

Application of Arima Models to Nigerian Inflation Dynamics

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Abstract

The objectives of this study were to empirically develop a univariate autoregressive integrated moving average (ARIMA) model suggested by Box & Jenkins (1976) for Nigerian inflation and analyze the forecasting performance of the estimated model between 1981 and 2010. In this study, the analyses were carried out with the aid of EVIEWS and Excel softwares. The study used the Ordinary Least Squares (OLS) technique for estimation purposes. On the basis of various diagnostic and selection evaluation criteria the best model was selected for the short term forecasting of Nigerian inflation. The study found ARIMA (2,2,3) as the most appropriate model under model identification, parameter estimation, diagnostic checking and forecasting inflation. In-sample forecasting was attempted and the estimated ARIMA model remarkably tracked the actual inflation during the sample period. The study concluded that Nigerian inflation is largely expectations-driven. The major inference that can be drawn in this study is that expectations that are formed about future levels of prices affect the current purchase decisions. It was recommended that, to put inflation under control, there is need for high transparency in monetary policy making and implementation.

Keywords: Inflation dynamics, ARIMA, expectations

1. Introduction

Concern over inflation is a legitimate policy concern. Occasionally, governments attempt to reduce price pressures as a means for improving social welfare by enabling the domestic economy to operate more efficiently. As a result, short-term price stabilization goals are frequently of critical importance in government policy programmes in developing economies. One of the objectives of Nigeria's economic policy during the past three decades has been the attainment of low and stable inflation. Achieving the objective of keeping inflation low and stable requires that its causes should be identified and understood. However, it is important to note that the extent to which this happens depends on the extent to which inflation has been anticipated and its behaviour understood.

The construction of time series economic models has become important in Nigeria because strategic decisions at all levels have been criticized for lack of analytical rigour and without the benefit of appropriate empirical framework (Adenikinju, Busari, & Olofin, 2009). The result has been that decision-making at all levels tend to rely upon macroeconomic forecasts that may not be anchored on scientific models that track major economic indices. Time series models will enable economic decision makers to exercise their judgemental analysis in a much more structured and quantified manner and to develop a more adequate understanding of macroeconomic time line. The aim of this study was to empirically develop a linear dynamic stochastic model and apply it in explaining the behaviour of inflation series in Nigeria between 1981 and 2010. This was done by developing and estimating a linear dynamic stochastic model based on Box and Jenkins (1976) *univariate autoregressive integrated moving average* (ARIMA) approach.

2. Review of Related Literature

Persistence inflation is perhaps the second most serious macroeconomic problem confronting the world economy today—second only to hunger and poverty in the “third World” (Dwivedi, 2008). Economists generally agree that a long sustained period of inflation is caused by a combination of cost factors, money supply, and decline in output (Barro & Grilli, 1997; Olofin, 2001). The prevailing view in mainstream economics is that inflation is caused by the interaction of the supply of money with output and interest rates (Odedokun, 1993; Stiglitz & Greenwald, 2003). Views of mainstream economics can be broadly divided into two camps: the “monetarists” who believe that monetary effects dominate all others in setting the rate of inflation (e.g. Friedman & Kuttner, 1993; Friedman & Schwartz, 1970), and the “Keynesians” who believe that the interaction of money, interest and output dominate other

effects (e.g. Olivera, 1964; Sunkel, 1960). Controversy between these viewpoints has led to differing prescriptions about the appropriate policy response.

A variety of models and empirical methods have been used in attempts to analyze inflation dynamics. Stockton & Glassman (1987) used ARIMA methodology to model inflation in the United States. They concluded that ARIMA models are theoretically justified and can be surprisingly robust with respect to alternative (multivariate) modelling approach.

An empirical analysis of causes of inflation in Nigeria by Asogu (1991) showed that real output, net exports, current money supply, domestic food prices and exchange rates were the major determinants of inflation in Nigeria. He concluded that fiscal and monetary tools together with growth in productivity may curtail inflationary pressures. Egwaikhide, Chete & Falokun (1994) used time series econometric technique of co-integration and error correction mechanism (ECM) to analyze the quantitative impact of monetary expansion and exchange rate depreciation on price inflation in Nigeria. The study showed that the Nigerian inflation seems to find explanation in both monetary and structural factors; and that official and parallel market exchange rates exert an upward pressure on the general price level. They recommended the use of a combination of policy measures to put inflation under effective control in Nigeria.

Moser (1995) studied inflation under long run and dynamic error correction model. His results confirmed the basic findings of earlier studies, namely, monetary expansion, driven mainly by expansionary fiscal policies, explain to a large extent the inflationary process in Nigeria. He identified other important factors influencing inflation in Nigeria as the devaluation of the naira as well as agroclimatic conditions. He found that the monetary effect was substantial as well as real income and exchange rate. Short run adjustments to disequilibria in the contemporaneous period were captured in the study. He concluded that concurrent monetary and fiscal policies have major impact on inflation in Nigeria. Fakiyesi (1996) studied inflation in Nigeria using the autoregressive distributed-lag model. The empirical results suggested that the prime determinants of the inflation function were the growth in broad money, the rate of exchange of the naira vis-à-vis the dollar, the growth of real income, the level of rainfall, and expected inflation.

Adamson (2000) concluded that growth in broad money, rate of exchange of the naira vis-à-vis the dollar, growth of real income, and price volatility were some of the variables that influence inflation behaviour in Nigeria. Odusola & Akinlo (2001) showed that inflation in Nigeria was largely determined by the absence of fiscal prudence on the part of government, parallel exchange rate shocks and output. Olubusoye & Oyaromade (2009) analyzed the main sources of fluctuation in Nigeria using the framework of error correction mechanism. The empirical results suggested that the prime determinants of the inflation function are the growth in nominal money stock, expected inflation, nominal interest and exchange rates, real income and foreign prices. Omoke & Ugwuanyi (2010) studied the empirical relationship between money, inflation and output in Nigeria by employing Cointegration and Granger-causality test analysis. The findings revealed that there is no existence of a cointegrating vector in the series used. The result suggests that monetary stability could contribute towards price stability in the Nigerian economy since the variation in price level was mainly caused by money supply. They concluded that inflation in Nigeria was to a large extent a monetary phenomenon.

Samad, Ali & Hossain (2002) applied the Box-Jenkins (ARIMA) methodology to forecast wheat and wheat flour prices in Bangladesh. They concluded that the ARIMA forecasts were satisfactory during and beyond the estimation period and could be used for policy purposes as far as price forecasts of the commodities were concerned. Valle (2002) used ARIMA and VAR models to forecast inflation in Guatemala. The results showed that ARIMA produced good results and the forecasts behaved according to the underlying assumptions of each model. Katimon & Demun (2004) applied the ARIMA model to represent water use behavior at the Universiti Teknologi Malaysia (UTM) campus. Using autocorrelation function (ACF), partial autocorrelation function (PACF), and Akaike's Information Criterion (AIC), they concluded that ARIMA model provides a reasonable forecasting tool for campus water use.

El-Mefleh & Shotar (2008) applied the Box-Jenkins (ARIMA) methodology to the Qatari economic data. They concluded that ARIMA models were modestly successful in ex-post forecasting for most of the key Qatari economic variables. The forecasting inaccuracy increased the farther away the forecast was from the used data, which is

consistent with the expectation of ARIMA models. Adebisi, Adenuga, Abeng, Omamukue & Ononugo (2010) examined the different types of inflation forecasting models covering ARIMA, VAR, and VECM models. The empirical results from ARIMA showed that ARIMA models were modestly successful in explain inflation dynamics in Nigeria.

3. Theoretical Framework and Methodology

The Box-Jenkins (1976) methodology refers to the set of procedure for identifying, fitting, and checking autoregressive integrated moving average (ARIMA) models with time series data (Hanke & Wichern, 2005; Roberts, 2006). Forecasts follow directly from the form of the fitted model. ARIMA methodology is not embedded within any underlying economic theory or structural relationship, and the forecasts from the models are based purely on the past behaviour and previous error terms of the series of interest (Hanke & Wichern, 2005; Roberts, 2006).

The Box-Jenkins (ARIMA) econometric modelling is a forecasting technique that completely ignores independent variables in making forecast. It takes into account historical data and decomposes it into *Autoregressive* (AR) process, where there is a memory of past events; an *Integrated* (I) process, which accounts for stabilizing or making the data stationary, making it easier to forecast; and a *Moving Average* (MA) of the forecast errors, such that the longer the historical data, the more accurate the forecasts will be, as it learns over time. ARIMA models therefore have three model parameters, one for the AR(p) process, one for the I(d) process, and one for the MA(q) process, all combined and interacting among each other and recomposed into the ARIMA (p,d,q) model. The ARIMA models are applicable only to a stationary data series, where the mean, the variance, and the autocorrelation function remain constant through time. The only kind of nonstationarity supported by ARIMA model is simple differencing of degree d . In practice, one or two levels of differencing are often enough to reduce a nonstationary time series to apparent stationarity (Hanke & Wichern, 2005; Pindyck & Rubinfeld, 1981; Roberts, 2006).

Any forecasting technique that ignores independent variables also essentially ignores all potential underlying theories except those that hypothesize repeating patterns in the variable under study. Since the advantages of developing theoretical underpinnings of a particular equation before estimating them have been emphasized in regression theory, why would we advocate ARIMA? The answer is that the use of ARIMA is appropriate when little or nothing is known about the dependent variable being forecasted or when all that is needed is one or two-period forecast (Hanke & Wichern, 2005; Roberts, 2006). In these cases, ARIMA has the potential to provide short-term forecasts that are superior to more theoretically satisfying regression models.

The ARIMA approach combines two different specifications (called *processes*) into one equation. The first specification is an *autoregressive* process (hence the AR in ARIMA), and the second specification is a *moving average* (hence the MA in ARIMA). ARIMA modelling advocates that there is correlation between a time series data and its own lagged data.

A p th-order autoregressive **process** expresses a dependent variable as a function of past values of the dependent variable, as in:

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t \quad (1)$$

where

Y_t is the response (dependent) variable being forecasted at time t .

$Y_{t-1}, Y_{t-2}, \dots, Y_{t-p}$ is the response variable at time lags $t-1, t-2, \dots, t-p$, respectively.

$\phi_1, \phi_2, \dots, \phi_p$ are the coefficients to be estimated.

ε_t is the error term at time t .

This equation is similar to the serial correlation error term function and to the distributed lag equation. Since there are p different lagged values of Y in the equation, it is often referred to as a “ p th-order” autoregressive process. More generally, the function can be written as:

A **q th-order moving-average process** expresses a dependent variable Y_t as a function of the past values of the q error terms, as in:

$$Y_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad (2)$$

where

Y_t is the response (dependent) variable being forecasted at time t .

μ is the constant mean of the process.

$\theta_1, \theta_2, \dots, \theta_p$ are the coefficients to be estimated.

ε_t is the error term at time t .

$\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}$ are the errors in previous time periods that are incorporated in the response Y_t .

Such a function is a moving average of past error terms that can be added to the mean of Y to obtain a moving average of past values of Y . Such an equation would be a “ q th-order” moving-average process.

To create an ARIMA model, we began with an econometric equation with no independent variables ($Y_t = \beta_0 + \varepsilon_t$) and added to it both the autoregressive (AR) process and the moving-average (MA) process.

$$Y_t = \beta_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad (3)$$

where the ϕ s and θ s are the coefficients of the autoregressive and moving-average processes, respectively.

Following Box and Jenkins (1976), an autoregressive moving average (ARIMA) model may be specified as thus:

$$CPI_t = \beta_0 + \phi_1 CPI_{t-1} + \phi_2 CPI_{t-2} + \dots + \phi_p CPI_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad (4)$$

where CPI_t is the inflation series and β_0, ϕ , and θ are the parameters to be estimated.

Before this equation can be applied to a time series, however, it must be assumed that series is *stationary*. If a time series is nonstationary, then steps must be taken to convert the series into a stationary one before ARIMA can be

applied. For example, a nonstationary series can often be converted into a stationary one by taking the first difference of the variable in question.

$$CPI_t^* = \Delta CPI_t = CPI_t - CPI_{t-1} \quad (5)$$

If the first differences do not produce a stationary series then first differences of this first-differenced series can be taken. The resulting series is a second-difference transformation:

$$CPI_t^{**} = (\Delta CPI_t^*) = CPI_t^* - CPI_{t-1}^* = \Delta CPI_t - \Delta CPI_{t-1} \quad (6)$$

In general, successive differences are taken until the series is stationary. The number of differences required to be taken before a series becomes stationary is denoted with the letter d . In practice, d is rarely more than two (2) (Makridakis, Wheelwright, & Hyndman, 1998).

The dependent variable in Equation 4 must be stationary, so the CPI in that equation may be CPI , CPI^* , or even CPI^{**} , depending on the variable in question. If a forecast of CPI^* or CPI^{**} is made, then it must be converted back into CPI terms before its use; for example, if $d = 1$, then

$$CPI_{T+1}^{\wedge} = CPI_T + CPI_{T+1}^* \quad (7)$$

This conversion process is similar to integration in mathematics, so the "I" in ARIMA stands for "integrated". ARIMA stands for **A**uto**R**egressive **I**ntegrated **M**oving **A**verage. (If the original series is stationary and d therefore equals 0, this is shortened to ARMA.)

As a shorthand, an ARIMA model with p , d , and q specified is usually denoted as ARIMA (p, d, q) with the specific integers chosen inserted for p , d , and q , as in ARIMA (2, 1, 1). ARIMA (2, 1, 1) would indicate a model with two autoregressive terms, one difference, and one moving average term:

$$\begin{aligned} ARIMA(2, 1, 1) : Y_t^* &= \beta_0 + \theta_1 Y_{t-1}^* + \theta_2 Y_{t-2}^* + \varepsilon_t + \phi_1 \varepsilon_{t-1} \\ \text{where } CPI_t^* &= \Delta CPI_t = CPI_t - CPI_{t-1} \end{aligned} \quad (8)$$

Forecasts are often more useful if they are accompanied by a confidence interval, which is a range within which the actual value of the dependent variable is expected to lie. This is given as:

$$CPI_{T+1}^{\wedge} \pm S_F t_c \quad (9)$$

where S_F is the estimated standard error of the forecast and t_c is the critical two-tailed t -value for the desired level of significance.

4. Empirical Analysis and Results

The first step in modelling a series is to check the structure of the data in order to obtain some preliminary knowledge about the stationarity of the series (existence of a trend or a seasonal pattern). Before performing formal tests, the graphs of the time series under study were plotted. Such plots give initial clue about the likely nature of the time series. The figures below show the line graph of the historical performance of the CPI series used in this study. Figure 1 shows the graph of the series at their level form while Figure 1.2 shows the graphs of the logarithmic values of the series.

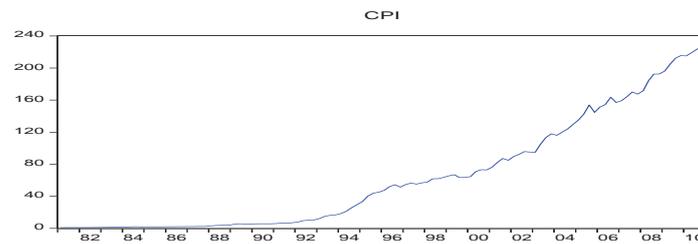


Figure 1: Variables at Levels

Source: Authors' Calculations.

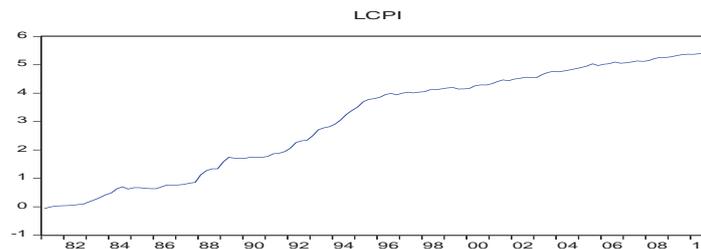


Figure 2: Logarithm of Variables

Source: Authors' Calculations.

Figures 1 and 2 show that there is little evidence to suspect the presence of structural break or outlier in the seven variables. However, the graphs reveal that constructing a model for the logarithmic values is likely to be more advantageous because the changes in the logarithmic series display a more stable variance than the changes in the original series. The logarithmic transformation helps to stabilize the variance of the series.

4.1. Unit Root Test for the CPI Series

A stationary series must be obtained before it can be used to specify and estimate a model. The unit roots test will help us to determine the stationarity of a series. The Augmented Dickey-Fuller (ADF) is used to test for the stationarity of the CPI series. The test results for the time series variable are presented in Table 1 below.

Table 1: Results of Unit Root Test

Variable	ADF Test Statistic	95% Critical ADF Value	Remark
D(LCPI)	-2.790	-2.887	Nonstationary
D(LCPI,2)	-13.321*	-2.887	Stationary
Note: * = significant at 1percent.			

Source: Authors' Calculations.

In the results shown above, the ADF test statistic for the variable is greater than the respective 95 percent critical values. In the final evaluation the consumer price index (CPI) became stationary after its second difference.

4.2. Model Identification, Estimation and Interpretation

The objective of this study was to analyze inflation dynamics with ARIMA model. ARIMA models are univariate models that consist of an autoregressive polynomial, an order of integration (d), and a moving average polynomial. Since the logarithm of CPI became stationary after second order difference (ADF test) the model that we are looking

at is ARIMA ($p, 2, q$). We have to identify the model, estimate suitable parameters, perform diagnostics for residuals and finally forecast the inflation series.

The following procedure was followed in estimating the univariate autoregressive integrated moving average (ARIMA) model that was specified. First, CPI series variable was transformed to stabilize the variable. Second, potential models were identified using the autocorrelation function (ACF) and the partial autocorrelation function (PACF) and estimated via Ordinary Least Squares (OLS) method. Third, the best model is selected using the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC). Fourth, the selected model was estimated and diagnostic tests of residuals were performed. Finally, the estimated model was used to forecast inflation and the forecast performance evaluated.

4.2.1 ARIMA Model Identification

Firstly, we computed the series correlogram which consists of ACF and PACF values as in Figure 1.3. We also calculated the Ljung-Box Q-statistics. We observed the patterns of the ACF and PACF, and then determine the parameter values p and q for ARIMA model. The correlogram for ACF and PACF of the second order difference series was plotted in Figure 3.

Correlogram of D(LCPI,2) Residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
** .	** .	1	-0.255	-0.255	7.8990	0.005
*** .	*** .	2	-0.356	-0.450	23.332	0.000
* .	*** .	3	-0.077	-0.435	24.069	0.000
. ***	. .	4	0.402	0.048	44.099	0.000
. .	. *	5	0.015	0.094	44.127	0.000
** .	* .	6	-0.330	-0.120	57.914	0.000
. .	* .	7	-0.019	-0.083	57.962	0.000
. **	. .	8	0.226	-0.059	64.558	0.000
. .	. .	9	0.061	-0.016	65.040	0.000
** .	** .	10	-0.323	-0.223	78.703	0.000
. .	* .	11	0.002	-0.178	78.703	0.000
. **	. .	12	0.281	0.002	89.283	0.000
. .	. *	13	0.070	0.095	89.937	0.000
*** .	* .	14	-0.356	-0.123	107.17	0.000
. .	* .	15	-0.048	-0.175	107.49	0.000
. ***	. .	16	0.359	0.011	125.35	0.000
. .	. .	17	0.038	-0.000	125.56	0.000
** .	* .	18	-0.341	-0.143	142.02	0.000
. .	. .	19	-0.006	-0.033	142.02	0.000
. **	. .	20	0.267	-0.036	152.31	0.000
. .	* .	21	0.006	-0.117	152.32	0.000
* .	. .	22	-0.163	0.047	156.23	0.000
. .	. .	23	-0.062	0.023	156.81	0.000
. *	. .	24	0.191	-0.031	162.31	0.000
. .	. .	25	0.049	0.005	162.67	0.000
** .	* .	26	-0.228	-0.095	170.64	0.000
. .	. .	27	0.005	-0.001	170.64	0.000
. *	* .	28	0.154	-0.071	174.37	0.000
. *	. *	29	0.139	0.115	177.44	0.000
** .	. .	30	-0.296	0.014	191.53	0.000
* .	* .	31	-0.102	-0.141	193.22	0.000
. **	. .	32	0.289	0.007	206.94	0.000
. .	. .	33	0.059	-0.043	207.52	0.000
** .	. .	34	-0.227	-0.059	216.22	0.000
* .	. .	35	-0.069	-0.003	217.04	0.000
. **	. .	36	0.242	0.058	227.18	0.000

Figure 3: Correlogram of the second order difference LCPI series

Source: Authors' Calculations.

In Figure 3, 36 lags of autocorrelation and partial autocorrelation were generated. The ACF died out after lag 2(AR) and PACF died out slowly after lag 4(MA). Thus, the p and q values for the ARIMA ($p, 2, q$) model were set at 2 and 4 respectively. So, we temporarily set our ARIMA model to be ARIMA (2, 2, 4).

From the correlogram of the second order differenced series, it seems an AR (1), or AR (2) might be adequate, while MA(1), MA(2), MA(3) or MA(4) might also be adequate. This therefore suggests the possibility of the following combinations of ARIMA: ARIMA(1,2,1), ARIMA(1,2,2), ARIMA(1,2,3), ARIMA(1,2,4) to ARIMA (2,2,4). From these possible ARIMA combinations, the AIC and SIC criteria were used to select the most desirable ARIMA model. The results of all the ARIMA combinations are presented in Table 3.

Table 3: ARIMA Models for Forecasting Inflation

Variable	ARIMA (1,2,1)	ARIMA (1,2,2)	ARIMA (1,2,3)	ARIMA (1,2,4)	ARIMA (2,2,1)	ARIMA (2,2,2)	ARIMA (2,2,3)	ARIMA (2,2,4)
C	-0.0003 (0.005)	-0.0004 (0.00)	-0.0004 (0.0023)	-0.0002 (0.69)	-0.000 (0.99)	-0.000 (0.98)	0.000 (0.94)	-0.000 (0.98)
AR(1)	0.35 (0.000)	0.03 (0.90)	-0.32 (0.66)	-0.35 (0.45)	0.003 (0.99)	0.17 (0.31)	-0.005 (0.67)	-0.005 (0.70)
AR(2)					-3.89 (0.0002)	-0.606 (0.000)	-0.97 (0.000)	-0.97 (0.000)
MA(1)	-0.99 (0.000)	-0.63 (0.006)	-0.24 (0.74)	-0.19 (0.68)	-0.55 (0.000)	-0.70 (0.0004)	-0.62 (0.000)	-0.58 (0.000)
MA(2)		-0.36 (0.11)	-0.52 (0.26)	-0.55 (0.027)		0.36 (0.033)	0.96 (0.000)	0.79 (0.000)
MA(3)			-0.23 (0.399)	-0.27 (0.08)			-0.69 (0.000)	-0.65 (0.000)
MA(4)				0.14 (0.22)				-0.17 (0.083)
R^2	0.33	0.34	0.35	0.35	0.35	0.37	0.48	0.48
\bar{R}^2	0.32	0.32	0.32	0.32	0.33	0.35	0.45	0.46
DW	1.93	1.99	2.05	2.02	2.07	2.08	1.86	1.97
AIC	-2.87	-2.87	-2.87	-2.86	-2.88	-2.90	-3.06	-3.06
SIC	-2.80	-2.78	-2.75	-2.71	-2.79	-2.78	-2.92	-2.90
RMSE	0.069	0.068	0.068	0.068	0.068	0.068	0.059	0.059
TIC	.98	0.98	0.98	0.99	0.96	0.96	0.57	0.58

Source: Authors' Calculations.

In selecting the best ARIMA model of inflation we subjected all the ARIMA models to Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). The results above show that ARIMA (2,2,3) is preferred to others since it has the lowest values of AIC and SBC.

4.2.2. ARIMA (2,2,3) Estimation and Interpretation

When we have identified the ARIMA model, the next step was to estimate the parameter coefficients. The parameter estimation of the model was conducted using the EViews software. Table 4 tabulates the results

Table 4: The Parsimonious ARIMA (2,2,3) Result

Dependent Variable: D(LCPI,2)

Variable	Coefficient	t-Statistic	Prob.
C	0.000119	0.076348	0.9393
AR(1)	-0.004500	-0.433202	0.6657
AR(2)	-0.974096	-88.37214	0.0000
MA(1)	-0.627584	-9.227985	0.0000
MA(2)	0.958881	108.9283	0.0000
MA(3)	-0.687395	-9.690985	0.0000
R-squared	0.475972		
Adjusted R-squared	0.452152		
F-statistic	19.98248		
Durbin-Watson stat	1.859533		
Inverted AR Roots	-.00+.99i	-.00-.99i	
Inverted MA Roots	.69	-.03+1.00i	-.03-1.00i

Source: Authors' Calculations.

In Table 4, ARIMA (2,2,3) results indicate that the coefficients of AR(2), and MA(3) were highly significant at 1% levels. The AIC (-3.06) and SIC (-2.92) were lower in values when compared to ARIMA(1,2,1), ARIMA(1,2,2), (1,2,3), (1,2,4), ARIMA(2,2,1), ARIMA(2,2,2), and ARIMA(2,2,4). The adjusted R-squared of ARIMA (2,2,3) which is 0.48 (48) was also higher when compared to other ARIMA models indicating that ARIMA (2,2,3) goodness of fit for forecasting is preferred to other ARIMA models.

From the *t*-statistics for the coefficient variables AR (*p*) and MA (*q*) in Table 4, the null hypothesis that the coefficients are equal to zero is rejected. The value for R-squared was 0.48 which implies that that about 48% of the variation in inflation in Nigeria is explained by past values of inflation and the past errors. The D-W statistic of 1.86 showed that there was little or no evidence to accept the presence of serial correlation in the model. Thus, the model equation can be formed as:

$$\Delta(LCPI_t, 2) = -0.0001 - 0.005LCPI_{t-1} - 0.97LCPI_{t-2} - 0.63\varepsilon_{t-1} + 0.96\varepsilon_{t-2} - 0.68\varepsilon_{t-3} \quad (4.2)$$

(0.076) (-0.43) (-88.37) (-9.23) (108.92) (-9.69)

The results showed that the coefficient of inflation expectation was negative and significant both in the first quarter lag and in the second quarter lag. This is consistent with the theoretical expectation

4.2.3 ARIMA (2,2,3) Diagnostic Tests

After estimating the parameters for ARIMA (2,2,3) model, it was also necessary to examine the statistical properties of the estimated ARIMA model in checking the model adequacy. The ARIMA (2,2,3) was tested for specification error, serial correlation, and heteroskedasticity.

Table 5: ARIMA (2,2,3) DIAGNOSTIC TEST

TEST	F-STATISTIC	P-VALUE
Specification Error: Ramsey RESET test	0.883	0.417
Serial correlation: Breusch-Godfrey serial correlation LM test	1.468	0.235
Autoregressive conditional Heteroskedasticity: ARCH LM test.	0.848	0.350

Source: Authors' Calculations.

The results reported in **Table 5** suggest that the model was well specified on the basis of the Ramsey RESET test and serially uncorrelated based on the Breusch-Godfrey serial correlation LM test. The ARCH autoregressive conditional heteroskedasticity test shows that there is no presence of volatility clustering in inflation quarterly data in Nigeria. The Jarque-Bera (JB) test for the residual from ARIMA (2,2,3) as presented in Figure 4, indicates that the residual from ARIMA (2,2,3) model is normally distributed at 1%.

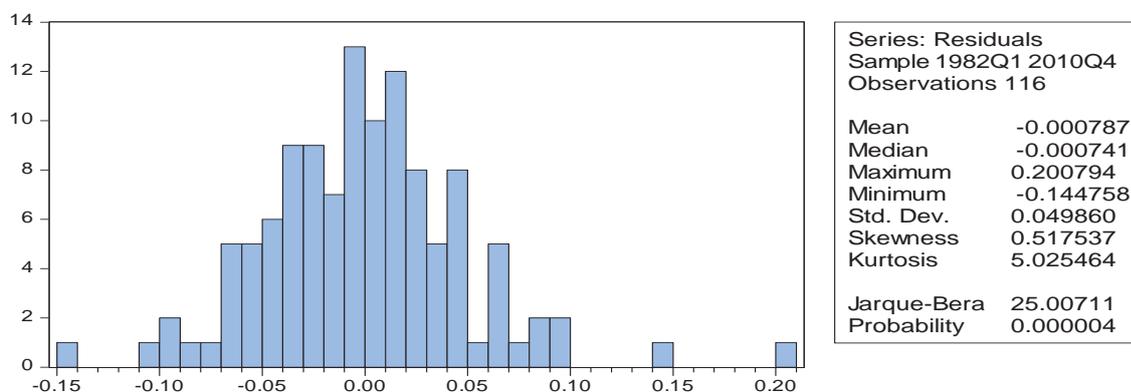


Figure 4 Histogram and normality test for ARIMA(2,2,3) residuals

Source: Authors' Calculations.

In Figure 4, the histogram and normality test are plotted. The mean value of the residuals is -0.0008 and the standard deviation is 0.049862. The values of skewness and kurtosis are 0.52 and 5.03 respectively. This means that the residuals have slight kurtosis and are slightly skewed to the left. Jarque-Bera test shows that the residuals series do not reject the null hypothesis of normally distributed at 5% significance level.

4.2.4 Forecast and Forecast Evaluation for ARIMA (2,2,3) Model

In the next step, the forecast of Nigerian inflation series using ARIMA (2, 2, 3) model was conducted. EViews software provides the one-step ahead static forecasts which are more accurate than the dynamic forecasts. The duration of forecasts is from 1981Q1 to 2010Q4. The forecasts are plotted in Figure 5.

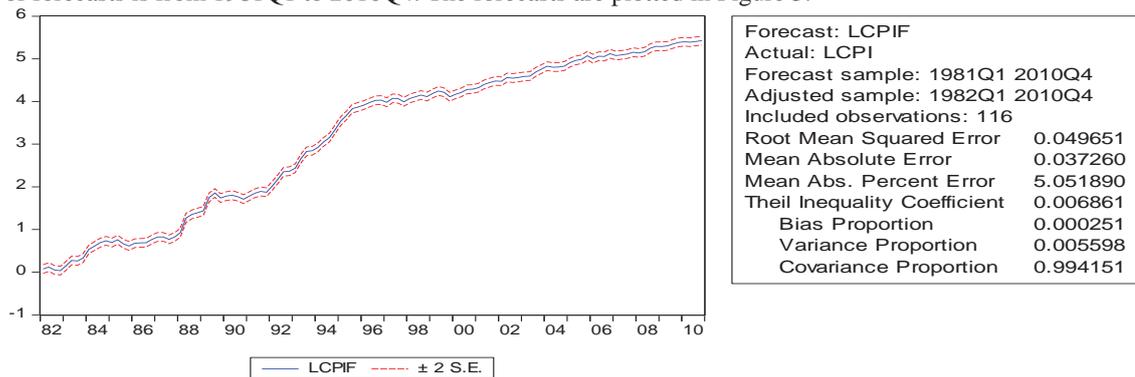


Figure 5 Forecast of inflation by ARIMA(2,2,3) model.
 Source: Authors' Calculations.

In Figure 5, the middle line represents the forecast value of inflation. Meanwhile, the lines which are above or below the forecasted quarterly inflation series show the forecast with ± 2 of standard errors. Some forecasting measurements such as root mean squared error (RMSE), mean absolute error (MAE), and Theil inequality coefficient are shown. These values will be compared with ARDL model forecast performance as stated in our objective.

In the forecasting stage, we calculated RMSE, MAE, and Theil Inequality coefficient values from ARIMA (2,2,3) model. These are tabulated in Table 6. If the actual values and forecast values are closer to each other, a small forecast error will be obtained. Thus, smaller RMSE, MAE, and Theil Inequality coefficient are preferred. Table 6 below provides information on these forecast measures. The results show the model is relevant for forecasting inflation in Nigeria.

Table 6: Forecasting Performance of ARIMA(2,2,3)

Forecast Performance	ARIMA(2,2,3)
RMSE	0.05
MAE	0.04
Theil Inequality Coeff.	0.01

Source: Authors' Calculations.

From Table 6 it can be concluded that the model is relevant for forecasting inflation in Nigeria. This is because the values are less than 5 percent

5. Discussion of Findings and Policy Implication

The objectives of this study were to identify a univariate autoregressive integrated moving average (ARIMA) model; estimate the model; and analyze the forecasting performance of the estimated model.

The study used the correlogram for autocorrelation function (ACF) and partial autocorrelation function (PACF) of the second order difference of inflation series to identify and estimate a parsimonious ARIMA model the ARIMA models. Diagnostic tests for serial correlation (Breusch-Godfrey serial correlation LM test), heteroskedasticity (ARCH test), normality (Jarque-Bera test), and specification error (Ramsey RESET test) of the model were performed. The results suggested that the model was well specified on the basis of the Ramsey RESET test and

serially uncorrelated based on the Breusch-Godfrey serial correlation LM test. The ARCH autoregressive conditional heteroskedasticity test showed that there was no presence of volatility clustering in inflation quarterly data in Nigeria. The Jarque-Bera (JB) test for the residual from ARIMA (2,2,3), indicated that the residual from ARIMA (2,2,3) model was normally distributed at 1%.

Thereafter, in-sample forecast of inflation dynamics using the ARIMA (2,2,3) model was conducted and the forecast performance evaluated using RMSE, MAE, and Theil Inequality coefficient. The ARIMA (2,2,3) univariate model was able to produce forecasts based on the historical patterns in the data. The results suggested that the model was relevant for forecasting inflation. This is consistent with the findings of Adebisi, Adenuga, Abeng, Omamukwe & Ononugbo (2010), Katimon & Demun (2004), Samad, Ali & Hossain (2002), and Valle (2002). From the parsimonious ARIMA (2,2,3) model, expected inflation was statistically significant in explaining Nigerian inflation dynamics. This is consistent with the results of Fakiyesi (1996) and Olubusoye & Oyaromade (2009). The major inference that can be drawn from the high significance of inflation expectation in this study is that expectations that are formed about future levels of prices affect the current purchase decisions. It is suggested that alternative models of inflation dynamics in Nigeria should consider expected inflation as a potential explanatory variable. It is recommended that, to put inflation under control, there is need for high transparency in monetary policy making and implementation.

6. Conclusion and Areas of Future Studies

It is now generally accepted that keeping low and stable rates of inflation is the primary objective of the Central Banks. Economic agents, private and public alike monitor closely the evolution of prices in the economy, in order to make decisions that allow them to optimize the use of their resources. In this context, it is very important to model and forecast inflation. ARIMA (2,2,3) model is the most appropriate model under model identification, selection, parameter estimation, diagnostic checking and forecast evaluation. The estimated inflation equation clearly showed that expected inflation was an important determinant of actual inflation during the estimation period. These findings also confirm that adaptive expectation holds in Nigeria since past inflation helps to predict future inflation. The Central Bank of Nigeria (CBN) identified the need to model inflation in Nigeria with the Gordon “triangle” model. This study therefore suggests analyzing Nigerian inflation series with the Gordon “triangle” model as an area of future study. Future studies in this area can also use a hybrid method, specifically ARIMA/GARCH model. This hybrid model is considered as an alternative model because it contains both qualities of Box-Jenkins and GARCH method.

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