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INFLATION FORECASTING IN NIGERIA: A BIG DATA APPROACH

RESEARCH DEPARTMENT

Macroeconomic Modeling Division

Michael A. Adebiyi
Adeniyi O. Adenuga
Toyin S. Olusegun
Oko O. Mbutor,
Osaretin Evbuomwan
Idoko A. Itodo
Obioma C. Asuzu
Nwamaka G. Nwafor
Tony A. Odu
Nuhu Ado
Umar Yusuf

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Central Bank of Nigeria
33 Tafawa Balewa Way
Central Business district
P.M.B. 0187, Garki
Abuja, Nigeria.

For further enquiries, you may reach us on: rsdpublications@cbn.gov.ng.

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EXECUTIVE SUMMARY

Two recent shocks arising from the COVID-19 pandemic and the Russia-Ukraine war have brought about emerging complexities and uncertainties in the global economy. These shocks have been known to alter economic sentiments and economic agents' response patterns to policies, necessitating the need to fine-tune the existing forecasting models of the Bank. This study, therefore, seeks to capture the emerging public sentiments in the economy, using big data sources and machine learning methods to improve the predictive power of the existing short-term inflation forecasting model (STIF) in Nigeria. The STIF provides useful input to policies aimed at achieving the objectives of price stability and the overall soundness of the Nigerian economy. Findings show that public sentiments strongly correlate with the headline, core, and food measures of inflation. In addition, the result indicates that both in-sample and out-sample models that include a sentiment index provide more stable and accurate forecasts than the models without the index for all components of inflation, given the lower RMSE values obtained. Thus, we conclude that the inclusion of public sentiments on inflation improves the headline inflation forecast from the STIF. The study suggests forward guidance monetary instruments in the form of "open mouth operations", sustain various interventions to stimulate real output and the framework that attracts and conserves foreign exchange to rein in inflation expectation in Nigeria.

1.0 INTRODUCTION

Globally, policy institutions, especially central banks, routinely rely on inflation forecasts to inform monetary policy decisions and to anchor inflation expectations. Thus, economic forecasts are fundamental to designing and implementing economic policies. Improving the accuracy of economic forecasts, therefore, remains a critical part of effective decision-making. Over the years, several efforts have been made to adequately compute economic indices that predict the behaviour of economic indicators. The methods have ranged from simple arithmetic techniques to dynamic factor models that incorporate principal components analysis. Stock and Watson (2016) contain a comprehensive review of several methods that have been used over time.

One factor which affects the precision of economic forecasts is changing expectations of economic agents in response to global shocks. Also, the noise generated in the data collection process can limit the forecast performance of carefully estimated models. So, the pre-estimation of models is imperative to ensure that data is of requisite quality, from a reliable source, and fit for use. Another setback to efficient forecasts is that various economic variables are non-synchronous, generated at different frequencies, and published by national statistical agencies with considerable lags. This makes comprehensive monitoring of the economy and complicates the process of policy design. Although the development and use of Nowcasting models, which rely on the continuous flow of economic information, have helped circumvent some of the issues related to timeliness, ensuring forecast accuracy remains daunting.

The CBN houses a suite of macro-econometric models that have been used to forecast inflation over the years. These include the Inflation Forecasting Model for Nigeria (Adebiyi et al., 2010), the

Dynamics of Inflation in Nigeria (Mordi et al., 2012), Short-Term Inflation Forecasting (STIF) model (Mordi et al., 2013), a Forecast Combination model (Adebiyi, 2018), among others. Although these models have proved reliable in predicting inflation over time, the increasing importance of inflation forecasting for monetary policy decision-making and the changing economic landscape necessitates continuous efforts to improve the forecasting performance of existing models. Also, considering the adverse legacy effects of COVID-19 pandemic on prices and the economic uncertainties brought about by the Russia-Ukraine war, the need to fine-tune the Bank's forecasting models is of significant policy imperative.

From an operations point of view, the Short-Term Inflation forecasting model (STIF) is the Bank's benchmark model for forecasting inflation. We observe that in the last five months (March – July, 2022), the average forecast error was -0.39 percentage point, suggesting marginal underprediction of headline inflation. This performance may have been driven partly by the emerging complexity of the drivers of inflation. To capture factors arising from changing public sentiments regarding inflation, this paper employs big data and machine learning methods to improve the forecast performance of the Bank's STIF, thereby enhancing the monetary policy decisions of the Bank.

Given the inherent characteristics of big data and its potential information content, it is expected that the inclusion of text-based indicators into the STIF could minimise its forecast errors. Thus, this study builds on the STIF, by incorporating *a constructed public perception index on inflation, generated from social media, particularly Twitter.*
Typically, 'alternative' or 'big' datasets could help address both issues of accuracy and timeliness of economic forecasts by complementing the published data by statistical agencies. Alternative datasets are often collected directly from companies or directly from consumers

without the interference of public statistical agencies. They are also generated from internet searches (i.e. google trends), media (i.e. broadcast/published news), social media (i.e. Twitter or Facebook), and the outcome of a business transaction (i.e. payment/transactions data). While there are benefits to these datasets, one, being that they are often sampled in real-time, which could be appealing in the monitoring of the economy, they could also provide a biased sample of the population. They may not accurately represent a specific economic variable; hence, special care has to be taken to eschew the downsides in the data extraction. On the other hand, official statistics are accurate measures of economic variables such as GDP or inflation and have well-specified and tested sampling methods; however, they are subject to publication delays and infrequent sampling periods. Thus, there is a trade-off between real-time availability and accuracy. Still, this challenge summarises the value addition of alternative indicators, as they complement, not replace, the official statistics published by government agencies.

Studies have provided evidence of forecast improvement after incorporating a sentiment-based index on media data (Tetlock, 2007) on trading volume (Jegadeesh & Wu, 2013) and stock returns (Kearney & Liu, 2014). Also, Ardia et al. (2019) improved the economic growth forecasts of the US by including sentiment values in their econometric models.

Sentiment analysis entails the use of big data techniques to extract subjective information such as opinions, attitudes, and feelings expressed in text, which are mapped into quantitative measures to produce sentiment indices. The index is then incorporated into existing econometric forecasting models to improve economic forecasts. There is growing appreciation for the use of sentiment analysis to improve inflation forecasts across many climes, such as South Africa

(Botha et al., 2022); the US (Sharpe et al., 2022); Romania (Simionescu, 2022); and the UK (Rambaccussing & Kwiatkowski, 2020), among others. These studies found considerable improvements in inflation forecasts after including text-based sentiments into their forecasting models.

Thus, this paper constructs a public perception index on inflation based on textual data obtained from Twitter. The sentiments are generated from the 'opinions' expressed about the developments and expectations of inflation in the Nigerian economy (inflation perception index). The computed index is then included in Bank's STIF to improve the forecasts of inflation in Nigeria.

The modelling strategy involves using the existing STIF (Mordi et al., 2012) as the benchmark model for forecasting inflation. The constructed index is then included in an improved model as a regressor to capture the role of inflation expectations. The results and forecasts from the improved STIF are then evaluated against those of the benchmark model.

The findings show that forecasts of inflation based on the improved STIF were superior to those generated from the benchmark model. The forecasts of different measures of inflation based on the improved STIF showed that core and food measures of inflation are expected to rise slightly in August 2022 and September 2022. However, food inflation is expected to moderate slightly in October 2022, while core inflation is expected to further rise marginally in the same month. The forecast of headline inflation showed a marginal increase in August, September, and October 2022.

The remaining sections of the study are organised as follows: Section 2 discusses the theoretical literature on inflation expectations and reviews studies on inflation forecasting using big data and machine learning techniques. Section 3 presents stylised facts on price developments in Nigeria over the last two decades, while Section 4 outlines the methodology, including details relating to the data used. Section 5 discusses and evaluates the results of the various models. Section 6 concludes with summary, policy implications, and recommendations.

2.0 LITERATURE REVIEW

2.1 Theoretical Framework

The section focuses on relevant theories that explain the role of big data in inflation forecasting, including cognitive narrative theory, adaptive expectation theory, and rational expectations theory. Other theories, such as the quantity theory of money, real theory, structural theory, and fiscal theory, are also reviewed. Theories of inflation sentiments or expectations encompass the behaviour and perception of economic agents towards changes in the price level, while monetary theory explains inflation in terms of changes in the growth of money supply per change in the growth of real output and velocity of money. The real theory uses the economy's structure (Ali, 1996), while structural theories focus on economy-specific bottlenecks. Moreover, the section reviews the findings of empirical studies on inflation forecasting using big data, consumer sentiments, and other factors that drive inflation.

2.1.1 Cognitive Narrative Theory (Market Sentiments)

The theory explains how social-psychological sentiments of economic agents influence macroeconomic outcomes (Nyman et al., 2014). It hinges on two emotions – "anxiety" about possible future loss and "excitement" about possible future profit. The theory explains that sentiments such as "positive or negative", "optimistic or pessimistic", are found in narrative texts of rational economic agents (Chong & Tuckett, 2015; Tuckett et al., 2015). Although sentiments about economic variables such as inflation, GDP, and interest rate cannot be directly observed, they are estimated using sample survey data and, more recently, big data approaches. Recently, several important studies have adopted these techniques. Using machine learning algorithms, earlier researchers have presented studies that capture the relationship between expectations and macroeconomic variables. For instance, while Ramey and Shapiro (1999) used news reports to identify changes in government spending likely to impact the economy, Choi and Varian (2012) employed Google search data to predict a range of economic indicators. Dominguez and Shapiro (2013) detect narrative shifts that could account for the slowness of economic recovery using newspaper and media sources. Furthermore, using data for the US economy, Baker et al. (2016) employed a method that constructs an uncertainty index by analysing the presence of words that indicate feelings of uncertainty in news media. The underlying idea in most of these studies is that changes in information about the economy may alter expectations and, thus, economic behaviour (Tuckett et al., 2015).

2.1.2 Theory of Expectation

Economic agents' expectations are informed predictions of future events (Muth, 1961). When economic agents anticipate inflation will increase, they perceive the real interest rate to fall. They spend more and save less to optimise consumption and investment over the long horizon. The theory of expectations has been widely explained under two major headings – adaptive and rational. Milani (2017) describes sentiment as that component of expectations that cannot be rationalised as coming from a near-rational forecasting model, which allows for learning by economic agents. Aggregate demand and supply shifts are channels by which inflation expectations affect actual Inflation, where Inflation responds to excess demand over supply, in addition to autonomous cost-price shocks (Bonatti et al., 2022). The relevant economic agents behind these shifts in aggregate demand and supply are households and firms, who affect Inflation through forward-looking decisions (Rudd, 2021).

2.1.2.1 Adaptive Expectations

The adaptive expectations (AE) theory can be traced back to the separate works of Phillip Cagan, Milton Friedman, and Marc Nerlove in the 1950s. However, the concept's origin is associated with Irvin Fisher's theories (de Lozanne, 2003). The adaptive expectations approach assumes that individuals base their expectations about the value of a variable for a given period on the most recent information available about that variable. More formally, AE states that individuals revise their expectations each period in proportion to the difference between the actual and expected rate of price change (Nunn & Elliott, 1975). If current inflation is consistent with expectations for this period, then the same inflation rate is expected for the next period. On the other hand, if the current inflation rate exceeds the forecast price, the current forecast price is revised upward to get the forecast price for the next period.

$$_{t+1}{}'\dot{P}_t^* = {}_t{}'\dot{P}_{t-1}^* + \beta(\dot{P}_t - {}_t{}'\dot{P}_{t-1}^*) \quad (1)$$

Where; $_{t+1}{}'\dot{P}_t^*$= the anticipated rate of price change at time t;

$_t{}'\dot{P}_{t-1}^*$= the rate of past inflation;

$\dot{P}_t$ = rate of inflation in the current period; and

$0 < \beta < 1$

Some authors refer to such behavior as "error learning", (Nunn & Elliott, 1975) because it implies that the prediction error contains useful information for making additional predictions. Comparing the adaptive and rational expectation theories on stock prices and interest rates, Chow (1991) opined that the adaptive expectation is not only a preferable version of expectation theories but also could be a useful working model in econometric practice. This is because economic agents do not necessarily act along the theoretical rational expectations but are rather motivated by what Keynes famously described as animal spirits (Milani, 2017).

2.1.2.2 Rational Expectations

The rational expectations (RE) hypothesis believes that expectations of firms tend to be distributed, for the same information set, about the theory's prediction. The theory of rational expectations was proposed by Muth (1961). It is an equilibrium concept that imposes the consistency condition that each agent's choice is the best response to the choices of others (Evans & Honkapohja, 2015). Rational expectations were derived from the thinking that adaptive expectations, or any other fixed weight distributed lag equation, may provide poor forecasts in certain contexts and that better forecasts may be readily available (Evans & Honkapohja, 2015). RE posits that individuals base their decisions on human rationality, information availability, and past experiences. All these are used to explain anticipated economic factors such as inflation and interest rates. Based on the recent discourse around big data and the implication of expectations on macroeconomic actions, a few techniques have been highlighted to better capture agent behaviour.

2.1.3 Monetary Theory of Inflation

The basic idea of the monetary theory of Inflation can be traced to Friedman (1963), who noted that "inflation is always and everywhere a monetary phenomenon"; that is, inflation increases when money supply rises more than the demand for money. This theory is based on the Quantity Theory of Money (QTM). The QTM is depicted as:

$$MV = Py, \tag{2}$$

Where M, P, V, and y represent money supply, the velocity of money, average price level, and total quantity of goods and services produced in an economy, respectively. The QTM defines the price level using the Fisher Equation of Exchange as follows:

$$P = V.(^{M}/_{y}), \tag{3}$$

Where, M/y is an index of money density, representing money stock per unit of output. Within the framework of Classical economics, the QTM explains how increases in the quantity of money (changes in M) tend to create Inflation (changes in P). In the original form of the theory, V is assumed to be constant, and y is assumed to be stable with respect to M, so that a change in M directly impacts P. In other words, if the money supply increases then the average price level will tend to rise, with little effect on real economic activity. Also, P is assumed to change in direct proportion to M.

This theory assumes further that changes in domestic aggregate demand, aggregate supply, or external flows are reflected in changes in money density, affecting inflation. Similarly, any upward adjustment in utility prices by the government or higher expected Inflation by other economic agents will add to Inflation as the additional demand for money generated by these factors for financing transactions at higher prices is met either with an accommodating increase in money supply or through increasing velocity (Ali 1996).

In summary, the monetarist model of Inflation is derived from the money demand function and is based on the hypothesis that Inflation varies positively with the rate of changes in money supply and negatively with the rate of changes in real income, ceteris paribus. In addition, monetarists explain cost increases in terms of changes in the money supply, especially if the monetary authorities adopt an accommodation policy that seeks to prevent real output from falling.

2.1.4 Real Theory

The real theory of inflation focuses on decomposing inflation by sources. This follows the full-cost pricing theory, wherein the market value-added price is defined as a weighted sum of various primary costs, with weights reflecting the share in total cost (Ali 1996). These costs envelop wages, profits, net indirect taxes, and impacts of terms of trade. These costs are captured in the following equation:

$$P\hat{d} = (W/TRn).(W/Y\hat{r}) + (R/TRn).(R/Y\hat{r}) + (NIT/TRn). (NIT/Y\hat{r}) - (En/TRn).(P\hat{e}) + (Mn/TRn).(P\widehat{m}) + e \quad (4)$$

Where, W= wages in nominal terms
R= Profits in nominal terms
NIT= Net indirect terms in nominal terms
Y= GDP
M= Imports
E = Exports
TR= Total resources (national accounts)
$P\hat{e}$ = Imports deflator
$P\widehat{m}$ = Exports deflator
n, r = denote nominal and rea prices, respectively.

Equation (4) explains inflation approximated by changes in domestic demand deflator $P\hat{d}$ through wage cost (W/TRn) profit cost (R/TRn), tax cost (NIT/TRn) and terms of trade [–(En/TRn)+ (Mn/Trn) Respectively. $(W/Y\hat{r})$, $(R/Y\hat{r})$, $(NIT/Y\hat{r})$, $(P\hat{e})$, $(P\widehat{m})$ represent the weights of wages, profit, tax, exports, and imports, respectively.

This equation notes that changes in total domestic demand deflator approximate inflation through changes in wage cost, profit cost, tax cost, and terms of trade, all duly weighted by their respective shares in total resources of the economy.

2.1.5 Structuralist Theory

Proponents cite the presence of structural bottlenecks, especially in developing countries, as key causes of inflation. They distinguish between basic or structural inflationary pressures and mechanisms that propagate such pressures (Udoh & Isaiah, 2018). Agenor and

Montiel (2015) identified major structural bottlenecks as including distortionary government policies and the conflict between investors and workers over the income distribution between products and wages. Others are inelastic food supply, foreign exchange, and government budget constraints. Generally, these bottlenecks lead to price increases, which are transmitted into the inflationary process.

2.1.6 Fiscal Theory

The central idea of this theory hinges on the fact that governments can influence price levels indirectly through fiscal policy, which includes the use of its present and future levels of debt and taxes. Here, the price level is determined by the value of government debt; hence the money supply is adjudged to be passive (Cochrane, 2023). The fiscal theory of the price level assumes that money is valuable only because the government accepts it as tax payment and suggests that individual transactions do not affect the price level. Simply put, the fiscal theory proposes that the price level adjusts such that the actual value of nominal debt equals the present value of primary surpluses. In addition, inflation arises from more money in the economy than is absorbed by net tax payments, not from more money than is required to mediate transactions or meet obligations. Kocherlakota and Phelan (1999) argue that fiscal policy influences inflation rates only if the government behaves fundamentally differently from households because households must meet intertemporal budget restrictions regardless of price trajectories. Furthermore, the government's debt policy offsets the inflationary impact of cyclical surplus shocks rather than causing price level disturbances by policy-induced shocks (Cochrane, 2001).

Interestingly, the theory assumes fiscal and monetary policies are intertwined. While the central bank or monetary authorities can determine expected inflation through its interest rate target, fiscal policy determines unexpected inflation. Thus, interest rate hikes only temporarily reduce inflation, but without fiscal support, the inflation situation would worsen.

2.2 Empirical Literature Review

2.2.1 Forecasting Inflation Using Big Data

Global economic events like the COVID-19 pandemic and financial crisis necessitated the deployment of big data to improve forecasting performance for better risk management (Brown et al., 2011). Though it is a developing field, many models have been used in big data forecasting. These models include but are not limited to Dynamic Factor Models, Seasonal Autoregressive Models, Factor Augmented Error Correction Models, and Factor Augmented Vector Autoregressive (VAR) models (Altissimo et al., 2010; Doz et al., 2012; Gupta et al., 2013; Bańbura & Modugno, 2014; Bańbura et al., 2015). Following the observed improved forecast performance, big data analytics is being incorporated into other research fields.

In economics, information from big data sources have been useful in forecasting key macroeconomic variables such as exchange rate, GDP, and inflation for policy making. Other areas where big data forecasting is gaining prominence include fashion, airlines, entertainment, and weather (Hassani & Silva, 2015). Tucker (2013) noted that with big data, it will soon be possible to predict every step taken by citizens.

Big data improves the inflation forecast performance in South Africa and Brazil (Figueiredo, 2010; Medeiros et al., 2021; Boaretto & Medeiros, 2022; Botha et al., 2022). Botha et al. (2022) investigate whether the use of machine learning techniques and big data influences the accuracy of inflation forecast in South Africa and found that the non-linear statistical learning forecasting models outperformed the Reserve Bank's short-term inflation forecasting model.

Figueiredo (2010) finds that models that utilised big data have proven to outperform other traditional time series models in forecasting inflation. FAVAR, Bayesian regression, Design for Manufacturing (DFM) with Cummulative GARCH, and other Big Data accommodating models perform better than other traditional time series models like structural VAR, GARCH, AR(p), and AR(p)-GARCH (Bernanke et al., 2005; De Mol et al., 2008; Alessi et al., 2009; Bordoloi et al., 2010; Bańbura et al., 2015). Specifically, Hassani and Silva (2015) affirm that the three most popular models used in Big Data forecasting are factor models, neural networks, and Bayesian models.

Boaretto and Medeiros (2022) asserted that three inflation forecasting approaches exist. These are the survey-based approach, aggregate price index variation approach, and computing the forecast for the aggregates from the combination of disaggregates forecasts approach. Ang et al. (2007) reveal that the survey-based approach models perform better than the traditional time series models such as ARIMA, regressions motivated by the Phillips curve, and several term structure specifications for forecasting inflation. This is due to their ability to capture experts' judgment and explore the bias of each survey (Faust & Wright, 2013; Gaglianone et al., 2017). It is worth noting that a useful way of assessing inflation forecast models is by their ability to match survey measures of inflation expectations (Faust & Wright, 2013). The injection of survey-based expectations in the data set to forecast inflation from traditional econometric models yields better forecast performance for all considered time horizons in Turkey. On the contrary, the naive moving average (MA) model provides a lower root mean square error (RMSE) than a survey-based model for all horizons, except for the first, in Brazil (Altug & Akmakli, 2016).

Ogunç et al. (2013) affirmed that the aggregate price index variation technique performs better at forecasting because it accounts for more economic data. The case of inflation in the Euro area fits into this approach because the index is broken down into three different parts; components related to different economic sectors, by countries, and bridging both. Some studies that employed traditional time series models unravel mixed results. For instance, Espasa and Albacete (2007) find that the breakdown by sectors and the application of models with cointegration restrictions can generate more accurate forecasts for several horizons compared to the approach that considers inflation for the euro area. On the other hand, Bruneau et al. (2007), Duarte & Rua (2007), and Moser et al. (2007) find favourable results for aggregating disaggregated forecasts against forecasting the aggregate directly for France, Portugal, and Austria, respectively.

In summary, recent global developments such as the financial crisis, the COVID-19 pandemic, and the Russia-Ukraine war that complicate economic fundamentals amidst technological advancement have created the need for the incorporation of big data in forecasting macroeconomic variables. The use of big data sources and techniques improved the accuracy of economic forecasts.

2.2.2 Consumer Sentiment and Inflation

Since the work of Keynes (1936), economists have acknowledged the role of expectations and sentiments in influencing economic decision-making (Algaba et al., 2020). However, literature on sentiment analysis and its role in determining macroeconomic outcomes is nascent in economics. Notwithstanding, scholars have recently given increasing attention to its role in the prediction of macroeconomic variables, such as inflation. This is because sentiments and emotions can profoundly affect the behaviour and decision-making process of economic agents, as observed in behavioural economics. As Angeletos et al. (2018) noted, sentiments could either contain fundamental information in the news or capture irrationality up to animal spirits in the noise. Sentiment acts as an external shock with a direct impact on market expectations, which in turn affect market outcomes (Angeletos et al., 2018).

Sentiment analysis or opinion mining is "the computational study of people's opinions, appraisals, attitudes, and emotions toward entities, individuals, issues, events, topics and their attributes" (Liu & Zhang, 2012). Traditionally, sentiments are measured mainly based on direct surveys or constructing a sentiment index using market variables. However, technological advancement and the explosive growth in social media adoption have made it possible to generate unstructured data on people's expectations and sentiments from multiple sources. In sentiment analysis, Twitter has been an increasingly used source of data because it provides a platform for sharing news and opinions. It is also a rich source of data for the analysis of emotions and public sentiments (Kraaijeveld & De Smedt, 2020). Li et al. (2018) also opined that Twitter represents a useful source for a broad range of global live-stream market information.

Scholars employ sentiment analysis and other modern approaches based on machine learning techniques to improve central banks' inflation forecast. For instance, Simionescu (2022) argued that sentiment analysis is a valuable technique to correctly discern public opinion on topics of interest and its inclusion into traditional models for forecasting inflation has yielded substantial forecast performance. This assertion corroborates the findings of other notable studies such as Jones et al. (2020) and Xu et al. (2022). A possible reason for the usefulness of sentiment indices is its ability to capture future uncertainties arising from structural changes, which point forecasts do not capture (Rambaccussing & Kwiatkowski, 2020). However, this differs remarkably from the finding of Clements and Reade (2020), which shows that, whereas sentiment narratives could predict the errors in the numerical forecasts of output growth, its past changes could not predict future changes in the point forecasts of Inflation.

Empirical evidence suggests that forecasting with the use of Google search data, pioneered by the works of Baker et al. (2016) outperforms both AR (1) models and survey-based predictors (Niesert, 2020). It has improved the mean absolute prediction error in the US inflation and consumption, UK housing market, Swedish private consumption, and German and Israeli unemployment (Askitas & Zimmermann, 2009; Suchoy, 2009; Guzman, 2011; Lindberg, 2011; McLaren & Shanbhogue, 2011; Vosen & Schmidt, 2011). Simionescu (2022) contends that sentiment forecasts based on narratives in the official publications of central banks outperformed numerical projections and a variety of combined forecasts, including those of the Central Bank of Romania. De Caigny et al. (2020) also assert that incorporating textual data into a Consumer Churn Prediction (CCP) model improves its predictive performance.

Sentiments from the Federal Reserve economic forecasts have been found to be strongly correlated with future economic performance, GDP, unemployment, and Inflation (Sharpe et al., 2022). It predicts positive monetary policy (fed funds rate) surprises and higher stock returns up to four quarters ahead. In a related study, Rambaccussing and Kwiatkowski (2020) affirm that newspaper sentiment does not improve nowcasts or short-term inflation forecasts. It, however, improves the forecasts of unemployment and output growth. Clements and Reade (2020) assert that sentiments derived from the narrative of the Bank of England's quarterly inflation reports can predict errors in the numerical forecasts of output growth, but not inflation. Also, past changes in sentiment predict subsequent changes in the point forecasts of output growth and Inflation.

Kraaijeveld and Smedt (2020) realise that Twitter sentiment has the power to predict the price returns of cryptocurrencies. Also, the introduction of the sentiment index improves the forecast performance of prices in the stock exchange market (Li et al., 2020; Wojarnik, 2021). To determine which sentiment index has more predictive power in forecasting stock market volatility, Liang et al. (2020) assert that the daily social media and internet media news sentiment indices significantly impact stock market volatility, while the sentiment index built by the traditional newspaper has no impact. In addition, the one-day-ahead out-of-sample forecast accuracy is influenced more by the indices generated from social media and internet media news. Also, the model incorporating the positive and negative social media sentiment indices exhibits superior forecasting performance. Third, the study finds that only the sentiment index built by Internet media news can improve the accuracy of mid-and long-run volatility forecasts. Finally, the two sentiment indices of social media and internet media news contain useful information to forecast the monthly stock market volatility.

To sum up, using text mining and machine learning techniques to generate relevant indices for forecasting macroeconomic variables is gaining momentum in research. The inclusion of such computed text-based indices has led to improvements in the predictive power of existing forecasting models.

2.2.3 Drivers of Inflation

Global inflation is driven by internal and external factors (Forbes et al., 2018; Nagy & Tengely, 2018; Pop & Murăraşu, 2018; Adeleye et al., 2019). The internal drivers of Inflation include the money supply, government expenditures, net food exports, domestic demand and supply, political instability or insecurity, and lending rates. In addition, Kohlscheen (2021) utilised machine learning techniques and found that consumer expectations significantly influence inflation in advanced economies.

The external drivers of Inflation are magnified by the increasing level of integration among countries into a global production process. This is inherent in the impact of international business cycles on inflation. As a result, exchange rate, imported inflation, and trade openness are the key external triggers of inflation (Rodriguez & Yoldas, 2016). Nagy and Tengely, (2018) revealed that domestic inflation is more sensitive to global factors than domestic factors in Hungary. Similarly, Adeleye et al. (2019) disclosed that inflation in Nigeria is driven majorly by external factors. In Kenya and Ethiopia, world food prices and exchange rates have a long-run impact, while money growth and agricultural supply shocks have short-to-medium-run effects on Inflation (Durevall & Sjo, 2012).

Gomez-Gonzalez (2021) asserts that countries with flexible exchange rate regimes and higher tax rates have more public debt-linked inflation. Considering the monetary policy regimes of Germany, the United States, Brazil, and Mexico, Garcés Díaz (2020) revealed that money stock and exchange rate are the drivers of price level movements and determination, respectively. In Asia, Osorio and Unsal (2013) discover that the roles of monetary and supply shocks in driving inflation are gradually waning. However, domestic demand pressures and spillovers, especially from China, drive inflation in the region. Negative policy rate shock, positive exchange rate shock, and positive global oil price shock are the drivers of inflation in Turkey (Yilmazkuday, 2022).

Al-Ezzee (2020) identified broad money supply (M2), government expenditure, nominal effective exchange rate, nominal interest, and consumer price index of main trading partners as the drivers of inflation in Bahrain. For Myanmar, the external factor proxied by oil price has no significant impact on inflation, but the main domestic driver of inflation is the budget deficit. The weakness of the banking sector contributes to a negative correlation between money supply and inflation in the country (Win, 2019). Bhattacharya (2014) identifies nominal interest rate shocks, credit growth, and growth shocks as the main drivers of inflation in Vietnam.

The decline in global demand, declining oil prices, and supply disruptions are the main factors that caused the global inflation rate to fall during the pandemic in 2020. Also, the sharp rise in global demand vis-a-vis inadequate supply brought about by the COVID-19 induced movement restrictions and the cost-push shock contributed to global inflationary pressure (Ha et al., 2021; Sheremirov, 2021; Del Negro et al., 2022). This corroborates the findings of Nguyen et al. (2017), Ruzima and Veerachamy (2015), and Kapur (2012), who asserted that domestic demand and supply shocks, as well as global shocks, particularly shocks to production, are the main drivers of Inflation in sub-Saharan Africa.

Countries with strong trade links and common monetary policies are likely to have similar trends in inflation. Alvarez et al. (2021) established a strong link between Inflation and economic integration in the euro area, evidenced by the co-movements of the inflation rates among member countries. Similarly, the convergence of inflation rates between East African Community (ECA) and EU member countries over time is attributable to the similarity of the nature of shocks hitting the member countries and the role that external factors play in driving Inflation (Egert, 2007; Dridi & Nguyen, 2019).

The drivers of inflation in advanced economies differ from those of emerging and developing economies (Adeleye et al., 2019). This is evident in the low and single-digit rates of inflation maintained by the Organisation for Economic Co-operation and Development (OECD) member countries over time compared with the high and double-digit rates of inflation in developing countries of sub-Saharan Africa. Ha et al. (2019) argue that Emerging Market and Developing Economies (EMDEs) do not enjoy stability-oriented and resilient monetary policy frameworks; therefore, inflation expectations are rarely anchored in EMDEs compared to advanced economies. For the EMDEs that do not operate inflation-targeting frameworks, exchange rate movements tend to have larger and more persistent effects on Inflation. Also, in EMDEs, domestic supply shocks contribute more than half as much to domestic inflation variation as all global shocks combined (Forbes et al., 2018; Ha et al., 2019). Jasova et al. (2020) affirmed that global and domestic output gaps were significant drivers of inflation before and after the financial crisis of 2008 in advanced economies and EMDEs. However, in the last decade, the impact of domestic output gaps in advanced economies declined, while in emerging economies, the effect of the global output gap declined.

In Nigeria, certain factors trigger inflation in addition to money supply. These include poor infrastructure, exchange market pressure, political instability, corruption, oil price volatility, financial instability, and double taxation (Dahiru & Sulong, 2017; Inim et al., 2020). Bawa et al. (2016) attribute the increase in inflation in Nigeria from single digits in the 1970s to double digits in the 1990s to climatic conditions, wages, production, currency devaluation, fiscal factors, the balance of payments, supply-side factors, and institutional factors.

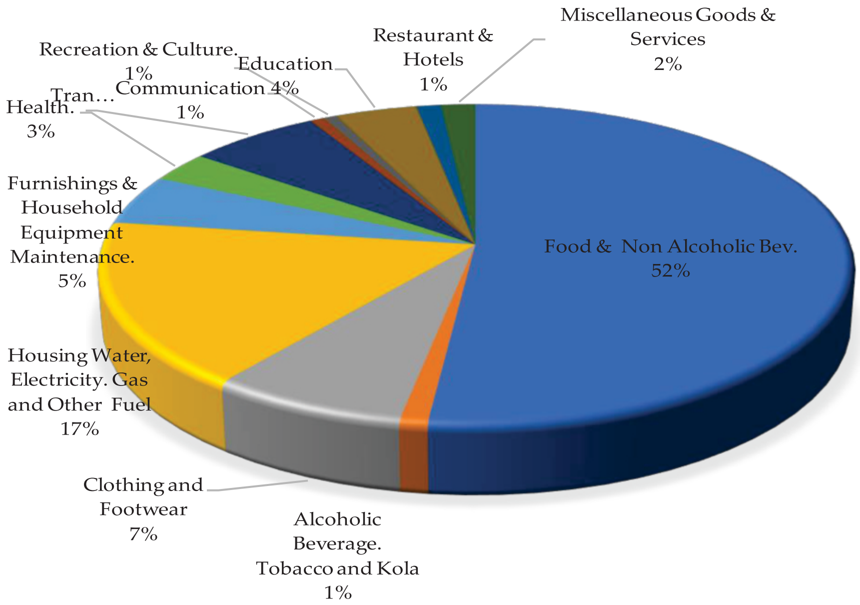
Therefore, it is evident that both internal and external factors drive inflation across the globe- these factors range from the traditional money supply to infrastructural as well as demand and supply imbalances. The more open a country is to the rest of the world, the more susceptible it becomes to external drivers of inflation. Also, the level of development of a country determines its inflation drivers. In addition, consumer sentiment (expectations) is one of the nonmonetary drivers of Inflation.

In this study, a measure of public sentiment computed from big data sources is included into the suite of models used by the Central Bank of Nigeria to make both conditional and unconditional forecasts of inflation. The analysis is done for the different components of inflation (i.e. food, core, and headline). The aim is to evaluate the usefulness of text-based indicators of public sentiments in improving the predictive power of the CBN's STIF.

3.0 STYLISED FACTS

This section highlights the trends in the components of inflation as computed by the National Bureau of Statistics. Figure 1 shows the weight of each component in the consumer price index (CPI). The food and non-alcoholic beverages index accounts for 51.8 per cent, representing more than half of the composite index. The implication is that changes in the food and alcoholic basket would significantly increase the overall index. Housing, water, electricity, gas & other fuel has the second largest weight of about 16.7 per cent, implying that the variations in this component also have a major effect on the general price level. The combined weight of the two components is 68.5 per cent, a clear indication that the duo se two components primarily drive changes in the headline inflation.

Figure 1: Components of the CPI Basket and their Weights



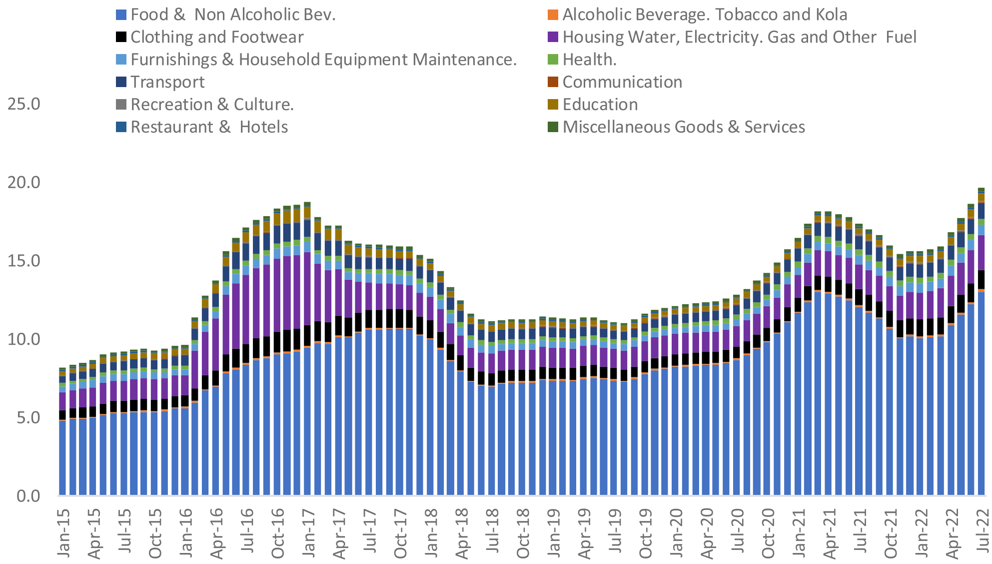
Source: Authors' compilation using data from the National Bureau of Statistics (NBS).

Headline inflation was within the single digit in 2015, averaging 9.0 per cent. However, it increased to double-digit in February 2016, at 11.4

per cent, and rose steadily to a peak of 18.7 per cent in January 2017. The rise in prices was driven largely by variations in housing, water, electricity, gas & other fuels, and food inflation. There was, however, a gradual decline to about 15.4 per cent in December 2017. The decline continued in 2018 as headline inflation fell to 11.6 per cent in May 2018 and hovered around 11.0 per cent until December 2019.

The outbreak of the COVID-19 pandemic at the end of 2019 resulted in supply chain disruptions and other logistics bottlenecks, which culminated to inflationary pressures. Thus, headline inflation rose from 12.1 per cent in January 2020 to 15.6 per cent in December 2020. The lingering effects of the pandemic and base effects also drove inflation to a peak of 18.2 per cent in March 2021 before declining steadily to 15.7 per cent in February 2022. For most of 2021, changes in the price level were driven largely by food and energy costs. Recent increases in price levels to 15.9 per cent in March 2022, 18.6 per cent, and 19.6 per cent in June 2022 and July 2022, respectively, could be explained by rising food and energy costs occasioned by the Russian-Ukraine war, as well as exchange rate pass-through to domestic prices. Over the years, headline inflation in Nigeria is driven mostly by food and non-alcoholic beverages. Housing, water, electricity, gas and other fuel also contributes significantly in driving inflation as shown in Figure 2.

Figure 2: Contribution of Components to Headline Inflation

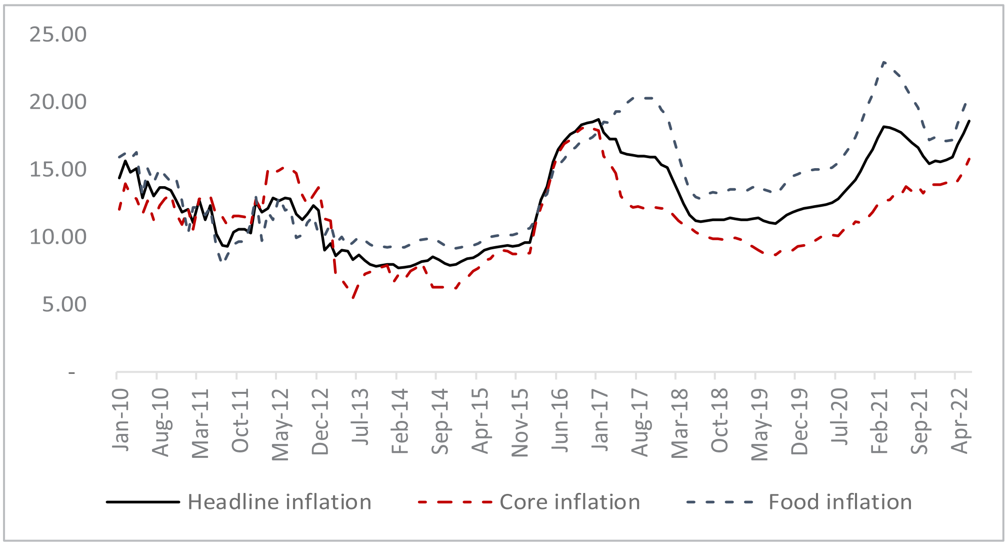


Source: Authors' compilation using data from National Bureau of Statistics (NBS).

Food inflation averaged 14.0 per cent from January 2015 to July 2022, peaking at 22.6 per cent in March 2021. It ranged between 7.0 per cent and 13.0 per cent between January 2010 and March 2016 but hovered between 12.0 per cent and 20.0 per cent during the economy's recovery from the 2016 recession and pre-COVID-19 era. Food inflation between January 2020 and July 2022 averaged 18.43 per cent (Figure 3). The volatility in food inflation could be attributed to fluctuations in agricultural output, changes in climatic conditions, exchange rate pass-through via imported food components and government intervention programmes geared towards the sector.

Core inflation was in the double-digit region between January 2010 and February 2013, peaking at 15.2 per cent in June 2012 and averaging 12.6 per cent within the period (Figure 3). Thereafter, it fell to a single-digit region hovering between 6.0 per cent and 9.0 per cent between March 2013 and January 2016. However, due to exchange rate pass-through effect and other supply-side factors, core inflation increased to double-digit between February 2016 and August 2018. It returned to single digit during the recovery period of August 2018 - April 2020 due to credit support from the government to critical sectors as well as effective exchange rate management. However, the outbreak of the COVID-19 pandemic resulted in supply-chain disruptions, which pushed core inflation into double-digit. Core inflation rose to 16.3 per cent in July 2022 from 13.9 per cent in December 2021, owing to rising energy costs which had ripple effects on other components of the CPI basket.

Figure 3: Headline, Food and Core Inflation

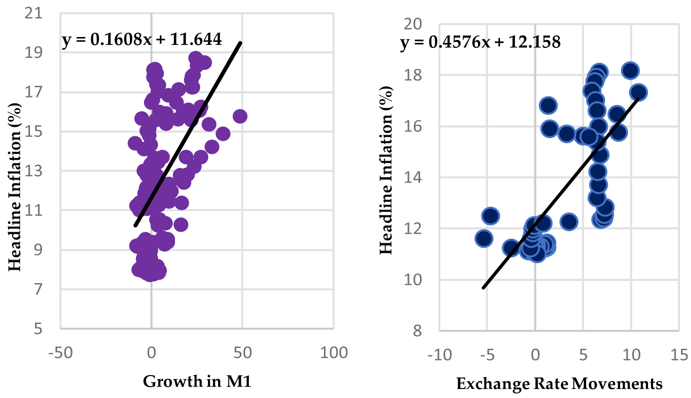


Source: Authors' compilation using Data from NBS.

The nature of relationships between headline inflation and selected variables are examined using scatter plots presented in Figures 4(a) - (f). A positive association between headline inflation and narrow money (M1) growth, the computed sentiment index, and exchange rate movements was observed during the review period, 2010 – 2021. Specifically, periods of rising inflation are associated with periods of expansion in narrow money, exchange rate depreciation, and increasing inflation perception index[1]. In some economies such as US and European countries, where public sentiments about inflation are high, central bankers influence the direction of key macroeconomic indicators, such as inflation and interest rates, without changing the policy rate through "open mouth operations." Open mouth operation is the ability of the central bank to achieve changes in its variable of interest without a corresponding change in the policy rate. Open-mouth operations or policy announcements can cause rates to deviate temporarily from their expected levels. The association coefficient of 0.46 between headline inflation and the exchange rate is relatively high and suggests a strong relationship between the two variables.

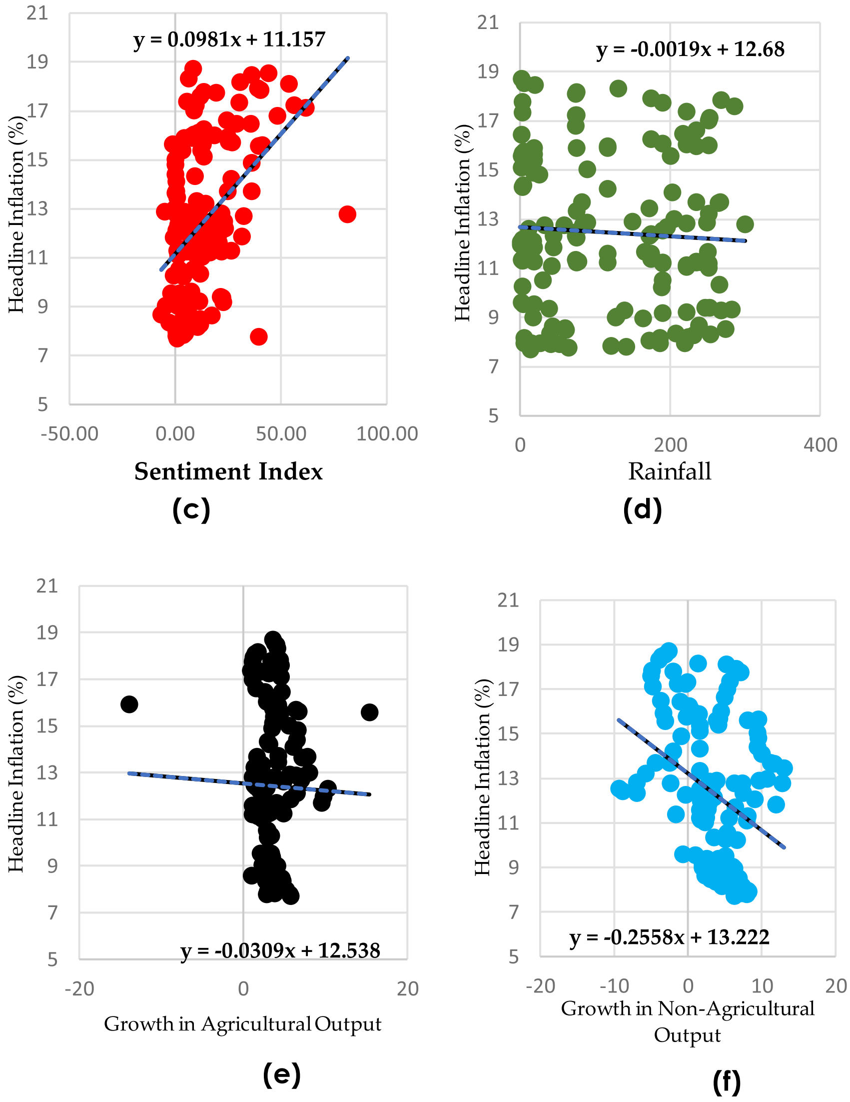
On the other hand, a negative association was observed between headline inflation and rainfall, indicating that disinflationary episodes are directly related to increased rainfall. Similarly, headline inflation is inversely related to agricultural and non-agricultural output, albeit the negative association was stronger with non-agricultural output.

Figure 4: Association between Headline Inflation and Selected Variables



(a) (b)

[1] The procedure employed for computing the inflation perception index is described in Section 4.1.1 of the paper.

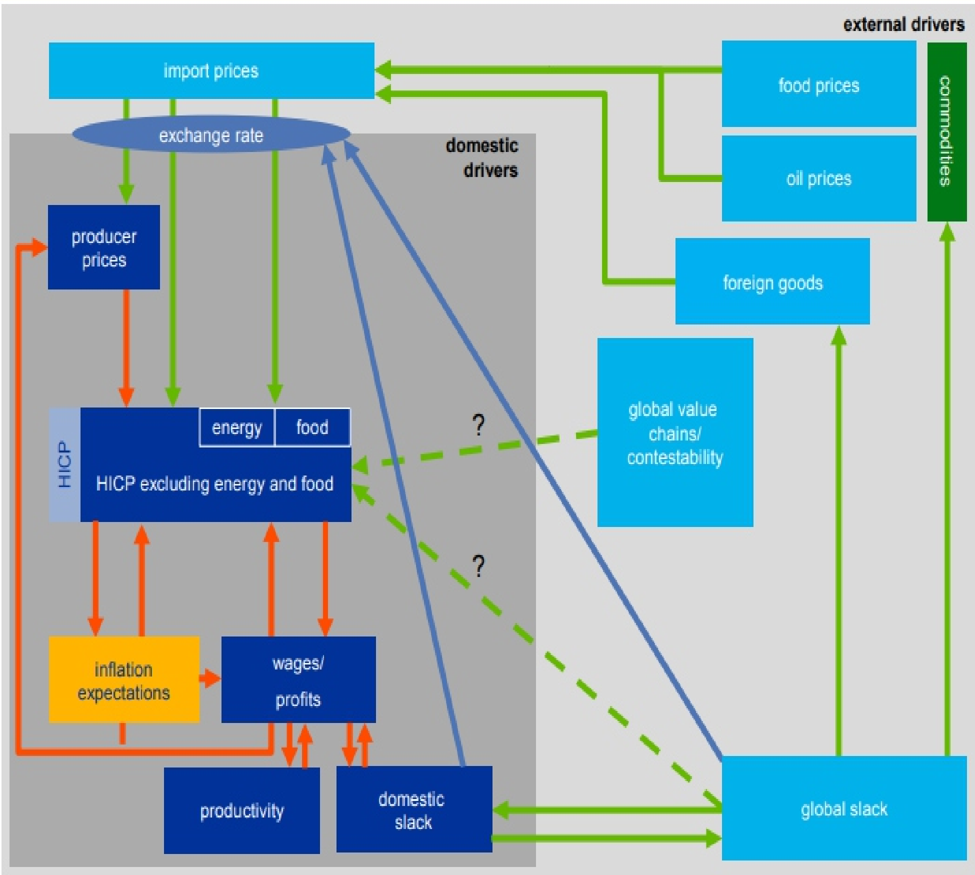


Source: Authors' computation.

3.1 Examining the Drivers of Inflation using Machine Learning

Figure 5 shows a stylised overview of domestic and external drivers of inflation. On the domestic front, variations in price level are due to the productivity and output in both the agricultural and non-agricultural sectors. From the external standpoint, inflation is driven by import prices of commodities such as energy and food. In addition, global slack is perceived as a driver of inflation given the transmission through supply chain disruptions and globalisation.

Figure 5: A Stylised Overview of Domestic and External Drivers of Inflation

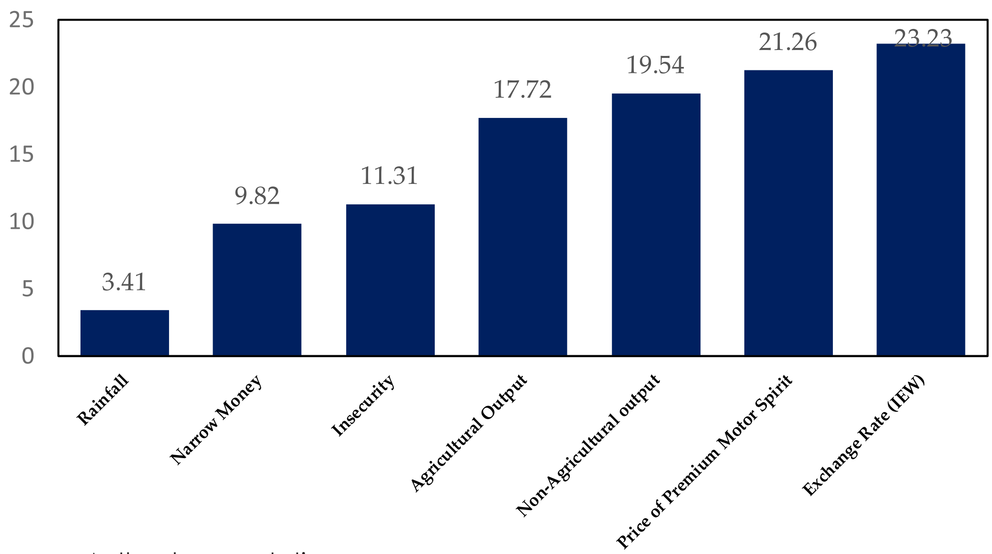


Source: Adapted from ECB (2017).

Note: the red arrows reflect the domestic drivers of inflation while the green arrows indicate the external factors. The Blue arrows indicate the importance of global and domestic slack are vital in explaining price pressures.

The study utilised a random forest algorithm to identify inflation drivers in Nigeria over the period 2010:M01 – 2021:M12. The sample size was informed by data availability. Over the review period, the exchange rate was found to be the strongest driver of inflation dynamics. This denotes that exchange rate pass-through is a crucial determinant of price variations. This was followed by the price of premium motor spirit and agricultural and non-agricultural output, which recorded relatively substantial contributions. Surprisingly, rainfall and insecurity were the least important over the review period.

Figure 6: Feature Importance, 2010:01 – 2021:M12



Source: Authors' computation.

Furthermore, sub-samples were taken over the review period to explore how the role of drivers of inflation may have changed over time. These sub-samples were informed by the business cycles of the Nigerian economy as explained in Table 1. The results from the time-varying analysis presented in Figures 7 (a) – (d) revealed that the role of the exchange rate in driving inflation was significant across all the sub-samples, as indicated by the feature importance score. This indicates that, in the case of Nigeria, price level changes are largely influenced by exchange rate developments. Additionally, the variation in non-agricultural output and the price of premium motor spirit were important drivers of inflation across the sub-samples. Across the selected sub-samples, rainfall was the least relevant variable for predicting inflation.

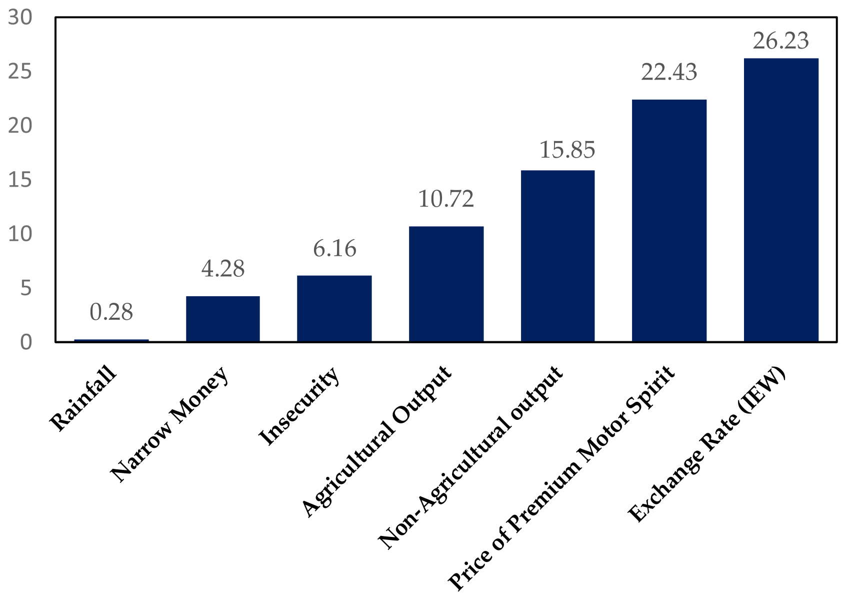
The results also revealed that the role of insecurity in predicting inflation varied across the sub-samples. For instance, while insecurity seemed less relevant as a driver of inflation during the pre-2016 recession, its importance grew during the recession and recovery periods but waned during the COVID-19 period. Similarly, agricultural output was found to exhibit varied level of importance across the sub-samples.

Table 1: Sub-samples

Scenarios	Sample Period	Economic Explanation
1	2012:M03 – 2016:M03	Pre-2016 recession
2	2016:M04 – 2017:M06	2016 recession period
3	2017:M07 – 2019:M12	Recovery and Pre-COVID-19 period
4	2020:M01 – 2021:M12	COVID-19 Period

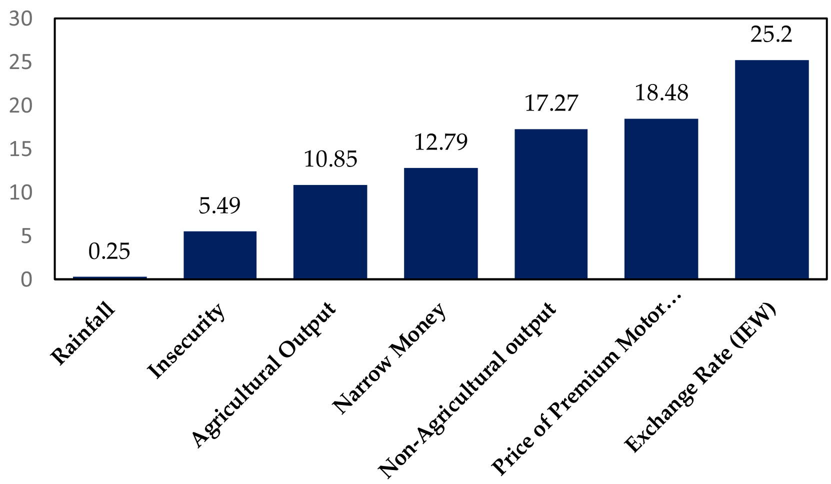
Source: Authors' compilation.

Figure 7(a): Feature Importance, Pre-2016 Recession



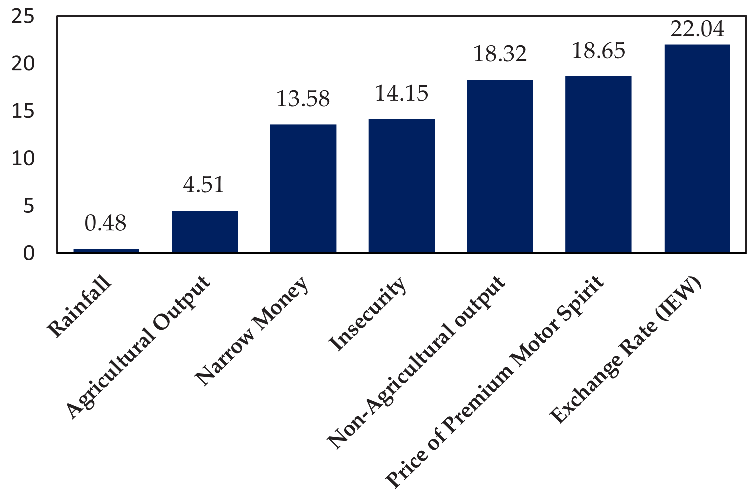
Source: Authors' compilation.

Figure 7(b): Feature Importance, 2016 Recession



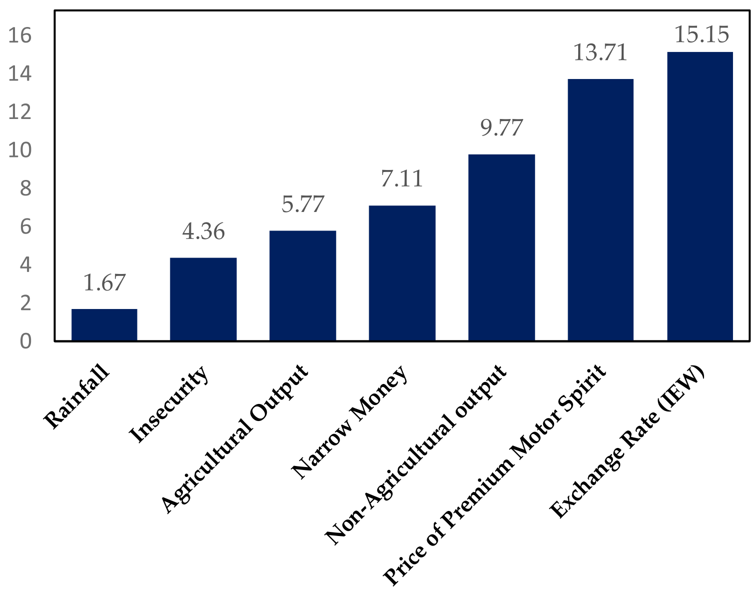
Source: Authors' computation.

Figure 7(c): Feature Importance, Recovery Period



Source: Authors' computation.

Figure 7(d): Feature Importance, COVID-19 Period



Source: Authors' computation.

4.0 METHODOLOGY

4.1 Data

The objective of this study is to improve on existing short-term inflation forecasting models of the Bank, using big data techniques. Consequently, the study utilises monthly data series on the headline, core, and food inflation for the period 2010M1 - 2022M6. The consumer price index (CPI) series for the headline, core, and food measures of inflation were sourced from the National Bureau of Statistics database.

The study also utilised financial, fiscal, and real sector variables that, based on theory, are expected to have implications for inflation dynamics in Nigeria. These include the annual growth rate of money supply (M1G), measured as the conditional growth rate of narrow money (M1). M1G is measured as the growth rate of M1, conditioned on its value over the preceding December. Other variables included the manufacturing purchasers' managers index (PMI) and non-manufacturing purchasers' managers index (NPMI); price of premium motor spirit (PMS); and the exchange rate at the importers and exporters window (IEW). The real Agricultural output (ARY); real non-Agricultural output, measured as the difference between real total output (RY) and ARY; and real government expenditure, which includes both total recurrent and capital expenditure were used. Data on these variables were sourced from the Statistics Database of the CBN.

In this study, three indices were constructed and included in the STIF of the CBN. The first index, the sentiment index (Sentiment), was computed using big data sources and techniques. Specifically, the index was derived based on textual data sourced from Twitter. The index measures public perception on inflation dynamics and its drivers in Nigeria. The other two indices are the monetary index for agricultural sector growth (ARI) and the monetary index for non-agricultural sector growth (NARI).

4.1.1 The Inflation Perception Index

The construction of the sentiment index involved two key stages: the data extraction stage and the computation of the index. In the first stage, tweets relating to inflation in Nigeria over the sample period are extracted over a specific period. Despite the prevalence of many social media sites, Twitter data was employed in this study as it captures news, individual sentiments, and market expectations.

Thus, 79,479 tweets referencing inflation in Nigeria over the period 01-01-2010 to 19-08-2022 were downloaded. Personal data on the source of the tweets were excluded from the data pool for privacy issues. The dataset included both tweets and replies to ensure the robustness of the data. Table 2 presents a cross-section of some of the extracted tweets.

Table 2: Sample of Some Extracted Tweets

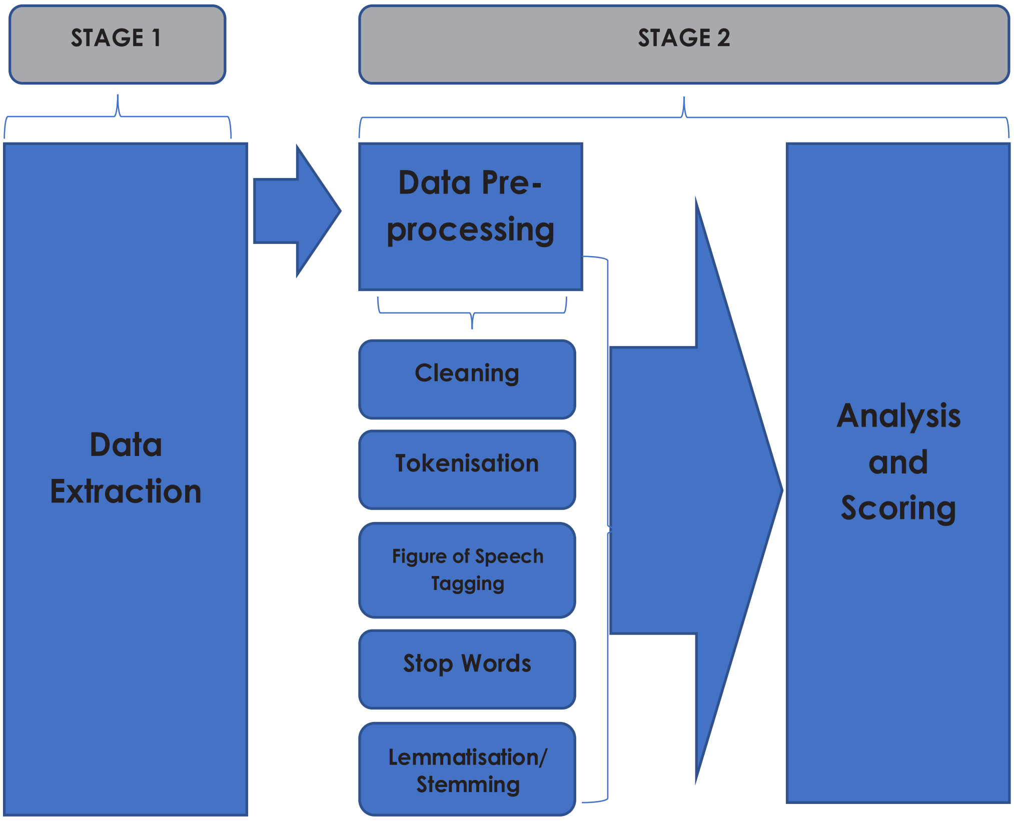
S/No	Timeline	Content
1	2011-07-21 12:06:55+00:00	"The rate of Inflation in Nigeria is Mad. No one pays attention to this, especially for Foodstuff. I'm well off, but I still feel the Pinch!"
2	2013-06-12 17:13:33+00:00	"Inflation is biting hard on d lower class in Nigeria"
3	2021-11-12 18:38:21+00:00	"Inflation in Nigeria is insane ...Everything is now twice or triple the price it was earlier this year..Omo ðŸ¤¬"

4	2022-07-27 15:44:25+00:00	"The two major determinants of inflation in Nigeria are: Exchange rate (Naira - Dollar) and Petrol Pump Price….."
5	2022-08-02 08:08:59+00:00	"Inflation: Nigeria's poultry feed price grew by 164% in 3 years. This is worrisome; sh ould we continue like this? "

In the second stage, the tweets are converted into structured data using a Natural Language Processing (NLP) technique using Python software that classifies the polarity of each tweet into positive, negative, or neutral. The paper adopts an analytic approach similar to the frameworks of Clements and Reade (2020), Kraaijeveld and De Smedt (2020), and Xu et al. (2022). The extracted tweets are first subjected to a series of pre-processing steps before sentiment scores are generated using Python's Natural Language Toolkit (NLTK) library, as seen in Figure 8.

The first step in the pre-processing stage involves removing special characters and punctuation marks such as #, @, !, and ?; after which each sentence is broken down into smaller parts called tokens in a tokenisation process. Each token is then categorised into its respective part of speech, ranging from noun, verb, pronoun, among others, to preserve the context in which the words were used.

Figure 8: Process of Sentiment Analysis



Source: Authors' conceptualisation.

Words that do not add value to the sentence and may count as noise, such as: is, have, we, and of, are removed from the corpus using the NLTK's list of stop words. Irrelevant words which are not included in the list of stop words, such as http and https are added as custom stop words. The stemming stage of pre-processing normalises tokens by reducing them to their base forms after removing the suffixes. In this stage, a word such as 'rising' is reduced to 'rise', and 'lower' reduced to 'low'.

The second stage of the sentiment analysis involves using the dictionary-based approach to generate the polarity of the pre-processed tweets. The wordnet dictionary of the NLTK was employed. The sentiments are categorised as positive, neutral, and negative, with the scores attached to these categories ranging from -1 to +1. Each negative word is assigned a score of -1, while neutral and positives words are assigned a score of 0 and +1, respectively. The total score of each tweet is computed as the average of all the sentiments scored in that tweet. The scores of the tweets for each month are summed to obtain the inflation perception index for the month.

4.1.2 The Monetary Indices

The monetary index for agricultural output, ARI, is the ratio of real agricultural GDP growth (ARYG) to narrow money growth (M1G). This index represents the level of agricultural output's monetary absorption. Similarly, the monetary index for the non-agricultural output, NARI, is the ratio of non-agricultural output growth to M1G, and describes the monetary absorption capacity of non-agricultural output. These indicators, ARI and NARI, are included as determinants food and core measures of inflation, respectively. An increase in ARI above unity implies agricultural output is growing higher, relative to growth in narrow money, resulting in less money chasing agricultural output. This is expected to reduce food inflation, and, consequently, headline inflation.

Conversely, a fall in ARI below unity implies agricultural output is growing at a rate lower than the growth in narrow money, implying that more money is chasing fewer agricultural output. This may lead to rising food inflation, and invariably result in higher headline inflation. The preceding analogy holds for increases and decreases in NARI; however, in this case, movements in the index are expected to impact core inflation directly and, subsequently, headline inflation.

The construction of the monetary indices for ARY and NARY required the transformation of ARY and NARY from their quarterly frequencies into monthly frequencies[2]. This was done using the quadratic sum extrapolation, as ARY and NARY are both flow variables. The monthly ARY and NARY series were converted into year-on-year growth rates before computing their respective ratios to M1G to arrive at the indices, ARI and NARI.

4.2 Modelling Strategy

The study employed two main estimation techniques to model inflation dynamics in Nigeria. These are the predictive regression (PR) model and Seasonal Autoregressive Integrated Moving Average Models with exogenous variables (SARIMA-X). The PR model was used in modelling and forecasting both food and core inflation, while the SARIMA-X was used for forecasting some input factors required for generating out-of-sample forecasts of food and core inflation.

4.2.1 The Predictive Regression Model

The predictive regression model used in this study follows the framework outlined in Tule et al. (2019) and Westerlund and Narayan (2012). The model, which utilises the ordinary least squares (OLS) estimation technique, is of the form:

$$food\_inf_t = \alpha + \beta Y_{t-1} + u_{1,t}, \quad (1)$$

$$core\_inf_t = \alpha + pX_{t-1} + u_{2,t}, \quad (2)$$

$$Headline\_inf_t = w_1 * food\_inf_t + w_2 * core\_inf_t, \quad (3)$$

[2]The monetary index for agricultural output, ARI and monetary index for non-agricultural output, NARI are usually released by NBS every quarter, while broad money growth is in monthly frequency. This frequency mismatch would make the construction of the monetary indices impracticable. There is therefore the need to convert ARI and NARI into monthly frequency.

Where, $Food\_imf_t$ is food inflation, Y_{t-1} is a one-period lag of a vector of exogenous variables driving food inflation; while $core\_imf_t$ is core inflation, and X_{t-1} is a vector of exogenous variables determining core inflation in Nigeria. Equation (3) is an identity, which expresses headline inflation as a weighted sum of the food and core measures of inflation. The respective weights of food and core inflation, w_1 and w_2 are consistent with those provided by the NBS in the headline CPI basket.

To assess the role of public perception about price developments in forecasting inflation, the computed inflation perception index is included in equations (1) and (2) as follows:

$$food\_inf_t = \alpha + \beta Y_{t-1} + \beta_f Sentiment + u_{1,t} \tag{4}$$

$$core\_inf_t = \alpha + pX_{t-1} + \beta_c Sentiment + u_{2,t} \tag{5}$$

The in-sample forecasts of core and food inflation were subsequently generated from these models, and the forecast performance of the models were evaluated using the Mean Squared Error (MSE) criterion. The idea is to determine whether incorporating the inflation perception index improves the forecasts of both food and core measures of inflation.

4.2.2 The SARIMA Model

Following Brockwell and Davies (1991), the seasonal autoregressive integrated moving average (SARIMA) model, *(SARIMA p, d, q) x (P, D, Q)$_S$* applied to inflation time series, y_t is specified as:

$$\alpha(L)\delta_d(L)\Phi(L^S)\Delta_D(L^S)y_t = \beta + \Theta(L^S)\theta(L)\omega_t, \tag{6}$$

Where, L is the lag operator s is the seasonal length and w_t is a Gaussian white-noise process with mean zero and variance σ^2. The seasonal length $s = 12$ is assumed since inflation series is generated monthly. $\delta_d(L)$ is the non-seasonal difference and $\Delta_D(L^s)$ is the seasonal difference operators where d and D are the orders of differencing. The non-stationary series, y_t is transformed to its stationary form y_t^* as follows:

$$y_t^* = (1-L)^d(1-L^s)^D y_t, \tag{7}$$

Where, $\alpha(L)$, $\Phi(L^s)$, $\Theta(L^s)$ and $\theta(L)$ are defined as; $\alpha(L) = 1 - \alpha_1 L - \cdots - \alpha_p L^p$, $\Phi(L^s) = 1 - \Phi_1 L^s - \cdots - \Phi_p L^{p_s}$, $\Theta(L^s) = 1 + \Theta_1 L^s + \cdots + \Theta_q L^{Q_s}$, and $\theta(L) = 1 + \theta_1 L + \cdots + \theta_q L^q$.

The transformation in equation (7) allows the replacement of the observed series with the differenced series in state-space modelling and forecasting integrated processes.

The autoregressive (AR) component, $\alpha(L)$, of the model in equation (3) is derived by multiplying the autoregressive lag polynomials $\alpha(L)$ and $\Phi(L^s)$

$$\alpha(L)^* = \alpha(L)\Phi(L^s) = \left(1 - \alpha_1 L - \cdots - \alpha_p L^p\right)\left(1 - \Phi_1 L^s - \cdots - \Phi_p L^{p_s}\right) \tag{8}$$

Correspondingly for the moving average part, the moving average lag polynomials $\Phi(L^s)$ and $\Phi(L)$ are multiplied to derive $[\theta(L)^*]$ as shown in equation (9):

$$\theta(L)^* = \theta(L)\Theta(L^s) = \left(1 + \theta_1 L + \cdots + \theta_q L^q\right)\left(1 + \Theta_1 L^s + \cdots + \Theta_q L^{Q_s}\right) \tag{9}$$

In line with the procedure outlined in Box and Jenkins (1979), the model selection process is in three stages. The first is to identify the orders of the $SARIMA\ (p, d, q)\ x\ (P, D, Q)_s$, the second is to estimate the model, and the third is to perform diagnostic checks on the residuals of the fitted model. This process is repeated if the model selected fails diagnostic checks. The values of d and D (integration orders) are chosen so that the series become stationary, and after that, the SARIMA models are estimated using maximum likelihood approach.

4.3 Implementation of the Model for Inflation

In implementing the modelling framework outlined for food and core inflation, the study performed series of both in-sample and out-of-sample forecasts to ensure robustness. In each case, the MSE is evaluated to assess whether the inflation perception index improves the performance of the Bank's STIF in forecasting food and core measure of inflation. The forecast of headline inflation is obtained by combining the forecast of food and core inflation.

It is important to note that generating the out-of-sample forecasts and simulations of both food and core measures of inflation requires determining the time path of each of the specified inflation drivers included in equations (1) and (2). Consequently, assumptions were made regarding some of the drivers, while models were developed to generate forecasts for the others.

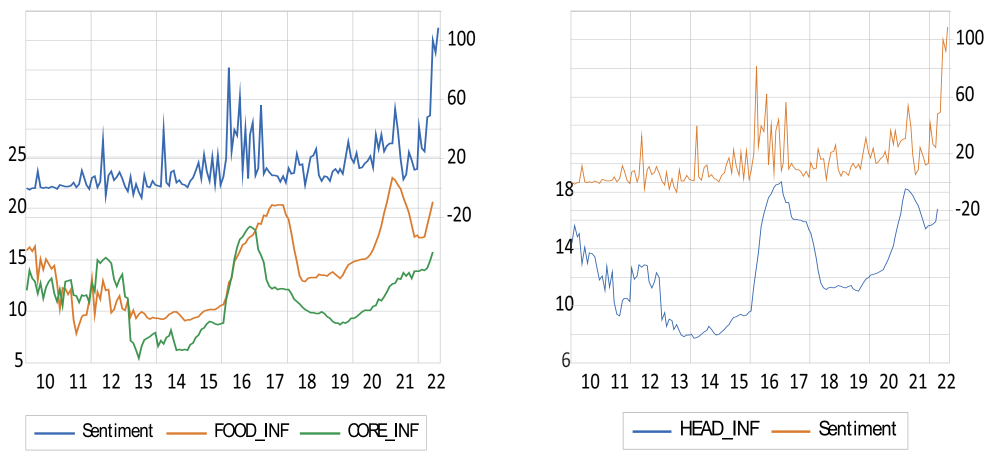
5.0 RESULTS

5.1 Trend and Correlation Analysis

Figure 9(a) and (b) present time series plots of the computed inflation perception index as well as the food, core, and headline measures of inflation. The index exhibited a clear upward and deterministic trend, with a similar trend observed in food and core measures of inflation, especially during the recession period of 2016 to 2017 and COVID-19 period of 2019 to 2022. Also, periods of high outcomes of food and core inflation were associated with periods of spikes in the computed inflation perception index. In Figure 9(b), the computed inflation perception index and headline inflation appear to co-move as is the case with food and core inflation in Figure 9(a). These tend to show that the inflation perception index could be a useful predictor of inflation in Nigeria.

Figure 9: Time Series Plot of Inflation Measures and the Inflation Perception Index

(a) **(b)**



Source: Authors' computation.

The results presented in Figures 9(a) and (b) are supported by the results of the dynamic correlations among the model variables. Food inflation recorded the highest (52.0 per cent) contemporaneous correlation with the inflation perception index, followed by headline inflation at 48.0 per cent. A higher level of correlation was observed between food inflation and the inflation perception index from the first to the ninth lag of the index). The dynamic correlation between core inflation and the inflation perception index was observed to be stronger from the 6th lag to the 12th lag of the index, while the correlation between headline inflation and the index was strong only at the 5th lag of the index.

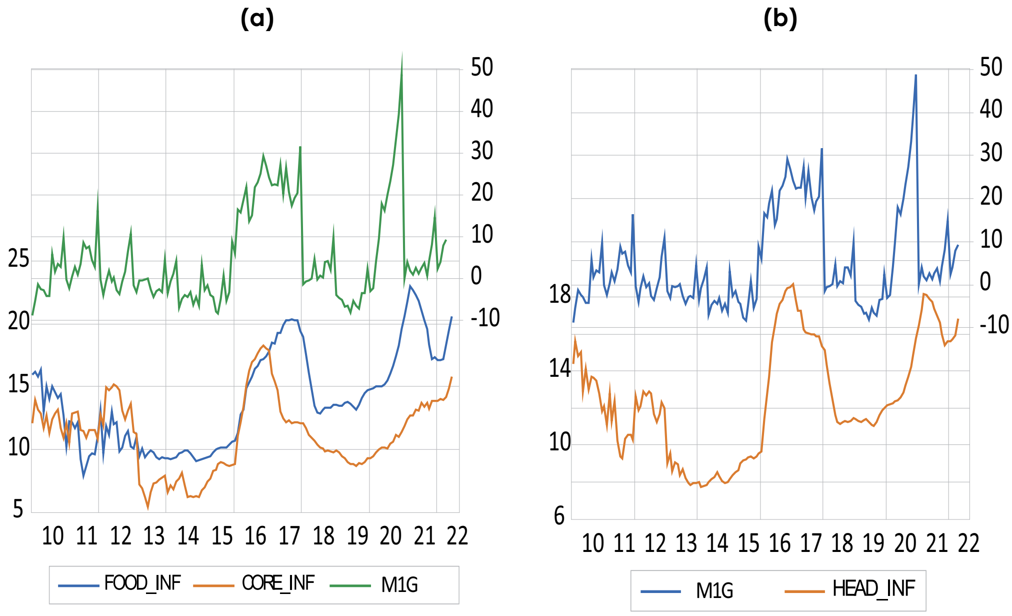
Table 3: Dynamic Correlations between Inflation Perception Index and Inflation

	Headline Inflation (HEAD_INF)	Food Inflation (FOOD_INF)	Core Inflation (CORE_INF)
SENTIMENT	0.48	0.52	0.25
SENTIMENT1	0.51	0.54	0.33
SENTIMENT2	0.55	0.57	0.41
SENTIMENT3	0.57	0.58	0.47
SENTIMENT4	0.58	0.59	0.48
SENTIMENT5	0.60	0.58	0.54
SENTIMENT6	0.61	0.56	0.62
SENTIMENT7	0.59	0.51	0.65
SENTIMENT8	0.57	0.50	0.63
SENTIMENT9	0.56	0.50	0.58
SENTIMENT10	0.5	0.46	0.56
SENTIMENT11	0.45	0.41	0.49
SENTIMENT12	0.39	0.34	0.44

Source: Authors' computation.

Figure 10 shows the relationship between growth in narrow money and components of inflation. In Figure 10(a), it can be observed that narrow money growth and the food and core inflation move in the same direction, with changing growth in narrow money driving changes in the three measures of inflation.

Figure 10: Time Series Plot of Narrow Money Growth and Inflation (Headline, Food and Core)



Source: Authors' computation.

The degree of correlation was observed to be stronger between headline inflation and narrow money growth up to its 4th lag, while the lags of narrow money growth (which started from the 5th to the 12th lag) were stronger with food inflation. Though positive, the correlation between narrow money growth and core inflation does not exhibit relationships superior to those highlighted by headline or food inflation.

Table 4: Dynamic Correlation between Narrow Money Growth and Inflation

	Headline Inflation (HEAD_INF)	Food Inflation (FOOD_INF)	Core Inflation (CORE_INF)
M1G	0.61	0.53	0.53
M1G1	0.64	0.58	0.54
M1G2	0.66	0.62	0.54
M1G3	0.69	0.66	0.54
M1G4	0.70	0.69	0.52
M1G5	0.69	0.70	0.50
M1G6	0.66	0.69	0.46
M1G7	0.63	0.67	0.44
M1G8	0.58	0.64	0.41
M1G9	0.54	0.61	0.37
M1G10	0.48	0.56	0.32
M1G11	0.42	0.5	0.28
M1G12	0.37	0.45	0.24

Source: Authors' computation.

5.2 Model Results

5.2.1 Food Inflation Models

Table 5 displays the parameter estimates of the benchmark and improved STIF models. Food inflation is driven by its one period lag, narrow money growth (M1G) lagged three months, non-manufacturing PMI (NPMI), rainfall (RAINFALL), the lag of rainfall (RAINFALL(-1)), as well as some seasonal and trend factors.

Table 5: The Estimated Food Inflation Models

Variable	Without Sentiment Coefficient	Without Sentiment Prob.	With Sentiment Coefficient	With Sentiment Prob.
FOOD_INF(-1)	0.92	0.00	0.89	0.00
M1G(-3)	0.03	0.00	0.03	0.00
LOG(NPMI)	0.61	0.08	0.61	0.08
LOG(RAINFALL)	-0.09	0.04	-0.08	0.10
LOG(RAINFALL(-1))	0.12	0.01	0.10	0.06
@SEAS(12)	0.34	0.11	0.35	0.10
@TREND	-0.61	0.00	-0.55	0.00
@TREND^2	0.00	0.00	0.00	0.00
@TREND^3	0.00	0.00	0.00	0.00
SENTIMENT			0.01	0.17

Source: Authors' computation.

The model with the sentiment includes all variables mentioned above and the constructed inflation perception index. Most of the model coefficients conform to a priori expectations and are significant at 5.0 per cent significance level for both models (with and without the inflation perception index). A unit increase in food inflation in the previous period leads to 0.92 increase in food inflation in the current period. In the case of non-manufacturing PMI, it is expected that increased business activities in the non-manufacturing sectors would increase inflationary pressure, contrary to our a priori expectation. An increase in rainfall has a dampening impact on food inflation, especially under the benchmark model. Sufficient rainfall improves agricultural output, thereby exerting downward pressure on food prices. The inflation perception index, though correctly signed, was insignificant. These results imply that food inflation in Nigeria is largely driven factors other than the inflation perception index.

5.2.2 Core Inflation Models

Table 6 shows the estimated coefficients and significant levels of the explanatory variables, namely, the index of narrow money and non-agricultural output (NARI), the exchange rate (IEW), manufacturing PMI (PMI), and the sentiment index (SENTIMENT). The one period lagged core inflation and exchange rate were found to be statistically significant at the 1.0 per cent level.

Table 6: The Estimated Core Inflation Models

Variable	Without Sentiment Coefficient	Without Sentiment Prob.	With Sentiment Coefficient	With Sentiment Prob.
CORE_INF(-1)	0.61	0.00	0.62	0.00
NARI	0.00	0.91	0.00	0.95
NARI(-1)	0.00	0.74	0.00	0.77
NARI(-2)	0.00	0.70	0.00	0.72
NARI(-3)	0.00	0.96	0.00	0.92
LOG(IEW)	12.67	0.00	12.51	0.00
LOG(PMI)	0.62	0.21	0.62	0.21
@TREND	-0.61	0.00	-0.60	0.00
@TREND^2	0.00	0.00	0.00	0.00
@SEAS(1)	0.31	0.02	0.31	0.02
SENTIMENT			0.00	0.72

Source: Authors' computation.

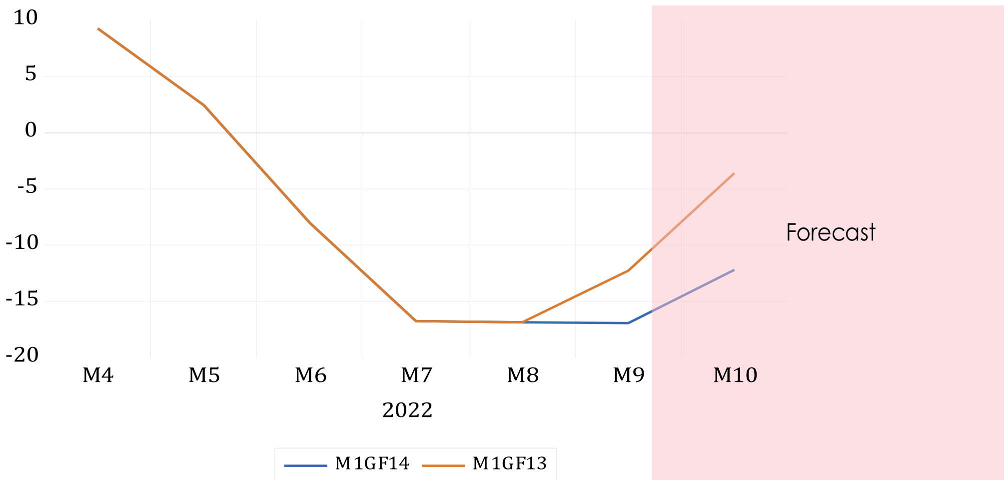
An exchange rate (depreciation) increase is supposed to adversely affect core inflation by raising the price level. The parameter for (NARI), explains the interaction of growth of non-agricultural production, that is, what is produced in the non-agricultural sector and narrow money growth. If this index is positive, there is expected upward pressure on core inflation. As with food inflation, the inflation perception index is correctly signed but statistically insignificant.

5.3 Forecasting Inflation using Sentiment Index

The study documented better forecasting performance of the IPI-augmented STIF model in both in-sample and out-of-sample forecasts. In generating out-of-sample forecasts of food, core, and headline inflation for 2022M8 to 2022M10, we made the following assumptions:

- MPR was kept at 14.0 per cent over the forecast horizon. This assumption is in line with the current value of MPR, which was adjusted upwards in July 2022 in reaction to the prevailing inflationary pressure in the country. In another scenario, MPR was assumed to remain constant at 13.0 per cent across the forecast horizon.
- The exchange rate at the Importer's and Exporter's window was kept at ₦417.38/USD$, representing its average value in July 2022.
- NPMI was kept at 50.4, being its value in July 2022.
- Rainfall was assumed to exhibit similar cycles as recorded in previous years.
- The narrow money growth (M1G) was specified as a function of MPR, an autoregressive term, and seasonal factors. Figure 11 shows that M1G was expected to rise steadily across the forecast period, albeit with a delay of 1 month under a scenario of MPR = 14.0 per cent.

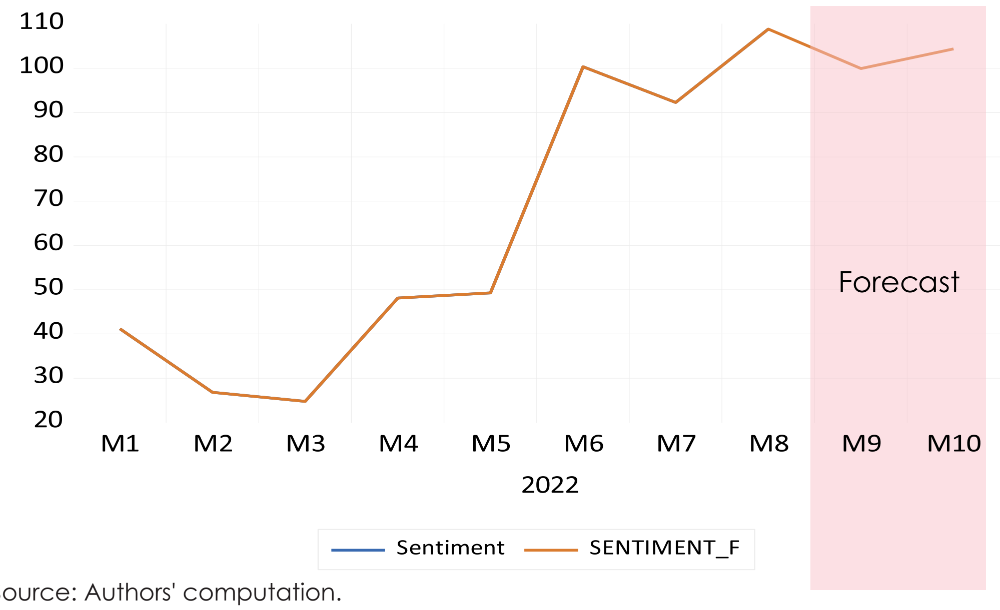
Figure 11: Narrow Money Growth Forecast



Source: NBS and Authors' computation.

The forecast of the inflation perception Index shown in Figure 12, reveals a moderation in its outlook over the forecast horizon.

Figure 12: Sentiment Index Forecast

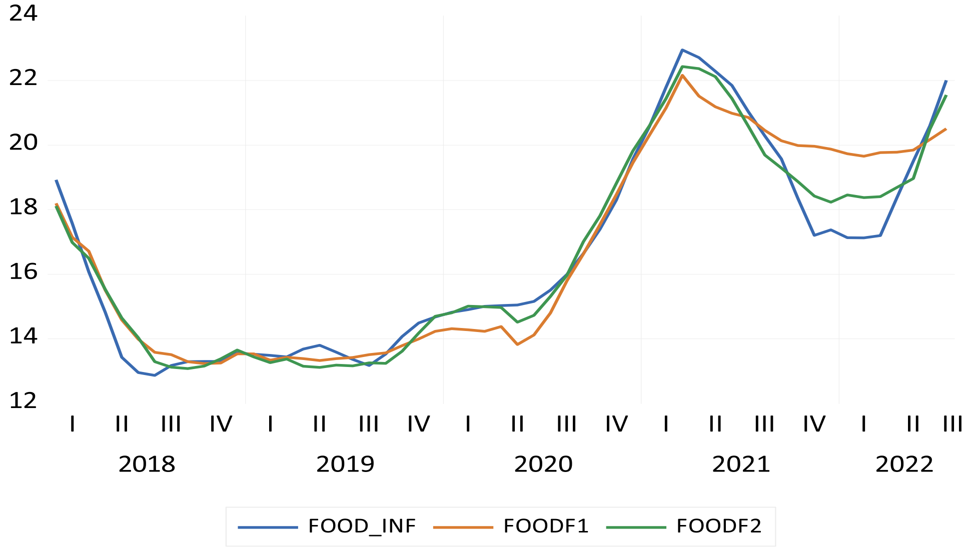


Source: Authors' computation.

5.4 In-sample Forecast Evaluation

This section discusses the forecast performance of the benchmark and improved STIF models. An ex-post forecast analysis was conducted to ascertain the predictive power of the estimated models and examine if the inclusion of the inflation perception index improves inflation forecasts for both food and core measures of inflation. The accuracy of the forecasts is evaluated using the Mean Squared Error (MSE), which measures the quality of point forecasts by showing how close the observed data points are to the predicted values. The model was estimated for 2018M01 to 2021M12, and in-sample forecasts were generated for the same period.

Figure 13: In-sample Forecast of Food Inflation

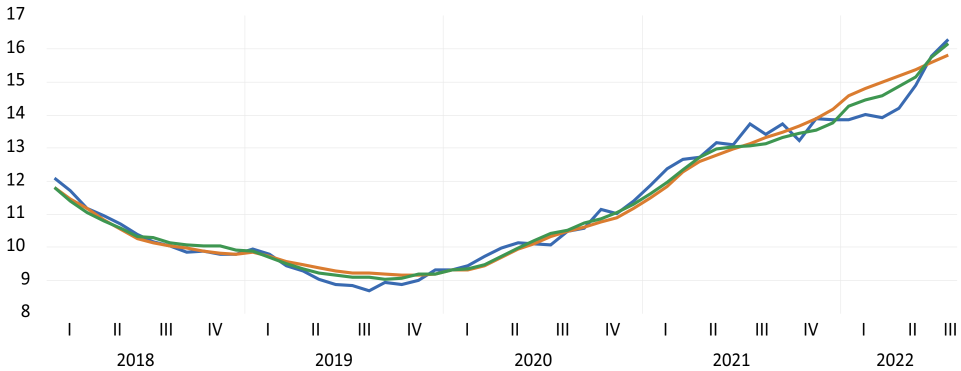


Source: Authors' computation.

Note: FOOD_INF are actual values of food inflation, while FOODF1 and FOODF2 represent forecasts based on the benchmark and improved STIF models, respectively.

The graph above presents the actual and predicted values of food inflation generated based on the models with and without the inflation perception index. This reveals that the benchmark model produces forecasts that mimic food. Likewise, the improved model, which includes the perception index, predicts food inflation quite well as most turning points were sufficiently captured. However, a cursory examination reveals that the improved model outperformed the benchmark model. This can be seen in the peaks and troughs of the series. Specifically, during the peak of food inflation in 2021M03, the gap between the actual and predicted values was narrower under the improved model, implying that the computed inflation perception index contains useful information for predicting future outcomes of food inflation. By implication, the forecast errors are expected to be lower under the improved model, making it a preferred model for forecasting food inflation in Nigeria.

Figure 14: In-sample Forecast of Core Inflation

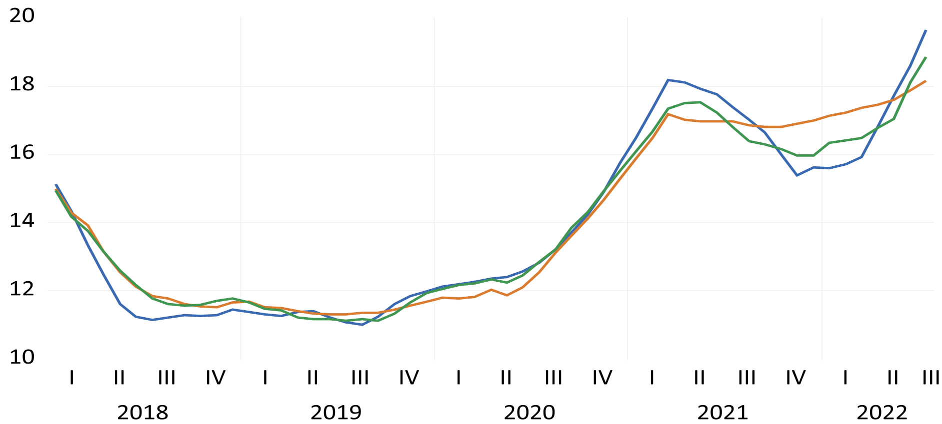


Source: Authors' computation. .

Note: CORE_INF are actual values of core inflation, while COREF1 and COREF2 represent forecasts based on the benchmark and improved STIF models, respectively.

Figure 14 presents actual and forecast values generated from the benchmark, and the improved STIF models. Both models produced fairly accurate predictions of core inflation with the improved model performing better than the model without inflation perception index particularly post-2020.

Figure 15: In-sample Forecast of Headline Inflation



Source: Authors' computation.

Note: HEAD_INF are actual values of headline inflation, while HEADF1 and HEADF2 represent forecasts based on the benchmark and improved STIF models, respectively.

Figure 15 presents the actual headline inflation and forecast values of headline inflation under the benchmark model and improved STIF model. Consistent with the forecast performances for food and core measures of inflation, the predicted values of headline inflation based on both models mimicked the actual headline inflation. However, a cursory examination reveals that the margin of errors is lower under the improved model as the gaps between the actual and predicted values were narrower than those obtained under the benchmark model. Thus, we can conclude that the computed inflation perception index improved the forecast of headline inflation.

Table 7: Mean Squared Errors from the In-sample Forecasts

Food		Core		Headline	
Without sentiment	With sentiment	Without sentiment	With sentiment	Without sentiment	With sentiment
1.020	0.297	0.123	0.070	0.463	0.185

Forecast Gain (%) 70.9 43.1 60.0

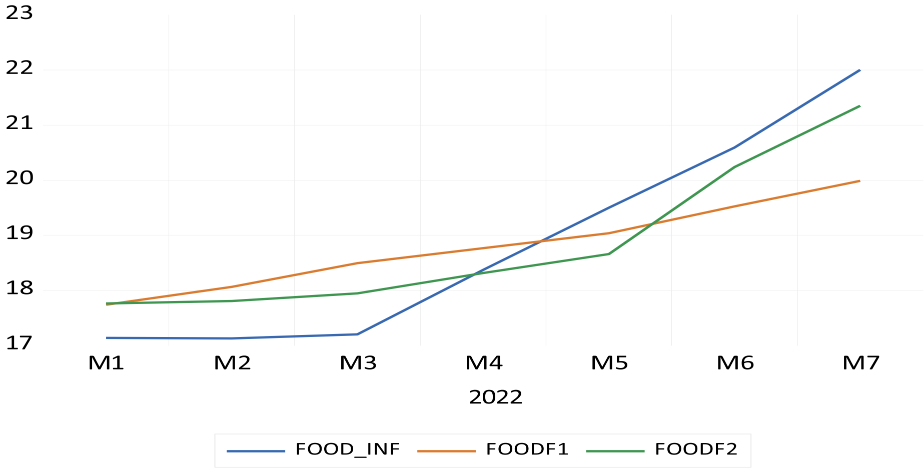
Source: Authors' computation.

Using the MSE criteria, it is evident that the improved models provide more accurate forecasts of the three measures of inflation than the benchmark STIF as it recorded lower MSE values. The improved model recorded the highest forecast gain under the food inflation as an improvement of 70.0 per cent was observed. The in-sample forecast gain for headline inflation was 60.0 per cent, while core inflation recorded the least gain of 43.1 per cent.

5.5 Out-of-sample Forecast Evaluation

To evaluate the out-of-sample forecast performance of the improved model, we produced forecasts of core and food measures of inflation over a seven-period horizon, covering the period 2022M01 to 2022M07. After that, we measured the forecast errors using the MSE across the forecast horizons. This process was also applied to the benchmark model to facilitate comparison of forecast performance across the two models

Figure 16: Out-sample Forecast of Food Inflation

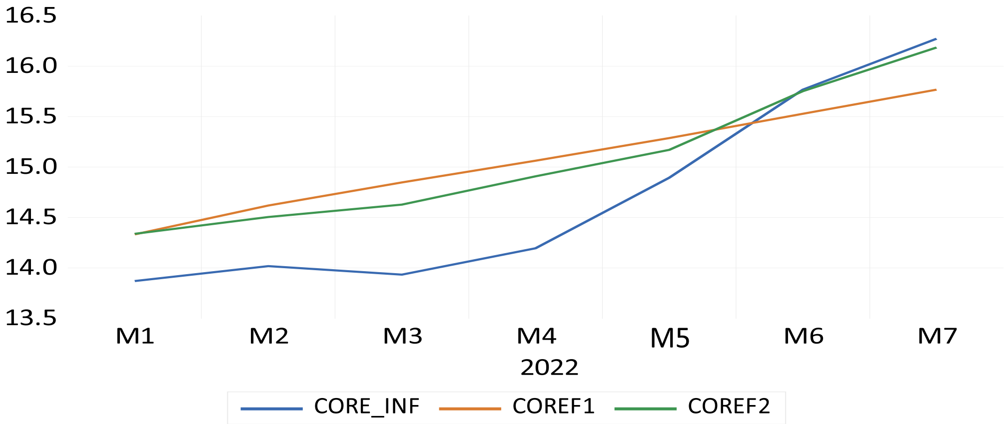


Source: Authors' computation.

Note: FOOD_INF are actual values of food inflation, while FOODF1 and FOODF2 represent forecasts based on the benchmark and improved STIF models, respectively.

Figure 16 above presents a plot of the actual food inflation alongside the forecasts generated from the benchmark and improved STIF models. The predicted values of food inflation based on the improved model mimicked the actual values of food inflation better than those generated from the benchmark model. In addition, compared with the improved model, the benchmark model appeared to substantially overpredict food inflation at shorter forecast horizons (M1 – M4) and under-predict at longer forecast horizons (M5 – M7).

Figure 17: Out-sample Forecast of Core Inflation

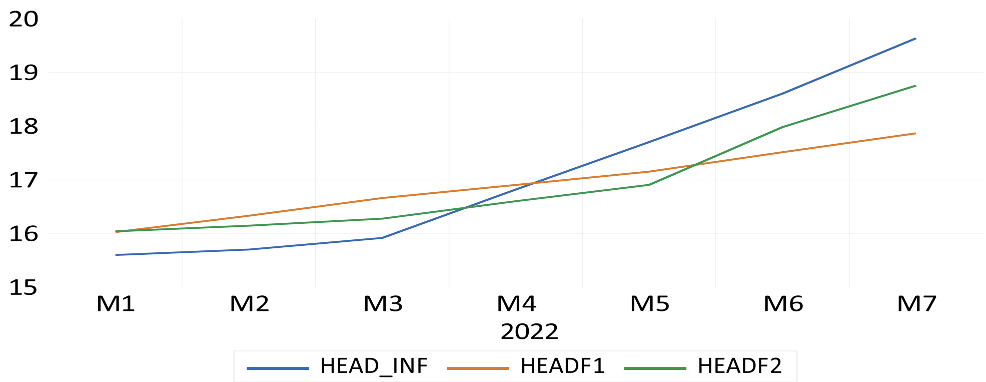


Source: Authors' computation.

Note: CORE_INF are actual values of core inflation, while COREF1 and COREF2 represent forecasts based on the benchmark and improved STIF models, respectively.

The actual and forecast values of core inflation are shown in Figure 17. A cursory examination of the chart reveals that the forecast values of core inflation obtained from the improved model better mimic the turning points of the actual core inflation series, indicating the superiority of the improved model over the benchmark STIF.

Figure 18: Out-sample Forecast of Headline Inflation



Source: Authors' computation.

Note: HEAD_INF are actual values of headline inflation, while HEADF1 and HEADF2 represent forecasts based on the benchmark and improved STIF models, respectively.

The out-of-sample forecasts of headline inflation, covering the period 2022M1 to 2022M7, are presented in Figure 18. These results further confirm the role of the computed inflation perception index in predicting inflation in Nigeria

Table 8: Mean Square Errors from the out-sample forecasts

Food		Core		Headline	
Without sentiment	With sentiment	Without sentiment	With sentiment	Without sentiment	With sentiment
1.21	0.38	0.38	0.22	0.82	0.34

Source: Authors' computation.

Using the MSE criterion, it is evident that the improved models provided more accurate forecasts of the three inflation types than the benchmark STIF given the lower MSE values.

Table 9 presents the forecasts of the three measures of inflation using the improved STIF model. The results showed that core and food measures of inflation are expected to rise slightly in August and September. However, food inflation, which accounts for 51.8 per cent in the CPI basket, is expected to moderate slightly in October, while the core, which contributes 48.2 in the CPI basket, is expected to further rise in the same month. The net impact on the headline is a marginal increase in August 2022, September 2022, and October, 2022.

Table 9: Forecasts of Inflation

	Food Inflation (Food_INF)	**Core Inflation (Core_INF)**	**Headline Inflation (Head_INF)**
2022M6	20.60	15.75	18.60
2022M7	22.02	16.26	19.64
2022M8f	22.91	16.74	19.81
2022M9f	23.08	17.06	20.05
2022M10f	23.00	17.38	20.17

Source: Authors' computation.

6.0 SUMMARY AND POLICY IMPLICATIONS OF FINDINGS

6.1 Summary

The study explored the usefulness of big data sources and techniques in deriving an index of public perception about inflation with a view to using same to improve the forecast performance of Nigeria's short-term inflation forecasting model (STIF).

The results showed that the computed inflation perception index was strongly correlated with the headline, core, and food measures of inflation. The study also documented the usefulness of the inflation perception index as its inclusion to the benchmark STIF led to substantial improvements in its forecast performance. In other words, the inclusion of the index provided more accurate in-sample and out-of-sample forecasts of inflation.

The study concluded that the computed text-based inflation perception index contains useful information for improving the forecasts of inflation in Nigeria.

6.2 Implications of Findings

I. Given the impact of the inflation perception index on the forecast accuracy of the benchmark STIF model, the Bank should consider incorporating the index in its inflation forecasting models;

II. The Bank should consider developing a unified framework for extracting and processing social media data for its analyses;

III. The bank should consider employing the inflation perception index to fine-tune its communication to anchor inflation expectations;

IV. Given the finding that narrow money has a significant effect on inflation, it is suggested that the Bank intensifies effort in encouraging savings to shift money holdings to other instruments away from cash and checking accounts;

V. With the evidence that consumer sentiments drive inflation, Management may consider complementing the available suite of monetary policy instruments with forward guidance in the form of "open mouth operations";

VI. As the MPR shows potency in controlling money supply, there is a need to strengthen liquidity management and other monetary operations to optimise the transmission mechanism of monetary policy;

VII. The Bank should sustain the various interventions that increase real output as a means of reining in inflation from the supply side; and

VIII. To address inflation upsurge from exchange rate pass-through, the Bank should sustain the current foreign exchange management framework to attract and conserve external reserve position of the country.

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