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TIME SERIES ANALYSIS TO MODEL AND FORECAST INFLATION RATE IN NIGERIA

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ABSTRACT: The stability of economy of any nation is at risk if inflation is not properly checked through constant analysis and study, hence this research work attempts to model inflation rate in Nigeria, test for the adequacy of the fitted model, forecast future inflation rate. Descriptive statistics, Box-Jenkins Methodology, Augmented Dickey Fuller Unit Root test was employed, the model of the inflation rate was determined using the correlogram. The order of the models and parameter of the models were confirmed from the information criterion computation. It was discovered to be normal from the Box-Pierce test statistic with value of 0.754. The inflation rate had an all-time high value of 28.20 and an all-time low value of 3.00 with a mean of 10.92. The series was found to be stationary from the Augmented Dickey Fuller Unit Root test. However, correlogram, autoregressive Moving average was also detected. ARIMA (0,1,1), ARIMA (1,1,1) and ARIMA (1,1,0) was compared. The best model was picked using the AIC, BIC and AIC_C. Therefore, the best model is ARIMA (0,1,1). Also, the inflation rate forecasted for a period of 36 months shows a parallel movement.

KEYWORDS: Box-Jenkins Methodology, Augmented Dickey Fuller Unit Root test, Autoregressive Moving average, inflation, correlogram.

1. INTRODUCTION

Various factors affect the stability of an economy; these factors can either be small (microeconomic factors) or large (macroeconomic factors). Every player (e.g. the common man, policy makers, government and its agencies etc.) has an important role to play. It is worthy of note that the direct and ripple effect of the macroeconomic factors or variables are very pivotal in the stability of an economy as they deal with aggregate and not just unit unlike the microeconomic. Among the macroeconomic variables that ensure economic stability, (e.g. exchange rate, interest rate, GDP etc.) inflation is one that poses a very big threat to economies all around the world, as a matter of fact, it is no respecter of any economy-developed, developing or under developed. It is seen to affect developing economies like Brazil, Venezuela, India, Pakistan, Germany, Israel, Bolivia, Zimbabwe and so on even though they employ stringent measures to curb it and its effect, it still goes on to affect them adversely. This is a more reason why constant forecasting has to be done so that policy makers can know what end they should work towards when it comes to inflation as it has proven to defy measures given its dynamic nature.

Inflation refers to a broad increase in prices across many goods and services in an economy over a sustained period of time. Conversely, inflation can also be thought of as the erosion in value of an economy's currency. Inflation is the rate at which the general level of prices for goods and services is rising and subsequently, purchasing power is falling. Kimberly Amadeo, a US Economy Expert defined inflation as “a devastating condition when prices just keep going up, eating away at your standard of living”.

Inflation is define as a persistent increase in the level of consumer prices or a persistent decline in the purchasing power of money caused by an increase in available currency and credit beyond the proportion of available goods and services of a particular country.

1.1 Inflation in Nigeria

Just as inflation is a menace in different economy, it is not different in Nigeria as it has significant impact as far back as the Civil war period (1967-1970).As with every other economies battling frantically against inflation, Nigeria’s inflation pattern is affected by different factors. One of which is war. War is a favorable condition for inflation to grow, typical examples of pre-war and post-war prices show that war and disasters cause serious inflation. In 1965 (Pre-war) 500 cups of rice sold for ₦14, however in 1971 (Post-war) same 500 cups of rice sold for ₦43. This shows the effect of war on the economy as the government pumps in a lot of money into circulation as they spend however the money is not pumped towards production or investment that will balance the amount of money in circulation. The inflation rate in Nigeria experienced some sinusoidal movement as there were drops in the inflation rate at various points. Government spending (such as pre-election spending, white elephant projects e.g. Udoji awards, Abebo salary awards, Structural adjustment program) affects the rate of inflation in Nigeria, as the government is seen to enter deficit spending at some points and also fraternize with a pal of inflation "borrowing". These things and more saw Nigeria inflation rate rise. Therefore, this research attempts to model inflation rate, test for the adequacy of the fitted model and forecast future inflation rate with the best model.

1.2 Measure of Inflation

Inflation is usually measured using price index and consumer price index. Inflation rate is the annualized percentage change in a general price index (normally the consumer price index) over time.

Price Index

A price index is a normalized average (typically a weighted average) of price relatives for a given class of goods or services in a given region, during a given interval of time. It is used to help to compare how these price relatives, taken as a whole, differ between time periods or geographical locations.

Consumer Price Index

The consumer price index (CPI) is a measure of the overall cost of the goods and services bought by a typical consumer. The goal of the consumer price index is to measure changes in the cost of living. This it does by taking into cognizance when calculating, various goods a typical consumer will purchase and their prices and calculation is done with respect to a certain year called the base year.

2.0 MATERIALS AND METHODS

Time Series as a Stochastic Process

A stochastic process is a family of time indexed random variables, $X(\omega, t)$; where ω belongs to a simple space and t belongs to an indexed set for a fixed t, $X(\omega, t)$ is a random variable. Thus, a time series is a realization or sample function from a stochastic process. With proper understanding that a stochastic process, $X(\omega, t)$ is a set of time-indexed random variables defined on a sample space. We simply write $X(\omega, t)$ as $X(t)$ or $X\ t$.

2.1 Box-Jenkins Methodology

In time series analysis, the **Box–Jenkins method,**[1] named after the statisticians George Box and Gwilym Jenkins, applies autoregressive moving average (ARMA) or autoregressive integrated moving average (ARIMA) models to find the best fit of a time-series model to past values of a time series.

The first step in developing a Box–Jenkins model is to determine if the time series is stationary and if there is any significant seasonality that needs to be modelled.

Detecting stationarity

Stationarity can be assessed from a run sequence plot. The run sequence plot should show constant location and scale. It can also be detected from an autocorrelation plot. Specifically, non-stationarity is often indicated by an autocorrelation plot with very slow decay.

Detecting seasonality

Seasonality (or periodicity) can usually be assessed from an autocorrelation plot, a seasonal subseries plot, or a spectral plot.

Differencing to achieve stationarity

Box and Jenkins recommend the differencing approach to achieve stationarity. However, fitting a curve and subtracting the fitted values from the original data can also be used in the context of Box–Jenkins models.

Seasonal differencing

At the model identification stage, the goal is to detect seasonality, if it exists, and to identify the order for the seasonal autoregressive and seasonal moving average terms. For many series, the period is known and a single seasonality term is sufficient. For example, for monthly data one would typically include either a seasonal AR 12 term or a seasonal MA 12 term. For Box–Jenkins models, one does not explicitly remove seasonality before fitting the model. Instead, one includes the order of the seasonal terms in the model specification to the ARIMA estimation software. However, it may be helpful to apply a seasonal difference to the data and regenerate the autocorrelation and partial autocorrelation plots. This may help in the model identification of the non-seasonal component of the model. In some cases, the seasonal differencing may remove most or all of the seasonality effect.

Identify p and q

Once stationarity and seasonality have been addressed, the next step is to identify the order (i.e. the p and q) of the autoregressive and moving average terms. Different authors have different approaches for identifying p and q. Brockwell and Davis (1991) [3] state "our prime criterion for model selection among ARMA(p,q) models will be the AICc", i.e.the Akaike information criterion with correction. Other authors use the autocorrelation plot and the partial autocorrelation plot,

Autocorrelation and partial autocorrelation plots

The sample autocorrelation plot and the sample partial autocorrelation plot are compared to the theoretical behavior of these plots when the order is known. Specifically, for an AR(1) process, the sample autocorrelation function should have an exponentially decreasing appearance. However, higher-order AR processes are often a mixture of exponentially decreasing and damped sinusoidal components.

For higher-order autoregressive processes, the sample autocorrelation needs to be supplemented with a partial autocorrelation plot. The partial autocorrelation of an AR(p) process becomes zero at lag p + 1 and greater, so we examine the sample partial autocorrelation function to see if there is evidence of a departure from zero. This is usually determined by placing a 95% confidence interval on the sample partial autocorrelation plot (most software programs that generate sample autocorrelation plots also plot this confidence interval). If the software program does not generate the confidence band, it is approximately $\pm 2 / \sqrt{N}$ with N denoting the sample size.

The autocorrelation function of a MA(q) process becomes zero at lag q + 1 and greater, so we examine the sample autocorrelation function to see where it essentially becomes zero. We do this by placing the 95% confidence interval for the sample autocorrelation function on the sample autocorrelation plot. Most software that can generate the autocorrelation plot can also generate this confidence interval. The sample partial autocorrelation function is generally not helpful for identifying the order of the moving average process. Hyndman & Athanasopoulos [4] suggest the following:

The data may follow an ARIMA(p,d,0) model if the ACF and PACF plots of the differenced data show the following patterns: the ACF is exponentially decaying or sinusoidal, there is a significant spike at lag p in PACF, but none beyond lag p.

The data may follow an ARIMA(0,d,q) model if the ACF and PACF plots of the differenced data show the following patterns. the PACF is exponentially decaying or sinusoidal there is a significant spike at lag q in ACF, but none beyond lag q.

In practice, the sample autocorrelation and partial autocorrelation functions are random variables and do not give the same picture as the theoretical functions. This makes the model identification more difficult. In particular, mixed models can be particularly difficult to identify. Although experience is helpful, developing good models using these sample plots can involve much trial and error.

Box–Jenkins model estimation

Estimating the parameters for Box–Jenkins models involves numerically approximating the solutions of nonlinear equations. For this reason, it is common to use statistical software designed to handle to the approach – fortunately, virtually all modern statistical packages feature this capability. The main approaches to fitting Box–Jenkins models are nonlinear least squares and maximum likelihood estimation. Maximum likelihood estimation is generally the preferred technique. The likelihood equations for the full Box–Jenkins model are complicated and are not included here. See ([BD91]) for the mathematical details.

Box–Jenkins model diagnostics

Model diagnostics for Box–Jenkins models is similar to model validation for non-linear least squares fitting. That is, the error term At is assumed to follow the assumptions for a stationary univariate process. The residuals should be white noise (or independent when their distributions are normal) drawings from a fixed distribution with a constant mean and variance. If the Box–Jenkins model is a good model for the data, the residuals should satisfy these assumptions.

If these assumptions are not satisfied, one needs to fit a more appropriate model. That is, go back to the model identification step and try to develop a better model. Hopefully the analysis of the residuals can provide some clues as to a more appropriate model.One way to assess if the residuals from the Box–Jenkins model follow the assumptions is to generate statistical graphics (including an autocorrelation plot) of the residuals.

3.0 INTERMEDIATE SECTION

The data used is a secondary data extracted from the monthly bulletin of the central bank of Nigeria www.cenbank.com and SAS (A Statistical package was employed in the data analysis and charting).

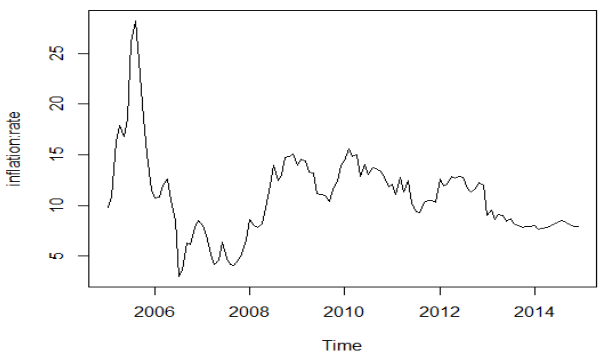

Figure 1: Time Plot of the Data

The Nigerian inflation rate in figure above does not exhibit seasonal variation. From the above time plot, there is an irregular movement in Nigerian inflation rate from January 2006 to December 2015.Since the p-value is greater than the significant level at 0.05 We therefore do not reject our $H_{0.}$ We then conclude that the inflation rate in Nigeria data is not stationary.

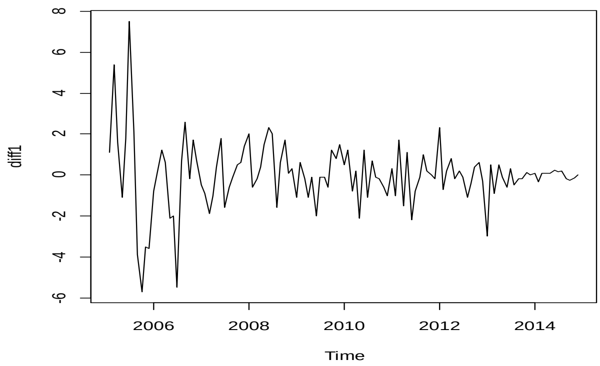

Figure 2: The Time Plot of the Differenced Data

Using Augmented Dickey-Fuller test, the following test statistics obtained from table:
Dickey-Fuller = -5.4196, Lag order = 4, p-value = 0.01.
Conclusion: Since the p-value is lesser than the significant level at 0.05 we therefore reject our H_0 and accept our H_1 We then conclude that Nigerian inflation rate data is stationary.
The figure 3 shows the autocorrelation function of the first differencing of the Nigerian inflation rate at various lags. Comparing the autocorrelations with their error limits, the significant autocorrelations are at lag 1, 11, 12. Applying the principle of parsimony MA (1) is selected since the ACF cuts off at lag 1.
The following significant models are suggested from the ACF and the PACF of the differenced data;
ARIMA (1,1,1),ARIMA (0,1,1) and ARIMA (1,1,0)
The Figure 5 is the qq-plot which indicates that most of the residuals are located on the straight line except some few residuals deviating from normality as that of ARIMA(1,1,1), so the assumption of normally distributed residual looks okay.
The figure 6 is the qq-plot which indicates that most of the residuals are located on the straight line except some few residuals deviating from normality as that of ARIMA(1,1,0), so the assumption of normally distributed residual looks okay.

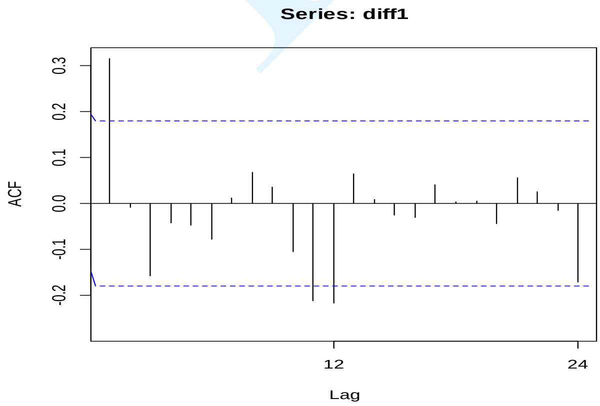

Figure 3: Autocorrelation Function of the Differenced Data of Nigerian Monthly Inflation Rate

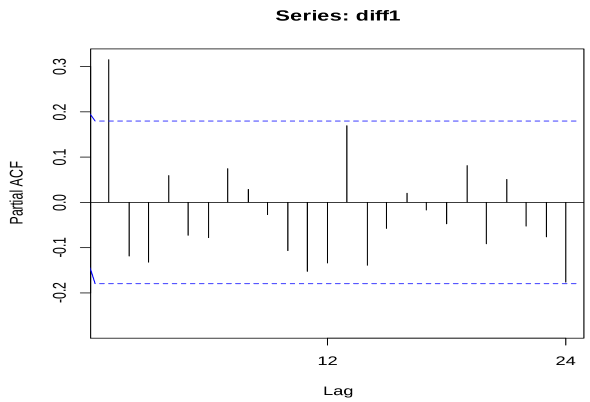

Figure 4: Partial Autocorrelation Function of the Differenced Data

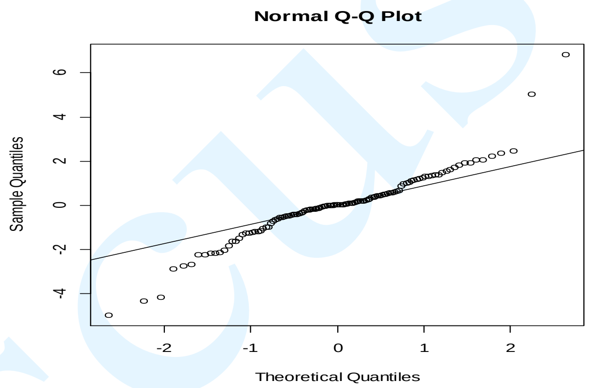

Figure 5: Diagnostic Test of ARIMA(1,1,1) of Nigerian Monthly Inflation Rate

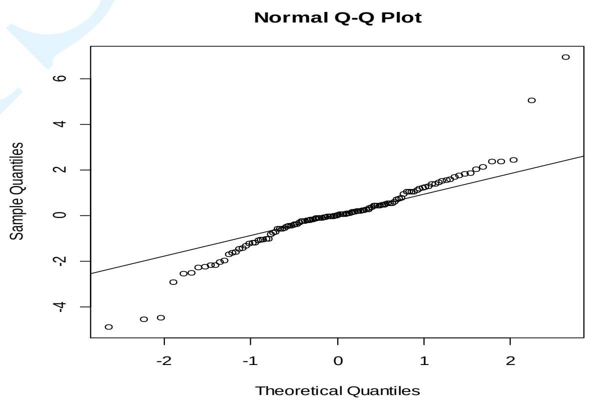

Figure 6: Diagnostic Test of ARIMA(1,1,0) of Nigerian Monthly Inflation Rate

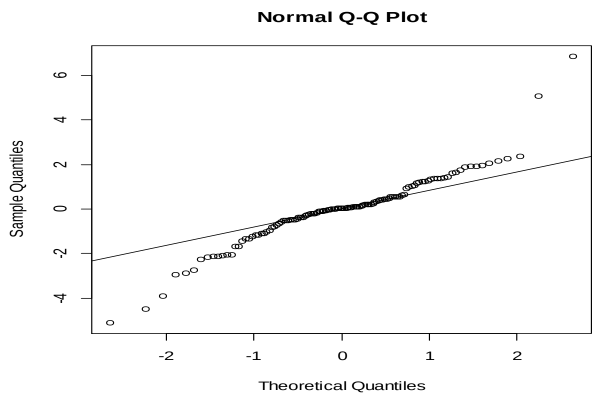

Figure 7: Diagnostic Test of ARIMA (0,1,1) of Nigerian Monthly Inflation Rate

The figure 7 is the qq-plot which indicates that most of the residuals are located on the straight line except some few residuals deviating from normality as that of ARIMA(0,1,1), so the assumption of normally distributed residual looks normal.

Table 1. Diagnostics Checking for Nigerian Monthly Inflation Rate

	AIC	BIC	AIC_C
ARIMA(1,1,1)	446.79	455.13	447.00
ARIMA(1,1,0)	445.59	451.15	445.70
ARIMA(0,1,1)	445.31	450.87	445.42

Selecting the Best Model for Forecasting Inflation Rate in Nigeria

When considering the diagnostics criterion, ARIMA(0,1,1) selects itself as the best model using AIC (Alkaike Information Criteria), AIC_C (Corrected Alkaike Information Criteria) and BIC (Bayesian Information Criteria). All the parameters in the model ARIMA(0,1,1) are significant at 5% level of significance, then we can say that ARIMA(0,1,1) is the best model in forecasting Nigerian inflation rate.

Fitting the Model for Nigerian Inflation Rate

ARIMA(0,1,1) model is the best model for forecasting Nigerian inflation rate. This is a non-seasonal autoregressive integrated moving average with one level of differencing with one AR term and one MA term. The model in terms of the differenced series Y_t is given as:

- $Y_t = c + \phi_1 x_{(t-1)} + \ldots + \varepsilon_t + \Theta_1 \varepsilon_{(t-1)}$
- Where Y_t is the differenced series,
- C and ϕ_1 are the constants with parameter 1 present in the AR(autoregressive) and ε_t, Θ_1 and Θ_2 are the constants with parameter 1,2 present in the MA(moving average) in the ARIMA model.

Testing the Adequacy of the Selected Model ARIMA(0,1,1)

Box-pierce test

$$\mathbf{Q(m)=n(n+2)\sum^{m}_{j=1} r^2_j / n-j}$$

X-squared = 0.0982, df = 1, p-value = 0.754Reject H_0 if p-value is less than the significant level otherwise we fail to reject H_0
since the p-value is greater than the significant level, we therefore do not reject our H_0 and conclude that the fitted model ARIMA(0,1,1) is independently distributed.

The Figure 8 diagram depicts the graphical representation of Nigerian inflation rate data in black line and its 3 years forecast (Starts=Jan 2016, Ends=Dec 2018) with its point forecast and 80% confidence interval in deep ash and its 95% confidence interval in light ash.

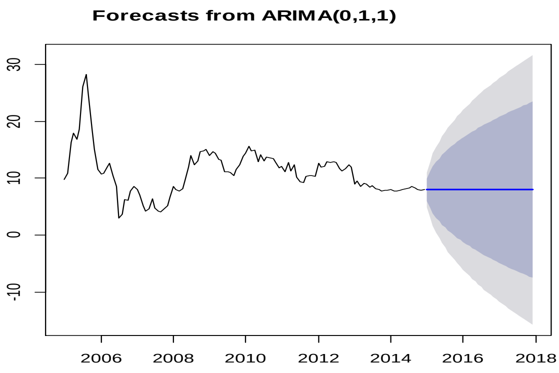

Figure 8: Graph of Nigerian Inflation Rate and its Forecast and Confidence Interval

4.0 RESULTS AND DISCUSSION

The graph of Nigerian inflation rate was plotted against time (the time plot), the graph shows a sharp increase in the inflation rate around 2006 and also discovered that there is no seasonal fluctuation in the Nigerian inflation rate data which means that there is no seasonal variation in the inflation rate but rather than irregular variation which may occur as a result of unusual weather or some political events.

From analysis carried out, the time plot does not exhibit trend. So therefore conclusion was made that there is an irregular movement in Nigerian inflation rate over time period. ARIMA models were subsequently developed for the inflation over the period of 2006 to 2016, after identifying various models. ARIMA(0,1,1) seems to be suitable model for forecasting Nigerian inflation rate.

The model developed was also used in forecasting for three years starting from 2016 to 2018 with both points forecast, 95% confidence interval forecast and also 80% confidence interval forecast for a better forecast values. The time plot of the forecasted values depicts a parallel movement with time.

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