Modeling Nigeria's Inflation Using Box-Jenkins Adopted Methodology

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Abstract: *The study is set out to develop a fitting model for inflation in Nigeria and evaluate the forecasting ability of the estimated model. The study used monthly Consumer Price Index (CPI) data from 1995 MOI to 2013 M12 in developing the model using ARIM Box-Jenkins methodology. The best fitted model was found to be ARIMA (1, 1, and 2) and its sample forecast performance is satisfactory. This paper finds out clearly that inflation is on higher rate and increasing which eventually has negative impact on the Nigerian economy. This paper examines Nigerian inflation using ARIMA Box-Jenkins methodology. The paper recommends that Nigeria inflation is on the increase and being a macroeconomic variable, a concrete measure should be taken in order to reduce the high level increase of the inflation so that it is reduced to an acceptable and economically viable rate.*
Keywords: *Inflation, Consumer price index*

1. Introduction

The goal of monetary policy the world over is attainment of price stability or the ability of the monetary authorities to maintain a tolerable rate of inflation all in an attempt to sustain the growth of the nation's economy. In Nigeria, as practiced in many countries, the Central Bank is saddled with the responsibility. This stems from the fact that inflation is a detriment top economic growth and brings uncertainty in production and consumption as Maku & Adelowokan (2013) observed a scenario of constant real wage income chasing few goods leading to adjustment in consumption pattern and eventual decline in consumption capacity and the standard of living.

The upsurge of inflation in Nigeria has its origin in the early 1970s in the aftermath of the country's civil war and the Udoji Committee which doubled the basic minimum wage in the public sector leading to widespread strikes and unrest in the private sector (Bayo 2005, Imobighe 2012 and Bamidele & Joseph 2014). Recent inflation data on Nigeria shows a rise from 57.16 percent in 1995, but reduced to 8.5 percent in 1997 and remained on a single digit through the year 2000. The year 2001 witnessed a sharp rise to 19 percent over the previous year's 7 percent. The upward trend continued in 2003 through the year 2005; it however recorded a single digit for the year 2013.

2. Review of Related Literature

2.1 Concept of Inflation

There is a consensus on the definition of inflation as a sustained rise in the general prices of goods and services with a resultant fall in purchasing power. The inflation rate is designed to measure the rate of increase of a price index. It is a percentage rate of change in price level over time. The term inflation and consumer price index (CPI) are used interchangeably in the literature. This is not unconnected with the fact that CPI is the most widely used measure of inflation as it captures wider range of goods and services sold directly to average consumers. Umaru & Zubairu (2012) asserted that CPI represents the cost of living and is, therefore, more appropriate for measuring the welfare of the people. Because of its availability on a more frequent basis, it is useful for monetary policy purposes.

According to the Central Bank of Nigeria (CBN), in Nigeria, the first CPIs were computed separately for the then Federal and Region Capitals. The indices for Lagos and Ibadan, Kaduna, Enugu had 1953 and 1957 as base years, respectively. The CBN in collaboration with Federal Office of Statistics (FOS) now National Bureau of Statistics (NBS), felt that the separate indices had some disadvantages. The Consumer Expenditure Survey (CES) conducted in 1957 was reviewed to reflect the felt need for a single national CPI. CES progressively became outdated. With the National Consumer Expenditure survey (NCES) conducted by NBS in 1974/75 which provided expenditure data from which item weights were derived for urban and rural indices the CPI adopted 1975 as the ruling base year.

However, CPI is continually updated and rebased and that informed the updating of the base. The mean expenditures were consequently revalued to take account of the time lag. Relative price changes between 1980 and 1985 were employed to update the CES estimates to 1985 values. The basket of the 1985-based CPI has been restructured to indicate commodity groups such as medical care and health expenses, recreation, entertainment, education and cultural services which were not classified when the 1975 base was used. Due to changes in consumption patterns overtime, NF3S conducted another CES between March 1996 and April 1997, and item weights derived from the survey data were updated to May 2003, the price reference period of the CPI series.

Currently, the consumption expenditure data are revalued to a new base period of November 2009, using the Nigerian Living Standard Survey (NLSS) outcome of 2003/2004 to arrive at the CPI series for all items, all items less farm produce and food categories. The monthly indices in the current table span 1995 to 2013.

2.2 Types and Causes of Inflation

There are four major types and causes of inflation traceable to classical, Keynesian, monetarists, neoclassical and the structural economics schools of thoughts. They are: the demand-pull, the cost-push, the mark-up and the structural inflation. In developing countries, the major type or source of inflation is the structural. Structural rigidities in agriculture, industrial production and instability of export prices do not only limit the capacity to import but also induces deficit spending (Fashoyin, 1986; Monteil, 1989; Coe & McDermott, 1997; Umaru & Zubairu ibid, Flarvey, 2012 & Sama, 2014).

2.3 Empirical Literature

The empirical findings in Fashoyin (ibid) identified ten structural variables (agricultural bottlenecks, industrial production, imports, exports, food import and production, trade union militancy, indirect taxation on companies, wage bill, government expenditure — deficit financing and money supply) as the determinants of inflation in Nigeria. Omoke & Ugwuanyi (2010) documented a causal relationship running from money supply to inflation in Nigeria, thus supporting the monetarist approach to inflation. Umaru & Zubairu (2012) also conducted the causality test on Nigeria time data from 1970 to 2010 and found income as causing inflation.

The use of ARIMA Box — Jenkins methodology in modelling time series and evaluating the forecast efficiency of the estimated model are many and varied in the literature. Meyler, Kenny & Quinn (1998)'s emphasis is on forecast performance which suggests more focus on minimizing out-of-sample forecast errors than on maximizing in-sample 'goodness of fit'. They found, using a quarterly data, a relatively parsimonious ARIMA representation optimal both for fitting the in-sample data and for maximizing the out-of-sample forecasting performance. This is an indication of the relative stability of Irish inflation during the period in question and the dominance of the seasonal influence.

Huwiler & Kaufmann (2013) also used a disaggregate data on Swiss economy and found that the ARIMA model yields fairly accurate inflation forecasts for the short-run and outperforms relevant benchmarks. Also, the results showed that estimating ARIMA models for expenditure items of the CPI and aggregating the forecasts from these models gives better results than directly applying the ARIMA method to the total CPI. This supports the view that the heterogeneous movements of the underlying price series contain useful information that can be exploited in the context of forecasting CPI inflation. Overall, by using the disaggregated A1UMA approach, price dynamics, seasonal patterns and the data collection frequency can he better modelled and predicted, since the model specifications may vary between individual expenditure items of the CPI.

Salam, Salam & Feridun (2006) estimated an ARIMA model with sufficient predictive powers using Pakistani monthly CPT data and Iftikhar & ituikhar-ui-amin (2013) used a set of yearly data CPI for the same economy for the period 1961-2012. The most appropriate model was foundto be ARIMA (1, 1,1) and was used to forecast the inflation rate fixed a year ahead which was estimated at 8.83%. Other studies in Box-Jenkins ARIMA methodology includes, Virkun & Sedliacik (2007) for Austria; Moriyama and Naseer (2009) for Sudan; Buelens (2012) for European economy and Suleman & Sarpong (2012) for Ghana. A combination of ARIMA and vector autoregressive (VAR) methodology is documented in the literature. Evidence can be found in Wilkie (1995), Valle (2002), Hakkio (2008), and Harvey & Cushing (2014) among others.

The autoregressive models of inflation developed on Nigeria's inflation following Box Jenkins Methodology identified by the author are the studies by Etuk et al (2012) based on annual data from 2003 to 2011, identified a seasonal integrated moving average (0. 1. 1) found to be adequate and efficient in forecast. Olajide et al (2012) developed ARIMA (1, 1, I) model using 1961 to 2010 yearly inflation series. The model was used for a year forecast standing at 16.27 percent. Okafor & Shaibu (2013) using annual CPI series from 1981 2010, estimated ARIMA (2. 2. 3) model remarkably tracked the actual inflation during the sample period. However, Maku & Adelowokan (2013) used multivariate autoregressive model including fiscal policy, monetary policy, and exchange rate and real output data for the period 1970 to 2011. All the parameters of the estimated model were found to be significant a 5 percent and that there is significant adjustment process of the dynamics of inflation rate in Nigeria. An observation from the literature revealed that the studies on Nigeria use annual inflation data for the different time periods. The identified models varied in spite of their good forecast performance.

3. Methodology

This section describes the data for the study and explains the method of analyzing the data. Several studies conducted on modeling inflation resorted to autoregressive model. The beauty of this methodology lies in its efficacy in using information on the past behavior of inflation to predict the future inflation rate. Few models developed for Nigeria inflation uses an annual data on Nigeria's inflation. This methodology according to Huwiler & Kaufmann (2013) will be further strengthened when it considers monthly data, *thus lubricating* the heterogeneity of the CPI data. It is against this backdrop that this paper will develop an autoregressive model of Nigeria's inflation from 1995 to 2013 using monthly CPI data and test the forecasting performance of the model.

3.1 Data Source

The study uses Nigeria's monthly CPI series from 1995:1 to 2013:12 sourced from the 2013 CBN statistical bulletin. The choice of monthly data is informed by the fact that a lengthy time series data is required for univariate time series forecasting. It is usually recommended that at least 50 observations be available' (Mcyler et al. (1998). Using Box Jenkins methods can be problematic if too few observations are available (Salam et al *op cit*). CPI is chosen because it "covers wider range of items than WPI since it includes services" (Sama *op cil*).

Table I: Reports the Descriptive Statistics and Figure 1: shows the plot of the series at level.

Table 1: Descriptive statistics of CPI

Test/Observation	Outcome
Mean	66.09561
Std. Dev.	39.12833
Skewness	0.641756
Kurtosis	2.215496
Jarque-Bera	21.49707
Probability	0.000021
Observation	228

Source: Author's computation (2015).

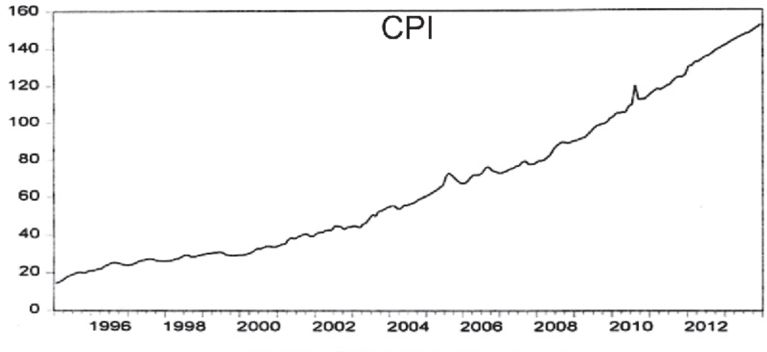

Figure 1: Plot of CPI at level

Figure 1 shows the rate at which inflation rises with some corresponding years starting from 1996 to 2012 that is almost of a decade.

Table 2: Correlogram of CPI at level

Date: 03/16/15 Time: 12:08
Sample: 1995M01 2013M12
Included observations: 228

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.1*******	.1*******	1	0.985	0.985	224.07	0.000
.1*******	.1. 1	2	0.970	-0.001	442.34	0.000
.1*******	.1. 1	3	0.955	-0.007	654.89	0.000
.1*******	.1. 1	4	0.940	0.004	861.91	0.000
.1*******	.1. 1	5	0.926	-0.001	1063.6	0.000
.1*******	.1. 1	6	0.912	-0.009	1259.8	0.000
.1******1	.1. 1	7	0.897	-0.007	1450.8	0.000
.1******1	.1. 1	8	0.883	-0.006	1636.6	0.000
.1******1	.1. 1	9	0.869	-0.004	1817.2	0.000
.1******1	.1. 1	10	0.854	-0.009	1992.8	0.000
.1******1	.1. 1	11	0.840	-0.008	2163.2	0.000
.1******1	.1. 1	12	0,826	-0.004	2328.8	0.000
.1******1	.1. 1	13	0.811	0.015	2489.3	0.000
.1******1	.1. 1	14	0.797	-0.011	2644.8	0.000
.1******1	.1. 1	15	0.782	-0.008	2795.5	0.000
.1*****1	.1. 1	16	0.768	-0.004	2941.3	0.000
.1*****1	.1. 1	17	0.754	0.006	3082.6	0.000
.1*****1	.1. 1	18	0.740	-0.008	3219.3	0.000
.1*****1	.1. 1	19	0.726	-0.006	3351.5	0.000
.1*****1	.1. 1	20	0.712	-0.002	3479.4	0.000
.1*****1	.1. 1	21	0.699	-0.007	3603.0	0.000
.1*****1	.1. 1	22	0.685	-0.016	3722.3	0.000
.1*****1	.1. 1	23	0.671	-0.003	3837.4	0.000
.1*****1	.1. 1	24	0.657	-0.019	3948.2	0.000
.1*****1	.1. 1	25	0.643	0.018	4055.1	0.000

Source: Author's computation, 2015.

The plot depicts a feature similar to stochastic trend and the correlogram also is typical of non-stationary series. The autocorrelation coefficients are very high and dying very slowly as the lag length increases. Given the visual features of the graph and the correlogram, we now test formally for unit root using Augmented Dickey- Fuller (ADF), Phillips-Perron (PP) and Kwiaktkowski-Phillips-Schmidt-Shin (KPSS) tests. Table 3 reports the summary of the unit root test results.

Table 3: Unit Root Test Result

Variable	ADF	PP	KPSS
CPI (at level)	-0.187556	0.424965	0.465966
CPI (at first diff.)	-16.48233***	17.68648***	0.081894***

Source: *Computed using E-views. ***, ** and * indicates significance at 1 percent, 5 percent and 10 percent level.*

The result shows that CPI series are 1(1). The plot and correlagram of the differenced series are depicted in fig. 2

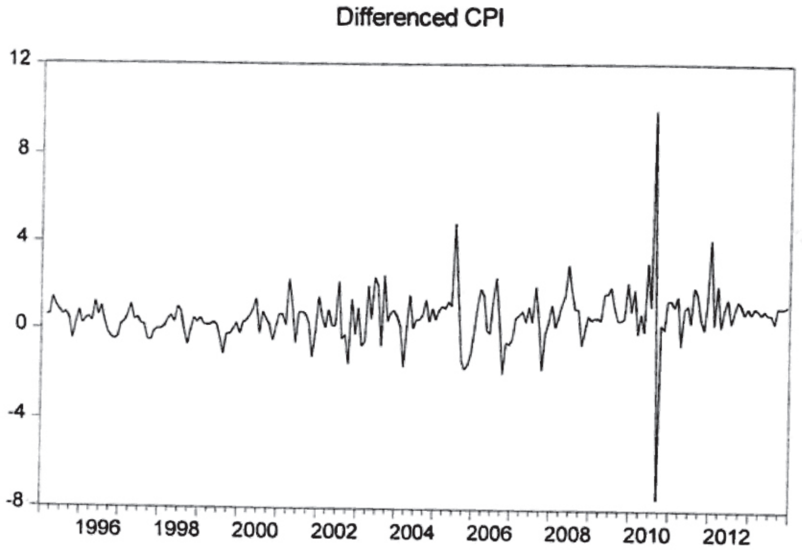

Fig. 2: *Plot of Differenced CPI*

Sample:1995M01 2013M12
Included observations: 227

Table 4: Correlogram of Differenced CPI Series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.1. 1	.1. 1	1	-0.047	-0.047	0.5128	0.474
.1* 1	.1* 1	2	0.114	0.112	3.4981	0.174
*1. 1	*1. 1	3	-0.115	-0.107	6.5823	0.086
.1. 1	.1. 1	4	0.000	-0.021	6.5823	0.160
.1. 1	.1. 1	5	0.023	0.048	6.7030	0.244
.1. 1	.1. 1	6	0.036	0.029	7.0151	0.319
.1. 1	.1. 1	7	0.034	0.027	7.2943	0.399
.1. 1	.1. 1	8	-0.016	-0.014	7.3537	0.499
.1. 1	.1. 1	9	-0.050	-0.051	7.9430	0.540
.1. 1	.1* 1	10	0.068	0.077	9.0446	0.528
.1. 1	.1* 1	11	0.064	0.078	10.031	0.528
.1**1	.1* 1	12	0.224	0.206	22.161	0.036
.1* 1	.1** 1	13	0.192	0.227	31.116	0.003
.1. 1	.1. 1	14	0.052	0.064	31.787	0.004
.1. 1	.1. 1	15	0.001	0.022	31.787	0.007
*1. 1	*1. 1	16	-0.115	-0.089	35.027	0.004
.1* 1	.1* 1	17	0.104	0.088	37.689	0.003
.1. 1	.1. 1	18	-0.021	-0.011	37.797	0.004
.1. 1	.1. 1	19	0.050	-0.009	38.430	0.005
.1. 1	.1. 1	20	-0.027	-0.010	38.609	0.007
.1. 1	.1. 1	21	0.025	0.037	38.769	0.010
.1* 1	.1* 1	22	0.089	0.100	40.784	0.009
.1* 1	.1* 1	23	0.131	0.107	45.144	0.004
.1. 1	.1. 1	24	0.065	-0.013	46.213	0.004
.1* 1	.1. 1	25	0.152	0.069	52.164	0.001

3.2 ARIMA Box-Jenkins Methodology

An AR1MA 'p, c/, q) model is a combination of Autoregressive (AR) which shows that there is a relationship between present and past values, a random value and a Moving Average (MA) model which shows that the present value has something to do with the past residuals. The general form of the ARIMAp, q) model is:

$$Yt - {}^{\Sigma p}{}_{t} = t\,\theta Y_{t-t+}\mu_t + {}^{\Sigma a}{}_{j=t}\theta^{\Sigma a}{}_{j} = t\,\theta\Sigma_t -_j$$

The notation ARIMA (p. q) refers to the model with p autoregressive terms and q moving average terms, This model contains the AR(p) and MA(q) models. ARIMA models in general, after choosing p and q, are fitted by least squares regression to find the values of the parameters which minimize the error term. It is generally considered good practice to find the smallest values of p and q which provide an acceptable fit to the data. The model is generally referred to as an ARIMA (p, d, q) model where d is the integrated aspect of the data that leads to differencing of the series in order to achieve a subsequent stationary series.

Box and Jenkins (1976) proposed this methodology. The method consists of four steps. They are: Identification, estimation, diagnostic checking and forecasting. Identification involves finding out the appropriate p, d and q of the tentative model. Use of correlogram's ACF and PACF as well as the formal unit root tests makes the job done.

In the estimation stage, each of the tentative models is estimated and the various coefficients are examined. In this second stage, the estimated models are compared using the Akaike information criterion (Al C) and the Schwartz Bayesian criterion (SBC). We want a parsimonious model, so we will choose the model with the smallest AIC and SBC values. Of the two criteria, the SDC is preferable. Also at this stage we have to be aware of the common factor problem. The Box-Jenkins approach necessitates that the series is stationary and the model invertible.

In the diagnostic checking stage we examine the goodness fit of the model. The standard practice at this stage is to plot the residuals and look for outliers and evidence of periods in which the model does not fit the data well. We must be careful here to avoid over fitting. Lastly, in forecasting we check the forecasting ability of model. The main advantage of ARIMA forecasting is that it requires data on the time series in question only. First, this feature is advantageous if one is forecasting a large number of time series. Second, this avoids a problem that occurs sometimes with multivariate models. ARIMA models have proven themselves to be relatively robust especially when generating short-run inflation forecasts. ARIMA models frequently outperform more sophisticated structural models in terms of short-run forecasting ability (Stockton & Glassman, 1987 and Litterman, 1986). Therefore, the ARIMA forecasting technique outlined in this paper will not only provide a benchmark by which other forecasting techniques may be appraised, but will also provide an input into forecasting in its own right. Buelens (2012) comparing different models, concludes that the performance of direct autoregressive distributed lag models over the indirect approach has improved.

4. Results and Discussions

Having identified the order of integration d = 1 from our unit root test result and the tentative p and q from the correlogram ACF and PACF of the differenced series, we now estimated the following models from which the best will he selected.

Table 5: Summary of Estimation Results

Model	SBC	Adj-R^2	Se	Inverted Roots
ARIMA (1,1,1)	3.308332	0.005011	1.228670	-0.76 (-0.69)
ARIMA (1,1,2)	3.323439	0.009362	1.225980	-0.5 (-0.69)
ARIMA (1,1,3)	3.342865	0.009406	1.225953	-0.02 (0.4)
ARIMA (2,1,1)	3.329851	0.007687	1.229752	0.17(-0.41)
ARIMA (2,1,2)	3.348689	0.008379	1.229323	-0.44 (0.42)
ARIMA (2,1,3)	3.371726	0.004881	1.231489	-0.4 (0.35)
ARIMA (3.1,1)	3.351379	0.008648	1.230770	0.32 (0.13)
ARIMA (3,1,2)	3.373769	0.005862	1.232499	0.24 (0.05)
ARIMA (3,1,3)	3.371708	0.027126	1.219247	0.48 (0.46)

***Source**: extract from estimation results using eviews. Inverted roots, AR (MA). Se = standard error*

The best fitted model possesses the lowest SBC, in this case the ARIMA (1. I.I). However, conducting diagnostics on the model prompted the choice of the next best fitted ARIMA (1, 1, 2) as it passed the routine checks. The empirical model is thus represented as:

LLCPI = 0.607628 — 0.4995? ICPL1 + O, 473999t...1 ÷ 0.122597
(o.086713}(g.33ys2) (0.339402) (0.1)
Adj-R2= 0.009362, SE= 1.22598, F-Statistic (Prob of F-Stat) = 1.708813 (0.16O6

The parameters of the model were found individually statistically insignificant with the exception of the constant term and also jointly insignificant.

4.1 Diagnostics

The tests were conducted on the residuals beginning with the correlogram whose AUF and PACF are expected to be insignificant individually and jointly. Most of the ACF and PACF values were found to be insignificant. However, the joint insignificance was achieved up to lag 12. Table 6 reports the other tests.

Table 6: Other Diagnostic Tests

Test	Test Statistic	Probability
Serial correlation (Brasuch-Godfrey)	X^2 (2) = 1.075796	0.5840
Whites Heteroskedasticity	X^2 (13) = 74.60122	0.0000

***Source:** Extract from estimation output using E-views 7.*

The tests show the absence of serial correlation and heteroscedaticity based on the reported statistics. Also, the ARIMA structure indicates that the roots lie inside the unit circle and that the ARIMA model is invertible. See Appendix.

4.2 Forecasting

Since one of the aims of the study is to check the foretasting ability of model using our estimated model, there are actual data for the forecasted variable for the forecast sample. Figure 3 reports a table of statistical results evaluating the forecast.

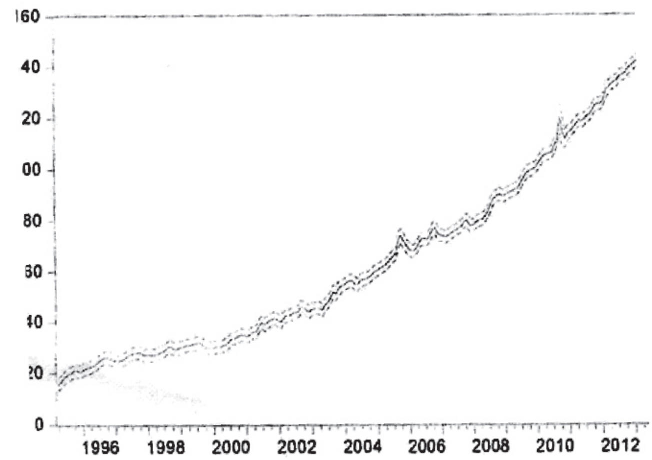

Fig. 3

Forecast: CPIF
Actual: CPI
Forecast sample: 1995M01 2013M12
Adjusted sample: 1995M03 2013M12
Included observations: 226

Root Mean Squared Error	1.215082
Mean Absolute Error	0.733140
Mean Abs. Percent Error	1.349083
Theil Inequality Coefficient	0.007887
Bias Proportion	0.000000
Variance Proportion	0.044129
Covariance Proportion	0.955871

The first two forecast error statistics depend on the scale of the dependent variable. These should be used as relative measures to compare forecasts for the same series across different models; the smaller the error, the better the forecasting ability of that model according to that criterion. The mean absolute per cent error is only 1.35. The remaining two statistics are scale invariant. The inequality coefficient always lies between zero and one, where zero indicates a perfect fit in this case its value of 0.007887 is near perfect. Small bias variance proportions further indicates the goodness in the forecast. (Fig. 3).

4.3 Major Findings

It is our major findings that inflation is increasing at a higher rate in Nigeria. Therefore, there is need for monetary authorities to take necessary measures in order to bring it down so that economic growth and development will be achieved.

5. Conclusion and Recommendation

The study used Box-Jenkins methodology in fitting the best ARIMA model for Nigeria's inflation. The fitted model was found to be ARIMA (1. 1, 2) with a near perfect forecast ability. However, controversial issues in model selection must be resolved by future researches. There should be harmony between information criteria, statistical significance and the post estimation diagnostics. It is recommended best on the findings of the result that necessary measures should be taken in order to bring down the level of inflation in Nigeria. And one of these measures is provision of macroeconomic solution that will bring down the level of inflation by the monitoring authorities.

References

Bayo, F. 2005: Determinants of inflation in Nigeria: An Empirical Analysis. *International journal of Humanities and Social Science Vol. 1 No. 18.*

Central Bank of Nigeria 2013: *Statistical Bulletin*, Retrieved From http://www.cenbank.org/documents/statbulletin.asp

Coe, D. T. & McDerrnot, J. 1997: Does the gap model work in Asia? *IMP Staff papers, Vol. 44, No. 1 (March).*

Fashoyin. T. 1986: "*Incomes and Inflation in Nigeria*", 1ongman Publishers ltd. New York

Flakkio. C. S. 2008: FCIE and CPI inflation differentials: converting economic Forecasts. *Economic Review) 2008, isuue QI, pp 51-68*

Buelens. C. 2012: Inflation forecasting and the crisis: assessing the impact on the performance of different forecasting models and methods, *Economic Papers, European Commission, Directorate-General for Economic and Financial affairs Publications B-1049 Brussels, Belgium*

Etuk, E. H., Uchendu, B. & Victoredema, U. A. 2012: Forecasting Nigerian Inflation rates by a seasonal ARIMA model. *Canadian Journal of Pure and Applied Scinces* VOL 6, No. 3, pp. 2179-2185, October 2012 Online JSSN: 1920-3853: Print TSSN; 1715-9997

Harvey. S. K. & Cushing J. M. 2004: Does using disaggregate components help in producing better forecasts for aggregate inflation? *Journal of Economics and Development Studies June* 2014, Vol. 2, No. 2, pp. 527-546 1SSN: 2334-2382 (Print), 2334-2390 (Online)

Harvey. S. K. 2012: *Essays in inflation and monetary dynamics in developing countries*. Ph.D. Dissertation. University of Nebraska-Lincoln.

Huwiler, M. & Kaufmann, D. 2013: Combining disaggregate forecast for inflation: The SNB's ARIMA model. *Swiss National Bank research papers*.

lftikhar, N. & iftikhar-uI-aniin 2013: Forecasting the inflation in Pakistan; 'The Box Jenkins Approach. *Wr1d Applied Sciences Journal* 28 (11): 1502-1505, 2013 ISSN 1818-4952

Maku. A. 0. & Adelowokan, 0. A. 2013: Dynamics of inflation in Nigeria: an autoregressive Approach. *European Journal of Humanities and Social Sciences* l. 2Z NO.1, 2013

Meyler, A., Kenny, 0. & Quinn, T. 1998: Forecasting Irish inflation using ARIMA Models, *Monthly Statistical Bulletin* Bangladesh, Dhaka: Bangladesh. Bureau of Statistics.

Montiel. P. 2009: *Empirical analysis of high inflation episodes in Argentina*, Brazil and Israel. IME Staff papers, Vol 36, No. 3 (September), 527— 549.

Moriyarna, K. & Naseer. A. 2009: Forecasting inflation hi Sudan. *IMF Working Paper* Middle East and Central Asia Department, WE/OP/I 32.

Okafor, C. & Shaibu, 1. 2013: Application of Arima Models to Nigerian Inflation Dynamics. *Research Journal of Finance and Accounting,* JSSN 22221697 Vol.4. No.3, 2013

Ojajide. J.T. Ayansola, O.A., Odusina, M. T. & TF. Oyenuga, 1. F. 2012: *Forecasting the inflation rate in Nigeria:* Box Jenkins Approach. Jowwal of Mathematics, 3(5,1' 15-19.

Omeke, P.C. and Ugwuanyi, C.U. 2010: Money, Price and Output: A Causality Test for Nigeria. *American Journal of Science Research* I&SW 1456-223X Issue 8, pp. 78-87. Euro Journals Publishing, Inc.

Omeke, P.C. & Ugwuanyi, C.U. 2010: Money, price and output: a causality test for Nigeria. America. *Journal of Scientific Research,* 8, 78-87.

Sama, M., Salam, S. & Ferjdun, M, 2006: Forecasting inflation in developing nations: The case of Pakistan. *International Research Journal of Finance and Economics, 3: 138-159.*

Suleiman. N. & Sarpong, S. 2012: Empirical approach to modelling and forecasting Inflation in Ghana. *Current Research Journal of Economic Theory* 4(3): 83-87. 2012.

Umaru, A. and A.A. Zubairn 2012: Effect of Inflation on the growth and development of the Nigerian economy: An empirical analysis". *International Journal of Business and Social Science,* 3(10).

Valle, HAS. 2002: Inflation forecasts with ARIMA and vector autoregressive models in Guatemala. *Economic Research Department*, Guatemala: Banco de Guatemala.

Virkun. N. S. & Sedlicik, T. 2007: *Forecasting the Austrian inflation rate. Case Study for the Course of Econometric Forecasting,* Winter Semester 2007.

Wilkie, D. 1995: More on a Stochastic Model for Actuarial Use. *British Actuarial Journal, pp. 777-964.*

Appendix

Correlogram of differenced CPI series

Sample: 1995M01 2013M12
Included observations: 226
Q-statistic
Probabilities adjusted
for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.1. 1	.1. 1	1	-0.004	-0.004	0.0037	
.1. 1	.1.1 1	2	-0.021	-0.021	0.1061	
.1. 1	.1.1 1	3	-0.052	-0.052	0.7227	
.1. 1	.1.1 1	4	0.034	-0.035	0.9927	0.319
.1. 1	.1.1 1	5	0.041	-0.038	1.3788	0.502
.1. 1	.1.1 1	6	0.031	0.027	1.6041	0.658
.1. 1	.1.1 1	7	0.044	0.042	2.0516	0.726
.1. 1	.1.1 1	8	-0.028	-0.023	2.2356	0.816
.1. 1	.1.1 1	9	-0.051	-0.045	2.8616	0.826
.1. 1	.1.1 1	10	0.056	0.059	3.6025	0.824
.1. 1	.1.1 1	11	0.054	0.052	4.3037	0.829
.1**1	.1** 1	12	0.220	0.216	15.965	0.068
.1* 1	.1** 1	13	0.193	0.216	24.934	0.502
.1. 1	.1* 1	14	0.053	0.102	25.605	0.007
.1. 1	.1. 1	15	-0.029	0.022	25.809	0.011
*1. 1	*1. 1	16	-0.110	-0.083	28.776	0.007
.1* 1	.1* 1	17	0.099	0.090	31.172	0.005
.1. 1	.1. 1	18	-0.001	-0.022	31.172	0.008
.1. 1	.1. 1	19	0.032	0.008	31.423	0.012
.1. 1	.1. 1	20	-0.021	0.026	31.533	0.025
.1. 1	.1. 1	21	0.002	0.027	31.533	0.025
.1* 1	.1* 1	22	0.102	0.104	34.150	0.018
.1* 1	.1* 1	23	0.118	0.105	37.672	0.010
.1. 1	.1. 1	24	0.051	-0.015	38.348	0.012
.1* 1	.1* 1	25	0.149	0.086	44.058	0.003

Dependent Variable: D(CPI)
Method: Least Squares
Sample (adjusted): 1995M03 2013M12
Included observations: 226 after adjustments
Convergence achieved after 18 iterations
MA Backcast: 1995M01 1995M02

Variable	Coefficient	Std. Error	t-statistic	Prob.
C	0.607628	0.086713	7.007345	0.0000
AR(1)	-0.499571	0.339982	-1.469407	0.1431
MA(1)	0.473999	0.339402	1.396572	0.1639
MA(2)	0.122579	0.074205	1.651900	0.1000
R_squared	0.022571	Mean dependent var		0.607522
Adjusted R - squared	0.009362 S.D	dependent var		1.231760
S.E. of regression	1.225980	Akaike info criterion		3.262899
Sum squared resid	333.6720	Schwarz criterion		3.323439
Log likelihood	-364.7076	Hannan-Quinn criter		3.287331
F-statistic	1.708813	Durbin-Watson stat		2.007025
Prob (F-statistic)	0.166066			
Inverted AR Roots	-50			
Inverted MA Roots	-24+26i	- 24-26i		

Inverse Roots of AR/MA Polynomia(s)
Specification: D(CP) C AR(1) MA(1) MA(2)
Sample: 1995M01 2013M12
Included observations: 226

AR Root(s)	Modulus	Cycle
-0.499571	0.499571	
No root lies outside the circle		
ARMA model is stationary		
MA Root (s)	Modulus	Cycle
-0.237000 ± 0.257702i	0.350113	2.714856

No root lies outside the unit circle.
ARMA model is invertible.