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Forecasting Nigerian Inflation using Model Averaging methods: Modelling Frameworks to Central Banks[1]

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Abstract
As a result of the adverse macroeconomic effect of inflation on welfare, fiscal budgeting, trade performance, international competitiveness and the whole economy, inflation still remains a subject of utmost concern and interest to policy makers. The traditional Philips curve as well as other methodologies have been criticized for their inability to track correctly the pattern of inflation, particularly, these models do not allow for enough variables to be included as part of the regressors, and judgment is often made by a single model. In this work, model averaging techniques via Bayesian and frequentist approach were considered. Specifically, we considered the Bayesian model averaging (BMA) and Frequentist model averaging (FMA) techniques to model and forecast future path of CPI inflation in Nigeria using a wide range of variables. The results indicated that both in-sample and out-of-sample forecasts were highly reliable, judging from the various forecast performance criteria. Various policy scenarios conducted were highly fascinating both from the theoretical perspective and the prevailing economic situation in the country.

Key words: Bayesian model averaging; Forecasting; Frequentist approach; Inflation rate; Nigeria

1. Introduction

The need to ensure an effective conduct of monetary policy by the central bank has made inflation forecasting very essential. Due to the traditional argument of lags in the monetary policy transmission mechanism, inflation forecast therefore plays a crucial role in the conduct of monetary policy. There are long lags between monetary policy actions and their impact on the economy. Policies responding only to the current state of the economy may not prove to be good stabilizers, therefore, it is generally recognized that central bank policies must be far-sighted.

[1] This is part 2 of the abridged version of the full report on Forecasting and Determining the Predictors of Inflation in Nigeria: A Bayesian Model Averaging Approach, submitted to the Department of Statistics, Central Bank of Nigeria.

There is no gainsaying the fact that a lot of progress and development has been made in terms of both theoretical and econometric modelling in the recent times, and forecasting inflation remains an arduous task requiring more attention and efforts. With the rapid changes in the Nigerian economy often caused by different shocks, the task of forecasting inflation has become even more difficult. The ambiguous and changing structure of the Nigerian economy further complicates this task. However, producing a real-time macroeconomic forecasting particularly, in a developing economy like Nigeria is such a complex and challenging problem. In advanced economies, forecasting process often employs a variety of formal models, which include structural and purely statistical. The forecasts of inflation are usually developed through an eclectic process that combines model-based projections, anecdotal and other "extra model" information as well as professional judgement.

The most common tool for inflation forecasting is probably the Phillips curve which uses a single measure of economic slack such as unemployment to predict future inflation. The Phillips curve equation uses the rate of unemployment or some other aggregate economic measures in predicting inflation rate. Some recent specifications of Phillips curve equations relate the current rate of unemployment to future changes in inflation rate. The main idea behind this specification is that there is a baseline rate of unemployment at which inflation tends to remain constant. There is, the popular feeling that inflation tends to rise over time when unemployment is below this baseline rate, and inflation falls when unemployment is above this baseline rate. The term non-accelerating inflation rate of unemployment (NAIRU) is used to describe this baseline unemployment rate. Hence, modern specifications based on it are referred to as NAIRU Phillips curves.

The NAIRU Phillips curves have become so popular in academic literature on inflation forecasting, and among policy making institutions, because of the view that inflation forecasts from these models are more accurate than forecasts from other models. Indeed, Blinder (1997) argues that “the empirical Phillips curve has worked amazingly well for a decade” and then concludes based on this empirical success that a Phillips curve should have “a prominent place in the core model” used for macroeconomic policy making purposes. The literature on studies based on the extension of Phillips curve is rather too voluminous but a few representative and prominent ones include Stock and Watson (1999), Ang et al. (2007), Stock and Watson (2008) and Groen et al. (2009).

However, the usefulness of Phillips curve for predicting inflation has been challenged and questioned by many authors. For instance, Atkeson and Ohanian (2001) obtained a short-run variant of the curve by regressing the quarterly change in the rate of inflation on the unemployment rate with a constant. The study shows that the short-run Phillips curve does not represent a stable empirical relationship that can be exploited for constructing a reliable inflation forecasts. The regression coefficient on the unemployment rate (which measures the slope of the short-run Phillips curve) varies significantly across different sample periods.

Substantial progress has been made by researchers in the aspect of using many predictors in forecasting inflation. Information in these large variables is combined in a sensible manner to prevent the estimation of a large number of unrestricted parameters. Stock and Watson (2001, 2002) submit that the best predictive performance is obtained by averaging forecasts constructed from several models. This popular approach is referred to in the literature as the Bayesian Model Averaging (BMA), initiated by Leamer (1978). BMA efficiently and systematically evaluates a wide range of predictor variables for inflation and (almost) all possible models that these predictors in combination can give rise to. Using the posterior probabilities of the models, weights are assigned to the different models to obtain a weighted model averaging.

In the present paper, the burning research questions is: How does a single model perform relative to averaging of several potential models in terms of forecasts? Therefore, the overarching objective of this paper is to analyse a wide spectrum of CPI inflation predictors and all possible models that can arise from combining the models using Bayesian Model Averaging. Specifically, the study objectives to be pursued are to: (1) analyse and forecasts from all the models combining predictors of price inflation based on BMA approach; and, (3) make policy scenarios based on the BMA forecasts.

The structure of the paper is as follows: Section 1 introduces the work. Section 2 reviews available literature on inflation modelling by apex banks, African banks, international monetary organizations, the Central Bank of Nigeria and individual researchers. Section 3 presents methodology on model averaging techniques, that is, the FMA and BMA. Section 4 presents the data, empirical results as well as some policy scenarios. Section 5 gives the summary, conclusion and renders policy implications.

2. Review of Literature

Various inflation forecasting models have been applied in forecasting inflation rates in apex banks of developed and developing countries. In Bank of Japan, Fujiwara and Koga (2002) presented a statistical forecasting method (SFM) that related many economic and financial time series data without making structural assumptions other than setting up the underlying variables. The SFM was built on many VAR models from combinations of the underlying variables. The data considered were the CPI, domestic wholesale price index, import price, industrial production index, investment, unemployment rate, monetary aggregate, government bond yield and effective exchange rate. The result showed that SFM could provide reliable forecasts information that cannot be extracted when a single structural-type estimating is used.

Bruneau et al. (2003) assessed the usefulness of dynamic factor models of Bank of France for generating headline and harmonized index of consumer prices (HICP) inflation forecast for the Euro area. The authors applied Stock and Watson’s (1999) out-of-sample methodology and estimated within the sample period 1988:01 and 2002:03 for inflation, with balanced and unbalanced panels. The total HICP, as well as its five main sub-components (manufacturing, services, processed food, unprocessed food and energy were used across the Euro countries. Their results showed evidence to support the improvement of factor/or combined factors in modelling than using the simple AR model for forecasting HICP core inflation and total inflation, and the overall results were found to be robust to potential data-snooping.

Since 2011, the Bank of England inflation forecasting platform developed a Central Organizing Model for Projection Analysis and Scenario (COMPASS). The model was designed to organize framework for predicting inflation. The model is a New Keynesian, Dynamic Stochastic General Equilibrium (DSGE) model estimated using Bayesian methods. From the onset, before the inception of Monetary Policy (MPC), the bank focused on both GDP and inflation (Bank of England, 2015), while MPC introduced other nine variables. Altogether, the Bank of England considered, in modelling and forecasting inflation, variables such as the real GDP, inflation, the unemployment rate, real private consumption, real total investment, nominal wages, nominal house prices, nominal household lending, nominal corporate lending, US real GDP and euro-area real GDP. The accuracy of Bank forecasts were then compared to forecasts from simple model, and for a subset of those eleven variables. The forecasts accuracy was also compared with UK private sector forecasters and other central banks, and the results indicated that Bank forecasts based on COMPASS resulted in smallest forecasts error as compared to other forecasts from other private sectors and other central banks (Bank of England, 2015).

In South African Reserve Bank, Fedderke and Liu (2016) considered the relative performance of models for forecasting inflation. These models included the classical Phillips curve, NKPC, monetarist and structural models for inflation. The variables considered with inflation included excess demand, unit labour cost, nominal wage rate, real labour productivity, exchange rate, real wage, supply-side shock, money balances, government expenditure and government surplus/deficit. By decomposing unit labour cost into changes in the nominal wage and real labour productivity, the authors found a strong positive association between inflation and nominal wages, while they observed weak negative association between real labour productivity and inflation. On the long run, supply side shocks revealed significant association with inflation, while as to demand side shocks, the output gap does not return a robust statistical association with inflation but growth in the money supply and government expenditure indicated consistent association with inflationary pressure.

Gaomab (1998) reviewed inflation dynamics for Namibian Bank for the past 24 years using data spanning between 1972 and 1996. The model applied cointegration technique and ECM, both with structural stability tests in making time series forecasts. The variables considered were the CPI, real GDP, broad money supply, nominal interest rate, US dollar ex change rate, South African CPI and US CPI. The results showed dominant influence of South African macroeconomy on Namibian inflation. On the long run, US economy, representing the influence of the rest of the world, also has considerable influence on Namibian prices.

Waiquamdee (2001) presented a Bank of Thailand Macroeconomic Model (BOTMM) which is a system of equations representing transmission mechanisms in the economy and the relationships among economic variables. This model gives information on the prospects for growth and inflationary trend and assists in monetary policy decisions. The BOTMM system incorporates a total of 17 equations with ECM properties. These are equations on consumption, private investment, volume of export and import, energy price, domestic retail oil price, public investment deflator, government consumption deflator, and export and import prices. The BOTMM has been in existence for the Bank since 1999 and has been providing satisfactory results, except with the limitation that it allows for short-period of observations and the coefficients in some equations are not stable.

Gonzalez et al. (2006) developed a short-run food inflation model to predict inflation in Colombia. The model disaggregated food items based on economic theory and employed least squares method with structural breaks in its specification. The results obtained indicated significant improvement of the model when food items were disaggregated into processed foods, unprocessed foods and food away from home. The findings further suggested the importance of combining forecasts from alternative models.

Bjornland et al. (2009) developed a system for generating model-based forecasts for Norwegian inflation rates by using a set of five models: the ARIMA, vector autoregressive (VAR), Bayesian VAR (BVAR), error correction models (ECM), factor model and dynamic stochastic general equilibrium (DSGE) models with each model having several model variants, resulting in a total of 80 model combinations. The variables considered were the GDP, interest rates, inflation, exchange rate, terms of trade, oil price, consumption growth, investment growth, export growth, employment rate and real wage growth. The data were sampled between 1987Q1 to 1998Q4, and forecasts were generated recursively from 1999 to 2008, and the performance of these models over this period was then used to derive weights that were used to combine the forecasts. The results showed that model combinations approach improved upon the point forecasts from individual models and outperformed Norges Banks forecasts for inflation. Norman and Richards (2010) estimated a range of single-equation models for Australian inflation. Having considered standard Phillips curve, the New-Keynesian Phillips Curve (NKPC) and other mark-up model on quarterly headline CPI, output gap, unit of labour costs growth and import prices, the standard Phillips curve model emerged the best, followed by the mark-up model in forecasting CPI inflation.

As reported in Figueiredo (2010), the Central Bank of Brazil applied a Bayesian VAR model with principal components and other model combinations such as unrestricted VAR, partial least square methodology (PLS), factor analysis and principal component model in forecasting inflation in Brazil. The author considered the real interest rate, nominal interest rate, money stock, industrial output, nominal exchange rate, regulated price and market price. It was found that the best forecasting model emerged when the forecasts were generated at 6-step ahead. Furthermore, factor model with targeted predictors presented the best forecast results, while PLS showed relatively poor result. The work further recommended the use of other rich-data approach such as the Bayesian Model Averaging (BMA) in modelling inflation. Younus and Roy (2016) applied Unrestricted VAR model in forecasting inflation rates in Bangladesh. The authors considered data spanning between July 2006 and June 2016. In the VAR system, real GDP growth rate, money supply (M2), private sector credit, exchange rate, and world food price index were considered along with the inflation rate. The result of the VAR model indicated strongest contribution of money supply (M2) and interest rates in predicting inflation rate.

Giannone et al. (2014) applied Bayesian Vector Autoregressive (BVAR) model to investigate the interrelationships between main components of the Harmonized CPI and its determinants and obtained reliable forecasts. Altug and Cakmakli (2015) formulated a statistical model that combined survey data on inflation expectations with actual inflation data on Brazil and Turkey. The authors considered the state space model; an autoregressive model; a backward-looking Phillips curve and a hybrid New Keynesian Phillips Curve. The results obtained indicated clear alignment of inflation forecasts with survey expectations, that is, the results showed superiority of predictive power of the proposed framework over the models without survey expectations.

In the case of Nigeria, Doguwa and Alade (2013) used four short term inflation forecasting models for Nigeria within the context of SARIMA and SARIMAX. They utilized monthly data from July 2001 to September 2013 across fourteen (14) variables sub-divided into endogenous and exogenous variables. The endogenous variables include consumer price index, Food consumer price index and core consumer price index. The endogenous variables comprises of price of petroleum motor spirit per litre, central government expenditure, nominal Bureau-de-change exchange rate, broad money supply, official nominal exchange rate, reserve money, net credit to central government, credit to private sector, average monthly rainfall in cereals producing north central zone and average monthly rainfall in vegetables producing southern zone. They found parsimonious SARMAX model to be relatively more effective in predicting inflation. Okafor and Shaibu (2013) adopted a univariate autoregressive integrated moving average (ARIMA) as suggested by Box and Jenkins (1976) to model and forecast inflation for Nigeria using CPI data from 1981 to 2010. The result found ARIMA (2,2,3) as the most adequate for the country as the in-sample forecast and the estimated ARIMA tracked fairly well the actual inflation for the sampled period. They submitted that inflation expectation largely drives actual inflation in Nigeria, hence advocated for monetary policy transparency. Omekara, Ekpenyong and Ekerete (2013) were of the view that inflation in Nigeria is periodic in nature. They used Periodogram and Fourier series analysis from 2003 to 2011 to model Nigerian monthly inflation rates. They attributed the periodicity of inflation rate to variations in government administration. The forecasts generated were found to be accurate for Nigeria.

Using monthly CPI data from 2003 through 2011, Amadi, Gideon and Nnoka (2013) proposed SARIMA (1,1,0) x (1, 1, 1) to be the most reliable model for monthly inflation rate of Nigeria. In their study on modelling and forecasting inflation for Nigeria, Otu et al. (2014) explored ARIMA in line with Box and Jenkins using monthly data covering the period October 2003 to November 2013. The out-of-sample forecast was between November 2013 and

November, 2014. They reported ARIMA (1,1,1)(0,0,1) as adequate for Nigeria. The study attributed the volatility of inflation in Nigeria to money supply, exchange rate depreciation, petroleum prices and low level of agricultural production.

Kelikume and Salami (2014) adopted a univariate model of the form of Box-Jenkins model and a multivariate model in the form of vector autoregression to forecast inflation for Nigeria using monthly data on changes in CPI and broad money supply from January 2003 to December 2012. The result, according to the authors reported the VAR model as the most adequate for forecasting inflation in Nigeria because it returned smaller RMSE. Adams et al. (2014) modelled the Nigerian CPI using ARIMA model in line with Box-Jenkins approach. They used CPI data between the period 1980 and 2010, and forecast for five years ahead (i.e. 2011 to 2015). The result favoured ARIMA (1, 2, 1) as the most suitable for Nigeria. Yemitan and Shittu (2015) employed Kalman filter technique to implement a state space model to forecast inflation for Nigeria using monthly data from January 1995 to December 2014. The authors introduced structural breaks to capture major political, monetary and macroeconomic events in the country. They concluded that Kalman filter technique is relatively more efficient than Box-Jenkins. They attributed the efficiency of Kalman filtration to availability of built-in which allows information update.

To test the efficacy of artificial neural networks (ANN) in inflation forecasting, Onimode et al. (2015) applied ANN and AR (1) on Nigeria monthly CPI data from November 2011 to October 2012 and submitted that neural network is more efficient than univariate autoregressive models in forecasting inflation up to four quarters ahead. Duncan and Martinez-Garcia (2015) using seasonally adjusted quarterly data on CPI from 1980Q1 to 2016Q4 of fourteen (14) Emerging Market Economies (EMEs) including Nigeria, adopted both Frequentist and Bayesian techniques to forecast inflation for Nigeria. The variable considered in the models include: exchange rate, commodity prices/index, global inflation and industrial production index. The findings support the adequacy of Random Walk based on Atkeson and Ohanian (RW-AO) as it produces the lowest RMSPEs. The authors therefore suggested that RW-AO should be used by the EMEs for inflation forecasting.

Employing a Univariate Autoregressive Integrated Moving Average (ARIMA) modelling in line with Box-Jenkins technique, Kuhe and Egemba (2016) forecasted inflation for Nigeria using annual CPI data from 1950 to 2014. They found ARIMA (3, 1, 0) to be the best fit for Nigerian CPI data. The out-of-sample forecast (i.e. 2015 to 2020) reveals a continuous rise in inflation throughout the period. In a comparative study to determine the more efficient model between ARIMA-Fourier and Wavelet models, Iwok and Udoh (2016) who obtained ARIMA-Fourier model by combining both the linear and sinusoidal components of the CPI utilized MSE, MAE, and MAPE of the two models to determine their adequacy and concluded that Wavelet model outperformed the ARIMA-Fourier model. They attributed the performance of Wavelet model to its flexibility in handling non-stationary data as well as the possibility of simultaneous utilization of information in both time-domain and the frequency domain. John and Patrick (2016) forecasted monthly inflation rate for Nigeria using data from January 2000 to June 2015 and found ARIMA (0,1,0) x (0,1,1) to be adequate because the in-sample forecast obtained was tightly close to the original series. Similarly, Chinonso and Justice (2016) applied Box-Jenkins ARIMA model on monthly urban and rural CPI from January 2001 to December 2015 to provide 29 months ahead inflation forecast for Nigeria. The study selected ARIMA (0,1,0), ARIMA (0,1,13) as the most suitable for forecasting inflation for Nigeria. By applying the VAR model, Inam (2017) determined and forecasted future path of inflation rate for Nigeria. The study utilized data on inflation rate, money supply, fiscal deficit, real exchange rate, interest rate, changes in import prices and real output over the period 1970 to 2012. The result conclude that immediate lag value of inflation largely fuels current and future inflation in Nigeria.

3. Methodology

3.1 Frequentist Model Averaging Technique

A sizable number of frequentist methods for model averaging have been developed in the literature, and a considerable number of them are on model selection methods. They are generally considered to be hard-threshold averages. The procedure described below follows the work of Moral-Benito (2015).

Consider the linear model in matrix form given as follows:

$$y = \beta X_A + X_B \gamma + \varepsilon \tag{1}$$

where y, X_A and ε are $T \times 1$ vectors of the dependent variable, the explanatory variable of interest and the random shocks, respectively. X_B is a $T \times k$ matrix of unsure or rather doubtful control variables which may or may not be included in the model, and β and γ $(k \times 1)$ contain the parameters to be estimated. There is altogether a total of 2^k possible models that can be estimated from (4) if we set some of the components of $\gamma = (\gamma_1, \gamma_2, ..., \gamma_k)'$ to be zeros, assuming that $\hat{\beta}_M$ is the estimator of β for the candidate model M such that $M \in (M_1, M_2, ..., M_{2^k})$. Generally, in many applied research, the practice is to take the selected model, and as given, and carry out statistical inference on this single estimate $\hat{\beta}_M$ while the actual estimator is:

$$\hat{\beta} = \begin{cases} \hat{\beta}_{M1}, & \text{if the first model is selected} \\ \hat{\beta}_{M2}, & \text{if the second model is selected} \\ . & \\ . & \\ . & \\ \hat{\beta}_{M2^k}, & \text{if the } 2^k \text{ - th model is selected} \end{cases} \tag{2}$$

Alternatively, (2) can be written as,

$$\hat{\beta} = \sum_{j=1}^{2^k} \tilde{\omega}_{M_j} \hat{\beta}_{M_j} \tag{3}$$

where $\tilde{\omega}_{M_j} = \begin{cases} 1, & \text{if the candidate model } M_j \\ 0, & \text{0therwise} \end{cases}$. The estimator in (3) suffers some major drawbacks particularly if model uncertainty is present, especially in the selection of the control variables for instance. Consider the smoothed weights ω_{M_j}, consequently therefore, the FMA estimator becomes:

$$\hat{\beta}_{FMA} = \sum_{j=1}^{2^k} \omega_{M_j} \hat{\beta}_{M_j} \tag{4}$$

where $0 \leq \omega_{M_j} \leq 1, \sum_{j=1}^{2^k} \omega_{M_j} = 1$. The FMA estimator of β given in equation (3) integrates model selection and parameter estimation. The asymptotic properties of the estimator has been discussed in Hjort and Claeskens (2003) and the asymptotic distribution is detailed in Claeskens and Hjort (2008). Notwithstanding, inference based on this limiting distribution still ignores the uncertainty involved in the model selection procedure because its variance is obtained by averaging the model specific variances. To overcome this challenge, Buckland *et al*. (1997) has proposed an alternative method to deal with the problem of misleading inference likely to arise if confidence intervals are constructed for FMA estimators. The method proposed takes extra model uncertainty into consideration by incorporating an extra term in the variance of the FMA estimator.

Another thorny issue with the FMA estimator is the choice of weights. The FMA estimator depends heavily on the weights selected for estimation. The weights can be fixed as noted earlier. However, the use of different weights will produce different asymptotic properties of the corresponding FMA estimators. Three classes of weight choice techniques have been proposed in the literature and they are well discussed in Moral- Benito (2015). The first is the weight choice based on information criteria which is probably the most commonly used approach in FMA. The different information criteria are of the form:

$$l_j = -2\log(L_j) + \varphi_j \tag{5}$$

where L_j is the maximized likelihood function for the *j*-th model, φ_j is a penalty term function of the number of parameters and/or the number of observations of model *j*. Consequently, Buckland *et al*. (1997) proposed the following as model weights:

$$\omega_{M_j} = \frac{\exp(-l_j/2)}{\sum_{h=1}^{2^k}\exp(-l_h/2)} \tag{6}$$

which are normalized to sum to unity.

Claeskens and Hjort (2003) proposed the use of the Focused Information Criterion (FIC) to select one single best model rather than information criteria such as the AIC and BIC in some circumstances. Such circumstances include when one model is best for estimating one parameter and another model is best for another parameter. It follows naturally that FIC can be employed as an alternative method of constructing FMA model weights. The second weight choice technique is based on Mallows' criterion. Mallows (1973) proposed a C_k statistic for model selection in linear regression. The C_k is defined as a criterion for selecting amongst *k* competing models with different number of parameters. It is defined as:

$$C_k = \frac{RSS(k)}{\sigma^2} - N + 2k \tag{7}$$

If model (k) is correct then C_k will tend to be close to or smaller than k. Therefore, a simple plot of C_k versus k can be used to decide amongst the model. Sequel to this, Hansen (2007) proposed to select the model weights in least-squares model averaging by minimizing the Mallows' criterion in what has now become Mallows Model Averaging (MMA) estimator. Although the MMA estimator is asymptotically optimal but the optimality fails under heteroscedasticity. Hansen (2008) considers forecast combination based on MMA. The method selects weights by minimizing a Mallows criterion. The third weight choice method is based on cross-validation criterion. The most recent paper on this is Hansen and Racine (2012) which proposes a Jackknife Model Averaging (JMA) for obtaining appropriate weights for averaging M models for improved estimation of an unknown conditional mean in the face of non-nested model uncertainty in heteroscedastic error settings. The JMA estimator selects weights by minimizing a cross-validation criterion. Unlike the MMA, the JMA is appropriate for more general linear models, that is, models with random errors with non-constant variances and where the candidate models can be non-nested.

3.2 Bayesian Model Averaging Technique

The use of BMA for forecast combination was first introduced by Min and Zellner (1993). The usefulness was demonstrated by Wright (2008, 2009). Stock and Watson (1999, 2004, 2005, 2006) have provided detailed empirical evidence demonstrating the gains in forecast accuracy through forecast combination, and have demonstrated the success of simple averaging (equal weights) along with BMA. The BMA implementation begins the formulation of all feasible models and specifying the prior beliefs about the probability that each model is the true one. After that the posterior probability that each model is the true one is computed. Finally, the forecasts from the different models are averaged using the posterior probabilities as weight.

This looks like a shrinkage methodology, but with the shrinkage over the possible models and not just over the parameters.

In situations where many potential explanatory variables exist, alternative models can be defined based on the set of explanatory variables they include. In general, if there are k potential explanatory variables in a study, then 2^k models are possible. It is obvious that as k gets larger, the number of possible models grows larger. Two major problems are usually confronted. First is how to handle this considerable number of models. The second relates to prior information about the models. These problems have largely been surmounted by Bayesian Model Averaging (BMA) as would be examined during this discussion.

Consider a linear regression model with a constant term, β_0, and k potential explanatory variables $X_1, X_2, ..., X_k$:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... \beta_k X_k + u \tag{8}$$

From model (8), there are 2^k different feasible models based on inclusion and exclusion of each regressor. If we let M_j for $j = 1, 2, 3, \dots, p$ denotes the different models under consideration, and having constructed the model space, the posterior distribution of any coefficient, say β_r, given the data D is:

$$\Pr(\beta_r|D) = \sum_{j:\beta_r \in M_j} \Pr(\beta_r|M_j, D) \Pr(M_j|D) \tag{9}$$

The logic of Bayesian inference requires one to obtain result for every model under consideration and average them. The weights in the averaging are the posterior model probabilities, $\Pr(M_j|D)$. These weights are the key feature for estimation via the BMA. The Posterior Model Probability (PMP) is the ratio of its marginal likelihood to the sum of marginal likelihoods over the entire model space, and is given by

$$\Pr(M_j|D) = \frac{\Pr(D|M_j)\Pr(M_j)}{\Pr(D)} = \frac{\Pr(D|M_j)\ \Pr(M_j)}{\sum_{i=1}^{2^k}\Pr(D|M_i)\Pr(M_i)} \tag{10}$$

where the marginal likelihood of the j^th model is

$$\Pr(D|M_j) = \int \Pr(D|\beta^j, M_j)\Pr(\beta^j|M_j)\,d\beta^j \tag{11}$$

and β^j is the vector of parameters from model M_j, $\Pr(\beta^j|M_j)$ is a prior probability distribution assigned to the parameters of model M_j, $\Pr(M_j)$ is the probability that M_j is the true model and $\Pr(D|\beta^j, M_j)$ is the likelihood. The posterior mean and standard deviation of $\beta = \beta^j$ (quantity of interest) are then constructed as

$$E[\beta|D] = \sum_{j=1}^{2^k}\hat{\beta}\Pr(M_j|D) \tag{12}$$

$$V[\beta|D] = \sum_{j=1}^{2^k}(Var[\beta|D, M_j] + \hat{\beta}^2)\Pr(M_j|D) - E[\beta|D]^2 \tag{13}$$

where $\hat{\beta} = E[\beta|D, M_j]$. Each Model implies a forecast density $f_1 \dots f_p$, where p is the last model. Similarly, each model produces a point forecast. In reality, the true model is unknown, thus leading to model uncertainty. In such situation, the point forecast density becomes

$$f^* = \sum_{j=1}^{2^k}\Pr(M_j|D)\,f_j \tag{14}$$

This implies that the point forecast in (9) weights each of the 2^k forecasts by the posterior density of the model. Thus, the weights in the averaging are the posterior model probabilities. In summary, the BMA approach simply involves the following three steps: (a) specifying the models, (b) specifying the model priors and (c) and specifying parameter priors. The only thing remaining is just computation once the three steps are accomplished.

4 Data Analysis and Discussion of Results

4.1 Data and Preliminaries

Monthly data were used in this study, these spanning January 2002 to June 2017, based on data availability across the needed variables. Three key measures of inflation are of interest in the empirical analysis. These are: all items consumer price index (CPI), core CPI (CCPI) and food CPI (FCPI). The macroeconomic variables considered in the report are classified into 10 groups as shown in Table 1.

INSERT TABLE 1 ABOUT HERE

The study adopts a factor-based approach to generate forecasts for each of the three measures of inflation. This is because of the size of the predictors and the possibility of related variables providing the same information in explaining the dependent variable. Therefore, principal component analysis employed in the study is based on the underlying dataset[2] consisting of 59 predictors which are classified into 10 groups as shown in Table 1. The principal components are extracted for each group and used in the BMA model estimation and forecasting. The results of the principal component analysis are presented in Tables 2 and 3. In Table 2, important characteristics of the extracted principal components are presented. For the monetary aggregates containing nine variables, three components were extracted and which accounts for 97.4 percent total variance.[3] The first component accounts for 70.02 percent of the total variance. For the seasonally adjusted monetary aggregates containing five variables, only one component was extracted which accounts for 95.17 percent total variance. For the interest rate indicators with 12 variables, two components are extracted. The first component accounts for 64.1 percent of total variance and cumulatively both components account for a total variance of 81.96 percent. The real sector has four variables. The PCA analysis extracted one component which accounts for 89.27 percent of the total variance. Exchange rates and capital market, each

[2] This total number includes both seasonally adjusted and unadjusted series. Only series having observations from January 2002 to June 2017 are included in the analysis.
[3] Components selection in the PCA was carried out based on eigenvalue greater or equal to 1, while those components with eigenvalues less than 1 are not reported.

has one component extracted with total variance of 98.09 percent and 84.64 percent respectively. The prices category has two extracted components, with the first accounting for 63.10 percent and both cumulatively accounts for 91.46 percent of the total variance. The agricultural and fiscal categories have one component each with total variance of 69.80 percent and 63.05 percent respectively. Lastly, for the external sector group, three components are extracted from the PCA analysis. The first component accounts for up to 42.95 percent and the three cumulatively accounts for 84.78 percent of the total variance.

INSERT TABLE 2 ABOUT HERE

The identified variables in the principal components are presented in Table 3. We present the results to include up to three components, as in the case of monetary aggregates and external sector indicators. Generally, the PCA results that are presented in the report agree with the peculiarity of the Nigerian economy. The first component of the monetary aggregates loads only six variables. In the seasonally adjusted series, the CPS contributes most follow by the broad money supply (M2) for both sets of data. For interest rate indicators, six-month interest time/time deposit rate (M6) loads most with 0.948 correlation as compared to other variants of interest rate in the principal component. For the real sector indicator, the highest loaded variable is the nominal gross domestic product (NGDP) for both sets of data. In the case of prices, the core consumer price index (CCPI) loads most with 0.99 correlation follow by all items CPI with 0.98 correlation. The rest of the results are presented in Table 3. In all, 18 PCAs, each representing an index for their respective category, are used as predictor variables in the BMA model estimation and forecasting.

INSERT TABLE 3 ABOUT HERE

4.2 Model Forecast Performance

The forecast performance of the BMA model is evaluated using the forecast standard error (std forecast) and the mean square error (MSE). The sample data is divided into two, namely, training sample (January 2002 to February 2016) and testing sample (March 2016 to June 2017). The Tables 4 to 6 present the results for the testing sample for all items consumer price index (CPI), core consumer price index (CCPI) and food consumer price index (FCPI), respectively. The tables show the actual observation, the mean of the forecast density and the forecast evaluation criteria. Altogether, the number of models visited by BMS (Bayesian Model Selection) package used for the analysis is 24107 out of model space of 262144. Generally, the results show low value (< 1.0) of MSE which ranges from 0.002 to 0.429. Looking at the CPI, the mean forecast values are very close to the actual value. Also, the estimated credible intervals give 95% confidence that inflation forecasts are within appreciable levels. Similarly, the results follow for CCPI and FCPI. In all, the forecasts appeared to be reliable judging from the various forecast performance criteria used.

INSERT TABLES 4-6 ABOUT HERE

4.3 Policy Scenarios and Simulations

In this section, analyses of three major policy scenarios are conducted. These are:

i. **Baseline Scenario** – assumes that all the predictor variables follow their historical pattern or movement up till June 2018.

ii. **Expansionary Monetary Policy (EMP) Scenario** – assumes a 5% monthly increase in money supply from July 2017 to June 2018.

iii. **Contractionary Monetary Policy (CMP) Scenario** – assumes a 5% monthly reduction in money supply from July 2017 to June 2018.

The baseline projections for the 59 predictor variables are made based on the assumption that the variables will continue to follow their historical behaviour. To implement this, three forecasting methods are employed and the best is selected based on the ability to track the historical movement very closely particularly their turning points. The methods are Holt-Winters' multiplicative exponential smoothing method, Holt-Winters' additive exponential smoothing method, and Holt-Winters' (no seasonal) smoothing method. The software used for the analysis is EViews 9 which can automatically search for the optimal smoothing parameters.[4]

Effects of Monetary Policy Scenarios on All Items Consumer Price Index (CPI)

Figure 1 presents the forecast of all items CPI from July 2017 to June 2018 based on three different scenarios (baseline, positive shock to M2 and negative shock to M2). With a positive shock of 5% to monetary policy via broad money supply (M2), the CPI rises marginally above the baseline scenario whereas a negative shock to M2 of the same magnitude leads to a huge drop in all items CPI relative to the baseline scenario. Thus, upholding monetarist view on inflation and supporting contractionary monetary policy as a veritable policy option for achieving significant and consistent downward inflationary trend.

INSERT FIGURE 1 ABOUT HERE

Effects of Monetary Policy Scenarios on Core Consumer Price Index (CCPI)

The response of the core CPI also follows the same pattern as the all item CPI. A positive shock to M2 scenario leads to marginal increase in Core CPI above the baseline scenario but a similar magnitude of negative shock yields a higher and consistent fall in the Core CPI (Figure 2).

INSERT FIGURE 2 ABOUT HERE

Effects of Monetary Policy Scenarios on Food Consumer Price Index (FCPI)

Figure 3 which presents the response of Food CPI to various types of shock to monetary aggregates indicates that the response of Food CPI follows the same pattern as those of all item CPI and Core CPI (Figure 3).

INSERT FIGURE 3 ABOUT HERE

[4] Details about the selected method for each predictor variable based on minimum sum of squared residuals (SSR) and the corresponding estimated values of the optimal smoothing parameters are available on request.

5 Summary and Conclusion

Considering the adverse macroeconomic effect of inflation on welfare, fiscal budgeting, trade performance, international competitiveness and the whole economy, it still remains a subject of utmost concern and interest to policy makers. Thus, the historical path of inflation is not only monitored by monetary authorities in both developed and developing countries, but attempt is also often made to determine its future path. This is done by using various methodologies which have been criticized to be defective in forecasting inflation. The large number of macroeconomic variables included in forecasting inflation, according to the critics of those methodologies, makes model selection cumbersome and difficult, hence the resort to the use of BMA which obtained the best predictive performance averaging forecasts constructed from several models. This study uses the Bayesian model averaging (BMA) methodology to determine the predictors of inflation for Nigeria as well as forecast its future path using a wide range of variables. The study derived eighteen (18) PCAs from sixty-three (63) independent variables divided into ten groups and adopted the BMA and Frequentist Model Averaging (FMA) as model averaging algorithms. Recognizing predictor variables as either focused or auxiliary regressors, three different measures of inflation were estimated as objective functions.

The results indicate that both in-sample and out-of-sample forecasts were highly reliable judging from the various forecast performance criteria. The values of MSE were very low (< 1.0) and ranges from 0.002 to 0.429; the mean forecast values of inflation rates were very close to the actual values and the estimated credible intervals give 95% confidence that inflation forecasts are within appreciable levels.

Various policy scenarios conducted were highly fascinating both from the theoretical perspective and the prevailing economic situation in the country. Given the available dataset both positive and negative shocks to monetary aggregates moderate CPI inflation but with higher magnitude for negative shocks. This study strongly recommends that, if the fiscal sector is expected to maintain the current trend of expenditure up to June 2018, the Central Bank of Nigeria, even with the objective of curtailing inflationary spiral, can embark on accommodative monetary policy. This stems from the fact that it is capable, given the current economic situation, of aiding recovery from recession without fueling inflation. It is however pertinent to mention that restrictive monetary policy still proves more effective and efficient in curtailing inflation.

References

Adams, S.O., Awujola, A. and Alumgudu, A.I. (2014). Modelling Nigeria's Consumer Price Index using ARIMA Model. *International Journal of Development and Economic Sustainability*, 2(2), 37 – 47.

Amadi, I. U., Gideon, W. O. & Nnoka, L. C. (2013). Time Series Models on Nigerian Monthly Inflation Rate Series. *International Journal of Physical, Chemical and Mathematical Sciences*, 2(2), 124-128.

Altug, S. and Cakmakli, C. (2015). Forecasting inflation using survey expectations and target inflation: Evidence for Brazil and Turkey. University of Amsterdam Working paper No IAAE2015-580.

Ang, A., Bekaert, G. and Wei, M. (2007). Do Macro Variables, Asset Markets, or Surveys Forecast Inflation Better? *Journal of Monetary Economics*, 54, 1163-1212.

Atkeson, A. and Ohanian, L.E. (2001). Are Phillips curves useful for forecasting inflation? *Quarterly Federal Reserve Bank of Minneapolis*, Winter 2001: pp. 1-12.

Bank of England (2015). Evaluating forecast performance. Independent Evaluation Office, Bank of England.

Bjornland, H.C., Gerdrup, K., Jore, A.S., Smith, C. and Thorsrud, L.A. (2009). Does forecast combination improve Norges Bank inflation forecasts? Working paper, Economics Department, Norges Bank, Norway.

Blinder A.S. (1997). Is there a core of practical macroeconomics that we should all believe? *American Economic Review*, 87, 240-250.

Bruneau, C., DeBandt, O. and Flageollet, A. (2003). Forecasting inflation in the Euro area. *Banque de France, Working paper series* NER #102.

Buckland, S.T., Burnham, K.P. and Augustin, N.H. (1997). Model selection: an integral part of inference. *Biometrics*, 53, 603-618.

Chinonso, U.E. and Justice, O.I. (2016). Modelling Nigeria's Urban and Rural Inflation usingBox-Jenkins Model. *Scientific Paper Series on Management, Economic Engineering in Agriculture and Rural Development*, 16(4), pp 61 – 68.

Claeskens, G., and Hjort, N.L. (2003). The focused information criterion. *Journal of the American Statistical Association*, *98*, 900-916.

Claeskens, G., and Hjort, N. L. (2008). *Model selection and model averaging*. Cambridge: Cambridge University Press.

Doguwa, I. S. and Alade, O. A. (2013). Short-term Inflation Forecasting Models in Nigeria. *CBN Journal of Applied Statistics*, 4(2), 1 – 29.

Duncan, R. and Martinez-Garcia, E. (2015). Forecasting Inflation with Global Inflation: When Economic Theory Meets the Facts. Paper presented at the 35th International Symposium on Forecasting, International Institute of Forecasters, Riverside, USA - June 21-24, 2015.

Fedderke, J. and Liu, Y. (2016). Inflation in South Africa: An assessment of alternative inflation models. *South African Reserve Bank Working Paper series* No. WP/16/03.

Figueiredo, F.M.D. (2010). Forecasting Brazilian inflation using a large dataset. *The Banco Central do Brasil Working paper series* No. 228.

Fujiwara, I. and Koga, M. (2002). A statistical forecasting method for inflation forecasting. Research and Statistics Department, *Bank of Japan working paper* 02-5.

Gaomab, M. (1998). Modelling inflation in Namibia. Bank of Namibia Occasional paper No. 1.

Giannone, D., Lenza, M., Momferatou, D. and Onorante, L. (2014). Short-term inflation projections: A Bayesian vector approach. *International Journal of Forecasting*, 30(3), 635-644.

Gonzalez, E., Gomez, M.I., Melo, L.F. and Torres, J.L. (2006). Forecasting food price inflation in developing countries with inflation targeting regimes: the Colombia case. Borradores de economia, 409.

Groen J., Paap, R. and Ravazzolo, F. (2009). Real-time Inflation Forecasting in a Changing World. Econometric Institute Report, 2009-19, Erasmus University Rotterdam.

Hansen, B.E. (2007). Least Squares Model Averaging. *Econometrica*, 75, 1175-1189.

Hansen, B.E. (2008). Least-squares forecast averaging. *Journal of Econometrics*, *146*(2), 342-350.

Hansen, B.E. and Racine, J.S. (2012). Jackknife model averaging. *Journal of Econometrics*, 167(1), 38-46.

Hjort, N. L. and Claeskens, G. (2003). Frequentist model average estimators. *Journal of the American Statistical Association*, *98*(464), 879-899.

Inam, U.S. (2017). Forecasting Inflation in Nigeria: A vector Autoregression Approach. *International Journal of Economics, Commerce and Management*, 5(1), 92 – 104.

Iwok, I.A. and Udoh, G.M. (2016). A Comparative study between the ARIMA-Fourier model and the Wavelet model. American Journal of Scientific and Industrial Research, 2016, 7(6):137-144.

John, E.E. and Patrick, U.U. (2016). Short-Term Forecasting of Nigeria Inflation Rates using Seasonal ARIMA Model. *Science Journal of Applied Mathematics and Statistics,* 4(3), 101-107.

Kelikume, I. and Salami, A. (2014). Time Series Modeling and Forecasting Inflation: Evidence from Nigeria. *The International Journal of Business and Finance Research*, 8(2), 41 – 51.

Kuhe, D.A. and Egemba, R.C. (2016). Modelling and Forecasting CPI Inflation in Nigeria: Application of Autoregressive Integrated Moving average Homoskedastic Model. *Journal of Scientific and engineering Research,* 3(2), 57-66.

Lansing, K.J. (2002). Can the Phillips curve help forecast inflation?, *FRBSF Economic Letter*, Federal Reserve Bank of San Francisco, issue Oct 4.

Leamer, E.E. (1978). Specification Searches: Ad Hoc Inference with Nonexperimental Data, Wiley, New York.

Mallows, C.L. (1973). Some comments on C p. *Technometrics*, *15*(4), 661-675.

Min, C.K. and Zellner, A. (1993). Bayesian and non-Bayesian methods for combining models and forecasts with applications to forecasting international growth rates. *Journal of Econometrics*, *56*(1-2), 89-118.

Moral- Benito, E. (2015). Model averaging in economics: An overview. *Journal of Economic Surveys*, *29*(1), 46-75.

Norman, D. and Richards, A. (2010). Modelling inflation in Australia. *Reserve Bank of Australia Research discussion Paper* No. RDP 2010-03.

Okafor, C. and Shaibu, I. (2013). Application of ARIMA models to Nigerian Inflation dynamics. Research Journal of Finance and Accounting, 4(3): 138-150.

Omekara, C.O., Ekpenyong, E.J. and Ekerete, M.P. (2013). Modeling the Nigeria Inflation Rates using Periodogram and Fourier Series Analysis. *CBN Journal of Applied Statistics,* 4(2), 51-68.

Onimode, B.M., Alhassan, J.K. and Adepoju, S.A. (2015). Comparative Study of Inflation Rates Forecasting Using Feed-Forward Artificial Neural Networks and Auto-Regressive (AR) Models. *International Journal of Computer Science Issues,* 12(2), 260-266.

Otu, A.O., Osuji, G.A., Jude, O., Ifeyinwa, M.H. and Andrew, I.I. (2014). Application of SARIMA Models in Modeling and Forecasting Nigeria's Inflation Rates. *American Journal of Applied mathematics and Statistics*, 2(1), 16 – 28.

Stock, J.H. and Watson, M.W. (1999). Forecasting inflation. *Journal of Monetary Economics*, *44*(2), 293-335.

Stock, J. H. and Watson, M.W. (2004). Combination forecasts of output growth in a seven-country data set. *Journal of Forecasting*, *23*(6), 405-430.

Stock, J.H. and Watson, M.W. (2005). An empirical comparison of methods for forecasting using many predictors. *Manuscript, Princeton University*.

Stock, J.H. and Watson, M.W. (2006). Forecasting with many predictors. *Handbook of economic forecasting*, *1*, 515-554.

Stock J. H. and Watson, M.W. (2008). Philips Curve Inflation Forecasts. *NBER Working Paper* No. 14322. vs. 0.3.0, URL: http://cran.r-project.org/web/packages/BMS/

Sims, C.A. (2002). The role of models and probabilities in the monetary policy process. *Brookings Papers on Economic Activity*, 1-40.

Waiquamdee, A. (2001). Modelling the inflation process in Thailand. *BIS Papers* No. 8: 252-263.

Wright, J.H. (2008). Bayesian model averaging and exchange rate forecasts. *Journal of Econometrics*, *146*(2), 329-341.

Wright, J. H. (2009). Forecasting US inflation by Bayesian model averaging. *Journal of Forecasting*, *28*(2), 131-144.

Yemitan, R.A. and Shittu, O.I. (2015). Forecasting Inflation in Nigeria by State Space Modeling. *International Journal of Scientific and Engineering Research*, 6(8), 778-786.

Younus, S. and Roy, A. (2016). Forecasting inflation and output in Bangladesh: Evidence from a VAR model. Research department and Monetary Policy Department of Bangladesh Bank Working Paper series WP No. 1610.

Zellner, A. (1986). On Assessing Prior Distributions and Bayesian Regression Analysis with g-prior Distributions, in Bayesian Inference and Decision Techniques: Essays in Honor of Bruno de Finetti. Goel, P.K. and A. Zellner, eds., North-Holland, Amsterdam.

Table 1: Variable groupings

Monetary aggregates	Real Sector indicators	Interest rates
Credit to private sector (CPS) Net credit to FGN (NCG) Foreign assets to DMBs (FA) Broad money supply (M2) Narrow money supply (M1) Broad money growth rate (M2g) Growth rate of M2 (M2g) Reserve money (RM) Seasonally Adj. Series Credit to private sector (CPS_D) Broad money supply (M2_D) Narrow money supply (M1_D) Reserve money (RM_D) Foreign assets to DMBs (FA_D)	Real GDP (RGDP) Nominal GDP (NGDP) Real Private Capital Expenditure (RPCE) Nominal Private Capital Expenditure (NPCE) Seasonally Adj. Series Real GDP (RGDP_D) Nominal GDP (NGDP_D) Real PCE (RPCE_D) Nominal PCE (NPCE_D)	Seven-day (7D) One month (1M) Three-month (3M) Six-month (6M) Twelve-month (12M) Average deposit rate (DR) Average lending rate (ALR) Prime lending rate (PLR) Maximum lending rate (MLR) Monetary policy rate (MPR) Treasury bills rate (TB)
Exchange rate indices	**Capital market indicators**	**Prices**
Official exchange rate (EXR) BDC exchange rate (EXRB) Nominal effect. exch. rate (NEER) Real effective exchange rate (REER)	All share index (ASI) Market capitalization (MC) Bond yields (BR)	Core CPI (CCPI) Food CPI (FCPI) All items CPI (CPI) Inflation rate (INF) Inflation expectations (IFE) Price of PMS (PMS/ltr)
External sector indicators	**Agricultural indicators**	**Fiscal indicators**
Foreign reserve (FER) Imports (IM) Import growth rates (IMg) Exports (EX) Export growth rates (EXg) Terms of trade (TOT) Seasonally Adjusted Series Imports (IM_D) Exports (EX_D)	Average rainfall (ARF) Nominal Agric. Production (ANY) Real Agric. Production (RAY) Seasonally Adj. Series Nominal Agric. Production (ANY_D) Real Agric. Production (ARY_D)	Federal account allocation (FAAC) Fiscal deficit to GDP ratio (FPGDP) FGN Total Expenditure (GE) Seasonally Adj. Series Federal account allocation (FAAC_D) FGN Total Expenditure (GE_D)
International indicators		
Global inflation rate (GIF) World food index (WFPI)		

Table 2: Characteristics of the extracted Principal components

Indicator	Seasonally Unadj. Series				Seasonally adj. series			
	Components	**Rotated eigenvalue**	**% Total variance**	**Cum. %**	**Components**	**Rotated eigenvalue**	**% Total variance**	**Cum. %**
Monetary aggregates	1	6.302	70.02	70.02	1	4.758	95.168	95.168
	2	1.437	15.96	85.98				
	3	1.028	11.42	97.40				
Interest rates	1	7.698	64.149	64.149				
	2	2.138	17.814	81.963				
Real sector	1	3.571	89.270	89.270	1	3.624	90.600	90.600
Exchange rates	1	1.962	98.085	98.085				
Capital market	1	1.693	84.643	84.643				
Prices	1	4.417	63.100	63.100				
	2	1.985	28.356	91.457				
Agricultural sector	1	2.094	69.797	69.797	1	1.993	99.630	99.630
Fiscal	1	1.891	63.045	63.045	1	1.589	79.458	79.458
External sector	1	2.577	42.945	42.945	1	1.786	89.321	89.321
	2	1.289	21.485	64.430				
	3	1.221	20.350	84.780				

Table 3: Identified principal components showing variables

	Seasonally Unadj. series (Component correlations)				Seasonally adj. series (Component correlations)			
Indicator	**Variables**	**1**	**2**	**3**	**Variables**	**1**	**2**	**3**
Monetary aggregates	CPS	.985	-	-	CPS_D	0.997	-	-
	M2	.979	-	-	M2_D	0.995	-	-
	DD	.975	-	-	M1_D	0.982	-	-
	M1s	.955	-	-	FA_D	0.957	-	-
	RM	.950	-	-	RM_D	0.946	-	-
	FA	.915	-	-				
	M1g	-	.832	-				
	M2g	-	.760	-				
	NCG	-	-	.910				
Interest rates	M6	0.948	-	-				
	M3	0.944	-	-				
	7D	0.944	-	-				
	M12	0.918	-	-				
	M1	0.917	-	-				
	M12	0.842	-	-				
	PLR	0.842	-	-				
	MPR	0.740	-	-				
	DR	0.677	-	-				
	TB	0.633	-	-				
	MLR	-	0.855	-				
	ALR	-	0.710	-				
Real sector	NGDP	0.981	-	-	NGDP_D	0.984	-	-
	NPCE	0.980	-	-	NPCE_D	0.983	-	-
	RGDP	0.964	-	-	RGDP_D	0.968	-	-
	RPCE	0.848	-	-	RPCE_D	0.867	-	-
Exchange rates	EXR	0.990	-	-				
	EXRB	0.990	-	-				
Capital market indicator	ASI	0.920	-	-				
	MC	0.920	-	-				
Prices	CCPI	0.990	-	-				
	CPI	0.989	-	-				
	FCPI	0.985	-	-				
	PMS	0.958	-	-				
	WFPI	0.753	-	-				
	IFE	-	0.970	-				
	INF	-	0.970	-				
Agricultural indicator	ARF	0.983	-	-	ANY_D	0.998	-	-
	ANY	0.937	-	-	ARY_D	0.998	-	-
	ARY	0.501	-	-				
Fiscal indicator	GEX	0.937	-	-	GEX_D	0.891		
	FPGDP	-0.736	-	-	FAAC_D	0.891		
	FAAC	0.687	-	-				
External sector indicator	IM	0.894	-	-	IM_D	0.945	-	-
	EX	0.788	-	-	EX_D	0.945	-	-
	FER	0.687	-	-				
	TOT	-	0.688	-				
	EXg	-	0.583	-				
	IMg	-	-	0.849				

Table 4: Forecasts for CPI

Period	Actual	Mean forecast	Std forecast	MSE forecast	5% CI	95% CI
2016M03	189.94	186.91	3.368	0.078	180.96	192.87
2016M04	192.99	189.23	3.361	0.064	183.38	195.09
2016M05	198.3	201.11	3.613	0.075	194.07	208.15
2016M06	201.7	206.58	3.861	0.043	196.63	215.81
2016M07	204.23	213.64	4.356	0.024	200.15	227.44
2016M08	206.29	217.78	4.668	0.019	203.25	236.05
2016M09	207.96	221.31	4.884	0.016	206.23	Infinity
2016M10	209.68	224.52	5.182	0.014	208.82	Infinity
2016M11	211.33	221.91	4.829	0.021	206.78	Infinity
2016M12	213.56	226.93	5.060	0.016	211.26	246.69
2017M01	215.72	228.97	5.433	0.016	212.18	Infinity
2017M02	218.95	230.43	5.384	0.018	213.84	250.17
2017M03	222.71	227.66	4.842	0.032	213.58	240.76
2017M04	226.27	224.48	4.690	0.055	211.96	236.01
2017M05	230.53	228.35	4.629	0.057	216.37	239.44
2017M06	234.17	230.48	4.507	0.058	219.75	240.52

Table 5: Forecasts for CCPI

Period	Actual	Mean forecast	Std forecast	MSE forecast	5% CI	95% CI
2016M03	186.42	185.21	3.766	0.097	178.71	191.70
2016M04	189.55	186.78	3.734	0.080	180.51	193.08
2016M05	194.7	203.36	3.995	0.012	196.40	210.35
2016M06	198.27	209.56	4.132	0.293	202.52	216.64
2016M07	200.69	218.83	4.516	0.0135	210.56	227.06
2016M08	202.4	222.89	4.876	0.0147	213.18	232.59
2016M09	204.34	227.00	5.068	0.0079	216.64	237.43
2016M10	205.86	231.12	5.383	0.0079	219.13	243.40
2016M11	207.33	227.60	5.008	0.042	216.72	238.67
2016M12	208.61	232.48	5.335	0.011	221.00	244.10
2017M01	210.03	235.25	5.734	0.007	223.93	246.55
2017M02	212.34	236.22	5.795	0.014	224.92	247.45
2017M03	215.14	231.53	5.259	0.147	221.82	241.21
2017M04	217.51	229.29	5.074	0.828	219.91	238.60
2017M05	220.05	232.73	4.988	0.508	223.70	241.73
2017M06	222.96	234.20	4.848	0.845	225.32	243.05

Table 6: Forecasts for FCPI

Period	Actual	Mean forecast	Std forecast	MSE forecast	5% CI	95% CI
2016M03	194.87	189.48	3.759	0.0406	182.77	196.27
2016M04	197.40	192.32	3.751	0.0443	185.73	198.97
2016M05	202.46	200.22	4.006	0.0732	192.49	208.24
2016M06	205.39	203.53	4.233	0.0540	193.90	214.68
2016M07	207.87	207.59	4.795	0.0356	195.00	224.65
2016M08	210.30	210.84	5.113	0.0290	196.91	230.48
2016M09	212.00	213.47	5.338	0.0255	198.73	234.56
2016M10	213.82	215.00	5.685	0.0225	198.97	Infinity
2016M11	215.70	214.17	5.290	0.0292	199.57	235.04
2016M12	218.58	219.45	5.421	0.0263	204.64	239.86
2017M01	221.40	218.04	5.925	0.0258	201.26	Infinity
2017M02	225.81	220.58	5.819	0.0276	204.56	242.30
2017M03	230.80	221.29	5.235	0.0249	207.87	237.76
2017M04	235.50	218.90	5.089	0.0073	206.36	233.51
2017M05	241.47	223.05	5.065	0.0047	210.67	237.29
2017M06	246.29	226.18	5.004	0.0023	214.31	239.39

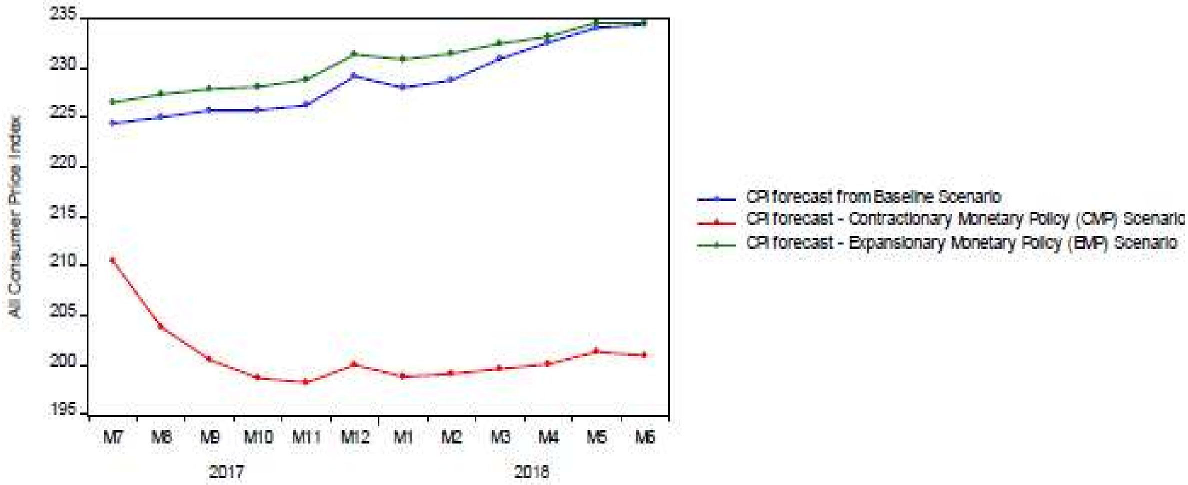

Figure 1: Effects of Monetary Policy Scenarios on All items Consumer Price Index

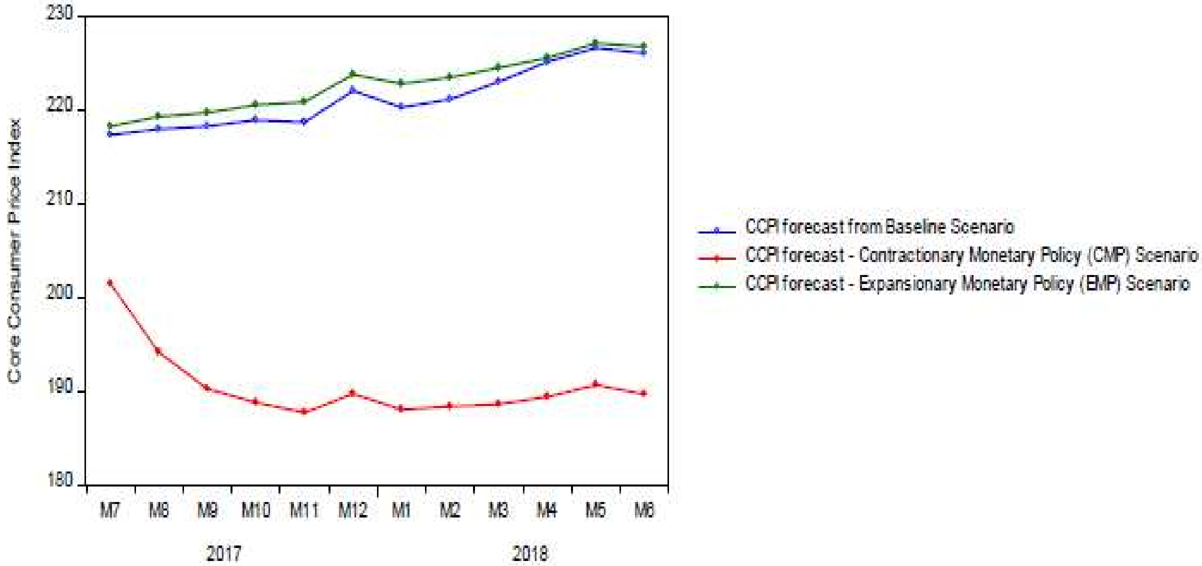

Figure 2: Effects of Monetary Policy Scenarios on Core Consumer Price Index

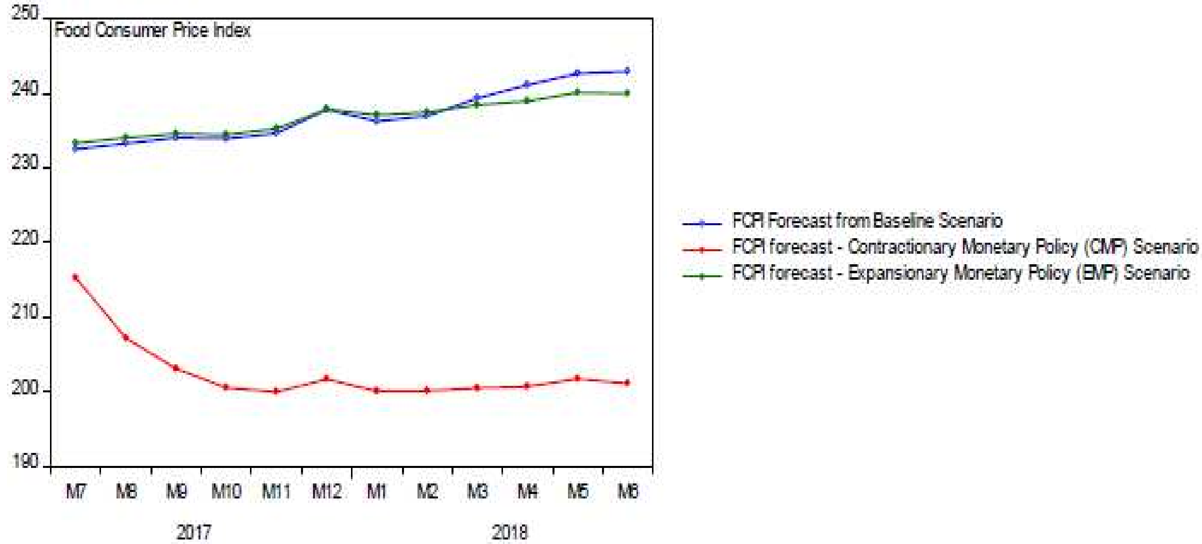

Figure 3: Effects of Monetary Policy Scenarios on Food Consumer Price Index