A Univariate Analysis of Money Demand in Nigeria

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Abstract: The objective of this study was to develop a univariate autoregressive integrated moving average (ARIMA) model suggested by Box-Jenkins (1976) for money demand in Nigeria using quarterly data from 1986 to 2018. The study used the correlogram of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the first-order difference of money demand series to identify and estimate a parsimonious ARIMA model. ARIMA (3,1,2) model was found to be the most appropriate model under model identification, selection, parameter estimation, diagnostic checking, and forecast evaluation. The results suggested that the ARIMA (3,1,2) model was adequate based on the Ljung-Box Q-statistic and efficient in forecasting demand for money based on the RMSE and MAE values. The estimated broad money demand equation showed that the lagged values of money demand were statistically significant in explaining actual broad money demand in Nigeria during the estimation period. The major inference that can be drawn from this study is that expectations that are formed about previous values of money demand affect the current values of money demand. To achieve a stable and sustained broad money demand function in Nigeria, it was recommended that the monetary authority should exhibit a high level of transparency in monetary policy formulation, presentation, implementation, and control.

Keywords: ARIMA, Box-Jenkins, Correlogram, PACF, Univariate.

INTRODUCTION

The importance of a stable money demand function in any economy cannot be overemphasized because, the stability of the money demand function is necessary for understanding how the formulation and implementation of an effective monetary policy is crucial in offsetting the fluctuations that may arise from the real sector of the economy, and it enables a policy-driven change in monetary aggregates so that the desired values of targeted macroeconomic variables are ensured (Anoruo, 2002; Khan & Ali, 1997; Busari, 2009; Essien, Onwioduokit, & Osho, 1996; Maravic & Palic, 2010; Owoye & Onafowora, 2007; Sober, 2013).

The formulation of appropriate demand for money model which is the basis for the execution of appropriate and sound monetary policies continues to remain a subject of disagreement amongst scholars (Maravic & Palic, 2010). Therefore, every fresh attempt at studying the demand for money in Nigeria must be vigorously justified. A sound monetary policy formulation presupposes theoretically coherent and empirically robust model of money demand. Amongst other things, the success of such a policy stance would depend, to a large extent, on the nature and stability of the MDF in Nigeria (Busari, 2009). The Central Bank of Nigeria (CBN) in 1974 adopted monetary targeting as the framework for the implementation of monetary policy. Till date, the Central Bank of Nigeria (CBN) is increasingly relying on the use of monetary targeting as the framework for the implementation of monetary policy. It thus appears that the efforts at understanding, applying, and implementing a stable money demand function in Nigeria have not yielded the expected results. One major reason adduced for Nigeria not meeting major policy targets has been the relatively weak scientific efforts at explaining the policy dynamics in Nigeria (Adenikinju, Busari, & Olofin, 2009) and as a result, policy decisions are not anchored on scientific models that track major macroeconomic indices (Adenikinju, Busari, & Olofin, 2009). The aim of this study was to empirically develop a univariate model and apply it in explaining the behaviour of money demand in Nigeria. This was done by developing and estimating a model based on Box and Jenkins (1976) autoregressive integrated moving average (ARIMA) approach. The motivation was derived from the fact that reliable and adequate

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estimates of money demand are very essential for planning and policy-making by the government and other relevant agencies.

LITERATURE REVIEW

Conceptually, money is an asset with a particular set of characteristics, most notably its liquidity (Carpenter & Lange, 2002). Like other financial assets, demand for money is part of a portfolio allocation decision, in which an agent's wealth is distributed among competing assets based on each asset's relative benefits (Tobin, 1969). Stable money demand is a precondition for an effective monetary policy, especially for countries pursuing a monetary targeting framework (Cziraky & Gillman, 2006; Owoye & Onafowora, 2007). As argued by Sriram (2001), there is a growing literature on the stability of the MDF in developing countries like Nigeria, due, largely to the move towards a flexible exchange rate system, globalization of capital markets, financial liberation, and innovation in domestic financial markets. The decade of the 1970s witnessed pioneering works on the subject by Ajayi (1974), Odama (1974), Ojo (1974), Teriba (1974), Tomori (1974), Iyoha (1976), and Fakiyesi (1980). Studies that are more recent have leveraged on the tremendous progress in economic research methodologies and econometrics to shift the debate to a higher level. Some of these studies include Akinlo (2006), Kumar, Webber, and Fargher (2010), Yamden (2011), Bassey, Bessong, and Effiong (2012), Aiyedogbon, Ibeh, Edafe, and Ohwofasa (2013), Iyoboyi and Pedro (2013), Nduka, Chukwu, and Nwakaire (2013), Imimole and Uniamikogbo (2014), Apere and Karimo (2014), Bassey, Solomon, and Okon (2017), Nwude, Offor, and Udeh (2018), and Tule, Okpanachi, Ogiji, and Usman (2018). As lively as the debates have been, the issue has remained unresolved (Yamden, 2011).

The autoregressive integrated moving average (ARIMA) models are a class of typical linear models which are designed for linear time series and capture linear characteristics in time series (Wang, Yu, & Lai, 2005). The ARIMA approach is a specific subset of univariate modelling, in which a time series is expressed in terms of past values of itself (the autoregressive component) plus current and lagged values of the error term (the moving average component). The method does not apply the econometric modelling approach of using explanatory variables suggested by economic theory, choosing instead to rely only on the past behaviour of the variable being modelled (Box & Jenkins, 1976; Meyler, Kenny, & Quinn, 1998). Pankratz (1983) has pointed out that the Box-Jenkins (ARIMA) approach is a powerful and flexible method for short term forecasting because ARIMA models place more emphasis on the recent past. Some studies have applied the Box-Jenkins (ARIMA) approach in modeling financial time series.

Stockton and Glassman (1987) used ARIMA methodology to model economic growth in the United States. They concluded that ARIMA models were theoretically justified and could be surprisingly robust with respect to alternative (multivariate) modelling approach. Upon finding the results for the United States, they commented that it was somewhat distressing that a simple ARIMA model of economic growth should turn in such a respectable forecast performance relative to the theoretically based specifications. Samad, Ali, and 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 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 economic growth in Guatemala. The results showed that ARIMA produced good results and the forecasts behaved according to the underlying assumptions of each model. Katimon and 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 provided a reasonable forecasting tool for campus water use. Moshiri and Foroutan (2006) modelled daily crude oil futures prices that are listed in MYMEX from 1983 to 2003. They discovered that linear ARMA (1, 3) model was the most suitable. El-Mefleh and 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.

The Box-Jenkins method has been used in attempts to analyse macroeconomic series in Nigeria. The table below shows a summary of the empirical studies done in Nigeria.

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Table 1 : Summary of empirical literature on application of ARIMA in Nigeria

Author	Variable	Country	Study Period	Method	Key Finding (s)
Adebiyi, Adenuga, Abeng, Omamukue, and Ononugo (2010)	Economic growth	Nigeria	1982-2008	ARIMA models	ARIMA models were modestly successful in explaining economic growth dynamics
Akpanta and Okorie (2014)	Crude oil prices	Nigeria	1982-2013	ARIMA models	ARIMA models were modestly successful in ex-post forecasting
Chamalwa, Rann, and Idris (2016).	Exchange rate	Nigeria	1981-2012	ARIMA models	ARIMA (2, 1, 2) is the best fit model.
Mohammed and Abdulmuahymin (2016)	Exchange rate	Nigeria	1972-2014	ARIMA models	ARIMA (0, 2, 1) is the best fit model.
Nyoni (2018)	Exchange rate	Nigeria	1960-2017	ARIMA models	ARIMA (1, 1, 1) is the best fit model.
Okafor and Shaibu (2013)	Inflation	Nigeria	1981-2010	ARIMA models	ARIMA (2,2,3) forecasts were satisfactory
Okafor and Shaibu (2017)	Economic growth	Nigeria	1986-2013	ARIMA models	ARIMA (4,1,2) was the most appropriate model
Olakorede, Olanrewaju, and Ugbede (2018)	Exchange rate	Nigeria	1980-2015	ARIMA models	ARIMA (0, 1, 1) is the best fit model.
Olatunji and Bello (2015)	Exchange rate	Nigeria	2000-2012	ARMA & ARIMA models	ARIMA (1, 1, 2) and ARMA (1, 1) models are optimal.
Onasanya and Adeniji (2013)	Exchange rate	Nigeria	1994-2011	ARIMA models	The best fit model is ARIMA (1, 2, 1) model.
Wiri and Tuaneh (2019)	Crude oil prices	Nigeria	1986-2017	ARIMA models	ARIMA (1, 1, 1) was the most adequate model.

Source: Researchers' survey (2019).

From the empirical literature, there is no evidence that the Box-Jenkins (ARIMA) methodology has been applied in modeling money demand in Nigeria. The application of ARIMA to time series variables in Nigeria have had two major limitations of the selection of parsimonious ARIMA model and diagnostic checking of the selected ARIMA model. This study differ from the reviewed studies because the Box-Jenkins ARIMA was applied to money demand (M2) in Nigeria and the Box-Jenkins ARIMA procedure of model identification, selection, parameter estimation, diagnostics checking, and forecasting performance evaluation of the selected model was strictly followed.

THEORETICAL FRAMEWORK AND METHODOLOGY

The common finding in time series multivariate regression analyses is that the error residuals are correlated with their own lagged values (serial correlation) which violate the standard assumption of regression theory that disturbances are not correlated with other disturbances. To deal with the issue, the Box-Jenkins (1976) autoregressive integrated moving average (ARIMA) methodology has been suggested (Hanke & Wichern, 2005; Roberts, 2006). This is because ARIMA methodology is not embedded within any underlying economic theory or

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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 major reasons why an ARIMA models are superior to time-series multivariate regressions are: (1) 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) and (2) ARIMA can sometimes produce better explanations of the residuals from an existing regression equation (in particular, one with omitted variables or other problems). In these cases, ARIMA has the potential to provide short-term forecasts that are superior to more theoretically satisfying regression models.

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). The Box-Jenkins (ARIMA) econometric modelling 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. 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). The auto-regressive integrated moving average (*ARIMA*) processes are built on the following basic assumptions:

1. Absence of outliers;
2. Shocks are randomly distributed with a mean of zero and constant variance over time;
3. Residuals are normally distributed;
4. Residuals are independent.

The Box-Jenkins methodology of forecast is different from most methods because it does not assume any particular pattern in the historical data of the series to be forecast. It uses an iterative approach of identifying a possible model from a general class of models. The chosen model is then checked against the historical data to see whether it accurately describes the series. The models fits well if the residuals are generally small, randomly distributed, and contain no useful information. If the specified model is not satisfactory, the iterative procedure continues until a satisfactory model is found. At this point, the model can be used for forecasting. The general methodology of the Box–Jenkins approach involves model identification, model estimation, diagnostic checking, and forecasting. 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 modeling 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. More generally, the function can be written as:

$$z_t = \delta + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots + \phi_p z_{t-p} + \varepsilon_t \qquad \textbf{(1)}$$

where

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

$z_{t-1}, z_{t-2}, \ldots, z_{t-p}$ is the response variable at time lags $t-1,\ t-2, \cdots,\ t-p,$ respectively.

$\phi_1, \phi_2, \cdots, \phi_p$ are the parameters to be estimated.

ε_t is the error term at time *t*.

Since there are *p* different lagged values of *Y* in the equation, it is often referred to as a "*p*th-order" autoregressive process.

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

$$z_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} \qquad \textbf{(2)}$$

where

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

μ is the constant mean of the process.

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

ε_t is the error term at time *t*.

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

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

To create an ARIMA model, we begin with an econometric equation with no independent variables ($z_t = \phi_0 + \varepsilon_t$) and add to it both the autoregressive (AR) process and the moving-average (MA) process.

$$z_t = \phi_0 + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots + \phi_p z_{t-p} + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} \qquad \textbf{(3)}$$

where $\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$ are random shocks, $\phi_1, \phi_2, \ldots, \phi_p$ and $\theta_1, \theta_2, \ldots, \theta_q$ are the autoregressive (AR) parameters and moving average (MA) parameters respectively. It can be proven that for this model $\delta = \mu(1 - \phi_1 - \phi_2 - \cdots \phi_p)$.

Model for non-seasonal series are denoted by ARIMA (*p*, *d*, *q*). Here *p* indicates the order of the autoregressive part, *d* indicates the amount of differencing, and *q* indicates the order of the moving average part. If the original series is stationary, *d* = 0 and the ARIMA models reduce to the ARMA models. A highly useful operator in time-series theory is the lag or backshift operator, *B* defined by $Bz_t = z_{t-1}$. The difference linear operator (Δ) is defined by:

$$\Delta z_t = z_t - z_{t-1} = z_t - Bz_t = (1 - B)z_t \qquad \textbf{(4)}$$

The stationary series y_t is obtained as the *d*th difference (Δ^d) of z_t,

$$y_t = \Delta^d z_t = (1 - B)^d z_t \qquad \textbf{(5)}$$

ARIMA (*p, d, q*) has the general form:

$$\phi_p(B)(1 - B)^d z_t = \delta + \theta_q(B)\varepsilon_t \qquad \textbf{(6)}$$

$$\phi_p(B) y_t = \delta + \theta_q(B)\varepsilon_t \qquad \textbf{(7)}$$

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

$$M2_t = \phi_0 + \phi_1 M2_{t-1} + \phi_2 M2_{t-2} + \cdots + \phi_p M2_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \qquad \textbf{(8)}$$

where $M2$ is the money demand rate series and ϕs and θs are the parameters to be estimated.

For the Box-Jenkins approach, this equation can be applied to a time series if the series is stationary. Hence, the input series for ARIMA needs to be stationary, that is, it should have a constant mean, variance, and autocorrelation through time. To determine the stationarity of the data, we can check through ADF or look through pattern of correlogram of ACF and PACF. According to the principle of parsimony, simple models are preferred to complex models when all things being equal (Hanke, Wichern, & Reitsch, 2001). The goal is to develop the simplest model that provides an adequate description of the major features of the data. A nonstationary series can often be converted into a stationary one by taking the first difference of the variable in question.

$$M2_t^* = \Delta M2_t = M2_t - M2_{t-1} \qquad \textbf{(9)}$$

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

$$M2_t^{**} = (\Delta M2_t^*) = M2_t^* - M2_{t-1}^* = \Delta M2_t - \Delta M2_{t-1} \qquad (10)$$

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 (Makridakis, Wheelwright, & Hyndman, 1998).

The dependent variable in Equation 10 must be stationary, so the *M2* in that equation may be $M2$, $M2^*$ or even $M2^{**}$. If a forecast of $M2^*$ or $M2^{**}$ is made, then it must be converted back into $M2$ terms before its use; for example, if $d = 1$, then

$$M\hat{2}_{T+1} = M2_T + M\hat{2}^*_{T+1} \qquad (11)$$

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:

$$ARIMA\,(2,1,1): M2_t^* = \phi_0 + \phi_1 M2_{t-1}^* + \phi_2 M2_{t-2}^* + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$
$$\text{where} \quad M2_t^* = \Delta M2_t = M2_t - M2_{t-1} \qquad (12)$$

Once a tentative model has been selected, the parameters for that model must be estimated. Parameters that are judged significantly different from zero are retained in the fitted model; parameters that are not significant are dropped from the model. Before using the model for forecasting, it must be checked for adequacy. Basically, a model is adequate if the residuals cannot be used to improve the forecasts. That is the residuals should be random. An overall check of model adequacy is provided by a χ^2 test based on the Ljung-Box *Q*-statistic. This test looks at the sizes of the residual autocorrelations as a group. If the *p*-value associated with the *Q*-statistic is small, the model is considered inadequate. One should consider a new or modified model and continue the analysis until a satisfactory model has been determined. Although ARIMA models involve differences, forecasts for the original series can be always computed directly from the fitted model. 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:

$$M\hat{2}_{T+1} \pm S_F t_c \qquad (13)$$

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.

ARIMA MODELLING

The following procedure was followed in estimating the univariate autoregressive integrated moving average (ARIMA) approach. First, the broad money demand 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 the ordinary least squares (OLS) method. Third, the best model was 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 broad money demand and the forecast performance evaluated.

Transformation of Money Demand Series

Before performing formal tests, the normality of the time series under study was checked, plotted. A normality test for the broad money demand series is plotted in Figure 1.

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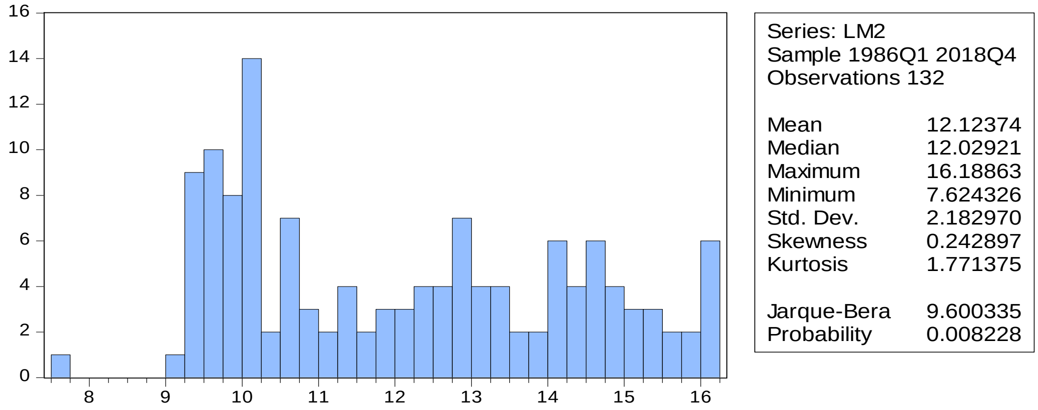

Figure 1: Histogram and normality test on broad money demand

Source: Authors' Calculations.

As summarized in Figure 1, the Jarque-Bera test indicates that the money demand series is not normally distributed at 5% significance level. Therefore, the series will require identifying their stationarity properties.

Unit Root Test for the Money Demand Series

The unit roots test is used to determine the stationarity of a series. The Augmented Dickey-Fuller (ADF) was used to test for the stationarity of the money demand series.

Table 2: ADF test for log of broad money demand

Null Hypothesis: LM2 has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.835199	0.3621
Test critical values:	1% level	-3.480818	
	5% level	-2.883579	
	10% level	-2.578601	

*MacKinnon (1996) one-sided p-values.

Source: Authors' Calculations.

According to the ADF test for broad money demand series in Table 2, the ADF test statistic is -1.835199 which is greater than the test critical values of -3.480818, -2.883579, and -2.578601 at 1%, 5%, and 10% significance levels. The *p*-value of 0.6155 strongly disagrees that the series is stationary. Thus, the broad money demand time series needed to be differenced to obtain a stationary series. The ADF test for first order difference from original broad money demand series is shown in Table 3.

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Table 3: ADF test for first difference broad money demand

Null Hypothesis: D(LM2) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=2)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.76350	0.0000
Test critical values:	1% level	-3.481217	
	5% level	-2.883753	
	10% level	-2.578694	

*MacKinnon (1996) one-sided p-values.

Source: Authors' Calculations.

From Table 3, the ADF test statistics for the first lagged difference series is -12.76350 which is smaller than the test critical values of -3.481217, -2.883753, and -2.578694at 1%, 5%, and 10% significance levels respectively. Hence, *p*-value indicates the ADF test statistic is significant. With the information obtained above, we have the stationary series after one lagged difference from the original broad money demand series. In the next step, we apply the Box-Jenkins approach to the first order difference of broad money demand.

ARIMA Model Identification

We computed the series correlogram which consists of ACF and PACF values. 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. In choosing the lag length, a rule of the thumb is to compute ACF up to 1/3 or ¼ of the length of the time series. The correlogram for ACF and PACF of the first order difference series was plotted in Figure 3.

Correlogram of D(LM2)

Sample: 1986Q1 2018Q4
Included observations: 131

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.120	-0.120	1.9302	0.165
.|. |	.|. |	2	0.003	-0.012	1.9314	0.381
.|. |	.|. |	3	-0.001	-0.002	1.9316	0.587
.|. |	.|. |	4	0.007	0.007	1.9389	0.747
.|. |	.|. |	5	-0.005	-0.003	1.9425	0.857
.|. |	.|. |	6	-0.035	-0.037	2.1156	0.909
.|. |	.|. |	7	0.060	0.052	2.6141	0.918
.|. |	.|. |	8	-0.058	-0.046	3.0865	0.929
.|. |	.|. |	9	0.003	-0.009	3.0879	0.961
.|. |	.|. |	10	-0.010	-0.010	3.1013	0.979
.|. |	.|. |	11	-0.015	-0.019	3.1328	0.989
.|. |	.|. |	12	-0.015	-0.020	3.1679	0.994
.|. |	.|. |	13	0.013	0.012	3.1917	0.997
.|. |	.|. |	14	-0.003	-0.007	3.1934	0.999
.|. |	.|. |	15	-0.013	-0.009	3.2206	0.999
.|. |	.|. |	16	-0.011	-0.017	3.2383	1.000
.|. |	.|. |	17	0.002	-0.002	3.2388	1.000
.|. |	.|. |	18	-0.005	-0.006	3.2427	1.000

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.|. |	.|. |	19	-0.013	-0.014	3.2682	1.000
.|. |	.|. |	20	-0.009	-0.016	3.2807	1.000
.|. |	.|. |	21	0.002	-0.001	3.2815	1.000
.|. |	.|. |	22	0.004	0.004	3.2846	1.000
.|. |	.|. |	23	-0.007	-0.006	3.2924	1.000
.|** |	.|** |	24	0.261	0.264	14.416	0.937
**|. |	**|. |	25	-0.266	-0.226	26.022	0.406
.|. |	.|. |	26	0.015	-0.030	26.058	0.460
.|. |	.|. |	27	-0.012	-0.017	26.083	0.514
.|. |	.|. |	28	-0.007	-0.018	26.092	0.568
.|. |	.|. |	29	0.006	0.013	26.099	0.620
.|. |	.|. |	30	-0.007	0.008	26.107	0.670
.|* |	.|. |	31	0.084	0.047	27.339	0.655
*|. |	.|. |	32	-0.107	-0.056	29.349	0.601
.|. |	.|. |	33	0.016	-0.020	29.397	0.647
.|. |	.|. |	34	-0.007	-0.004	29.405	0.692
.|. |	.|. |	35	0.001	0.004	29.405	0.735
.|. |	.|. |	36	-0.024	-0.031	29.509	0.769

Figure 3: Correlogram of the first order difference LM2 series

Source: Authors' Calculations.

In Figure 3, 36 lags of autocorrelation and partial autocorrelation were generated. From the figure, the ACF started dying sinusoidally after lag 6 (AR) and PACF died out after lag 6 (MA). Thus, the *p* and *q* values for the ARIMA (*p*, 1, *q*) model were set at 6 and 6 respectively. This therefore suggests the possibility of the following combinations of ARIMA: ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (1,1,3), ARIMA (1,1,4), ARIMA (1,1,5), ARIMA (1,1,6); ARIMA (2,1,1), ARIMA (2,1,2), ARIMA (2,1,3), ARIMA (2,1,4), ARIMA (2,1,5), ARIMA (2,1,6); ARIMA (3,1,1), ARIMA (3,1,2), ARIMA (3,1,3), ARIMA (3,1,4), ARIMA (3,1,5), ARIMA (3,1,6); ARIMA (4,1,1), ARIMA (4,1,2), ARIMA (4,1,3), ARIMA (4,1,4), ARIMA (4,1,5), ARIMA (4,1,6); ARIMA (5,1,1), ARIMA (5,1,2), ARIMA (5,1,3), ARIMA (5,1,4), ARIMA (5,1,5), ARIMA (5,1,6); and ARIMA (6,1,1), ARIMA (6,1,2), ARIMA (6,1,3), ARIMA (6,1,4), ARIMA (6,1,5), ARIMA (6,1,6). From these thirty six (36) 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 4.

ARIMA Model Selection and Estimation

Once tentative ARIMA (p,d,q) models have been selected, the parameters for the models must be estimated.. The parameters in ARIMA models are estimated by minimizing the sum of squares of the fitting errors with the aid of Views software. Table 4 shows the results

Table 4: ARIMA model selection for broad money demand

Criteria	**ARIMA (1,1,1)**	**ARIMA (1,1,2)**	**ARIMA (1,1,3)**	**ARIMA (1,1,4)**	**ARIMA (1,1,5)**	**ARIMA (1,1,6)**
AIC	2.13	2.15	2.16	2.18	2.17	2.21
SIC	2.20	2.24	2.27	2.31	2.32	2.38
	ARIMA (2,1,1)	**ARIMA (2,1,2)**	**ARIMA (2,1,3)**	**ARIMA (2,1,4)**	**ARIMA (2,1,5)**	**ARIMA (2,1,6)**
AIC	1.99	2.14	2.16	2.18	1.92	1.95
SIC	2.09	2.26	2.29	2.33	2.09	2.15
	ARIMA	**ARIMA**	**ARIMA**	**ARIMA**	**ARIMA**	**ARIMA**

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	(3,1,1)	(3,1,2)	(3,1,3)	(3,1,4)	(3,1,5)	(3,1,6)
AIC	2.15	1.86*	2.19	1.89	2.20	2.20
SIC	2.26	1.99*	2.34	2.07	2.40	2.32
	ARIMA (4,1,1)	**ARIMA (4,1,2)**	**ARIMA (4,1,3)**	**ARIMA (4,1,4)**	**ARIMA (4,1,5)**	**ARIMA (4,1,6)**
AIC	2.20	2.19	2.06	2.40	2.21	2.25
SIC	2.34	2.35	2.24	2.28	2.43	2.49
	ARIMA (5,1,1)	**ARIMA (5,1,2)**	**ARIMA (5,1,3)**	**ARIMA (5,1,4)**	**ARIMA (5,1,5)**	**ARIMA (5,1,6)**
AIC	2.13	2.01	2.23	2.22	2.26	2.14
SIC	2.28	2.19	2.43	2.44	2.51	2.41
	ARIMA (6,1,1)	**ARIMA (6,1,2)**	**ARIMA (6,1,3)**	**ARIMA (6,1,4)**	**ARIMA (6,1,5)**	**ARIMA (6,1,6)**
AIC	2.25	2.09	2.25	2.43	2.28	2.29
SIC	2.43	2.30	2.47	2.28	2.55	2.58

Source: Authors' Calculations.

In selecting the best ARIMA model of broad money demand we subjected all the ARIMA models to Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). The results in Table 4 above show that ARIMA (3,1,2) model is preferred to other ARIMA model since it has the lowest value of AIC of 1.86 and the lowest value of SIC of 1.99.

ARIMA (3,1,2) Model Diagnostics and Interpretation

Before using the model for forecasting, it must be checked for adequacy. A model is adequate if the residuals cannot be used to improve the forecasts. An overall check of model adequacy is provided by a χ^2 test based on the Ljung-Box *Q*-statistic. This test looks at the sizes of the residual autocorrelations as a group. If the *p*-value associated with the *Q*-statistic is small, the model is considered inadequate. Figure 4 illustrates the correlogram of the residuals for ARIMA (3,1,2) model.

Correlogramm of Residuals

Sample: 1986Q1 2018Q4
Included observations: 128
Q-statistic probabilities adjusted for 5 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.054	-0.054	0.3846	
.|* |	.|* |	2	0.104	0.101	1.8033	
*|. |	*|. |	3	-0.101	-0.092	3.1743	
.|. |	.|. |	4	-0.027	-0.047	3.2732	
.|* |	.|* |	5	0.094	0.113	4.4805	
.|. |	.|. |	6	-0.058	-0.054	4.9403	0.026
.|. |	.|. |	7	-0.017	-0.052	4.9803	0.083
.|. |	.|. |	8	-0.001	0.031	4.9804	0.173
.|. |	.|. |	9	0.042	0.048	5.2319	0.264
*|. |	*|. |	10	-0.092	-0.120	6.4380	0.266
.|. |	.|. |	11	-0.002	-0.006	6.4386	0.376
.|. |	.|. |	12	0.029	0.073	6.5558	0.477

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.|. |	.|. |	13	-0.015	-0.044	6.5901	0.581
.|. |	*|. |	14	-0.034	-0.070	6.7557	0.663
.|. |	.|* |	15	0.029	0.081	6.8761	0.737
.|. |	.|. |	16	-0.007	-0.002	6.8831	0.808
.|. |	*|. |	17	-0.047	-0.109	7.2193	0.843
.|. |	.|. |	18	0.014	0.040	7.2480	0.889
.|. |	.|* |	19	0.025	0.083	7.3450	0.921
.|. |	*|. |	20	-0.055	-0.132	7.8168	0.931
.|. |	.|. |	21	-0.017	-0.041	7.8606	0.953
.|. |	.|* |	22	0.066	0.175	8.5475	0.953
.|. |	.|. |	23	-0.014	-0.055	8.5799	0.969
.|** |	.|* |	24	0.233	0.154	17.271	0.572
**|. |	*|. |	25	-0.240	-0.159	26.608	0.147
.|. |	.|. |	26	0.028	-0.018	26.738	0.180
*|. |	.|. |	27	-0.079	-0.057	27.756	0.184
.|. |	.|. |	28	0.006	-0.002	27.761	0.225
.|. |	.|. |	29	0.061	0.061	28.385	0.244
.|. |	.|. |	30	-0.048	-0.033	28.773	0.274
.|. |	.|. |	31	0.062	0.022	29.432	0.292
.|. |	.|. |	32	-0.059	-0.013	30.033	0.313
.|. |	.|. |	33	0.010	-0.031	30.050	0.361
.|. |	.|. |	34	-0.063	-0.034	30.756	0.377
.|. |	.|. |	35	0.036	0.032	30.990	0.416
.|. |	.|. |	36	-0.026	-0.043	31.111	0.461

Figure 4: Correlogram of LM2 residual series

Source: Authors' Calculations.

From Figure 4, the probability values are large. This means that the ARIMA (3,1,2) model is adequate. We can therefore interpret the model. The model equation is extracted from Table 4 and is stated as:

$$\begin{array}{lllllll} \Delta LM2_t & = 0.02 - 0.63\Delta LM_{t-1} & -1.02\Delta LM_{t-2} & -0.03\Delta LM_{t-3} & +0.65\varepsilon_{t-1} & +1.23\varepsilon_{t-2} \\ \text{t-statistic:} & (5.39)\ \ (-6.15) & (-13.21) & (0.32) & (7.46) & (14.49) \\ \text{Prob. value:} & [0.00]\ \ [0.00] & [0.00] & [0.75] & [0.00] & [0.00] \end{array} \qquad (14)$$

R-squared = 0.30

F-statistic = 10.37 (0.00)

D-Watson = 2.1

Note:

*t-values are in brackets.

**probability values are in braces.

From the model, the coefficient of multiple determination (*R*-squared) of ARIMA (3,1,2) is 0.30 which implies that about 30% of the variation in broad money demand in Nigeria is explained by past values of broad money demand and the past errors. It also indicates that the dependency on the estimated value by the series is not strong. This can be understood by the fact that ARIMA models are univariate models. The *F*-test which is used to determine the overall statistical significance of a regression model shows that the overall regression is statistically significant at 1% level. From the *t*-statistics for the coefficient variables *AR* (*p*) and *MA* (*q*), the null hypothesis that the coefficients are equal to zero is rejected. These results indicate that *ARIMA* (3,1,2) has a satisfactory goodness-of-fit. The *ARIMA* (3,1,2) results indicate that the coefficients of money demand is negative and significant at 1% levels both in the first period lag and in the second period lag [that is *AR* (1) and *AR* (2)] but negative and insignificant in the third period lag [that is *AR* (3)]. The results also indicate that the coefficients of *MA* (1) and *MA* (2) were positive and significant at 1% level. The Durbin-Watson (D-W) statistic is approximately

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two (2) which means that there is no existence of a serial correlation in the residuals.

Forecast Evaluation of ARIMA (3,1,2) Model

The forecast of broad money demand series using **ARIMA (3,1,2)** model was conducted. The duration of forecasts is from 1986 to 2018. The forecasts are plotted in Figure 5.

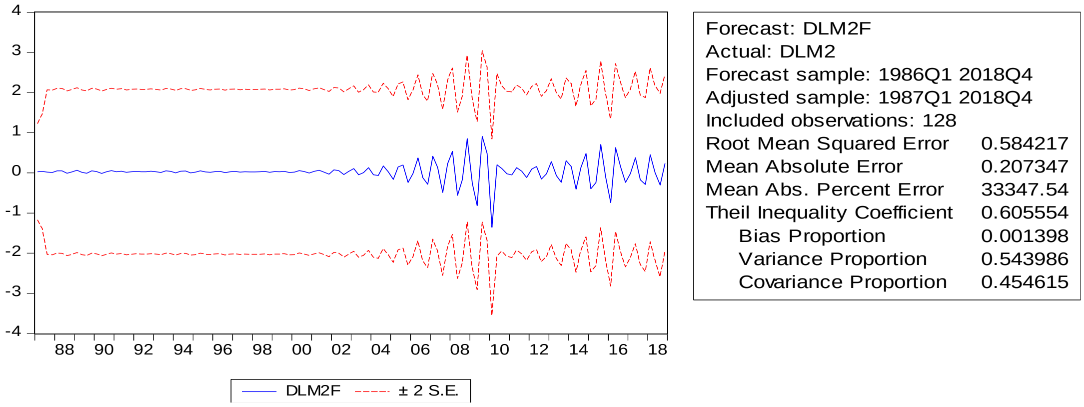

Figure 5: Forecast of money demand by ARIMA (3,1,2) model.

Source: Authors' Calculations.

In Figure 5, the middle line represents the forecast value of broad money demand. Meanwhile, the lines which are above or below the forecasted annual broad money demand series show the forecast with ± 2 of standard errors. Some forecasting measurements such as root mean squared error (RMSE) and mean absolute error (MAE) are shown. Smaller RMSE and MAE are preferred. From the results we can conclude that the model is relevant and efficient for forecasting broad money demand in Nigeria because RMSE is 0.58 and MAE is 0.21.

SUMMARY OF FINDINGS, CONCLUSION, AND POLICY IMPLICATION

The objective of this study was to develop a reliable univariate ARIMA model suggested by Box and Jenkins (1976) for broad money demand in Nigeria. The study used the correlogram of autocorrelation function (ACF) and partial autocorrelation function (PACF) of broad money demand series to identify and estimate a parsimonious ARIMA model. Diagnostic test for model adequacy was performed based on the Ljung-Box *Q*-statistic and the result suggested that the model was adequate. ARIMA (3,1,2) model was the most appropriate model under model identification, selection, parameter estimation, diagnostic checking and forecast evaluation. Thereafter, forecast of broad money demand using the ARIMA (3,1,2) model was conducted and the forecast performance evaluated using RMSE and MAE. The results showed that **ARIMA (3,1,2)** model was relevant for forecasting broad money demand in Nigeria. The efficiency of the ARIMA model is consistent with the findings of Adebiyi, Adenuga, Abeng, Omamukwe, and Ononugbo (2010), Mohammed and Abdulmuahymin (2016), Nyoni (2018), Okafor and Shaibu (2013), Okafor and Shaibu (2017), Olakorede, Olanrewaju, and Ugbede (2018), and Wiri and Tuaneh (2019).

The estimated broad money demand equation clearly showed that expected broad money demand was an important determinant of actual broad money demand during the estimation period. The major inference that can be drawn from this study is that expectations that are formed about previous values of broad money demand affect the current values of broad money demand. It is recommended that, to achieve a stable and sustained broad money demand, there is need for high transparency in monetary policy formulation, presentation, implementation, and control.

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REFERENCES

1. Adebiyi, M.A., Adenuga, A.O., Abeng, M.O., Omanukwe, P.N. & Ononugbo, M.C. (2010). Inflation forecasting models for Nigeria. *Central Bank of Nigeria Occasional Paper*, No. 36. Abuja: Research and Statistics Department.
2. Adenikinju, A., Busari, D., & Olofin, S. (2009). *Applied econometrics and macroeconometric modelling in Nigeria*. Ibadan: Ibadan University Press.
3. Aiyedogbon, J.O., Ibeh, S.E., Edafe, M., & Ohwofasa, B.O. (2013). Empirical analysis of money demand function in Nigeria: 1986-2010. *International Journal of Humanities and Social Science*, *3* (8), 132-139.
4. Ajayi, S.I. (1974). The demand for money in Nigerian economy: Comments and extension. *The Nigerian Journal of Economics and Social Studies*, *16* (1), 165-174.
5. Akinlo, A.E. (2006). The stability of money demand in Nigeria: An autoregressive distributed lag approach. *Journal of Policy Modeling*, *28* (4), 445-452.
6. Akpanta, A.C., & Okorie, I.E. (2014). Application of Box-Jenkins techniques in modelling and forecasting Nigeria crude oil prices. *International Journal of Statistics and Application, 4* (6), 263-291.
7. Anoruo, E. (2002). Stability of the Nigerian M2 money demand function in the SAP period. *Economics Bulletin*, *14* (3), 1-9.
8. Apere, T.O., & Karimo, T.M. (2014). The demand for real money balances in Nigeria: Evidence from a partial adjustment model. *European Journal of Business, Economics and Accountancy*, *2* (2), 1-14.
9. Bassey, E.B., Bessong, P.K., & Effiong, C. (2012). The effect of monetary policy on demand for money in Nigeria. *Interdisciplinary Journal of Contemporary Research in Business*, *4* (7), 430-439.
10. Bassey, N.E., Solomon, U.U., & Okon, U.E. (2017). Modelling the demand for money function in Nigeria: Is there stability? *Bulletin of Business and Economics*, *6* (1), 45-57.
11. Box, G.E.P., & Jenkins, G.M. (1976). *Time series analysis: Forecasting and control*. San Francisco: Holden-Day.
12. Busari, D. T. (2009). Money demand function in Nigeria: Issues and further considerations. *Applied econometrics and macroeconometric modelling in Nigeria*. Ibadan: Ibadan University Press.
13. Carpenter, S. B., & Lange, J. (2002). Money demand and equity markets. Board of Governors of the Federal Reserve System and Cornerstone Research.
14. Chamalwa, H. A., Rann, H. B., & Idris, I. M (2016). Modeling of Nigerian foreign exchange (Naira/1.0$) using disbursement data (1981-2010). *The International Journal of Humanities & Social Studies*, *4* (8), 34 - 40.
15. Cziraky, D., & Gillman, M. (2006). Money demand in an EU accession country: A VECM study of Croatia. *Bulletin of Economic Research*, *58* (2), 73-159.
16. El-Mefleh, M.A., & Shotar, M. (2008). A contribution to the analysis of the economic growth of Qatar. *Applied Econometrics and International Development Journal*, *8* (1), 18-35.
17. Essien, E.A., Onwioduokit, E.A., & Osho, E. T. (1996). Demand for money in a debt-constrained economy: A case study of Nigeria. *CBN Economic and Financial review*, *34* (2), 579-605.
18. Fakiyesi, T. (1980). Demand for money in Nigeria: Analysis of the distributed lag structure. *The Nigerian Journal of Economics and Social Sciences*, 23-39.
19. Hanke, J.E., Wichern, D.W., & Reitsch, A.G. (2001). *Business forecasting* (7th ed.). New Jersey: Prentice-Hall.
20. Hanke, J.E., & Wichern, D.W. (2005). *Business forecasting* (8th ed.). New York: Pearson Educational Incorporated.
21. Imimole, B., & Uniamikogbo, S.O. (2014). Testing for the stability of money demand function in Nigeria. *Journal of Economics and Sustainable Development*, *5* (6), 123-130.
22. Iyoboyi, M., & Pedro, L. M. (2013). The demand for money in Nigeria: Evidence from bounds testing approach. *Business and Economic Journal*, 76, 1-13.
23. Iyoha, M.A. (1976). The demand for money in Nigeria. *The Nigerian Journal of Economic and Social Studies*, 11, 386-296.
24. Katimon, A., & Demun, A.S. (2004). Water use at Universiti Teknologi Malaysia: Application of *ARIMA* model. *Jurnal Teknologi*, *41* (B), 47-56.
25. Khan, A., & Ali, S. (1997). The Demand for money in Pakistan: An application of cointergation and error correction modelling. *Savings Development*, 48-61.
26. Kumar, S., Webber, D.J., & Fargher, S. (2010). Money demand stability: A case study of Nigeria. MPRA Paper 26074, University Library of Munich, Germany.
27. Makridakis, S., Wheelwright, S.C., & Hyndman, R.J. (1998). *Forecasting: Methods and applications*. New York: John Wiley & Sons.

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28. Maravic, J., & Palic, M. (2010). Econometric analysis of money demand in Serbia. Working Paper.
29. Meyler, A., Kenny, G., & Quinn, T. (1998). Forecasting inflation using ARIMA models. *Central Bank of Ireland Technical Paper 3/RT/98.*
30. Mohammed, M. B., & Abdulmuahymin, S. A. (2016). Modeling the exchange rate ability of Nigerian currency (Naira) with respect to US Dollar. *International Journal of Scientific & Engineering Research*, *7* (7), 86 - 104.
31. Moshiri, S., & Foroutan, F. (2006). Forecasting nonlinear crude oil futures prices. *The Energy Journal, 27* (4), 81-95.
32. Nduka, E.K., Chukwu, J.O., & Nwakaire, O.N. (2013). Stability of demand for money in Nigeria. *Asian Journal of Business and Economics*, *3* (4), 1-11.
33. Nwude, E.C., Offor, K.O., & Udeh, S.N. (2018). Determinants and stability of money demand in Nigeria. *International Journal of Economics and Financial Issues*, *8* (3), 340-353.
34. Nyoni, T. (2018). Modeling and forecasting Naira/USD exchange rate in Nigeria: A Box-Jenkins ARIMA approach. *Munich Personal RePEc Archive* (MPRA) Paper No. 88622.
35. Odama, J.S. (1974). The demand for money in the Nigerian economy: A comment. *The Nigerian Journal of Economic and Social Studies*, *16* (1), 178-188.
36. Ojo, O. (1974). The demand for money in the Nigerian economy: Some comments. *The Nigerian Journal of Economic and Social Studies*, *16* (1), 149-152.
37. Okafor, C., & Shaibu, I. (2013). Application of ARIMA models to Nigeria inflation dynamics. *Research Journal of Finance and Accounting*, *4* (3), 138-150.
38. Okafor, C., & Shaibu, I. (2017). Autoregressive integrated moving average (ARIMA) model for economic growth in Nigeria. *Nasarawa Journal of Administration* (NJA), *10* (1), 22-40.
39. Olakorede, N.M., Olanrewaju, S.O., & Ugbede, M.Y. (2018). A univariate time series autoregressive integrated rate between Nigerian Naira and US Dollar. *American Journal of Theoretical and Applied Statistics*, *7* (5), 173-179.
40. Olatunji, O. M., & Bello, A. (2015). A suitable model for the forecast of exchange rate in Nigeria (Nigerian Naira versus US Dollar). *International Journal of Science and Research* (IJSR), *4* (5), 2669-2676.
41. Onasanya, O. K., & Adeniji, O. E. (2013). Forecasting of exchange rate between Naira and US dollar using time domain model. *International Journal of Development and Economic Sustainability*, *1* (1), 45-55.
42. Owoye, O., & Onafowora, O.A. (2007). M2 targeting, money demand, and real GDP growth in Nigeria: Do rules apply? *Journal of Business and Public Affairs*, *1* (2), 1-20.
43. Pankratz, A. (1983). *Forecasting with univariate Box-Jenkins models*: *Concepts and cases.* New York: John Wiley & Sons.
44. Pindyck, R., & Rubinfeld, D. (1981). *Econometric models and economic forecasts.* Singapore: McGraw-Hill.
45. Roberts, F.S. (2006). *Discrete mathematical models with application to social, biological and environmental problems.* New York: Prentice Hall.
46. Samad, Q.A., Ali, M.Z., & Hossain, M.Z. (2002). The forecasting performance of the Box-Jenkins Model: The case of wheat and wheat flour prices in Bangladesh. *The Indian Journal of Economics*, LXXXII (327), 509-518.
47. Sober, M. (2013). Estimating a function of real demand for money in Pakistan: An application of bounds testing approach to cointegration. *International Journal of Computer Application*, *79* (5), 32-50.
48. Sriram, S. S. (2001). A survey of recent empirical money demand studies. *International Monetary Fund Staff Papers*, (3), 334-365.
49. Stockton, D., & J. Glassman, (1987). An evaluation of the forecast performance of alternative models of economic growth. *Review of Economics and Statistics*, *69* (1), 108-117.
50. Teriba, O. (1974). The demand for money in the Nigerian economy: Some methodological issues and further evidence. *The Nigeria Journal of Economic and Social Studies*, *401* (16), 153-164.
51. Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money Credit and banking,* February, 1, 15-29
52. Tomori, S. (1974). The demand for money in the Nigerian economy: A rejoinder. *Nigerian Journal of Economic and Social Studies*, *16* (11), 179-187.
53. Tule, M.K., Okpanachi, U.S., Ogiji, P., & Usman, N. (2018). A reassessment of money demand in Nigeria. *CBN Journal of Applied Statistics*, *9* (1) 47-75.
54. Valle, H.A.S. (2002). Economic growth forecasts with ARIMA and vector autoregressive models in Guatemala. *Economic Research Department,* Guatemala: Banco de Guatemala.
55. Wang, S., Yu, L., & Lai, K. K. (2005). Crude oil price forecasting with TEI@I methodology. *Journal of*

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Systems and Complexity, *18* (2), 145-166.
56. Wiri, L., & Tuaneh, G.L. (2019). Modelling the Nigeria crude oil prices using ARIMA, pre-intervention and post-intervention model. *Asian Journal of Probability and Statistics*, 3 (1), 1-12.
57. Yamden, B.P. (2011). The demand for money in Nigeria. *European Journal of Business and Management, 3* (6), 63-85.

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