Predicting Inflation Component Drivers in Nigeria: A Stacked Ensemble Approach

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Predicting Inflation Component Drivers in Nigeria: A Stacked Ensemble Approach

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Abstract

This study undertakes a disaggregated analysis of inflation in Nigeria using the stacked ensemble approach, a machine learning algorithm that compensates for the weakness of an ensemble, a base learner, with the strength of another. This approach gives flexibility of a synergistic performance of stacking each base learner and produces a formidable model that yields best forecasts. We analyse the test data, out-of-sample, and our analyses reveal robust inflation predictions. We also show that food CPI is the major driver of headline, urban, and rural inflation, while 'bread and cereals' is the main driver of food inflation in Nigeria. Drilling further, biscuits, agric rice, garri white are the top sources of price movements in bread and cereal. Our study further show that some CPI sub-components which are significant drivers of inflation have lower weights in the CPI basket while others have higher weights. Therefore, allocation of CPI weights without recourse to understanding the relative importance of inflation driver may undermined price stability policies in Nigeria. The study notes that tracing and tracking the sources of inflation down to the least sub-component would enhance inflation management policies in Nigeria.

keywords: Headline Inflation; Stacked Ensemble; Machine Learning; Base Learner

JEL: C53, E37

Data Availability Statement: The data that support the findings of this study are available upon request.

Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The views expressed in this paper are those of the authors, and do not necessarily reflect the views of anyone else affiliated with the Central Bank of Nigeria. Any correspondence should therefore, be shared through the emails provided.

MAJOR COMMENTS

1. **Reviewers Comment:** for every section of the literature, it is important to stress the novelty of this manuscript with respect to the others, since it seems to be partially missing now.

The authors specifically created a paragraph in section 1, introductory section, to explain and show the novelty of the paper. In addition, the authors added more information about the novelty of the paper to each section of the literature as requested. You will see this information at the end of each literature review sections, except section 2.4 which narrates the stylized facts of inflation in Nigeria. Particularly, we show how our study is different from other studies.

2. **Reviewers Comment:** they should cite the most relevant papers in the literature of inflation forecasting in general.

There is existing inflation forecast studies in the paper but the reviewers recommendation provided an opportunity for the authors to add more than five latest studies to the paper.

3. **Reviewers Comment:** In this direction, the authors should also better outline why the application of ML to Nigeria's inflation data is particularly relevant from both an economic and statistical point of view.

The application of machine learning in Nigeria from economic and statistical point is included at the end of section 2.4.

4. **Reviewers Comment:** First, they should cite other papers in the literature, using machine learning to forecast inflation.

This information was already provided in section 2.3 but by the reviewers recommendation, we added more than six other studies to the section.

5. **Reviewers Comment:** papers aiming at goals similar to the one of this manuscript, i.e. papers focusing on detecting key inflation determinants (e.g. Giannone et al., 2014).

Papers aiming at predicting and forecasting inflation key drivers such as Giannone et al. (2014) are included in section 2.3. We dedicated a paragraph to studies that focus on the prediction of inflation drivers and its disaggregation while the second paragraph is dedicated to studies that focus on inflation forecast in general. The paper, Giannone et al. (2014), as suggested by the reviewer, afforded us the opportunity to add other studies that used CPI-inflation to predict and forecast inflation. About three more studies were added to this section.

6. **Reviewers Comment:** In particular, by definition, core inflation should exclude the most volatile components of inflation, however, from Figure 1, this does not seem to be the case. I suggest including some explanations on why inflation in Nigeria is such a

special case.

Figure 1 in the paper depicts the plot of Core 1 inflation. The significant volatility exhibited by the Core 1 inflation is largely attributed to volatile PMS, gas and utility prices as Nigerias computation of the Core 1 inflation does not exclude energy prices. In addition, the high exchange rate market pressure, which has constantly plagued the Nigerian economy, also contributed significantly to the fluctuation of prices of many of the items in the core basket. This is because the Nigerian economy is highly import dependent. This exact statement is in footnote 2 of figure 1.

7. **Reviewers Comment:** I suggest focusing more on the model validation, by showing the relative mean square forecasting errors of the proposed model with respect to the baseline ARIMA model. Moreover, it is also necessary to show the results of a statistical test.

The results section focusses purely on model validation using the RMSEs. In fact, many of the figures and the MSE results of the ARIMA, and base learners have been taken to the appendix section. In addition, the authors included the coefficient of the determination, R-square, of the stacked ensemble of each meta learner in the model. The authors used H2o package in R, the algorithm of this package is very flexible with stacked ensemble model, but it does not report models p-values. While the package can report the p-values of each variable, it is yet to provide p-values for models so, the authors could not obtain the p-values for each model. The p-values of each predictor would have been included in the appendix but for the long list of more than one hundred p-values, current space in this paper is too small, hence, the authors opted to remove it and replace the model significance with R-square instead. Although, the authors emphasized on the accuracy of the model to predict inflation by focusing on the accuracy of predicting out-of-sample inflation. Since this objective was achieved, we believe using the R-squared is not out of place to augment the performance of the model. The authors can afford to send each predictor p-values if requested.

8. **Reviewers Comment:** From the results of the paper, it is not clear the forecasting horizon chosen and if the variation over time of the forecasting accuracy is statistically significant.

The authors initial forecast horizon is just a month forecast but for the reviewers recommendation, the authors increased the forecast horizons from one to twenty-five months. The forecast horizon figure is included in the appendix. The ML models are combined in forecasting inflation horizons.

Minor comments

1. From the title of Figure 3 it is unclear what is represented in that figure. I would recommend to adjust this.

Response: This has been adjusted.

2. Please clarify at page 24 lines 11-18 the statement about electricity, which seems to be inconsistent. **Response:** The statement has been refined.
3. Please better explain the meaning of "importance parameter" shown in Figures 6 and 8.

Response: The importance parameter is a machine learning in-built phrase that is used to identify drivers based on a specific algorithm. The phrase is now well polished, and its meaning and purpose has been added to footnote 18.

4. Please note that equation 3.17 looks incomplete.

Response: The equation has been adjusted; the parentheses are now in appropriate places.

5. Please make a careful check of the typos and of the language.

Response: The typos and errors have been corrected

6. As an example for the point above: while the results are indubitably interesting, referring to them as "amazingly great" (see page 28, l.47) is unnecessarily bold and not fitting a scientific manuscript.

Response: The phrase has been rephrased and other typos and errors have been corrected.

1 Introduction

Intellectual discourse on dynamics and drivers of inflation has received overwhelming attention in modern macroeconomic renditions. This profound attention stems from the deleterious effects associated with persistent and unrestrained inflation in an economy. Beyond this point, inflation is known to generally impose constraints on a spectrum of important macroeconomic variables such as savings, investments, exchange rate, trade balance, wellbeing, competitiveness and other parameters of economic performance (Ashraf et al. 2013; Mbutor 2013; Shaibu and Osamwoni 2020; Tumala et al. 2017). In Nigeria, unfortunately, inflation has been consistently high, stuck in double digits for many years. Over the period 2018-2020 headline inflation in Nigeria averaged 11.95 per cent compares to an average of 20.5 per cent in the past forty years. Notably, persistent and high inflation rates aggravated poverty in a country where over 82.5 million citizens are already below the poverty line. Fixed income earners are usually worse off as the drop in their purchasing power, arising from higher prices and results in misallocation of consumption and thus deterring welfare (Krugman et al., 1982). Therefore, the effective management and control of inflation is crucial for the attainment of macroeconomic stability which begins with clarity on the future path of inflation and its drivers. Hence, the need for efficient forecasting models. But this is by no means a trivial task as central banks painstakingly attempt to forecasts with utmost precision the future course of inflation without which monetary policy will be rendered ineffective (Doguwa and Alade, 2013).

Existing studies have adopted several short term forecasting models to predict inflation trend. These models vary from multivariate (Kelikume and Salami 2014; Gaomab 1998; Capolongo and Pacella 2020) to univariate structural models (Akdogan et al. 2012; Junttila and Korhonen 2011 Pufnik and D. (2006)). Specific examples include the augmented Philips curve models (Greon et al. 2013; Stock and Watson 2008) and random walk models. These models are however, not without shortcomings. They suffer from overfitting problem which results from low dimensionality¹. In essence, overfitting occurs when a complex model fits the trained data so well but does not fit the test data as much, thereby weakening the predictive power of the model. In other words, the model with overfitting problems yields a low prediction error with the training sample but a high prediction error for out-of-sample forecast. For this reason, most time series models are less robust, hence, yield less accurate forecasts. To rectify the overfitting problem, it is important to pre-select the predictors using a theoretical construct which fine-tunes the parameters of the training sample. This is also called hyperparameters method. Solving overfitting problems has been a major breakthrough in Machine Learning (ML) algorithms and this has been applied to inflation forecasting with high degree of accuracy.

Recently, some ML models, such as the Principal Components Analysis (PCA), Random Forest (RF), LASSO regression (Least Absolute Shrinkage and Selection Operator), Decision Trees etc, have been used to forecast inflation and other macroeconomic variables (*see details in Baybuza 2018 and Medeiros et al. 2019*). However, in spite of their numerous advantages, a standalone model or an ensemble approach may be insufficient in addressing the variance-bias problem associated with ML algorithms. Therefore, a better approach, such as stack ensemble, becomes desirable in addressing the challenge. A stacked ensemble approach involves

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¹ A potentially large number of predictors with a small number of observations is what Stock and Watson (2011) referred to as curse of dimensionality.

combining the estimated parameters of these models, through a meta-learner to obtain final predictions. Meta-learner, which is also called super-learner, is selected by comparing the loss function estimated by the Root Mean Squared Errors (RMSE) with that of other base learners. The approach combines predictions of these learners by eliminating the weakness of each but complementing the corresponding strength of the other to produce more accurate prediction. [Capistran et al. \(2010\)](#) shows that best forecasts are obtained by combining individual models to make better use of the information contained in them. So far, studies on inflation forecasting have been conducted in isolation from inflation drivers and most of these studies have focused on other macroeconomic variables. This study focuses on inflation forecasting using two-ping approach: first is the identification of inflation drivers and second is forecasting using those drivers. This strategy would be implemented using the Stacked Ensemble Approach, in the context of the Nigerian economy. To the best of our knowledge, this study is the first to adopt the stacked ensemble approach to track the sources of inflation and then use the same drivers to predict inflation. To do this, we disaggregate the consumer price index (CPI-inflation) data into different components and conduct a comparative analysis of the base learners by stacking each base learner into an ensemble model in order to understand the dynamics of inflation in Nigeria. In addition, we trace the sources of inflation by identifying the main drivers of each inflation component. Finally, we predict the test data of each inflation component, as well as obtain a over twenty-five months horizon forecast. Using the stacked ensemble approach, we train two ensembles, namely RF and Gradient Boosting Machines (GBMs), and a Generalized Linear Model (GLM) to serve as base learners. We trained each of this base learner to obtain the meta-learner for our stacked ensemble and afterwards isolate the most important properties for predicting inflation using Nigeria data. This approach is peculiar to this study. Our results are notably robust, when compared with the baseline model, the two individual ensembles, and the GLM.

The study will be useful to economists and policy makers, as it proposes the use of machine learning for inflation forecasting in Nigeria. The paper also offers procedural insight into implementing this approach. Finally, the study will help the government direct policy to specific components of CPI in controlling inflation. For instance, food CPI is assigned a higher weight among inflation components in the CPI basket, however, specific items in the food CPI basket have varying weights and the contribution to food inflation dynamics could be directed to specific component driving food inflation rather than a broad-based policy approach. The rest of the paper is structured as follows; section two contains a brief review of the theoretical and empirical literature. Section three contains discussion of the methods, while section four presents the results of the study. Finally, section five contains the summary, conclusion and policy recommendations.

2 Literature Review

The theoretical underpinnings of inflation drivers are embodied in the expositions of orthodox economists, from the Classical to the Neo-Structuralist. Leading monetarists ([Brunner and Meltzer 1976](#); [Friedman 1956](#); [1970](#); [Parking 1975](#)) perceive the growth in money supply as the main driver of inflation and its acceleration. For the Keynesians, inflation is driven by excessive spending relative to available goods and services, at full employment. Thus, money supply in excess of potential output will, in effect, drive inflation ([Javed et al., 2010](#)). Structuralists are

persuaded that inflation reflects imbalances in an economy, especially in developing countries. Such imbalances include infrastructural bottlenecks, emergence of monopolistic and oligopolistic market structures (market imperfection), agricultural bottlenecks, government budget constraints, income elasticities, distortion in government policies and exchange rates misalignment among others (Agnor and Montiel 1996; Kirkpatrick and Nixon 1987). A plethora of empirical studies have lends credence to this view. In Nigeria, inflation has been found to be driven by changes in money supply, exchange rate, net exports, interest rates, fiscal factors, agro-climatic factor and real output (Agnor et al. 2018; Asogu 1991; Bayo 2011; Fakiyesi 1996; Imimole and Enoma 2011; Moser 1995; Odusanya and Atanda 2010). Other determinants include petroleum prices, expected inflation, lagged CPI and real exchange rate (Olubusoye and Oyaromade, 2008).

Similarly,an empirical study by Younus and Roy (2016) suggests that money supply (M2) and interest rates are the most relevant variables in predicting inflation in Bangladesh.

2.1 Review of Inflation Disaggregation

Based on a disaggregated analysis, some scholars have argued that core inflation can efficiently predict headline inflation (Crone and Novac 2013; Le Bihan and Sedillot 2000; Tekatli 2010; Freeman (1998)). justifying why its preference as a guide for monetary policy (Miskin, 2007). There are, however, counter-arguments. First of such arguments is that core inflation loses its predictive power due to iyt's exclusin of certain consumption items. Also, changes in energy consumption caused by changes in price will eventually exert pressure on all other prices in the economy (Bullard, 2011). Stock and Watson (2008) rightly argued that measuring and forecasting inflation is a difficult task, and adopting the right approach is critical for effective monetary implementation . This, according to (Atuk and Ozmen, 2009) requires the disaggregation of inflation into its transitory and persistent components. Headline inflation, which is the transitory component, poses a challenge in the process of determining its underlying trend. This is due to its susceptibility to shocks which are beyond the control of policy makers(Odo et al. 2016; Roger 1998). This shortcoming necessitated the call for exclusion of items driving volatility in general price level (Bryan and Cecchetti 1994; Cecchetti and Wiggins 1997) thereby birthing the concept of Core inflation which is regarded as a persistent component of inflation. Core inflation is further disaggregated into Core 1 and Core 2, where Core 1 excludes food beverages and tobacco Core 2 excludes food, beverage, tobacco, energy prices, and mortgage interest from the food basket. This exclusion is based on the fact that, historically, food and energy have proven to be highly volatile (Pincheira et al., 2016). Again, Pincheira et al. (2016) empirically investigates the ability of core inflation to forecast headline inflation in 33 countries using in-sample and out-of-sample analyses. The in-sample analysis confirmed predictabililty from core to headline while out-of-sample analysis showed that core predicted headline inflation in about two-third of the countries in the study. In this study, we decompose items in the CPI basket and focus on the important components which can provide information on the main sources of inflation. This approach gives a clear direction of inflation direction in Nigeria.

2.2 Review of Methods of Inflation Forecasting

The literature is rich with empirical studies on inflation forecasting. These studies adopt diverse models and methods across countries in their quest to obtain higher precision in fore-

casting inflation. Specifically, (Stock and Watson, 2007) and (Gurkaynak et al., 2005) employed unobserved components stochastic volatility model. Cogley and Sbordone (2008) used the New Keynesian Model while De-Graeve et al. (2009) adopted on New Keynesian Phillips curve (NKPC) approach. Medium-scale macro-finance Dynamic Stochastic General Equilibrium (DSGE) Model was used by Gonzales et al. (2011); penalised likelihood by Dotsey et al. (2017), while Clark and Doh (2011) used bayesian methods to forecast inflation. An extensive review on inflation forecasting methods has been done by (Faust and Wright, 2013). Since early 1960s, Phillips curve models have been the work-houses for inflation forecasting. However, in the past two decades or so, empirical studies have queried the predictive power of Phillips curve models, given the models inability to outperform the naive models Atkeson and Ohanian (2001) and (Dotsey et al., 2017) found that forecasts from our Phillips curve models tend to be unconditionally inferior to those of univariate models. There is evidence in the literature that Phillips curve models alone are not sufficient for robust inflation forecasting. Stock and Watson (1999) proposed the introduction of supply side variables for better performance. Univariate and multivariate models have also been employed for inflation forecasting over the years. Univariate models (based on ARIMA and ARCH models) are usually adopted for short term forecasting, while multivariate models (VAR and cointegration) are famous for long term forecasting (Fawad et al., 2015). Even the renowned Phillips curve are mostly based on VAR models. These models have been used to analyze and forecast inflation in several countries. For instance, Pufnik and D. (2006) used a univariate model to forecast inflation in Croatia while Gaomab (1998) used multivariate model to forecast inflation in Namibia. Akdogan et al. (2012) employs an ARIMA model in forecasting inflation in Turkey and compared the results obtained with those of other models and found that models with more economic information produce better forecasts. Kelikume and Salami (2014) employed both univariate and multivariate models to forecast inflation in Nigeria and found that VAR model produced smaller errors in terms of the minimum square error (MSE) and concluded forecasts were the closest to actual inflation in Nigeria. It has, however been argued that univariate models are mere scientific guesses with some degree of confidence and are poor in predicting turning points. Such models therefore, provide weak forecast when volatile and high frequency data are involved (Meyler et al., 1998). Multivariate models, on the other hand, have been criticized for being too complex and prone to misspecification errors and overfitting problems. Bjornland et al. (2009) used a combination of six models, namely; Vector Autoregressive (VAR), Bayesian Vector Autoregressive (BVAR), Autoregressive Integrated Moving Average (ARIMA), Error Correction Model (ECM), Factor Model and Dynamic Stochastic General Equilibrium (DSGE) models to forecast inflation in Norway. Among the variables adopted were interest rates, inflation, exchange rate, oil price, investment growth and employment rates for the period spanning 1987-1998. The result showed that model combination approach yield better forecast than individual models.

Findings of Amadi et al. (2013) suggested that SARIMA was the best model in forecasting monthly inflation rate in Nigeria. Similarly, Doguwa and Alade (2013) proposed four short term forecasting models using SARIMA and SARIMAX processes. The models incorporated some endogenous variables which include PMS price, government expenditure, net credit to central government, average monthly rainfall in cereals producing north central zone, nominal Bureau-de-change exchange rate, broad money supply (M2), official nominal exchange rate, reserve money, credit to the private sector and average monthly rainfall in vegetables producing Southern zone. Based on the result, the paper recommended that all-item CPI, estimated

using SARIMAX model, should be adopted for short-term forecasting of headline inflation in Nigeria. It also suggested that SARIMA model was the best for forecasting core inflation in Nigeria. [Omekara and Ekerete \(2013\)](#) employed Periodogram and Fourier series analysis to model monthly inflation in Nigeria. The forecasts were found to be accurate and reliable. [Okafor and Shaibu \(2013\)](#) adopted ARIMA model in line with Box Jenkins (1976) to forecast inflation using CPI data from 1981 to 2010. The paper found ARIMA (2,2,3) as the most appropriate for the country. On the contrary, [Yemitan and Shittu \(2015\)](#) applied Kalma filter technique and found it more efficient compared with Box Jenkins. The ARIMA model, is the baseline for identifying inflation drivers in our study alongside the cross validated and hyper-parameter tuning of the ensembles, RF and GBM, and the cross validated and hyper-parameter tuning of the GLM. These methods address the fundamental questions of what is the best model should be, but because each of ensemble method has its peculiar weakness hence, a cross validated stacked ensemble approach is adopted to resolve the weakness in each each ensemble. This is one of the strengths of this study. To apply the stacked ensemble method, we found that the optimal hyper-parameters we obtained provides the best predictive accuracy. In addition, we confirmed that the base learners have high variability and are uncorrelated.

2.3 Review of Inflation Drivers and Its Forecasts Using Machine Learning

In a sense, inflation narratives have been influenced by studies exploring its drivers and forecasts. In many cases, these strands of literature have been explored separately. In exploring inflation drivers, some empirical studies that employ machine learning algorithm are identified. [Benalal et al. \(2004\)](#) investigates whether forecasts of the Harmonized Index of Consumer Prices (HICP) components outperform those of the overall HICP. [Giannone et al. \(2014\)](#) constructed Bayesian Vector Autoregressive model (BVAR) that captures the inter-relationships between the main components of the HICP and their determinants in the Euro area, while [Oren et al. \(2021\)](#) used the Recurrent Neural Networks (RNNs) for predicting disaggregated inflation components of the Consumer Price Index (CPI). In addition to the identification of inflation drivers, machine learni has been employed in inflation forecasting. [Inoue and Lutz \(2008\)](#) adopted bagging, factor models, and other linear shrinkage estimators to forecast inflation in the US. Similarly, [Medeiros and Mendesy \(2016\)](#) employ adaLASSO to forecast US inflation while [Medeiros et al. \(2019\)](#) show that LASSO and Random Forest produce better forecasts than the standard benchmarks. Other ML methods that have been used for inflation forecasting include heuristic and variable selection method [Kapetanios et al. \(2016\)](#), shrinkage and complete subset regression (CSR) method ([Gracia et al., 2017](#)). [Baybuza \(2018\)](#), in particular applied several ML methods such as RF, Least Absolute Shrinkage and Selection Operator (LASSO), Ridge, Elastic Net and Boosting to forecast inflation in Russia. Findings of the study confirm the possibility of forecasting inflation with a higher level of precision compared to other traditional models like Random Walk and Autoregression.

There are four important features of ML; nonlinearities, regularization, cross-validation and alternative loss function, out of which nonlinearity feature was found to be the true game changer for macroeconomic forecasting ([Coulombe et al., 2019](#)). [Gracia et al. \(2017\)](#) used ML methods to forecast inflation in Brazil and found that LASSO model is best for shorter forecast. Similarly, [Gu et al. \(2018\)](#) found significant improvement in the prediction of out-

of-sample (test data) stock return using ML methods on 30,000 samples, over 900 baseline signals and hundreds of predictors. [Medeiros et al. \(2019\)](#) in forecasting US inflation found that ML models, with a large number of covariates, are systematically more accurate than the benchmarks for several forecasting horizons both in the 1990s and the 2000s. The ML method that deserves more attention is the RF, which dominated all other models in several cases. [Malhotra and Maloob \(2017\)](#) employed gradient Boosted Regression Trees (BRT) technique of ML to analyze inflation in India and submitted that all predictor variables used in the model were significant in predicting food inflation in India. Expanding the frontiers, [Onimode et al. \(2015\)](#) used the artificial neural networks (ANN) and found that neural network is more efficient than univariate autoregressive models in forecasting inflation up to four quarters ahead. This study differs from other studies as it proposes the application of a robust approach in identifying inflation drivers and providing a forecast for its components. In essence, we obtained the drivers to identify the source of each CPI-inflation components, predict the out-of-sample CPI-inflation data, and forecast inflation in twenty-five horizons.

2.4 Stylised Facts on Inflation Trends in Nigeria (1973 - 2020)

Since the early 1970s, inflation management has remained a major macroeconomic challenge in Nigeria. The first oil boom of 1973 brought about a sudden surge in government revenue, as a result, government began to embark on massive developmental projects across the country, as part of its reconstruction efforts after the civil war ([Asekunowo, 2016](#)). Resultantly, there was a sudden spike in money stock in the economy without a corresponding increase in production of goods and services. Inflationary pressure was further aggravated by the enormous increase in minimum wage following the recommendation of the Udoji committee in 1974. Inflation rate in Nigeria soared to an average of 33.7% in 1975. As inflationary pressure continued to mount, policy makers came under intense pressure to respond appropriately. One of the policy responses was the change in monetary policy framework from exchange rate targeting to monetary targeting in 1974. Other policy measures, include credit expansion to productive sector of the economy and the liberalisation of import, which encouraged huge importation of cheaper goods. Consequently, by 1979, inflation rate had fallen to 11.8% ([Nse et al., 2018](#)). Again, inflationary pressure began to mount up in the early 80s as the country had become largely import dependent, with attendant balance of payment problems. By 1984, inflation had risen to 41.2%, necessitated the devaluation of the naira and the adoption of price control measures to bring down inflation to 5.5% and 5.4% in 1985 and 1986, respectively. Inflation in Nigeria reached an all-time high in 1995, when it rose to 79.9%. By 1999 it had fallen to 6.6%, consequent upon the adoption of effective monetary, fiscal and exchange rate policy.

Over the period 2003 to 2005, inflation rate in Nigeria averaged 15.7%, owing to increasing budget deficits. However, following the implementation of sound monetary and fiscal policies, coupled with robust agricultural harvests, inflation rate declined to an average low of 5.4% by 2007 ([Doguwa, 2012](#)). The advent of the Global Financial Crisis resulted in another spike in inflation rate as it rose to 12.6% by 2009. The rate of inflation remained high at over 12% in 2012, owing to non-monetary factors such as severe flooding in some regions which disrupted farming and consequently, elevated food prices. By 2013, CPI inflation had declined to 8%. This could not, however, be sustained as a result of persistent oil price shock between 2014 and 2018. Again, recovery in oil price led to a decrease in inflation rate to an average of 11.4% in 2019.

A disaggregated analysis of inflation trend in Nigeria showed co-movements in headline, core and food components for most years except for periods between 1998-1999 and 2001-2004 (see *Figure 1 below*)².

Figure 1: Quarterly Headline, Core, and Food Inflation (1996 -2020)

Most recently, the three inflation components in Nigeria have trended upward. This was attributed, largely, to the adverse effect of COVID-19 pandemic and the liberalisation of energy prices, including the removal of fuel subsidy aimed at improving the fiscal position of government, and the introduction of cost reflective pricing of electricity which exacerbated inflation pressure. According to the National Bureau of Statistics (NBS), headline and core inflation for August 2020 stood at 13.22% and 10.52% respectively, was the highest in 29 months since March 2018 (13.24%)³.

²Figure 1 is the plot of Core 1 inflation. The fluctuation of core 1 inflation in Nigeria is due to the components included in the basket of its computation. National Bureau of Statistics (NBS) does not exclude energy prices such as premium motor spirit (PMS), gas, and utility prices. In addition, the high exchange rate market pressure has also contributed significantly to the fluctuation of prices of many of the items in the core basket. This is because the Nigerian economy is highly import dependent and many of the item in core 1 basket are also imported.

³See Figure 2 for inflation trend in Nigeria from January to August 2020.

Figure 2: Headline and Core Inflation in Nigeria (Jan -Aug 2020)

Recent empirical study of inflation persistence in Nigeria by [Tule et al. \(2020\)](#), using fractional cointegration VAR model, revealed evidence of high inflation persistence with a lower trend after the global financial crisis. Inflation data of Nigeria from 1973–2013 shows that out of forty-seven (47) year observations, headline inflation has hovered or persisted around double digits for 37 years. This is as shown in [Figure 3](#).

Figure 3: Annual Headline Inflation in Nigeria (1970-2020)

Comparatively, recent inflation trends in Nigeria, specifically from 2013, have shown no remarkable deviation in headline, rural and urban inflation trends. Though inflation appears to follow the same upward trend in both urban and rural areas, it is lower in rural region compared to the urban. This is understandably, the result of the differences in consumption patterns. Regardless, inflation in Nigeria remains a macroeconomic challenge with deteriorating effect on citizens welfare. There is therefore, the need for further empirical studies to enhance the management of inflation. More information in *Figure 4*.

Figure 4: Inflation - Headline, Urban and Rural

The importance of applying ML to Nigerias inflation data at both economic and statistical standpoint cannot be overemphasized. From the economic perspective, ML provides a pathway to where policy on inflation should be directed. From statistical standpoint, most econometric models that use inflation variables in Nigeria suffer from curse dimensionality problem, a statistical problem that emanates from organizing and analyzing data in high-dimensional-spaces. This problem limits the forecast ability of many of the extant models, this is because information extracted from the few predictors may not be sufficient to forecast inflation with higher accuracy. Therefore, ML algorithms offer the flexibility of fine-tuning predictor parameters in the event of model overfitting. This flexibility enriches ML models and enhances the sophistication of providing a better statistical relevance to the existing tools of analysis in Nigeria. In addition, ML approach is not entirely a standalone algorithm, as other timeseries model might be, it offers many options where models can be stacked or unstacked.

3 Methods

Consider the following forecasting model,

$$y_{t+h} = T(X_t) + U_{t+h} \quad (3.1)$$

Where y_{t+h} is the variable at time $t + h$, $X_t = (X_{1t}, \dots, X_{nTt})'$ is nT -vector of explanatory variables, U_t is a difference process of martingale. The objective is to estimate the target function $T(X_t)$. The model and forecast performance is evaluated by the predictive accuracy of a loss function. The loss function is estimated using the Root Mean Square Error(RMSE) and it is calculated thus,

$$RMSE = \sqrt{\frac{1}{T - T_o - 1} * \sum_{t=T_o}^T (y_t - \hat{y}_t)^2} \quad (3.2)$$

The objective is to minimize the square error although, other reported loss functions, for only base learners, are Mean Squared Error(MSE), Mean Absolute Error(MSE), and Root Mean Square Logarithmic Error(RMSLE). However, RMSE is commonly used for both classification and regression models. We compare the traditional inflation model, Autoregression Integrated Moving Average (ARIMA) as a baseline model⁴, with other base learners.

Predictions are obtained from the test data and the prediction from the training data are used to check for model overfitting and performance.

3.1 ARIMA Model

ARIMA is a univariate model that is fitted with Box-Jenkins method and it is specified by three order parameters(p, d, q). p is the Auto-Regressive (AR) parameter that specified the

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⁴Some of these univariate models such as Autoregression Moving Average (ARMA) and UNobserved Components and a Stochastic Volatility (UC-SV) model has been found to be less accurate and less robust when compared with machine learning ensemble models(see [Baybuza 2018](#); [Coulombe et al. 2019](#); [Medeiros et al. 2019](#) for details).

number of lags to include in the model. The AR(2) process is presented as;

$$X_t = \alpha + \theta_1 X_{t-1} + \theta_2 X_{t-2} + \epsilon_t \quad (3.3)$$

Where X_t is time series, θ_1 , and θ_2 are coefficients of the AR terms in period one and two. The d component is the degree of differencing that is integrated in the order ($I(d)$). It is used for stabilizing data when the assumption of stationarity fails. In other words, it also represents the number of times a time series must be differenced to induce stationarity. The q component is the Moving Average (MA) that makes up the non-seasonal aspect of ARIMA model. The $MA(q)$ represents the combination of the previous error terms of the model. q is the order of previous error term to include in the model. The example of $MA(2)$ is given as,

$$X_t = \beta + \phi_1 \epsilon_{t-1} + \phi_2 \epsilon_{t-2} + \epsilon_t \quad (3.4)$$

Where ϕ_1 and ϕ_2 are coefficients of the MA terms in period one and two. Therefore, the main ARIMA model is given by combining equation 3.3 and 3.4. The time series X_t is stationary if $d = 0$ else ARIMA(p,d,q) reduces to ARMA(p,q)

$$X_t = \phi_0 + \sum_{i=1}^p \theta_i X_{t-i} - \sum_{i=1}^q \phi_i \epsilon_{t-i} + \epsilon_t \quad (3.5)$$

This study uses Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for model selection. The two criteria are conjecture on the extent to which the fitted values approximates the true value of the model. Furthermore, AIC and BIC are statistical function that penalize the goodness of fit used in estimating the statistical model. This penalty prevents model overfitting, however, as the number of estimated parameters increase, the penalty increases.

3.2 Ensemble models-Base Learners

There are three base learners in our ensemble catalogue that motivate our interest in this study. These include; RF, GBMs, and Generalized Linear Models (GLM). New predictions are made by combining the predictions from the individual base models that make up the ensemble. RF and GBM are all ensemble models because each uses decision trees as its base-learner. RF is applicable where data has high variance and low bias and GBM is useful where there is low variance and high bias such that each ensemble strength is the other's weakness and vice-versa.

1. **Random Forest:** RF is based on an algorithm in which decision trees are bootstrapped on the original training data then, new data are formed and new predictions are made by averaging all predicted values from the decision trees⁵. Constructing decision trees in stages help to divide the entire sample space, using a quality function $Q(X, 1, p)$, into two sub-samples. The first sample is given as $X_1(i, p) = \{X|X_i \leq p\}$ while the second sample is given as $X_2(i, p) = \{X|X_i > p\}$. Each sub-sample is therefore, broken down iteratively and stops when individual criterion is specified and n leaf corresponding to each to each

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⁵The main idea is to minimize the sum of the weighted average variance within the resulting sub-samples (Bradley and Brandon, 2020). Using the tree constructed, we can predict values for the target variables with the newly created values of the explanatory variables. The decision tree models allow us to create an effective nonlinear dependence by minimizing the variance target variable.

sub-sample are created (Baybuza, 2018). While the tree holds the regression solutions that breaks down the sub-sample into two, the leaf nodes holds the quality function, which is the predicated values of the explanatory variables. The quality function is given below;

$$Q(X, i, P) = H(X) - \frac{|X_1|}{|X|}H(X_1) - \frac{|X_2|}{|X|}H(X_2) \quad (3.6)$$

Where $H(X)$ is the information criterion and it explains homogeneity of the explanatory variables in the sub-sample. According to Baybuza (2018), The purpose is to maximize the homogeneous characteristics of the explanatory variables but minimize the spread prevalent in the explanatory variables so that;

$$H(X) = \frac{1}{|X|} \sum (y_i - \frac{1}{|X|} \sum y_j)^2 \quad (3.7)$$

Along this process, RF⁶ is not only capable of reducing variance and minimizing overfitting but introduces, a more random component into the tree building process, enhancing the robustness and predictive performance of the ensemble model.

For example we can fit $\mathbf{L}$ independent weak learners, one for each sub-sample;

$$w_1(\cdot), w_2(\cdot), w_3(\cdot).....w_L(\cdot) \quad (3.8)$$

and then aggregate them into some kind of averaging process in order to get an ensemble model with a lower variance. For example, we can define our strong model, such that

$$s_L(\cdot) = \frac{1}{L} \sum_{l=1}^L w_l(\cdot) \quad (3.9)$$

Important variable are identified and measured based on the sum of the reduction in the loss function (e.g., SSE) attributed to each variable at each split in a given tree. Therefore, for bagged decision trees, we compute the sum of the reduction of the loss function across all splits and then aggregate this measure across all trees for each feature(variable). The features with the largest average decrease in loss functions are considered most important (Fisher et al., 2018).

Identifying important driver for each of our response variable in RF is obtained through a permutation-based approach (PB). Permutation approach capture the most important explanatory variable. This is obtained by calculating the increase in the model's prediction error after permuting the variable (Bradley and Brandon, 2020). In the PB⁷ approach

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⁶In other words, random forests are modification to bagged decision trees that build a large collection of de-correlated trees to further improve predictive performance (Breiman, 2001).

⁷Permuting the value of an important explanatory variable in the training data will degrade the training performance of model. This is because a permuted variable will reduce the relationship between and explanatory variables and the response variable (target variable). The approach uses the difference between some baseline performance, such as Root Mean Squared Error (RMSE) and the performance measure obtained after permuting the values of a particular explanatory variable in the training data set. In other words, an explanatory variable is important in driving a response variable if permuting its values increase the chances of higher model error relative to the other explanatory variables, since the model relied on the important variable for its prediction.

(see [Bradley and Brandon 2020](#) for more detail on permutation), the out-of-the bag(OOB) sample for each tree is passed down the tree and the prediction accuracy is obtained, the values of each explanatory variable are randomly permuted and the accuracy is again computed. Due to random shuffling of explanatory values, there is a decrease in the level of accuracy; this decrease is then averaged over all trees for each explanatory variable. The explanatory variable with the largest average decrease in accuracy are considered most important ([Bradley and Brandon 2020](#); [Breiman 2001](#)).

To increase the predictive strength and avoid tree correlation and many noisy predictors, we increase the hyperparameter⁸, m_{try} , and number of tree, $ntree$, to 1000 each while we decrease the tree depth to maximum of 30 and also use 10-fold cross validation for the RF.

2. **Gradient Boosting Machines** : GBMs, which was first proposed by [Friedman \(2000\)](#), build an ensemble of shallow trees in sequence with the aim of learning each tree and improve on the previous errors. The shallow trees are weak learners and thus, produce weak predictions but they can be "boosted" to produce a strong and powerful ensemble models ([Bradley and Brandon, 2020](#)). Recall that new predictions are made by combining the predictions from the individual base models that make up the ensemble (e.g., by averaging in regression). While RF is effectively applicable to models with high variance but low bias, therefore, averaging prediction across decision trees (as in RF), reduces variance of models but boosting work effectively with models with high bias with low variance ([Greenwell et al., 2018](#)). In addition, while RF trained the base models independently, GBMs do not. [Baybuza \(2018\)](#) describes the algorithm as follows;

- The first model is trained on the 100% of the sample such that;

$$b_1(x) = \arg \min_b \sum_i 1'(b(x_i) - y_i)^2 \quad (3.10)$$

- The ensemble GBM algorithm leads to the first trained base ensemble

$$B_1(x) = b_1(x) \quad (3.11)$$

- The residuals, which is the difference between the actual value and the predicted value based on the first GBM model are then calculated, such that

$$e_i^1 = y_i - B_1(x_i) \quad (3.12)$$

- The model below is then trained on the residuals

$$b_2(x) = \arg \min_b \sum_{i=1}^l (b(x_i) - e_i^1)^2 \quad (3.13)$$

Whereas an explanatory variable is "least important" if permuting its values render the model error relatively unchanged, since the model did not recognize the explanatory variable for the prediction.

⁸The parameter that controls the split-randomization of the explanatory variables; [Segal \(2004\)](#) showed that data with many noisy predictors can have an improved performance if the m_{try} is higher.

- We also add a new model to the previous algorithm using a step reduction relating to a certain co-efficient $\gamma \in (0, 1)$. This method improves the model and avoids model overfitting and a new model is obtained;

$$B_2(x) = B_1(x) + \gamma b_2(x) \quad (3.14)$$

- The process is iteratively run until the final model, which is given below, is produced.

$$B_N(x) = \sum_{i=1}^N \gamma^{i-1} b_i(x) \quad (3.15)$$

The training cycles are completed when the algorithm terminates and the variable of importance measure are obtained in similar procedure as RF.

Unlike RF, our GBM was trained with $ntrees = 5000$, maximum depth⁹ of 3, minimum rows of 5, learning rate¹⁰ of 0.01, and 10-fold cross validation.

3. **Generalized Linear Models (GLM):** The basic idea behind GLM estimation is to fit a regression model such that the predicted probability, $\hat{P}(X_i)$, of our response variable is close as much as possible to the probability of response variable being observed. To yield an estimate equivalent to ordinary linear regression normal, we use "family = gaussian", which assumes an errors to be distributed normally. This idea can be fully formalized in a "likelihood function", as follows;

$$l(\beta_0, \beta_1) = P(x_i) \prod_{i:y=1} (1 - P(x'_i)) \prod_{i':y'=1} \quad (3.16)$$

The estimates, $\hat{\beta}_0$ and $\hat{\beta}_1$ are chosen to maximize this likelihood function and the resulting estimates are the predicted probability of the response variable.

Once our regression model is identified, we interpret how the features are influencing the results. Our variable of importance is determined by the magnitude of absolute value of the z - statistics for each coefficient, and it is similar in structure to random forest.

3.3 Stacked Ensemble

Methods based on RF still have significant bias, while method based on GBM have variance issues so, hence stacking these ensembles tends to solve the variance-bias trade off prevalent in machine learning. Stacking involves training a new learning algorithm to combine the predictions of several base learners. First, the base learners are trained using the available training data, then a combiner or meta algorithm, called the super learner, is trained to make a final prediction drawing on the predictions of the base learners. Super learners will learn an optimal combination of the base learner predictions and will typically perform equally or better than any of the individual models that make up the stacked ensemble (Bradley and Brandon, 2020). The algorithm is simple but it evolves in three phases;

⁹ values range between 3 – 8. A higher depth allow the model to capture specific interactions but increase the chances of over-fitting while a smaller depth is computationally efficient and may avoid over-fitting.

¹⁰evaluates the impact of each tree on the final outcome. It also controls the speed at which the algorithm proceeds down the gradient descent or learns.

1. Set up the ensemble

- Specify a list of $\mathbb{L}$ base learners
- Specify a meta learning algorithm

2. Train the ensemble

- Train each of the $\mathbb{L}$ base learners on the training set.
- Perform k -fold cross validation (CV) on each of the base learners and collect the cross-validated predictions from each.
- The N CV predicted values from each of the $\mathbb{L}$ algorithms can be combined to form a new $N \times \mathbb{L}$ feature matrix

$$n \left\{ \begin{bmatrix} p_1 \end{bmatrix} \dots \begin{bmatrix} p_L \end{bmatrix} \begin{bmatrix} y \end{bmatrix} \right\} \rightarrow n \left\{ \overbrace{\begin{bmatrix} Z \end{bmatrix}}^L \begin{bmatrix} y \end{bmatrix} \right\} \quad (3.17)$$

Where $p_1, \dots, p_L$ are the predicted values, $N \times \mathbb{L}$ is the Z , and y is the response vector.

- Train the meta learning algorithm on $y = f(Z)$. The ensemble model consists of the base learning models and the meta learning model, which can then be used to generate predictions on new data.

3. Predict on new data

- To generate ensemble predictions, first generate predictions from the base learners.
- Feed those predictions into the meta learner to generate the ensemble prediction.

4. Variable of importance for stacked ensemble: One novelty in this study is the use of the permute approach to measure the feature of importance of the meta learner from stacked ensemble. To the best of our knowledge, this study is the first that measure feature of importance directly from the stacked ensemble. After stacking the base learners and select the meta learner for the stacked ensemble, we compute the variable of importance score by calculating the percentage increase in the model's prediction error after feature permutation. We follow the traditional permutation approach of base learners as described in [Bradley and Brandon \(2020\)](#). Following the usual performance degradation for permuting the training data set, we use the difference between the RMSE and the measure obtained after permuting the values of a specific feature in the training data set. The permutation-based variable/feature of importance algorithms for the feature set as hand is derived below;

I Compute the *RMSE* loss function in equation 3.2

II for variable in the training data set i in $\{1, 2, 3, \dots, p\}$ do the following

- randomize the training data set
- apply the stacked ensemble model
- estimate *RMSE* or any loss function
- simulate the model using a fraction of the training data set

- III set the prediction metrics
- IV compute the feature importance by obtaining the difference between the permuted loss and the original loss.
- V Sort variable in descending order.

The results will demonstrate the generalizability and interpretability of the stacked ensemble model.

3.4 Data Description

We use monthly CPI data from June 2010 to April 2020 using a machine learning interface which yielded 119 observations. Data was obtained from the National Bureau of Statistics (NBS) and it was filtered and sub-grouped into headline (Headline), headline less farm produce (core 1), headline less farm produce and energy (core 2). We also grouped the data into urban and rural inflation. The components of headline, urban, and rural each has 61 variables, core inflation has 57 variables, and core 2 has 52 variables. We incorporate the `h2o` object in cloud computing from R data frame into this study to make our ensemble models algorithms more flexible and seamless for prediction. It is common to use ensemble models to forecast inflation with the test data by selecting a forecast range date but we believe that there is a tendency for some data within certain date range to be influenced by common external factors, thus, causing similarities in their patterns. For instance, test data that falls within the period of recession, are likely to yield similar patterns. To address this, we use a split command that randomly selects 70% of the sample as the training data and the remaining 30% as the test data. So, the idea is to predict a randomly selected test data. This eliminates any issue that may likely arise from range dates effects. By tradition, in macroeconomic models, variables are transformed into stationary series, in the event that they are non stationary, to avoid spurious results, however, latest study by [Baybuza \(2018\)](#) shows that transformed variables performed poorly for machine learning methods especially, the RF ensemble model. We follow the same procedure as ([Baybuza, 2018](#)).

4 Results

In this section we present our main results for inflation using the CPI data. The first subsection, fields the baseline results, the ARIMA model. The time series nature of all the inflation components are capture in this section. The results includes the drift parameters of all the inflation subgroups. The second subsection presents the performance of the base learners and the baseline model. These include analysis of different loss functions for training data set and cross-validation for different base learners, selecting a meta learner for training the stacked ensemble model. The third subsection presents the model performance and predict inflation subgroups. The last subsection deals with variable selection and variable importance for stacked ensemble model. We did this by identifying specific component drivers of inflation and make predictions afterwards.

4.1 The Baseline Results

The results of the ARIMA model is displayed in [Table 1](#) below. The results suggest that headline inflation dampens the trend in linear exponential smoothing. This is because the drift parameters has one autoregressive term, two seasonal differences that renders the Headline inflation nonstationary, and one lagged forecast errors in predicting the equation. The headline inflation is also the only feature in the suit of inflation components with only autoregressive term. However, all other components require linear exponential smoothing because they require two differencing to render inflation variable stationary. Similar to headline inflation, other inflation components have one lagged forecast errors for prediction. In a nutshell, headline inflation is different from other components inflation due to its autoregressive term.

Table 1: The Baseline Model

	Headline	CORE 1	CORE 2	URBAN	RURAL
Drift	(1,2,1)	(0,2,1)	(0,2,1)	(0,2,1)	(0,2,1)
AR(1)	0.2907	-	-	-	-
MA(1)	-0.8995	-0.8793	-0.8904	-0.8719	-0.8937
σ^2	1.916	2.262	2.609	3.269	2.819
AIC	315.56	329.67	321.83	334.26	322.26
BIC	323.03	334.65	326.81	339.07	327.08
log-likelihood	-154.78	-162.84	-158.92	-165.13	-159.13

The variance of the inflation components are also reported. The results show that Headline inflation is less volatile than other components, while urban inflation is more persistent than other components.

4.2 Performance of the Base Learner Models versus ARIMA

We present two loss functions namely; *MSE* and *RMSE* for each base learners for our training data in [Table 2](#) and cross validation ¹¹ in [Table 4](#). Building 1000 trees, with maximum depth of 30 and maximum tries of 10, on 119 observations (*see Table 8 in Appendix C for details*) with more than 50 predictors, RF appears to have a lower accuracy on the training data, when compared with other base learners and and the baseline model. Unlike RF, GLM has a better accuracy than all the base learners and the baseline model. However, we cannot conclude so at this point, since generalization on test data has not been made yet. Since the predictors represent about 40% of the observations, the likelihood of high variation or noisy predictors could have been responsible for accuracy differences across the base learners. For detailed analysis, we tried building a shallow model with lower trees and lower depth and adopt a hyperparameter tuning strategy, through a grid search, the results did not seems different from our initial experiment. In our case, higher *RMSE* in RF or any of the base learners for the training data should not pose a problem, since all the base learners are communed into stack ensemble model and the performance of the stacked model is what matters ultimately.

¹¹ The process involve splitting the training data set into two parts

Table 2: Different Loss Functions for Base Learners and ARIMA Model-Training Data

		Headline	Core 1	Core 2	Urban	Rural
Random Forest	MSE	8.3955	5.8182	5.5240	8.2512	6.9754
	RMSE	2.8975	2.4121	2.3503	2.8725	2.6411
GBM	MSE	2.6738	2.1448	1.8429	3.4532	2.9332
	RMSE	1.6352	1.4645	1.3575	1.8583	1.7127
GLM	MSE	0.0010	0.0333	0.0900	0.0019	0.0019
	RMSE	0.0324	0.1826	0.3000	0.0441	0.0433
ARIMA (Baseline)	MSE	1.8322	2.1871	2.000	3.1524	2.7179
	RMSE	1.3536	1.4789	1.4144	1.7755	1.6486

Our study,therefor preliminary concludes that GLM outperforms the GBM, RF and the baseline model for all the inflation component. The baseline ARIMA model clearly outperforms GBM in Headline inflation, urban, and rural inflation while GBM perform better in core 1 and core 2 inflation forecasts. A lower *RMSE* on the training data set for GLM and GBM does not imply that the two base learners generalize on our data effectively, since we have not yet evaluated each on the test data¹². However, this is the first stage of selecting the best meta learner to train the stacked ensemble so, higher loss functions are no threat or problem at the moment and a lower loss functions are not considered perfect as well. We retain *RMSE* as the sole loss function for this study because it is the most widely used in model evaluation and forecasts.

Although the *RMSE* of RF is higher than other base learners for training data set in [Table 2](#), we realized that it generalizes better on the test data in [Table 4a](#)¹³ since its *RMSE* for the test data largely mirrors its *RMSE* for the training data set. While the baseline model clearly overfits across the inflation components, the GBM fairly generalizes, especially on core 2. However, GLM which yielded lower *RMSE* on the training data set but fails to generalize well on the test data on all inflation subgroups, in fact, it conspicuously suffers from marginal over-fitting. Although, this poses no serious concern for our stacked ensemble model, since the staked ensemble generates its own *RMSE* independent of the base learner *RMSE*. In sum, a lower *RMSE* on training data set only for any base learner is insufficient to conclude on its predictive power or performance relative to other models until evaluation is carried out on the test data. This is the second stage of selecting our meta learner to train the stacked ensemble. The baseline model clearly suffers from overfitting problem despite auto-selecting the parameters. The results show that the inflation series are not all linear thus, needing some exponential smoothing.

¹² The exclusion of food and farm produce from headline inflation, core 1, and exclusion of food, all farm produce, and energy from headline inflation, core 2, render core 1 and core 2 to be less volatile than headline inflation.

¹³appendix A

The results in [Table 2](#) and [Table 4a](#) reveal the optimal strategy to choose the best performing model. The results are obtained from the training data set (in-sample). However, [Table 3](#) depicts the validation results, the test (out-of-sample) CPI data, of the stacked ensemble and the ARIMA models. The stacked ensemble model did not only generalize on the test data, it outperform the baseline model¹⁴. We stacked the ensemble model, using each base learner as a meta learner. In addition, the performance of the models reveal that

Table 3: Model Validation of ARIMA and the Stacked Ensemble

	Meta Learner	Headline	Core 1	Core 2	Urban	Rural
Stacked Ensemble (R^2)		0.94	0.91	0.93	0.92	0.89
	Random Forest	2.69	2.30	2.08	3.61	3.39
	GBM	4.06	2.52	2.48	3.52	3.31
	GLM	2.64	2.41	2.23	2.79	2.58
ARIMA		6.30	4.81	4.42	8.58	7.95

The *RMSE* is standardized for all the ensembles. The meta learner with the lowest *RMSE* across the inflation components are chosen for meta learner for stacked ensemble model. RF as a meta learner performs better than GBM and GLM for headline, core 1, and rural inflation. Whereas, GLM performed better than other base learners for core 2 and urban inflation, if used as the meta learner for the stacked ensemble model. The model with the lowest bias¹⁵ as a meta learner are trained on the stacked ensemble and consequently use to predict and select inflation drivers. The coefficient of determination (R^2) of our models validates the superiority of stacked ensemble over the ARIMA model. The R^2 of the inflation components, out-of-sample, are at least 90%, hence, the stacked ensemble significantly out perform the ARIMA model both in evaluation, validation, and in performance.

4.3 The Model Performance and Prediction of Inflation Components

Based on the *RMSE* in [Tables 4a](#), training the stacked ensemble model with RF, yields better forecast performance in headline, core 1, and rural inflation, while GLM produces forecasts which outperforms other base learners in core 2 and urban inflation. The model prediction and the selection of most important drivers, using the test data, for each inflation subgroup absolutely yields the same result when we switched RF for GLM as a meta learner for the stacked ensemble model. The predictive accuracy of the stacked ensemble on training and test data for all inflation subgroups is demonstrated in [Figure 10](#).

¹⁴The results are consistent with [Baybuza \(2018\)](#), [Coulombe et al. \(2019\)](#), and [Medeiros et al. \(2019\)](#) studies.

¹⁵ see [Table 4](#) in Appendix A for details, it is calculated as the difference between the *RMSE* of CPI using the training data and *RMSE* of the predicted CPI using the test data.

(a) Test for Headline

(b) Test for Core 1

(c) Test for Core 2

(d) Test for Urban

(e) Test for Rural

Figure 5: Model Performance Actual vs Predicted

As mentioned earlier, the $RMSE$ of the training data reported in Table 4a revealed that GLM and GBM generally outperforms RF because they have lower $RMSE$. However, when we trained each base learner as a meta learner for our stacked ensemble in Table 4b, the $RMSE$ s were standardized and that process changed the potential model selection for our predictions. RF becomes potentially accurate for all inflation subgroups when we generalize it on the test data, except for core 2 and urban inflation. However, criteria for selecting a trained meta learner for stacked ensemble is not limited to the size of the $RMSE$ of the training data but to how well the training data predicts the subgroup inflation. The predicted values of the training inflation data tracks the actual inflation data pretty well; this is not surprising since the stacked ensemble model is trained on the same data thus, predicting its value may not be an issue. But the model did not generalize well on the predicted value of the training data when we trained stacked model using the GBM as a meta learner. This is because the bias of GBM is higher than other base learners when used as a meta learner for the stacked ensemble.

A trained model does not suffer from model overfits¹⁶ if it generalizes well on the test data. Using the stacked ensemble models for predicting and forecasting inflation as reported in Figure 10, the predicted test data fits the actual CPI data of all the inflation subgroups very well. This is because our strategy of selecting the meta learner to train our stacked ensemble model works perfectly. This strategy yields a smaller $RMSE$ of the test data for almost all our ensemble models across the subgroup inflation in Table 4b. Therefore, suggesting that stacked model is more accurate for predicting inflation in Nigeria than a standalone model, as it is common in econometric analysis. The jumps might be due to a smaller randomly selected sample; as mentioned earlier, we performed a random split of 70% for training data and 30% were randomly allocated to test data consequently, the predicted and actual test data may not converge well. But this is not a concern at this point.

4.4 Variable of Importance using Stacked Ensemble

The main idea of this section is to use our stacked ensemble model to select the most important predictors, which are the main drivers, for the inflation components. To do this, we first trained a new learning algorithm that combine all the inflation predictors of the base learners then, a meta algorithm, also known as super learner, is trained with 70% of the CPI data to make a selection of the most important variable. This way, the stacked ensemble models outperforms individual base learners and has proved to asymptotically create an optimal system for learning(see Laan et al. 2003). The stacked ensemble whose trained meta learner yields the best performance and generalizes well on the test data is use for selecting important inflation subgroup drivers and for prediction. Consequently, we use RF to select important drivers of headline, core 1, and urban inflation and use GLM to select important driver of core 2 and rural inflation, this is because the meta learner for the stacked model has the lowest bias. We identified ten most important predictors in each subgroups however, some of the components of the inflation subgroups also have subcomponents. For instance, food as a component also have about nine subcomponents which are also predictors for food inflation. Table 7 depicts food as the most important driver for headline, urban, and rural inflation. This is not surpris-

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¹⁶Although, the $RMSE$ of the test data of RF in Table 4a is higher than the $RMSE$ of the test data of GBM and GLM but RF seems to generalize better relatively because the $RMSE$ of its test data of all inflation subgroups are much lower than $RMSE$ of its training data.

ing because food has the highest weight, 50.7%, in the inflation baskets in Nigeria. Moreover, research has shown that households spend more than 50% of their income on food therefore, it is not surprising for our stacked algorithms to identified it as the most important driver. Our modeling does not include the weight of the predictors but the stacked model was able to identify food as the most important driver because it recognizes the pattern of food CPI is more sensitive to income changes when compared with other predictors, implying that policy may have huge implication for household spending. While electricity is the fifth most important driver for headline inflation, it is the eighth most important driver for rural inflation. Electricity is an issue in Nigeria and its inability to come up as one of the first-tenth most important driver in urban inflation is not surprising. Majority of the urban households and firms already created alternative source of energy but such alternatives are not common in rural areas therefore, spending on electricity will be more sensitive to inflation in the rural areas in Nigeria. Air transportation is the second most important driver for Headline and urban inflation but the most important driver for core 1 inflation. Fuels and lubricants for personal transport equipment is the fourth most important driver for headline, fifth most important driver for rural inflation, and sixth most important driver for core 1 inflation. After excluding all farm produce and energy from headline, carpets and flooring become the most important driver for core 2 inflation and medical services appears as the most second important driver. So, changes in income spending on carpets and flooring and medical services can cause changes in CPI in Nigeria.

Having identified food as the most important driver for headline inflation, we examine the nine components¹⁷ (see *Table 9 in Appendix G for details*) and identify the component that is important in driving food inflation. So, we use our stacked ensemble algorithm to select the most important driver of food inflation and predict same using the test data. *Table 5* reveals that GLM, as a meta learner for the stacked ensemble model, can best predict food inflation driver than other two base learners because it has a lower bias when compared to others.

Figure 6 shows the most important driver of food inflation.

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¹⁷Including Bread and cereals, meat, fish, milk, cheese and eggs as a subcomponent, oil and fats, as a subcomponent, fruits, vegetables, potatoes, yam, and other tubers as a subcomponent, and sugar jam etc as a subcomponent.

Figure 6: Variable of Importance for Food

From the above figure, bread and cereals is the most important variable¹⁸, vegetables as the second most important driver, and meat as the third. However, fish is the last most important driver of food inflation. This is also not surprising, among the components of food inflation bread and cereals has the highest weight and this weight is 21.7% out of 50.7% of the food inflation from headline inflation. This result implies that the total household expenditure on bread and cereals is almost half of total expenditure on food. The low weight of vegetables among the classes or components food inflation, is about 5% out of 50.7% of the food inflation, does not pose a barrier for its position as one of the leading drivers in food inflation. The implication of the results is that vegetables may not occupy a large proportion of the household expenditures but changes in household consumption may help policy makers understand and control food inflation. Potatoes, Yam Other Tubers are the component of food inflation with the highest weight after bread and cereals but it is the fourth most important food driver. So, despite their relatively larger share of household expenditure on food, they are not as important to drive inflation as meat and vegetables in Nigeria. Household income on fish should not pose a serious concern for controlling food inflation, since they are the least important driver for food inflation.

We present the performance of the stacked ensemble for food inflation in [Figure 7](#). The Figure shows the predicted CPI for training and test data.

¹⁸ The importance variable parameters are the important predictors designed to determine the drivers. The derivations of different variable of importance of each algorithms are explained in section 3.2.

Figure 7: Food CPI

Figure 7a depicts the actual training CPI and the predicted CPI data. The performance is not surprising since it was the data that was used to train our model however, it will help to explain whether the predicted CPI data in Figure 7b have similar pattern with the CPI for the training data. We could therefore, conclude that our actual CPI data generalizes well on the predicted CPI of the test data. The model performed poorly when meta learner was switched to GBM and RF.

The bread and cereals in food inflation component have twenty-three subcomponents for food inflation. Therefore, the main goal is to identify the most important driver of bread and cereals inflation by following the same procedure as food inflation. We start with the stacked ensemble model results for each meta learner, these results are in depicted in Table 6. The results show that RF clearly overfits while GBM and GLM generalizes well on test data but GLM is better because of its lower bias therefore, we selected GLM as our meta learner. As usual, we trained GBM as the main meta learner but its performance is not as good as performance of GLM. The ten most important driver for bread and cereal inflation is depicted in Figure 8, and the prediction of training and test CPI data is available in Figure 9.

Figure 8: Variable of Importance for Bread and Cereals

The foremost driver of bread and cereal inflation is biscuits and the second most important driver is sausage. Rice agric is the third most important driver but it is the component of bread cereal inflation with the highest weight; out of 21.6% weight of bread cereals in food inflation, rice and agric shares 3.1%. However, cabin biscuits has 0.36% weights out of the total weight of bread and cereal inflation. By weight, rice agric, garri yellow, rice local, maize grain, millet, and sorghum are the six most important predictors, their individual weight is at least more than 2%, but only rice agric and millet are in the tenth most important drivers of bread and cereals inflation. In addition, components that are too low by weights mostly drive cereal and bread inflation. This suggests that changes in households expenditure allocated to components of bread and cereals which has a lower weights can pose a threat to inflation management in Nigeria. Unfortunately, lack of monetary target, in the medium-term, of these food subcomponents might have been responsible as to why food inflation has been difficult for monetary authority to control; if these items have a lower weights but are important drivers of the food subcomponents inflation then, it is possible that government might have ignored its impact on headline inflation due to its negligible weights.

Cabin biscuit, rice agric, garri white, and semovita turnout as the topmost bread and cereals driver, Bread and cereal is the main food inflation driver, while food inflation is the main headline, urban, and rural inflation driver. Moreover, air transportation, household textile, liquid fuels also top the ten most important driver in core 1 inflation while carpets and flooring, which has about 0.03% in the entire inflation weight, are the main driver in core 2 inflation. Some of the components may have lower weights but they are very significant in driving inflation in Nigeria. In fact, the performance of our model is very robust in capturing the predicted bread and cereals CPI data pretty well. [Figure 9a](#) shows the actual and predicted CPI for bread and cereal using the training sample while [Figure 9b](#) reveals the actual and predicted CPI for bread and cereals using the test data.

(a) Training for Bread and Cereals CPI.

(b) Test for Bread and Cereals CPI

Figure 9: Bread and Cereals CPI

The two figures are similar and it shows that our stacked ensemble has a predictive ability over standalone model. This is because when we randomly split the data, the stacked ensemble model predicts and forecasts the randomly selected test data accurately. Doing so, attests to the better predictive performance of the stacked ensemble model.

Forecast horizons of selected inflation variables of our model is depicted in [Figure 11](#). The RMSE forecast from the first to ninth horizon is below 9.5 but a 1.7 point jump from 8.8 in ninth horizon to 10.5 in tenth horizon is noticeable. However, the forecast was fairly stable starting from from twentieth horizon.

5 Conclusion and Policy Recommendation

To our knowledge, this is the first study to use stacked ensemble to identify and analyse inflation drivers for any country. It is also the first to employ stacked ensemble to identify importance variables. The variable of importance extracted from the stacked ensemble was very stable across the forecast horizon and the evidence suggests that "biscuits", agric rice, garri white are the main drivers of "bread and cereal" prices, while "bread and cereal", "vegetables", and "meat" majorly drive food inflation drivers and food is the main inflation driver in Nigeria ¹⁹. Shifting focus from headline to food inflation subcomponents, such as bread and cereal, to understand inflation drivers reveal a piece-wise information that may not be discernable if the price indices were not disaggregated

In terms of methodology, this study affirms the flexibility and viability of ML algorithms in predicting inflation in Nigeria. As evidenced from our results, each base learner was trained as a meta learner for our stacked ensemble. The results identified "RF" as the best performing meta learner for training the stack ensemble model. Since some of the CPI subgroups are best

¹⁹We identified food as the main driver for headline, urban, and rural inflation thus, we analyze food inflation components to gain more insight into relevant drivers, while air transportation is the core 1 main driver, carpet and flooring is the main driver for core 2 inflation. Among the food components, "bread and cereals" are the main driver while "vegetables" is the second most important driver of food inflation. Cabin biscuits, a components of Bread and cereals CPI and subcomponent of food CPI, is the main inflation driver our stacked ensemble model was able to identified.

predicted with the "RF". It thus, suggests that some inflation data are better predicted by nonlinear models. Recent advances in ML methods can improve forecasts where the target variable can be explained by multiple predictors and more than two-dimensional space. In this regards, stacked ensemble deserves special attention, given its ability to compensate the weakness of a base learner with the strength of another base learner. Consequently, the synergistic performance of stacking each base learner produces a formidable model that yields the highest level of forecast accuracy. In this study, we analysed the test data, out-of-sample, and our results showed strong accuracy in predicting inflation, as the time horizon increases, contrary to recent studies (*see Medeiros et al. (2019)*), the accuracy of our model in predicting out-of-sample data did not diminish. In addition, volatility problems did not constrain the prediction. The more volatile and the less volatile inflation (core 2) subgroups, such as "core 1" and "core 2", were all predicted with high accuracy. Effectively tracing the source of inflation based on disaggregated framework is critical in the design of inflation management policies. However, a misallocation of weights in the CPI basket will stymied the successful control of inflation in Nigeria.

6 Appendix

A Model Performance Using RMSE

Table 4: Model Performance Using RMSE

(a) Ensemble Models for Base Learners

Base Learner		Headline	Core 1	Core 2	Urban	Rural
Random Forest	Training	2.89	2.40	2.36	2.86	2.64
	Test	2.42	2.07	2.01	2.31	2.19
	Bias	0.47	0.33	0.35	0.55	0.45
GBM	Training	1.64	1.46	1.36	1.86	1.71
	Test	1.88	1.75	1.38	1.96	1.94
	Bias	-0.24	-0.28	-0.02	-0.11	-0.23
GLM	Training	0.03	0.22	0.30	0.04	0.04
	Test	0.51	2.47	3.58	0.50	0.47
	Bias	-0.48	-2.26	-3.28	-0.45	-0.42
ARIMA (Baseline)	Training	1.35	1.48	1.41	1.78	1.65
	Test	6.30	4.81	4.42	8.58	7.95
	Bias	-4.95	-3.33	-3.01	-6.80	-6.30

(b) Stacked Ensemble Model

Meta Learner		Headline	Core 1	Core 2	Urban	Rural
Random Forest	Data					
	Training	2.68	2.38	2.15	2.99	3.25
	Test	2.69	2.30	2.08	3.61	3.39
	Bias	-0.01	0.08	0.06	-0.62	-0.14
GBM	Training	3.57	2.80	2.82	3.99	3.69
	Test	4.06	2.52	2.48	3.52	3.31
	Bias	-0.49	0.29	0.34	0.47	0.38
GLM	Training	3.26	2.56	2.27	3.25	2.92
	Test	2.64	2.41	2.23	2.79	2.58
	Bias	0.62	0.15	0.04	0.46	0.34

B Training (in-sample) Inflation Data

(a) Training for Headline

(b) Training for Core 1

(c) Training for Core 2

(d) Training for Urban

(e) Training for Rural

Figure 10: Model Performance Actual vs Predicted: Training

C Forecast Horizon

Figure 11: 24-Months Forecast Horizons of Headline, Core1 and Core 2

D Model Performance: Food

Table 5: Model Performance: RMSE Stacked Ensemble Model

Meta Learner	Food	
Random Forest	Training	28.10
	Test	18.09
	Bias	10.02
GBM	Training	22.28
	Test	8.92
	Bias	13.36
GLM	Training	14.24
	Test	8.90
	Bias	5.34

E Model Performance: Bread and Cereals

Table 6: Model Performance: RMSE Stacked Ensemble Model

Meta Learner		Bread and Cereal
Random Forest	Training	4.57
	Test	7.87
	Bias	-3.30
GBM	Training	5.49
	Test	3.33
	Bias	2.16
GLM	Training	4.94
	Test	4.87
	Bias	0.07

F Variable of Importance for Stacked Ensemble Models

Table 7: Variable of Importance for Stacked Ensemble Models

Ranks	Headline	Core 1	Core 2	Urban	Rural
1	food	Air Transport	Carpets and Floorings	food	food
2	Air Transport	Spirits	Medical Services	Air Transport	Motor cycles
3	Household textiles	Glassware, HH Utensils	Audio-visual etc	Shoes , footwear	Narcotics
4	Fuels	Household textiles	Other transport serv	Telephone equip	Solid Fuels
5	Electricity	Audio-visual etc	Hairdressing salons	Hairdressing salons	Fuels
6	Telephone equip	Fuels	Household Textile	Audio Visuals	Road Transport
7	Soft Drinks	clothing materials	Jewellery etc	Jewellery etc	Carpets and Floorings
8	Hospital services	Non-durable HH goods	Rec. and Sport Serv	Appliances etc	Electricity
9	Liquid Fuel	Footwear Repair	Telephone services	Narcotics	house rents
10	Non-durable HH goods	Carpets floor	Appliances, Articles etc	Water supply	Coffee, tea and cocoa

G Consumer Price Index Labels and Categories

Table 8: Consumer Price Index Labels and Categories

coicop		WT
0100	FOOD AND NON ALCOHOLIC BEVERAGES	518.00
0110	Food	507.03
0111	Bread and cereals	216.66
0112	Meat	47.78
0113	Fish	44.51
0114	Milk, cheese and eggs	12.75
0115	Oils and fats	36.33
0116	Fruit	22.99
0117	Vegetables	54.35
0118	Potatoes,Yam Other Tubers	60.56
0119	Sugar, jam, honey, chocolate and confectionery	11.10
0121	Coffee, tea and cocoa	6.25
0122	Soft Drinks	4.73
0200	ALCOHOLIC BEVERAGES, TOBACCO AND NARCOTICS	10.87
0211	Spirits	1.08
0212	Wine	1.07
0220	Tobacco	4.51
0230	Narcotics	4.20
0300	CLOTHING AND FOOTWEAR	76.50
0311	Clothing materials, other articles of clothing and clothing accessories	25.08
0312	Garments	29.84
0314	Cleaning, repair and hire of clothing	5.14
0321	Shoes and other footwear	13.35
0322	Repair hire of Footwear	3.09
0400	HOUSING, WATER, ELECTRICITY, GAS AND OTHER FUELS	167.34
0411	Actual and imputed rentals for housing	77.44
0441	Water supply	11.01
0442	Miscellaneous services relating to the dwelling	1.32
0451	Electricity	16.16
0452	Gas,	1.01
0453	Liquid Fuel	37.86
0454	Solid Fuels	22.54
0500	FURNISHINGS, HOUSEHOLD etc	50.26
0511	Furniture and furnishings	8.35
0512	Carpets and other floor coverings	0.38
0513	Repair of Furnure	0.22
0520	Household textiles	1.60
0531	Major household appliances whether electric or not	3.63
0533	Repair of household appliances	1.42
0540	Glassware, tableware and household utensils	3.52
0561	Non-durable household goods	30.50

0562	Domestic services and household services	0.64
0600	HEALTH	30.04
0611	Pharmaceutical products	12.62
0621	Medical Services	8.96
0622	Dental services	0.18
0623	Paramedical services	6.81
0630	Hospital services	1.44
0700	TRANSPORT	65.08
0711	Motor cars	8.05
0712	Motor cycles	3.67
0713	Bicycles	2.76
0721	Vehicle Spare Parts	10.05
0722	Fuels and lubricants for personal transport equipment	14.22
0723	Maintenance and repair of personal transport equipment	0.21
0724	Other services in respect of personal transport equipment	0.06
0732	Passenger transport by road	24.30
0733	Passenger transport by air	1.72
0734	Passenger transport by sea and inland waterway	0.05
0800	COMMUNICATION	6.80
0810	Postal services	0.85
0820	Telephone and telefax equipment	2.33
0831	Telephone and telefax services	3.61
0900	RECREATION AND CULTURE	6.91
0911	Audio-visual, photographic and information processing equipment	6.07
0912	Photographic Development	0.20
0922	Musical Instrument	#NULL!
0941	Recreational and sporting services	0.50
0943	Games of chance	0.12
1000	EDUCATION	39.44
1011	Books Stationeries	39.44
1100	RESTAURANTS AND HOTELS	12.12
1111	Catering services	1.83
1112	Accommodation services	10.29
1200	MISCELLANEOUS GOODS AND SERVICES	16.63
1211	Hairdressing salons and personal grooming establishments	8.66
1213	Appliances, articles and products for personal care	0.14
1231	Jewellery, clocks and watches	0.36
1251	Insurance	0.78
1271	Other services n.e.c.	6.69
1400	Headline	1,000.00
1500	Headline Less Farm Produce	512.83
1600	Headline Less Farm Produce And Energy	405.26
1700	Imported Food	132.60

H Bread and Cereals: Components of Food Inflation

Table 9: Bread and Cereals: Components of Food Inflation

Headline: (Average prices of items)	1000
ITEM LABEL	Weight
Bread and Cereals (CPI)	214.8
BREAD UNSLICED 500g	9.247808
CABIN BISCUIT: LOCAL MANUFACTURE 800g PACK	3.649741
CASSAVA FLOUR,SOLD LOOSE	2.448905
CORN FLAKES 350g	0.671713
CORN FLOUR 2kg	0.209199
CUSTARD 300g	0.343941
EKO(AGIDI/KAFA)	10.02935
FRITTERS (PUFF-PUFF)	0.349214
GARI WHITE,SOLD LOOSE	11.35872
GARI YELLOW,SOLD LOOSE	28.4767
GUINEA CORN FLOUR,SOLD LOOSE	1.731423
MAIZE GRAIN WHITE SOLD LOOSE	24.79892
MAIZE PASTE-WHITE(OGI/AKAMU)	5.222746
MILLET (JERO OR MAIWA) SOLD LOOSE	23.65974
PLANTAIN FLOUR	3.537417
POP CORN	0.025521
RICE AGRIC SOLD LOOSE	30.90623
RICE LOCAL SOLD LOOSE	27.79251
RICE,IMPORTED HIGH QUALITY SOLD LOOSE	1.172488
SAUSAGE BEEF (GALA)	0.338921
SEMOVITA 2kg	0.189945
SORGHUM (GUINEA CORN) WHITE OR BROWN,SOLD LOOSE	22.13676
YAM FLOUR,SOLD LOOSE	6.502086

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