Short-Term Inflation Forecasting Models for Nigeria

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Short-term inflation forecasting is an essential component of the monetary policy projections at the Central Bank of Nigeria. This paper proposes four short-term headline inflation forecasting models using the SARIMA and SARIMAX processes and compares their performance using the pseudo-out-of-sample forecasting procedure over July 2011 to September 2013. According to the results the best forecasting performance is demonstrated by the model based on the all items CPI estimated using the SARIMAX model. This model is, therefore, recommended for use in short-term forecasting of headline inflation in Nigeria. The forecasting performance up to eight months ahead, of the models based on the weighted sum of all items CPI components is relatively bad. For forecast of food inflation up to ten months ahead SARIMA is recommended, but for eleven to twelve months ahead the SARIMAX model performs better. However, the SARIMA model for core inflation consistently outperforms the SARIMAX model and should therefore be used to forecast core inflation.

Keywords: Consumer Price Index, SARIMA Process, SARIMAX Process, Statistical Loss Function, Forecast Evaluation

JEL Classification: C22, E17, E31

1.0 Introduction

The monetary authorities of a large number of countries including Nigeria have decided that price stability, that is, a low and stable inflation rate, is the main contribution that monetary policy can give to economic growth. Accordingly, predicting the future course of inflation in a precise manner is a crucial objective to maintain this goal, especially in inflation targeting environment. The Central Bank of Nigeria has the maintenance of monetary and price stability as one of its mandate. Various monetary policy instruments are deployed by the Bank to achieve this mandate and the effect of applying any particular instrument can be felt only after a certain period of time. Therefore, the Bank is attempting to develop and improve models that will

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provide relatively precise and reliable forecast of the headline, food and core inflation so that it can react in time and neutralize inflationary or deflationary pressures that could appear in the future.

Short-term inflation forecasting is an indispensable component of the monetary policy projection, and therefore, continuous efforts are made to improve the process at the Central Bank of Nigeria. One way is to improve the model of short-term forecasting of the Consumer Price Index (CPI) with both seasonal ARIMA and seasonal ARIMAX processes, where, along with direct forecasting of the all items CPI, an attempt will also be made to forecast changes in the 12 international classification of individual consumption by purpose (COICOP) divisional indices of the CPI. This approach may provide a more detailed insight into the sources of future inflationary or deflationary pressures. It will also allow for the determination of whether a forecast of developments in the CPI obtained by the weighted sum of the index's components forecasts is more reliable than a direct forecast.

In this paper, we estimate series of forecasting models that are frequently used in the short-term forecasting studies of most central banks. While working with the forecasting models, we employ the all items CPI and its various components as well as the food and core CPI, as our main variables of interest. A forecasting model with a good in-sample fit does not necessarily imply that it will have a good out-of-sample performance. This paper therefore applies pseudo out-of-sample forecasting technique to evaluate the forecasting performance of the estimated models.

The objective of this paper is to critically examine the proposed short-term forecasting models with the view to assessing their pseudo out-of-sample forecast accuracy using three classical statistical loss functions: - the mean absolute error (MAE), the root mean squared error (RMSE) and the mean absolute percent error (MAPE); to determine which of the models are more precise and reliable over the 12 months forecast horizon. In general, the smaller the value of the statistical loss function the better the forecast.

For ease of exposition, the paper is structured into seven sections; with section one as the introduction. Section two reviews both the theoretical and empirical literature. While section three discusses the methodology, the empirical analysis and results are presented in section four. Performance evaluations of the estimated models are contained in section five. Section six provides 12 month forecast of inflation types conditional on the future paths of the exogenous variables. The final section concludes the paper.

2.0 Review of Theoretical and Empirical Literature

An empirical analysis of causes of inflation in Nigeria by Asogu (1991) indicated that real output, money supply, domestic food prices, exchange rate and net exports were the major determinants of inflation in Nigeria. Moser (1995) and Fakiyesi (1996) studied Nigeria's headline inflation using both the long-run and the dynamics error correction model and autoregressive distributed lag approaches, respectively. Their results confirmed that the basic findings of Asogu (1991) and agro-climatic conditions were the major factors influencing inflation in Nigeria. Also, using the framework of error correction mechanism, Olubusoye and Oyaromade (2008) found that the lagged CPI, expected inflation, petroleum prices and real exchange rate significantly propagate the dynamics of inflationary process in Nigeria. More recently, Adebiyi *et al* (2010) examined the different types of inflation forecasting models including ARIMA and showed that ARIMA models were modestly successful in explaining inflation dynamics in Nigeria.

A lot of empirical research has been conducted in the area of short-term forecasting using ARIMA models. Akdogan *et.al* (2012) produced short-term forecasts for inflation in Turkey, using a large number of econometric models such as the univariate ARIMA models, decomposition based models, a Phillips curve motivated time varying parameter model, a suit of VAR and Bayesian VAR models and dynamic factor models. Their result suggests that the models which incorporate more economic information outperformed the random walk model at least up to two quarters ahead.

Mordi *et al* (2012) developed a short-term inflation forecasting framework to serve as a tool for analyzing inflation risks in Nigeria. Their framework follows mostly a structural time series model for each CPI component constructed at a certain level of disaggregation. Short term forecasts of the all items CPI is made as a weighted sum of the twelve CPI components forecasts. Thereafter, the all items CPI and the twelve CPI components are used to calculate short-term inflation forecasts. The framework is intended to serve as a tool for analyzing inflation risks with the aid of fan charts and given its disaggregated nature, appears informative and capable of improving the credibility of the policy maker.

Pufnik and Kunovac (2006) provided a method of forecasting the Croatia's CPI by using univariate seasonal ARIMA models and forecasting future values of the variables from past behavior of the series. Their paper attempts to examine whether separate modeling and aggregating of the sub-indices improves the final forecast of the all items index. The analysis suggests that given a somewhat longer time horizon (three to twelve months), the most precise forecasts of all items CPI developments are obtained by first forecasting the index's components and then aggregating them to obtain the all items index.

Alnaa and Ferdinand (2011) used ARIMA approach to estimate inflation in Ghana using monthly data from June 2000 to December 2010. They found that ARIMA (6,1,6) is best for forecasting inflation in Ghana. Also, Suleman and Sarpong (2012) employed an empirical approach to modeling monthly CPI data in Ghana using the seasonal ARIMA model. Their result showed that ARIMA (3,1,3) (2,1,1)[12] model was appropriate for modeling Ghana's inflation rate. Diagnostic test of the model residuals with the ARCH LM test and Durbin Watson test indicates the absence of autocorrelations and ARCH effect in the residuals. The forecast results inferred that Ghana was likely to experience single digit inflation values in 2012.

Akhter (2013) forecasted the short-term inflation rate of Bangladesh using the monthly CPI from January 2000 to December 2012. The paper employs the seasonal ARIMA models proposed by Box *et al* (1994). Because of the presence of structural break in the CPI, the study truncates the series and using data from September 2009 to December 2012 fitted the seasonal ARIMA (1,1,1) (1,0,1)[12] model. The forecasted result suggests an increasing pattern and high rates of inflation over the forecasted period of 2013.

Omane-Adjepong *et al* (2013) examined the most appropriate short-term forecasting method for Ghana's inflation. The monthly dataset used was divided into two sets, with the first set used for modeling and forecasting, while the second set was used as test. Seasonal ARIMA and Holt-Winters approaches are used to obtain short-term out of sample forecast. From the results, they concluded that an out of sample forecast from an estimated seasonal ARIMA (2,1,2)(0,0,1)[12] model far supersedes any of the Holt-Winters' approach with respect to forecast accuracy.

Meyler et *al* (1998) outlined the practical steps which need to be undertaken to use ARIMA time series models for forecasting Irish inflation. They considered two alternative approaches to the issue of identifying ARIMA models – the Box Jenkins approach and the objective penalty function methods. The approach they adopted is 'unashamedly' one of model mining with the aim of optimizing forecast performance.

3.0 Methodology

The method of analysis adopted in this study is the Box and Jenkins (1976) and Box *et al* (1994) procedure for fitting seasonal ARIMA model. The Box *et al* (1994) define the time series $\{y_t\}_{t\epsilon Z}$ as a seasonal ARIMA (p,d,q)(P,D,Q)[S] process if it satisfies the following equation:

$$\emptyset(L)\varphi(L^s)(1-L)^d(1-L^s)^D y_t = \theta(L)\Theta(L^s)\epsilon_t \qquad (1)$$

where L is the standard backward shift operator, φ and Θ are the seasonal autoregressive (AR) and moving average (MA) polynomials of order P and Q in variable L^s:

$$\varphi(L^s) = 1 - \varphi_1 L^s - \varphi_2 L^{2s} - \cdots - \varphi_P L^{Ps} \qquad (2)$$

$$\Theta(L^s) = 1 + \Theta_1 L^s + \Theta_2 L^{2s} + \ldots + \Theta_Q L^{Qs} \qquad (3)$$

The functions Ø and θ are the standard autoregressive (AR) and moving average (MA) polynomials of order p and q in variable L:

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p \qquad (4)$$

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q \qquad (5)$$

As an illustration, the SARIMA (1,1,1)(1,0,1)[12] model is a multiplicative model of the form:

$$(1-\phi_1 L)(1-\varphi_1 L^{12})\Delta y_t = (1+\theta_1 L)(1+\Theta_1 L^{12})\epsilon_t \qquad (6)$$

Using the properties of operator L, it follows that equation (6) can be expressed as:

$$\Delta y_t = \phi_1 \Delta y_{t-1} + \varphi_1 \Delta y_{t-12} - \varphi_1 \phi_1 \Delta y_{t-13} + \theta_1 \epsilon_{t-1} + \Theta_1 \epsilon_{t-12} + \theta_1 \Theta_1 \epsilon_{t-13} + \epsilon_t$$

where Δ is the difference operator. Also d and D are orders of integration and $\{\epsilon_t\}_{t\epsilon Z}$ is a Gausian white noise with zero mean and constant variance. Ideally S equals 12 for monthly data and 4 for quarterly data. The details of ARIMA modeling procedure are contained in Box and Jenkins (1976), Pankratz (1983) Box *et al* (1994) and Asteriou and Hall (2007). For the CPI series under study, the estimates of the parameters which meet the stationarity and invertibility conditions are obtained using the Eviews software. The Box *et al* (1994) procedure outlined above assumes that (i) the underlying distribution of the series under study is normal, (ii) the variance is constant and (iii) that the relationship between the seasonal and non – seasonal components is multiplicative. When one or all of these conditions are violated the fitted model may be inadequate for the series under study.

The SARIMAX (or structural SARIMA) process differs from the SARIMA process ostensibly because it takes cognizance of an exogenous input, which consists of additional exogenous variables that could explain the behavior of the dependent variable. Thus, we define the time series $\{y_t\}_{t\epsilon Z}$ as a SARIMAX (p,d,q) (P,D,Q)[S] process if it satisfies the following equation:

$$\emptyset(L)\varphi(L^s)(1-L)^d(1-L^s)^D(y_t - \psi' X_t) = \theta(L)\Theta(L^s)\epsilon_t \qquad (7)$$

The vector X_t constitutes other relevant exogenous variables that are difference stationary and ψ is the vector of parameter values. As an illustration, the seasonal ARIMAX (1,1,1) (1,0,1)[12] model with r exogenous and integrated variables $\{x_{it}, i=1,2\ldots r\}$ is a multiplicative model of the form:

$$\Delta y_t = c + \sum_{i=1}^{r} \gamma_i \, \Delta x_{it} + \mu_t \qquad (8)$$

with the autoregressive term $\{\mu_t\}_{t\epsilon Z}$ satisfying the following condition:

$$(1-\phi_1 L)(1-\varphi_1 L^{12})\mu_t = (1+\theta_1 L)(1+\Theta_1 L^{12})\epsilon_t \qquad (9)$$

where c is a constant and $\{\gamma_k, k=1,2\ldots r\}$ are the parameters of the r exogenous variables used in the model. Using the properties of operator L, it follows that equation (9) can be expressed as:

$$\Delta y_t = c + \sum_{i=1}^{r} \gamma_i \Delta x_{it} + \phi_1 \mu_{t-1} + \varphi_1 \mu_{t-12} - \varphi_1 \phi_1 \mu_{t-13} + \theta_1 \epsilon_{t-1} + \Theta_1 \epsilon_{t-12} + \theta_1 \Theta_1 \epsilon_{t-13} + \epsilon_t$$

where Δ and ϵ_t are as defined in equation (6).

Table 1: List of Endogenous and Exogenous Variables

Endogenous Variable	Definition
CPI	Headline Consumer Price Index
Fod	Food Consumer Price Index
Cor	All items less farm produce CPI (core)
Exogenous Variable	
Fue	Price of petroluem motor spirit per litre
Gex	Central Government Expenditure
BDC	Bureau-de-change nominal naira exchange rate
M2	Broad Money Supply
Wds	Official nominal naira exchange rate
RM	Reserve Money
NCG	Net Credit to Central Government
CPS	Credit to Private Sector
R1C	Average monthly rainfall in cereals producing north west and north east zones
R2T	Average monthly rainfall in tubers producing north central zone
R3V	Average monthly rainfall in vegatables producing southern zone
μ	Autoregressive term
ε	Moving Average term

On the choice of the exogenous variables, Omotosho and Doguwa (2012) noted that the literature is replete with theories of inflation, some of which include demand pull[2], cost push[3], Keynesian theory[4], quantity theory of money[5], purchasing power parity theory[6] and structural theory.[7] These

[2] This focuses on excess demand as a major determinant of inflation and highlights factors such as increased government and private sector investment spending.

[3] This highlights factors such as increased money wages and higher prices of domestically produced or imported raw materials

[4] This combines both the demand pull and cost push factors and argues that money influences prices indirectly via interest rates.

[5] This posits that a change in money supply is accompanied by a proportionate change in prices. Money supply is the key variable in this quantity theory model of inflation

theories and earlier empirical studies of inflation in Nigeria by Asogu (1991), Fakiyesi (1996), Moser (1995) and Olubusoye and Oyaromade (2008) guide the choice of the exogenous variables used in this paper. Overall, the exogenous variables considered for inclusion in the short-term forecasting models are selected based on their theoretical, empirical and situational relevance. Presented in Table 1 is the list of considered endogenous and exogenous variables.

The sample for the estimation and forecast evaluation spans the period July 2001 to September 2013 (147 observations) and is divided into two parts. The first part is the training sample, which includes all monthly data up to June 2011 (120 observations), and the second part is the forecasting sample, which includes the remaining data from July 2011 to September 2013 (27 observations). The paper uses the training sample to estimate the parameters of the forecasting models, while the forecasting sample is used for forecast evaluation.

In the spirit of Meyler *et al* (1998), Pufnik and Kunovac (2006) and Akdogan *et al* (2012), this paper applies a pseudo out-of-sample forecast technique, which is aimed at replicating the experience that a forecaster faces in a forecasting practice to evaluate the forecasting performance of the proposed models. The paper uses the training sample to estimate the parameters of the forecasting models and as a first step in our forecasting practice obtain one to twelve months ahead forecasts starting from July 2011 up to June 2012 from these models. The paper stores these forecasts by putting the first forecast (July 2011) as first entry in the series 1 step ahead, the second forecast (August 2011) as the first entry in the series 2 steps ahead and so on to the twelfth forecast (June 2012) as the first entry in the series 12 steps ahead.

The actual data for July 2011 is added to the training sample after which the parameters of the models are re-estimated. Using the re-estimated models, we forecast the values from August 2011 up to July 2012. We then store these forecasts by putting the first forecast (August 2011) as the second entry in the series 1 step ahead, the second forecast (September 2011) as the second entry in the series 2 steps ahead and so on to the twelfth forecast (July 2012) as the second entry in the series 12 steps ahead.

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[6] This emphasises the role of exchange rate in the inflationary process, especially in countries practicing flexible exchange rate regime.

[7] This explains that inflation can be caused by structural rigidities in the economy. These include land tenure, lack of storage facilities, poor harvest, and overdependence on rainfall.

The above exercise is performed repeatedly until we reach the end of the pseudo out-of-sample period (September 2013). In this way, each of the forecast exercise yielded 12 series obtained as forecasts from one month ahead to 12 months ahead, which are then stored accordingly. A series of 16 observations was generated for each time horizon. We tested the quality of the obtained forecasts using three classical statistical loss functions: Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE) and Root Mean Squared Error (RMSE), defined as follows. Let the series $y_{1t}, y_{2t}, \ldots, y_{16t}$ be the actual inflation numbers and $\hat{y}_{1t}, \hat{y}_{2t}, \ldots, \hat{y}_{16t}$ be the forecast values for the forecast horizon t = 1, 2, 3,….12, then:

$$MAE_t = \frac{1}{16}\sum_{i=1}^{16}|y_{it} - \hat{y}_{it}| \quad (10)$$

$$MAPE_t = \frac{1}{16}\sum_{i=1}^{16}\frac{|100(y_{it} - \hat{y}_{it})|}{y_{it}} \quad (11)$$

$$RMSE_t = \sqrt{\frac{1}{16}\left\{\sum_{i=1}^{16}(y_{it} - \hat{y}_{it})^2\right\}} \quad (12)$$

The two scaled-dependent statistical loss functions: MAE_t and $RMSE_t$ and the scaled-independent measure $MAPE_t$ for the t forecast horizon (t=1, 2 .., 12) are used to compare the forecast performances of the estimated short-term forecasting models.

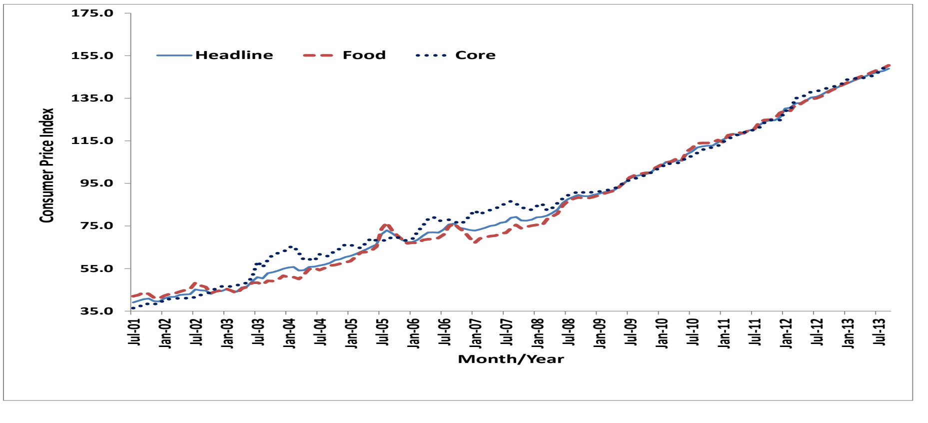

Fig 1: Nigeria's Headline, food and core consumer price indices.

4.0 Empirical Analysis and Results

This paper uses actual CPI data from the National Bureau of Statistics (NBS) covering the period July 2001 to September 2013. Fig 1 shows the trends in headline; core and food CPI used in the study period for model selection, parameter estimation and forecast evaluation. A detailed trend analysis of Nigeria's inflation and its volatility has been done recently in Omotosho and Doguwa (2012) and Mordi, et al (2012). The overall basket of products for calculating the CPI by the NBS is divided into 12 basic product groups in accordance with COICOP. So the all items CPI is a weighted sum of the 12 basic sub-indices such as food and non-alcoholic beverages; alcoholic beverages, tobacco and kola; clothing and footwear; amongst others. Thus,

$$CPI = \beta + \sum_{i=1}^{12} w_i CPI_i \quad and \quad \sum_{i=1}^{12} w_i = 1 \qquad (13)$$

where β is the aggregation error. However, from March 2012 this aggregation error was eliminated and β =0 as illustrated in Fig 2. The sub-indices CPI_i and w_i, i= 1, 2 …, 12 are presented in Table 2.

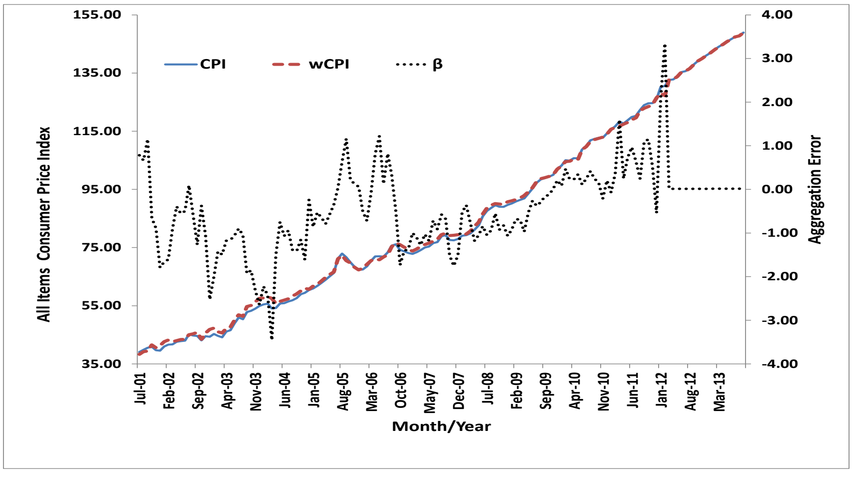

Fig 2: Nigeria's all items CPI and Derived CPI from the 12 COICOP Divisions.

At present, the NBS does not publish the CPI disaggregated into processed food and farm produce sub-indices used in price analysis by the Bank. As noted by Pufnik and Kunovac (2006) this level of disaggregation is more appropriate for modeling because the product groups are more homogenous, while in the 12 COICOP classifications, very different products and services are placed in the same group. For example, the transport group includes oil derivatives, whose price changes depend on changes in the price of crude oil in the international market, and vehicles, whose price changes greatly depend on the exchange rate and market competition.

Table 2: Headline CPI Sub-Indices and their Weights in the Basket of Products

Sub Index	Denoted by	Index Definition	Weight
CPI_1	Fna	Food and Non-Alcoholic Beverages	0.5180
CPI_2	Abt	Alcoholic beverages, tobacco and kola nuts	0.0109
CPI_3	Cft	Clothing and Footwear	0.0765
CPI_4	hwe	Housing, Water, Electricity, Gas and other Fuels	0.1673
CPI_5	Fhe	Furnishing, Household Equipment and Maintenance	0.0503
CPI_6	Hea	Health	0.0300
CPI_7	Trp	Transport	0.0651
CPI_8	Coc	Communication	0.0068
CPI_9	Rct	Recreation and Culture	0.0069
CPI_{10}	Edu	Education	0.0394
CPI_{11}	Rsh	Restaurant and Hotels	0.0121
CPI_{12}	Mgs	Miscellaneous Goods and Services	0.0166
All Items CPI			**1.000**

Checking the order of integration of included variables is crucial in any time series modeling. The Augmented Dickey Fuller (ADF) and Philips Perron tests are used to test the stationarity properties of the data. Both tests indicate that all the variables listed in Tables 1 and 2 are first difference stationary, except R2T that is level stationary. Box and Jenkins argue that parsimonious models produce much better forecasts than over parameterized models. They introduced a three-stage method at selecting a parsimonious seasonal ARIMA model for the purpose of estimating and forecasting a univariate time series. The three stages comprise: identification, estimation and diagnostic checking. The three stage approach was used in this paper. Furthermore, all the endogenous and exogenous variables used in the paper are in their natural logarithmic form, except Wds, BDC, NCG, R1C, R2T and R3V.

Before using these parsimonious models for statistical inference, the residuals ϵ_t are generally examined for evidence of serial correlation. The Breusch-Godfrey serial correlation LM test is used to test the null hypothesis of no serial correlation up to a specific order in the residuals. Also to test the null hypothesis that there is no autoregressive conditional heteroskedasticity (ARCH) effect in the residuals, we employ the ARCH LM test. Accepting the null hypothesis will indicate that there is no ARCH effect in the residuals.

Table 3: Parameter Estimates of the $\Delta SMhcpi_t$ and $\Delta SXhcpi_t$ models

Estimated Models:	$\Delta SMhcpi_t$		$\Delta SXhcpi_t$	
Parameter	Estimate	Standard Error	Estimate	Standard Error
c	0.0089[a]	0.0004	0.0005[a]	0.0002
γ_1			0.3764[a]	0.0126
γ_2			0.5896[a]	0.011
γ_3			-0.0034	0.0038
γ_4			-0.0044	0.0034
γ_5			1.92E-05[a]	6.47E-06
γ_6			-8.15E-06[c]	4.87E-06
γ_7			-8.51E-06[b]	4.29E-06
$\emptyset_1$	0.7528[a]	0.0744	0.2271[a]	0.0165
$\emptyset_2$			0.3224[a]	0.0944
φ_1	-0.2856[a]	0.0758	-0.5474[a]	0.0805
θ_1	- 0.6277[a]	0.0981	-0.9999[a]	0.0262
θ_2	-0.0069	0.0941		
θ_3	-0.3574[a]	0.0892		
Θ_1	0.9310[a]	0.0221	0.8748[a]	0.0234
BG LM Test	1.1385		1.0166	
P-Value	(0.325)		(0.366)	
AIC	-6.021		-8.906	
SC	-5.845		-8.569	
ARCH LM Test	1.0433		1.0973	
P-Value	(0.309)		(0.297)	
Adjusted R - Squared	0.4979		0.9717	

a = significant at 1 per cent level

b = significant at 5 per cent level

c = significant at 10 per cent level

All variables are in log form except NCG, R1C, R2T, R3V, Wds, Bdc

4.1 Parsimonious Headline Inflation Models

In this section we shall provide parsimonious models of the headline CPI directly using SARIMA and SARIMAX processes. The training sample data from July 2001 to June 2011 consisting of 120 monthly observations will be used in the model estimation.

The parsimonious SARIMA headline CPI model fitted as SARIMA (1,1,3) (1,0,1) [12] and denoted by $\Delta SMhcpi_t$ is defined by

$$\Delta SMhcpi_t = c + \mu_t$$

$$(1 - \emptyset_1 L^1)(1 - \varphi_1 L^{12})\mu_t = (1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3)(1 + \Theta_1 L^{12})\epsilon_t \quad (14)$$

The SARIMAX headline CPI model fitted as SARIMAX (2,1,1)(1,0,1)[12] and denoted by $\Delta SXhcpi_t$ is defined by

$$\Delta SXhcpi_t = c + \gamma_1 \Delta Cor_t + \gamma_2 \Delta Fod_t + \gamma_3 \Delta Fue_t + \gamma_4 \Delta RM_{t-4} + \gamma_5 \Delta R1C_{t-1} + \gamma_6 \Delta R2T_{t-2} + \gamma_7 \Delta R3V_t + \mu_t$$

$$(1 - \emptyset_1 L - \emptyset_2 L^2)(1 - \varphi_1 L^{12})\mu_t = (1 + \theta_1 L)(1 + \Theta_1 L^{12})\epsilon_t \quad (15)$$

The parameter estimates of equations (14) and (15) and the diagnostics are also presented in Table 3.

4.2 Parsimonious Weighted Sum Headline Inflation Models

In this section we shall provide parsimonious model estimates of the twelve individual CPI sub-indices using the processes described in equations (1) and (7) from which the two weighted sums of the parsimonious model sub-indices will provide the two headline CPI models $WSMhcpi_t$ and $WSXhcpi_t$ using SARIMA and SARIMAX processes, respectively.

The SARIMA food and non-alcoholic beverages CPI model selected as SARIMA (3,1,3)(1,0,1)[12] and denoted by $\Delta SMfna_t$ is given by

$$\Delta SMfna_t = c + \mu_t$$

$$(1 - \emptyset_1 L - \emptyset_2 L^2 - \emptyset_3 L^3)(1 - \varphi_1 L^{12})\mu_t = (1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3)(1 + \Theta_1 L^{12})\epsilon_t \quad (16)$$

The SARIMAX food and non-alcoholic beverages CPI model fitted as SARIMAX (3,1,3)(1,0,1)[12] and denoted by $\Delta SXfna_t$ is defined by

$$\Delta SXfna_t = c + \gamma_1 \Delta Gex_t + \gamma_2 \Delta M2_t + \gamma_3 \Delta NCG_{t-3} + \gamma_4 \Delta R1C_t + \gamma_5 \Delta R2T_t + \gamma_6 \Delta R3V_t + \mu_t$$

$$(1 - \emptyset_1 L - \emptyset_2 L^2 - \emptyset_3 L^3)(1 - \varphi_1 L^{12})\mu_t = (1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3)(1 + \Theta_1 L^{12})\epsilon_t \qquad (17)$$

Table 4: Parsimonious Models of other CPI Components indices

Sub Index	Dependent Variable	Model	Exogenous Variable	Equation Number
Cft	$\Delta SMcft_t$	SARIMA (3,1,3) (1,0,1)[12]		(20)
	$\Delta SXcft_t$	SARIMAX (3,1,3) (1,0,1)[12]	ΔBdc_{t-3}, ΔBdc_{t-5}, ΔGex_{t-3}, ΔGex_{t-7}, $\Delta M2_{t-1}$	(21)
hwe	$\Delta SMhwe_t$	SARIMA (4,1,3) (1,0,1)[12]		(22)
	$\Delta SXhwe_t$	SARIMAX (1,1,1) (1,0,1)[12]	ΔBdc_{t-1}, ΔFue_{t-1}, ΔGex_{t-3}, $\Delta M2_{t-2}$, $\Delta R1C_{t-1}$, $\Delta R3V_t$	(23)
Fhe	$\Delta SMfhe_t$	SARIMA (3,1,3) (1,0,1)[12]		(24)
	$\Delta SXfhe_t$	SARIMAX (3,1,3) (1,0,1)[12]	ΔBdc_{t-3}, ΔBdc_{t-4}, ΔFue_{t-2}, ΔGex_{t-2}, $\Delta M2_{t-3}$, $\Delta R1C_t$	(25)
Hea	$\Delta SMhea_t$	SARIMA (2,1,2) (1,0,1)[12]		(26)
	$\Delta SXhea_t$	SARIMAX (2,1,3) (1,0,1)[12]	ΔBdc_{t-2}, ΔCPS_{t-1}, ΔCPS_{t-2}, ΔGex_{t-7}, ΔGex_{t-10}, $\Delta M2_{t-2}$, $\Delta M2_{t-5}$	(27)
Trp	$\Delta SMtrp_t$	SARIMA (2,1,2) (1,0,1)[12]		(28)
	$\Delta SXtrp_t$	SARIMAX (2,1,1) (1,0,1)[12]	ΔCPS_{t-1}, ΔFue_{t-2}, ΔGex_{t-3}, ΔGex_{t-9}, ΔRM_{t-1}, $\Delta R2T_{t-2}$, $\Delta R3V_{t-2}$	(29)
Coc	$\Delta SMcoc_t$	SARIMA (3,1,3) (0,0,1)[12]		(30)
	$\Delta SXcoc_t$	SARIMAX (1,1,4) (1,0,1)[12]	ΔGex_t, ΔGex_{t-9}, $\Delta M2_t$, $\Delta M2_{t-2}$, $\Delta R1C_{t-1}$, $\Delta R2T_{t-2}$, ΔWds_{t-3}, ΔWds_{t-4}	(31)
Rct	$\Delta SMrct_t$	SARIMA (3,1,3) (1,0,1)[12]		(32)
	$\Delta SXrct_t$	SARIMAX (3,1,2) (1,0,1)[12]	ΔCPS_{t-4}, ΔFue_{t-1}, ΔGex_{t-1}, ΔGex_{t-3}, ΔRM_{t-2}, $\Delta R1C_{t-3}$, $\Delta R2T_{t-1}$	(33)
Edu	$\Delta SMedu_t$	SARIMA (2,1,3) (1,0,1)[12]		(34)
	$\Delta SXedu_t$	SARIMAX (2,1,3) (1,0,1)[12]	ΔFue_{t-3}, ΔGex_{t-2}, ΔRM_{t-2}, ΔWds_t, ΔWds_{t-1}	(35)
Rsh	$\Delta SMrsh_t$	SARIMA (4,1,4) (1,0,1)[12]		(36)
	$\Delta SXrsh_t$	SARIMAX (3,1,3) (1,0,1)[12]	ΔCPS_{t-3}, ΔGex_{t-1}, ΔGex_{t-8}, ΔNCG_t, ΔNCG_{t-5}, ΔRM_{t-2} ΔRM_{t-3}, ΔWds_{t-1}, ΔWds_{t-4}	(37)
Mgs	$\Delta SMmgs_t$	SARIMA (1,1,2) (1,0,1)[12]		(38)
	$\Delta SXmgs_t$	SARIMAX (3,1,3) (1,0,1)[12]	ΔFue_t, ΔGex_{t-2}, ΔRM_{t-4}, $\Delta R1C_{t-1}$, ΔWds_t, ΔWds_{t-1}	(39)

The SARIMA alcoholic beverages, tobacco and narcotics CPI model selected as SARIMA (2,1,1)(1,0,1)[12] and denoted by $\Delta SMabt_t$ is given by

$$\Delta SMabt_t = c + \mu_t$$

$$(1 - \emptyset_1 L - \emptyset_2 L^2)(1 - \varphi_1 L^{12})\mu_t = (1 + \theta_1 L)(1 + \Theta_1 L^{12})\epsilon_t \qquad (18)$$

Table 5(a): Parameter Estimates of the CPI components models

Estimated Models:	$\Delta SMfna_t$	$\Delta SXfna_t$	$\Delta SMabt_t$	$\Delta SXabt_t$	$\Delta SMcft_t$	$\Delta SXcft_t$	$\Delta SMhwe_t$	$\Delta SXhwe_t$
Denoted by	ΔSM_1	ΔSX_1	ΔSM_2	ΔSX_2	ΔSM_3	ΔSX_3	ΔSM_4	ΔSX_4
Parameter	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
c	0.0101[a]	0.0079[a]	0.0068[a]	0.0081[a]	0.0051[a]	0.0037[c]	0.0083[a]	0.0099[a]
γ_1		-0.0034[b]		-0.0388[b]		-0.0013[a]		-8.6E-04[a]
γ_2		0.0782[a]		-0.1447[a]		-0.0009[a]		0.0365[c]
γ_3		9.84E-09[b]		0.0038[a]		-0.0042[c]		0.0023
γ_4		1.43E-04[a]		0.0065[a]		0.0086[a]		-0.1029[a]
γ_5		-6.87E-05[b]				0.0676[c]		-4.05E-05[b]
γ_6		5.23E-05[b]						1.24E-04[a]
$\emptyset_1$	-0.5213[a]	0.3842[b]	-1.2472[a]	0.0153	0.3301[a]	0.2401[c]	-0.1923[c]	0.8072[a]
$\emptyset_2$	-0.5898[a]	-0.5139[a]	-0.3274[a]	-0.4346[a]	0.2475[a]	0.4481[a]	0.3856[a]	
$\emptyset_3$	-0.7434[a]	-0.3244[c]		-0.2943[a]	-0.7581[a]	-0.5844[a]	0.4674[a]	
$\emptyset_4$							-0.3131[a]	
φ_1	-0.3768[a]	0.5043[a]	-0.3833[a]	0.4187[a]	0.5172[a]	-0.3121[a]	0.3616[a]	-0.042
θ_1	0.7712[a]	-0.0286	0.9133[a]	-0.4546[a]	-0.4567[a]	-0.5150[a]	0.4699[a]	-0.9994[a]
θ_2	0.7667[a]	0.4459[a]		0.9696[a]	-0.125	-0.2817	-0.3159[a]	
θ_3	0.9870[a]	0.7302[a]			0.8566[a]	0.9027[a]	-0.9184[a]	
Θ_1	0.9439[a]	-0.9507[a]	0.9011[a]	-0.9307[a]	-0.9817[a]	0.9569[a]	-0.9459[a]	-0.9599[a]
BG LM Test	0.029	0.953	0.093	1.171	1.168	2.262	1.542	1.295
P-Value	(0.972)	(0.390)	(0.911)	(0.316)	(0.315)	(0.111)	(0.220)	(0.279)
AIC	-5.267	-5.324	-4.979	-5.571	-4.274	-4.928	-4.997	-5.258
SC	-5.038	-4.929	-4.828	-5.238	-4.045	-4.542	-4.742	-5.141
ARCH LM Test	0.362	0.132	5.375	0.36	0.059	1.103	1.484	0.001
P-Value	(0.549)	(0.717)	(0.022)	(0.550)	(0.809)	(0.315)	(0.704)	(0.982)
Adjusted R - Squared	0.437	0.492	0.5343	0.603	0.365	0.667	0.662	0.731

a = significant at 1 per cent level
b = significant at 5 per cent level
c = significant at 10 per cent level
All variables are in log form except NCG, R1C, R2T, R3V, Wds, Bdc

The SARIMAX alcoholic beverages, tobacco and narcotics CPI model selected as SARIMAX (3,1,2)(1,0,1)[12] and denoted by $\Delta SXabt_t$ is defined by

$$\Delta SXabt_t = c + \gamma_1 \Delta Cps_{t-7} + \gamma_2 \Delta Edu_{t-4} + \gamma_3 \Delta Gex_{t-1} + \gamma_4 \Delta Gex_{t-8} + \mu_t$$
$$(1 - \emptyset_1 L - \emptyset_2 L^2 - \emptyset_3 L^3)(1 - \varphi_1 L^{12})\mu_t = (1 + \theta_1 L + \theta_2 L^2)(1 + \Theta_1 L^{12})\epsilon_t \qquad (19)$$

The selected SARIMA and SARIMAX models for the remaining ten all items CPI sub-indices are presented in Table 4 as equations (20) to (39).

The parameter estimates of equations (14) to (39) and the diagnostics are presented in Tables 3, 5(a), 5(b) and 5(c). Almost all the regression results suggest the absence of ARCH effect and lack of autocorrelations in the residuals. In addition, all the AR and MA roots are inverted indicating that the estimated models are adequate for statistical inference.

Table 5(b): Parameter Estimates of the CPI components models

Estimated Models:	$\Delta SMfhe_t$	$\Delta SXfhe_t$	$\Delta SMhea_t$	$\Delta SXhea_t$	$\Delta SMtrp_t$	$\Delta SXtrp_t$	$\Delta SMhcoc_t$	$\Delta SXcoc_t$
Denoted by	ΔSM_5	ΔSX_5	ΔSM_6	ΔSX_6	ΔSM_7	ΔSX_7	ΔSM_8	ΔSX_8
Parameter	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
c	0.0079^{a}	0.0074^{a}	0.0060^{a}	0.0061^{a}	0.0062^{a}	0.0097^{a}	0.0091	0.0047
γ_1		$6.7E-04^{b}$		$-9.92E-04^{a}$		-0.0733^{a}		0.0115^{a}
γ_2		-0.0011^{a}		-0.0888^{a}		-0.0327		-3.85E-04
γ_3		0.1911^{a}		-0.1387^{a}		-0.0108^{a}		-0.1263^{b}
γ_4		-0.0038^{b}		0.0039^{b}		0.0037		$- 0.2056^{a}$
γ_5		-0.0212^{c}		0.0051^{a}		0.0465^{c}		$9.49E-05^{c}$
γ_6		$7.94E-05^{a}$		0.1522^{a}		$7.49E-05^{c}$		$1.61E-04^{a}$
γ_7				0.1299^{a}		$-7.76E-05^{c}$		-0.0032^{a}
γ_8								-0.0022^{c}
$\emptyset_1$	0.6185^{a}	-1.0604^{a}	-0.2845	0.0637	1.2946^{a}	-0.7658^{a}	-0.8849^{a}	$- 0.2771^{c}$
$\emptyset_2$	-0.7679^{a}	-0.2605^{c}	0.5747^{a}	0.5368^{a}	-0.5517^{a}	-0.4265^{a}	0.0989	
$\emptyset_3$	0.7173^{a}	0.2842^{a}					0.5737^{b}	
φ_1	-0.3167^{c}	0.0632	0.4537^{a}	-0.1896^{a}	0.4892^{a}	-0.2822^{a}		$- 0.1343^{b}$
θ_1	-0.8924^{a}	0.5527^{a}	-0.1125	-0.2075	-1.7559^{a}	0.59399^{a}	1.1219^{a}	0.7348^{a}
θ_2	0.7711^{a}	$- 0.5572^{a}$	$- 0.7012^{a}$	$- 0.4658^{a}$	0.9831^{a}		0.2092	-0.6744^{a}
θ_3	-0.8785^{a}	-0.9758^{a}		$- 0.3048^{b}$			-0.4904	-0.0836
θ_4								0.5623^{a}
Θ_1	0.4846^{a}	-0.9433^{a}	-0.9324^{a}	0.9788^{a}	-0.9077^{a}	0.9183^{a}	0.0505	0.9694^{a}
BG LM Test P-Value	2.227 (0.114)	0.633 (0.534)	0.327 (0.722)	1.037 (0.360)	0.149 (0.862)	0.192 (0.826)	1.1 (0.337)	0.249 (0.780)
AIC SC	-4.667 -4.438	-5.633 -5.233	-3.354 -3.177	-4.865 -4.446	-4.049 -3.873	-4.719 -4.358	-2.909 -2.716	-3.948 -3.506
ARCH LM Test P-Value	0.01 (0.921)	0.22 (0.640)	3.862 (0.052)	0.124 (0.726)	3.096 (0.082)	0.141 (0.709)	2.098 (0.150)	1.962 (0.165)
Adjusted R - Squared	0.219	0.676	0.504	0.799	0.342	0.571	0.171	0.722

a = significant at 1 per cent level
b = significant at 5 per cent level
c = significant at 10 per cent level
All variables are in log form except NCG, R1C, R2T, R3V, Wds, Bdc

Table 5(c): Parameter Estimates of the CPI components models

Estimated Models:	$\Delta SMrct_t$	$\Delta SXrct_t$	$\Delta SMedu_t$	$\Delta SXedu_t$	$\Delta SMrsh_t$	$\Delta SXrhs_t$	$\Delta SMmgs_t$	$\Delta SXmgs_t$
Denoted by	ΔSM_9	ΔSX_9	ΔSM_{10}	ΔSX_{10}	ΔSM_{11}	ΔSX_{11}	ΔSM_{12}	ΔSX_{12}
Parameter	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
c	4.98E-04	0.0013	0.0084[a]	0.0071[a]	0.0125[a]	0.0098[a]	0.0095[a]	0.0051[a]
γ_1		0.0338		0.1329[a]		0.0495[b]		0.1063[a]
γ_2		0.0713[c]		-0.0078[b]		-0.0122[a]		-0.0088[a]
γ_3		0.0079[a]		0.0908[a]		3.20E-03		0.0751[a]
γ_4		-0.0057[b]		0.0024[c]		-2.42E-08[a]		7.29E-05[a]
γ_5		0.0364[c]		-0.0011		-2.13E-08[a]		0.0052[a]
γ_6		1.15E-04[a]				0.1107[a]		-0.0044[a]
γ_7		1.29E-04[a]				0.0952[a]		
γ_8						-0.0043[a]		
γ_9						0.0018		
$\emptyset_1$	-0.3164[a]	0.6492[a]	0.6311[a]	1.4645[a]	-1.8442[a]	0.3311[a]	-0.9241[a]	-0.5988[a]
$\emptyset_2$	-0.2527[a]	-0.6004[a]	-0.7876[a]	-0.5603[a]	-1.0074[b]	-0.1666		-0.5563[a]
$\emptyset_3$	-0.7753[a]	0.2617[a]			0.2222	0.2141[c]		-0.1922[c]
$\emptyset_4$					0.3832[b]			
φ_1	0.5575[a]	-0.3071[a]	0.4266[a]	0.4143[a]	0.3864[a]	0.4375[a]	-0.5297[a]	0.0634
θ_1	0.2860[a]	-0.8120[a]	-1.1871[a]	-1.8947[a]	1.8556[a]	-0.4244[a]	0.6935[a]	0.0980[b]
θ_2	0.2736[a]	0.9999[a]	1.3455[a]	0.8558[b]	0.9884[c]	0.4121[a]	-0.3050[a]	0.0526
θ_3	0.9871[a]		-0.5142[a]	0.0696	-0.4447	-0.9877[a]		-0.9166[a]
θ_4					-0.5774[a]			
Θ_1	-0.9572[a]	0.9616[a]	-0.9559[a]	-0.9600[a]	-0.9404[a]	-0.8978[a]	0.9711[a]	-0.9737[a]
BG LM Test	2.773	2.407	1.843	1.261	2.572	1.756	2.449	2.351
P-Value	(0.068)	(0.097)	(0.164)	(0.289)	(0.082)	(0.180)	(0.092)	(0.102)
AIC	-3.884	-4.281	-3.84	-4.026	-3.969	-4.393	-3.295	-4.433
SC	-3.655	-3.878	-3.634	-3.681	-3.679	-3.894	-3.144	-4.032
ARCH LM Test	0.004	0.041	1.178	0.103	0.002	0.047	1.503	0.079
P-Value	(0.948)	(0.841)	(0.674)	(0.749)	(0.967)	(0.829)	(0.223)	(0.778)
Adjusted R - Squared	0.511	0.698	0.705	0.696	0.353	0.532	0.59	0.734

a = significant at 1 per cent level
b = significant at 5 per cent level
c = significant at 10 per cent level
All variables are in log form except NCG, R1C, R2T, R3V, Wds, Bdc

The two parsimonious weighted sum headline CPI models, $WSMhcpi_t$ and $WSXhcpi_t$ are given as:

$$\text{WSMhcpi} = \beta + \sum_{i=1}^{12} w_i \exp\{SM_i\} \quad (40)$$

$$\text{WSXhcpi} = \beta + \sum_{i=1}^{12} w_i \exp\{SX_i\} \quad (41)$$

where w_i are the component weights, ΔSM_i and ΔSX_i (i=1, 2, …, 12) are given in Tables 5 (a), (b) and (c) and β is as defined in equation (13).

Table 6: Parameter Estimates of Core and Food CPI models

Estimated Models:	**$\Delta SMcor_t$**	**$\Delta SXcor_t$**	**$\Delta SMfod_t$**	**$\Delta SXfod_t$**
Parameter	Estimate	Estimate	Estimate	Estimate
c	0.0077[a]	0.0084[a]	0.0093[a]	0.0064[a]
γ_1		8.78E-04[a]		-0.0129
γ_2		-0.0234[b]		0.0077[a]
γ_3		-0.0027[a]		0.0951[a]
γ_4		-0.0296[b]		7.72E-09
γ_5		5.84E-09[a]		1.22E-04[a]
γ_6		6.67E-05[a]		7.39E-05[b]
γ_7		-4.51E-05[a]		
γ_8		5.08E-05[a]		
$\emptyset_1$	1.6285[a]	0.0453	0.8132[a]	-0.5324[a]
$\emptyset_2$	-0.8112[a]	-0.3038[a]		-0.4689[a]
$\emptyset_3$	0.1259	0.2453[b]		-0.8694[a]
φ_1	-0.4583[a]	0.2713[a]	-0.4859[a]	-0.2752[a]
θ_1	-1.7519[a]	-0.0192	-0.6850[a]	0.5698[a]
θ_2	0.7548[a]	0.0239	-0.3006[a]	0.5572[a]
θ_3		-0.9976[a]		0.9626[a]
Θ_1	0.9417[a]	-0.9822[a]	0.9126[a]	0.8569[a]
BG LM Test P-Value	0.797 (0.454)	1.781 (0.176)	0.37 (0.692)	1.336 (0.269)
AIC SC	-5.122 -4.918	-6.251 -5.782	-4.94 -4.789	-5.511 -5.092
ARCH LM Test P-Value	5.541 (0.021)	0.362 (0.549)	0.448 (0.505)	0.172 (0.679)
Adjusted R - Squared	0.434	0.733	0.296	0.601

a = significant at 1 per cent level
b = significant at 5 per cent level
c = significant at 10 per cent level
All variables are in log form except NCG, R1C, R2T, R3V, Wds, Bdc

4.3 Core Inflation Models

In this section we shall provide model estimates of core CPI using the SARIMA and the SARIMAX processes. The SARIMA core CPI model selected as SARIMA (3,1,2)(1,0,1)[12] and denoted by $\Delta SMcor_t$ is given as

$$\Delta SMcor_t = c + \mu_t$$
$$(1-\emptyset_1 L-\emptyset_2 L^2-\emptyset_3 L^3)(1-\varphi_1 L^{12})\mu_t = (1+\theta_1 L+\theta_2 L^2)(1+\Theta_1 L^{12})\epsilon_t \quad (42)$$

The SARIMAX core CPI model selected as SARIMAX (3,1,3) (1,0,1) [12] and denoted by $\Delta SXcor_t$ is defined as

$$\Delta SXcor_t = c + \gamma_1 \Delta Bdc_{t-9} + \gamma_2 \Delta Fue_{t-2} + \gamma_3 \Delta Gex_{t-1} + \gamma_4 \Delta M2_{t-2} + \gamma_5 \Delta NCG_{t-13} + \gamma_6 \Delta R1C_t + \gamma_7 \Delta R1C_{t-3} + \gamma_8 \Delta R2T_{t-1} + \mu_t$$

$$(1-\emptyset_1 L-\emptyset_2 L^2-\emptyset_3 L^3)(1-\varphi_1 L^{12})\mu_t = (1+\theta_1 L+\theta_2 L^2+\theta_3 L^3)(1+\Theta_1 L^{12})\epsilon_t \quad (43)$$

4.4 Food Inflation Models

In this section we shall provide parsimonious models of food CPI using the SARIMA and the SARIMAX processes. The SARIMA food CPI model selected as SARIMA (1,1,2)(1,0,1)[12] and denoted by $\Delta SMfod_t$ is given by

$$\Delta SMfod_t = c + \mu_t$$

$$(1-\emptyset_1 L)(1-\varphi_1 L^{12})\mu_t = (1+\theta_1 L+\theta_2 L^2)(1+\Theta_1 L^{12})\epsilon_t \quad (44)$$

The SARIMAX food CPI model selected as SARIMAX (3,1,3) (1,0,1) [12] and denoted by $\Delta SXfod_t$ is defined by

$$\Delta SXfod_t = c + \gamma_1 \Delta Fue_{t-1} + \gamma_2 \Delta Gex_{t-9} + \gamma_3 \Delta M2_t + \gamma_4 \Delta NCG_{t-4} + \gamma_5 \Delta R1C_t + \gamma_6 \Delta R2T_{t-1} + \mu_t$$

$$(1-\emptyset_1 L-\emptyset_2 L^2-\emptyset_3 L^3)(1-\varphi_1 L^{12})\mu_t = (1+\theta_1 L+\theta_2 L^2+\theta_3 L^3)(1+\Theta_1 L^{12})\epsilon_t \quad (45)$$

The parameter estimates of equations (42) to (45) and the diagnostics presented in Table 6 suggest the absence of ARCH effect (except for core SARIMA) and lack of autocorrelation in the residuals. Also, the assumption that the AR and MA roots are inverted is satisfied inferring that the fitted models are adequate for statistical inference.

5 Performance Evaluations of the Estimated Models

This section examines the four parsimonious short-term forecasting models for headline inflation and the two models each for core and food inflation, with the view to assessing their pseudo out-of-sample forecast accuracy. The statistical loss functions employed for this purpose are the mean absolute error (MAE), the root mean squared error (RMSE) and the mean absolute percent error (MAPE). The performance evaluation of the competing models is to determine which of them are more precise and reliable for forecasting headline, core and food inflation over the 12 months forecast horizon.

The main purpose of fitting SARIMA and SARIMAX CPI models is to project the CPI series forward beyond the sample period. In forecasts, there are two inevitable sources of error, namely: error due to ignorance of future innovations $\{\epsilon_{n+k}$, k=1, 2, .., m}, and error due to differences between true and estimated parameter values. Here we shall deal with the first source of error. Suppose y_t equals CPI_t. We assume that observations on y_t are available for periods 1 to n, and that all m forecasts are made conditional on information available at time n. Thus:

y_{n+k} = unknown value of y in future period n+k,
$\hat{y}_{n+k}$ = forecast of y_{n+k} made on the basis of information available at time n.

Therefore, we define the forecast error ϵ_{t+k} for the entire forecast horizon as

$$\epsilon_{n+k} = y_{n+k} - \hat{y}_{n+k}, \quad k = 1, 2, \dots m \tag{46}$$

It has been shown in the literature that the minimum MSE forecast of y_{n+k} is the conditional expectation of $\hat{y}_{n+k}$, given information available at time n. Using these parsimonious CPI forecast models, this paper estimates the year-on-year headline inflation rate π_t for each of the parsimonious models as:

$$\pi_t = 100(\hat{y}_t / y_{t-12} - 1) \tag{47}$$

where

$\hat{y}_t$ = forecast of CPI_t obtained from the parsimonious CPI model.

y_{t-12} = actual CPI_{t-12} value at period t-12.

Table 7: Statistical Loss Functions for Competing Headline CPI models

Forecast Horizon	MAE				MAPE			
	$\Delta SMhlin_t$	$\Delta SMWhlin_t$	$\Delta SXWhlin_t$	$\Delta SXhlin_t$	$\Delta SMhlin_t$	$\Delta SMWhlin_t$	$\Delta SXWhlin_t$	$\Delta SXhlin_t$
1	0.73	1.07	1.31	0.46	6.27	9.31	11.65	3.91
2	1.09	1.41	1.59	0.54	9.25	11.97	13.89	4.58
3	1.24	1.56	1.50	0.50	10.44	13.00	13.12	4.25
4	1.26	1.73	1.92	0.49	10.85	14.29	16.94	4.21
5	1.46	2.05	2.02	0.52	12.74	16.92	18.29	4.41
6	1.81	2.41	2.21	0.52	16.03	20.66	19.65	4.47
7	2.09	2.52	2.01	0.46	19.05	21.80	17.80	3.93
8	2.16	3.13	1.98	0.51	20.18	27.90	17.69	4.51
9	2.06	3.30	1.99	0.53	20.01	29.90	17.79	4.97
10	2.18	3.07	1.60	0.50	21.87	28.34	15.01	4.76
11	2.24	3.36	1.74	0.47	23.07	32.50	17.57	4.62
12	2.50	3.35	2.28	0.51	26.51	32.81	23.65	5.27

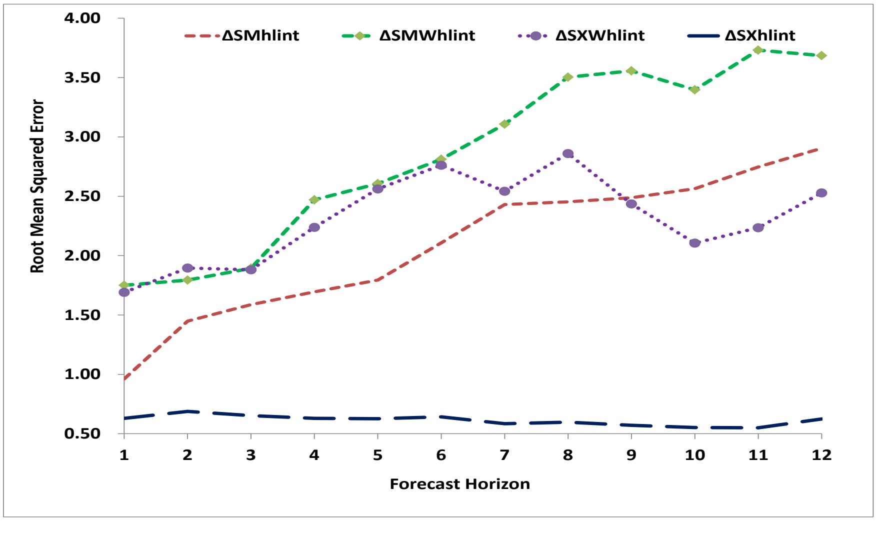

Fig 3: Root Mean Squared Error of the competing Headline Inflation models

We then compute the MAE, MAPE and RMSE of equations (10), (11) and (12) for the inflation forecast based on the parsimonious CPI forecast models using the performance evaluation framework described in section three. The results of the computations are presented in Table 7 and Fig 3 for headline

Table 8: Statistical Loss Functions for Competing Core CPI models

Forecast Horizon	MAE		MAPE	
	$\Delta SMcor_t$	$\Delta SXcor_t$	$\Delta SMcor_t$	$\Delta SXcor_t$
1	0.95	1.35	7.27	10.12
2	1.52	1.79	11.62	13.37
3	1.95	2.41	14.57	17.65
4	2.07	2.78	15.08	20.75
5	2.21	2.57	16.10	19.34
6	2.51	2.83	18.94	21.39
7	2.28	2.79	17.64	21.25
8	2.71	3.13	22.65	24.31
9	2.90	3.12	26.57	24.76
10	2.75	3.16	27.58	27.28
11	2.92	3.24	30.27	30.04
12	2.81	3.37	31.16	33.96

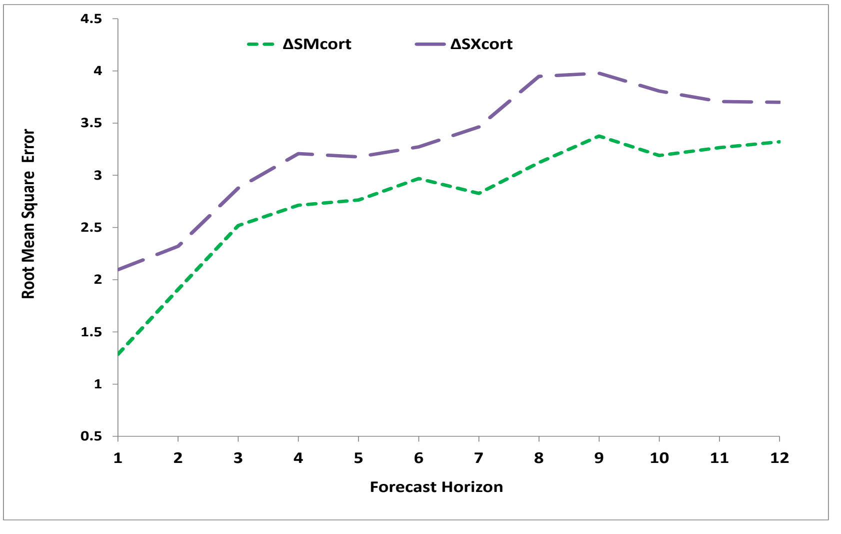

Fig 4: Root Mean Squared Error of the competing Core Inflation models

inflation. All the three performance evaluation measures presented in Table 7 and Fig 3 provide very similar results for headline inflation. That the SARIMAX model selected consistently provides the smallest forecast error in the entire forecast horizon by all the performance measures and should therefore be used for short-term headline inflation forecast. It is followed by the SARIMA model up to about six to seven month forecast horizon. Thereafter, the model based on the weighted sum SARIMAX performs better than the other two models.

While the MAE measure presented in Table 8 for core inflation suggests that the SARIMA model performed better in the entire forecast horizon, the MAPE measure indicates that for nine and ten months forecast horizon, the SARIMAX model maybe preferred. However, the RMSE measure given in Fig 4 indicates that the SARIMA based model has consistently return a lower error than the SARIMAX and is therefore recommend for use in forecasting core inflation in the 12 months forecast horizon.

Table 9: Statistical Loss Functions for Food CPI models

Forecast Horizon	MAE		MAPE	
	$\Delta SMfod_t$	$\Delta SXfod_t$	$\Delta SMfod_t$	$\Delta SXfod_t$
1	0.93	1.22	8.70	11.40
2	1.33	2.01	12.25	18.59
3	1.02	2.73	9.05	25.03
4	1.27	3.09	11.39	28.01
5	1.49	3.40	13.65	30.90
6	1.49	3.26	13.42	29.22
7	1.46	3.31	13.06	30.75
8	1.59	3.05	14.81	28.31
9	1.51	2.53	14.69	23.84
10	1.75	2.05	17.13	19.23
11	1.89	1.73	18.30	16.21
12	2.04	1.17	20.26	11.24

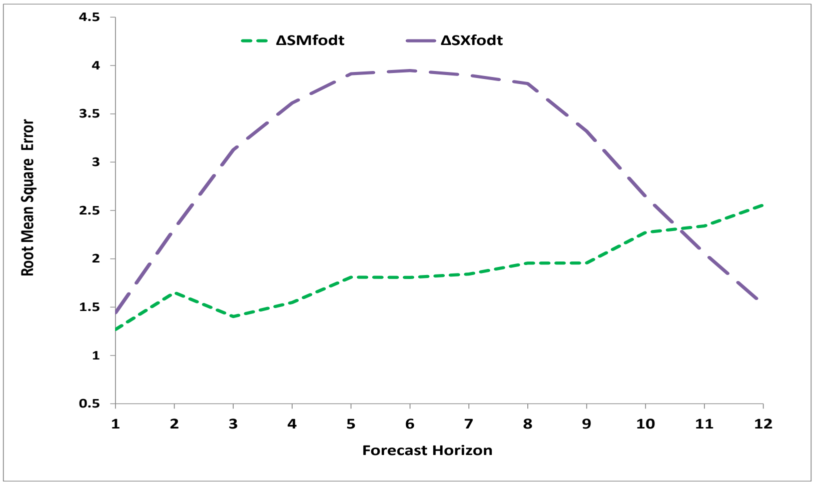

Fig 5: Root Mean Squared Error of the competing food Inflation models

All the three performance evaluation measures presented in Table 9 and Fig 5 for food inflation provide very similar results. While the SARIMA model selected consistently provides the smallest forecast error up to ten month ahead forecast, the SARIMAX model performs better in the eleventh and twelve months ahead forecast.

6. Twelve Months Forecast

6.1 Headline Inflation

The observed monthly headline CPI, between July 2001 and December 2013 was first differenced stationary. Thereafter, the parameters of the $\Delta SXhcp_t$ model defined in equation (15) were re-estimated from the actual data spanning July 2001 to January 2014. Using static forecasting procedure we provide 12 months ahead forecast of headline CPI and then computed the headline inflation rates using equation (47). The forecast values and their 95 per cent confidence region are presented as a fan chart in Fig 6. The twelve months interval forecasts of headline inflation suggest with 95.0 per cent level of confidence, that the headline inflation would be in the region of [7.3%, 12%] in the next twelve months. As the level of confidence diminishes, the interval estimate also narrows. For instance, at 25.0 per cent confidence we would expect headline inflation to hover within the band of [7.7%, 11.5%].

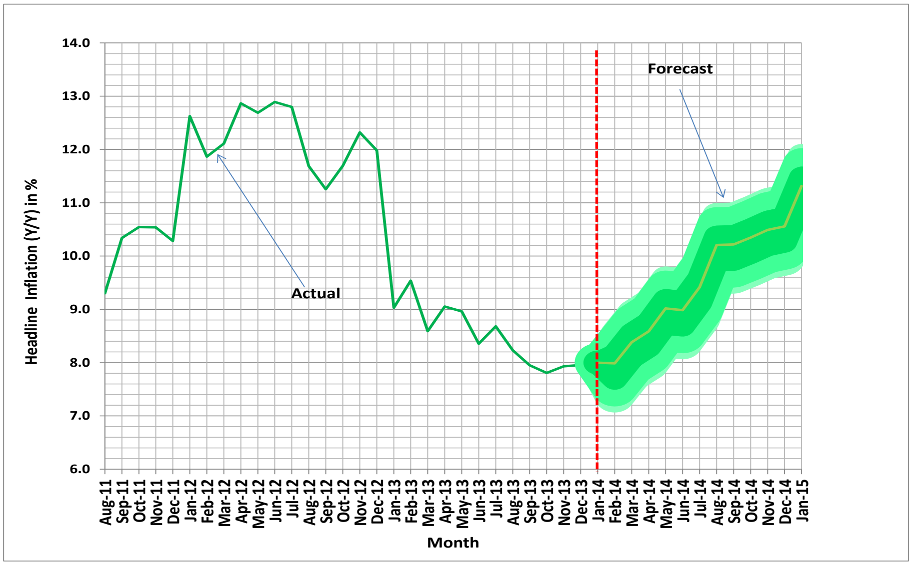

Fig 6: Fan Chart of Headline Inflation (February 2014 to January 2015)

6.2 Core Inflation

The observed monthly core CPI, between July 2001 and January 2014 was first differenced stationary. Thereafter, the parameters of the $\Delta SMcor_t$ model defined in equation (42) were re-estimated from the actual data spanning July 2001 to January 2014. Using static forecasting procedure we provide 12 months ahead forecast of core CPI and then computed the core inflation rates using equation (47). The forecast values and their 95 per cent confidence region are presented as a fan chart in Fig 7. The interval forecasts of core inflation suggest with 95.0 per cent level of confidence, that the core inflation would be in the region of [4.2%, 11.8%] in the next twelve months. As the level of confidence diminishes, the interval estimate also narrows. For instance, at 25.0 per cent confidence we would expect core inflation to hover within the band of [6.1%, 9.8%].

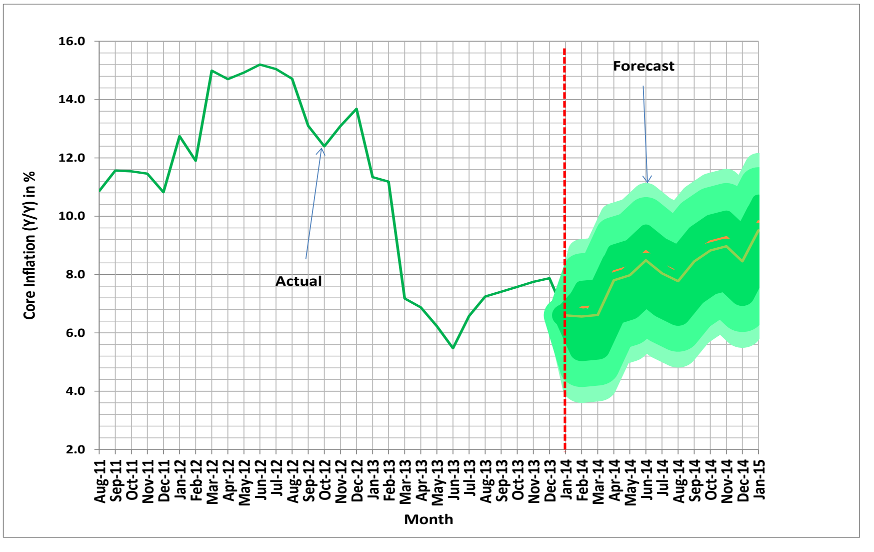

Fig 7: Fan Chart of Core Inflation (Feb 2014 to Jan 2015)

6.3 Food Inflation

The observed monthly food CPI, between July 2001 and January 2014 was first differenced stationary. Thereafter, the parameters of $\Delta SMfod_t$ model defined in equation (44) were re-estimated from the actual data spanning July 2001 to January 2014. Using static forecasting procedure we provide 12 months ahead forecast of food CPI and then computed the food inflation rates using equation (47). The forecast values and their 95 per cent confidence region are presented as a fan chart in Fig 8.

The interval forecasts of food inflation suggest with 95.0 per cent level of confidence, that the food inflation would be in the region of [7.1%, 15.4%] in the next twelve months. As the level of confidence shrinks, the interval estimate also narrows. For instance at 25.0 per cent confidence level we would expect food inflation to hover within the band of [9.3%, 13.2%].

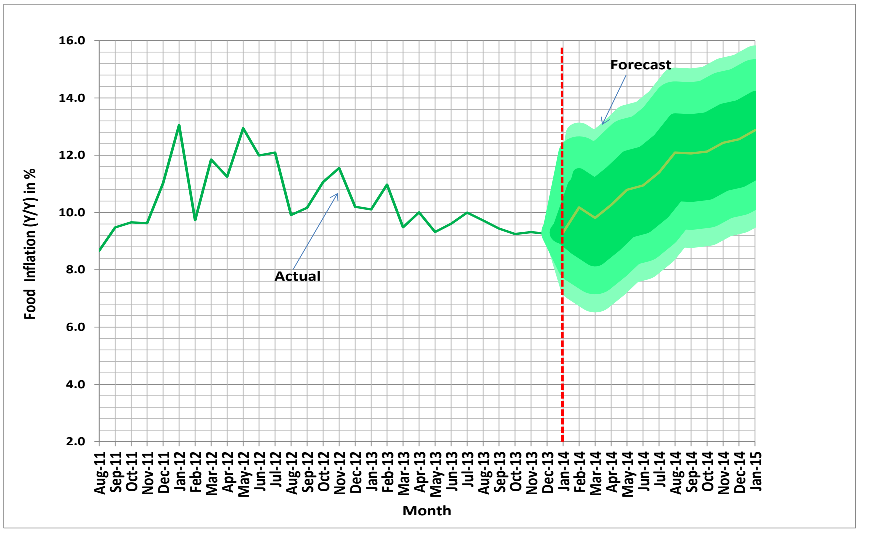

Fig 8: Fan Chart of Food Inflation (Feb 2014 to Jan 2015)

These forecasts are based on the assumptions that the exogenous variable RM year-on-year growth will not exceed the assumed path as indicated in Fig 9, fuel would remain at ₦97 per liter, and rainfall would be a repeat of 2013.

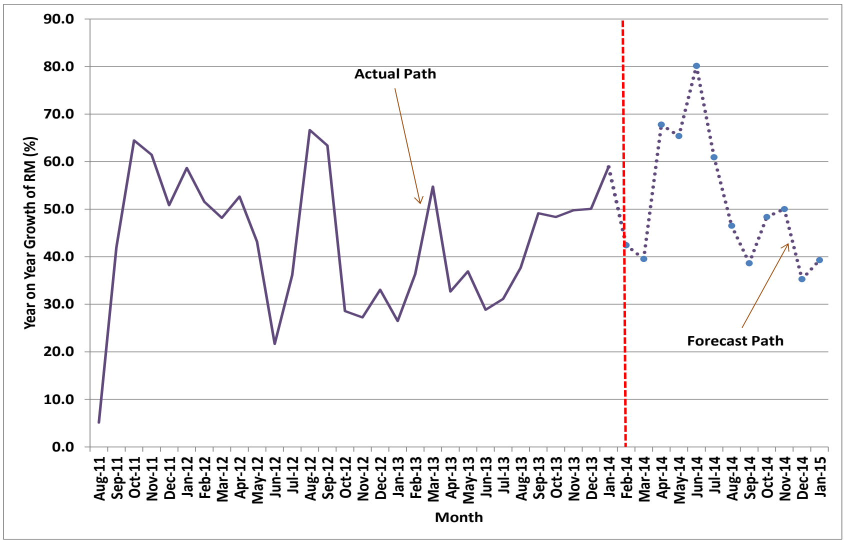

Fig 9: Year-on-Year Growth in Reserve Money

7.0 Summary and Conclusions

The Central Bank of Nigeria has the maintenance of monetary and price stability as one of its core mandate. The Bank deploys various monetary policy instruments to achieve this mandate. However, the effect of applying any particular instrument can be felt only after a certain period of time. Therefore, the models proposed in this paper will provide relatively precise and reliable short term forecast of the headline, food and core inflation so that the Bank can react in time and neutralize inflationary or deflationary pressures that could appear in the future.

Employing the SARIMA and SARIMAX processes, the paper estimated four parsimonious short-term models for headline inflation and evaluated these models based on their pseudo out of sample forecast performance. The results indicated that of the four competing models, forecast of headline inflation from one to twelve months should be done using the parsimonious SARIMAX model, with the pump price of fuel per liter, core and food price indices, reserve money and average monthly rainfall in the cereals, tubers and vegetables producing zones of the country as the exogenous variables. This model appeared to be consistently more precise than the other three competing models.

The other two alternative measures of inflation that the Bank also monitors closely are the core and food inflation. This paper also estimated two parsimonious models each for the two inflation types and assessed them based on their pseudo out of sample forecast performance. The SARIMA models estimated for food and core CPI appeared to be consistently more precise than the SARIMAX models and should therefore be used to forecast these inflation types.

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