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Econometric Insights: Analyzing Food Price Fluctuations in Nigeria Using Consumer Price Index Data

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ABSTRACT

The Food Consumer Price Index (FCPI) stochastic dynamics are examined in this study using robust time-series econometric modelling. The study assesses inflationary trends in the domestic food industry using 15 years of longitudinal data from the Central Bank of Nigeria Statistical Bulletin. First-order differencing was used after preliminary diagnostics showed non-stationarity in the raw series. Autocorrelation functions (ACF), partial autocorrelation functions (PACF), and the Augmented Dickey-Fuller (ADF) test ($p < 0.05$) were used to thoroughly validate the transformed series' stationarity. The least-squares method of trend analysis shows that food prices are consistently rising at a growth rate of 18.057 units. With the lowest Akaike Information Criterion (AIC = 147.09) and Mean Square Error (MSE = 62.45), ARIMA(2,1,1) was found to be the best predictive framework through comparative model evaluation. The model residuals are white noise, indicating sufficient capture of the underlying data patterns, according to post-estimation diagnostic tests. The findings suggest that targeted, periodic tightening of monetary policy is required to stabilise the CPI and reduce food price volatility in Nigeria.

Keywords: Time Series Analysis, ARIMA Modeling, FCPI, Inflationary Trends, Econometric Forecasting.

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INTRODUCTION

Time series analysis (TSA) remains a cornerstone of econometric modeling, defined as the study of variables recorded in chronological order to capture underlying dynamics and patterns (Hyndman & Ahanasopoulos, 2021). Unlike cross-sectional data, time series models such as those popularized by Box (2013) account for autoregressive dynamics, allowing researchers to model the mean of a variable conditional on its historical values and external predictors.

In the context of developing economies like Nigeria, the Consumer Price Index (CPI) for food is a critical metric. As food consumption represents a primary household expenditure, even marginal fluctuations in food prices significantly impact the national standard of living and purchasing power (World Bank, 2022). Consequently, the central bank and apex monetary authority of Nigeria prioritizes price stability to mitigate the adverse effects of inflation, which can erode currency value, discourage investment, and worsen social conditions (Central Bank of Nigeria, 2023).

Despite the complexity of global market cycles, monthly CPI forecasting provides a "litmus test" for the efficacy of government economic policies (International Monetary Fund, 2024). A number of statistical models have been applied for CPI forecasting, among are the Autoregressive variants such as the Integrated Moving Average (ARIMA), Fractionally Integrated Moving Average (ARFIMA), and Conditional Heteroscedasticity (ARCH). This research utilizes time series methodologies specifically Autoregressive (AR), Moving Average (MA), and Autoregressive Moving Average (ARMA) models to analyze and forecast the Nigerian Food Consumer Price Index (FCPI). By modeling these trends, this study aims to provide Fiscal authories with a robust empirical basis for navigating inflationary pressures and ensuring long-term economic stability.

The contributions of this study are threefold:

1. To identify and estimate the optimal parameters for and AR(ƥ), ARMA (ƥ, q) and ARIMA (ƥ, đ, q) models to characterize the underlying dynamics of food inflation in Nigeria.
2. To analyze the longitudinal trends and seasonal fluctuations within the Nigerian food market to identify historical patterns of price volatility.
3. To perform a comparative evaluation of projected Food Consumer Price Index (FCPI) rates, assessing the predictive accuracy and future trajectories of the developed models.

Recent research continues to demonstrate the effectiveness of ARIMA-based models in inflation forecasting due to their ability to capture temporal patterns and provide reliable short-term forecasts. For instance, Ibrahim *et al.* (2022) applied ARIMA models to forecast Nigeria's CPI and exchange rates using monthly data from 2010 to 2022. Their results showed that the ARIMA framework effectively captured the dynamics of CPI fluctuations and produced reliable forecasts that could assist monetary authorities in economic planning. Similarly, Masaya and Bura (2024) analyzed Nigeria's CPI using a seasonal time series approach and reported that a SARIMA model provided a good fit for the observed data. Their findings indicated that incorporating seasonal components improves the accuracy of CPI predictions because price movements often exhibit recurring annual patterns. Studies conducted outside Nigeria also confirm the suitability of ARIMA-type models for CPI forecasting. Other researchers have explored inflation forecasting using similar time series frameworks.

For example, recent work on Nigeria's inflation dynamics employed ARIMA models with stationarity tests using the tools of AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) to select the finest model parameters (Mikailalsys, 2025). The findings indicated that ARIMA models can effectively represent the autoregressive and moving average structure of inflation series and provide useful short-term projections for economic policy formulation. In addition, SARIMA models have been used to capture seasonal variations in CPI data. The role of monetary policy variables in inflation forecasting remains a critical area of inquiry. Their analysis revealed that while time series models are mathematically robust, the inclusion of monetary indicators enhances the capacity to explain the underlying drivers of Nigerian inflation. Additionally, innovative spectral techniques have emerged. The literature shows that time series models particularly ARIMA and its seasonal enhancements remain important tools for analyzing and forecasting CPI and inflation. These models are widely adopted because they rely on historical observations to identify underlying patterns in economic data.

2. MATERIALS AND METHODS

The study used the monthly Food Consumer Price Index (FCPI) data in Nigeria, spanning a fifteen-year period from January 2008 to December 2022. this is obtained from the Central Bank of Nigeria (CBN) statistical bulletin. This specific timeframe was selected to capture diverse economic cycles, including periods of significant price volatility, currency fluctuations, and policy shifts within the Nigerian agricultural and financial sectors. The use of monthly frequency ensures a sufficient sample size (N = 180 observations) to satisfy the requirements for high-resolution time series modeling and to accurately capture seasonal variations in food pricing in Nigeria.

2.1 Exploratory Data Analysis

The time plot was used as a preliminary analytical tool to examine the behavior of the Consumer Price Index (CPI) series over time. Visual inspection of the time series plot provides important descriptive information about the structure of the data, including the presence of trends, seasonal patterns, cyclical movements, and irregular fluctuations. This graphical approach helps in understanding the underlying characteristics of the data and provides guidance for selecting an appropriate time series model.

2.2 Stationary Testing

We employ the Augmented Dickey-Fuller (ADF) test (Ivanovski and Ivanovska, 2024) and this involve the three sets of models in Equations (1-3):

Pure random walk model with no intercept and no trend

$$\Delta y_t = \text{Ъ} y_{t-1} + \sum_{j=1}^{p} \beta_j \, \Delta y_{t-j} + \varepsilon_t \tag{1}$$

With an intercept only

$$\Delta y_t = \alpha_o + \text{Ъ} y_{t-1} + \sum_{j=1}^{p} \beta_j \, \Delta y_{t-j} + \cdots \ldots + \varepsilon_t \tag{2}$$

Both an intercept and a linear time trend.

$$\Delta y_t = \alpha_o + \delta_t + \text{Ъ} y_{t-1} + \sum_{j=1}^{p} \beta_j \, \Delta y_{t-j} + \cdots \ldots + \varepsilon_t \tag{3}$$

The null hypothesis ($H_o : \text{Ъ} = 0$) implies non-stationarity. If H_o is not rejected, successive differencing is applied to achieve an integration order đ.

The resulting test statistics will be compared against the Dickey-Fuller critical values and significance levels. In event that the series is found to be non-stationary, successive differencing will be used until stationarity is attained, which is a prerequisite for identifying the integration order đ in ARIMA (ƥ, đ, q) process.

2.3 ARIMA and SARIMA Models

The ARIMA, a univariate time series model consisting of three polynomials, an autoregressive polynomial (ƥ), an order of integration (đ) and a moving average (q) (Nwosu, 2024).

The autoregressive process AR process of order (ƥ) and ARIMA (ƥ, đ, q) are represented in equation (4) and (5)

$$y_t = \phi_0 + \sum_{i=1}^{ƥ} \phi_i y_{t-i} + \varepsilon_t \tag{4}$$

$$y_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \tag{5}$$

where ϕ_i and θ are autoregressive and moving average coefficients respectively, ε_t value of the random shock at time t such that ε_t ~ $(0, \sigma^2)$ for y_{t-1}

The ARMA (ƥ, q) model in Equation (6) can be simplified by a backward shift operator B to obtain

$$y_t = \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \tag{6}$$

$$(฿)\nabla^d y_t = \theta(฿)w_t \tag{7}$$

Equation (5) can therefore be expressed as $ARMA(p, d, q)$ where $\nabla^d = (1 - ฿)^d$ with $\nabla^d y_t$ and $đ^{th}$ consecutive differencing.

Generally, the time series $\{X_t\}$ utilizes a lag operator ฿ to process SARIMA (ƥ, đ, q)$(P.D.Q)s$.

Seasonal ARIMA model may be written as:

$$\emptyset_p(฿)\Phi_P(฿^S)^d(1 - ฿^S)Y_t = \theta_q(฿)\Theta_q(฿^S)\varepsilon_t \tag{8}$$

in equation (1), ฿ is a lag operator defined as $฿^k Y_t = Y_{t-k}$;

$$\emptyset_p(฿) = 1 - \emptyset_1฿ - \emptyset_2฿^2 - \cdots - \emptyset_P฿^P \tag{9}$$

$$\Phi_p(฿^S) = 1 - \Phi_s฿^s - \Phi_2฿^{2s} - \cdots - \Phi_P฿^{Ps}$$

$$\Theta_q(฿) = 1 - \Theta_1฿ - \Theta_2฿^2 - \cdots - \Theta_q฿^P$$

$$(B^S) = 1 - \Theta_s฿^s - \Theta_2฿^{2s} - \cdots - \Theta_q฿^{Qs} \tag{10}$$

where $\phi(\text{₿})$and $\theta(\text{₿})$ are polynomials of order þ and q respectively; $\Phi_p(\text{₿}^S)$ and $\Theta_q(\text{₿})$ are polynomial in ₿ of degrees P and Q, respectively; D is the number of seasonal differences; Q is the order of seasonal moving average; and s is the length of season.

2.4 ETS State-Space Framework

The Error, Trend, Seasonality (ETS) model provides an alternative by decomposing the series into level L_t , trend T_t , and seasonal S_t components. Unlike ARIMA, which focuses on the autocorrelation of the data, ETS relies on exponential smoothing to weight recent observations more heavily given in Equation (11)

$$y_t = L_{t-1} + T_{t-1} + L_{t-s} + \varepsilon_t \tag{11}$$

2.5 Model Building

The basic steps used for building univariate time series model involves four stages: model identification, estimation, diagnostic and forecasting adopted from The Box–Jenkins methodology.

Identification: Analysis of Autocorrelation (ACF) and Partial Autocorrelation Functions (PACF) plots to suggest potential orders. The ACF is denoted in Equation (12)

$$\rho_k = \frac{E[(\omega_t - \overline{\omega})(\omega_{t-k} - \overline{\omega})]}{E[\omega_t - \overline{\omega}]^2} \tag{12}$$

and PACF is denoted in Equation (13)

$$= \rho_0 + \sum_{k=1}^{K} \rho_{kk}\, \omega_{t-k} \tag{13}$$

where ρ_{kk} is the k^{th} autoregressive coefficient, $k = 1,2, \dots, K$..

The optimal model was chosen using Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (SBIC), and Hannan–Quinn Criterion (HQC).

Parameters are estimated using the Ordinary Least Squares Estimation (OLSE) or Maximum Likelihood Estimation (MLE) method. Coefficient will be obtained using

$$\hat{\emptyset} = \sum_{t=2}^{n}(\omega_{t-1})(\omega_t) \Big/ \sum_{t=2}^{n} \omega_{t-1}^2 \tag{14}$$

Model Selection: The optimal model is selected by minimizing the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC) denoted in Equation (15).

AIC: (2s – 2 In (L)); **SBIC:** (s In(n) – 2 In (L)) (15)

where s is parameters, L likelihood and n sample size

The stability of the estimated model is diagnosed using the Ljung-Box Q-Statistic in Equation (16)

$$Q(m) = n(n+2)\sum_{j=1}^{m}\frac{r_j^2}{n-j} \quad (16)$$

where r_j denotes the residual autocorrelation at lag j.

Forecast Evaluation: The predictive performance is validated using out-of-sample testing.

We evaluate accuracy through three standard metrics using Equations (17-19).

Mean Absolute Forecast Error (MAFE) $= \frac{1}{n}\sum_{t=1}^{n}|\varepsilon_t|$ (17)

Root Mean Square Forecast Error (RMSFE) $= \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\varepsilon_t)^2}$ (18)

Mean Absolute Percentage Error (MAPE) $= \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\varepsilon_t}{y_t}\right| X\ 100$ (19)

$where\ t = 1, \ldots \ldots, n \qquad \varepsilon_t = (\hat{y}_t - y_t)$

3. RESULTS AND DISCUSSION

Figure 1 presents the time plot of the quarterly Food Consumer Price Index (FCPI) rate over the study period. A key feature of the plot is the absence of visible cyclical or seasonal fluctuations, as the series follows a predominantly upward trajectory without regular repeating patterns. This suggests that the FCPI is largely driven by trend components rather than seasonal effects. Given that both the average and variance seem to fluctuate over time. The Augmented Dicey–Fuller (ADF) test results are consistent with the presence of a unit root, which is further supported by the increasing slope and lack of average reversion.

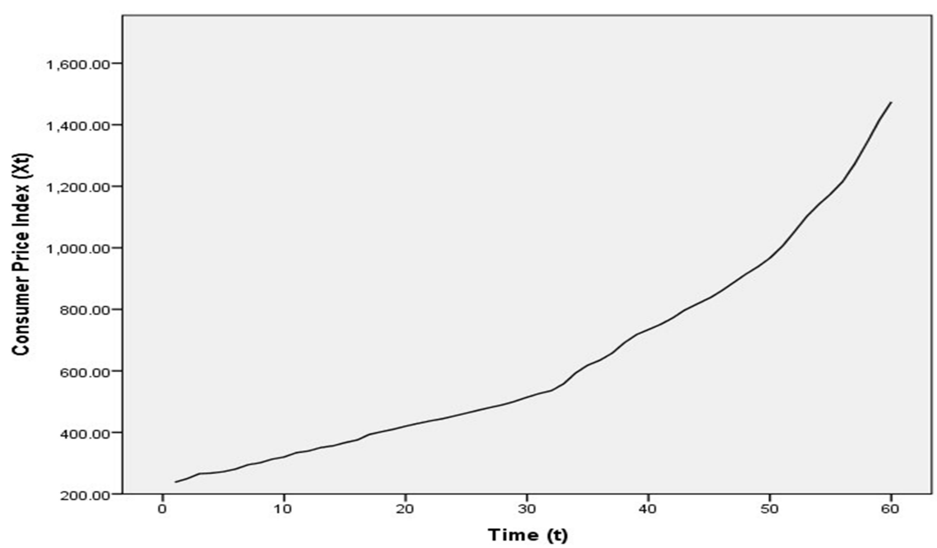

Figure 1: Time Plot of Quarterly Food Consumer Price Index (FCPI) Rate between 2008-2022

Table 1 presents the parameter estimates of the linear trend model for the Food Consumer Price Index (FCPI). The intercept coefficient is estimated at 86.483 with a p-value of 0.001, indicating that the baseline level of the series is statistically significant. Similarly, the time trend coefficient (18.057) is highly significant with a t-value of 24.416 and p-value <0.001, leading to accepting the alternative null hypothesis.

A positive and significant coefficient of the time variable suggests the presence of a strong upward trend in the FCPI over the study period. This implies that food prices have been increasing consistently over time, reflecting persistent inflationary pressure in the food sector. These findings justify the application of time series models that account for trend behavior in forecasting the FCPI.

Table 1: Model Summary for the Linear Trend

Model	Parameter	S.E of (□$_{i)}$	t-test value	P-value	Decision	Conclusion
Intercept	86.483	25.939	3.334	0.001	Reject H_0	Significant
T	18.057	0.740	24.416	0.000	Reject H_0	Significant

3.1 Trend Line Analysis of FCPI (2008-2022)

To evaluate the long-term trajectory of the Nigerian Food Consumer Price Index, a linear trend model was estimated by regressing the index values against time. The resulting trend equation is expressed as:

$T_t = 86.483 + 18.057t$

The intercept ($\beta_0 = 86.483$) represents the estimated baseline index at the start of the study period, while the slope coefficient ($\beta_1 = 18.057$) indicates a significant average monthly increase in the food price index over the fifteen-year horizon. This positive coefficient quantitatively confirms a persistent inflationary trend in the Nigerian food market.

The presence of a clear upward trend in Figure 1 also implies that the original FCPI series is likely non-stationary, as the mean level of the series changes over time. Consequently, statistical techniques such as differencing and unit root testing (e.g., Augmented Dickey–Fuller test) are required to achieve stationarity before fitting time series models such as ARIMA or SARIMA.

The comparison between the estimated trend line and the observed FCPI values in Figure 2 shows that although the trend model accurately depicts the series' overall long-term direction, the actual FCPI shows accelerating growth and short-term variability around this trend. This further justifies the application of advanced time series models, such as ARIMA or SARIMA, which are capable of modelling both trend and stochastic fluctuations in the data.

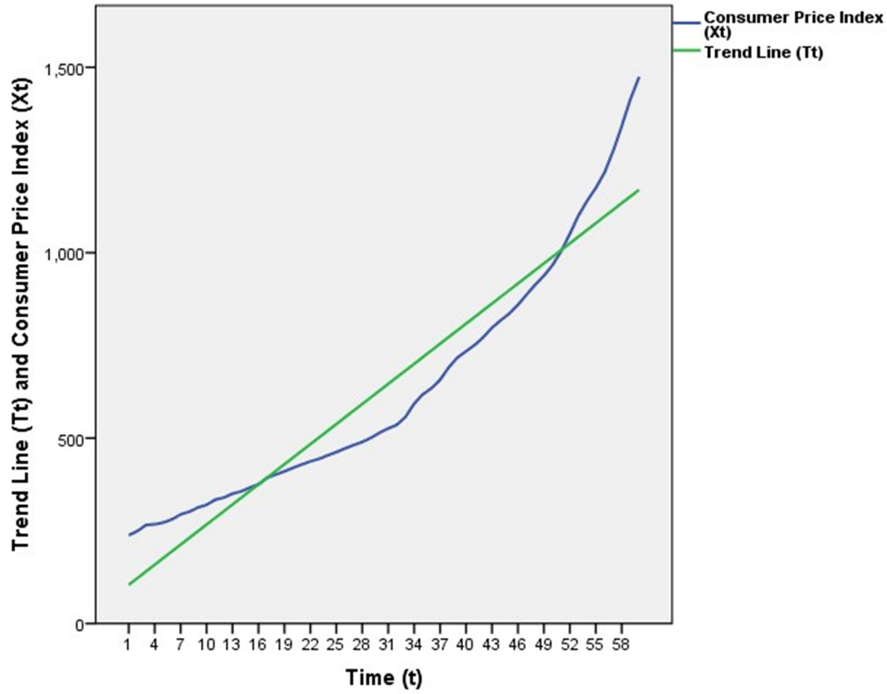

Figure 2: Observed Values Versus the OLS Linear Trend

The foremost stage of the series, the observed FCPI values are higher than the estimated trend values. This suggests that actual prices were above the long-term average growth path during the early periods. However, as time progresses, the FCPI values move closer to the trend line and eventually begin to increase at a faster rate than the estimated trend, especially toward the later periods of the series. This divergence indicates that the growth in consumer prices accelerates beyond the long-run linear trend. The trend line itself shows a steady linear increase, reflecting the underlying long-term direction of the FCPI series. The steady upward slope suggests that prices have been going up slowly over time, which is in line with the idea that inflation is putting pressure on the economy.

Another important observation from the figure is the presence of short-term fluctuations around the trend line. These deviations represent irregular or cyclical movements in the FCPI series that may arise from temporary economic shocks, seasonal variations in food supply, changes in exchange rates, or government policy adjustments. Despite these short-term variations, the dominant pattern of the series remains an upward trend. Toward the final periods of the time horizon, the observed CPI rises sharply and significantly exceeds the trend line. This sharp increase may reflect heightened inflationary pressure or structural economic changes, leading to a rapid rise in consumer prices. Given that the mean level varies over time, such behaviour raises the possibility that the CPI series may display non-stationary characteristics.

3.2 Autocorrelation Function

Therefore, to confirm the seasonality in the data, the level autocorrelation and partial autocorrelation function plots of the time series data shown in Figure 3 and Figure 4 are known to expose properly the seasonality in time series data. The observed series ACF and PACF plots shows that the data is non-seasonal since there is no significant spike at equal interval on the plots.

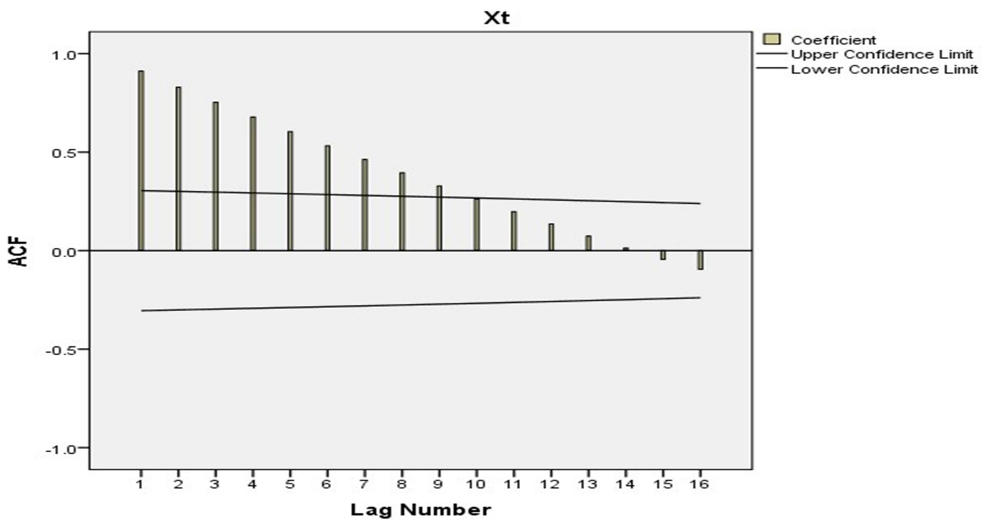

Figure 3: Observed series ACF plots to determine the seasonality in the data

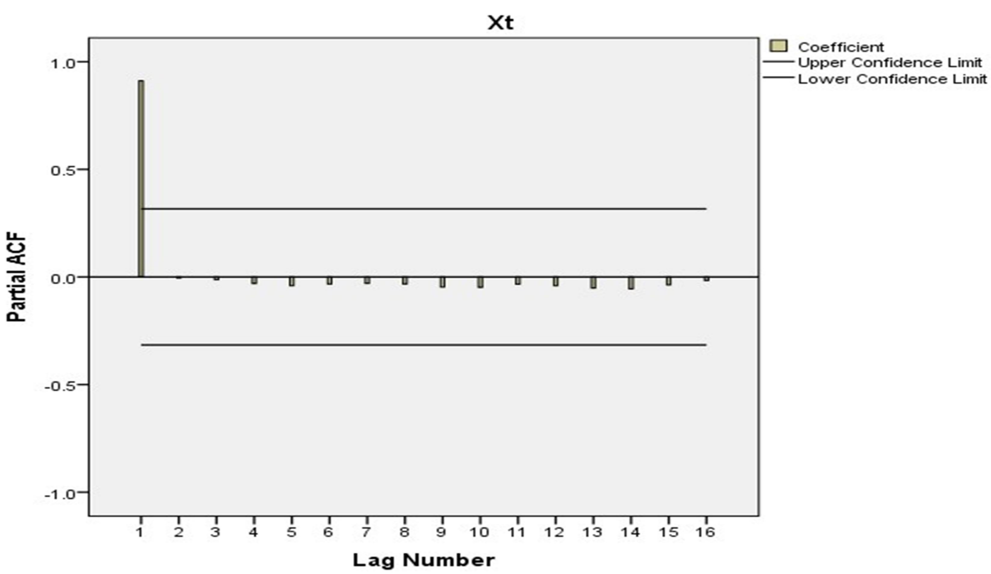

Figure 4: Observed series PACF plots to determine the seasonality in the data

3.3 Test for Stationarity

Based on Table 2 result of the Augmented Dickey-Fuller (ADF) unit root test, led to examine stationarity of the series. Test statistic is −3.4781 with a lag order of 2 and a corresponding p-value of 0.06301.

Decision: we accept H_0 if $P > 0.05$

Table 2. Augmented Dickey-Fuller Test

DF	Lag Order	P-value	Decision	Conclusion
-3.4781	2	0.06301	Accept H_0	The series is not stationary

This result implies that the series is not stationary at the level, meaning that its statistical properties, average and variance, adjust over time. This outcome consistent with an upward trend in the time plot, indicate the presence of a deterministic or stochastic trend component. Because non-stationarity can result in spurious regression results, the series cannot be directly used for standard time series modelling. In order to solve this problem, the series must be transformed to achieve stationarity, usually by first differencing. Before fitting models, additional preprocessing, such as differencing, is necessary because the ADF test verifies that the series is not stationary.

3.4 Transforming Non-Stationary Time Series (Differencing)

Figure 5 presents the time plot of the transformed FCPI series, obtained after applying natural logarithm and first differencing. This transformation is commonly used to stabilize variance and remove trend, thereby achieving stationarity.

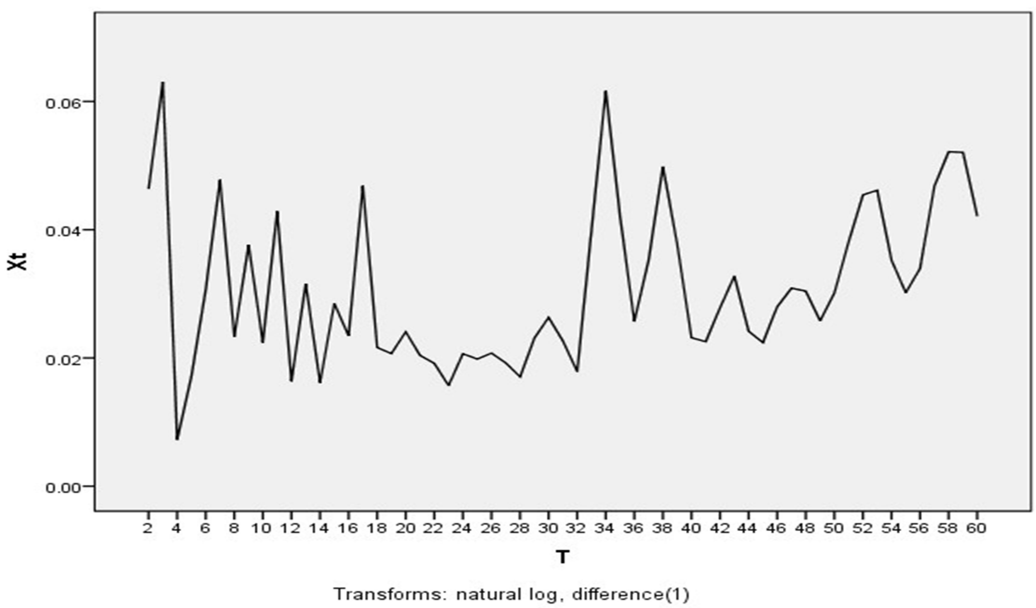

Figure 5: Time Plot of the Log-Tranformed and First Differenced FCPI Series

The transformed series fluctuates around a relatively constant mean, with values mostly lying between 0.02 and 0.05. Unlike the original series, which exhibited a strong upward trend, this plot shows no visible long-term trend, indicating that the differencing process has successfully removed the trend component. In addition, the variability of the series appears relatively stable over time, implying that the variance is approximately constant. This further supports the conclusion that the transformation has addressed heteroscedasticity and improved the statistical properties of the series. There is no clear evidence of seasonality or cyclic behavior in the transformed data, as the movements do not follow any repeating pattern. Instead, the series resembles a white noise or weakly dependent process, which is suitable for time series modeling.

Table 3. First Difference Augmented Dickey-Fuller (ADF) Test Results for the Nigerian FCPI Series.

DF	Lag Order	P-value	Decision	Conclusion
-1.04193	2	0.0000	Reject H_0	The series is stationary

The series is stationary at first difference according to the Augmented Dickey-Fuller (ADF) test, which was carried out and displayed in Table 3. This is done to guarantee the validity of the time series models and prevent the pitfalls of spurious regression. The results, summarized in Table 3 above, evaluate the null hypothesis (H_0) that the series contains a unit root (non-stationary). Since it verifies that average, variance, and autocovariance of the FCPI series stay constant over time, achieving stationarity is a basic requirement for moving average and autoregressive modelling. The test specification used a lag order of 2. In order to ensure that the error term approximates white noise, this lag length was found to adequately account for higher-order serial correlation in the residuals. The ACF and PACF plots from Figures 6 and 7 are shown below to support the stationary test claim made above.

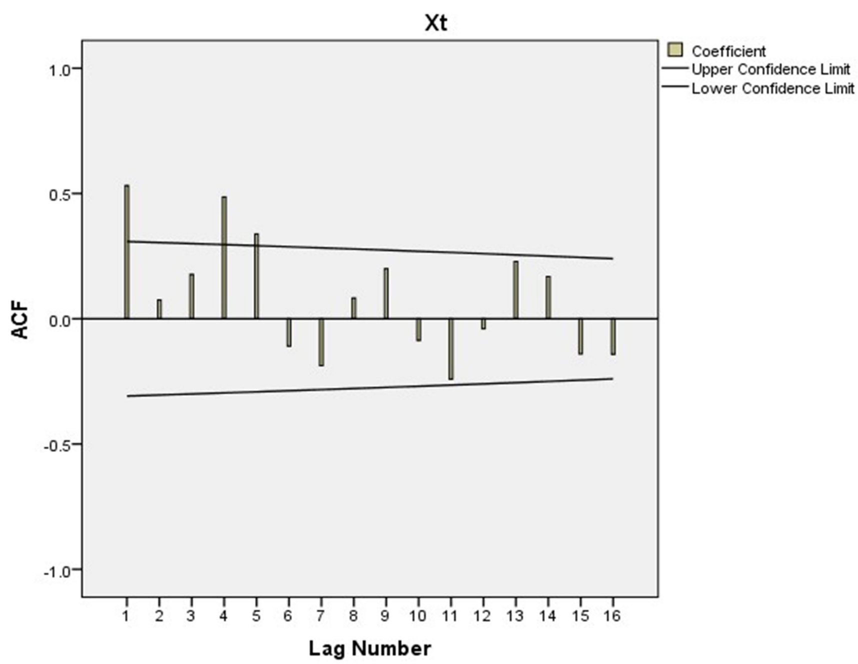

Figure 6: Observed series ACF plots to determine the seasonality in the data

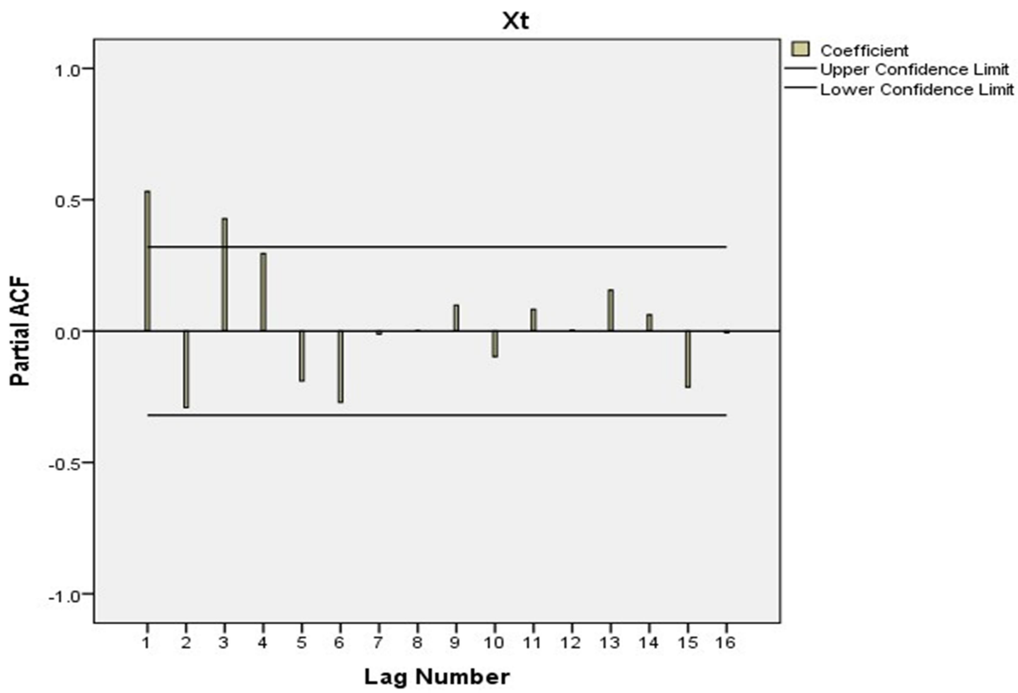

Figure 7: Observed series PACF plots to determine the seasonality in the data

3.5 Model Selection Criteria

While their PACF cuts off, the simulated model's ACF and the observed data above both decay. Since the PACF plot is used to determine the order of the AR process, it was evident that both the observed data PACF and the simulated PACF cut off at the first two lags (order 2). This demonstrates that the AR (2) model is the best fit for the data. By changing the order of the AR process, the model's order will be determined. Because it was differenced once to make it stationary, the series from the Augmented Dickey Fuller is integrated of order 1, or d = 1. ARIMA (þ, đ, q) = ARIMA (þ, 1, q) because the model is an autoregressive integrated and moving average model. After adjusting þ and q, we use the model's MSE (Sigma^2), Log Likelihood, and Akaike Information Criterion (AIC) to evaluate its suitability. The model with the lowest AIC is the best one.

Table 4. Showing the MSE, Log Likelihood AIC of ARIMA (þ, đ, *q*)

ARIMA (þ, 1, q)	MSE (Sigma^2)	Log Likelihood	AIC
(1, 1, 0)	68.14	-242.349	108.16
(1, 1, 1)	72.03	-247.318	317.84
(1, 1, 2)	82.02	-253.829	251.07
(2, 1, 0)	71.83	-246.612	194.34
(2, 1, 1)	62.45	-204.251	147.09
(2,1, 2)	89.63	-235.428	184.43

Based on Table 4, the model suitability was assessed using the Akaike Information Criterion (AIC), Log Likelihood (LL), and Mean Square Error (MSE) in accordance with parsimony principle. Best forecasting architecture for the Nigerian Food CPI is the model that maintains statistically significant coefficients while having the lowest AIC and sigma square. The residuals estimated from the fitted model were used to diagnose the ARIMA (2, 1, 1), which has the lowest AIC = 147.09, the lowest Sigma^2 = 62.45, and the Log Likelihood = -204.251. The model was tested using the Box-Pierce test . P-values for the test are below 0.05. The test result concludes that the model residuals are independent and distributed.

3.6 Estimates of the Parameters of the Identified Model

(a) Table 5. Model Parameter for ARIMA (2,1,1)

ARIMA Parameters								
					Estimate	Std Error	t	Sig.
VALUE-Model 1	VALUE	Transformation	Constant		87.645	190.706	0.460	0.646
			AR	Lag 1	0.489	0.196	-2.493	0.013
			AR	Lag 1	-.602	0.190	-3.168	0.000
			Difference		1			
			MA	Lag 1	-.303	0.063	-4.809	0.000

Fom Table 5, ARIMA (2,1,1) can be written mathematically as:

$X_t = 87.645 - 0.489X_{t-1} - 0.602X_{t-2} + \varepsilon_t - 0.303\varepsilon_{t-1}$

3.7 Ljung Box-Pierce Test for Residual Independence

Table 6 presents the result of the Ljung Box-Pierce test, which is used to examine whether the residuals from the fitted time series model are independent and distributed or free from autocorrelation. The test yields an X-squared statistic of 24.9402 with 58 degrees of freedom and a p-value of 0.0000. Since the p-value is less than the 5% significance level (0.05), the null hypothesis (H_0) of no autocorrelation in the residuals is rejected. This result suggests that the residuals are not independently distributed, implying the presence of serial correlation in the model errors. In other words, the fitted model has not fully captured all the underlying patterns in the data, and some structure remains in the residuals. The presence of autocorrelation in the residuals indicates that the model may be inadequate or mis specified. This could arise from an incorrect choice of model order, omission of important components such as seasonality, or failure to properly difference the series.

Table 6. Ljung Box-Pierce Test

X-squared	DF	P-value	Decision	Conclusion
24.9402	58	0.0000	Reject H_0	The model residuals are not independent

H_0: The model residuals are not independently distributed (auto-correlated)

Decision: Reject H_0 if $P < 0.05$

3.8 Model Forecast

Table 7 presents the projected values of the Food Consumer Price Index (FCPI) generated from the fitted time series model for the forecast horizon extending from 2023 to 2030. The forecasts are presented on a quarterly basis, providing an estimate of the expected movement of the CPI over the next eight years. The forecast results indicate a consistent upward trajectory in the Food Consumer Price Index, reflecting ongoing inflationary pressure in the economy. The gradual but continuous increase in FCPI implies that the cost of consumer goods, particularly food and agricultural items, may continue to rise over time. Because they emphasise the significance of putting in place suitable monetary and fiscal policies to control inflation and stabilise consumer prices in the future, these projections offer policymakers and economic planners useful information.

Table 7: ARIMA (2,1,1) Forecast Results for Nigerian Food Consumer Price Index (FCPI)

YEAR	Qtr1	Qtr2	Qtr3	Qtr4
2023	1187.960	1206.017	1224.074	1242.131
2024	1260.188	1278.245	1296.302	1314.359
2025	1332.416	1350.473	1368.530	1386.587
2026	1404.644	1422.701	1440.758	1458.815
2027	1476.872	1494.929	1512.986	1531.043
2028	1549.100	1567.157	1585.214	1603.271
2029	1621.328	1639.385	1657.442	1675.499
2030	1693.556	1711.613	1729.670	1747.727

4. CONCLUSION

This research provided a rigorous longitudinal analysis of the Nigerian Food Consumer Price Index (FCPI) from 2008 to 2022, addressing a critical empirical gap in the study of food-specific inflationary trends. The specific volatility and stochastic behaviour present in Nigeria's food market are highlighted by this study's disaggregated approach, whereas larger macroeconomic studies frequently generalise the effects of inflation. The empirical findings show that the FCPI has a consistent upward trend and notable seasonal variations. Through an evaluation of the ARIMA, SARIMA, and ETS frameworks, the study found economical models that could accurately predict these complex dynamics. The results demonstrate that the persistent increase in food prices is a major threat to the country's food security and a major factor in the decline of household purchasing power rather than just a reflection of overall inflationary pressure.

In the end, the FCPI's detected instability acts as a high-fidelity diagnostic for the efficacy of the country's current economic policies. This study concludes that the continuous volatility will continue to deter investment and deteriorate social conditions in the absence of data-driven, predictive monetary interventions. As a result, the models created here offer Central Bank and budgetary authorities a solid statistical basis for transitioning to a more resilient and anticipatory framework for economic management.

5. RECOMMENDATIONS

Based on the empirical evidence and the predictive performance of the time series models developed in this study, the following recommendations are proposed. The central bank and apex monetary authority of the country should transition from reactive to proactive inflation targeting. Given the Food CPI's ongoing upward trend, the monetary authorities should periodically adjust contractionary measures, like controlling the Cash Reserve Ratio (CRR), to stabilise purchasing power when model forecasts surpass predetermined inflationary thresholds. Budgetary restraint should be given precedence over needless public spending by the nation's fiscal authorities. Government organisations and stakeholders should incorporate sophisticated forecasting frameworks (like the ARIMA and ETS models found in this study) into their decision-making procedures in order to reduce the socioeconomic volatility linked to food prices.

Prior to consumer price spikes, a real-time "Inflation Early Warning System" would allow for the strategic release of grain reserves or temporary tariff adjustments. Future macroeconomic modelling must take into consideration structural breaks and regime changes within the Nigerian economy. To ensure that econometric models remain robust in the face of abrupt market volatility, researchers should go beyond linear assumptions and incorporate exogenous shocks, such as agricultural disruptions caused by climate change or currency fluctuations.

REFERENCES

1. Masaya, A.B. & Bura, I. U (2024). Application of Time Series Model on Consumer Price Index (CPI). *BW Academic Journal*, *1*(3), 1–13. Retrieved from https://www.bwjournal.org/index.php/bsjournal/article/view/2139
2. Box, G. (2013). Box and Jenkins: Time series analysis, Forecasting and Control. In *A Very British Affair: Six Britons and the Development of Time Series Analysis During the 20th Century* (pp. 161-215). London: Palgrave Macmillan UK.
3. Central Bank of Nigeria, (2021), Central Bank of Nigeria annual statistical bulletin, Central Bank of Nigeria, Abuja.
4. Central Bank of Nigeria. (2023). *Monetary policy report*. Central Bank of Nigeria.
5. Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and practice* (3rd ed.). OTexts. https://otexts.com/fpp3/
6. Ibrahim, A., Sani, U. M., & Olokojo, V. O. (2023). Forecasting Consumer Price Index And Exchange Rate Using Arima Models: Empirical Evidence From Nigeria. *Fudma Journal Of Sciences*, *6*(6), 114-124. https://doi.org/10.33003/fjs-2022-0606-1136
7. International Monetary Fund. (2024). *World economic outlook: Inflation and policy responses*. IMF.
8. Aliyu Baba Masaya, & Ibrahim Usman Bura. (2024). Application of Time Series Model on Consumer Price Index (CPI). *BW Academic Journal*, *1*(3), 1–13.Retrievedfrom https://www.bwjournal.org/index.php/bsjournal/article/view/2139
9. Ivanovski, Z., and Ivanovska, N. (2024). The Augmented Dickey-Fuller test for the Stationarity of the Final Public Consumption and GDP Time Series of the Republic of North Macedonia. *UTMS Journal of Economics*, *15*(2). 109-124

10. National Bureau of Statistics (NBS). (2022). Consumer Price Index Report.
11. Nwosu, I. G. (2024). Forecasting Nigeria's Inflation Rates (2009–2024) using SARIMA Models. *Statistics and Mathematical Research Journal*, *12*(2), 44-56. https://doi.org/10.5281/zenodo.17368249
12. World Bank. (2022). *Food price inflation and household welfare in developing economies*. World Bank.