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Timeseries Analysis of All Shares Index of Nigerian Stock Exchange: A Box-Jenkins Approach

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Abstract: This study was aimed at analyzing the Nigerian Stock Exchange All Share Index. The data was extracted from the Central Bank of Nigeria's Statistical Bulletin and it covered the period of January 1985 to September 2014. The Box and Jenkins approach of model identification, parameter estimation and diagnostic checking was adopted in the analysis with the aid of S-plus Package. From the analysis, the result revealed that Autoregressive model of order two AR (2) after differencing once gives Akaike Information Criteria (AIC) of 6682.4416 which is an optimal order for Nigeria Stock Exchange All Share Index, the model is $X_t = 0.47X_{t-1} + 0.5123X_{t-2}$. Therefore, the model generated shows that ARIMA (2, 1, 0) is adequate to define the optimal order of Nigerian Stock Exchange All Share index.

Keywords: Autocorrelation, Partial Autocorrelation, Autoregresive Integrated Moving Average (ARIMA), Autoregresive Moving Average (ARMA), Autoregresive (AR), Moving Average (MA), Differencing, All Share Index, Stationary Series

1 Introduction

The Stock Exchange Market has been one of the most popular investments in the recent past due to its high returns. The Market has become an integral part of the global economy to the extent that any fluctuation in this market influences personal and corporate financial lives and the economic health of a country (Agwuegbo et al 2010). The stock market forecasting is marked more by its failure than by its successes since stock market prices reflect the judgments and expectations of investors, based on the information available. If things look good, the prices move upward so quickly that recipients of cheerful information have little or no time to act upon it.

The accuracy in forecasting the stock market prices or at least predicting the trend correctly is of crucial importance for any future investment in a dynamic global economy. Over the years, economists and finance analysts have consistently maintained that an unregulated market price is the best yardstick reflecting the true scarcity or worth of a commodity. One can easily evaluate the Nigerian Stock Market (NSM) or the Nigerian Stock Exchange (NSE) performance by the use of Stock Market Index or Returns.

Stock market returns are predictable from a variety of financial and macroeconomic variables and has long been an attraction for equity investors. Recently increasing attention has shifted to the Stock Market Index as a method of measuring a section of the Stock Market. The Stock Market Index are regarded as an important indicator by the investing public at large and can be used as a benchmark by which investor or fund manager compares the returns of their own portfolio . (Senol 2012)

A stock market index is a tool used by investors and financial managers to describe the market, and to compare the return on specific investments. A stock index is a method of measuring the value of a section of the stock market. A market index tracks the performance of a specific basket of stocks considered to represent a particular market of sector of the Nigerian economy.

Thus, the need to predict the stock price to meet the fundamental objectives of investors and operators of the stock market for gaining more benefits cannot be overemphasized. This issue has attracted the attentions of researchers and statisticians the world all over. Stock market is influenced by numerous factors and this has created high controversy in the field. Many methods and approaches for

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percimoneous models are available in the literature. This study exclusively deals with time series forecasting model, in particular, the Autoregressive Integrated Moving Average (ARIMA) models. These models were described by Box-Jenkins.

The Box-Jenkins approach possesses many appealing and attractive features. It allows the users who have only data on past years quantities, stock (share) as an example, to forecast time series data, for example, shares. Box-Jenkins approach also allows for the use of several time series, for example stock, to explain the behaviour of another series, for example dividend, of these other time series data are correlated with a variable of interest and if there appear to be some cause for this correlation (Agwuegbo et al 2010).

Box-Jenkins (ARIMA) modeling has been successfully applied in various stock-market activities. The following are example where time series analysis and forecasting are effective: price indices, currency's rate of exchange, migration rate, etc.

As economy develops, more funds are needed to meet the rapid expansion. Consequently, people source for funds to meet up with numerous competing challenges. The stock market serves as variable tool in the mobilization and allocation of saving among competing uses which are critical to the growth and efficiency of the economy. The growing importance at stock market in developing countries around the world over the last decades has shifted the focus of researchers to explore efficient ways of predicting stock market activities to enhance the benefit derived from them. While numerous scientific attempts have been made, no method has been discovered to accurately predict price movement.

Abdul (2008) compared the method of utilizing prices using ARIMA to deal with the problems of price expectation whereas Chattfield (2004) showed that the behavioural-based adaptive expectations where a sub-class of both the exponentially weighted moving average and the ARIMA (0,1,1) model. Naylor et al (2012) examined Box-Jenkins approach in contrast to Whartons econometric model and observed that ARMA models was better in acuracy for forcasting than Whartons model.

Comparing prices of commodities and values has always been a task in economic situation. Many different methods of comparing , estimating and forcasting for the future stocks and commodities dealing with autocorrelation has been suggested by different authors among whom are :Durbin and Watson (1951), Box, et al (1994) Leuthold (2001), Lirby (2004), (2006), Durbin (2012) and Malkiel (2013).

In this paper, we are going to use the components of All Share Index (ASI) of the Nigerian Stock Exchange (NSE) which comprises of monthly value of All Share Index for the period of January 1985 to September 2014.

2.0 Methodology

2.1 Autoregressive (AR) Model

An Autoregressive (AR) model of order P satisfied the following:

$$X_t = \mu' + \sum_{k=1}^{p} \phi_{kk} X_{t-k} + \varepsilon_t$$

$$X_t = \mu + \phi_{11} X_{t-1} + \phi_{22} X_{t-2} + \phi_{33} X_{t-3} + \ldots + \phi_{pp} X_{t-n} + \varepsilon_t \quad (1)$$

For t = 0 where $\varepsilon_t = 0$

For $n > 0$ where the error term $\varepsilon_t > 0$ is a series of independently, identically distributed (i.i.d) random variables and asumed to be normally distributed and μ is some constant. p denotes the order of autoregressive model, defining how many previous values the current value is related to.

2.2 Moving Average (MA) Model

Moving Average (MA) model of order q is given as:

$$X_t = \mu' + \sum_{k=1}^{p} \phi_{kk} X_{t-k} + \varepsilon_t$$

$$X_t = \mu + \phi_{11} X_{t-1} + \phi_{22} X_{t-2} + \phi_{33} X_{t-3} \ldots \phi_{qq} X_{t-q} + \varepsilon_t \quad (2)$$

For t = 0 where $\varepsilon_t = 0$

The error (or noise) term in this equation ε_t is the one step ahead forecasting error which can be expressed as a function of previous forecasting errors. It shows that MA (q) models make forecast based on the error made in the past, and so one can learn from the error made in the past to improve current forecast.

2.3 Autoregressive Moving Average (ARMA) Models

This is Autoregressive Component of order p and Moving Average Component.of order q

In a situation where AR (q) and MA(p) were not able to solve the case at hand, a combination of the two produces another interesting model known as Autoregressive moving average (ARMA)(p, q) model where p is the number autoregressive component and q is the number of moving average component. This model is as presented as follows The Form ARMA (p, q) model is given by the equation:

$$X_t - \sum_{k=1}^{p} \phi_{kk} X_{t-k} = \mu + \sum_{j=1}^{q} \phi_{jj} X_{t-j} + \varepsilon_t ; X_{t-j} \geq 0 \quad \begin{aligned} & X_t - \phi_{11} X_{t-1} + \phi_{22} X_{t-2} + \phi_{33} X_{t-3} + \ldots + \phi_p X_{t-p} \\ & = \mu + \phi_{11} X_{t-1} + \phi_{22} X_{t-2} + \phi_{33} X_{t-3} \ldots \phi_{qq} X_{t-q} + \varepsilon_t \end{aligned}$$

(3)

Where $t \geq 0$; X_t is the observed data point.

μ is some constants and ϕ_k, θ_j are defined as for AR and MA model respectively

2.4 Autoregressive Integrated Moving Average (ARIMA) Model

In statistics, $ARIMA(p,d,q)$ models, sometimes called the Box-Jenkins models after the iterative Box-Jenkins methodology usually used to estimate them, are typically applied to time series data for forecasting.

Given a time series $X_{t-1}, X_{t-2}, \ldots, X_2, X_1$ the ARIMA model is a tool for understanding and, perhaps, predicting future values in the series. The model consists of three parts: An Autoregressive (AR) part, a Moving Average (MA) part and the Differencing part (I). The model is usually then referred to as the *ARIMA* (p,d,q) models where p is the order of the Autoregressive part, d is the order of differencing and q is the order of the moving Average part. For example, an *ARIMA* $(1,1,1)$ model means that the model contains one Autoregressive (p) parameter and one Moving

Average (q) parameter for the time series data after it was differenced once to attain stationary.

If $d = 0$ the model becomes ARMA, which is linearly stationary, ARIMA $(d \geq 0)$ is a linear non-stationary model. If the underlying time series is non-stationary, taking the difference of the series with itself makes it stationary, and then ARMA model is applied onto the difference part.

2.5 Forecasting Using Arima Models

Forecasting X_t from $X_{t-1}, X_{t-2}, \ldots, X_2, X_1$ using

ARIMA consist of the following steps: the Model identification, parameter estimation, and diagnostics. Model identification is the first step of these processes. The data would be examined to check for the most appropriate class of ARIMA processes by selecting the order of the consecutive and seasonal differencing, required in the making the series stationary, as well as specifying the order of the regular and seasonal autoregressive and moving average model necessary to adequately represent the time series model.

The Autocorrelation Function (ACF) and the Partial Autocorrelation function (PACF) are the most important elements of the time series analysis and forecasting. The ACF measure the amount of linear dependence between observations in a time series that are separated by lag_k. The PACF plots help to determine how many Autoregressive term are necessary to reveal one or more of the following characteristics: time lag where high correlations appear, seasonality of the series trend either in the mean level or in the variance of the series.

2.6 Measure of Forecasting Accuracy

The forecast error is the difference between the actual value and the forecast value for the corresponding period. $\mathrm{E}_t = A_t - F_t$ Where E_t is the forecasting error at period t, A_t is the Actual Value at period t and F_t is the forecast for period t. These are as shown in Table1

Table 1: Formulas For Measuring Forecasting Accuracy

ERROR MEASUREMENT	FORMULA
Mean Absolute Error (MAE)	$MAE = \frac{1}{T}\sum_{t=1}^{T}\varepsilon_t$
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{\varepsilon_t}{A_t}\right)$
Mean Squared Error (MES)	$MSE = \frac{1}{T}\sum_{t=1}^{T}\varepsilon_t^2$

Out of these MAPE and MAE are the commonly used once. MAPE and MAE are related with how close the forecast value is to the actual value. The lower the MAPE and MAE value, the better is the forecast. But they deal only with the absolute difference between the forecast value and the actual values.

2.7 Differencing and Unit Root

In the full class of $ARIMA(p,d,q)$ models, consider an autoregressive model of order one as follows:

$$X_t - \mu = \rho[X_{t-1} - \mu] + \varepsilon_t \tag{4}$$

Now if $|\rho| < 1$, then one can substitute the time $t-1$in equation (4) to obtain

$$X_{t-1} - \mu = \rho[X_{t-1} - \mu] + \varepsilon_{t-1} \tag{5}$$

and with further back substitution arrive at

$$X_t - \mu = \sum_{t=1}^{n}\rho^i + \varepsilon_{t-1} + \varepsilon_t \tag{6}$$

Which is convergent expression satisfying the stationary conditions. However, if $|\rho| = 1$ the infinite sum does not converge so one require an initial value say

$$X(0) = \mu$$

where

$$X_t = \mu + \sum_{t=1}^{n}\varepsilon_{t-1} + \varepsilon_t \tag{7}$$

is the initial value plus an un-weighted sum of $\varepsilon' s$ or 'shocks' they are permanent and the variance of X grows without bound over time. This type of series is called a random walk. Many stock series are believed to follow this or some closely related model. The failure of forecasts to return to mean in such a model implies that the best forecast of the future is current value and hence the strategy of buying low and selling high is pretty much eliminated in such a model whether high or low is unknown (Neylon et al 2012).

Any Autoregressive model like $X_t = \phi_{11}X_{t-1} + X_{t-2}$ is associated with a 'characteristic equation' whose root determine the stationarity or non-stationarity of the series.

That is

$$X_t - X_{t-1} = -[1 - \alpha_1 - \alpha_2]X_t + \alpha_2 X_{t-1} + X_{t-2} + \varepsilon_t \tag{8}$$

The covariance of $(X,Y)$is given by:

$$\text{cov.}(X,Y) = E(X-\mu_x)(Y-\mu_y)$$

$= \sum_x \sum_y [X-\mu_x][Y-\mu_y]$ for (X,Y) discrete.

Also $\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}[(X-\mu_x)(Y-\mu_y)]f(xy)dxdy$ for (X,Y) continuous.

Recall that

$$E[(X-\mu_x)(Y-\mu_y)] = E(X,Y)$$

$$E[(X-\mu_x)(Y-\mu_y)] = \mu_x, \mu_y \qquad (9)$$

Then the function

$$R(K) = Cov.(k_t, X_{t+k})$$
$$= (X_t-\mu_x)(Y_{t+k}-\mu_y)$$
$$= \mathrm{E}(X_t-\mu_x)(Y_{t+k}-\mu_y) \qquad (10)$$

where μ is constant at time t and $k = 0, \pm1, \pm2 \ldots$ Recall further that the correlation coefficient ρ_{xy} is given by:

$$\rho_{xy} = \frac{Cov.(X,Y)}{\sigma_x \sigma_y}$$
$$= \frac{E(X,Y)-\mu_x\mu_y}{\sigma_x\sigma_y}$$

Where $-1 \le \rho_{xy} \le 1$

Now for the stationary system X_t

The variance of $X_t = \sigma_x^2$

$X_t = \sigma^2$

Therefore' $\rho_{xy} = \frac{R(X)}{\sigma^2}$ and $\rho_k = \frac{R(X)}{R(0)}$

Thus the autocorrelation function at lag K is given by

$$\rho_k = \frac{E(X_t-\bar{X})(X_t-\bar{X}_{t-k})}{\sqrt{\mathrm{E}\left(X_t-\bar{X}\right)}} \qquad (11)$$

Which exhibits the following propoerties $R(0) = \mathrm{var}(X) = \sigma^2$. This implies that $R(K) = R(-K) \Rightarrow \rho_K = \rho_{K-1}$ and

$$R(K) = R(0) \Rightarrow -1 \le \rho_K \le 1$$

Also the partial autocorrelation function denoted by ϕ_{kk}, where $k = 1,2,\ldots,K$ and it is defined by

$$\phi_{kk} = \frac{\rho'_k}{\rho_k} \qquad (12)$$

Where ρ_k is a general form of Yule Walker's equation written as $\rho_k = \begin{pmatrix} 1 & \rho_1 & . & . & . & \rho_{n-1} \\ \rho_1 & 1 & . & . & . & \rho_{n-2} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ \rho_{n-1} & \rho_{n-2} & . & . & . & 1 \end{pmatrix}$ and ρ'_k is when the last column ρ_k is replaced by the vector $\begin{pmatrix} \rho_1 \\ \rho_2 \\ . \\ . \\ . \\ \rho_k \end{pmatrix}$. Thus $\phi_{11} = \rho_1$, $\phi_{22} = \frac{\begin{vmatrix} 1 & \rho_1 \\ \rho_1 & \rho_2 \end{vmatrix}}{\begin{vmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{vmatrix}} = \frac{\rho_2-\rho_1^2}{1-\rho_1^2}$,

$$\phi_{33} = \frac{\begin{vmatrix} 1 & \rho_1 & \rho_1 \\ \rho_1 & 1 & \rho_2 \\ \rho_2 & \rho_2 & \rho_3 1 \end{vmatrix}}{\begin{vmatrix} 1 & \rho_1 & \rho_2 \\ \rho_1 & 1 & \rho_1 \\ \rho_2 & \rho_1 & 1 \end{vmatrix}} = \frac{\rho_1^3 - \rho_1\rho_2^2 - \rho_1^2\rho_3 - 2\rho_1\rho_2 - \rho_3}{2\rho_1^2\rho_2 - 2\rho_2^2 - \rho_1^2 + 1}, \text{ etc}$$

3 Illustrative Example

The following data obtained from Central Bank of Nigerian (CBN) Statistical Bulletin comprises of 357 univariate data set collected every last working day of the month from January 1985 to September 2014 chronologically and presented in Table 2 and the time plot is also presented in Figure I.

The focal assumption of time series analysis is stationarity of the series out of other assumption like randomness of the series and normality of the series. In view of this, autocorrelation coefficient is obtained and presented in Table 3 and its autocorrelogarm is also presented in Figure II.

The data do provide sufficient evidence (Table 2 and Figure II) to conclude that the series is not stationary. It is noted that the autocorrelation coefficients of the first several lags are significantly different from zero for instance, autocorrelation coefficient of lag 1, lag 2, lag 3, …, lag 16 = 0.97, 0.94, 0.90,…,0.16 respectively which individually is less than the 0.14 and the autocorrelation coefficients gradually regressed towards zero rather than dropping exponentially, this shows that a trend exist in the series. The ACF for the series decays very slowly indicating that it is non-stationary. Non-stationary stochastic processes tend to generate series whose estimated autocorrelation function fail to die out rapidly; that is, the estimated autocorrelations for non-stationary processes tend to persist for a large number of lags. Persistently large values of r_k then indicate that the time series is non-stationary and that at least one difference is needed. Since the theoretical autocorrelations and partial autocorrelations are only independent of time for stationary processes, it is necessary to difference the original series until it can be assumed to be a realization of a stationary process. The result of first differencing is presented in Table 4. The stationarity test was conducted to check if it has been reached by plotting the corrrelogram of the first difference series to view its behaviour (Figure III). The next step is to obtain the autocorrelation coefficient function and partial autocorrelation function for the differenced series using s-plus and the result is presented in Table 5 and Figure IV

The model strategy involves model identification, parameter estimation and diagnostic check. The model for the monthly official All Share Index of Nigerian Stock Exchange is achieved by estimating the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). The selection of a time series model is frequently accomplished by matching estimated autocorrelations coefficients with the theoretical autocorrelation. The matching of the first 50 estimated autocorrelations function (ACF) and partial autocorrelations function (PACF) of the underlying stochastic processes suggested that the series were stationary. The estimated ACF and PACF are as shown in Table 6 and Figures V. With the matching of the ACF with the PACF, the model is identified as an AR (2) model

Akaike's Information Criterion (AIC) provides the best fit for an autoregressive model to a set of data. The model with the smallest value of the AIC is judged to be the most appropriate. The AIC obtained for all the models is presented in Table 7. The AIC revealed that the best fit for the model is an AR (2). The test for model appropriation result was as shown in Table 8.

TABLE 7: AIC FOR MODEL IDENTIFICATION

Lag	0	1	2	3	4	5	6	7	8	9
AIC	407.85	2.95	2.00	3.33	4.93	2.85	3.21	5.19	6.88	8.88

The AIC for the ARIMA $(p, d, q)$was examined and is as shown in Table 7

TABLE 8: AIC TEST FOR MODEL APPROPRIATION

Model	ARIMA(1,1,0)	ARIMA(0,1,0)	ARIMA(1,1,0)	ARIMA(2,1,0)
AIC	6680.8524	6682.4416	6846.2087	6675.4542

The corresponding fitted ARIMA (2, 1, 0) model as generated by S-plus is

$$X_t = \phi_{11} X_{t-1} + \phi_{22} X_{t-2} + \varepsilon_t$$

The AIC for the model is 6675.45418.

The parameter for the estimated model is as follows:

$$\phi_{11} = \rho_1 = 0.47$$

$$\phi_{22} = \frac{\begin{vmatrix} 1 & \rho_1 \\ \rho_1 & \rho_2 \end{vmatrix}}{\begin{vmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{vmatrix}}$$

$$\phi_{22} = \frac{\rho_2 - \rho_1^2}{1 - \rho_1^2} = \frac{0.62 - 0.47^2}{1 - 0.47^2} = \frac{0.3991}{0.7791.} = 0.5123$$

And the model becomes

$$X_t = 0.47 X_{t-1} + 0.5123 X_{t-2}$$

The diagnostic check for model adequacy is conducted and presented in table

Table 9: Display Of The Measure Of Forcasting Accuracy

Model	MSE	MEA	MAPE
ARIMA(2,1,0)	0.7578	0.7265	0.2801
ARIMA(1,1,0)	0.8567	0.7716	0.2973
ARIMA(0,1,0)	0.8822	0.7961	0.3066

Almost all the plots are based on the examination of the residuals, $\varepsilon_t = y_t - \hat{y}_t$, where $\hat{X}_t$ is the fitted value, or some functions of the residuals. Thus ARIMA (2, 1, 0) model appears quite adequate for the monthly Nigerian Stock Exchange Index as can be seen in Table 9.

Thus, the forecast for the month of October 2014, November 2014, December 2014 and January 2015 are shown using:

$$X_t = \phi_{11} X_{t-1} + \phi_{22} X_{t-2} + \varepsilon_t$$

With $\phi_{11} = 0.47$, $\phi_{22} = 0.5123$and the model $X_t = 0.47 X_{t-1} + 0.5123 X_{t-2}$ the forecast for All Share Index of the Nigerian Stock Exchange for October 2014, November 2014, December 2014 and January 2015 are 40460, 40220, 39630, and 39230, respectively.

4.0 Discussion And Conclusion

Having used Box-Jenkins method as tool to provide accurate forecast for the series, the following conclusions can be drawn:

Model identification indicated that ARIMA (2, 1, 0) given as $X_t = 0.47X_{t-1} + 0.5123X_{t-2}$ is best fit for this index. This was supported by forecasting results of different ARIMA models as the forecasting performance of ARIMA (2, 1, 0) was better than other ARIMA models. The All Share Index of the Nigerian Stock Exchange is non-random. The investigations show that the series is void of seasonal component. The forecast for All Share Index of the Nigerian Stock Exchange for October 2014, November 2014, December 2014 and January 2015 are 40460, 40220, 39630, and 39230, respectively thus, the All Share Index will decrease in the next four months.

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Appendix

Table 2 all share index of nigerian stock exchange (1985 – 2014)

Year/Month	January	February	March	April	May	June	July	August	September	October	November	December
1985	111.30	112.20	113.40	115.60	116.50	116.30	117.20	117.00	116.90	119.10	124.60	127.30
1986	134.60	139.70	140.80	146.20	144.20	147.40	150.90	151.00	155.00	160.90	163.30	163.80
1987	166.90	166.20	161.70	157.50	154.20	196.10	193.40	193.00	194.90	154.80	193.40	190.90
1988	190.80	191.40	195.50	200.10	199.20	206.00	211.50	217.60	224.10	228.50	231.40	233.60
1989	239.73	251.00	256.90	257.50	257.10	259.20	269.20	281.00	279.90	298.40	311.20	325.30
1990	343.00	349.30	356.00	362.00	382.30	417.40	445.40	463.60	468.20	480.30	502.60	513.80
1991	528.70	557.00	601.00	625.00	649.00	651.80	688.00	712.10	737.30	757.50	769.00	783.00
1992	794.00	810.70	839.10	844.00	860.50	870.80	879.70	969.30	1,022.00	1,076.50	1,098.00	1,107.60
1993	1,113.40	1,119.90	1,130.50	1,147.30	1,186.90	1,187.50	1,180.80	1,195.50	1,217.30	1,310.90	1,414.50	1,543.80
1994	1,666.30	1,715.30	1,792.80	1,845.60	1,875.50	1,919.10	1,926.30	1,914.10	1,956.00	2,023.40	2,119.30	2,205.00
1995	2,285.30	2,379.80	2,551.10	2,785.50	3,100.80	3,586.50	4,314.30	4,664.60	4,858.10	5,068.00	5,095.20	5,092.20
1996	5,135.10	5,180.40	5,266.20	5,412.40	5,704.10	5,798.70	5,919.40	6,141.00	6,501.90	6,634.80	6,775.60	6,992.10
1997	7,268.30	7,699.30	8,561.40	8,729.80	8,592.30	8,459.30	8,148.80	7,682.00	7,130.80	6,554.80	6,395.80	6,440.50
1998	6,435.60	6,426.20	6,298.50	6,113.90	6,033.90	5,892.10	5,817.00	5,795.70	5,697.70	5,671.00	5,688.20	5,672.70
1999	5,494.80	5,376.50	5,456.20	5,315.70	5,315.70	5,977.90	4,964.40	4,946.20	4,890.80	5,032.50	5,133.20	5,266.40
2000	5,752.90	5,955.70	5,966.20	5,892.80	6,095.40	6,466.70	6,900.70	7,394.10	7,298.90	7,415.30	7,164.40	8,111.00
2001	8,794.20	9,180.50	9,159.80	9,591.60	10,153.80	10,937.30	10,576.40	10,329.00	10,274.20	11,091.40	11,169.60	10,963.10
2002	10,650.00	10,581.90	11,214.40	11,399.10	11,486.70	12,440.70	12,458.20	12,327.90	11,811.60	11,451.50	11,622.70	12,137.70
2003	13,298.80	13,668.80	13,531.10	13,488.00	14,086.30	14,565.50	13,962.00	15,426.00	16,500.50	18,743.50	19,319.30	20,128.94
2004	22,712.88	24,797.43	22,896.40	25,793.00	27,730.80	28,887.40	27,062.10	23,774.30	22,739.70	23,354.80	23,270.50	23,844.50
2005	23,078.30	21,953.50	20,682.40	21,961.70	21,482.10	21,564.80	21,911.00	22,935.40	24,635.90	25,873.80	24,355.90	24,085.80
2006	23,679.40	23,843.00	23,336.60	23,301.20	24,745.70	26,316.10	27,880.50	33,096.40	32,554.60	32,643.70	32,632.50	33,189.30
2007	36,784.50	40,730.70	43,456.10	47,124.00	49,930.20	51,330.50	53,021.70	50,291.10	50,229.00	50,201.80	54,189.90	57,990.20
2008	54,189.92	65,652.38	63,016.56	59,440.91	58,929.02	55,949.00	53,110.91	47,789.20	46,216.13	36,325.86	33,025.75	31,450.78
2009	21,813.76	23,377.14	19,851.89	21,491.11	29,700.24	26,861.55	25,286.61	23,009.10	22,065.00	21,804.69	21,010.29	20,827.17
2010	22,594.90	22,985.00	25,966.25	26,453.20	26,183.21	25,384.14	25,844.20	24,268.20	23,050.60	25,042.20	24,764.70	24,770.52
2011	27,356.59	26,181.18	24,696.95	25,041.68	25,829.75	24,923.34	23,826.99	21,497.61	20,373.00	20,934.96	20,003.36	20,773.98
2012	20,875.83	20,123.51	20,652.47	22,109.76	22.170.96	21,599.57	23,302.22	23,750.82	26,011.64	26,430.92	26,494.44	28,078.81
2013	31,853.91	33,075.14	33,536.25	33,440.57	37,794.75	36.168.31	37,806.45	36,248.53	36,585.08	37,622.74	38,920.85	41,329.19
2014	40,571.62	39,558.99	38,748.01	38,485.56	41,474.39	42,482.49	42,039.06	41,532.33	41,210.10			

Table 3 Autocorrelation Coefficients For The Monthly Nigerian Stock Exchange (Nse) All Share Index

Lag	ACF
0	1.00
1	0.97
2	0.94
3	0.90
4	0.85
5	0.80
6	0.74
7	0.69
8	0.63
9	0.57
10	0.51
11	0.45
12	0.39
13	0.32
14	0.27
15	0.21
16	0.16
17	0.11
18	0.06
19	0.02
20	0.02

Table 4 First Differenced Series From Monthly All Share Index Of Nigerian Stock Exchange

0.9	1.2	2.2	0.9	-0.2	0.9	-0.2	-0.1	2.2	5.5	2.7	7.3	5.1	1.1	5.4	-2	3.2	3.5	0.1	4
4	5.9	2.4	0.5	3.1	-0.7	-4.5	-4.2	-3.3	41.9	-2.7	-0.4	1.9	-40.1	38.6	-2.5	-0.1	0.6	4.1	4.6
6.8	5.5	6.1	6.5	4.4	2.9	2.2	6.125	11.27	5.9	0.6	-0.4	2.1	10	11.8	-1.1	18.5	12.8	14.1	17.7
6.3	6.7	6	20.3	35.1	28	18.2	4.6	12.1	22.3	11.2	14.9	28.3	44	24	24	2.8	36.2	24.1	25.2
20.2	11.5	14	11	16.7	28.4	4.9	16.5	10.3	8.9	89.6	52.7	54.5	21.5	9.6	5.8	6.5	10.6	16.8	39.6
0.6	-6.7	14.7	21.8	93.6	103.6	129.3	122.5	49	77.5	52.8	29.9	43.6	7.2	-12.2	41.9	67.4	95.9	85.7	80.3
94.5	171.3	234.4	315.3	485.7	727.8	350.3	193.5	209.9	27.2	-3	42.9	45.3	85.8	146.2	291.7	94.6	120.7	221.6	360.9
132.9	140.8	216.5	276.2	431	862.1	168.4	-138	-133	-310	-467	-551	-576	-159	44.7	-4.9	-9.4	-128	-185	-80
-142	-75.1	-21.3	-98	-26.7	17.2	-15.5	-178	-118	79.7	-141	0	662.2	-1014	-18.2	-55.4	141.7	100.7	133.2	486.5
202.8	10.5	-73.4	202.6	371.3	434	493.4	-95.2	116.4	-251	946.6	683.2	386.3	-20.7	431.8	562.2	783.5	-361	-247	-54.8
817.2	78.2	-207	-313	-68.1	632.5	184.7	87.6	954	17.5	-130	-516	-360	171.2	515	1161	370	-138	-43.1	598.3
479.2	-604	1464	1075	2243	575.8	809.6	2584	2085	-1901	2897	1938	1157	-1825	-3288	-1035	615.1	-84.3	574	-766
-1125	-1271	1279	-480	82.7	346.2	1024	1701	1238	-1518	-270	-406	163.6	-506	-35.4	1445	1570	1564	5216	-542
89.1	-11.2	556.8	3595	3946	2725	3668	2806	1400	1691	-2731	-62.1	-27.2	3988	3800	-3800	11462	-2636	-3576	-512
-2980	-2838	-5322	-1573	-9890	-3300	-1575	-9637	1563	-3525	1639	8209	-2839	-1575	-2278	-944	-260	-794	-183	1768
390.1	2981	487	-270	-799	460.1	-1576	-1218	1992	-278	5.82	2586	-1175	-1484	344.7	788.1	-906	-1096	-2329	-1125
562	-932	770.6	101.9	-752	529	1457	61.2	-571	1703	448.6	2261	419.3	63.52	1584	3775	1221	461.1	-95.7	4354
-1626	1638	-1558	336.6	1038	1298	2408	-758	-1013	-811	-262	2989	1008	-443	-507	-322				

Table 5 Autocorrelation Coefficients Of The First Differenced Series

Lag	ACF		Lag	ACF
0	1.00		26	-0.02
1	-0.47		27	0.00
2	0.04		28	-0.11
3	0.07		29	-0.02
4	0.01		30	-0.07
5	0.02		31	-0.02
6	0.05		32	0.12
7	0.04		33	0.05
8	0.00		34	0.07
9	0.04		35	0.04
10	0.07		36	0.02
11	0.07		37	-0.02
12	0.00		38	-0.02
13	-0.10		39	-0.04
14	-0.08		40	-0.06
15	0.00		41	-0.05
16	-0.03		42	-0.02
17	0.08		43	-0.02
18	-0.03		44	0.01
19	-0.03		45	0.17
20	0.01		46	0.00
21	-0.10		47	-0.08
22	-0.04		48	-0.09
23	-0.06		49	-0.05
24	-0.02		50	-0.01
25	-0.02			

Table 6: Autocorrelation And Patial Autocorrelation Function Of The First Differenced Series

Lag	ACF	PACF		Lag	ACF	PACF
0	1.00	1.00		26	-0.02	0.02
1	-0.47	0.47		27	0.00	-0.01
2	0.04	0.62		28	-0.11	-0.09
3	0.07	-0.08		29	-0.02	0.06
4	0.01	0.03		30	-0.07	-0.13
5	0.02	0.01		31	-0.02	0.07
6	0.05	0.02		32	0.12	0.03
7	0.04	0.01		33	0.05	-0.03
8	0.00	0.00		34	0.07	0.09
9	0.04	0.04		35	0.04	-0.05
10	0.07	0.03		36	0.02	0.05
11	0.07	-0.03		37	-0.02	-0.05
12	0.00	0.03		38	-0.02	0.02
13	-0.10	-0.10		39	-0.04	-0.03
14	-0.08	0.03		40	-0.06	-0.06
15	0.00	-0.01		41	-0.05	0.02
16	-0.03	-0.03		42	-0.02	-0.01
17	0.08	0.08		43	-0.02	0.02
18	-0.03	-0.10		44	0.01	0.01
19	-0.03	0.06		45	0.17	0.09
20	0.01	-0.03		46	0.00	-0.09
21	-0.10	-0.07		47	-0.08	-0.01
22	-0.04	0.03		48	-0.08	-0.02
23	-0.06	-0.08		49	-0.05	0.01
24	-0.02	0.03		50	-0.01	0.00
25	-0.02	-0.04				

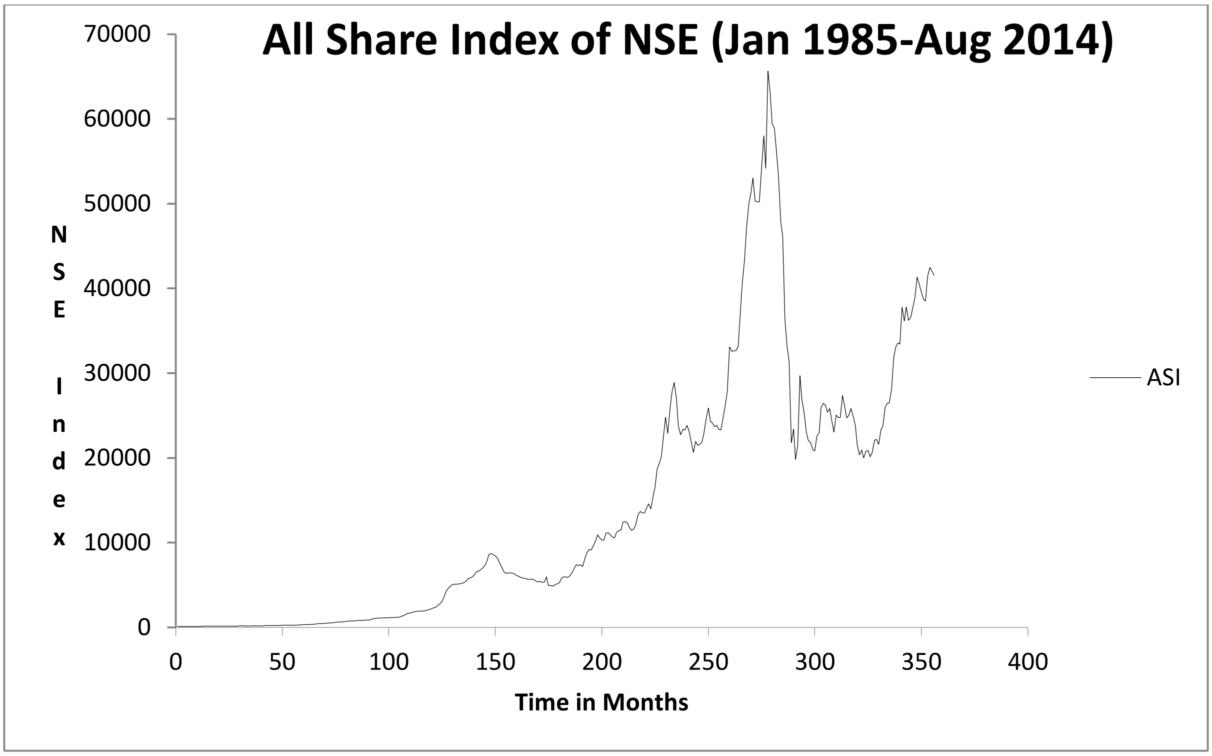


Figure I: Correlogram Of Nigeria Stock Exchange (Nse) Index

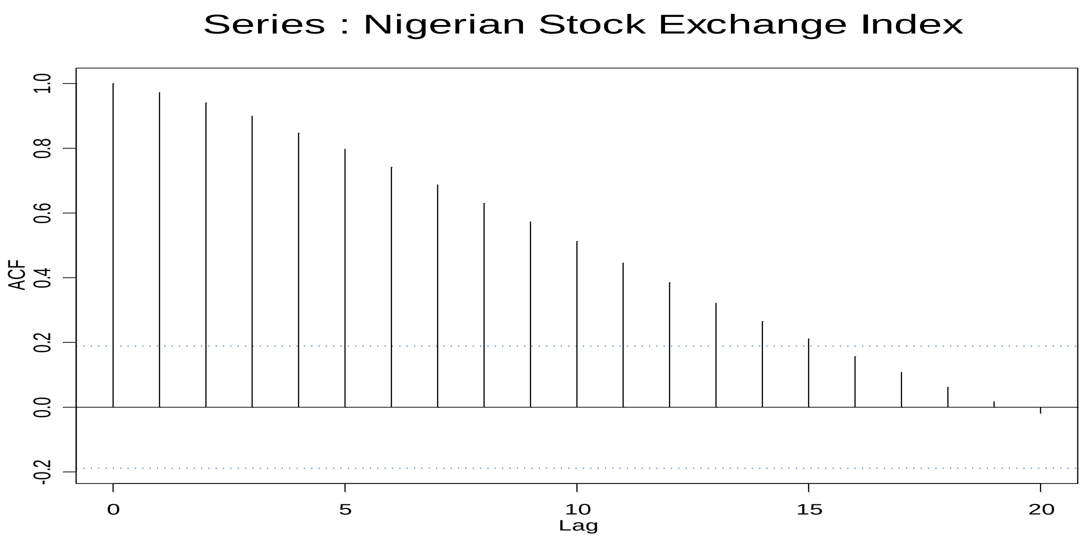


Figure Ii: Autocorrelogram Of Monthly Nigerian Stock Exchange (Nse) All Share Index

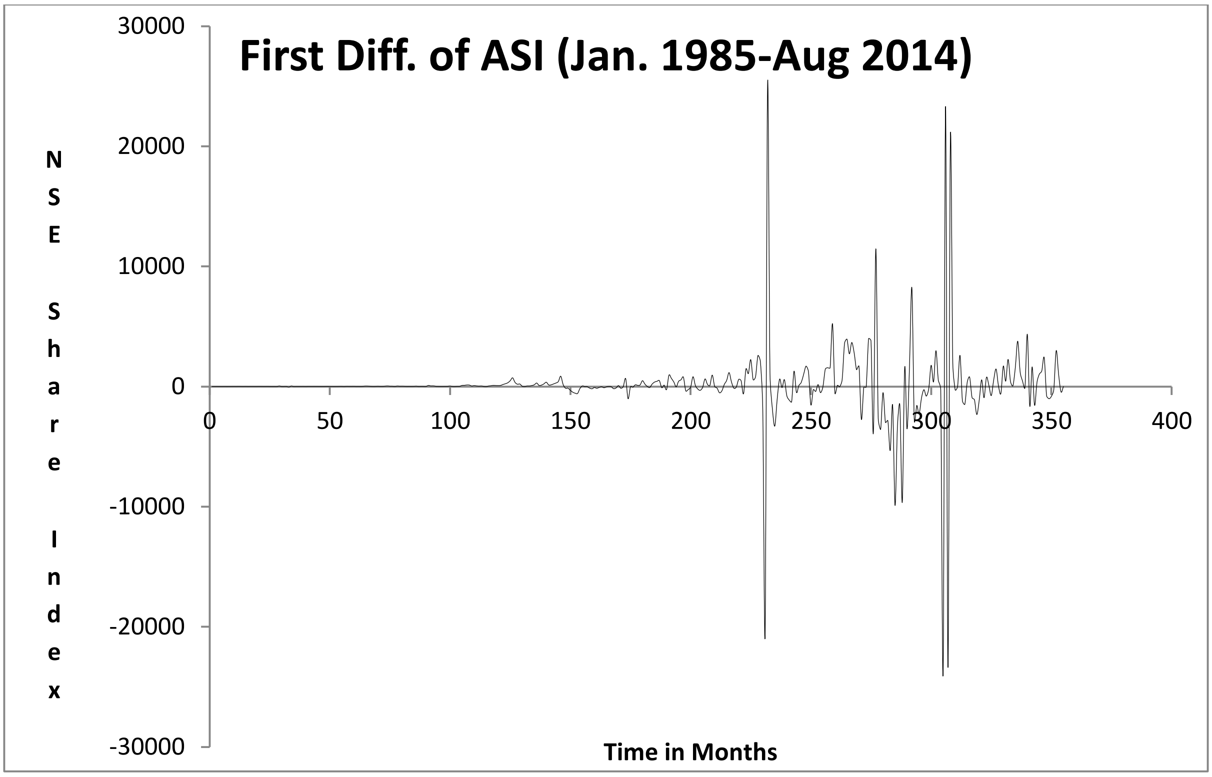


Figure Iii: The Correlogram Of First Differenced Series Of The Monthly All Share Index Of The Nigerian Stock Exchange

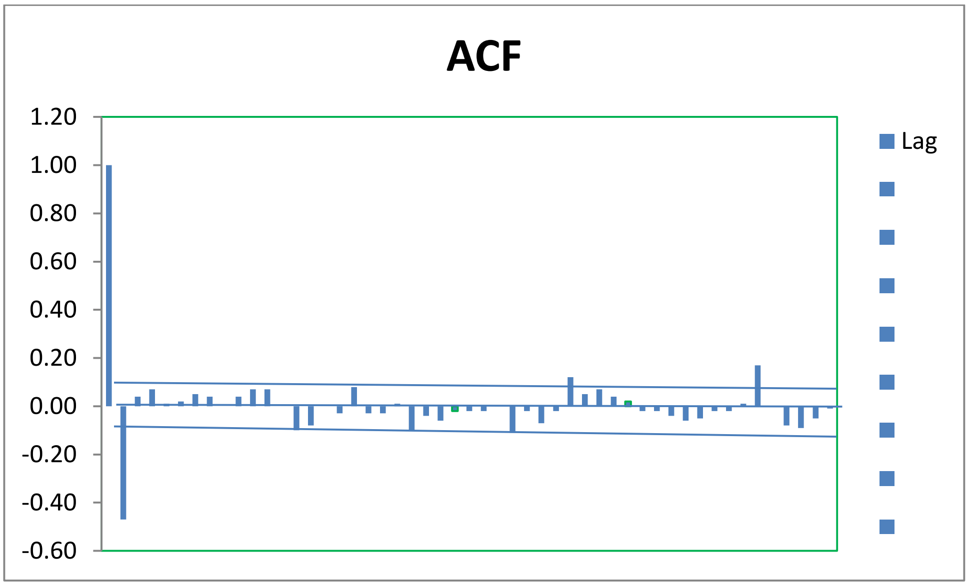
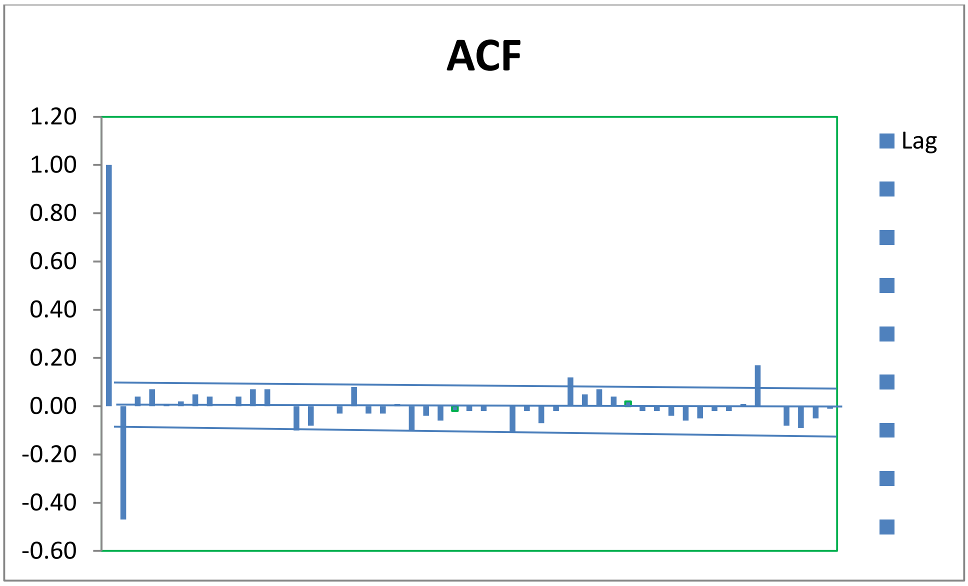


Figure 4.4: Autocorrelogram of First Differenced Series of The Monthly All Share Index



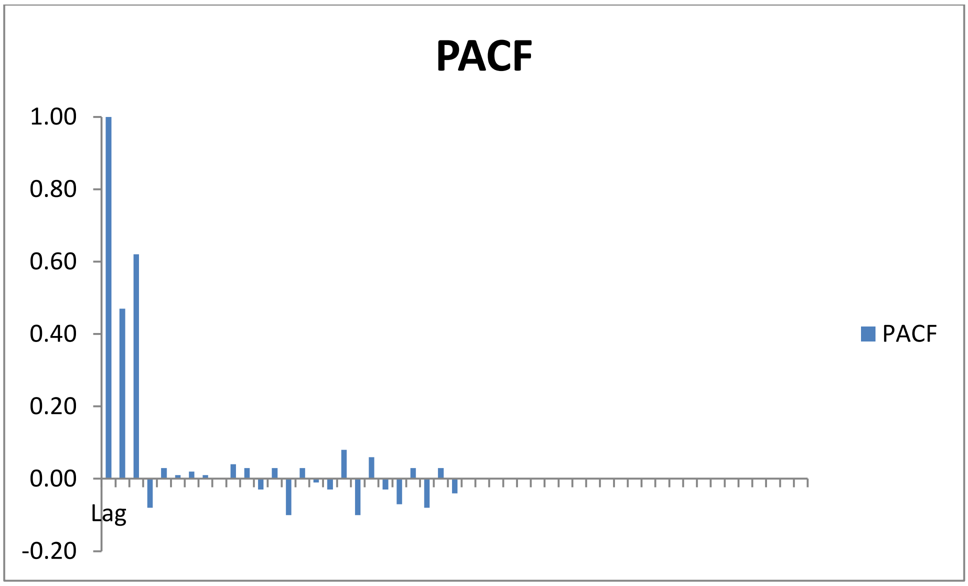


Figure 5: Autocorrelogram and Partial Autocorrelogram of First Differenced Series of The Monthly All Share Index