

Forecasting food price inflation in Nigeria and identifying its drivers using machine learning models

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Abstract

Persistent food price inflation has become one of Nigeria's most pressing macroeconomic and food security challenges, yet evidence on the most effective forecasting approaches and the principal drivers of food inflation remains limited. This study forecasts food price inflation in Nigeria over a two-year horizon and identifies its key determinants using monthly food price data. The analytical framework combines conventional time-series techniques with regularized econometric and machine learning models, including Autoregressive (AR), Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), Elastic Net, Partial Least Squares (PLS), and Artificial Neural Network (ANN). Time-series diagnostics confirmed that the food inflation series was stationary in levels, while the Akaike Information Criterion selected an AR (12) specification as the optimal benchmark model. Comparative out-of-sample evaluation revealed that the regularized regression models outperformed both the benchmark AR model and the nonlinear machine learning models. Elastic Net achieved the highest forecasting accuracy (RMSE = 9.94), followed by LASSO (RMSE = 9.95) and Ridge Regression (RMSE = 10.02), whereas PLS and ANN exhibited substantially poorer predictive performance. Feature selection results identified historical food prices as the most robust predictor of future food price inflation. Ridge Regression further highlighted exchange rate movements, pump prices, the food price index, and rainfall as important complementary predictors, underscoring the roles of inflation persistence, macroeconomic conditions, energy costs, and climatic factors in shaping food price dynamics. The findings demonstrate that parsimonious regularized regression models provide more accurate and interpretable forecasts than complex nonlinear algorithms in a structurally volatile macroeconomic environment. The study recommends strengthening inflation monitoring systems through regularized forecasting models while implementing coordinated macroeconomic, energy, and agricultural policies that improve domestic food production, enhance climate resilience, stabilize exchange rates, and reduce transportation costs to promote food price stability and food security in Nigeria.

Introduction

Nigeria has experienced persistent macroeconomic instability over the past decade, with food inflation emerging as one of its most pressing economic and social challenges. In July 2024, the country's food inflation rate reached 39.53%, accounting for approximately 17.30% of the overall inflation rate (NBS 2024). This unprecedented increase reflects the combined influence of global food market disruptions and domestic structural constraints. Rising international commodity prices, exchange rate depreciation, high transportation costs following the removal of fuel subsidies, insecurity in major food-producing regions, climate-related production shocks, increasing production costs, and weaknesses in agricultural supply chains have collectively intensified inflationary pressures within Nigeria's food system (Popoola et al. 2023). Consequently, the prices of staple commodities including rice, beans, maize, bread, yam, potatoes, vegetable oils, and other essential food items have increased substantially, significantly raising the cost of living for households across both rural and urban communities.

The consequences of persistent food price inflation extend far beyond higher consumer prices. Rising food prices reduce households' purchasing power and force families to adjust consumption patterns by reducing both the quantity and quality of food consumed. Such adjustments often lead to inadequate dietary diversity, poorer nutritional outcomes, increased vulnerability to food insecurity, and declining physical and mental well-being. In addition, households frequently divert expenditure away from essential non-food needs such as healthcare, education, housing, and productive investments in order to meet basic food requirements. These coping strategies may provide temporary relief but often deepen long-term poverty and reduce household resilience to future economic shocks. The burden of food inflation is particularly severe among low-income households, rural residents, female-headed households, and smallholder farming families, who allocate a much larger proportion of their income to food purchases than wealthier households (Mustafa et al. 2021; OECD 2026).

The social and political implications of rising food prices have also become increasingly evident in Nigeria. The nationwide "End Bad Governance" protests of 2024 highlighted widespread public dissatisfaction with deteriorating living standards, rising food prices, and declining household welfare. Beyond their economic consequences, these protests disrupted commercial activities, reduced investor confidence, and demonstrated the extent to which food inflation can evolve into a broader social and political challenge. Similar experiences across developing countries have shown that persistent food inflation can increase social unrest, exacerbate poverty, and undermine national economic stability when effective policy responses are absent. According to the Food and Agriculture Organization (FAO 2025; Meludu et al., 2023), more than 25.3 million Nigerians are projected to experience acute food insecurity, substantially exceeding earlier estimates. This trend poses a significant obstacle to achieving Sustainable Development Goal 2, which seeks to eliminate hunger and ensure universal access to safe, nutritious, and sufficient food by 2030.

Given these far-reaching consequences, controlling food inflation has become an important policy objective for governments and monetary authorities. However, designing effective interventions requires more than understanding the historical behaviour of food prices; policymakers also require reliable forecasts that anticipate future inflationary pressures before they materialize. Accurate forecasts enable governments to implement timely macroeconomic adjustments, strengthen strategic food reserves, improve market surveillance, stabilize food supply chains, and design evidence-based agricultural and trade policies capable of mitigating future food crises. Forecasting food inflation therefore serves not merely as a statistical exercise but as an essential decision-support tool for proactive policy formulation.

Nevertheless, forecasting food price inflation remains particularly challenging because food prices are influenced by numerous interacting factors whose relationships evolve over time. Domestic food inflation reflects the combined effects of agricultural production, weather variability, transportation costs, exchange rate movements, energy prices, international commodity markets, government policies, consumer demand, market expectations, and structural supply constraints. These factors interact in highly nonlinear and dynamic ways, generating complex inflationary patterns that are often difficult to capture using conventional forecasting techniques. Moreover, frequent structural changes including

exchange rate reforms, fuel subsidy removal, climate shocks, insecurity, and global supply disruptions have increased the volatility of Nigeria's food markets, making accurate forecasting considerably more difficult. As a result, minimizing forecast errors and improving predictive accuracy have become central objectives of contemporary inflation research (Nakorji and Aminu 2022).

The growing complexity of food price dynamics has consequently stimulated increasing interest in developing more robust forecasting approaches capable of accommodating nonlinear relationships, structural changes, and high-dimensional datasets. While conventional econometric models remain valuable for causal inference and policy evaluation, their predictive performance may deteriorate when relationships among variables become highly complex or unstable. These limitations have motivated researchers to explore alternative data-driven approaches that can improve forecast accuracy while uncovering complex patterns embedded within large economic datasets. In recent years, advances in machine learning have transformed macroeconomic forecasting by providing flexible predictive algorithms capable of modelling nonlinear relationships with relatively few restrictive assumptions. Consequently, machine learning has emerged as one of the most promising approaches for forecasting inflation and identifying the key factors driving price dynamics in increasingly uncertain economic environments.

Extensive empirical literature has documented the adverse consequences of food price inflation on household welfare across both developed and developing economies. Previous studies consistently report that rising food prices reduce real incomes, increase poverty and food insecurity, worsen nutritional outcomes, and disproportionately affect vulnerable households because food constitutes a larger share of their total expenditure (Shrestha and Chaudhary 2012; Ellahi et al. 2015; Eric et al. 2018; Van Campenhout et al. 2018; Yasrizal et al. 2018; Khoiriyah et al. 2020; Layani et al. 2020; Umaroh and Pangaribowo 2020; Woldemichael et al. 2022; Ullah and Uçak 2023; Hodjo et al. 2024). Similar findings have been reported for Nigeria, where studies have shown that food price inflation significantly reduces household welfare, increases food insecurity, and alters food consumption behaviour (Olubokun 2018; Adekunle et al. 2020; Adeyonu et al. 2021; Chigozirim et al. 2021; Ewubare and Olise 2021; Omotayo et al. 2022; Shehu et al. 2023; Fajobi et al. 2024; Ibrahim 2024). Collectively, these studies have substantially advanced understanding of the socioeconomic consequences of food inflation and provided valuable evidence for designing social protection and food security policies.

Despite these important contributions, the overwhelming majority of previous studies have focused primarily on estimating the welfare effects of food price changes rather than predicting future inflationary movements. Most have employed conventional econometric techniques, including variants of the Almost Ideal Demand System (AIDS), Quadratic Almost Ideal Demand System (QUAIDS), Error Correction Models, Vector Autoregressive models, and Compensating Variation approaches. These methods are particularly valuable for testing economic theory, estimating elasticities, and quantifying causal relationships between food prices and household welfare. However, they are not specifically designed to maximize forecasting accuracy in environments characterized by structural breaks, nonlinear relationships, and rapidly changing market conditions. As food markets become increasingly

volatile, policymakers require analytical tools capable of anticipating future inflationary trends rather than merely explaining historical outcomes.

Recent advances in artificial intelligence and machine learning have transformed macroeconomic forecasting by introducing flexible predictive algorithms capable of modelling complex and nonlinear relationships without imposing restrictive functional-form assumptions. Unlike conventional econometric approaches, which are largely theory-driven and require explicit model specification, machine learning methods are primarily data-driven and emphasize predictive performance. These algorithms automatically learn hidden relationships within large datasets, accommodate interactions among numerous variables, and often provide superior forecasting accuracy where economic relationships are unstable or highly nonlinear. Consequently, machine learning has become an increasingly important analytical framework for forecasting macroeconomic indicators, including inflation, exchange rates, commodity prices, energy demand, and financial market behaviour.

Several recent studies have demonstrated the effectiveness of machine learning techniques in inflation forecasting across different countries. Andree (2021) employed machine learning techniques to estimate food price inflation from incomplete survey data, illustrating their usefulness in real-time monitoring. Aras and Lisboa (2022) developed explainable machine learning models that improved inflation forecasting while enhancing model interpretability. Similarly, Medeiros et al. (2021), Araujo and Gaglianone (2023), Mahajan and Srinivasan (2020), Mishra et al. (2023), Momo et al. (2021), and Yang and Guo (2021) reported that machine learning algorithms frequently outperform traditional econometric models when forecasting inflation in complex economic environments. Other studies have advocated hybrid modelling strategies that combine econometric methods with machine learning algorithms to exploit the complementary strengths of both approaches (Ülke et al., 2018; Malhotra 2021). While econometric models remain indispensable for economic interpretation and policy analysis, machine learning techniques have demonstrated considerable advantages in predictive accuracy, handling high-dimensional datasets, modelling nonlinear relationships, and identifying hidden patterns within complex economic systems.

Within Nigeria, however, empirical applications of machine learning to inflation forecasting remain relatively limited. Existing studies have largely concentrated on aggregate inflation forecasting or the broader determinants of inflation, with comparatively little attention devoted specifically to food price inflation. For example, Akande et al. (2022) applied ensemble machine learning techniques to predict inflation components, while Awopegba and Awe (2024) investigated inflation drivers using machine learning algorithms. Nakorji and Aminu (2022) also explored inflation forecasting using predictive approaches. Although these studies represent important advances in the Nigerian literature, they primarily focus on aggregate inflation rather than food-specific inflation, often employ a limited range of predictive algorithms, and provide relatively little evidence regarding the comparative forecasting performance of classical autoregressive models and contemporary machine learning methods. Furthermore, relatively few studies have simultaneously evaluated forecast accuracy and examined the

principal macroeconomic and structural factors driving food price inflation using explainable predictive techniques.

This omission is important because food price inflation differs fundamentally from aggregate inflation. Food prices are considerably more sensitive to climatic variability, agricultural production cycles, transportation costs, exchange rate fluctuations, energy prices, market integration, and supply chain disruptions than many non-foods consumer prices. Consequently, forecasting food inflation requires models capable of capturing these unique dynamics and identifying the variables that exert the greatest influence on future price movements. Identifying these drivers is equally important because accurate forecasts alone provide limited policy value unless policymakers understand the mechanisms generating inflationary pressures. A comprehensive analytical framework should therefore combine accurate prediction with interpretable evidence regarding the relative importance of macroeconomic, climatic, and market-related determinants of food inflation.

Against this background, this study contributes to the literature in several important ways. First, it develops out-of-sample forecasts of Nigerian food price inflation over a two-year horizon using a comprehensive market price dataset. Second, it provides a systematic comparison of the predictive performance of benchmark autoregressive models, regularized regression techniques (Ridge, LASSO, Elastic Net), Partial Least Squares regression, and Artificial Neural Networks using multiple forecast accuracy measures. Third, beyond evaluating forecasting performance, the study identifies and compares the principal drivers of food price inflation through correlation analysis and regularized regression methods, thereby improving understanding of the macroeconomic, market, and climatic factors influencing food price dynamics. Finally, by integrating predictive modelling with empirical driver identification, this study contributes to the emerging literature on machine learning applications in agricultural and macroeconomic forecasting while providing practical evidence to support proactive food price stabilization, inflation management, and food security policy in Nigeria.

The findings of this study have important implications for monetary authorities, agricultural policymakers, market analysts, and development partners seeking to strengthen Nigeria's food system. Reliable forecasts of food price inflation can improve inflation targeting, facilitate timely market interventions, strengthen strategic food reserve planning, and enhance the design of fiscal, monetary, and agricultural policies aimed at reducing food price volatility. More broadly, the study suggests how contemporary predictive analytics can complement traditional economic approaches in addressing one of the most pressing development challenges confronting Nigeria and many other low- and middle-income countries.

Literature review

Conceptual framework

The conceptual framework (Fig. 1) presents the theoretical and analytical foundation underpinning this study. It illustrates the dynamic relationship between the determinants of food price inflation, the predictive modelling process, the expected outputs, and their policy implications. The framework is grounded on the premise that food price inflation is a multidimensional phenomenon influenced by interacting macroeconomic, market, agricultural, climatic, and global factors. These factors jointly determine movements in food prices and provide the explanatory variables used to forecast future food price inflation and identify its principal drivers.

The first component of the framework comprises the drivers of food price inflation, which are classified into five broad categories. The macroeconomic factors include exchange rate, money supply, interest rate, government expenditure, and inflation expectations. These variables influence aggregate demand, production costs, and monetary conditions, thereby affecting food prices either directly or indirectly. Exchange rate depreciation, for instance, increases the domestic prices of imported food commodities, agricultural inputs, and machinery, while expansionary monetary policies may stimulate inflationary pressures through increased liquidity in the economy.

The second category consists of cost and market factors, including fuel price, transportation cost, fertilizer price, wage rate, and market integration. These variables directly affect production, processing, and distribution costs throughout the food supply chain. In Nigeria, transportation costs constitute a significant proportion of food marketing costs due to inadequate infrastructure and long marketing distances. Similarly, fluctuations in fuel prices following the removal of fuel subsidies increase transportation and production costs, which are subsequently transmitted to consumers through higher food prices.

The third category comprises agricultural supply factors, represented by agricultural output, food production index, livestock production, and input availability. Since domestic food supply is largely determined by agricultural production, any reduction in output caused by declining productivity, inadequate input use, pest infestation, or insecurity in farming communities can generate supply shortages and upward pressure on food prices. Conversely, improvements in agricultural productivity and input availability contribute to increased food supply and enhanced price stability.

The fourth category includes climatic and environmental factors, namely rainfall, temperature, drought index, and extreme weather events. Agricultural production in Nigeria is predominantly rain-fed, making food supply highly vulnerable to climate variability. Adverse climatic conditions reduce crop yields, disrupt planting and harvesting calendars, and increase production risks, thereby contributing to food price volatility. Incorporating climatic variables into the predictive framework therefore enhances the ability of the forecasting models to capture environmental influences on food price dynamics.

The final category consists of global and external factors, including global food commodity prices, global oil prices, trade openness, and foreign inflation. Owing to increasing market integration, domestic food prices are no longer determined solely by local conditions but are also affected by developments in international markets. Rising global commodity prices, international oil price shocks, and inflation in

major trading partners may be transmitted to domestic food markets through imports, exchange rate adjustments, and higher production costs.

These explanatory variables constitute the inputs to the modelling component of the framework. The study adopts a comparative modelling strategy by integrating a benchmark econometric model with several machine learning algorithms. The benchmark autoregressive (AR) model serves as the conventional forecasting approach against which the predictive performance of the machine learning models is evaluated. The machine learning models include Ridge Regression, LASSO Regression, Elastic Net Regression, Partial Least Squares Regression, and Artificial Neural Networks. Each algorithm offers distinct advantages in handling multicollinearity, high-dimensional data, nonlinear relationships, variable selection, and predictive accuracy. Their comparative evaluation enables the identification of the most suitable model for forecasting food price inflation under Nigeria's complex economic environment.

To ensure reliable and robust predictions, the framework incorporates model training and validation procedures, including time-series cross-validation, hyperparameter tuning, and robustness checks. These procedures minimize overfitting, improve model generalization, and enhance the reliability of out-of-sample forecasts. Given the dynamic nature of inflation, validation using time-dependent data is particularly important because it preserves the temporal structure of observations and produces forecasts that more closely resemble real-world conditions.

The modelling process generates two principal outputs. The first is food price inflation forecasting, which provides out-of-sample monthly forecasts over a 24-month horizon together with measures of forecast uncertainty. Accurate forecasts enable policymakers to anticipate inflationary pressures before they materialize and facilitate proactive policy responses.

The second output is the identification of the key drivers of food price inflation. Through variable importance analysis and regularized regression techniques, the framework identifies the macroeconomic, market, climatic, and agricultural variables that contribute most significantly to food price dynamics. Understanding these drivers extends the usefulness of the forecasting exercise beyond prediction by providing empirical evidence on the mechanisms underlying food price inflation and highlighting the variables that require policy attention.

The final component of the framework highlights the policy relevance of the study. Reliable forecasts and evidence on the principal determinants of food price inflation provide valuable information for monetary authorities, agricultural policymakers, and development agencies. The findings can support timely policy interventions, food supply stabilization, inflation-targeting strategies, strategic grain reserve management, early warning systems, and evidence-based decision-making aimed at enhancing food security and macroeconomic stability.

The framework also incorporates a feedback loop, recognizing that food price inflation is a dynamic process rather than a one-time event. New market information, policy reforms, structural changes, climatic shocks, and global economic developments continuously influence the explanatory variables

and may alter future inflation dynamics. Consequently, predictive models should be periodically updated with new data to maintain forecasting accuracy and policy relevance. This iterative process reflects the adaptive nature of machine learning and reinforces the framework's suitability for analyzing evolving food price dynamics in Nigeria.

In all, the conceptual framework suggests that food price inflation is the outcome of complex interactions among macroeconomic, market, agricultural, climatic, and global factors. By integrating these determinants within a comparative econometric and machine learning framework, the study not only forecasts future food price inflation but also identifies the most influential drivers, thereby providing a robust evidence base for proactive food price management and sustainable food security policies in Nigeria.

Methodology

Study area

This study was conducted in Nigeria, a country in West Africa, north of the equator, with approximate geographical coordinates of 9.0820°N and 8.6753°E latitude and longitude, respectively. The country (Fig. 2) is bordered in the north by Niger, in the northeast by Chad, east by Cameroon, and west by the Republic of Benin. Nigeria has 36 states, and its Federal Capital Territory (FCT) is in Abuja. Lagos is the largest city by population and the centre of economic activities in Nigeria.

The city is one of the fastest-growing cities in the world and has Africa's busiest port. The country's official language is English and it has a total land area of 923,768 km² or 356,669 miles. Nigeria is the most populous country in Africa and ranks sixth globally. As of March 5, 2025, Nigeria's estimated population is approximately 235.9 million. Nigeria's real GDP in the third quarter of 2024 was 20.12 trillion naira, while its nominal value was 71.13 trillion naira (NBS, 2024). The Nigerian economy relies on agriculture as the primary source of livelihood for most of its citizens (about two-thirds) and contributes about 28.65% to overall GDP in real terms in Q3 2024 (25.01% to nominal GDP) (NBS, 2024). The major crops produced are maize, cassava, rice, beans, cocoa, groundnuts, kolanut, rubber, banana, yams, plantains, sesame, soybeans, millet, palm kernels, palm oil, sorghum, melon and cashew nuts. Nigeria remains the highest producer of cassava and yams globally. FAO data shows Nigeria produced approximately 60.8 and 61.2 million metric tons of cassava and yams, respectively, in 2022 (FAO, 2022). Despite these, Nigeria has not been able to meet the country's food demand, thereby leading to high food insecurity. The persistent food insecurity in Nigeria was intensified by high prices of food items, conflict relating to insurgency (especially in the North-East), armed banditry, pastoralist and farmer communal crisis, kidnapping, cattle rustling and climate change (FEWSNET, 2020). However, food prices significantly affect food insecurity in Nigeria because they have become more unstable and keep increasing, resulting in a higher demand for research on food inflation with practical and sustainable approaches.

Data sources and description

This study used food price data obtained from World Food Programmes (WFP) open data platform. WFP dataset, comprising 68,261 monthly food price observations collected between February 2015 and May 2026 across 66 distinct markets, 38 food commodities, and 14 Nigerian States. All price observations are denominated in Nigerian Naira (NGN) and recorded at a monthly frequency, with timestamps referenced to West African Standard Time (WAT). This temporal resolution renders the dataset well suited for time-series modeling and food inflation analysis. The Price Export dataset originates from officially documented price monitoring exercises and provides detailed information on commodity type, market location, administrative identifiers, price levels, date of observation, currency, and units of measurement. The wide coverage across markets and commodities allows the data to capture substantial spatial and commodity-specific heterogeneity in food price dynamics. The Price Date variable was converted from string format to a proper datetime object. Observations with invalid or missing dates were removed to ensure temporal consistency. This preprocessing step reduced the dataset from 68,261 to 54,211 observations, representing a loss of approximately 20.6% of records. The removed observations were primarily attributed to incomplete date entries and formatting inconsistencies in the original data collection process. The dataset was then sorted chronologically to ensure absence of temporal leakage, correct lag construction and proper alignment for time-series models.

Machine learning (ML) models

Machine learning was utilized to describe the food inflation trend, forecast food inflation, and identify the drivers of food inflation in Nigeria. ML has recently become a standard forecasting tool among scholars worldwide, especially for inflation forecasting. In Nigeria, various traditional methods have been adopted for inflation forecasting, with little attention to the machine-learning approach (Nakorji and Aminu, 2022). Several ML approaches have been adopted and compared in the literature to forecast inflation. Some of these are penalized regression (Least Absolute Shrinkage and Selection Operator (LASSO), ridge regression, elastic net), Artificial Neural Network (ANN), and partial least squares regression (Nakorji and Aminu, 2022; Sarangi et al., 2021); Support Vector Regression (SVR), Random Forest Regressor (RFR), decision tree, Adaptive Boosting, gradient boosting, and Extreme Gradient Boosting (XGBoost) (Momo et al., 2021); 50 models, including forecast combinations, tree-based methods (such as random forest and xgboost), breakeven inflation, and survey-based expectations (Araujo and Gaglianone, 2023); Random Forest (RF), Gradient Boosting Machines (GBMs) and Generalized Linear Models (GLM) (Akande et al., 2022). Due to the literature's controversies about the effectiveness and performance of various ML techniques, food inflation will be forecasted using several ML algorithms.

This study's model selection is based on recommendations from previous empirical studies. The selected models offer greater flexibility by not depending on strict data assumptions, outperforming traditional models, and being capable of handling continuous dependent variables such as the inflation

rate. In contrast, some can handle continuous and categorical dependent variables (such as Artificial Neural Networks) (Nakorji and Aminu, 2022; Noble and Chidi, 2024). Other criteria include relevance, applicability, and simplicity.

Benchmark model

Autoregressive (AR) model

The autoregressive model of order p $AR(p)$, which uses only lagged values of the target variables, is specified following Aras and Lisboa (2022) and Medeiros et al. (2021).

$$y_{t+h/t}^h = \alpha_h + \sum_{j=1}^p \gamma_{hj} y_{t-j+1} \quad (1)$$

Where y_t represents the dependent variable (food price), h is the forecasting horizon, and p is the number of lags to be set to a value.

Shrinkage models

The shrinkage models were specified following Nakorji and Aminu (2022).

1. Ridge regression model

Unlike Ordinary Least Square Regression, the ridge regression model aims to minimize the residual sum of squares (RSS) and the sum of squares of penalized coefficients of the model. This model can be specified as:

$$Y = a_0 + \sum b_i X_i \quad (2)$$

Where Y is the food inflation rate, b_i is the vector of coefficients, and X_i is the matrix of explanatory variables.

Ridge regression aims to minimize RSS:

$$RSS + \lambda \sum_{k=1}^P b_k^2$$

3

Where λ is the regularization parameter that controls the strength of the penalty, b_k^2 is the squares of the coefficients upon which the penalty was imposed.

1. Least Absolute Shrinkage and Selection Operator (LASSO) Regression Model

LASSO placed a penalty on the sum of the absolute values of the coefficients of a model; from the above equation, LASSO seeks to minimize:

$$RSS + \lambda \sum_{k=1}^P |b_k|$$

4

1. Elastic net regression model

Elastic net is a penalized regression that strengthens the ridge and LASSO regression limitations. Unlike ridge regression, it performs feature selection and groups the features that LASSO fails to do. It minimizes the residual sum of squares, both the sum of squares and the absolute values of the model coefficients. It minimizes the RSS as follows:

$$RSS + \lambda_1 \sum_{k=1}^P |b_k| + \lambda_2 \sum_{k=1}^P b_k^2$$

5

1. Partial Least Square (PLS) regression model

PLS predicts the dependent variable based on vast sets of independent variables. The model is specified as follows:

$$X = TP^T + E$$

6

$$Y = TQ^U + F$$

7

$$Y = \alpha + \beta X + \epsilon \quad (8)$$

Where X is the matrix of predictors, Y is the response matrix, E, F, and ϵ are the error terms, T and U are the factor matrix, and P and Q are the orthogonal loading matrices, respectively.

1. Artificial Neural Network (ANN) Model

The net input is calculated as:

$$y_{in} = X_1W_1 + X_2W_2 + X_3W_3 + \dots \dots \dots X_nW_n$$

9

Where y_{in} is the net input, X_s represent the independent variables, and the W_s are the weights attached to each input variable.

To calculate the dependent variable, the activation function (F) is applied over the net input:

$$Y = F(y_{in})$$

10

Y is the food inflation rate and F is the activation function.

Model selection

The models were compared using the root mean squared error (RMSE), the mean absolute error (MAE), and the median absolute deviation from the median (MAD). They are specified following Medeiros et al. (2021):

$$RMSE_{m,h} = \sqrt{\frac{1}{T - T_0 + 1} \sum_{t=T_0}^T e_{t,m,h}^2}$$

11

$$MAE_{\backslash \text{varvec}m, \backslash \text{varvec}h} = \frac{1}{T - T_0 + 1} \sum_{t=T_0}^T |e_{t,m,h}^2| \quad (12)$$

$$MAD_{m,h} = \text{median} \left[\left| e_{t,m,h}^2 - \text{median} \left(e_{t,m,h}^2 \right) \right| \right] \quad (13)$$

Where $e_{t,m,h}^2 = \pi_t - \pi_{t,m,h}$ and $\pi_{t,m,h}$ is the inflation forecast for month t by model m with information up to t - h.

Commodity selection and classification

To focus the analysis on welfare-relevant food items, the dataset was filtered to include staple food commodities, which constitute a significant share of household consumption in Nigeria. Commodities were classified into nutritionally meaningful categories, including cereals, tubers, legumes, vegetables, fruits, and protein sources. This classification facilitates both descriptive analysis and later interpretation of inflation dynamics across food groups, while avoiding dilution of results by non-essential or infrequently consumed items.

Construction of food price inflation

Food price inflation was constructed from observed price levels by computing percentage changes over time following aggregation across markets and commodities. This transformation serves two primary purposes. First, it eliminates unit dependence inherent in price-level data, enabling meaningful comparison across commodities with different units of measurement. Second, it improves the statistical properties of the series by stabilizing variance and reducing non-stationarity commonly present in nominal price levels.

Prices are first aggregated to a consistent market–commodity–time level using arithmetic means. For each commodity-market-month combination, the average price is calculated across all available observations. This simple averaging approach treats all price observations within a given market-commodity-time cell equally, which is appropriate given the relatively balanced nature of the data collection across markets., after which month-on-month (MoM) and year-on-year (YoY) inflation rates are calculated. The MoM inflation rate captures short-run price dynamics and seasonal fluctuations, while the YoY inflation rate reflects longer-term price pressures and mitigates seasonal effects. Formally, food price inflation is computed as:

$$MoM\ Inflation_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}} \right) \times 100 \quad (14)$$

$$YoY\ Inflation_t = \left(\frac{P_t - P_{t-12}}{P_{t-12}} \right) \times 100 \quad (15)$$

where P_t denotes the average price at time t .

The resulting inflation series serves as the dependent variable in all subsequent machine-learning models, including the benchmark autoregressive specification and the shrinkage and nonlinear forecasting models. By working with inflation rates rather than price levels, the analysis aligns with standard macroeconomic practice and ensures consistency with policy-relevant definitions of food price inflation.

External data integration

To account for key structural and macroeconomic drivers of food price inflation, several external exogenous datasets were integrated with the core food price inflation series. These datasets capture supply-side, cost-push, and macroeconomic transmission channels that are not directly observable from food price data alone. Firstly, monthly average Premium Motor Spirit (PMS) pump prices were incorporated to proxy transportation and distribution costs within food supply chains. Given the strong dependence of rural food markets on road transportation, fluctuations in fuel prices are expected to exert significant pass-through effects on food prices. Secondly, the FAO Global Food Price Index was merged at monthly frequency to capture international food price movements and global commodity market pressures. This variable reflects external price signals that may transmit to domestic food markets through imports, substitution effects, and expectations. Thirdly, monthly average exchange rate data were included to account for macroeconomic conditions and currency depreciation effects. Exchange rate movements influence food prices through imported food items, agricultural inputs (such as fertilizers and machinery), and fuel costs, making it a critical determinant of domestic food inflation dynamics. Finally, monthly average rainfall data were integrated to capture climatic conditions affecting agricultural production. Rainfall variability directly influences crop yields, seasonal availability, and food supply in rural Nigeria, thereby playing a central role in food price formation. All external datasets were aligned temporally and merged with the food inflation series using a monthly time index, ensuring

consistency in frequency and timing. The inclusion of these exogenous variables enables the estimation of augmented econometric and machine-learning models that explicitly account for observable drivers of food price inflation, thereby improving interpretability and robustness relative to purely autoregressive specifications.

Results

4.1. Trends in food prices across food groups in Nigeria

Figure 3 illustrates the evolution of food prices across major food groups in Nigeria between 2016 and 2026. The time-series plots reveal a persistent upward trend in food prices across all food categories, with noticeable periods of accelerated price increases rather than a smooth long-run trajectory. This pattern indicates that food price movements in Nigeria have been characterized by recurrent inflationary shocks arising from macroeconomic and structural factors rather than gradual market adjustments.

The pronounced acceleration observed from 2022 onwards coincides with a period of heightened macroeconomic instability characterized by exchange rate depreciation, increasing energy prices, persistent insecurity in major food-producing regions, climate-related production disruptions, and the removal of fuel subsidies, all of which substantially increased production, processing and transportation costs (Popoola et al. 2023; NBS 2024). These findings reinforce concerns that Nigeria's food inflation is increasingly driven by a combination of domestic structural constraints and macroeconomic policy shocks.

The results further demonstrate considerable heterogeneity in price dynamics across food groups, suggesting that the transmission of inflationary pressures differs according to commodity characteristics, production systems, storage capacity, and market structure. Animal-source foods, particularly eggs and meat, exhibited the fastest and most sustained price increases throughout the study period. The sharp escalation in prices after 2023 reflects the vulnerability of livestock production systems to rising feed costs, higher energy prices, transportation expenses, and exchange rate depreciation, all of which significantly increase production costs. Livestock production is generally more input-intensive than crop production; consequently, increases in the prices of imported feed ingredients, veterinary products, fuel, and electricity are rapidly transmitted to consumer prices. The pronounced volatility observed in these commodities also suggests that animal-source foods are particularly sensitive to supply disruptions and cost-push inflation, making them among the most inflation-prone components of Nigerian food markets.

Staple food commodities, including cereals and tubers, exhibited relatively moderate price increases during the early years of the study period but experienced a marked structural shift from 2022 onwards. Given that cereals constitute the major source of calories for most Nigerian households, the sustained increase in their prices has important implications for food security and household welfare. The observed trend is consistent with the increasing costs of agricultural inputs, insecurity in major food-producing regions, adverse climatic conditions, and disruptions to domestic food supply chains, all of which have constrained agricultural production and market availability. Although cereals and tubers are

predominantly produced domestically, the findings suggest that local food markets remain highly susceptible to macroeconomic instability through higher transportation costs, rising input prices, exchange rate depreciation, and inflationary spillovers from other sectors of the economy. This observation supports earlier studies that identified production constraints, insecurity, and macroeconomic instability as important drivers of food price increases in Nigeria (Nakorji and Aminu 2022; Awopegba and Awe 2024).

Similarly, prices of oils and legumes displayed persistent upward trends, particularly after 2023. Vegetable oils exhibited especially strong price increases, reflecting their greater exposure to international commodity markets, exchange rate fluctuations, and increasing domestic processing costs. Since edible oils rely partly on imported raw materials, processing equipment, and packaging materials, depreciation of the domestic currency substantially raises production costs and retail prices. Legumes followed a similar trajectory, although with comparatively lower volatility, suggesting relatively stronger domestic supply conditions but continued exposure to increasing production and marketing costs.

In contrast, vegetables, fruits, and condiments recorded comparatively lower absolute price levels throughout the study period but nevertheless exhibited sustained upward trends. Although these commodities are generally more perishable and seasonal, the persistent increase in their prices indicates that inflationary pressures have become pervasive across the Nigerian food system rather than being confined to specific commodity groups. Rising transportation costs, post-harvest losses, inadequate cold-chain infrastructure, and climate-induced supply fluctuations likely contributed to the gradual increase observed in these food categories. The results therefore suggest that even relatively low-cost food items have become progressively less affordable, reducing dietary diversity and limiting households' ability to substitute towards cheaper food alternatives during periods of high inflation.

In essence, three important observations emerge from the analysis. First, food price inflation has become broad-based, affecting virtually all food groups irrespective of their production systems or market characteristics. This finding suggests that Nigeria's recent inflationary episode reflects systemic pressures rather than isolated commodity-specific shocks. Second, inflationary pressures differ considerably across food groups, with animal proteins and edible oils experiencing the largest and most persistent price increases due to their greater dependence on energy-intensive production systems, imported inputs, and complex supply chains. Third, the sharp acceleration in food prices after 2022 indicates the emergence of a new inflationary regime characterized by greater price volatility and more rapid price transmission throughout the food system. This structural shift implies that food markets have become increasingly sensitive to macroeconomic disturbances, policy reforms, and external shocks.

These findings are broadly consistent with previous studies that reported increasing food price volatility and persistent inflationary pressures in developing economies arising from exchange rate depreciation, rising energy costs, supply chain disruptions, and climatic variability (Andree 2021; Nakorji and Aminu

2022; Awopegba and Awe 2024). The results also reinforce earlier evidence that persistent increases in food prices reduce food affordability, weaken household purchasing power, and exacerbate food insecurity, particularly among low-income households that allocate a substantial proportion of their income to food expenditure (Omotayo et al. 2022; Melgar-Quinonez 2023). From a policy perspective, the observed trends highlight the need for coordinated macroeconomic stabilization, investment in agricultural productivity, improvements in rural infrastructure, strengthened food supply chains, and targeted interventions aimed at reducing production and marketing costs. Such measures are essential to mitigate future food price shocks, improve market resilience, and enhance national food security.

Trends in prices of selected food items in Nigeria

Figure 4. illustrates the trends in prices of selected food commodities in Nigeria between 2016 and 2026. The results indicate a persistent increase in prices across all commodities, although the magnitude and timing of the increases differ considerably. A notable structural shift occurred from 2022 onwards, when prices accelerated sharply across most food items. This period coincides with heightened macroeconomic instability characterized by exchange rate depreciation, rising transportation and energy costs following the removal of fuel subsidies, insecurity in food-producing regions, and climate-related production disruptions (Popoola et al. 2023; NBS 2024). The simultaneous increase across commodities suggests that recent food inflation is driven by broad macroeconomic and structural factors rather than isolated commodity-specific shocks.

Staple foods such as rice, maize, yam, and cassava products exhibited sustained price increases, reflecting rising production costs, supply chain disruptions, and insecurity in major agricultural regions. Given their importance in household diets, persistent increases in the prices of these staples pose significant risks to food affordability and food security. Animal-source foods, particularly meat and eggs, recorded the fastest and most volatile price increases, largely due to their dependence on feed, energy, transportation, and other production inputs. Similarly, vegetable oils experienced substantial price increases, reflecting their exposure to exchange rate fluctuations, increasing processing costs, and international commodity market dynamics.

Although fruits, vegetables, and condiments maintained relatively lower price levels, they also exhibited consistent upward trends, indicating that inflationary pressures have become pervasive across Nigeria's food system. The rising prices of these commodities may reduce dietary diversity as households substitute nutritious foods with cheaper alternatives during periods of high inflation.

Overall, the findings indicate that food price inflation in Nigeria has become broad-based, affecting virtually all food commodities regardless of their production systems. This pattern is consistent with previous studies that identified exchange rate depreciation, rising energy costs, production constraints, and supply chain disruptions as major drivers of food inflation in Nigeria (Nakorji and Aminu 2022; Awopegba and Awe 2024). The results further support evidence that persistent food price increases reduce household purchasing power and exacerbate food insecurity, particularly among low-income households (Omotayo et al. 2022; Melgar-Quinonez 2023). These findings underscore the need for

policies that strengthen domestic agricultural production, improve market infrastructure, stabilize exchange rates, and reduce production and transportation costs to enhance food price stability and food security.

Food price inflation in Nigeria

Figure 5 presents the trend in food price inflation in Nigeria from 2016 to 2026. The results reveal that food inflation remained relatively moderate during the early years of the study period but accelerated markedly from 2022 onwards, indicating a clear structural shift in the inflationary process. This sharp increase coincides with heightened macroeconomic instability characterized by exchange rate depreciation, rising energy and transportation costs following the removal of fuel subsidies, insecurity in food-producing regions, and climate-induced supply disruptions (Popoola et al. 2023; NBS 2024). These findings suggest that recent food inflation in Nigeria has been driven largely by cost-push and supply-side factors rather than demand pressures alone.

The figure also shows increased volatility in food inflation after 2022, reflecting greater instability in domestic food markets. Such fluctuations indicate that food prices have become increasingly sensitive to macroeconomic shocks, production constraints, and supply chain disruptions. This pattern is consistent with the growing vulnerability of Nigeria's food system to both domestic and external shocks, including exchange rate movements, rising input costs, and global commodity price fluctuations (Nakorji and Aminu 2022; Awopegba and Awe 2024).

The persistent upward trend in food inflation has important implications for household welfare and national food security. Sustained increases in food prices reduce purchasing power, limit access to nutritious diets, and disproportionately affect low-income households that devote a larger share of their income to food expenditure (Omotayo et al. 2022; Melgar-Quinonez 2023). The findings therefore reinforce the need for proactive policies aimed at stabilising food prices through exchange rate stability, increased agricultural productivity, improved rural infrastructure, strengthened food supply chains, and timely market interventions. More importantly, the observed volatility highlights the importance of developing reliable forecasting models capable of providing early warning signals to support evidence-based food price stabilization and inflation management.

Time series data preparation for modelling: stationarity diagnostics

Augmented Dickey–Fuller test

Figure 6 presents the results of the Augmented Dickey–Fuller (ADF) test used to examine the stationarity of the food price inflation series. The null hypothesis of a unit root was rejected at the conventional significance level, indicating that the food price inflation series is stationary in levels. This finding implies

that the statistical properties of the series, including its mean and variance, remain relatively stable over time despite short-term fluctuations, making it suitable for time-series forecasting.

The stationarity of the series supports the use of autoregressive and machine learning models without further differencing, thereby preserving the original information contained in the data. From an economic perspective, the result is consistent with the notion that inflation rates, unlike absolute price levels, tend to fluctuate around a long-run equilibrium following temporary macroeconomic shocks. Consequently, future food inflation is expected to depend primarily on its historical values and prevailing economic conditions rather than exhibiting an indefinite upward trend.

These findings provide a sound statistical foundation for the subsequent forecasting analysis, as stationary series generally produce more reliable parameter estimates, reduce the likelihood of spurious relationships, and improve the predictive performance of both conventional econometric and machine learning models.

Selection of the autoregressive lag order

Figure 7 presents the selection of the optimal autoregressive lag order based on the Akaike Information Criterion (AIC). Among the candidate models evaluated, the AR (12) specification produced the lowest AIC value, indicating the best balance between model goodness-of-fit and parsimony. This finding suggests that incorporating twelve monthly lags adequately captures the temporal dependence in food price inflation without introducing unnecessary model complexity or overfitting. The result indicates that food price inflation exhibits strong serial dependence, with current inflation partly influenced by its historical values.

The selection of a 12-month lag structure is economically intuitive given the monthly frequency of the data. It implies that food price inflation in Nigeria follows an annual cyclical pattern, reflecting the influence of agricultural production and marketing cycles, harvest and lean seasons, climatic conditions, and recurring fluctuations in production and distribution costs. Since agricultural output in Nigeria remains highly seasonal and largely dependent on rainfall, food prices tend to exhibit predictable annual movements that are transmitted across successive months. In addition, macroeconomic factors such as exchange rate movements, energy prices, transportation costs, and policy changes often exert persistent effects on food prices, reinforcing the importance of longer lag structures in explaining inflation dynamics.

The result further indicates that food price inflation possesses considerable persistence, whereby inflationary shocks are not immediately dissipated but continue to influence future price movements over several months. Such persistence is characteristic of food markets where production constraints, supply chain disruptions, and input cost increases gradually pass through to retail prices. Consequently, incorporating a full annual lag structure enables the model to capture both short-term price persistence and recurring seasonal effects, thereby improving its ability to generate reliable forecasts.

The AR (12) model therefore provides a robust benchmark against which the forecasting performance of the machine learning models is evaluated. Establishing this benchmark is particularly important because it enables an objective assessment of whether more advanced predictive algorithms can outperform a well-specified conventional time-series model. The selected lag structure also provides a strong statistical foundation for subsequent forecasting, ensuring that both historical persistence and seasonal dynamics are adequately represented in the comparative analysis.

Forecasting food price inflation in Nigeria for the next two years

Figure 8 presents the historical trend and two-year forecast of food price inflation in Nigeria generated using the autoregressive (AR) model. The historical series exhibits pronounced fluctuations, characterized by recurring inflationary spikes and periods of heightened volatility. These patterns reflect the combined effects of exchange rate depreciation, rising energy and transportation costs, supply chain disruptions, insecurity in food-producing regions, and structural weaknesses within Nigeria's food system (Popoola et al. 2023; NBS 2024). The sharp increase in food inflation observed after 2022 further indicates the emergence of a more volatile inflationary environment driven predominantly by cost-push and supply-side factors.

The historical trend also suggests a high degree of persistence in food price inflation, indicating that current inflation is strongly influenced by previous inflationary conditions. This finding justifies the use of an autoregressive framework and suggests that inflationary shocks are transmitted gradually through the food system rather than dissipating immediately. Such persistence is consistent with agricultural production cycles, delayed price transmission, and the gradual pass-through of increases in production and marketing costs to retail food prices (Nakorji and Aminu 2022; Awopegba and Awe 2024). The periodic spikes observed in the series further indicate the sensitivity of Nigeria's food markets to policy reforms, seasonal supply shortages, exchange rate fluctuations, and other external shocks.

The AR model forecasts indicate that food price inflation is likely to moderate over the next two years, with inflation fluctuating within a relatively narrow range compared with the extreme volatility observed in the historical period. Although the projections suggest some easing of inflationary pressures, they do not indicate a return to the relatively low inflation rates experienced before 2022. Instead, the forecasts imply that food inflation may remain persistently elevated, reflecting the continued influence of structural constraints within the agricultural sector and broader macroeconomic challenges. This suggests that, in the absence of substantial policy interventions or improvements in domestic food production and market efficiency, food prices are likely to remain under sustained upward pressure.

The relatively smooth forecast trajectory reflects the autoregressive model's reliance on historical inflation dynamics and the assumption that past behaviour provides useful information for predicting future outcomes. While this characteristic enables the model to capture underlying persistence, it also implies that unexpected events such as major policy reforms, extreme climatic conditions, exchange rate shocks, geopolitical developments, or severe supply disruptions may not be fully anticipated.

Consequently, the AR forecasts should be interpreted as projections based on historical patterns rather than precise predictions under all future economic conditions.

From a policy perspective, the persistence of elevated food inflation underscores the need for proactive measures aimed at improving domestic food supply, stabilizing exchange rates, reducing production and transportation costs, and strengthening agricultural value chains. Reliable forecasts such as those presented in this study can support early warning systems and evidence-based policy interventions, enabling governments to respond more effectively to emerging inflationary pressures before they translate into severe welfare losses. This is particularly important because sustained food inflation reduces household purchasing power, undermines food affordability, and exacerbates food insecurity, especially among low-income households that spend a substantial proportion of their income on food (Omotayo et al. 2022; Melgar-Quiñonez 2023).

Forecast performance of the Autoregressive (AR) model

Table 1 presents the out-of-sample forecasting performance of the autoregressive (AR) model. The model produced a Root Mean Squared Error (RMSE) of 10.31, a Mean Absolute Error (MAE) of 6.98, and a Median Absolute Deviation (MAD) of 4.28, indicating a reasonable level of forecasting accuracy. The relatively lower MAD compared with the MAE suggests that most prediction errors are moderate, with only a few large deviations, implying that the model performs consistently under normal market conditions.

The satisfactory performance of the AR model indicates that historical food price inflation contains substantial predictive information for future inflation. This result is consistent with the strong persistence observed in the historical series, where inflationary shocks are transmitted gradually through the food system rather than dissipating immediately. By exploiting these temporal dependencies, the AR model is able to capture the underlying trend and seasonal dynamics of food price inflation, providing a useful benchmark for forecasting.

Despite its reasonable predictive performance, the negative out-of-sample (R^2) indicates that the AR model has limited ability to explain the full variability in future food inflation relative to a simple benchmark forecast. This limitation is unsurprising given the highly volatile nature of Nigeria's food markets, where inflation is influenced by exchange rate fluctuations, fuel price increases, climatic variability, supply chain disruptions, insecurity, and policy reforms (Popoola et al. 2023; NBS 2024). Because the AR model relies solely on historical inflation values, it cannot explicitly account for these exogenous drivers or sudden structural changes that frequently characterize Nigeria's food system.

Overall, the findings suggest that while the AR model provides a reliable baseline by capturing persistence and seasonal behaviour in food price inflation, its forecasting performance is constrained by the absence of explanatory variables describing the underlying economic environment. This highlights the need for more flexible forecasting approaches capable of modelling complex and nonlinear relationships between food inflation and its macroeconomic, market, and structural determinants.

Consequently, the AR model serves as an appropriate benchmark against which the predictive performance of the machine learning models is subsequently evaluated.

Table 1
Forecast performance of the autoregressive (AR) model

Metric	Value
Root Mean Squared Error (RMSE)	10.3070
Mean Absolute Error (MAE)	6.9846
Median Absolute Deviation (MAD)	4.2772
(R ²)	-0.0416

Source: Author’s Computation (2025)

Forecast performance of econometric and machine learning models

Table 2 compares the out-of-sample forecasting performance of the benchmark autoregressive (AR) model with shrinkage-based econometric models and nonlinear machine learning approaches. Overall, the results demonstrate that relatively parsimonious linear models outperform more complex nonlinear models in forecasting food price inflation in Nigeria. This suggests that, despite the complexity of the food system, a substantial proportion of the predictive information is embedded in historical inflation patterns and a limited number of macroeconomic variables.

The AR (12) model produced a competitive forecasting performance, recording an RMSE of 10.31 and the lowest MAD (4.28) among all models. This finding indicates that food price inflation exhibits strong persistence and seasonal dynamics, which are adequately captured by lagged inflation values. The result is consistent with the stationarity and serial dependence identified in the earlier analyses, reinforcing the suitability of autoregressive models as benchmark forecasting tools for monthly food inflation series.

Among the econometric models, Elastic Net achieved the highest forecasting accuracy (RMSE = 9.94), closely followed by LASSO (RMSE = 9.95) and Ridge Regression (RMSE = 10.02). Although the improvements over the AR model are relatively modest, they demonstrate that incorporating carefully selected macroeconomic variables can enhance forecast accuracy. The superior performance of the regularization methods suggests that penalized regression effectively addresses multicollinearity while retaining the most informative predictors, thereby improving model generalization. The positive out-of-sample (R^2) values for these models further indicate better predictive performance than the benchmark forecast.

The variable selection results provide additional insight into the drivers of food price inflation. LASSO retained only the lagged food price inflation variable, indicating that historical inflation contains the strongest predictive information over the forecast horizon. In contrast, Ridge Regression and Elastic Net also retained exchange rate and pump price variables, highlighting the importance of macroeconomic conditions and energy costs in shaping food price dynamics. This finding is economically plausible because exchange rate depreciation increases the cost of imported food products and agricultural inputs, while higher fuel prices raise production, processing, and transportation costs throughout the food value chain (Popoola et al. 2023; NBS 2024). These results therefore suggest that food price inflation in Nigeria is influenced primarily by inflation persistence, with exchange rate movements and energy costs providing additional predictive information.

Table 2
Forecast performance of econometric and machine learning models

Model	RMSE	MAE	MAD	(R ²)
AR (12)	10.307	6.985	4.277	-0.042
Ridge Regression	10.018	7.888	6.671	0.016
LASSO Regression	9.945	7.690	6.023	0.030
Elastic Net	9.942	7.759	6.263	0.031
PLS Regression	16.514	15.247	17.114	-1.674
ANN	17.924	16.707	18.518	-2.150

Source: Author’s computation (2025)

Note

Forecast accuracy is evaluated using out-of-sample data. RMSE, MAE, and MAD are the primary criteria for model comparison.

Conversely, the Partial Least Squares (PLS) Regression and Artificial Neural Network (ANN) models recorded substantially larger forecast errors and strongly negative out-of-sample (R^2) values, indicating poor predictive performance. The relatively weak performance of these more complex models suggests that the available data may not contain sufficient nonlinear structure to justify their additional flexibility. Furthermore, the limited sample size, high volatility of food inflation, and frequent structural changes in Nigeria's macroeconomic environment may have reduced the ability of these models to generalize effectively beyond the training data, resulting in poorer out-of-sample forecasts.

Overall, these findings are consistent with previous studies demonstrating that parsimonious linear and regularized regression models frequently outperform more complex machine learning algorithms in macroeconomic and inflation forecasting, particularly when datasets are relatively small and

characterized by structural instability (Medeiros et al., 2021; Aras and Lisboa 2022; Araujo and Gaglianone 2023). From a practical perspective, the results suggest that forecasting food price inflation in Nigeria does not necessarily require highly sophisticated nonlinear algorithms. Instead, models that combine historical inflation with a limited number of carefully selected macroeconomic predictors provide more accurate, interpretable, and policy-relevant forecasts. These findings have important implications for inflation monitoring and food policy, as they demonstrate that relatively simple and transparent forecasting models can provide reliable early warning signals to support timely policy interventions aimed at stabilizing food prices and strengthening food security.

Forecast performance of econometric and machine learning models

Figure 9 provides a visual comparison of the forecasting performance of the econometric and machine learning models. The figure clearly shows that the shrinkage regression models—Elastic Net, LASSO, and Ridge Regression consistently achieved lower forecast errors than the benchmark AR (12) model, although the improvements were relatively modest. This indicates that incorporating a small number of relevant macroeconomic predictors can enhance forecast accuracy without substantially increasing model complexity.

In contrast, the PLS Regression and Artificial Neural Network (ANN) models recorded considerably larger prediction errors, confirming their weaker out-of-sample performance. The large deviations observed for these models suggest that greater model complexity does not necessarily translate into improved forecasting accuracy for Nigeria's food price inflation. Rather, the results indicate that the underlying inflation process is characterized by relatively stable linear relationships and strong temporal persistence, which are more effectively captured by parsimonious econometric models than by highly flexible nonlinear algorithms.

The visual evidence further reinforces the superiority of Elastic Net, LASSO, and Ridge Regression over the benchmark AR model, with Elastic Net providing the best overall forecasting performance. The close performance of these regularized regression models also highlights the importance of incorporating key macroeconomic variables, particularly exchange rate movements and fuel prices, while simultaneously controlling for multicollinearity through regularization. These findings are consistent with previous studies reporting that regularized linear models often outperform more complex machine learning techniques in macroeconomic forecasting, particularly where datasets are relatively small and characterized by structural instability (Medeiros et al., 2021; Aras and Lisboa 2022; Araujo and Gaglianone 2023). Overall, the figure suggests that, for forecasting food price inflation in Nigeria, simpler and more interpretable models provide more reliable and policy-relevant predictions than complex nonlinear approaches.

Key drivers of food price inflation in Nigeria

Correlation with food price inflation

Table 3 presents the pairwise correlations between selected explanatory variables and food price inflation. The results indicate that all variables are positively correlated with food price inflation, suggesting that increases in these market characteristics are generally associated with higher inflationary pressures. However, the relatively modest correlation coefficients imply that no single variable independently explains food price inflation, highlighting the complex and multidimensional nature of inflation dynamics in Nigeria.

Among the variables examined, price volatility exhibits the strongest positive correlation with food price inflation ($r = 0.245$), indicating that periods characterized by greater price fluctuations are generally associated with higher inflation rates. This finding suggests that instability in food markets contributes more to inflationary pressures than average price levels alone. Frequent price fluctuations may reflect supply shocks arising from climatic variability, exchange rate depreciation, rising transportation costs, insecurity in food-producing areas, and disruptions within agricultural value chains, all of which have been identified as major drivers of food inflation in Nigeria (Popoola et al. 2023; NBS 2024).

Table 3
Correlation with inflation rate

Feature	Correlation Coefficient
Price Volatility	0.245
Price Mean	0.203
Number of Markets	0.130
Number of Commodities	0.123

Source: Author’s Computation (2025)

The mean food price also suggests a positive association with food inflation ($r = 0.203$), indicating that sustained increases in average food prices are accompanied by higher inflation rates. Although the relationship is weaker than that of price volatility, it suggests that persistent increases in food prices continue to contribute to overall inflationary pressures, particularly when production costs and market inefficiencies remain elevated.

The number of markets ($r = 0.130$) and number of commodities ($r = 0.123$) exhibit comparatively weaker positive correlations with food price inflation. These results suggest that market size and commodity coverage alone have limited direct influence on inflation dynamics. Instead, food price inflation appears to be driven more by changes in market conditions and price instability than by the breadth of market participation or commodity availability. This observation is consistent with the view that macroeconomic conditions, exchange rate movements, transportation costs, and structural constraints play more

prominent roles in shaping food price inflation than simple measures of market coverage (Nakorji and Aminu 2022; Awopegba and Awe 2024).

In essence, the relatively low pairwise correlations indicate that food price inflation cannot be adequately explained by any single predictor in isolation. This finding justifies the application of regularized regression techniques, such as Ridge and LASSO, which are capable of simultaneously evaluating multiple correlated predictors, addressing multicollinearity, and identifying the variables that contribute most to forecasting food price inflation.

Top features from ridge regression

Table 4 presents the variables identified by the Ridge regression model as the most important predictors of food price inflation in Nigeria. The results indicate that food price has the largest positive coefficient ($\beta = 0.313$), confirming that historical food prices remain the strongest predictor of future food price inflation. This finding reflects the persistence of inflationary pressures within the food system, whereby previous increases in food prices continue to influence subsequent price movements through gradual cost pass-through, inflation expectations, and market adjustments.

Among the macroeconomic variables, exchange rate ($\beta = 0.139$) and pump price (PMS) ($\beta = 0.121$) emerged as important positive predictors of food price inflation. The positive effect of exchange rate is economically plausible, as depreciation of the Nigerian naira increases the cost of imported food commodities, agricultural inputs, machinery, and processing equipment, thereby raising domestic food prices. Similarly, higher fuel prices increase transportation, processing, and distribution costs across agricultural value chains, with these additional costs ultimately transmitted to consumers. These findings are consistent with previous studies identifying exchange rate depreciation and rising energy costs as major contributors to food price inflation in Nigeria (Popoola et al. 2023; Nakorji and Aminu 2022; Awopegba and Awe 2024).

Table 4
Top features from ridge regression

Feature	Coefficient
Price	0.313
Exchange Rate	0.139
Pump Price (PMS)	0.121
Food Price Index	0.103
Rainfall Average	-0.101

Source: Author’s Computation (2025)

The Food Price Index ($\beta = 0.103$) also contributes positively to food inflation, suggesting that broad increases in food market prices reinforce inflationary pressures across commodity groups. This result indicates that food inflation reflects not only the behaviour of individual commodities but also broader market-wide price movements affecting the entire food system.

Conversely, average rainfall exhibited a negative coefficient ($\beta = -0.101$), indicating that favourable rainfall conditions are associated with lower food price inflation. Adequate rainfall improves agricultural production, increases food availability, and eases supply constraints, thereby moderating upward pressure on food prices. In contrast, poor rainfall and climate variability reduce crop yields, disrupt food supply, and contribute to higher food prices. This finding underscores the importance of climatic conditions in shaping agricultural output and food price stability in Nigeria, where crop production remains predominantly rain-fed.

Unlike LASSO, Ridge regression retains all explanatory variables while shrinking their coefficients to minimize the effects of multicollinearity. Consequently, the model provides a more comprehensive assessment of the relative importance of the predictors without excluding potentially relevant variables. Overall, the findings suggest that food price inflation in Nigeria is primarily influenced by inflation persistence, while exchange rate movements, fuel prices, aggregate food market conditions, and climatic factors provide additional predictive information. These results highlight the need for coordinated macroeconomic stabilization policies alongside investments in agricultural productivity and climate resilience to improve food price stability and strengthen national food security.

Features selected by LASSO regression

Table 5 presents the variables selected by the Least Absolute Shrinkage and Selection Operator (LASSO) regression. The model retained only food price as a predictor of food price inflation, assigning it the largest coefficient ($\beta = 0.510$), while shrinking the coefficients of all other variables to zero. This finding indicates that historical food prices contain the strongest predictive information for future food price inflation over the study period.

The selection of a single predictor suggests that much of the predictive information contained in the remaining variables is already embedded in food prices. Macroeconomic factors such as exchange rate movements, fuel prices, and climatic conditions influence food inflation primarily through their effects on production, processing, transportation, and marketing costs, which are ultimately reflected in prevailing food prices. Consequently, once historical food prices are included in the model, these variables contribute relatively little additional predictive information. This finding highlights the dominant role of inflation persistence in explaining short-term food price dynamics.

The LASSO results also demonstrate the effectiveness of regularization in identifying the most parsimonious forecasting model. By eliminating less informative predictors, LASSO reduces model complexity and the risk of overfitting while maintaining predictive accuracy. Such parsimonious models

are particularly useful for inflation forecasting because they are easier to interpret and implement in practice.

Table 5
Features selected by
LASSO regression

Feature	Coefficient
Price	0.510

Source: Author’s Computation (2025)

Overall, the findings suggest that historical food prices are the single most informative predictor of future food price inflation in Nigeria. Nevertheless, this does not imply that other macroeconomic variables are unimportant. Rather, their influence appears to operate indirectly through food prices, consistent with the transmission of exchange rate depreciation, rising fuel costs, and other production shocks into domestic food markets (Popoola et al. 2023; Nakorji and Aminu 2022; Awopegba and Awe 2024). From a policy perspective, the results underscore the importance of stabilising food markets through measures that address the underlying drivers of food price increases, including exchange rate stability, lower transportation costs, and improved agricultural productivity.

Cross-model consistency in the identification of key drivers of food price inflation in Nigeria

Table 6 summarizes the consistency of the variables identified across the correlation analysis, Ridge Regression, and LASSO Regression models. The results demonstrate a high degree of agreement regarding the dominant role of food price in explaining food price inflation. Food price was consistently identified by all three approaches, confirming that it contains the strongest predictive information and represents the most robust determinant of food price inflation in Nigeria. The consistency of this finding across different modelling techniques enhances confidence in its reliability and suggests that inflation persistence is a defining characteristic of Nigeria's food inflation process.

Although price volatility exhibited a positive correlation with food price inflation, it was not retained by the regularized regression models. This suggests that while price instability is associated with inflation, its predictive contribution overlaps substantially with that of historical food prices. Similarly, exchange rate, pump price, and the Food Price Index were retained only by the Ridge Regression model, indicating that these variables provide additional predictive information when multiple correlated predictors are considered simultaneously. Their inclusion highlights the importance of macroeconomic conditions, energy costs, and broader food market developments in influencing food price dynamics through cost-push inflation and exchange rate pass-through mechanisms (Popoola et al. 2023; NBS 2024).

Table 6
Cross-model consistency

Variable	Correlation Analysis	Ridge Regression	LASSO Regression	Interpretation
Food Price	Positive	Positive	Positive	Most robust predictor; consistently identified across all models, indicating strong inflation persistence.
Price Volatility	Positive	Not Selected	Not Selected	Reflects market instability but provides limited additional predictive information after accounting for historical food prices.
Exchange Rate	Not Significant	Positive	Not Selected	Important macroeconomic driver; exchange rate depreciation increases production and import costs, contributing to food inflation.
Pump Price (PMS)	Not Significant	Positive	Not Selected	Represents a major cost-push factor through higher transportation, processing, and distribution costs.
Food Price Index	Not Significant	Positive	Not Selected	Captures broad food market conditions and reinforces aggregate inflationary pressures across food commodities.
Average Rainfall	Not Significant	Negative	Not Selected	Supply-side stabilizer; favourable rainfall enhances agricultural production and moderates food price inflation.

The negative coefficient for average rainfall in the Ridge model further emphasizes the role of climatic conditions in moderating food price inflation. Improved rainfall enhances agricultural production and food availability, thereby easing supply constraints and reducing inflationary pressures. This finding reinforces the importance of climate resilience and sustainable agricultural production in maintaining food price stability.

Overall, the consistency of the results across the different analytical approaches suggests that food price inflation in Nigeria is characterized by strong inflation persistence, while macroeconomic variables and climatic conditions provide complementary predictive information. The agreement between the models strengthens the robustness of the findings and suggests that relatively parsimonious econometric techniques are sufficient to identify the principal drivers of food price inflation. From a policy perspective, these results underscore the need for integrated interventions that combine macroeconomic stabilization with measures aimed at improving agricultural productivity, strengthening food supply chains, and enhancing resilience to climate-related shocks.

Collectively, the forecasting results demonstrate that Nigerian food price inflation is characterized by strong temporal persistence, while exchange rate movements, fuel prices and climatic conditions

provide complementary predictive information. Regularized regression models consistently outperformed conventional autoregressive and nonlinear machine learning models, suggesting that parsimonious models are better suited for inflation forecasting in data environments characterized by moderate sample sizes and structural instability. These findings provide a robust empirical basis for developing early warning systems and targeted macroeconomic and agricultural policies aimed at improving food price stability.

Discussion

This study used the conventional time-series and machine learning approaches for forecasting food price inflation in Nigeria while identifying the major factors driving inflationary dynamics. The findings show that food prices increased persistently across all food groups during the study period, with a marked acceleration from 2022 onwards. The broad-based nature of the price increases suggests that recent food inflation reflects systemic macroeconomic and structural pressures rather than isolated commodity-specific shocks. The relatively faster growth in the prices of animal-source foods and edible oils further indicates that commodities requiring energy-intensive production processes and imported inputs are more vulnerable to cost-push inflation. These findings are consistent with previous studies that attributed rising food prices in Nigeria to exchange rate depreciation, insecurity, increasing energy costs, supply chain disruptions, and climate-related production shocks (Popoola et al. 2023; Awopegba and Awe 2024).

The trend in aggregate food price inflation further confirms the emergence of a more volatile inflationary regime after 2022. This pattern suggests that inflationary pressures have become increasingly persistent, reducing household purchasing power and threatening food security, particularly among low-income households that devote a larger share of their income to food expenditure. The observed increase in inflation volatility highlights the need for reliable forecasting systems capable of providing early warning signals for timely policy interventions.

The stationarity analysis confirmed that the food inflation series was stationary in levels, indicating that inflation fluctuates around a stable long-run mean despite short-term shocks. This statistical property justified the application of both autoregressive and machine learning models without additional differencing and suggests that historical inflation contains useful information for predicting future price movements. Furthermore, the selection of an AR(12) specification indicates that food price inflation follows an annual seasonal cycle, reflecting recurring agricultural production patterns, harvest cycles, and persistent macroeconomic influences. Similar seasonal persistence has been reported in studies of food inflation in developing economies, where climatic conditions and production cycles strongly influence food price behaviour.

Although the benchmark AR model produced reasonably accurate forecasts, the comparison of forecasting models demonstrated that the regularized regression approaches performed better overall. Elastic Net achieved the highest forecasting accuracy, closely followed by LASSO and Ridge regression,

whereas Partial Least Squares regression and Artificial Neural Networks recorded substantially larger prediction errors. These findings suggest that the underlying process governing food price inflation in Nigeria is characterized largely by persistent linear relationships and a relatively small number of influential predictors rather than complex nonlinear interactions. The results therefore support previous evidence that parsimonious regularized regression models frequently outperform more sophisticated machine learning algorithms in macroeconomic forecasting when data are characterized by structural instability and relatively limited observations (Medeiros et al. 2021; Aras and Lisboa 2022; Araujo and Gaglianone 2023).

The two-year forecast further indicates that although food price inflation may moderate gradually, it is likely to remain above historical levels. This finding implies that recent inflationary pressures are unlikely to disappear without structural improvements in agricultural production, market efficiency, and macroeconomic stability. Consequently, food inflation is expected to remain an important challenge for household welfare and food security unless effective policy interventions are implemented.

The analysis of inflation drivers provides additional insights into the mechanisms underlying food price dynamics in Nigeria. The positive association between food inflation and price volatility indicates that unstable food markets intensify inflationary pressures, while the relatively weaker correlations observed for market coverage variables suggest that macroeconomic conditions are more important than the number of commodities or markets in explaining inflation. The Ridge regression results reinforce this conclusion by identifying historical food prices as the strongest predictor of future inflation, reflecting the persistence of inflationary shocks. Exchange rate movements and PMS pump prices also emerged as important determinants, highlighting the transmission of currency depreciation and rising transportation costs through the food supply chain. Although rainfall contributed to the predictive models, its comparatively smaller influence suggests that macroeconomic factors currently exert stronger short-term effects on food inflation than climatic conditions.

In all, the findings demonstrate that accurate forecasting of food price inflation in Nigeria does not necessarily require highly complex artificial intelligence models. Instead, transparent regularized regression techniques that combine historical inflation with a limited number of macroeconomic indicators provide more accurate and interpretable forecasts while identifying the principal drivers of inflation. These findings underscore the importance of coordinated macroeconomic and agricultural policies aimed at stabilizing exchange rates, reducing transportation and energy costs, strengthening domestic food production, improving market infrastructure, and enhancing climate resilience. Integrating such forecasting models into national inflation monitoring and early-warning systems would improve evidence-based policymaking and support more proactive responses to future food price shocks.

Conclusion

This study examined the dynamics, forecasting performance, and key drivers of food price inflation in Nigeria using monthly food price data and a combination of conventional econometric and machine

learning approaches. The findings reveal that food price inflation has exhibited a persistent upward trend over the study period, with a pronounced acceleration after 2022. This pattern reflects the combined effects of exchange rate depreciation, rising energy and transportation costs following fuel subsidy removal, climatic variability, insecurity in food-producing regions, and structural inefficiencies within Nigeria's agricultural and food marketing systems. Time-series diagnostics further showed that the food inflation series is stationary and characterized by strong temporal persistence, indicating that past inflation provides valuable information for predicting future food price movements.

The comparative forecasting analysis demonstrated that parsimonious regularized regression models outperform both the benchmark autoregressive model and more complex nonlinear machine learning algorithms. Among the competing models, Elastic Net produced the highest forecasting accuracy, followed closely by LASSO and Ridge Regression, whereas Partial Least Squares (PLS) Regression and Artificial Neural Network (ANN) exhibited considerably poorer out-of-sample performance. These findings suggest that, under conditions of moderate sample size and structural volatility, relatively simple and interpretable forecasting models provide more reliable predictions than highly flexible nonlinear algorithms. The feature selection analysis further identified historical food prices as the most robust predictor of future food price inflation, while exchange rate, pump price, food price index, and rainfall emerged as important complementary predictors. Collectively, these results indicate that food price inflation in Nigeria is characterized by strong inflation persistence, with macroeconomic conditions, energy costs, and climatic factors providing additional predictive information.

The findings provide important policy insights for improving food price stability and strengthening food security in Nigeria. First, the superior performance of the regularized regression models suggests that government institutions, particularly the National Bureau of Statistics, the Central Bank of Nigeria, and the Federal Ministry of Agriculture and Food Security, should incorporate these models into routine inflation monitoring and early warning systems. More accurate forecasts would enable policymakers to anticipate inflationary pressures and implement timely interventions before they escalate into severe food security and welfare challenges.

Second, the significance of exchange rate movements and pump prices highlights the need for coordinated macroeconomic policies that promote exchange rate stability, improve foreign exchange availability for agricultural inputs, and reduce transportation and energy costs across agricultural value chains. Investments in rural road infrastructure, logistics, and market integration would further lower marketing costs and improve the efficiency of food distribution.

Third, the negative relationship between rainfall and food price inflation underscores the importance of strengthening climate resilience within the agricultural sector. Expanding irrigation facilities, promoting climate-smart agricultural practices, improving access to weather information, and encouraging the adoption of drought-tolerant crop varieties would reduce production risks, stabilize food supply, and moderate inflationary pressures arising from climatic shocks.

Fourth, the persistence of food price inflation suggests that long-term structural interventions remain essential. Policies aimed at increasing domestic agricultural productivity through improved access to quality seeds, fertilizers, mechanization, extension services, storage facilities, and affordable agricultural credit would enhance food availability and reduce the vulnerability of food prices to supply disruptions. At the same time, improving market information systems and reducing post-harvest losses would strengthen the efficiency of food markets and enhance price stability.

Finally, because persistent food price inflation disproportionately affects poor and food-insecure households, macroeconomic stabilization policies should be complemented by well-targeted social protection programmes, including food assistance, conditional cash transfers, school feeding programmes, and nutrition support for vulnerable populations. Such interventions would cushion households against temporary food price shocks while longer-term structural reforms improve the resilience of Nigeria's food system. Overall, this study suggests that combining robust forecasting techniques with coordinated macroeconomic, agricultural, and social protection policies offers a practical pathway towards achieving more stable food prices, improved household welfare, and enhanced food security in Nigeria.

Declarations

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Author's contribution Conception and design of the study: OSA, ACA, LOB; data collection: OSA, OKA, ASC; statistical analysis: OSA, ASC; interpretation of results OSA, ACA, LOB, OKA; writing of the original manuscript: OSA, OKA; manuscript review and editing: OSA, OKA, ASC; supervision: ACA, LOB; methodology: OSA, LOB, OKA; project administration: OSA, ACA, LOB, ASC; visualization: OSA, OKA; validation: OSA, OKA, ASC; data curation: OSA.

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Data availability

The data will be made available upon reasonable request from the author.

Conflict of interests

The authors declare that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical consideration

The Department of Agriculture and Industrial Technology Review Board of Babcock University approved this study.

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Figures

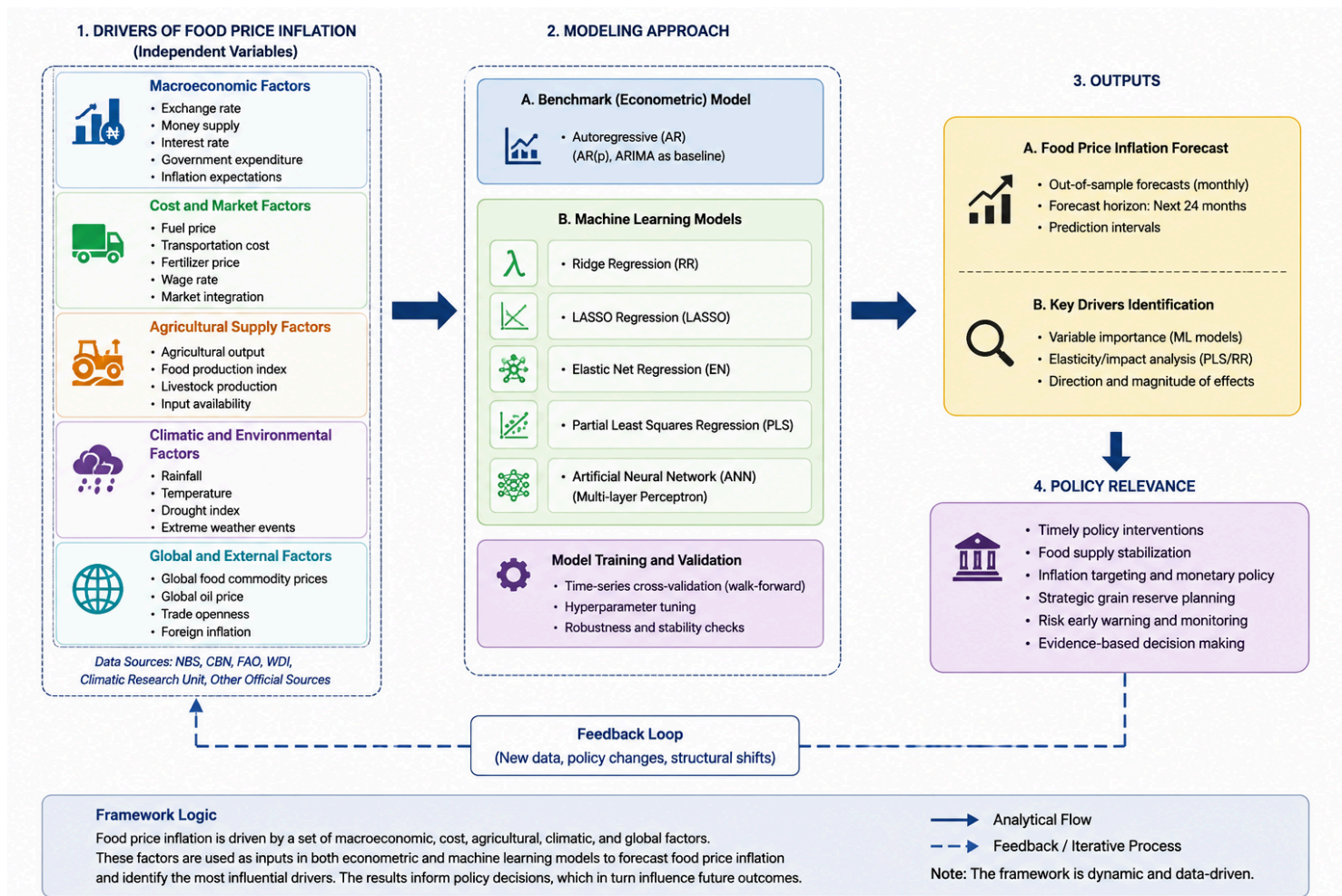


Figure 1

Conceptual framework for forecasting food price inflation and identifying its key drivers in Nigeria

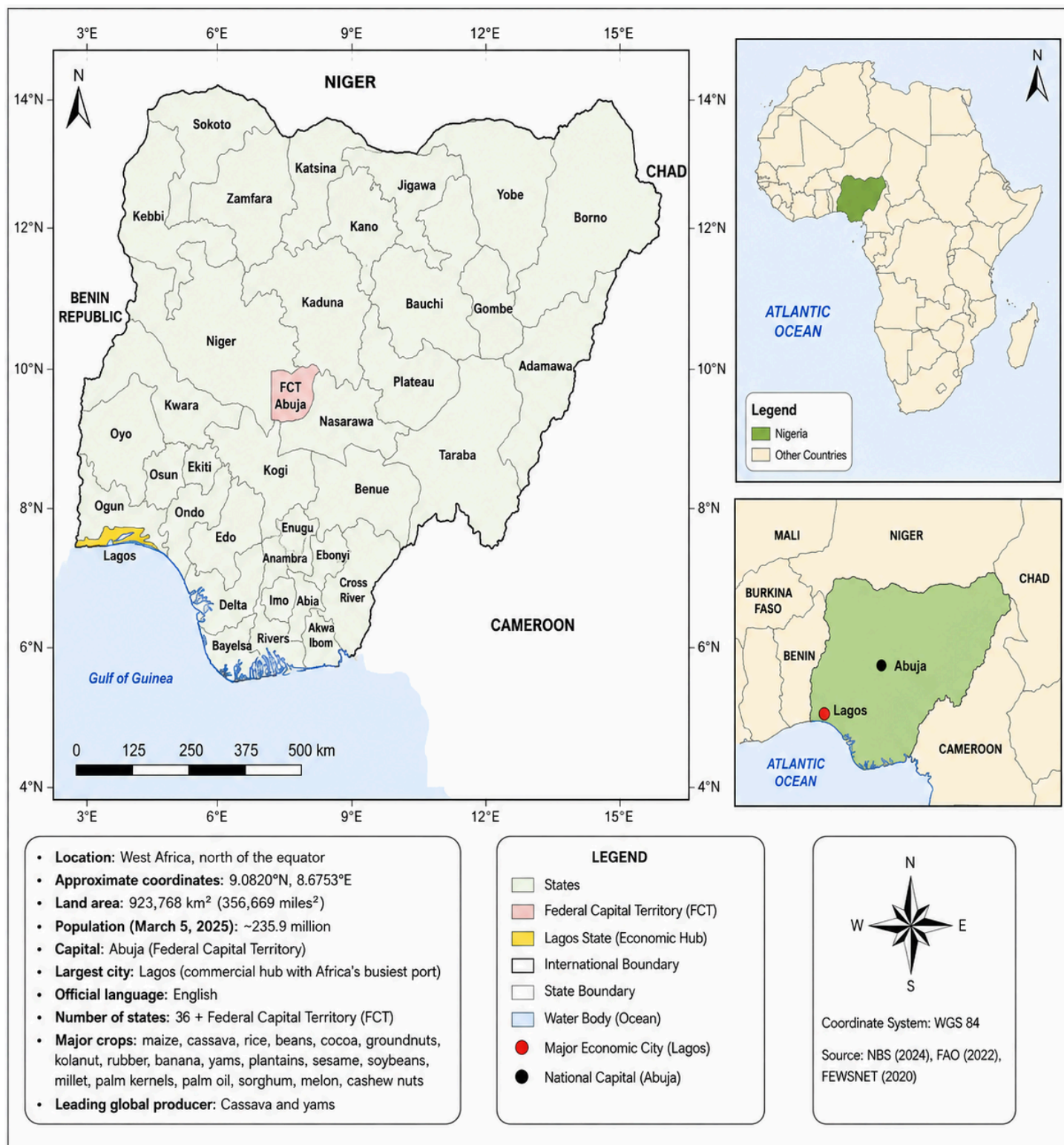


Figure 2

Map of Nigeria

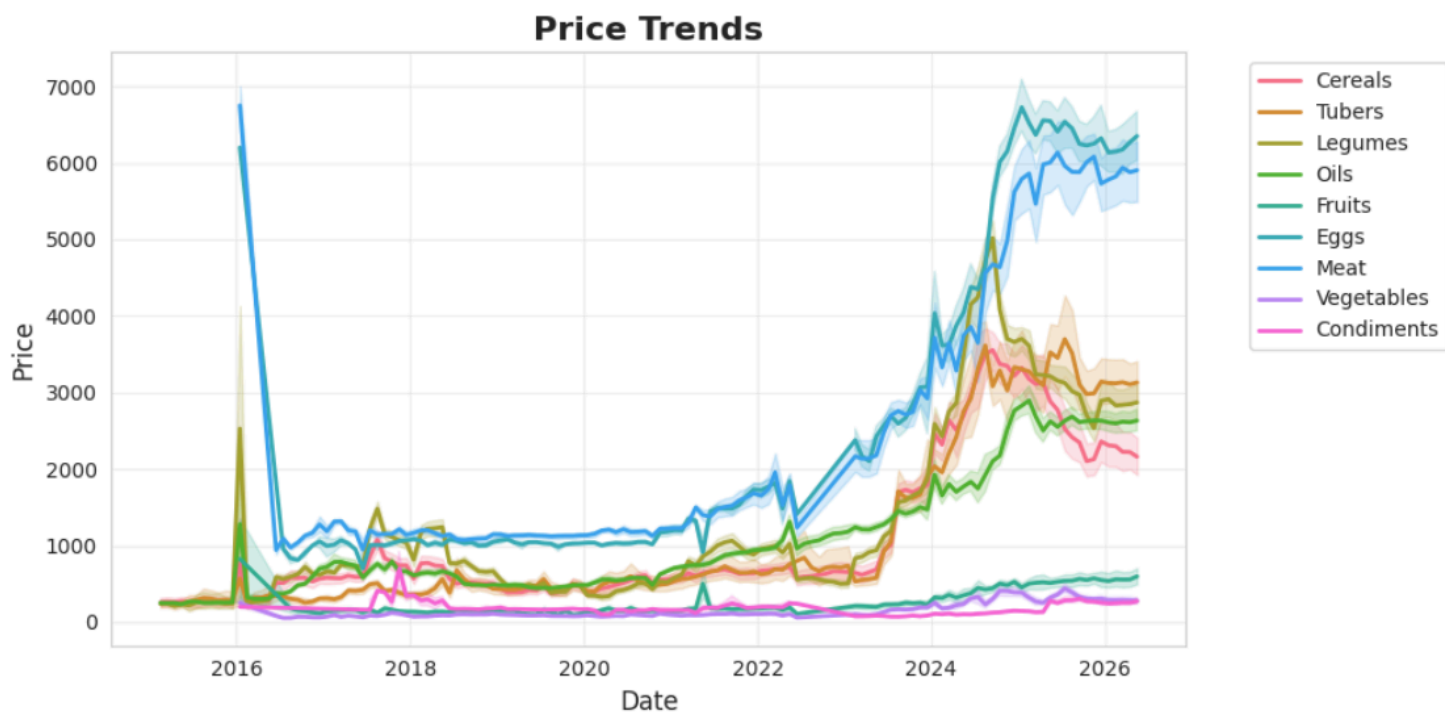


Figure 3

Trends in prices of food groups in Nigeria, 2016 – 2026

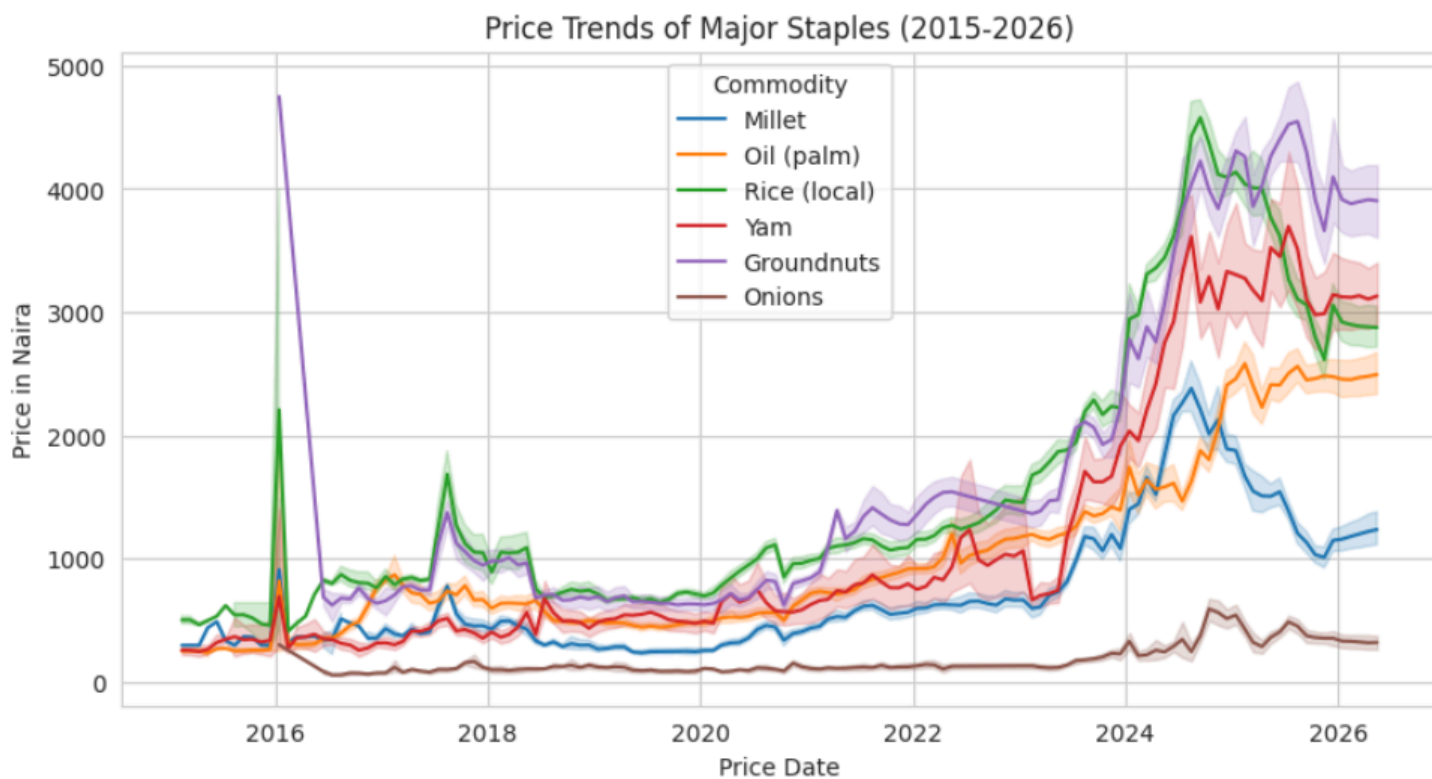


Figure 4

Trends in prices of selected food items in Nigeria, 2016 – 2026

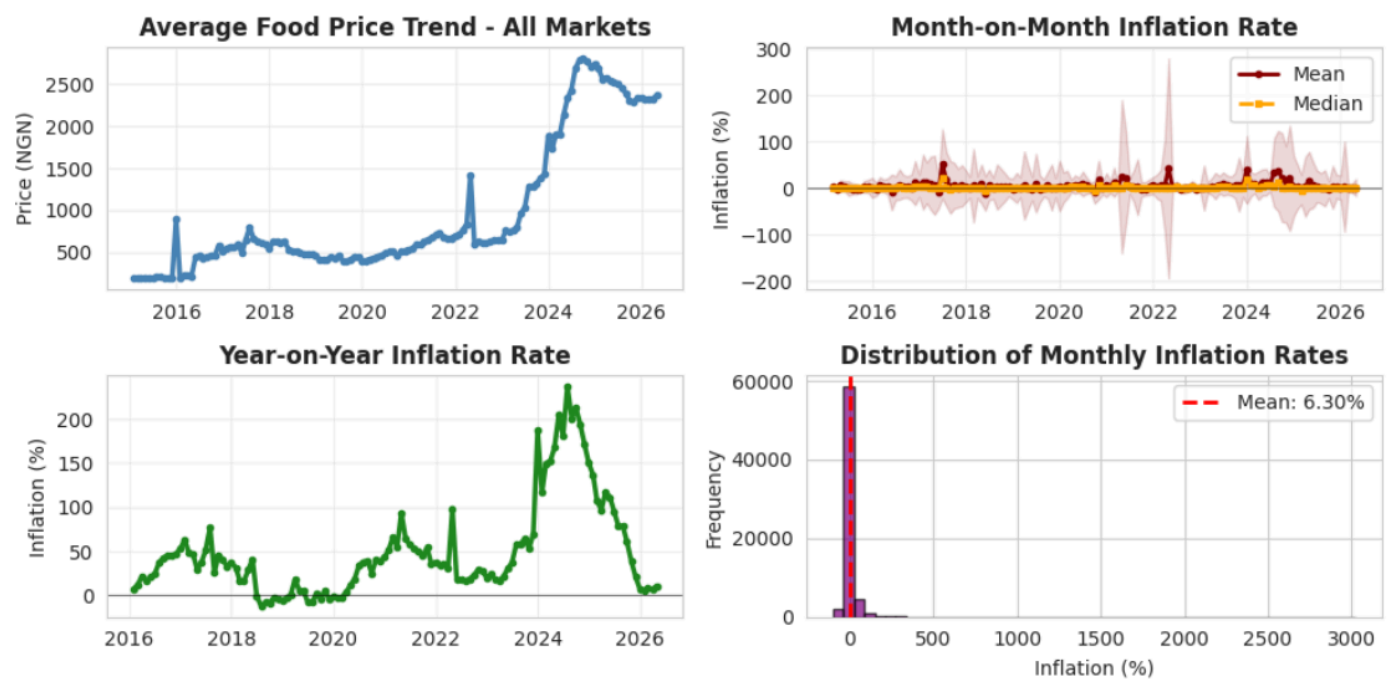


Figure 5

Food price inflation in Nigeria, 2016 – 2026

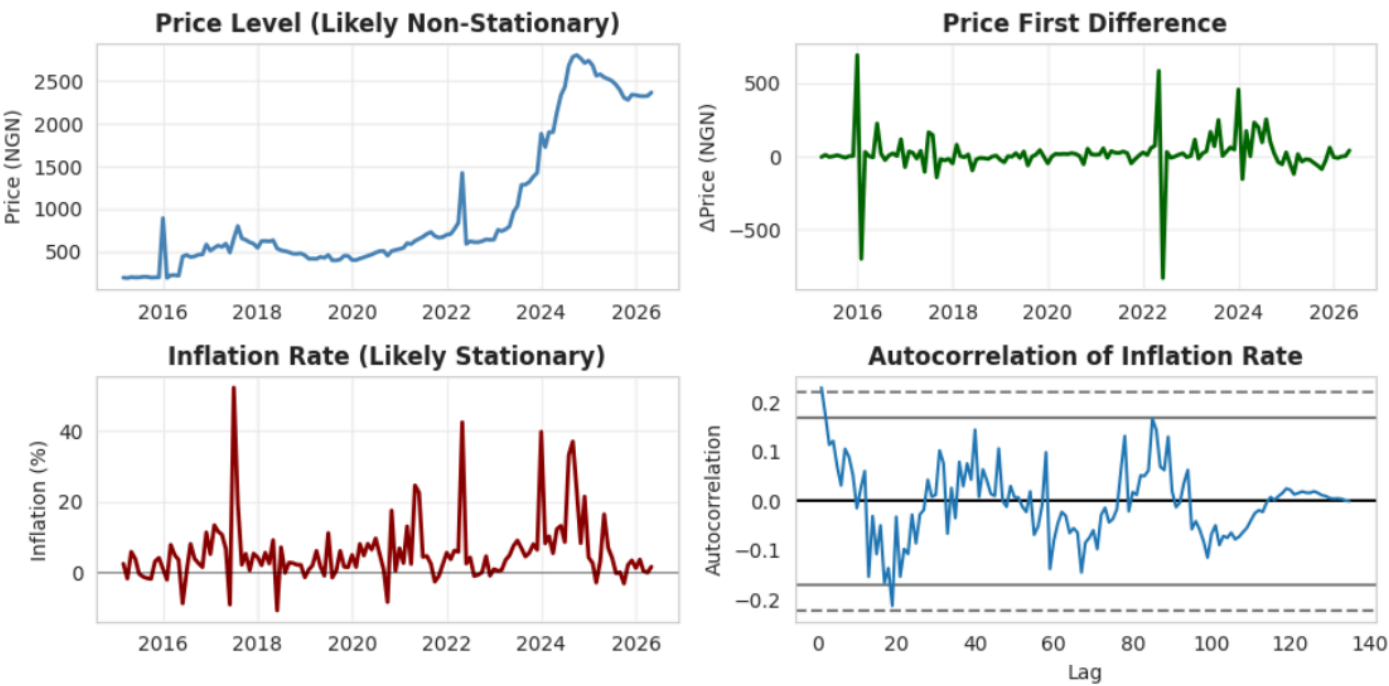


Figure 6

Augmented Dickey–Fuller test

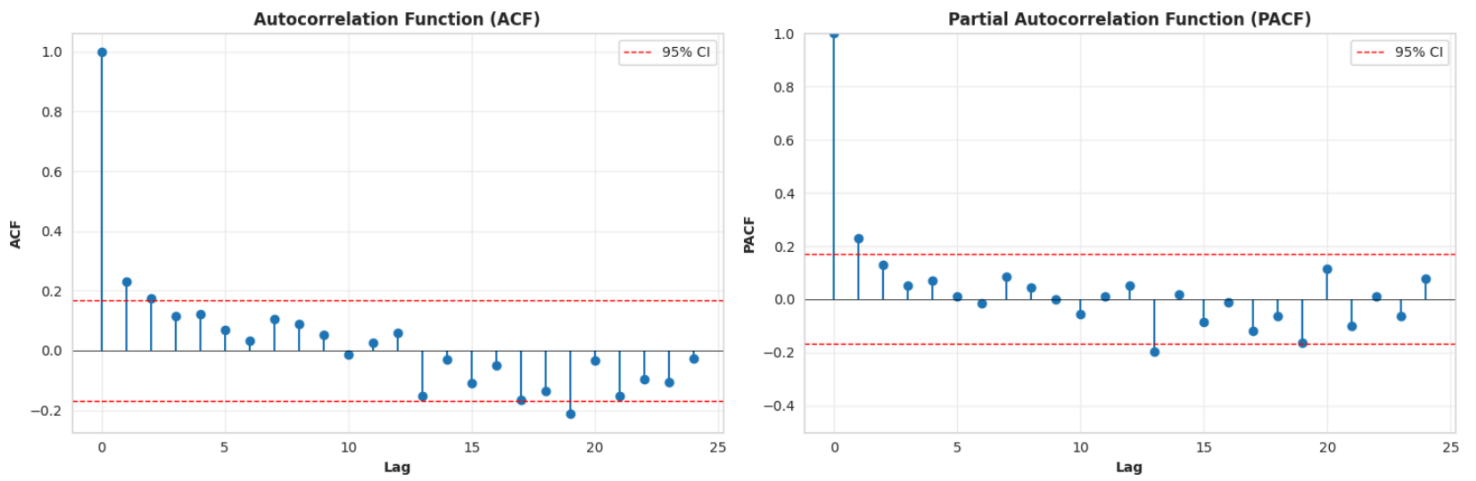


Figure 7

Selection of the autoregressive lag order

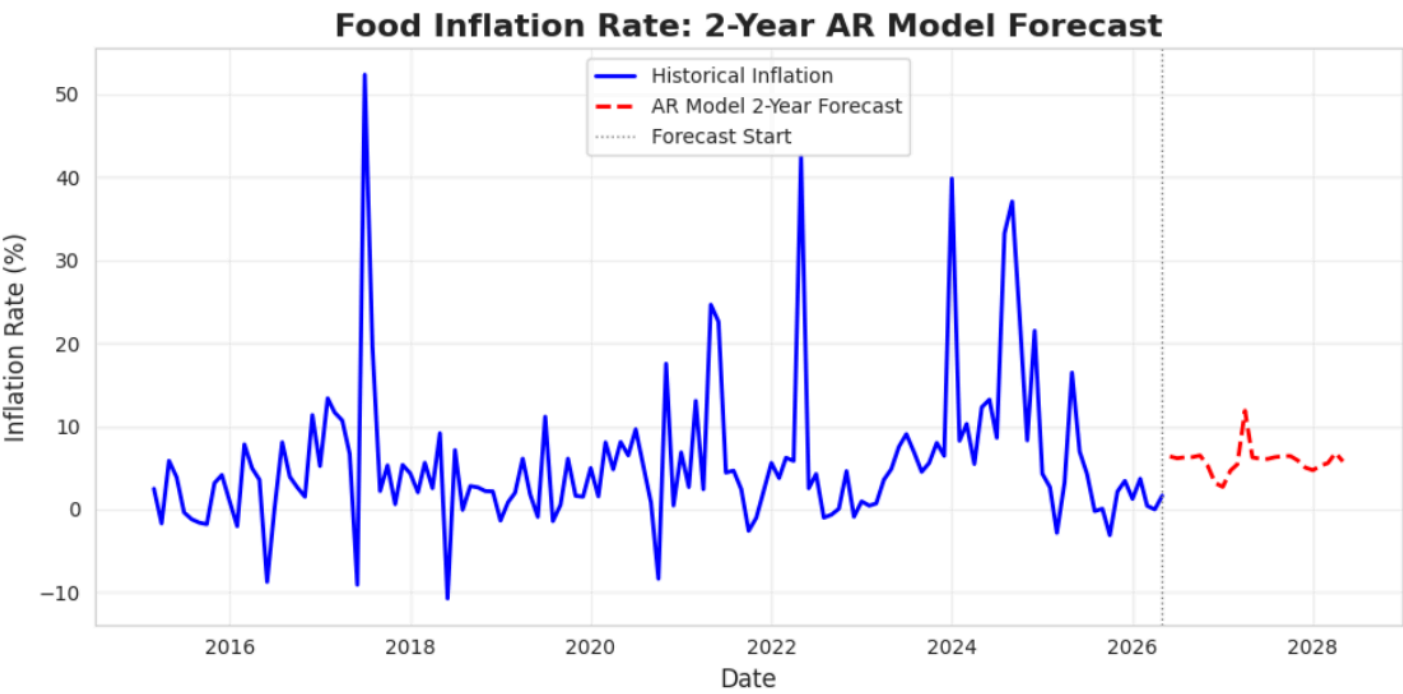


Figure 8

Forecasting food price inflation in Nigeria for the next two years

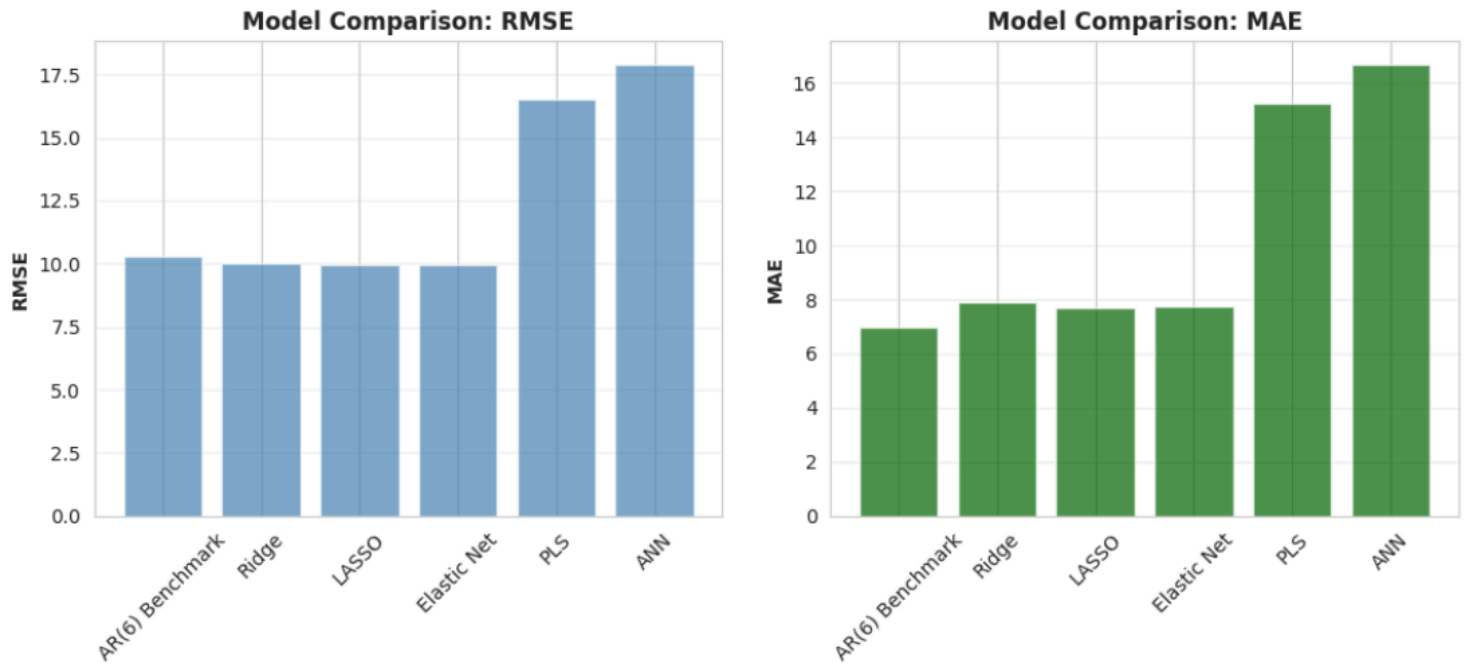


Figure 9

Forecast performance of econometric and machine learning models