Prediction of Stock Price using Autoregressive Integrated Moving Average Filter ((Arima (P,D,Q))

By Olayiwola Olaniyi Mathew, Apantaku Fadeke Sola, Bisira Hammed Oladiran & Adewara Adedayo Amos

Federal University of Agriculture, Nigeria

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The data were collected from Nigerian Stock exchange and Central Securities Clearing System (CSCS). Time plot was used to detect the presence of time series components in the daily stock prices of Nigerian breweries from 2008 to 2012 and to check if the series is stationary. The structure of dependency was measured by using autoovariance, the auto-correlation and partial autocorrelation. An autoregressive model and moving average model were fitted to stationary series to predict the future stock prices. Alkaike Information Criteria (AIC) was used to determine the order of the fitted autoregressive model.

Keywords : *stationary series, autocorrelation, partial autocorrelation, AIC, arima.*

GJSFR-F Classification : *MSC 2010: 00A05*

PREDICTION OF STOCK PRICE USING AUTOREGRESSIVE INTEGRATED MOVING AVERAGE FILTER ARIMA P,D,Q

Strictly as per the compliance and regulations of :

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The time plot showed an irregular upward trend. A first difference of the non stationary series made the series stationary. The plots of the Autocorrelation and Partial Autocorrelation showed that stationary has been introduced into the original non-stationary series in which most of the Plotted points decaying to zero sharply. The plot of Akaike Information Criterion showed that the order of the fitted autoregressive model was 8. The ARIMA model diagnostic check showed that the fitted ARIMA model had a reasonable fit for the original series. Predicted stock price ranges from 138.66 to 141.49.

Keywords : stationary series, autocorrelation, partial autocorrelation, AIC, arima.

I. Introduction

The Nigerian Stock Exchange was established in 1960 as the Lagos Stock Exchange. In December 1977, it became The Nigerian Stock Exchange, with branches established in some of the major commercial cities of the country. At present, there are six branches of The Nigerian Stock Exchange. Each branch has a trading floor. The branch in Lagos was opened in 1961; Kaduna, 1978; Port Harcourt, 1980; Kano, 1989; Onitsha, February 1990; and Ibadan August 1990; Abuja, October 1999 and Yola, April 2002 and has Lagos as the Head Office of The Exchange. The Exchange started operations in 1961 with 19 securities listed for trading. Today, there are more than 262 securities listed on The Exchange, which includes 11 government Stocks, 49 Industrial

Authors α σ : Department of Statistics, Federal University of Agriculture, Abeokuta, Ogun State, Nigeria. E-mail : laniyimathew@yahoo.com
Author ρ : Department of Mathematics, Lagos State Polytechnic, Ikorodu, Lagos State, Nigeria.
Author ω : Department of Statistics, University of Ilorin. E-mail : aaadewara@gmail.com

loan (Debenture/Preference) Stocks and more than 194 Equity/Ordinary Shares of Companies.

a) Objective of the Study

This study was designed to look at the behavior of stock price of Nigerian Breweries Plc with passage of time and to fit Autoregressive Integrated Moving Average Filter for the prediction of stock price of the Nigerian Breweries Plc.

b) Source of Data

The data are secondary data obtained from Nigerian Stock exchange and Central Securities Clearing System (CSCS).

II. LITERATURE REVIEW

The financial system of any economy is seen to be divided between the financial intermediaries (banks, insurance companies and pension funds) and the markets (bond and stock markets). In Nigeria, the banking sector covers a larger percentage of equities listed on the floor of the exchange. Banks are significant to the world economy and make up a good portion of the equity market. The global financial sector has nearly $6 trillion in market capitalization, implying that banks account for a significant share in the global economy. In 2008, the financial stock worldwide, specifically equity market capitalization and outstanding bonds and loans, was estimated at US$ 175 trillion and this increased to US$ 212 trillion by the end of 2010 (Roxburgh et al., 2011). Banks are instrumental in providing capital for infrastructure, innovation, job creation and overall prosperity while playing an integral role in society because they affect the spending of individual consumers and the growth of entire industries (Cogan, 2008). Banks play a delegated role of monitoring investments on behalf of investors (Diamond, 1984) and have the capability of reducing liquidity risk thereby creating investment opportunity (Diamond and Dybvig, 1983).

To facilitate this demand in the financial system, the stock markets have grown considerably in the developed and developing countries over the last two decades.

For some developing economies, the stock exchanges are relatively large. The market capitalization of exchanges in Malaysia and Jordan represents a higher share of GDP than in France or Germany, while India's stock exchange lists more companies than the stock markets of all other countries except the USA. But on the other hand, for many other developing countries, the markets until the mid-1980s generally suffered from the classical defects of bank dominated economies, that is, shortage of equity capital, lack of liquidity, absence of foreign institutional investors, and lack of investor confidence in the stock market (Agarwal 1997).

Chittedi (2009) stated that the reason for studying the behavior of stock prices, is to prevent future capital market crash. The 2008/2009 financial crisis revealed that the power of globalisation can take a problem from one corner of the globe to multiple destinations (Chittedi, 2009). The crisis began in the US subprime mortgage sector, causing house prices to decline, economic activity to reduce and risk aversion to increase. It caused the failure of several large US based financial firms and had ramifications on household consumption (Naudé, 2009). The crisis rapidly spread to other parts in the world thereby causing failure of banks in Europe and decline in various stock indices as well as significant reductions in the market value of equities and commodities (Usman, 2010). The crisis spread further to other developed countries, as well as to emerging markets through a range of financial and real sector channels (Stephanou, 2009). The work of Demirguc-Kunt and Levine (1996), Singh (1997) and Levine and Zervos (1998)

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find that stock market development plays an important role in predicting future economic growth in situations where the stock markets are active.

III. Methodology

Time plot was used to detect the presence of time series components in the daily stock prices of Nigerian breweries from 2008 to 2012 and to check if the series are stationary. The series depend on time and the right assumption is that the series behave the same way with passage of time, the nature or structure of this dependency was measured by using auto-covariance, the auto-correlation and partial autocorrelation. An autocorrelation of +1 represents perfect positive correlation (i.e. an increase in one time series will lead to a proportionate increase in the other time series), while a value of -1 represents perfect negative correlation. The partial autocorrelation was to determine the rate of serial dependence of the stock prices as it moves along with time. An autoregressive model and moving average model were fitted to stationary series to predict or forecast the future stock prices. Alkaike Information Criteria (AIC) was used to determine the order of the fitted autoregressive model. The reasonable fit of the fitted autoregressive model was assessed by carrying out diagnostic checks.

a) Autocovariance, Autocorrelation and Partial Autocorrelation

The mathematical representation of both the auto-covariance and auto-correlation are given as:

Let X_t be a stationary time series with mean μ and variance σ^2, and assume for ease of notation that t takes on integer values $t = \pm 0, \pm 1, \dots$. The autocovariance function of X_t at lag k is defined as:

$$\gamma(k) = E(X_t - \mu)(X_{t-k} - \mu) \tag{1}$$

The autocorrelation function at lag k is defined as:

$$\rho(k) = \frac{\gamma(k)}{\gamma(0)} = \frac{\gamma(k)}{\sigma_x^2} \tag{2}$$

The partial autocorrelation denoted as $\emptyset_{kk}$ was obtained by substituting γ_k for $\hat{\gamma}_k$ by a recursive method given by Durbin (1960) as follows:

$$\emptyset_{k+1,k+1} = \frac{\hat{\gamma}_{k+1} - \sum_{j=1}^{k} \hat{\emptyset}_{kj} \gamma_{k+1-j}}{1 - \sum_{j=1}^{k} \emptyset_{kj} \hat{\gamma}_{jk}} \quad \text{and} \quad \hat{\emptyset}_{k+1,j} = \hat{\emptyset}_{kj} - \hat{\emptyset}_{k+1,k+1} \hat{\emptyset}_{k,k+1-j} \tag{3}$$

b) Autoregressive Filter (Ar (P))

The mathematical representation of the autoregressive model of order p is defined below:

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \dots + \emptyset_p X_{t-p} + a_t \tag{4}$$

where a_t is the white noise, p denote the order of the AR and $\emptyset_p$ denote the AR parameter.

c) Moving Average Filter (Ma (Q))

The mathematical representation of the moving average model of order q denoted as MA (q) is given by:

$$X_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q} \tag{5}$$

where a_t is the white noise, q denote the order of the MA and θ_q denote the MA parameter.

d) Autoregressive Moving Average Filter (Arma (P,Q))

An ARMA (p,q) where p and q denotes the order of the autoregressive and moving average models respectively of stochastic process X_t is given by:

$$X_t = \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} - a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \qquad 6$$

Where $\emptyset_p$ and θ_q are the AR and MA parameters and a_t is the white noise.

e) Autoregressive Integrated Moving Average Filter ((Arima (P,D,Q))

Box and Jenkins (1976) developed a methodology for fitting ARMA models to different data. These are known as autoregressive integrated moving-average (ARIMA) models. The ARIMA (p,d,q) where p denote the order of the AR, d denote the order of differencing and q denote the order of MA. The mathematical representation of ARIMA (p,d,q) model is given by:

$$\nabla^d \emptyset(B) X_t = \theta(B) a_t$$

where $\nabla = (1 - B)$, B is the backward shift operator given as $BX_t = X_{t-1}$, $\emptyset$ and θ are the AR and MA parameter respectively.

f) The Yule-Walker Equations

According to *Insightful (July, 2001)*, let $\gamma(k)$ be the auto-covariance of the AR(p) process x_t. The autoregressive parameters satisfy the Yule-Walker equations:

$$\sum_{k=1}^{p} \gamma(k-i)\alpha_k = \gamma(i), \quad i = 1,2,\dots,p \qquad 7$$

g) Burg's Algorithm

As an alternative to using the Yule-Walker equations for fitting autoregressive models is Burg's approach. Burg's approach is based on estimating the kth partial correlation coefficient by minimizing the sum of forward and backward prediction errors. *(Insightful: July, 2001)*:

$$SS(a_{k,k}) = \sum_{t=k+1}^{n} \left\{ [x_t - a_{1,k}x_{t-1} - \cdots - a_{k,k}x_{t-k}]^2 + [x_{t-k} - a_{1,k}x_{t-k+1} - \dots - a_{k,k}x_t]^2 \right.$$
$$8$$

Given all of the coefficients for the order k-1model, Equation (8) is a function only of $a_{k,k}$. The function essentially measures how well the order k model predicts forwards and backwards. The algorithm is optimal in the sense of maximizing a measure of entropy.

h) Alkaike Information Criteria (Aic)

A way of selecting the order of the AR process is to find an order that balances the reduction of estimated error variance with the number of parameters being fit. One such measure is Akaike.s Information Criterion (AIC). Simply put, the AIC is a tool for determining the order of the fitted autoregressive model. For an order k model, this criterion can be written as:

$$AIC(k) = nlog(\hat{\sigma}_{\varepsilon,k}^2) + 2k \qquad 9$$

If the series is an AR process, then the value of k that minimizes $AIC(k)$ is an estimate of the order of the autoregression.

Notes

IV.   DISCUSSION OF RESULTS

The time plot in figure 1 below possesses an irregular upward trend. This means that the series is not stationary. To make it stationary, we need to difference the series at an appropriate time lag k.
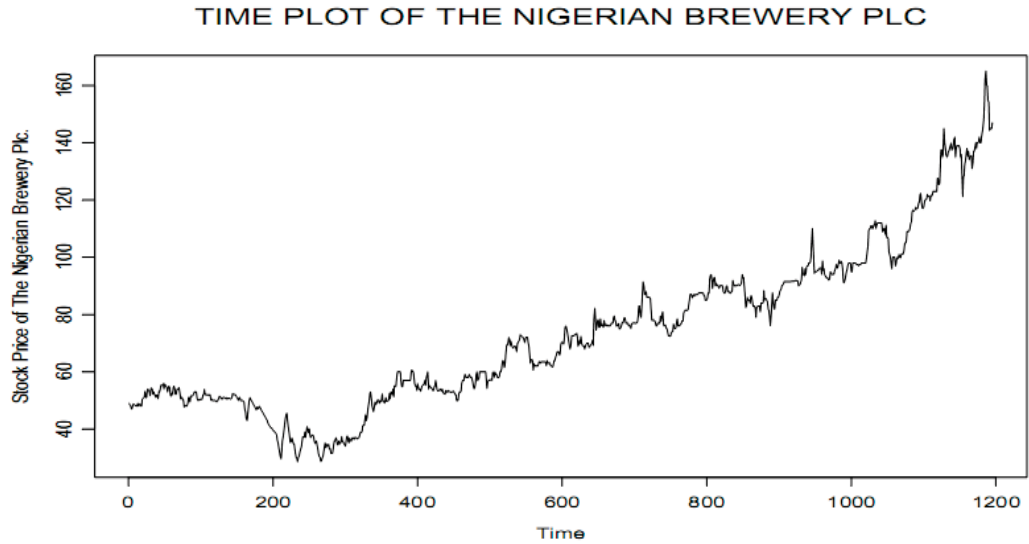
TIME PLOT OF THE NIGERIAN BREWERY PLC

Fig. 1 : Time Plot for the Stock Price of the Nigerian Brewery Plc

A first difference of the non stationary series in figure 1 yields the figure 2 below. From the fig 2, the series can be judged to arise from a random process with zero mean and constant variance.
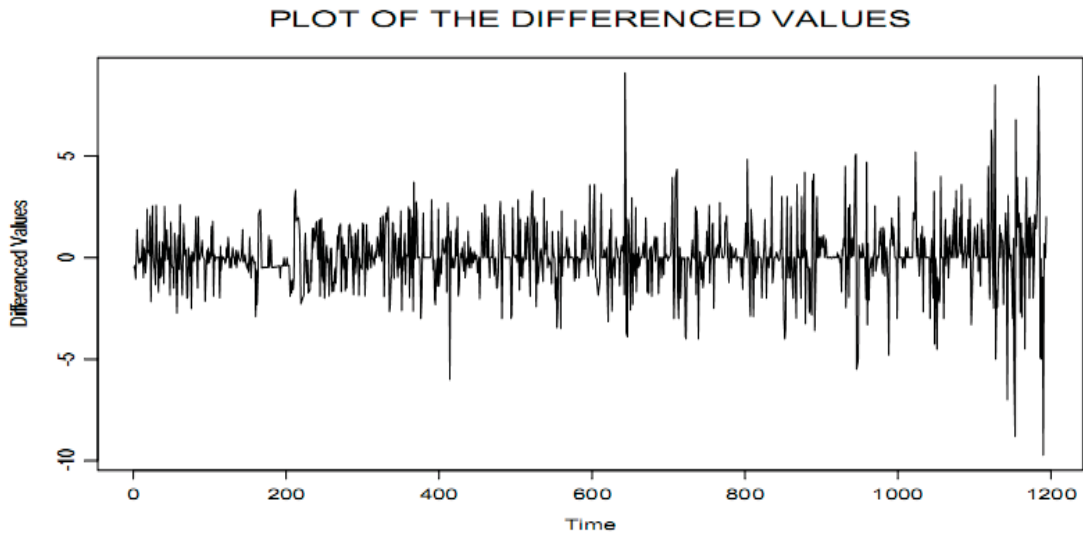
PLOT OF THE DIFFERENCED VALUES

Fig. 2 : Plot of the Differenced Values

The plots of the Autocorrelation and Partial Autocorrelation in figures 3 and 4 respectively also implies that stationarity has been introduced into the original non-stationary series in figure 1 with most of the Plotted points decaying to zero sharply.

MODEL IDENTIFICATION

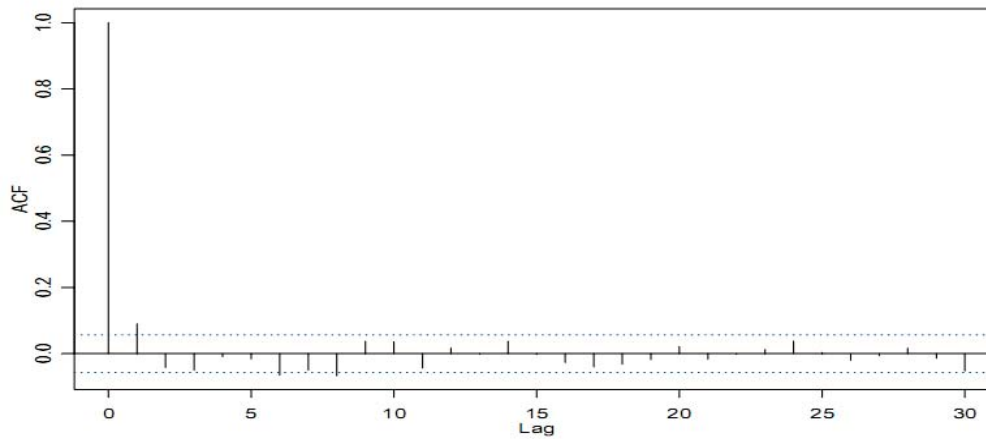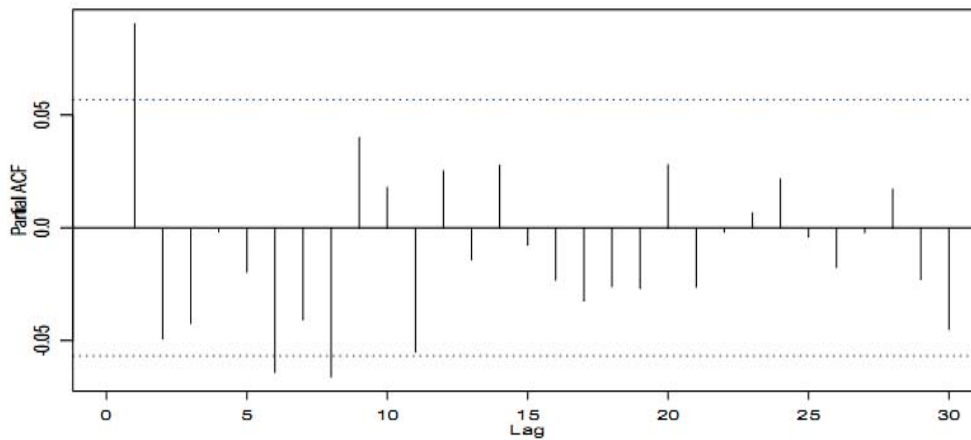Fig. 3 : Plots of the Autocorrelation

Fig. 4 : Partial Autocorrelation

Fitting Autoregressive Model to the stationary series, the following AR parameters were obtained:

$$\emptyset_1 = 0.086195609, \emptyset_2 = -0.050680792, \emptyset_3 = -0.046775400, \emptyset_4 = -0.005039509,$$

$$\emptyset_5 = -0.018359770, \emptyset_6 = -0.063492854, \emptyset_7 = -0.034724455, \emptyset_8 = -0.066127158$$

a) Autoregressive Model Order Identification Process

The identification of the order of the fitted Autoregressive Model was done by plotting its Akaike Information Criterion (AIC) as shown in fig 5. In detecting the correct order for the fitted autoregressive model, it is necessary to examine the value at which the AIC gives a minimum value, bearing in mind that the first AIC value is for order zero. The minimum value at which the plot Akaike Information Criterion gives a minimum is 8 which make the order of the fitted autoregressive model to be 8.
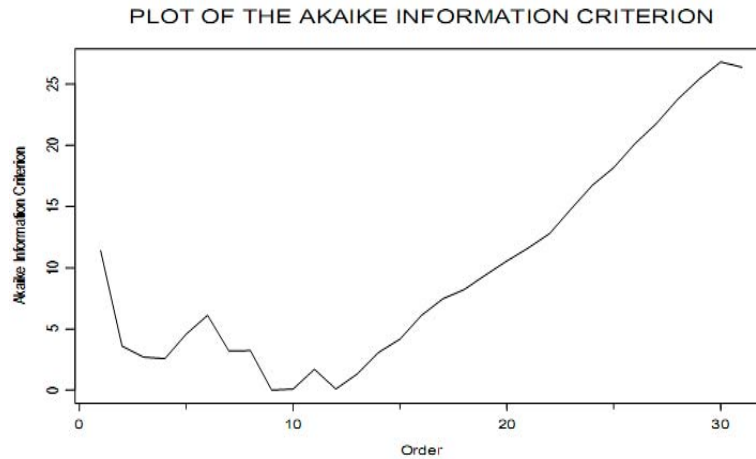
Notes

PLOT OF THE AKAIKE INFORMATION CRITERION

Fig. 5 : Plot of the Akaike Information Criterion

The reasonable fit of the fitted autoregressive model was assessed by carrying out diagnostic checks. By observing the plots of Autocorrelation and Partial Autocorrelation of residual, as shown in fig. 6 and fig 7 below, if they all possess the property of stationarity. The plots of the Autocorrelation and Partial Autocorrelation of this residual in figures 6 and fig. 7 respectively also implies that the residual possess stationarity property with most of the plotted points decaying to zero sharply.
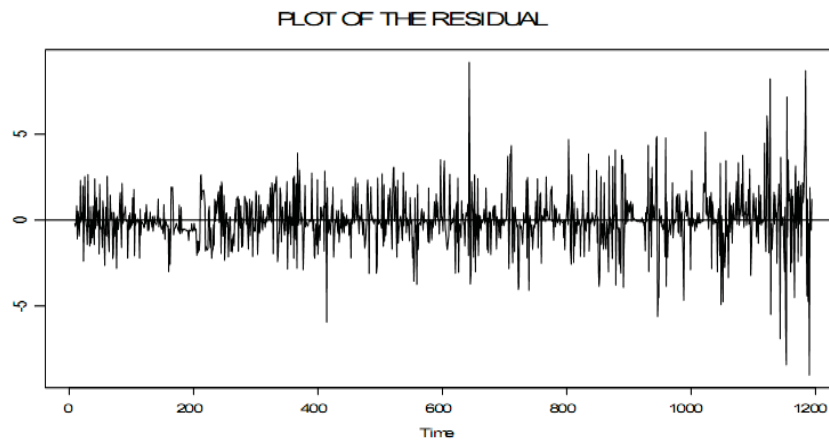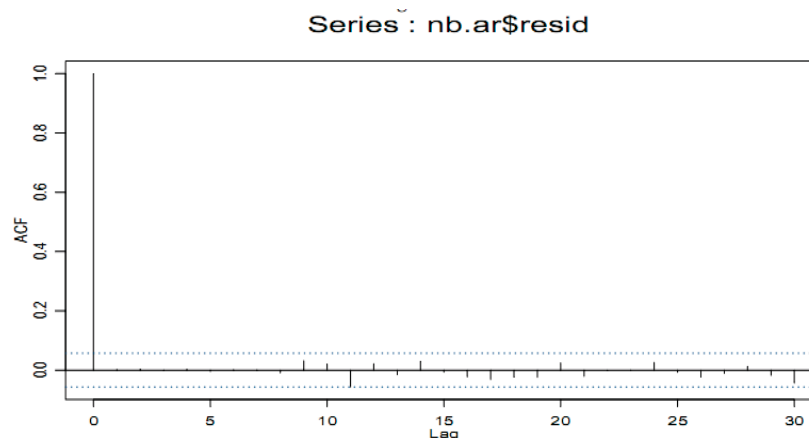
PLOT OF THE RESIDUAL

Fig. 6

Series : nb.ar$resid
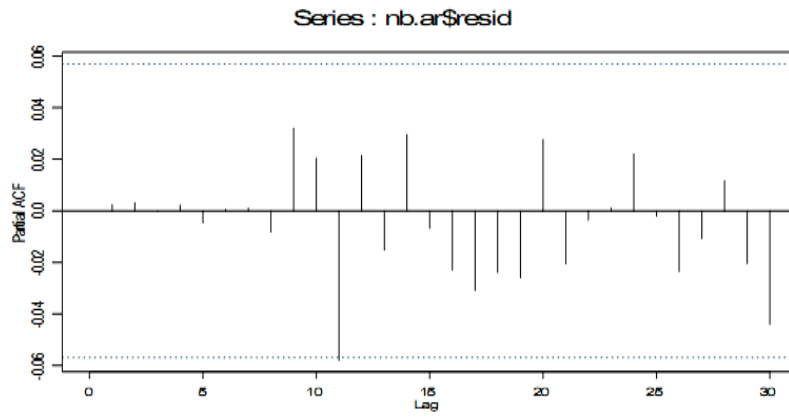
Fig. 7

Series : nb.ar$resid

Fig. 8

Hence we have the Autoregressive model as:

$$X_t = 0.086195609X_{t-1} - 0.050680792X_{t-2} - 0.046775400X_{t-3} - 0.005039509X_{t-4}$$

$$-0.018359770X_{t-5} - 0.063492854X_{t-6} - 0.034724455X_{t-7} - 0.066127158X_{t-8}$$

Fitting ARIMA (8,1,2) to the stationary series, we have the following AR and MA parameters respectively as:

AR : -0.46742, -0.0039, -0.09095, -0.0429, -0.02584, -0.07834, -0.08245, -0.08556 and MA : 0.39996, 0.54668

The ARIMA model diagnostic check in fig. 9 below contains the plots of resulting residual, the autocorrelation and partial autocorrelation and the p value at each time lag. The plots of acf and pacf of the residual with almost all the plotted points decaying to zero sharply attests to the stationarity condition being met and hence the fitted ARIMA model is a reasonable fit for the original series.
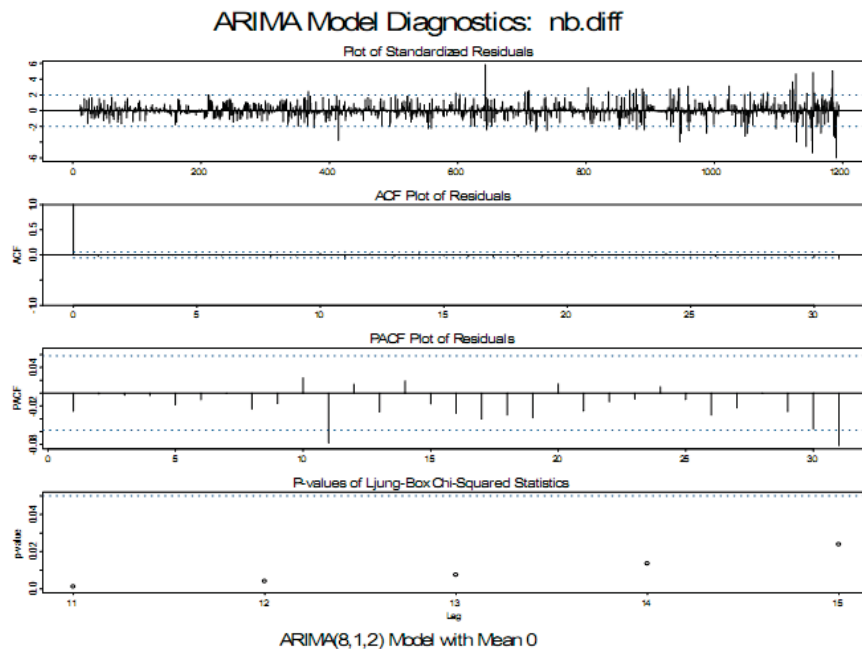
MODEL DIAGNOSIS

ARIMA Model Diagnostics: nb.diff

ARIMA(8,1,2) Model with Mean 0

Fig. 9

b) Forecasting

The predicted stock price of the Nigerian Breweries Plc with the corresponding standard error and 95% Confidence interval are shown in the table below. The predicted price ranges from 138.66 to 141.49

Time	Forecasted Price	S. E	95% C.I	
			Lower	Upper
1	138.66	6.32	126.2728	151.0472
2	138.79	6.38	126.2852	151.2948
3	139.41	6.38	126.9052	151.9148
4	140.57	6.38	128.0652	153.0748
5	140.26	6.38	127.7552	152.7648
6	140.39	6.38	127.8852	152.8948
7	140.68	6.39	128.1556	153.2044
8	141.02	6.39	128.4956	153.5444
9	141.49	6.39	128.9656	154.0144
10	141.09	6.40	128.546	153.634
11	141.10	6.41	128.5364	153.6636
12	140.95	6.41	128.3864	153.5136
13	141.02	6.41	128.4564	153.5836
14	140.93	6.42	128.3468	153.5132
15	140.91	6.42	128.3268	153.4932
16	140.88	6.43	128.2772	153.4828
17	140.89	6.43	128.2872	153.4928
18	140.94	6.43	128.3372	153.5428
19	140.93	6.43	128.3272	153.5328
20	140.95	6.43	128.3472	153.5528
21	140.94	6.44	128.3176	153.5624
22	140.95	6.44	128.3276	153.5724
23	140.95	6.44	128.3276	153.5724
24	140.95	6.44	128.3276	153.5724
25	140.94	6.45	128.298	153.582
26	140.94	6.45	128.298	153.582
27	140.94	6.45	128.298	153.582
28	140.94	6.45	128.298	153.582
29	140.94	6.46	128.298	153.582
30	140.94	6.46	128.298	153.582

V. CONCLUSSION

The time plot showed an irregular upward trend. A first difference of the non stationary series made the series stationary. The plots of the Autocorrelation and Partial Autocorrelation showed that stationary has been introduced into the original non-stationary series in with most of the Plotted points decaying to zero sharply. The plot of Akaike Information Criterion showed that the order of the fitted autoregressive model was 8. The ARIMA model diagnostic check showed that the fitted ARIMA model had a reasonable fit for the original series. Predicted stock price ranges from 138.66 to 141.49.

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