TIME SERIES MODELING AND FORECASTING INFLATION: EVIDENCE FROM NIGERIA

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ABSTRACT

A major concern of entrepreneurs and monetary authorities in Nigeria in the past decades was successful prediction general price level movements. The results allow successful planning on the part of monetary authorities and continued profit drive on the part of entrepreneurs and investors. This study uses a univariate model in the form of Autoregressive Integrated Moving Average model developed by Box and Jenkins and multivariate time series model in the form of Vector Autoregressive model to forecast inflation for Nigeria. This paper use changes in monthly consumer price index obtained from the National Bureau of Statistics and the Central bank of Nigeria over the period 2003 to 2012 to predict movements in the general price level. Based on different diagnostic and evaluation criteria, the best forecasting model for predicting inflation in Nigeria is identified. The results will enable policy makers and businesses to track the performance and stability of key macroeconomic indicators using the forecasted inflation.

JEL: E3 E17, E31

KEYWORDS: Modeling Inflation, Forecasting, ARIMA, VAR

INTRODUCTION

Maintaining a reasonable degree of price stability and ensuring an adequate expansion of credit to foster steady and sustainable economic growth have been the primary goals of monetary policy. A challenging problematic macroeconomic economic issue confronting nation states and monetary authorities today is tracking and predicting the movement in the general price level. Nigeria like most developing countries has had significant gaps between policy formulation, policy implementation and policy targets. In most cases, policy goals lag behind targets and are often unattainable due primarily to the prevalence of policy inconsistencies driven by the inability of monetary authorities to predict inflation and its real determinants. Inflation is a major monetary policy performance indicator and is a useful indicator in informing the public about trends in the movement of leading and lagging macroeconomic indicators. The knowledge of these indicators drives inflationary expectation and therefore serves as a nominal anchor for bargaining process and fixed contracts (Moser, Rumler and Scharler, 2004). Generally, a clear understanding of inflation forecasting techniques is crucial for the success of monetary policy in tracking the movement of macroeconomic aggregates and in maintaining stabile and sustainable economic growth.

This paper compares Vector Autoregressive (VAR) model and Autoregressive Integrated Moving Average (ARIMA) model for forecasting the rate of change of the Nigerian Consumer Price Index (CPI). The main attraction to VAR modeling is that it has a natural basis for testing conditional predictability unlike the ARIMA model which is poor in predicting turning points but is relatively robust in generating short term forecast. Thus most empirical analysis on forecasting has focused on the use of VAR while ARIMA is used as a benchmark forecasting tool. Forecasts of the models with the highest predictive accuracy are then evaluated using a range of criteria that characterize optimal forecasts.

Following the introductory section, the rest of the paper is organized as follows: Section 2 summarizes the theoretical and empirical literature. Section 3 describes the models, methods and sources of data. Section 4 compares the forecasting performance of the models and evaluates the resulting models with the highest predictive accuracy. Section 5 concludes the paper.

LITERATURE

The central role of monetary policy in developed, emerging and developing economies is the maintenance of price stability and ensuring of adequate expansion of credit to foster economic growth and development. Generally, economists across economic divides differ in their analysis of the root causes of inflation and in the way and manner the inflationary spiral should be managed and controlled. While the monetarists hold the strong view that sustained growth in money supply not matched by corresponding growth in output will cause inflation at the long run (Milton Friedman 1956, 1960, 1971), structuralist economist explain the long run inflationary trend in developing countries in terms of structural rigidities, market imperfections and social tensions such as relative elasticity of food supply, foreign exchange constraints, protective measures, rise in demand for food, fall in export earnings, hoarding, import substitution, industrialization and presence of political instability (Thirwell, 1974; and

Aghevei and Khan 1977). Given the monetarists view and structuralist view on the root causes of inflation, it is increasingly difficult to forecast inflation in not only developed economies but also in OECD countries and in particular in emerging and developing economies. The empirical studies conducted by Olga, Kamps and Nadine (2009), and Stock and Watson (2008) found that over the longer term (3-year), forecasting horizon, and monetary indicators contain useful information for predicting inflation in most New Member States (NMS) countries of the European Union (EU).

Models of inflation forecast and accuracy has evolved in several studies ranging from extrapolation to econometric modeling. The early study of inflation forecast by Landsman and Damodaran (1989) in which the univariate autoregressive integrated moving average method was used drew the conclusion that, ARIMA parameter estimator improves the forecast accuracy of the model because of its lower mean squared percentage error. Although, inflation forecasting with autoregressive integrated moving average method (ARIMA) compares favorably with other forecasting models such as the vector autoregressive method (VAR), and the Bayesian VAR, it has been shown that the ARIMA performs poorly forecasting turning points and yields poor forecast values when applied to volatile and high frequency data (Meyler, Kenny and Quinn (1998). Ho and Xie (1998), using the ARIMA framework, concluded that the ARIMA model is a viable alternative that gives satisfactory results in terms of its predictive performance. According to Wayne (1998), the use of the vector autoregressive model in forecasting exhibits significant degree of predictive accuracy when compared with other forecasting models. This same conclusion was reached by Meyler et al (1998). Applying the Bayesian VAR approach forecasting, they found the VAR approach improves forecasting performance.

Black, Corrigan and Dowd (2000), comparing an AR (1) with the Mean Absolute Percentage Errors (MAPEs) of different models adding one variable at a time, found the money supply variable to improve the forecast values of inflation significantly, while the study by Jacobson, Jansson, Vredin and Warne (2001) shows that VAR model with long-run restrictions is useful for both forecasting inflation and for analyzing other issues that are central to the conduct of monetary policy. Using a VAR model, Gottschalk and Moore (2001) assessed the link between monetary policy instruments and inflation in Poland. The result showed that although the exchange rate was found to be effective with respect to output and prices, direct linkage between interest rate and inflation do not appear to be very strong. Toshitaka (2001), found mark-up relationship in estimating and forecasting inflation; excess money supply and the output gap were of importance in determining long run equilibrium correlation model of inflation. Other studies on inflation forecasting in different region produced mixed results. Fritzer, Moser and Scharler (2002), found VAR models outperform ARIMA in terms of forecasting accuracy while Bokhari and Feridun (2006), indicate that VAR models do not perform better than the ARIMA model. Espasa, Poncela and Senra (2002), concludes that ARIMA models outperformed the VECM and dynamic factor models while Hubrich K. (2003), found that VAR models outperformed the autoregressive forecasting models.

The study by Alnaa and Ahiakpor, (2005) followed the same pattern as other models proving the VAR modeling technique to be highly efficient in its predictive ability. But, the study by Binner, Bissoondeeal, Elger, Gazely and Mullineux (2005) drew a different conclusion. Using Neural Networks (NN) forecasting model-a nonlinear forecasting approach, they found the VAR and ARIMA modeling technique to be statistically inferior to the Neural Network model.Recent studies by Clausen and Clausen (2010), using Phillips curves showed that model forecasting based on ex post output gaps generally improve the accuracy of inflation forecasts compared to an AR (1) forecast model. The literature is rich in the support of the forecasting strength of ARIMA modeling technique in forecasting (Hill and Fildes, 1984; Libert, 1983; Poulos, Kvanli, and Pavur, 1987; Texter and Ord, 1989). Although, recent studies in Nigeria, have shown the VAR modeling technique to be highly useful in predicting short run forecast (Adebiyi, Adenuga, Abeng, Omanukwe and Ononugbo 2010, Uko and Nkoro 2012), there is however a need to revisit the forecasting ability of both ARIMA and VAR model in Nigeria.

METHODOLOGY

This study forecasts core inflation in Nigeria with the aid of *a* univariate time series model in the form of an Autoregressive Integrated Moving Average (ARIMA) model developed by Box and Jenkins and a multivariate time series Vector Autoregressive model (VAR). The choice of both models is linked to resent forecasting success in both ARIMA and VAR modeling. Our objective is to establish the best forecasting model in tracking price movements in Nigeria. The data used in this study is sourced from the Central Bank of Nigeria Statistical Bulletin and the National Bureau of Statistics. The frequency of the data is monthly and the period covered is 2003:01 to 2012:06. The variable used is the rate of change in the consumer's price index, broad money supply (M2) and our focus is to forecast core inflation. The INF and M2 data gathered was estimated and analyzed with E-views 7 estimation software. Modeling and forecasting inflation with the Box-Jenkins methodology requires the following systematic steps. The first step is the data collection and examination stage, the second step is the identification of the data, while the third step is the estimation of the model. The fourth and fifth step is the diagnostic checks and forecasting stage respectively.

ARIMA Model

ARIMA entails the use of Box-Jenkins methodology which requires that the sample data be at least more than 50 observations (Meyler et al 1998) and even when sample observations is greater than 50 there is need to examine the data for the existence of structural breaks which if present in the data will necessitate only the examination of a sub-section of the data or the need to introduce a dummy variable but in this case, the data was stationary at levels as shown by Figure 1 and 2, this can easily be verified in the. augmented Dickey-Fuller test of unit root with 5 per cent level of significance reported in Table 1 below The estimation of a univariate time series variable with the autoregressive integrated moving average method ARIMA (p,d,q), requires identification of the appropriate value of p, d and q. Where p denotes the number of autoregressive term, d equals the number of times the series has to be differenced to obtain an I(0) series and q measures the moving average term. The chief identification tool is the plot of the autocorrelation function (ACF), the partial autocorrelation function (PACF), the correlograms and the augmented Dickey and the Fuller (1971, 1981) test for unit roots. From Figure 1 and 2, it can be seen that the series is stationary.

Figure 1: Autocorrelation Function

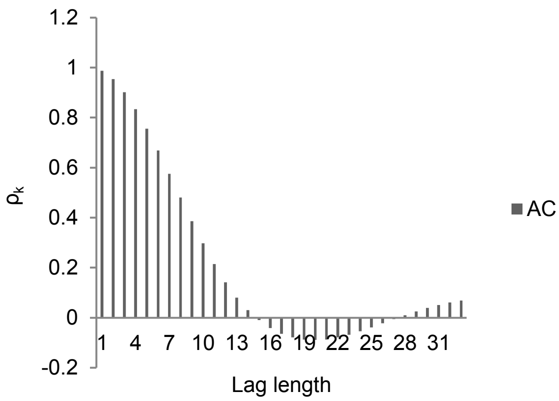


Figure 2: Partial Autocorrelation Function

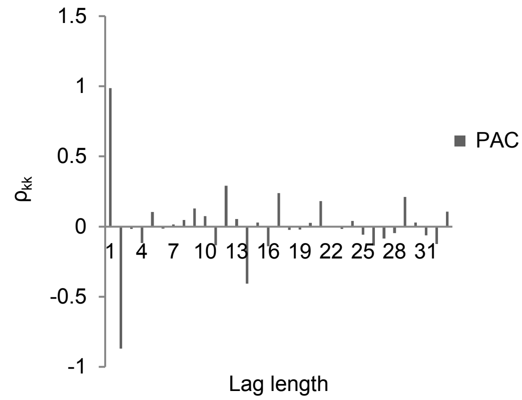


Figure 1 and 2 is the Autocorrelation and Partial Autocorrelation functions showing that the core inflation series is stationary at levels and that it is an Autoregressive Moving Average (ARMA) process. This is seen in the pattern.

Table 1: Unit Root Teston Core Inflation with Intercept and a Linear Trend

		T-Statistics	Prob.	Status
Augmented Dickey-Fuller test Statistics		-3.4590**	0.0490	I(0)
Test Critical Values :	1% level	-4.0420		
	5% level	-3.4504		
	10% level	-3.1505		

*the table is the result of the augmented dickey-fuller (adf) which indicates the core inflation series is integrated or stationary at levels. ** indicates significance at 5 per cent level.*

Having obtained the order of integration (d), our next step is to obtain the ARMA pattern in the inflation series by considering the autocorrelation function (ACF), the partial autocorrelation function (PACF) and the associated correlograms. This process involves using the Box-Jenkins methodology where the ACF and the PACF plots are used to predict p and q in the ARMA model. The selection of p and q is usually based on the following characteristics of the ACF and the PACF plots. If data is purely AR (p), then ACF will decline steadily and PACF will cut off suddenly after p lags but if data is purely an MA (q), ACF will cut off suddenly after q lags and PACF will decline steadily. An ARMA (p, q) model usually exhibits a complex pattern in the ACF and PACF function. From the plot of the autocorrelation function and the partial autocorrelation function reported in Figure 1 and 2, we got a clear pattern to help predict p and q. The criteria used in this case are;

$$BIC = Log\left(\frac{rss}{n}\right) + \left(Log(n) * \frac{k}{n}\right) \tag{1}$$

$$HQC = Log\left(\frac{rss}{n}\right) + \left(2 * Log(Log(n)) * \frac{k}{n}\right) \tag{2}$$

$$AIC = Log\left(\frac{rss}{n}\right) + \left(2 * \frac{k}{n}\right) \tag{3}$$

Where, SC = Schwarz criterion, HQC= Hannan-Quinn criterion and AIC = Akaike information criterion, K = the number of coefficient estimated, rss = residual sum of squares and n = the number of observations With the aid of the correlogram and the partial correlogram reported in Figure 1 and 2, we obtained the identified model which is seen clearly in the plot of the ACF and the PACF function reported in Figure 1 and 2. The selection of the ARMA (p, q) model in equation (4) is based on the ACF and the PACF function reported in Figure 1 and 2. Since the core inflation variable was stationary at levels as shown in the unit root test reported in Table 2, there was no need to difference the variable. The graph of the correlogram reported in Figure 1 and 2 reveals some interesting patterns. First, both the ACF function (Figure 1) and the PACF function (Figure 2) exhibits some form of exponential decay. The spikes from the graph shows the ACF to be statistically significant at lags 1, 2, and 14 while for the PACF, lags 1, 2, 12 and 14 appeared to be statistically different from zero The tentatively identified ARMA (p, q) model is specified as follows;

$$CINFL = \delta + \alpha_1 CINF_{t-1} + \alpha_{12} CINF_{t-12} + \alpha_{14} CINF_{t-14} + \beta_1 U_{t-1} + \beta_2 U_{t-2} + \beta_{12} U_{t-12} + \beta_{14} U_{t-14} \quad (4)$$

Where; CINFL is inflation series at levels; α_1, α_{12} *and* α_{14} are the coefficients of the AR (p) process while β_1, β_2, β_{12} *and* β_{14} are the coefficients of the MA (q) process. AR (p) is autoregressive process while MA (q) is moving average process.

VAR Model

The seminal work by Sims (1980) brought a succor to the modeling of multivariate autoregressive models with the use of an unrestricted vector autoregressive model (VAR). Conventionally, in the VAR modeling technique, we consider several endogenous variables together with each endogenous variable explained by its lagged values and the lagged values of all other endogenous variables in the model. In VAR estimation and forecasting, a unit root test is not necessary because of the loss of information, observation (Sims 1980). In modeling and forecasting inflation with VAR, we used a univariate autoregressive framework, in which the model is specified describing the interdependence of money supply (broad money supply) and core inflation. In its simplest form, we express the set of n variables collected in the n x 1 vector Y_t on their own lags and those of the other variables in the model. The model can be expressed as;

$$Y_t = \alpha + \beta_{1i} Y_{t-1} + \beta_{2i} Y_{t-2} + \ldots + \beta_{pi} Y_{t-p} + u_t \quad (5)$$

The coefficient matrix β_{1i} are the n x n matrix (made up of the inflation and money supply variables) and u_t is an n x 1 vector of serially uncorrelated random error which is assumed to have a multivariate normal distribution $u_t \sim iidN(0, \sum_u)$.

Assuming Y_t is an n x 1 column vector composed of all the variables in our study, the VAR model simply relates current values of Y_t to past values of Y_t and an n x 1 vector of innovations U_t. This can be written precisely as follows;

$$y_{1t} = \beta_1 + \beta_{11} y_{1t-1} + \beta_{12} y_{2t-1} + \alpha_{11} y_{1t-2} + \alpha_{12} y_{2t-2} + \in_{1t} \quad (6)$$

$$y_{2t} = \alpha_1 + \beta_{21} y_{1t-1} + \beta_{22} y_{2t-1} + \alpha_{21} y_{1t-2} + \alpha_{12} y_{2t-2} + \in_{2t} \quad (7)$$

The VAR equation can be written more compactly as;

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + u_t \qquad (8)$$

Where α , is an n x 1 vector and β_j's are n x n metrics.

RESULTS AND ANALYSIS

After successful identification of the ARMA (p, q) process, we proceed to estimate the ARMA (p, q) process with EVIEW 7 estimation software. The result of the ARMA process is reported in Table 2. Thereafter, we proceed to check the reasonableness of the model fit to the data. This is done by simply obtaining the ACF and the PACF from the residual of the regression estimate reported in Table 2.

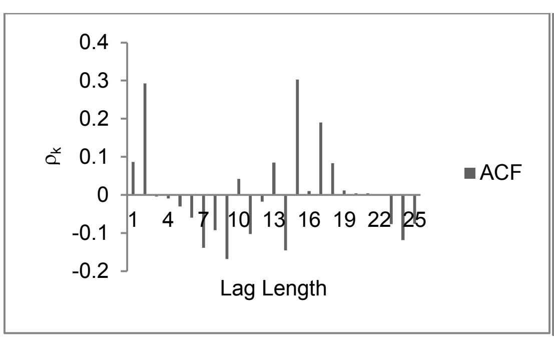
Table 2: Estimated ARMA (p, q) Coefficient

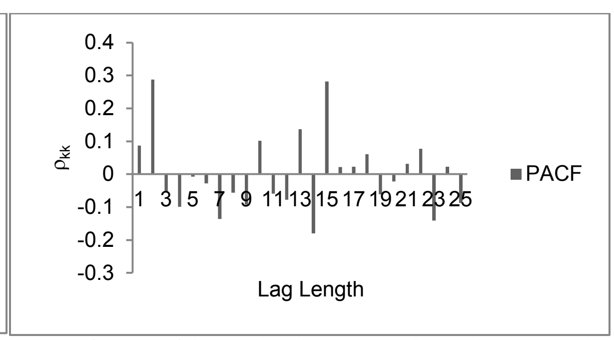
Variables	Coefficient		Std. Error	T-Statistic	Prob.
C	10.210	1.0247	9.9637	0.0000	
AR (1)	0.9709	0.0154	62.996***	0.0000	
AR (12)	-0.2555	0.0389	-6.5681***	0.0000	
AR (14)	0.1892	0.0385	4.9124***	0.0000	
MA (1)	0.8045	0.0750	10.727***	0.0000	
MA (2)	0.2108	0.0571	3.6923***	0.0004	
MA (12)	-0.0764	0.0301	-2.5338***	0.0130	
MA (14)	0.4434	0.0428	10.345 ***	0.0000	
R-squared	0.9959	Adjusted R-squared	0.9956		
F-statistic	3268.8***	Durbin-Watson	1.7836		

*The table shows that 99 per cent of the systematic variation in core inflation is explained by it lag. The *** indicates that AR, MA and F-statistics are significant at the 1% level while the Durbin-Watson shows the absence of serial correlation.*

The model diagnostic check entails examining the graphical analysis of the residuals plot of the estimated model and the autocorrelogram plot of the residuals to verify whether the residuals of the estimated models are purely random. This is seen clearly in Figure 3 where the residual of the autocorrelation function at various the lags hover around zero with the exception of lags 2, 9 and 15 while in Figure 4 the residual of the partial autocorrelation function at various lags hover around zero with the exception of lags 2, 15 and 23. The estimated ARMA (p, q) model can therefore be accepted as a purely random walk hence there is need to look for another ARIMA model. We however, proceed to forecasting core inflation with the ARMA (p, q) model with the forecast shown in Table 5 below. To determine the appropriate lag length for the VAR model, we employ the Akaike information criterion (AIC) and Schwarz criterion (SC). This is determined precisely with the aid of E-view 7 estimating software shown in Table 3 below and the period with the lowest criterion was asterisked.

Figure 3: Residual Autocorrelation Function Figure 4: Residual Partial Autocorrelation Function





Note: Figure 3 and 4 is the Autocorrelation and partial autocorrelation function of the residual showing that the residual is a random walk.

Table 3: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2063.8	0.0000	0.0000	39.727	39.778	39.747
1	-1607.2	886.70	0.0000	31.024	31.177	31.086
2	-1527.0	152.70	0.0000	29.559*	29.813*	29.662*
3	-1524.6	4.4521	0.0000	29.590	29.946	29.734
4	-1522.8	3.4246	0.0000	29.631	30.088	29.816
5	-1521.0	3.1998	0.0000	29.673	30.233	29.900
6	-1519.1	3.3489	0.0000	29.713	30.374	29.981
7	-1515.9	5.4911	0.0000	29.728	30.491	30.038
8	-1513.1	4.5463	0.0000	29.753	30.618	30.103

*Note: * indicates lag order selected by choosing the lowest AIC and SC.*

From the VAR estimate in Table 4 below, the intercept (C) for the inflation model was positive and statistically significant at the 5 per cent level showing that inflation cannot be zero at any point in Nigeria. Furthermore, while the parameters for lag inflation was significant at the 1 per cent level as shown by the T-statistics although with different direction of impact, the lag broad money supply was not significant in explaining the variation in current inflation. While the immediate past period inflation will increase current inflation, the two periods past inflation will cause current inflation to fall.

Table 4: Vector Autoregression Estimate

Variables	CINF	M2
C	0.4187	1.7473
	[2.3901]**	[1.7737]
CINF(-1)	1.8475	20649
	[38.893]***	[-0.7730]
CINF(-2)	-0.8744	15022
	[-18.335]***	[0.5601]
M2(-1)	0.0000	0.9273
	[-0.0780]	[9.5022]
M2(-2)	0.0000	0.0740
	[-0.0000]	[0.7550]
R^2	0.9941	0.9947
Adjusted- R^2	0.9939	0.9945
F-statistics	4,495.8***	4,963.3***
Durbin-Watson Stat	2.0591	2.0292

*Note: CINF is the core inflation series and M2 is the broad money supply, while numbers in brackets are the lag length, numbers in parenthesis are the T-statistics. ** and *** indicate 5 and 1 per cent level of statistical significance respectively.*

Furthermore, the adjusted R^2 shows that more than 99 per cent of the systematic variation in inflation is explained by lag inflation and money supply although money supply is not significant. Overall, the model was significant at the 1 per cent level with a high F-statistic of 4,495.8 and the Durbin-Watson statistic shows the absence of serial autocorrelation in the model. The result of the ARIMA and the VAR model shows a good fit as shown by the Adjusted R-squared. While current inflation is explained by over 99 percent systematic variation in the independent variables in the ARIMA model, the VAR model also showed predictive power given the value of its coefficient of determination and adjusted coefficient of determination values of 0.9941 and 0.9939 respectively.

The F-statistics for both models show an overall significance at the 1 per cent level. While the AR and MA's were all significant at the 1 per cent level in the ARIMA model, the VAR model only lag inflation was significant at the 1 per cent level while all the lags of money supply was not significant in determining variation in inflation confirming the earlier findings of Salami and Kelikume (2012) that inflation is not always and everywhere a monetary phenomenon. Since our aim is to predict and forecast inflation and compare the forecast values of the ARIMA with that obtained from the VAR model, we generated the forecast values directly using the Eview 7 estimating software.

Table 5: Forecast Comparism of the VAR and ARIMA Model

months	actual cinf	arima forecast	var forecast
2012m05	12.40	10.235	12.197
2012m06	12.70	10.227	12.102
2012m07	13.00	10.219	11.929
2012m08	13.30	10.212	11.689
2012m09	13.50	10.205	11.397
2012m10	-	10.199	11.064

Table 5 show a comparison of the ARIMA and VAR forecast with actual core inflation published by the Central Bank of Nigeria. The forecast result shows the VAR forecast to be closer to the actual inflation values. CINF is core inflation.

CONCLUSION

Current inflation in Nigeria which is 11.3 per cent in September 2012 (All Item Consumers Price Index) is expected to increase in the last quarter of 2012 following severe flooding and the washing away of farm lands in the earlier part of the year. Predicting price movements under periods of volatile food price increases has been made much more difficult. This study forecasts inflation in Nigeria using monthly data over the periods 2003:01 to 2012:06. Two methods used extensively in the literature for forecasting inflation are the Vector Autoregressive Method (VAR) and the Autoregressive Integrated Moving Average Method (ARIMA). This paper uses these methods for study with the sole objective of comparing both forecasting method. While the ARIMA model was a univariate time series model, the VAR model was a multivariate model that incorporates the interdependency amongst several endogenous variables.

The result of our estimate from both ARIMA and VAR model tracks actual inflation values for the period 2012: 06 to 2012: 09. However, the VAR model had smaller errors in terms of the minimum square error and is the closest approximate to current inflation in Nigeria. The study forecasted core inflation using VAR for the month of 2012:10 to be 11.06 percent. A major limitation of this study is that it focused on two major forecast tool the VAR method and the ARIMA method and neglected the use of neural network analysis. In addition only core inflation was used as a measure of inflation. Subsequent studies on inflation forecasting in Nigeria should attempt to forecast inflation across a wider spectrum of inflation measures.

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