in Nigeria over two decades (January 2003 to September 2024). Adopting a Bayesian Seasonal Autoregressive Integrated Moving Average, (SARIMA) framework, the analysis incorporates prior knowledge and provides robust uncertainty quantification in parameter estimation and forecasting. Markov Chain Monte Carlo (MCMC) technique was used to sample from posterior distributions, yielding insights into the persistence of inflation volatility and its implications for monetary policy. This approach provides decision-makers with actionable forecasts and credible intervals, contributing to the literature on Bayesian time series modeling in developing economies.

Keywords: ARIMA, Autoregressive, Forecasting, Inflation Rate, SARIMA, Stationarity.

INTRODUCTION

Inflation, characterized by sustained increases in the general price level of goods and services, is a complex macroeconomic phenomenon with far-reaching implications for economic stability and growth. Traditional (Classical) time series models, such as Autoregressive integrated moving average, (ARIMA) and Seasonal autoregressive integrated moving average, (SARIMA) have been widely used to model inflationary dynamics. In literature, there are several studies using Box-Jenkins methodology for modelling inflation phenomenon. While most research on the threshold effect of inflation on economic growth is predominantly based on cross-country panel analyses (Sarel, 1996; Khan and Senhadji, 2001; Mallik and Chowdhury, 2001;), there is a growing recognition of the unique characteristics of individual economies, particularly in developing countries. These peculiarities necessitate country-specific studies, as they provide insights tailored to the economic realities and challenges of the nation under examination. This study is motivated by the need to explore these specific dynamics.

Despite extensive studies on inflation, the unique characteristics of Nigeria's economy, marked by volatile exchange rates, oil dependence, and structural imbalances, necessitate localized analysis. In this context, several country-specific investigations into the inflation-economic growth relationship have emerged, offering nuanced findings relevant to the unique socio-economic conditions of developing nations. Examples include Ahmed and Mortaza (2005) for Bangladesh, Hussain (2005) and Mubarik (2005) for Pakistan, Hodge (2005) for South Africa, Fabayo and Ajilore (2006) and Chimobi (2010) for Nigeria, and Frimpong and Oteng-Abayie (2010) for Ghana, Baciu 2015 confirmed that the ARIMA models tends to perform better in terms of forecasting compared to other time series model for Romania inflation data. However, these models rely on point estimates, limiting their ability to fully quantify uncertainty and incorporate prior knowledge.

Bayesian approaches to time series modeling have gained traction for their ability to handle uncertainty and incorporate prior beliefs. The foundational work of Box and Jenkins (1970) on ARIMA models paved the way for analyzing economic data, but recent studies highlight the advantages of Bayesian inference in extending these models. Studies in developing economies, such as those by Ahmed and Mortaza (2005) for Bangladesh and Chimobi (2010) for Nigeria, emphasize the need for tailored approaches to inflation modeling.

In Nigeria, several scholars have applied Bayesian methods to understand inflation dynamics. For example, Olubusoye (2015); Ogundeji and Busari (2024) both applied Bayesian Model Averaging to identify key drivers of inflation in Nigeria. The studies addressed model uncertainty and enhanced predictive accuracy. Similarly, Adebiyi *et al.,* (2024), in their study *"Monetary Policy and Inflation Dynamics in Nigeria: A Bayesian DSGE Approach,"* employed a Bayesian Dynamic Stochastic General Equilibrium (DSGE) model to analyze the impact of monetary policy on Nigeria's inflation dynamics, providing valuable insights into policy effectiveness.

Globally, scholars have also demonstrated the utility of Bayesian methods in inflation modeling. Wright (2008), in *"Forecasting U.S. Inflation by Bayesian Model Averaging,"* showed that Bayesian Model Averaging could improve U.S. inflation forecasts by combining information from multiple models, thereby enhancing forecast accuracy. Korobilis *et al.,* (2021), in the paper *"The Time-Varying Evolution of Inflation Risks,"* developed a Bayesian quantile regression model with time-varying parameters to forecast inflation risks, effectively capturing the dynamic nature of inflation.

This study contributes to the literature by applying Bayesian SARIMA models to inflation data from Nigeria, quantifying uncertainty, and providing actionable insights for policy formulation. This study, we leveraged Bayesian SARIMA models to analyze Nigeria's inflation trends. The Bayesian framework enhances traditional approach by providing posterior distributions for parameters, enabling policymakers to assess uncertainty in both model parameters and forecasts. This is especially crucial in a developing economy like Nigeria, where inflation dynamics are influenced by volatile exchange rates, oil price shocks, and structural imbalances.

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MATERIALS AND METHODS

The study explored key Bayesian time series models, focusing on how Bayesian methods are applied to classic models like autoregressive (AR), moving average (MA), and the combination of AR and MA models such as ARMA and ARIMA and the Seasonal ARIMA known as SARIMA. These models are foundational in time series analysis, and the Bayesian framework enhances them by allowing for the incorporation of prior information and better handling of parameter uncertainty. Mathematical rigor and techniques such as Markov Chain Monte Carlo (MCMC) methods are key components of Bayesian inference in these models.

Autoregressive (AR) Model

The Autoregressive (AR) model describes a time series in which the current observation x_t is a linear combination of its previous values plus a noise term. Box and Jekins (1976), Marriott and Newbold (2000). In a classical AR model of order p (AR(p)), the model is expressed as:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + \epsilon_t \quad (1)$$

where $\epsilon_t \sim N\ (0, \sigma^2)$ is white noise and $\phi_1,\ \phi_2, \ldots \phi_p$ are the autoregressive coefficients. $\phi_1,\ \phi_2, \ldots \phi_p$ are treated as random variables rather than fixed values. The key steps in constructing a Bayesian AR model are:

i. **Priors on AR Coefficients**: Prior distributions are assigned to the autoregressive coefficients ϕ_1, $\phi_2, \ldots \phi_p$. Common choices for these priors include:

$$\phi_i \sim N(0, \tau^2),\ i = 1, \ldots, P$$

where τ^2 represents the prior variance. These priors reflect the belief that the AR coefficients are normally distributed around zero, with uncertainty controlled by the variance τ^2.

ii. **Likelihood Function**: Given the AR(p) model, the likelihood function for the observed time series data $\{x_1, x_2, \ldots, x_T\}$ is:

$$p(\, x_1, \ldots, x_T \mid \phi_1, \ldots, \phi_p, \sigma^2\,) = \prod_{t=p+1}^{T} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{\left(x_t - \sum_{i=1}^{p} \phi_i x_{t-i}\right)^2}{2\sigma^2}\right) \quad (2)$$

iii. **Posterior Distribution:** Using Bayes' theorem, the posterior distribution of the parameters is obtained by combining the prior and the likelihood:

$$p(\, \phi_1, \ldots, \phi_p, \sigma^2 \mid x_1, \ldots, x_T\,) \propto p(\, x_1, \ldots, x_T \mid \phi_1, \ldots, \phi_p, \sigma^2\,) \cdot p(\phi_1) \ldots p(\phi_p) \quad (3)$$

Since the posterior distribution is often analytically intractable, MCMC methods such as the Gibbs sampler or Metropolis-Hastings algorithm are used to sample from the posterior distribution.

iv. **Predictive Distribution:** Once the posterior distribution of the parameters is obtained, the predictive distribution for future observations can be derived:

$$p(\, x_{T+1} \mid x_1, \ldots, x_T\,) = \int p(\, x_{T+1} \mid \phi_1, \ldots, \phi_p, \sigma^2\,) \cdot p(\, \phi_1, \ldots, \phi_p, \sigma^2 \mid x_1, \ldots, x_T\,)\, d\phi_1 \ldots d\phi_p\, d\sigma^2$$

The predictive distribution incorporates the uncertainty about the parameters and provides probabilistic forecasts rather than point estimates.

Moving Average (MA) Model

Moving Average (MA) model represents the current value of a series as a linear combination of past error terms (or shocks) Marriott and Newbold (2000). In a Bayesian context, the MA model is enhanced by incorporating prior distributions for the parameters, allowing for a more flexible representation of uncertainty. MA(q) model, the parameters $\theta_1, \theta_2, \ldots \theta_q$ are treated as random variables, and the model estimation proceeds as follows:

$$y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \quad (4)$$

Where: μ is the mean of the series,
$\theta_1, \theta_2, \ldots, \theta_q$ are the MA parameters,
$\epsilon_t \sim \mathcal{N}(0, \sigma^2)$ is white noise.

Bayesian ARMA and ARIMA Models

Autoregressive Moving Average (ARMA) models combine both autoregressive (AR) and moving average (MA) processes to capture more complex dynamics in time series data. Bayesian versions of these models offer a structured way to quantify parameter uncertainty and incorporate prior knowledge. Dickey and Fuller (1979)

i. Bayesian ARMA (p, q) Model

The **ARMA (p, q)** model is given by:

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \quad (5)$$

Where: μ is the intercept,
$\phi_1, \ldots, \phi_p$ are the AR parameters
(coefficients for the lagged values of the time series),
$\theta_1, \ldots, \theta_q$ are the MA parameters
(coefficients for the lagged error terms),
$\epsilon_t \sim \mathcal{N}(0, \sigma^2)$ is the white noise.
In the **Bayesian ARMA model**, place priors on the unknown parameters $\phi_i, \theta_j, \sigma^2$. For example $\phi_i \sim \mathcal{N}\left(0, \sigma^2_{\phi_i}\right)$ and $\theta_j \sim \mathcal{N}\left(0, \sigma^2_{\theta_j}\right)$

ii. Bayesian ARIMA (p, d, q) Model

The **ARIMA (p, d, q)** model adds **differencing** to the ARMA model to handle non-stationary data. It is given by:

$$(1 - B)^d y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \quad (6)$$

Where B is the backshift operator, and d is the order of differencing. The differencing transforms non-stationary time series into stationary ones before fitting the ARMA model. **Bayesian ARIMA models** use priors for $\phi_i, \theta_j, \sigma^2$ and apply MCMC methods to estimate the posterior distribution of the parameters, providing more flexibility and better handling of parameter uncertainty compared to classical estimation methods.

Bayesian SARIMA Model

The Seasonal Auto-regressive Integrated Moving Average (SARIMA) model is extended into a Bayesian framework: (Marriott and Newbold (2000)

$$Y_t = \alpha Y_{t-1} + \beta_1 Y_{t-12} + \beta_2 Y_{t-24} + \gamma_1 \varepsilon_{t-1} + \cdots + \gamma_4 \varepsilon_{t-4} + \varepsilon_t \quad (7)$$

Y_t: *The dependent variable (interest rate) at time t.*
ε_t: *The error term (residual) at time t.*
α: Coefficient for $Y_{t-1,}$ representing the strength of the non − seasonal AR(1)
β_1, β_2: Coefficients for Y_{t-12}, Y_{t-24} representing the strength of the seasonal AR
$\gamma_1, \ldots, \gamma_4$: *Coefficients for* $\varepsilon_{t-1}, \cdots \varepsilon_{t-4}$ *representing the strength of the MA*
The Bayesian approach model of the inflation rate as:
Posterior(θ|Data) ∝ Prior(θ)·Likelihood (Data|θ)

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Where: θ includes α, β, γ, and σ^2. Priors are assumed to be normal for autoregressive and moving average parameters and inverse gamma for variance terms.

RESULTS

The monthly inflation data from January 2003 to September 2024 was obtained from the Central Bank of Nigeria website (https://www.cbn.gov.ng/rates/inflrates.html). A time series plot revealed persistent trends and seasonal patterns, validating the need for a seasonal ARIMA model.

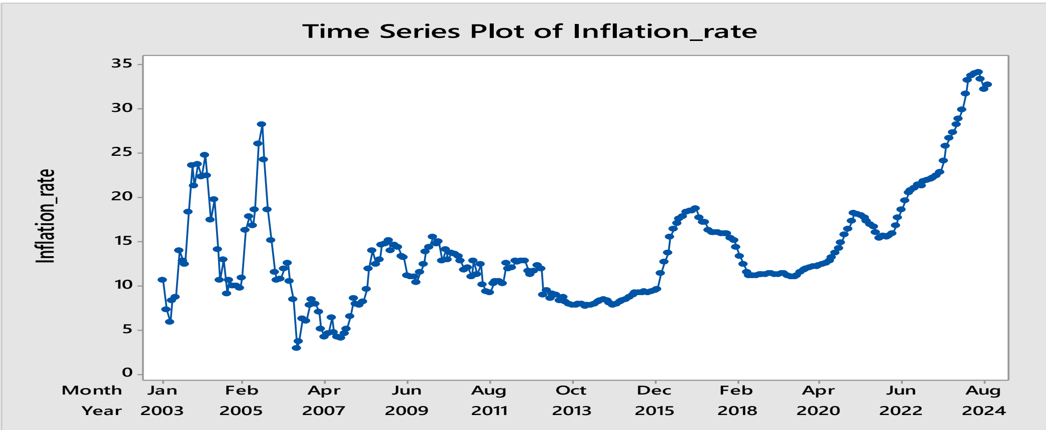

Figure 1: Time Series Plot of Nigeria Inflation Rate

A visual inspection of the time plot (as in figure 1) indicates that Nigeria Inflation rate have shown that mean and variance are not constant. Therefore, the series is nonstationary.

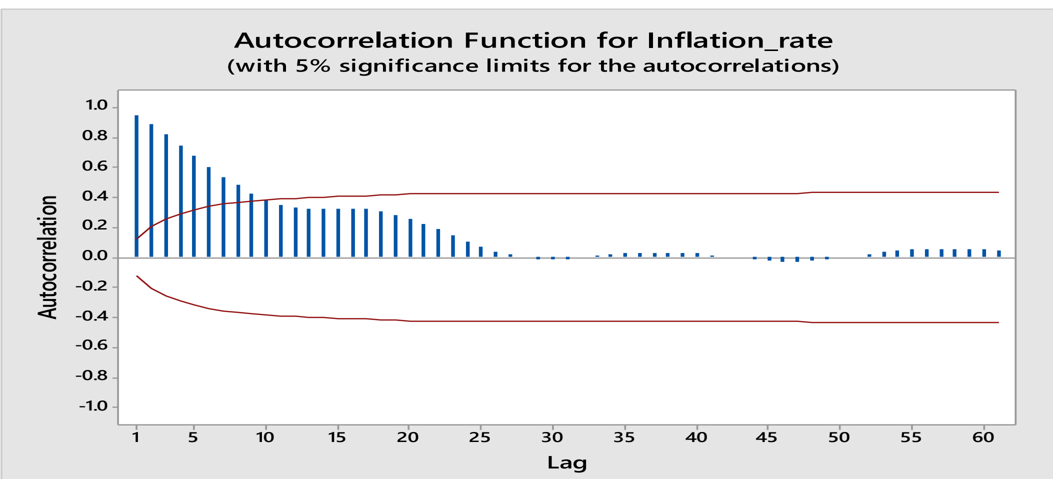

Figure 2: Autocorrelation Function Plot of Nigeria Inflation Data

A visual examination of the Autocorrelation plot (Figure 2) confirms that the Nigerian Inflation rate is nonstationary. This is because the auto-correlation function did not decay exponentially fast to zero.

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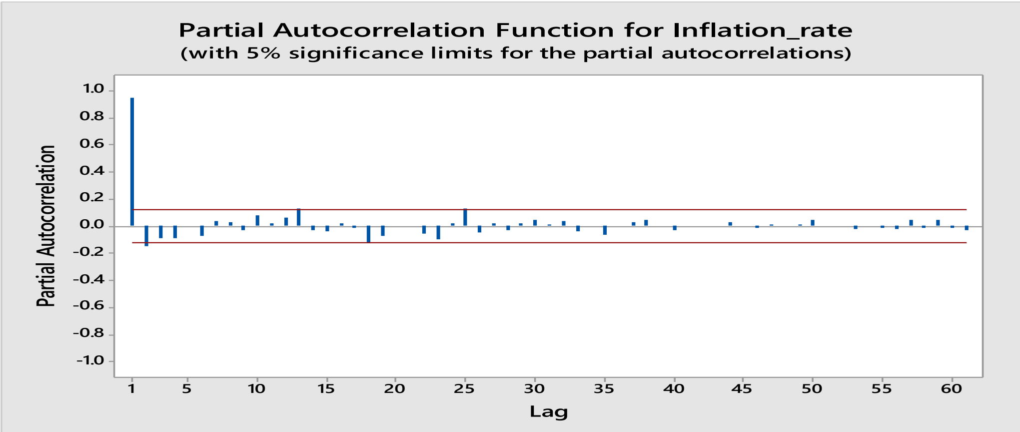

Figure 3: Partial Autocorrelation Function Plot of Nigeria Inflation Data

The result in Figure 3 shows a significant spike at lag 1 very close to 1 which indicate that the data is not stationary. Hence, we then difference the data to achieve stationarity. The series was transformed by taking the first difference as well as seasonal differencing were done on the values in the series so as to attain stationarity in the first moment. The time plot for the differenced series as shown in Figures 4 and 5 respectively.

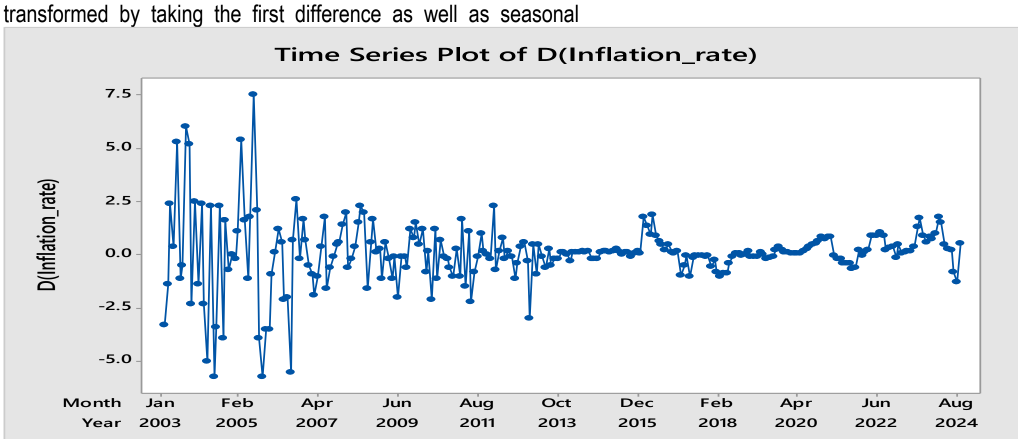

Figure 4: Time Plot of Differenced Data

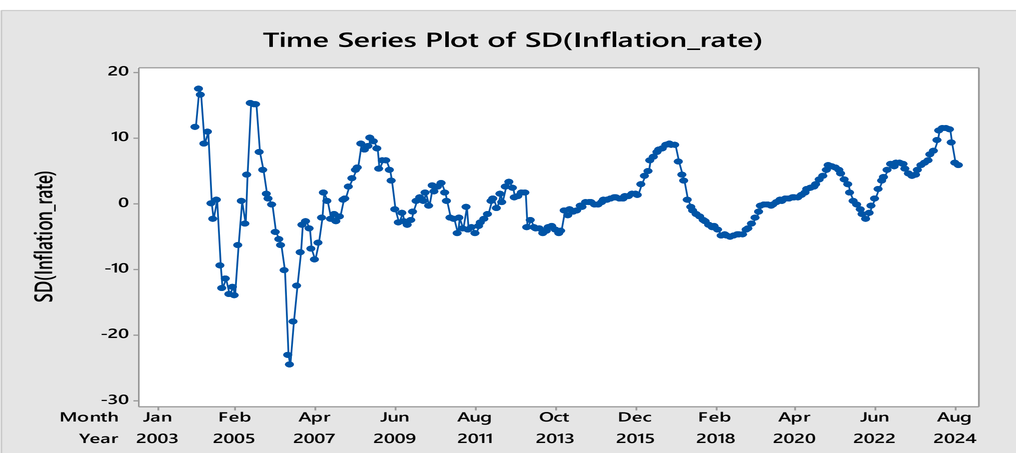

Figure 5: Time Plot of Seasonal Differencing

From Figure 1, it is established that the monthly inflation rate data in Nigeria was not stationary

.

MCMC Simulation
Using non-informative priors for initial parameters to let the data primarily influence estimates. Parameters were estimated using MCMC with 2000 iterations and 4 chains, implemented in R using rstan and bsts packages. The best fitted model was then selected based on the least mean squared error (MSE) and Bayesian SARIMA (1, 1, 0) (2, 1,4)$_{12}$ model was selected among others as the best model as shown in table 1.

Table 1: Selecting the Best SARIMA Model

SARIMA MODEL	MSE
SARIMA (1, 1, 0) (2, 1, 4)$_{12}$	1.002 ***
SARIMA (1, 1, 0) (1, 1, 3)$_{12}$	1.087
SARIMA (1, 1, 0) (2, 1, 2)$_{12}$	1.252
SARIMA (2, 1, 0) (2, 1, 2)$_{12}$	1.267
SARIMA (2, 1, 0) (2, 1, 3)$_{12}$	1.044
SARIMA (2, 1, 0) (2, 1, 4)$_{12}$	1.097
SARIMA (3, 1, 0) (1, 1, 4)$_{12}$	1.086
SARIMA (3, 1, 0) (2, 1, 4)$_{12}$	1.093
SARIMA (3, 1, 0) (2, 1, 3)$_{12}$	1.112
SARIMA (3, 1, 0) (2, 1, 2)$_{12}$	1.284

Table 2: Summary of Bayesian SARIMA Model (1,1,0) (2, 1, 4)12

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat Bul	k_ESS	Tail_ESS
Intercept	0.46	0.29	-0.11	1.01	1.00	4386	3195
AR(1)	1.00	0.02	0.97	1.03	1.00	4409	2940
SAR(1)	-0.23	0.06	-0.34	-0.11	1.00	2565	2726
SAR (2)	-0.07	0.02	-0.11	-0.03	1.00	3544	2732
SMA(1)	0.29	0.09	0.12	0.45	1.00	2190	2541
SMA(2)	-0.01	0.08	-0.18	0.15	1.00	2949	2782
SMA(3)	-0.05	0.08	-0.21	0.11	1.00	2158	2537
SMA(4)	0.04	0.06	-0.07	0.16	1.00	2563	2946

Interpretation of Results

i. Intercept (Baseline Value): The intercept estimate (0.46) is not statistically significant because its 95% credible interval (-0.11, 1.01) includes 0. This suggests that the baseline level of the series, after accounting for all lagged effects, is uncertain.

ii. Non-Seasonal AR Component: AR(1) has a strong and significant positive estimate (1.00), with a narrow credible interval (0.97, 1.03). This indicates a high level of autocorrelation at lag 1, meaning that the current value of the time series strongly depends on the immediate past value.

iii. Seasonal AR Components: SAR(1) (-0.23): Significant with a negative effect, suggesting an inverse relationship between values separated by one seasonal lag (12 months).

iv. SAR(2) (-0.07): Significant but weaker negative effect at the second seasonal lag (24 months), indicating a diminishing seasonal influence over longer periods.

v. Seasonal MA Components: SMA(1) (0.29): Positive and significant, indicating that immediate lagged errors (1 season ahead) play a significant role in the model.

vi. SMA(2), SMA(3), SMA(4): These are not statistically significant, as their credible intervals include 0. This suggests that further lagged errors

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beyond 1 season have minimal or no influence on the time series.

R_{hat} is an important indicator of whether the chains have mixed well and converged to the target posterior distribution. All R_{hat} values are 1.00, indicating excellent convergence, and the results are reliable (see Table 2).

Effective Sample Sizes: Both bulk and tail effective sample sizes (k_ESS and Tail_ESS) are sufficiently high for all parameters, ensuring accurate estimation and credible intervals.

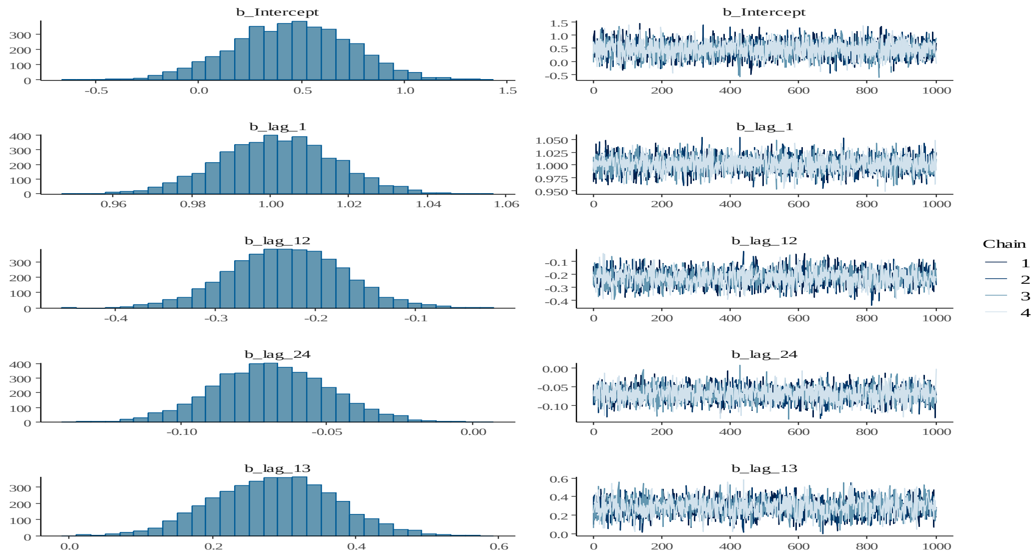

Figure 6: Trace Plots (Right) and Posterior Distributions (Left) of the Model Parameters

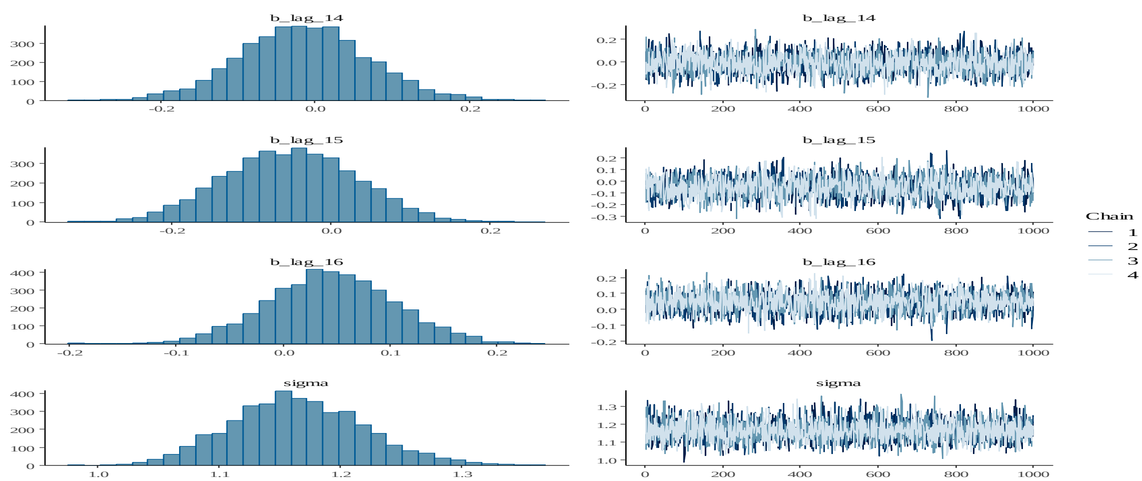

Figure 7: Trace Plots (Right) and Posterior Distributions (Left) of the Model Parameters

The Figure 6 and 7 show the trace plots and posterior distributions of selected parameters in the Bayesian SARIMA model $(1,1,0)(2,1,4)_{12}$. Each row corresponds to a parameter of the model. The histograms on the left represent the posterior distributions of the parameters. These distributions provide insight into the uncertainty of the parameter estimates. A well-defined posterior (for example, narrow and unimodal) suggests precise parameter estimation. The plots on the right show the trace of the MCMC samples across iterations for each parameter. A well-mixed trace plot, with no visible trends or patterns, indicates good convergence of the MCMC chains. Trace plots and R-hat values were used to confirm MCMC convergence.

The parameter σ, representing the residual variance, has a well-defined posterior centered around 1.1, this suggests that the model has effectively captured the variability in the data.

DISCUSSION

The inflation rate in Nigeria shows strong persistence, as indicated by the highly significant AR(1) component. This means that inflation rates are heavily influenced by recent historical trends, underscoring the need for sustained macroeconomic policy to address persistent inflationary pressures.

Seasonal patterns are evident, with significant SAR(1) and SAR(2) components. This suggests that inflation rates in Nigeria fluctuate cyclically, likely driven by agricultural cycles, festive seasons, or

other recurring economic events that impact food prices and other consumables.
The significant SMA(1) component indicates that short-term shocks or unexpected changes in inflation rates (e.g., fuel price hikes, currency fluctuations) tend to persist for about a year, affecting the predictability of inflation.
Error terms beyond one seasonal lag (for example, SMA(2), SMA(3), SMA(4)) have no significant effect, indicating that historical deviations from expected inflation fade over time.

Forecasts
Forecasts for the next 12 months were generated with 95% credible intervals and predicted error, October 2024 to September 2025. A closer look at Table 3, shows that the forecast generated follows a seasonal trend from a high of 32.58986 to a low of 31.70736 and back to a high of 32.5331, over the 12 months forecasted. Forecast error in this case can be interpreted in terms of uncertainty rather comparison with real observations. Hence the choice of Prediction Interval Width, (PI Width) as a measure of forecast uncertainty. The Prediction Interval Width (PI Width) ranges between 4.6 and 5.0 across the forecast horizon suggesting a moderate level of uncertainty in the model's prediction. The PI Width remains relatively consistent over time, varying only slightly from 4.60468 to 4.97088 suggesting that the model is stable in its confidence levels across the 12-month period, meaning there is no significant increase or decrease in uncertainty over time.

Table 3: In and Out Sample Forecasts with 95% Credible Intervals and Prediction Error

Date	Forecast	Lower bound	Upper bound	Prediction Error (PI Width)
Oct. 2024	32.58986	30.24909	34.85377	4.60468
Nov.2024	32.36965	29.97270	34.77916	4.80646
Dec. 2024	32.27800	29.79803	34.58434	4.78631
Jan. 2025	32.15485	29.70867	34.44054	4.73187
Feb. 2025	31.86378	29.43489	34.07654	4.64165
Mar. 2025	31.70736	29.37508	34.06763	4.69255
Apr. 2025	31.80653	29.30493	34.09023	4.78530
May. 2025	31.93072	29.46797	34.31751	4.84954
Jun. 2025	32.00516	29.52132	34.38684	4.86552
Jul. 2025	32.23086	29.72082	34.58694	4.86612
Aug. 2025	32.53331	29.93396	34.88124	4.94728
Sep. 2025	32.23086	29.72481	34.69569	4.97088

Conclusion
This study reveals the following as findings from the results of using Bayesian SARIMA models on inflation rates in Nigeria:

i. The estimated intercept of 0.46 is not statistically significant, as its 95% credible interval (-0.11, 1.01) includes 0. This suggests that the inflation rate in Nigeria, after accounting for short-term and seasonal effects, does not have a stable baseline trend and may be influenced by external economic factors or noise.
ii. AR(1) (1.00): A highly significant positive value, with a narrow credible interval (0.97, 1.03), indicates that Nigeria's inflation rate is strongly dependent on its immediate past values. This highlights a persistent trend where past inflation strongly influences the current rate.
iii. SAR(1) (-0.23): Significant with a negative estimate, suggesting that inflation rates exhibit inverse relationships on a yearly (12-month) basis. This indicates seasonal fluctuations where a high inflation rate in one year might correspond to a lower rate the following year at the same time.
iv. SAR(2) (-0.07): Significant but weaker, indicating diminishing seasonal effects over a longer period (24 months or 2 years).
v. As regards of the impact of Error Terms (Seasonal Moving Average Components, SMA(1) (0.29): Significant and positive, showing that immediate error terms (lagged by 1 season or 12 months) have a substantial effect on the inflation rate. This means that the inflation rate's deviations from expectations tend to persist in the short term.
vi. SMA(2), SMA(3), SMA(4): Not significant, suggesting that error terms further into the past have minimal or no influence on Nigeria's current inflation rate.

The Bayesian approach provides a richer analysis compared to classical methods by quantifying uncertainty in model parameters and forecasts. The results indicate persistent inflationary pressures in Nigeria, underscoring the importance of robust monetary policies. Credible intervals offer policymakers actionable insights with quantified risks, enabling more informed decisions.

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