# Autoregressive Integrated Moving Average Modeling of Nigeria Inflation Rate Before and within the Early Part of Covid-19 Era (1996-2020)

**Justin Odadami Ejukwa, Isaac Didi Essi, & Deebom Zorle Dum**
Department of Mathematics,
Rivers State University, Port Harcourt, Nigeria.

***Abstract***
*The study examines Autoregressive Integrated Moving Average modeling of Nigeria Inflation Rate before and early part of COVID-19 Era (1996-2020). The study seeks to determine the trend in the movement of inflation within the period under investigation, to identify the appropriate form of the model, in the order of Autoregressive, Moving Average and its differencing component and how it fits to Nigeria inflation rate, and examine the forecasting ability of the selected ARIMA model. In order to fit the ARIMA model to the data, unit root test, the autocorrelation and partial autocorrelation function were conducted to determine the stationary level of the series and also to identify the appropriate order of the AR and MA models. The data used in this study were extracted from the Central Bank of Nigeria statistical online data base. It spanned from January, 1996 to May, 2020. We conclude from the result of the analysis that the best fitted model for the data was ARIMA (I, I, I). Recommendations were made in the study based on the result of the findings.*

***Key Words:*** *Autoregressive, Moving, Average, Modeling, Inflation Rate*

## INTRODUCTION

In trying to examine the Nigerian economy and its many challenges, it is imperative to give adequate attention to inflation as its behavioral characteristics has tremendous influence on other economic variables like exchange rate, lending rate to mention a few. More so, as it makes government, investors and the general public become anxious as the price of goods and services continue to increase over time. The problems associated with inflation can better be understood by attempting to define it.

Inflation is a process of continuous rise in prices of goods and services or on the other hand, continuous devaluation of money over a time period. During the corona virus era countries were and are still struggling with the challenge of reducing inflation as many manufacturing industries and other economic activities were shut down to contain the spread.

Therefore, it is imperative to direct attention to the corona virus (covid-19) pandemic which made Nigeria to implement social distancing, lockdowns and travel restrictions which could result to large scale shocks to both demand and supply. According to Diewert and Fox (2020), these sudden changes in expenditure pattern introduce significant bias in the consumer price index (CPI) used to measure inflation as noted.

The real-time effect of the global lockdown on production, employment and consumption or consumer expenditure have been widely documented. However, much less is known about how much influence or effect the corona virus crisis has on the characteristics inflation rate experienced in Nigeria. Mallory (2018) opined that single equation models like the ARIMA are generally used in a forecasting context.

A proper statistical model should express inflation rate as coming from a single stationary probability distribution which is normally distributed with mean and variance. Less obvious is that the mean of this series is or might be changing over time. To correct for a changing mean or correlation over time in the inflation rate series, an autoregressive integrated moving average (ARIMA) model can be used (Mallory, 2018).

ARIMA models did not initially enjoy widespread use in the business community, mostly due to the difficult, time consuming and highly subjective procedure described by Box and Jenkins to identify the proper form of the model for a given data set. It is however, the benchmark against which the other time series methods will be compared.

Forecasting a time series like inflation rate is often of tremendous commercial value. In most manufacturing companies, it drives the fundamental business planning, procurement and production activities. Any error in forecasting will ripple down throughout the supply chain. So, in order to save costs and improve efficiency it is important to get the forecasts accurate. Not only in manufacturing, the techniques and concepts behind time series forecasting are applicable in any business environment. This study therefore, the aim of the study was to provide empirical evidence of the impact of inflation rate on microeconomic variables before and during the early part of the covid 19 Era in Nigeria. The specific the objectives include to;

determine the trend in the movement of inflation within the period under investigation, Identify the appropriate form of the model, the order of AR, MA and the differencing component, determine an appropriate ARIMA model for modelling inflation rate, use the monthly inflation rate data in Nigeria to evaluate and examine forecasting ability of the appropriate ARIMA model.

## METHODOLOGY

This chapter focused mainly on the approaches and techniques employed in arriving at the results and they include the following:

### 3.1 Source of Data/Software Used for Data Analysis

The data used for this study was extracted from the central Bank of Nigeria statistical data base website www.cbn.gov.ng. The variables used was monthly data on Nigeria inflation rate within the period January 1996 to May 2020. The software used for the data analysis is Eview version 10 released by IHS Markit (2020).

### 3.2 Model Specification

A model is a simplified system used to simulate some aspect of the real economy. The method specified for this study is the Box-Jenkins approach (Box and Jenkins 1976) which accommodates the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA model attempts to identify patterns in the historical data and decomposes it into an 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 valid for forecast; and a Moving Average (MA) of the forecast error, such that the longer the historical data, the more accurate the forecast will be as it leans over time. ARIMA model therefore has three model parameters, the AR (P) process, I(d) process and the MA (q) process, all combined and interacting with each other which later recomposed into an ARIMA (p.d.q) model.

### 3.3 Autoregressive (AR) Model

The first component, AR term uses the p lags of a time series to improve forecast. The AR part of ARIMA indicates that the evolving variable of interest is regressed on its own lagged (prior) values. An AR (p) model has the form shown in equation 1

$$y_t = \mu + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + \varepsilon_t \qquad (3.1)$$

$$= \mu + \sum_{i=1}^{P} \alpha_i \, y_{t-i} + \varepsilon_t$$

Where;

$y_t$ = The response (dependent) variable being forecasted at time t

$y_{t-1}$ = The lag of the series or the response variable at time lag (Stimulus)

$\alpha_1, \ldots, \alpha_p$ = Are the coefficient of lag that the model estimates

$\mu$ = Is the intercept term also estimated by the model

$\varepsilon_t$ = Error term at time t

This equation demonstrates that the forecast value of inflation at time t depends on its value in the previous time period and a constant.

### 3.4 Moving Average (MA) Model

The third component the MA (q) model uses the q lags of forecast errors to improve the forecast. The MA part indicates that the regression error is a linear combination of error terms whose values occurred contemporaneously and at various times in the past. An MA (q) model has the form shown in equation 2

$$y_t = \beta_o + \beta_1\varepsilon_{t-1} + \beta_2\varepsilon_{t-2} + \ldots + \beta_q\varepsilon_{t-q} + \varepsilon_t \qquad (3.2)$$

$$= \beta_0 + \sum_{i=1}^{q} \beta_i \, \varepsilon_{t-i} + \varepsilon_t$$

Where:

$y_t$ = The response (dependent) variable being forecasted at time t

$\beta_0$ = The constant mean of the process

$\beta_1, \beta_2, \ldots \beta_q$ = The coefficient to be estimated

$\varepsilon_t$ = is the error term at time t

$\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$ = the error in previous time period that are incorporated in the response $y_t$.

This equation indicates that y at time t is equal to a constant plus a moving average of the current and past white noise error terms. But if no differencing occurred to make it stationary then an ARMA model is generated with d equal zero.

### 3.4 Autoregressive Moving Average (ARMA)

The autoregressive moving average refers to the model with p autoregressive terms and q moving average terms. An autoregressive (AR) and moving averaging (MA) is ARMA (p,q) if it is stationary as shown in equation 3

$$\boldsymbol{y_t = \varepsilon_t + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}} \qquad (\mathbf{3.}3)$$

#### 3.4.1 Integral Order (I)

The second component is the integrated stochastic process. A time series is integrated of the first order, I (1), if it has to be differenced once to make it stationary. In general, if a time series has to be differenced d times to make it stationary, that time series is said to be integrated of order d, denoted as I(d), (Gujarati, 2003).

### 3.5 Autoregressive Integrated Moving Average (ARIMA)

**ARIMA (p,d,q) Model**

To create an ARIMA model, we begin by combining or adding both the autoregressive (AR) process, the moving average (MA) process and the integrated part (I) together as shown in equation (3.4)

$$y_t = \mu + \varepsilon_t + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \ldots + \beta_q \varepsilon_{t-q} \quad (3.4)$$

$$y_t = \mu + \varepsilon_t + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j} \Rightarrow y_t = \nabla^d y_t = (1-B)^d y_t$$

In summary ARIMA (p,d,q) model can be specified using the backshift operator as

$$\phi(B)(1-B)^d Y_t = \theta(B)\varepsilon_t$$

The model in equation 3.4 can be written in words to mean predicted inflation at time t equal constant plus white noise term plus linear combination lags of inflation at time t (up to p lags) plus linear combination of lagged forecast errors (up to q lags).

### 3.6 Model Identification

Identification methods are rough procedures applied to a data set to indicate the kind of representational model, which is worthy of further investigation. The aim is to identify an appropriate sub class of models from the general ARIMA family. The autocorrelation function (ACF), partial autocorrelation function (PACF) and the resulting correlograms which are simply the plots of the ACF and PACF against the lag length are principal tools used for identification process. They are used to help guess the form of model and also to obtain approximate estimates of the parameters.

#### 3.6.1 Autocorrelation Function (ACF)

One simple test of stationarity is based on the so-called autocorrelation function (ACF). The ACF at lag k, denoted by $\rho_k$ is defined by equation (3.5)

$$\rho_k = \frac{y_k}{y_O}$$

$$\rho_k = \frac{Cov(X_t, X_{t-k})}{\sigma_t, \sigma_{t-k}} \quad (3.5)$$

Note that if k = 0, $\rho_o = 1$

Since both covariance and variance are measured in the same units of measurement. $\rho_k$ is a unit less, or pure number. It lies between -1 and +1 as any correlation coefficient does.

The coefficient of correlation between two values in a time series is called the autocorrelation function (ACF). The ACF for a time series $y_t$ is given as shown in equation (3.6)

$$Corr(y_t, y_{t-k}), k = 1, 2 \quad (3.6)$$

This value of k is the time gap being considered and is called the lag. A lag 1 autocorrelation (k = 1) is the correlation between values that are one time period apart. The autocorrelation function is a rough indicator of whether a trend is present in the series. A slow decay in ACF is indicative of a large characteristics root, a true unit root process or a trend stationary process. Formal test can help to determine whether a system contains a trend and whether the trend is deterministic or stochastic.

The ACF identifies the order of MA: Non-zero at lag q, zero for lag > q. It tells us how many MA terms are required to remove any autocorrelation in the stationary series. Auto correlation is a type of serial dependence. Specifically, autocorrelation is when a time series is linearly related to a lagged version of itself. Autocorrelation is useful because its presence gives important information about the variable and potential problems with the model. According to Nosedal (2019), the ACF is an excellent tool in identifying the order of MA(q) process because after lag q it is expected to cut off. However, the ACF is not as useful in the identification of the AR(p) process for which it will most likely have a mixture of exponential decay and damped sinusoid expressions. Hence such behaviour, while indicating that the process might have an AR structure, fails to provide further information about the order of such structure. It is therefore important to define and employ the partial autocorrelation (PACF) of a time series.

### 3.4.2 Partial Autocorrelation Function (PACF)

The partial auto correlation function (PACF) identifies the order of the autoregressive process (AR): Non zero at lag p; zero for lags > p. This function plays an important role in data analysis aimed at identifying the extent of the lag in an autoregressive model. Box, Jenkins, Reinsel (2008). For an AR model, the theoretical PACF "shut off" past the order of the model. The phrase "shut off" means that in theory the partial autocorrelations are equal to 0 beyond that point. Put differently, the number of non-zero partial autocorrelation gives the order of the AR model. By the order of the model' we mean the most extreme lag of x that is used as a predictor.

For a time, series, the $h^{th}$ order partial autocorrelation is the partial correlation of $y_i$ with $y_{i-h}$, conditional on $y_{i-1}, \ldots y_{i-h+1}$ as shown in equation (3.7)

$$\frac{Cov(y_i, y_{i-h}/ y_{i-1}, ..., y_{i-h+1})}{\sqrt{Var(y_i/y_{i-1},...., y_{i-h+1})Var(y_{i-h}/y_{i-1}, ..., y_{i-h+1})}} \tag{3.7}$$

The first order partial autocorrelation is therefore the first-order autocorrelation. The correlogram (also called auto correlation function ACF plot or Autocorrelation plot) helps gives us a visual picture of the serial correlation in data that changes over time (i.e time series data). Correlogram can give you a good idea of whether or not pairs of data show autocorrelation. They cannot be used for measuring how large that autocorrelation is. The correlogram and Augmented Dickey Fuller test allows us to find the appropriate value of (p,d.q)

### 3.6 Model Estimation

There are two methods suggested in Box, et al (2008) for estimating parameters of the ARIMA model and they include: the maximum likelihood estimation method and ordinary least square (OLS) estimation

### 3.7.1 Maximum Likelihood Estimation

Maximum likelihood estimation (MLE) is a method of estimating the parameters of a probability distribution by maximizing a likelihood function, so that under the assumed statistical model the observed data is most probable.

Consider the linear regression model in equation (3.8)

$$Y_t = x_t^1 b_o + \varepsilon_t \quad (t = 1, \ldots, T) \qquad (3.8)$$

Where ($y_t$, $x_t^1$) are *iid*, the regressors are stochastic, $x_t^1$ is the $t^{th}$ – row of the x matrix, and $\varepsilon_t/x_t \sim iid.\ N(O, \sigma_t^2)$

It follows that;

$y_t/x_t \sim iid.\ N(x_t^1 b_o, \sigma_t^2)$

The exact likelihood function of the linear regression model is defined in equation 9

$$L(y;x;\delta_o) = \prod_{t-1}^{T} L_t(y_t, x_t, \delta_o) \qquad (3.9)$$

Where;

$L_t$ is the (exact) likelihood function for observation t.

$L_t(y_t, x_t, \delta_o) = fy_t/x_t(y_t/x_t, \delta_o)\, x f x_t(x_t)$

The exact likelihood function is given in equation 10

$$L(y, x, \delta_o) = \prod_{t-1}^{T} fy_t/x_t(y_t/x_t, \delta_o) \prod_{t-1}^{T} fx_t(x_t) \qquad (3.10)$$

If $f_x$ does not depend on $\delta_o$

$$L(y/x, \delta_o) = \prod_{t-1}^{T} fy_t/x_t(y_t/x_t, \delta_o) \qquad (3.11)$$

$$= \prod_{t-1}^{T} (\sigma_t^2 2\pi)^{-1/2} \exp\left(-\frac{1}{2\delta_t}(y_t - x_t^1 b_o)^2\right) \qquad (3.12)$$

$$= (\sigma_t^2 2\pi)^{-T/2} \exp\left(-\frac{1}{2\delta_t^2}\sum_{t-1}^{T}(y_t - x_t^1 b_o)^2\right) \qquad (13)$$

and the conditional log-likelihood function is given by equation 14

$$\ell(y/x;\delta_o) = -\frac{T}{2}\log(\sigma_t^2) - \frac{T}{2}\log(2\pi) - \frac{1}{2\sigma_t^2}\sum_{t-1}^{T}(y_t - x_t^1 b_o)^2 \qquad (3.14)$$

### 3.7.2 Ordinary Least Square (OLS) Estimation

The ordinary least square estimation is a statistical procedure to find the best fit for a set of data points by minimizing the sum of squares of residuals made in the result of every single equation. AR (1) estimation;

Let ($x_t$) be a covariance – stationary process defined by the fundamental representation (/ϕ/ < 1).

$$x_t = \phi x_{t-1} + \varepsilon_t \qquad (3.15)$$

Where ($\varepsilon_t$) is the innovation process of ($x_t$)

The ordinary least square estimation of ϕ is defined in equation 16 to be

$$\hat{\phi}_{o/s} = \left(\sum_{t-1}^{T} x_{t-1}^2\right)^{-1}\left(\sum_{t-2}^{T} x_{t-1} x_t\right) \qquad (3.16)$$

MA (1) estimation;

Let ($x_t$) be a covariance – stationary process defined by the representation (/θ/<1)

$X_t = \varepsilon_t + \theta\varepsilon_{t-1}$

Where ($\varepsilon_t$) is the innovation process of ($x_t$).

The ordinary least square estimator is defined as having minimum variance. An estimator that is unbiased and has the minimum variance of all other estimators is the best and most efficient.

### 3.8 Model Estimation Steps

#### 3.8.1 Time Plot

A time plot or time series graph displays observations (data) against time and it is good in showing how data changes over time. Evidence of seasonality is often evident from the time plot.

#### 3.8.2 Descriptive Statistics

Descriptive statistics is used to test for normality and the test statistics is determine using Jarque Bera formula as shown (3.17). This is determine using both descriptive statistic of Skewness and kurtorsis.

$$x^2 = \frac{N}{6}\left[S^2 + \frac{(k-3)^2}{4}\right] \qquad (3.17)$$

Where;

N = is the number of sample or size of the variable
K = Kurtosis
S = Skewness statistics

The hypothesis for a descriptive test statistic is given as thus;
**$H_0$:** Normally distributed versus
**$H_A$:** Not normally distributed

#### 3.8.3 Unit Root Test

There are various statistical tests that can be performed to describe the time series data. One test of stationarity (no stationarity) that has gained popularity in recent years is the unit root test. A time series is said to be stationary if it doesn't increase or decrease with time linearly or exponentially (no trend), and if it doesn't show any kind of repeated patterns (no seasonality) or if there is no presence of unit root. Mathematically, this is described as having constant mean and constant variance over time. The most basic approach for understanding this is to plot the data and check if there's any hint at the presence of underlying trends or seasonality. The stationarity test will utilize the Augmented Dickey-Fuller (ADF) technique (Dickey-Fuller, 1981).

$$\Delta x_{i,t} = Kx_{i,t-1} + \sum_{k=1}^{n} \beta_{i,k}\, \Delta x_{i,t-k} + \varepsilon_{k,t} \qquad (3.18)$$

An anatomy of an ADF equation will be
$\Delta x_{i,t}$ = The 1st differenced value of x
$Kx_{i,t-1}$ = The 1st lagged value of x
$\sum_{k=1}^{n} \beta_{i,k}\, \Delta x_{i,t-k}$ = These are the nth lagged of 1st differenced of value of x
$\varepsilon_{k,t}$ = The error term

### 3.9 Model Selection Technique

One of the techniques for selecting a good model is the use of Akaike information criteria (1973) to compare different models on a given outcome. The best model is then the model with the lowest AIC score. Akaike (1973) showed that the selection of the "best" model is determined by an AIC score as shown in equation 19

$$\text{AIC} = 2k - 2\log\left(L\left(\hat{\theta}/y\right)\right) \qquad (3.19)$$

Where K is the number of estimable parameters (degree of freedom) and log $L\left(\hat{\theta}/y\right)$ is the log likelihood of its maximum point of the model estimated and the constant 2 remains for historical reasons (Burnham and Anderson, 2002).

### 3.10 Diagnostic Check

This is done after choosing a particular ARIMA model and also estimated its parameters, it is important to know whether the chosen model fits the data set reasonably. One easy test of the chosen model is to see if the residuals estimated from this model are white noise. If they are, we can accept the particular fit, if not, we just have to start over again.

### 3.11 Forecasting

Making predictions of the future based on past and present data is an essential part of time series analysis. Forecasting is done by taking into account events in the past and present to predict what will happen in the future. The forecast is done by constructing the Root Mean Square Error (RMSE) using the residuals of the estimated models. The study utilized the RMSE to determine and or predict horizons of the estimated model as shown in equation 20

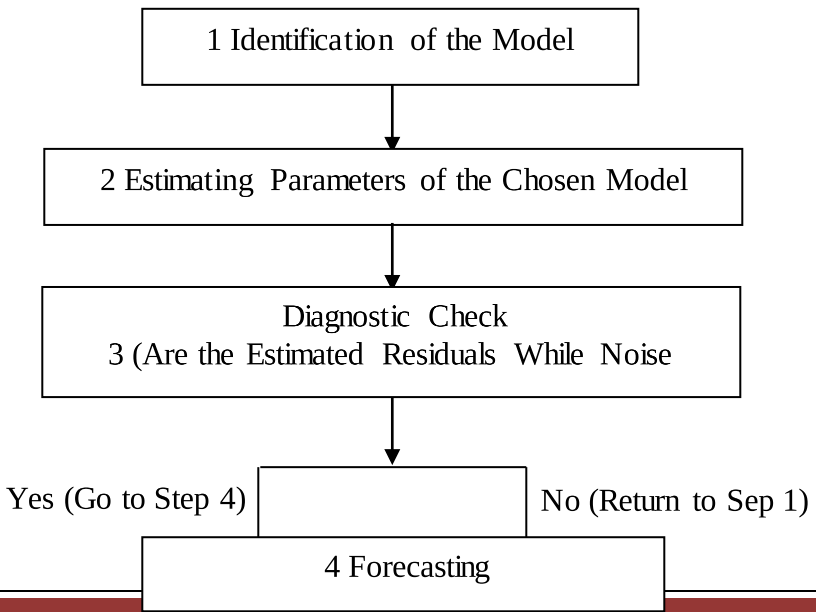
$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{M}(y_i - \hat{y}_i)^2}{n}} \qquad (3.20)$$

Where;

$\left(\hat{y}_i - y_i\right)^2$ = difference squared

n = Sample size

**Flow Chart on Box-Jenkings Methodology**



**RESULTS**.

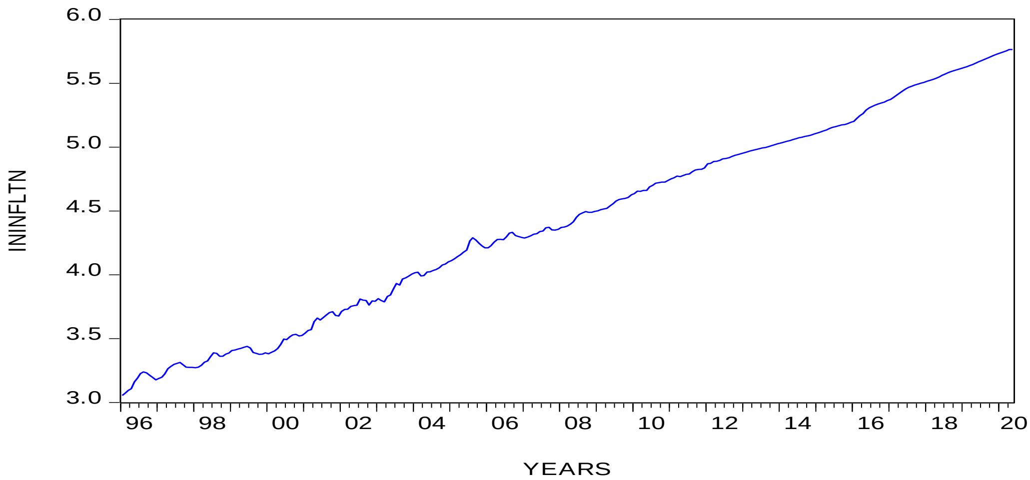



**Figure. 1: Time Series Plot for the Raw Data**

This shows that there was a continuous increase in inflation across the period under investigation. More so, the increase from May 2019 to May 2020 was very rapid. In other to detrend the increasing inflation rates, the raw series of the data was differenced to remove unit root and also to ensure stationarity in the series

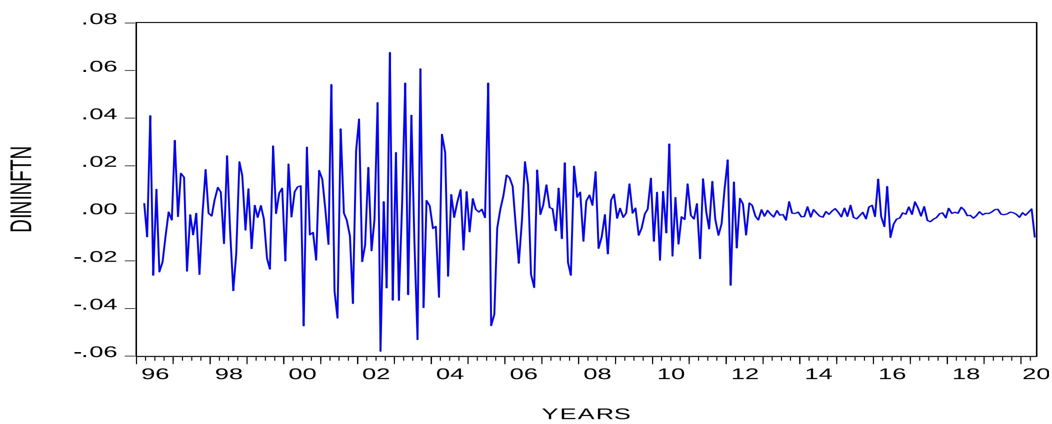



**Figure.2: Time Plot for the differenced Series**

This is the time plot of the log transformed raw series as shown in figure1 was done to determine the presence of trend and unit root. The log transformation was done to deal with the issue of skewed data, increase in the variability of the data and make the data conform more closely to normal distribution. The time plot shows an upward trend from January 1996 to May 2020

Date: 10/04/20 Time: 20:37
Sample: 1996M01 2020M05
Included observations: 292

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.267 | 0.267 | 21.072 | 0.000 |
| | | 2 | 0.079 | 0.008 | 22.914 | 0.000 |
| | | 3 | -0.035 | -0.062 | 23.269 | 0.000 |
| | | 4 | -0.139 | -0.124 | 29.006 | 0.000 |
| | | 5 | -0.090 | -0.020 | 31.434 | 0.000 |
| | | 6 | -0.181 | -0.155 | 41.316 | 0.000 |
| | | 7 | -0.182 | -0.117 | 51.252 | 0.000 |
| | | 8 | -0.139 | -0.084 | 57.125 | 0.000 |
| | | 9 | -0.102 | -0.071 | 60.259 | 0.000 |
| | | 10 | 0.080 | 0.083 | 62.186 | 0.000 |
| | | 11 | 0.190 | 0.122 | 73.262 | 0.000 |
| | | 12 | 0.258 | 0.148 | 93.737 | 0.000 |
| | | 13 | 0.088 | -0.072 | 96.131 | 0.000 |
| | | 14 | 0.020 | -0.019 | 96.258 | 0.000 |
| | | 15 | 0.016 | 0.022 | 96.341 | 0.000 |
| | | 16 | -0.117 | -0.105 | 100.63 | 0.000 |
| | | 17 | -0.107 | -0.029 | 104.20 | 0.000 |
| | | 18 | -0.139 | -0.027 | 110.21 | 0.000 |
| | | 19 | -0.135 | -0.022 | 115.92 | 0.000 |
| | | 20 | -0.116 | -0.066 | 120.17 | 0.000 |
| | | 21 | 0.018 | 0.076 | 120.27 | 0.000 |
| | | 22 | 0.122 | 0.040 | 124.97 | 0.000 |
| | | 23 | 0.141 | 0.007 | 131.36 | 0.000 |
| | | 24 | 0.048 | -0.089 | 132.09 | 0.000 |
| | | 25 | 0.127 | 0.111 | 137.25 | 0.000 |
| | | 26 | 0.054 | -0.016 | 138.20 | 0.000 |

**Figure.3: Correlogram of the differenced Series**

Figure 3 is the correlogram of the first difference of the log transformed data. This was done to determine the autocorrelation and partial autocorrelation coefficient of the first set of lags. Therefore, the tentative models were selected based on spikes on the autocorrelation function and partial autocorrelation function of the correlogram. The spikes were significant at lag 1, lag 4, lag 6, lag 7, lag 11 and lag 12.

**Table 1: Estimated Results for the ARIMA Models**

| Model | Constant (C ) | AR(y) | MA(β) | ϒ | AIC | SIC | Least AIC |
|---|---|---|---|---|---|---|---|
| ARIMA (1,1,1) | 4.406<br>(0.611) | 0.999<br>(0.000) | 0.379<br>(0.000) | 0.000<br>(0.000) | -5.469 | -5.418 | **-5.469** |
| ARIMA (4,1,4) | 4.397<br>(0.000) | 0.999<br>(0.000) | 0.489<br>(0.000) | 0.002<br>(0.000) | -3.206 | -3.156 | |
| ARIMA (6,1,6) | 4.423<br>(0.000) | 0.998<br>(0.000) | 0.247<br>(0.000) | 0.004<br>(0.000) | -2.507 | 2.456 | |
| ARIMA (7,1,7) | 4.436<br>(0.000) | 0.997<br>(0.000) | 0.377<br>(0.000) | 0.005<br>(0.000) | -2.362 | -2.311 | |
| ARIMA(12.1,12) | 4.433<br>(0.000) | 0.993<br>(0.000) | 0.677<br>(0.000) | 0.008<br>(0.000) | -1.772 | -1.722 | |
| ARIMA (1,1,4) | 4.402<br>(0.227) | 1.000<br>(0.000) | 0.183<br>(0.001) | 0.000<br>(0.000) | -5.311 | -5.261 | |
| ARIMA (4,1,6) | 4.410<br>(0.000) | 0.000<br>(0.000) | 0.169<br>(0.001) | 0.002<br>(0.000) | -3.086 | -3.036 | |
| ARIMA (6,1,4) | 4.399<br>(0.000) | 0.997<br>(0.000) | 0.765<br>(0.000) | 0.003<br>(0.000) | -2.878 | -2.828 | |
| ARIMA (6,1,1) | 4.427<br>(0.000) | 0.999<br>(0.000) | 1.000<br>(0.148) | 0.001<br>(0.000) | -3.634 | -3.584 | |
| ARIMA (7,1,6) | 4.430<br>(0.000) | 0.997<br>(0.000) | 0.333<br>(0.000) | 0.005<br>(0.000) | -2.311 | -2.341 | |
| AR1MA (6,1,7) | 4.427<br>(0.000) | 0.998<br>(0.000) | 0.320<br>(0.000) | 0.004<br>(0.000) | -2.548 | -2.498 | |
| ARIMA (12,1,1) | 4.441<br>(0.000) | 0.996<br>(0.000) | 1.000<br>(0.688) | 0.004<br>(0.000) | -2.534 | -2.514 | |
| ARIMA (7,1,12) | 4.419<br>(0.000) | 0.997<br>(0.000) | 0.597<br>(0.000) | 0.004<br>(0.000) | -2.589 | -2.539 | |
| ARIMA (12,1,7) | 4.440<br>(0.000) | 0.994<br>(0.000) | 0.796<br>(0.000) | 0.058<br>(0.000) | -2.085 | -2.034 | |
| ARIMA (6,1,12) | 4.411<br>(0.000) | 0.998<br>(0.000) | 0.574<br>(0.000) | 0.003<br>(0.000) | -2.788 | -2.738 | |
| ARIMA (12,1,6) | 4.434<br>(0.000) | 0.997<br>(0.000) | 0.987<br>(0.000) | 0.004<br>(0.000) | -2.415 | -2.365 | |
| ARIMA (4,1,12) | 4.400<br>(0.000) | 0.999<br>(0.000) | 0.540<br>(0.000) | 0.002<br>(0.000) | -3.390 | -3.339 | |

Table 1 is the model estimated results for the ARIMA model. Thirteen ARIMA models were estimated based on suspected spikes on the autocorrelation function and partial autocorrelation function suggesting the following combinations of those models shown in table 4.3. In selecting the best ARIMA model for modeling inflation rate in Nigeria between January 1996 to May 2020, all the estimated ARIMA models were subjected to Akaike information (AIC) and Schwarz information criteria (SIC). The result shows that ARIMA (1, 1, 1) is preferred to others since it has the least value of AIC and SIC.

In table 4.3, ARIMA (1, 1, 1) indicates that the coefficients AR (1) and MA (1) were highly significant at 0,05% level of significance. The AIC (-5.467) and SIC (-5,413) were the lowest value when compared to others. The impact of volatility in the selected model is significant and is at 0.023%. For the goodness of fit test, the adjusted R-square and R-square were 1.000 and 1.000 respectively and this simply means that about 100% of the variation in inflation in Nigeria is explained by past values of inflation rate and past errors obtained from its residuals. The Durbin Watson statistic (1.834) was greater than the value of the R-square, this simply means that there was little or no trace of evidence to conclude that there is the presence of serial correlation in the selected model. The inflation rate time series of the selected ARIMA (1,1,1) process can be described as

$$y_t = 4.406 + 0.999\, y_{t-1} + 0.379\, \varepsilon_{t-1}$$

Out of sample forecast was generated for the month of June 2020 to March 2021 as shown in table 2

**Table 2: Forecasting Performance of ARIMA (1,1,1)**

| Date | Predicted | Observed |
|---|---|---|
| Jun-20 | 0.0001389 | 0.3899994 |
| Jul-20 | 0.0001389 | 0.4899998 |
| Aug-20 | 0.0001389 | 0.2800007 |
| Sep-20 | 0.0001389 | 1.2300000 |
| Oct-20 | 0.2099659 | 0.6599998 |
| Nov-20 | -0.9760849 | 0.9300003 |
| Dec-20 | 0.9244578 | 0.3299999 |
| Jan-21 | -0.2308346 | -0.1900005 |
| Feb-21 | 0.8298905 | -0.4399986 |
| Mar-21 | 0.6060707 | -0.4200001 |

## Conclusion

This study investigated ARIMA modelling of Nigeria inflation rate before and during the early part of covid-19 era. To achieve the aim of the study, four objectives and research questions were set to guide the study and the objectives include, to determine the trend in the movement of inflation within the period under investigation, identify the appropriate form of the model, the order of AR, MA and the differencing component, determine an appropriate ARIMA model for modelling inflation rate and use the monthly inflation rate data in Nigeria to evaluate and examine forecasting ability of the appropriate ARIMA model.

The results show that there was clearly evidence of an upward trend in the movement of inflation rate and inflation equation also shows evidence that inflation rate is high within the period under investigation. The movement of inflation rate between November 2019 to May 2020 is significantly different from other period under investigation as the rise in inflation rate is very rapid, with little or no fluctuation as seen in figure 1. Therefore, the real time effect of covid-19 characterized by global lockdown on production and other economic activities had influence on inflation rate pattern between November 2019 to May 2020. The series correlogram allowed us to choose appropriate order of AR and MA parameter as AR (1) and MA (1) with a first difference d (1). Therefore, ARIMA (1,1,1) is the most appropriate model for modelling inflation rate in Nigeria. However, model diagnostic check was carried out to check the robustness of the model. The result shows no presence of heteroscedasticity and there was no serial correlation in the residual obtained from the model. To evaluate and examine the forecasting ability of ARIMA (1,1,1), out of sample forecast was generated from the month of June 2020 to March 2020.

**REFERENCES**

Benmouiza, K. & Cheknane, A. (2013). Forecasting Hourly Global Solar Radiation Using Hybrid K-means and Nonlinear Autoregressive Neural Network Models. *Energy Conversion, Management*, 75, 561-569.

Box, G. E. P & Jenkins GM (1994). *Time Series Analysis Forecasting and Control*, Prentice Hall.

Box, G. E. P., Jenkins, G.M. & Reinsel, G. C. (2008). *Time Series Analysis, Forecasting and Control*. Hoboken, NJ: Wiley. 98-104.

Central Bank of Nigeria (2015). Financial Policies by the Apex Bank of Nigeria. Central Bank of Nigeria Publications. Retrieved from http:/www.cbn.org.ng.

Changyong, F., Hongyue, W., Naiji, L., Tian, C., Ying, L. & Xim, M. (2014). Log-transformation and its implication for data analysis. *Shangai Achives of psychiatry* 26(2); 105-109.

Dania, E. N. (2013). Determinants of inflation in Nigeria: 1970-2010. *The business and Management Review*, 3(2), 88-92.

Dickey, D. & Fuller W. (1979). Distribution of the estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association*, 74, 427-431.

Duncan, R. & Martinez G. (2018). "New Perspective on Forecasting inflation in Emerging Market Economics: An Empirical Assessment"., Globalization and Monetary Policy Institute Working, (388).

Ekpenyong, E. J. & Udoudo, U. P. (2016). Short Term Forecasting of Nigeria Inflation Rate Using Seasonal ARIMA Model. *Science Journal of Applied Mathematics and Statistics*, 4(3), 101-107.

Etuk, H. (2012). Forecasting Nigerian Inflation Rates by a Seasonal ARIMA Model. *Canadian Journal of Pure and Applied Science*, 6(3), 2179-2185.

Friedman, M. & John, M. K. (1970). Federal Reserve Bank Richmond Econ Rev, 83, 1-23.

Frisch, H. (1990). Theories of inflation. *Cambridge Survey of Economic Literature*, 3(2), 217-218.

Gujarati, D. N. (2013). Basic Econometrics (African Edition), McGraw-Hill Education, (753-758).

Imad, M. & Kelly, B. (2014). The Unbeatable Random Walle in Exchange Rate Forecasting: Reality or Myth? *Journal of Macroeconomic*, 40, 69-81.

John, E. E. & Patrick, U. U. (2016). Short-term Forecasting of Nigeria Inflation Rates using Seasonal ARIMA Model. *Science Journal of Applied Mathematics and Statistics*, 4(3), 101-107.

Laidler, D. E. W. & Parkin M. J. (1975). Inflation – A Survey. *European Journal*, 85(340), 741-809

Friedman, M. (1970). The Center-Revolution in Monetary Theory. *Science Journal of Applied Mathematics and Statistics*, 2(1), 90-100.

Mallory, M. L. (2018). Basic Time-Series Analysis, Single Equation Models: ARIMA, 1-2.

Mustapha, A. M. & Kubalu, A. I. (2016). Application of Box-Jenkins Inflation Dynamics. *Journal of Art and Social Sciences*, 2(1),98 – 105.

Nau, R. (2014). Notes on the random walk model. Fuqua School of Business, Duke University Press. 15-17.

Nyoni, T. & Nathaniel, S. P. (2018). Modeling Rates of Inflation in Nigeria: An Application of ARIMA, ARIMA and GARCH Models.

Okafor, C. & Shaibu, I. (2013). Application of ARIMA model to Nigerian Inflation Dynamics, *Research Journal of Finance and Accounting*. 4(3), 138-150.

Olajide, J. T., Ayansola, O. A., Odusina M. T. & Oyemiga, I. F. (2012). Forecasting the Inflation Rate in Nigeria. Box-Jenkins Approach. *IOSR Journal of Mathematics* 3(5), 15-19.

Ord, K. & Lowe, S. (1996). Automatic forecasting, *the American Statistician*, 50, (1), 88-94.

Osuolale, P. P., Ayanniyi, W. A., Adesina, A. R. & Mathew T. O. (2017). Time Series Analysis to Model and Forecast Inflation Rate in Nigeria. *Anale Serial Informatical,* 15(1), 174-178.

Popoola, O. P., Ayanrinde, A. W., Rafui, A. A. & Odusina, M. T. (2017). Time Series Analysis to Model and Forecast Inflation rate in Nigeria. *Annals Computer Science Series*, 15(1),

Stellwagen, E. (2012). Exponential Smoothing: The Work House of Business Forecasting, Foresights, 2(1), 23-28.

Udegbunam, E. C. & Onu, I. J. (2016). Modeling Nigeria's Urban and Rural Inflation Using Box-Jenkins Model Scientific Paper Series Management, Economic Engineering in Agriculture and Rural Development.