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# On Investigative Study of All Share Index of Nigerian Stock Exchange Using GARCH Model Approach

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***Abstract:***
*Most time series analysis have used different technical and fundamental approach in modeling result varies base on the approach used or applied. In these view, the aim of this study is to investigate the all Share Index of the Nigeria Stock Exchange rate using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach and to test the existing models and select the best model for the data.*
*An upwards trend was observed from the time plot of the original series from the quarters along the years. The autocorrelation function plot of the original data was plotted to confirm the presence of seasonal variation in the data, the ACF plot indicated that the data is seasonal since there is significant spikes at equal interval in the plots. The model of best fit was identified to be Autoregressive model of order 1. The model suitability was judged using Akaike Information Criterion (AIC), Log Likelihood and Mean Square Error (MSE). The model with the lowest AIC is known to be the model of best fit. The ARIMA (1, 1, 3) has the lowest Akaike Information Criterion (AIC), the lowest Sigma square (MSE), lowest BIC and the Log Likelihood.*
*The coefficient of GARCH (-1): is positive and statistically significant.As the GARCH coefficient value is higher than the ARCH coefficient value, we can conclude that the volatility is highly persistent and clustering.*
*The forecast shows that there will be increase in All Share index of the Nigeria Stock Exchange.*
*It was suggested that the activities of the Nigeria stock exchange should be made more transparent as this will bring about confidence in the mind of investors and people will be encouraged to invest.*
***Key Word:*** *Autocorrelation, AIC, Forecast, Heteroscedasticity, Time plot, Volatility*

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## I. Introduction

Time-series analysis methods in general combine various statistical and pattern recognition techniques while using information presented in the time-ordering of samples. Historically, time-series analysis is divided by two major fields of study: the first is explorative and descriptive analysis and the second is forecasting. While the descriptive analyses focus on the understanding of the time-series generating processes itself by finding trends, periodicity and some hidden features within the time-series, the predictive analyses aim at forecasting the future of the time-series generating process based on the information found by conducting descriptive analyses. Both descriptive and predictive analyses are based on the identification of some pattern in the time-series which can be formally described and can correspond to the time-series generating process.

In Nigeria, the Nigerian Stock Exchange (NSE) was established in 1960 as Lagos Stock Exchange which started operation in 1961. It is one of the major stock markets in sub-Saharan Africa. Nevertheless, one of the principal objectives for establishing the Nigerian Stock Exchange is to provide an avenue for investors to buy and sell securities.

However, within the last decade the behaviour of the market has become unpredictable as a result of dwindling economic growth thereby affecting investors' confidence to continuously invest in the stock market.

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 [2]. 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.

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 [24].

The stock market of any country provides an avenue (trading facilities and the enabling environment) for participants including individual and institutional investors to exchange their holdings such as equity and debt securities. Put differently, a stock exchange is an organised institution where the securities of companies listed on such an exchange are traded freely. The key function of the stock market is to act as an intermediary between savers and borrowers. The stock market in any country is very vital to economic growth and development because it mobilizes the domestic resources in the economy and channels them to productive investments. The gauge of the stock market performance is its market index and a number of factors influence this movement ranging from economic, political, socio-cultural and international [23].

Arguably, some fundamental macroeconomic variables such as interest rate, exchange rate, inflation rate, etc could play major roles in determining stock prices or stock market index movement. It has been noted in some financial jurisdictions that monetary policy and macroeconomic events had a great influence on the volatility of stock prices. This means that macroeconomic variables may influence investors in deciding whether or not to invest on stocks and shares [12].

The essence of this research work is to determine the trend of All Share Index (ASI) of the Nigeria Stock Exchange (NSE) during the period of January 2001 to December 2020 and to develop a predictive model for future occurrences.

Over the past three decades, Nigeria has implemented numerous policy initiatives and measures in the management of its Stock market. Although very little was achieved because the structure in place could not support sustainable Stock market management.

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 of value of a section of the stock market.

This study will emphasize on the issues of modelling on the Nigeria Stock Exchange in Nigeria using GARCH model approach in order to make a reasonable decision.

There are so many literatures abound in GARCH modeling on stock market returns in several countries.

The stock market is the focus of investment analysts, economists and policy makers because it may be relied upon to measure changes in general economic activities using the stock prices of listed companies of the Nigerian Stock Exchange (NSE). [18] mentioned that the stock market provides the fulcrum for capital market activities and it is often cited as a barometer of business direction. The saving sector needs to employ their savings in more beneficial and ambitious projects and the productive sectors always require financial sources to assist them to perform more in the economy. Stock market performance helps to transfer funds from people who have amassed surplus to those who have a paucity of funds [15].

GARCH models usually indicate a high persistence of the conditional variance. The Autoregressive Conditional Heteroscedasticity (ARCH) as well as the GARCH models captures volatility clustering and leptokurtosis. In situations where their distributions are symmetric, they fail to model the leverage effect. To address this problem, many nonlinear extensions of GARCH have been proposed, such as the Exponential GARCH (EGARCH), Glosten-Jagannathan-Runkle GARCH (GJR-GARCH), Power GARCH (PGARCH) and Threshold GARCH(TGARCH). Thus, the estimates of a GARCH model in the persistence parameter may suffer from a substantial upward bias. Therefore, models in which the parameters are allowed to change over time may be more appropriate for modeling volatility [8].

[26] studied the Weak-form efficient market hypothesis of Ghana, Mauritius, Egypt and South Africa. Their results show that the South African stock market is weak form efficient, whereas the other markets are weak form inefficient. Their results imply that the stock returns from the Ghana, Mauritius and Egypt are predictable from historical prices. Hence, they fitted an ARIMA model (Egypt ARIMA (*1, 0, 1*); Ghana (*1, 0, 2*); and Mauritius (*2, 0, 1*)) to the excess return data of the three markets using the Box-Jenkins method. They used the ARIMA model to generate one-period forecasts for the subsequent 12 periods for these three countries. The ARIMA forecasts in all the markets outperformed the naïve Model.

In a similar study, [22] used ARIMA (*1, 0, 1*) among other tests to examine the weak form efficiency of the Dhaka Stock Exchange. Their results reject the null hypothesis of random walk for all share index and general price index. On the basis of Akaike's Information Criterion, R2, and Autocorrelation Functions, they found ARIMA (*3,0,2*) and ARIMA (*1,0,1*) respectively, as the best fitted model with all coefficients significant at 1% level of significance. They divided their sample data into two sub-samples. The first sub-sample was named historical period: the second sub-sample was named validation period. Then they employed ARIMA (*3,0,2*) and ARIMA (*1, 0, 1*) to generate data for the validation period and examine how the fitted value deviates from the actual values. They found that the fitted values derived from the models and actual data is all but well fitted.

[21] also carried out a study on stock market prices and the random walk hypothesis, He employed run test and the correlogram/ partial autocorrelation function, and the result showed that the Nigerian stock market is efficient in the weak form. For time lag and a different Instrument GARCH (1.1) that can handle volatility clustering, give a significant reason for recon ducting this study, taking a detailed empirical examination of the randomness of stock prices on the Nigerian stock exchange (1985- 2011).

[4] examined the univariate ARIMA forecasting model on the Amman Stock Exchange (ASE) general daily index between 4/1/2004 and 10/8/2004; with out-of-sample testing undertaken on the following seven days. Four diagnostic tests were performed to select the best model describing the data, namely: R-square, adjusted R-square, Akaike's Information Criterion (AIC), and Schwarz Information Criterion (SIC). On the basis of these four diagnostic tests, ARIMA (*4, 1, 5*) model was chosen as the best model that explains the data and is suitable for accurate forecasting. The selected model predicted that the ASE would continue to grow by 0.195% for seven days starting on 11/8/2004. This forecast, however, was not consistent with actual performance during the period of the prediction since the ASE declined by 0.003%. He concluded that the forecast error implies the ASE tends towards weak form efficiency.

[25] focused on measuring forecast performance of ARIMA (p,d,q) and ARFIMA (p,d,q) models for stationary type series that exhibit Long memory properties. They analyzed UK Pound/US Dollar exchange rate data using the Root mean Square forecast Error (RMSFE) and Mean Absolute Percentage Forecast Error (MAPFE) as measurement criteria, for a period ranging from January 1971 to December 2008. They found ARFIMA (*3,d,0*) model to be better than ARMA(*4,0*) model using residual variance of the model. They concluded that the estimated forecast values from ARFIMA model is more realistic and closely reflect the current economic reality in the two countries as indicated by the forecast evaluation tools and that although some series may appear to be stationary and supported by ADF test, they could still exhibit the characteristics of long memory process. They therefore recommended efficient data exploratory exercise before carrying out time series data analysis as this would reveal all the hidden characteristics of the series which could assist in the choice of the appropriate model that would yield optimal forecast values.

Similarly, from the ARIMA scheme's perspective of forecasting the Nigerian stock market returns, [19] studied the estimation and performance of subset autoregressive integrated moving average (ARIMA) models. They estimated parameters for ARIMA and subset ARIMA processes using numerical iterative schemes of Newton-Raphson and the Marquardt- Levenberg algorithms. The performance of the models and their residual variance were examined using AIC and BIC. The result of their study showed that the SARIMA model outperformed the ARIMA model with smaller residual variance. On the other hand, [11] studied the NSE market returns series using monthly data of the All-Share-Index for the period January 1985 through December 2008. In his study, an ARIMA (1,1,1) model was selected as a tentative model for predicting index points and growth rates. The results revealed that the global meltdown destroyed the correlation structure existing between the NSE All-Share-Index and its past values. [2] also studied the daily returns process of the Nigerian Stock Market using Discrete Time Markov Chains and martingales. Their study provided evidence that the daily stock returns process follows a random walk, but that the stock market itself is not efficient even in weak form.

[10] examined the volatility of daily stock returns of Nigerian insurance stocks using twenty six insurance companies' daily data from December 15, 2000 to June 9, 2008 as training data set and from June 10, 2008 to September 9, 2008 as out-of sample data sets. Their result of ARCH (1), GARCH (1, 1) TARCH (1, 1) and EGARCH (1, 1) shows that in model evaluation and out-of-sample forecast of stock price returns, EGARCH is more suitable as it performed better than other models.

[3] used ARIMA model for rainfall forecasting in Baghdad, Iraq. In this study, rainfall forecast for four years was achieved showing similar trends compared to the original data. [14] used a SARIMA model for rainfall forecasting in the Mahanadi River

[5] worked on Stock Price Prediction Using ARIMA Model. They applied ARIMA model to build a stock price predictive model using published data from New York Exchange and Nigerian Stock Exchange. Their Research showed that the ARIMA model was strong for short term prediction of stock prices.

Time series analysis is one of the best methods of analyzing stock market because the data are collected on daily basis ordered by time. A time series is a set of data collected at equal intervals. In finance, time series data could be data on daily exchange rate, daily shares prices, daily shares index and so on. Time series data could be stationary or non-stationary. A sequence or series is stationary or strictly stationary if there is no systematic change in its mean and variance. This stationarity calls for volatility model. Thus, the volatility of stock markets has been the object of numerous developments and applications over the past two decades. In this respect, the most widely used class of time series models is certainly that of generalized autoregressive conditional heteroscedastic (GARCH) [16].

[13] used SARIMA model for forecasting of mean monthly reference crop evapo-transpiration in Bokaro (India). [7] indicated the best performance of hybrid wavelet neural network models in drought forecasting in the Awash River Basin (Ethiopia). [28] forecasted water demand of the Calgary City (Canada) using extreme learning machines (ELM). This study showed a greater overall performance of hybrid wavelet transformed ELM (WA-ELM) model as compared to the ELM model. Using a boosting ensemble multi-wavelet extreme learning machine (Multi-WA-ELM) model improved water quality forecasting as compared to individual WA-ELM and ELM models [6].

[20] studied the Prediction of Returns on All-Share Index of Nigerian Stock Exchange using monthly return share index from 1985 to 2014. They applied Box-Jenkins approach to evaluate the data. Their research revealed that ARIMA (1, 1, 2) model fitted the data and residuals from the estimated model appeared uncorrelated.

The extreme learning machine model has shown better forecasting ability as compared to the support vector machine model for forecasting monthly groundwater levels at two observation wells located in Canada [28]. A hybrid least square support vector regression-gravitational search algorithm (HLGSA) was successfully used for predicting monthly river flows in Astor and Shyok catchments (Pakistan) [1]. [30] have demonstrated the importance of the use of different climate phenomenon indices together with different artificial intelligence techniques for reservoir monthly inflow forecasting.

[17] showed that for each monthly stream flow and water temperature series, seasonal differencing in ARIMA models is the best stationarization method in terms of periodic effect elimination and model forecasting accuracy as compared to seasonal standardization and spectral analysis. The SARIMA model also performed best among Thomas-Fiering and Spectral Analysis types of stochastic mathematical models in forecasting flow of five rivers in the Atrak basin, north-eastern Iran [27].

Furthermore, this study will adopts a modified version of time series on monetary approach to balance of payments in order to analyze the determinants of foreign reserves in Nigeria.

## II. Material And Methods

In this study, time plots for All Share Index on the Nigeria Stock Exchange will display series of cyclical behavior and this is due to seasonal changes from month to month across the year.

GARCH is a statistical model used in analyzing time-series data where the variance error is believed to be serially autocorrelated. GARCH models assume that the variance of the error term follows an autoregressive moving average process. It adds three new hyper-parameters to specify the autoregression (AR), differencing (I) and moving average (MA) for the seasonal component of the series, as well as an additional parameter for the period of the seasonality.

The plots of the AC and PAC neither decay exponentially to zero or cut off which is a characteristic of autoregressive (AR) model. The reverse, does not suggest moving average (MA) also. The two corellograms exhibit characteristics of autoregressive moving average (ARMA) based on the inability to display a characteristic pattern, which suggests it to be a mixed model of AR and MA. Model order is determined based on the minimum value of Akaike Information (AIC) criterion. For each of the series, a grid search over all possible values of (p,q), (that is the order of autoregression and moving average) will set up and the corresponding model orders that give minimum Information values (AIC) are picked.

**Generalized Autoregressive Conditional Heteroskedasticity (GARCH)**

Although GARCH models can be used in the analysis of a number of different types of financial data, such as macroeconomic data, financial institutions typically use them to estimate the volatility of returns for stocks, bonds, and market indices. They use the resulting information to help determine pricing and judge which assets will potentially provide higher returns, as well as to forecast the returns of current investments to help in their asset allocation, hedging, risk management, and portfolio optimization decisions.

GARCH models are used when the variance of the error term is not constant. That is, the error term is heteroskedastic. Heteroskedasticity describes the irregular pattern of variation of an error term, or variable, in a statistical model.

Essentially, wherever there is heteroskedasticity, observations do not conform to a linear pattern. Instead, they tend to cluster. Therefore, if statistical models that assume constant variance are used on this data, then the conclusions and predictive value one can draw from the model will not be reliable. The variance of the error term in GARCH models is assumed to vary systematically, conditional on the average size of the error terms in previous periods. In other words, it has conditional heteroskedasticity, and the reason for the heteroskedasticity is that the error term is following an autoregressive moving average pattern. This means that it is a function of an average of its own past values.

An ARCH (m) process is one for which the variance at time t is conditional on observations at the previous *m* times, and the relationship is;

$$\mathrm{Var}_{(yt|yt-1,\ldots,yt-m)}=\sigma_t^2=\alpha_0+\alpha_1 y_{t-1}^2+\cdots+\alpha_m y_{t-m}^2$$

with certain constraints imposed on the coefficients, the $y_t$ series squared will theoretically be AR(m).

A GARCH model uses values of the past squared observations and past variances to model the variance at time t. As an example, a GARCH(1,1) is

$$\sigma_t^2=\alpha_0+\alpha_1 y_{t-1}^2+\beta_1\alpha_{t-1}^2$$

In the GARCH notation, the first subscript refers to the order of the $y^2$ terms on the right side, and the second subscript refers to the order of the $\sigma^2$ terms.

## III. Result

The data for the study is a secondary data. It is a yearly All Share Index of the Nigeria Stock Exchange from January 2000 to December 2019. This makes the data point to be 240. It was sourced from the Central Bank of Nigeria Statistical Bulletin

**Table 1:Table of the Original data on All Share Index of the Nigeria Stock Exchange from January 2000 to December 2019**

| YEAR | JAN | FEB | MAR | APR | MAY | JUN | JUL | AUG | SEPT | OCT | NOV | DEC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 | 22,594.00 | 22,985.00 | 25,966.25 | 26,453.20 | 26,183.21 | 25,384.14 | 25,844.18 | 24,268.24 | 23,050.59 | 25,042.16 | 24,764.65 | 24,770.52 |
| 2011 | 26,830.67 | 26,016.84 | 24,621.21 | 25,041.68 | 25,866.62 | 24,980.20 | 23,826.99 | 21,497.61 | 20,373.00 | 20,934.96 | 20,003.36 | 20,730.63 |
| 2012 | 20,875.83 | 20,123.51 | 20,652.47 | 22,045.66 | 22,066.40 | 21,599.57 | 23,061.38 | 23,750.82 | 26,011.64 | 26,430.92 | 26,494.44 | 28,078.81 |
| 2013 | 31,853.19 | 33,075.14 | 33,536.25 | 33,440.57 | 37,794.75 | 36,164.31 | 37,914.33 | 36,248.53 | 36,585.08 | 37,622.74 | 38,920.85 | 41,329.19 |
| 2014 | 40,571.62 | 39,558.89 | 38,748.01 | 38,492.13 | 41,474.40 | 42,482.48 | 42,097.50 | 41,532.31 | 41,210.10 | 37,550.24 | 34,543.05 | 34,657.15 |
| 2015 | 29,562.07 | 30,103.81 | 31,744.82 | 34,708.11 | 34,310.37 | 33,456.83 | 30,180.30 | 29,684.84 | 31,217.77 | 29,177.72 | 27,617.45 | 28,642.25 |
| 2016 | 23,916.15 | 24,570.73 | 25,306.22 | 25,062.41 | 27,663.16 | 29,597.79 | 28,009.93 | 27,599.03 | 28,335.40 | 27,220.09 | 25,333.39 | 26,874.62 |
| 2017 | 26,036.24 | 25,329.08 | 25,516.34 | 25,758.51 | 29,498.31 | 33,117.48 | 36,864.71 | 35,504.62 | 35,439.98 | 36,680.29 | 37,944.60 | 38,243.19 |
| 2018 | 44,343.65 | 43,330.54 | 41,504.51 | 41,268.01 | 38,104.54 | 38,278.55 | 37,017.78 | 34,848.45 | 32,766.37 | 32,466.27 | 30,874.17 | 31,430.50 |
| 2019 | 30,557.20 | 31,721.76 | 31,041.42 | 29,159.74 | 31,069.37 | 29,966.87 | 29,851.29 | 27,525.81 | 27,630.56 | 26,355.35 | 27,002.15 | 26,842.07 |

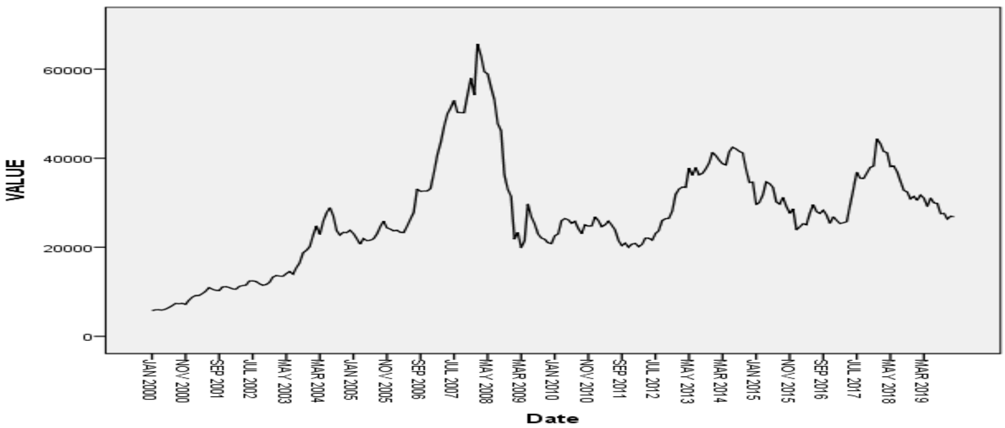


**Figure 3.1:Time plot of the original data**

The plot above shows the All Share Index of the Nigeria Stock Exchange for a period of 20 years, the record slander between January 2000 to December 2019. It can be observed from the time plot.

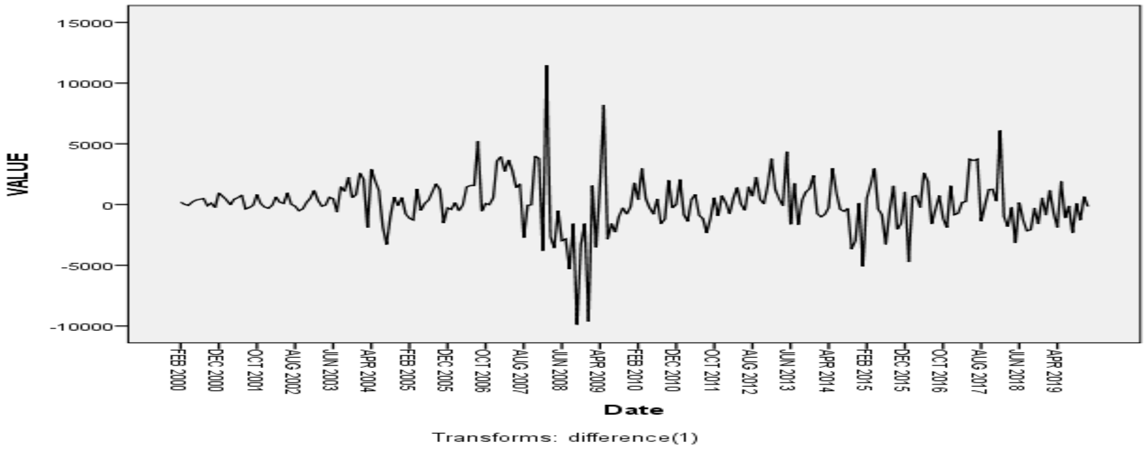


**Figure 3.2:Time plot of the difference data**

The figure above depicts the time plot of the All Share Index of the Nigeria Stock Exchange after the first difference.

## 3.2 Autocorrelation Function and Partial Autocorrelation Function

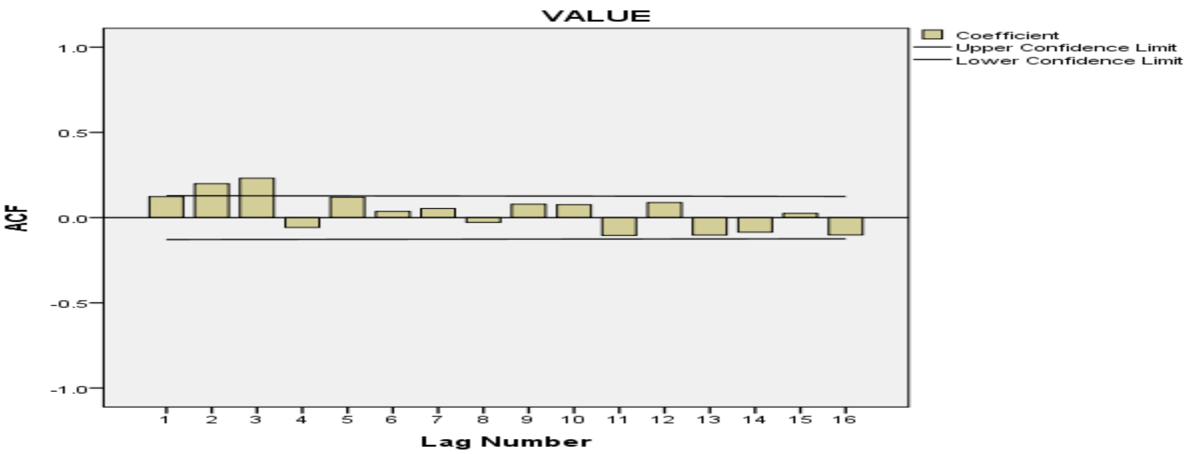


**Figure 3.3: Autocorrelation Function**

The figure above shows the ACF plot.On this plot, there is a significant correlation at lag 1 followed by correlations that are not significant. This pattern indicates an autoregressive term of order 1.

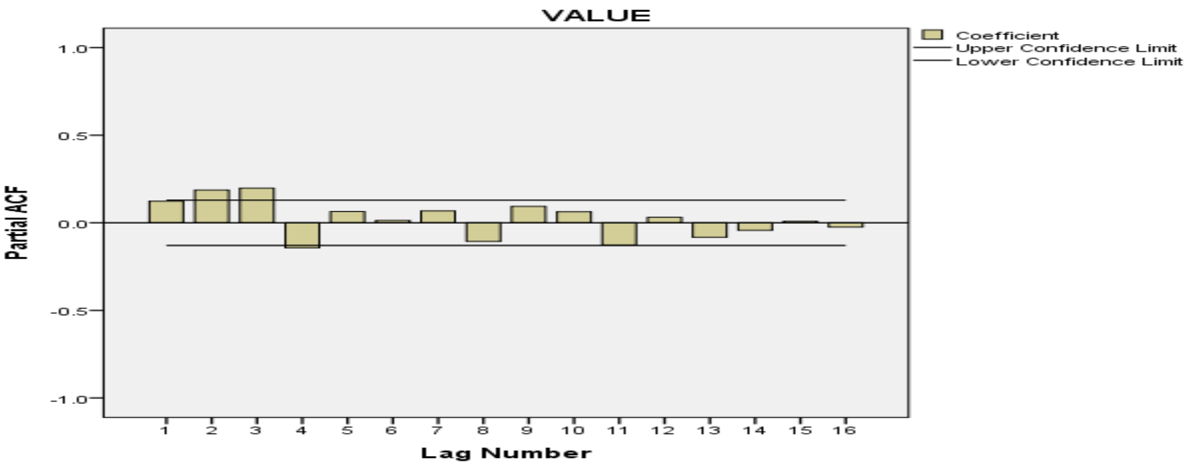


**Figure 3.4: Partial Autocorrelation Function**

The figure above shows the Partial Autocorrelation Function plot.On this plot, there is a significant correlation at lag 1 that decreases after a few lags. This pattern indicates an autoregressive term**.**

### 3.3: Fitting of the ARIMA models

The lags suggested for the Autoregressive and the Moving average terms by the correlograms obtained for the autocorrelation and partial autocorrelation functions are used to fit the models presented below.

**Table 3.2: Estimating Models Parameters**

| Fitted ARIMA models | BIC |
|---|---|
| ARIMA (0,1,1) | 15.389 |
| ARIMA (1,1,0) | 15.385 |
| ARIMA (1,1,1) | 15.374 |
| ARIMA (1,1,2) | 15.381 |
| ***ARIMA (1,1,3)*** | ***15.367*** |
| ARIMA (1,1,4) | 15.394 |
| ARIMA (2,1,1) | 15.387 |
| ARIMA (2,1,2) | 15.471 |
| ARIMA (2,1,3) | 15.392 |

From Table 3.2 ARIMA (1,1,3) exhibits the lowest BIC, hence it is chosen as the best suitable model for forecasting.

### 3.4 Estimates of the Parameters of the Identified Model

The maximum likelihood estimates of the parameters of the models for exchange rate were obtained with the aid of a SPSS statistical software. The results obtained are as given in table below.

**Table 3.3: ARIMA (1,1,3) Model Parameters**

| ARIMA Model Parameters | | | | | Estimate | SE | t | Sig. |
|---|---|---|---|---|---|---|---|---|
| VALUE-Model_1 | VALUE | No Transformation | Constant | | 87.645 | 190.706 | .460 | .646 |
| | | | AR | Lag 1 | -.489 | .196 | -2.493 | .013 |
| | | | Difference | | 1 | | | |
| | | | MA | Lag 1 | -.602 | .190 | -3.174 | .002 |
| | | | | Lag 2 | -.239 | .074 | -3.228 | .001 |
| | | | | Lag 3 | -.303 | .063 | -4.836 | .000 |

Hence, the ARIMA (1,1,3) can be written mathematically as

$X_t = \quad -0.489X_{t-1} + \varepsilon_t - 0.602\varepsilon_{t-1} + 0.239\varepsilon_{t-2} + 0.303\varepsilon_{t-3}$

### 3.5: GARCH Analysis

**Table 3.4: Parameter Estimate of GARCH (1,1)**

| Variable | Coefficient | Std. Error | z- Statistic | Prob. |
|---|---|---|---|---|
| C | 8.370855 | 1.058446 | 7.908626 | 0.0000 |
| RESID(-1)^2 | 0.258358 | 0.030466 | 8.480263 | 0.0000 |
| GARCH | 0.826311 | 0.013728 | 60.18964 | 0.0000 |

**Table 3.5: Maximum likelihood estimates of AR(1)-GARCH(1,1) model for All Share Index**

| Prob. (f-stat.) | Mean Dependent Variable | S.D. Dependent Variable | AIC | Schwarz Criterion (BIC) | Hannan-Quinn Criterion |
|---|---|---|---|---|---|
| 0.0000 | 63.79659 | 111629.607 | 14.71847 | 14.74738 | 14.72990 |

The table 3.5 above shows that the ARCH term (the coefficient of RESID (-1)^2) is negative and statistically not significant.The Leverage Effect (C) is positive and statistically significant (indicating presence of leverage effect). GARCH term (the coefficient of GARCH(-1)) is positive and statistically significant. As the GARCH coefficient value is higher than the ARCH coefficient value, we can conclude that the volatility is highly persistent and clustering.

### 3.6 Hypothesis Testing

$H_0$: Unit Root exists
$H_1$: Unit Root does not exist

Decision rule: Reject $H_0$ if $F_{cal}$ is greater than $F_{tab}$ otherwise do not reject.
Since $F_{cal}$ (38.11435) is greater than $F_{tab}$ (0.05), therefore reject $H_0$

Conclusion: Unit root does not exist.

### 3.7 Forecasting

Forecasts using ARIMA (1,1,3) for the next four years:
Since the model is tested adequate, next is to make forecast using the various estimated model. The forecast Nigeria stock exchange rate for the period of 20 years is represented with the first 20 rows in Tables 4.4 for quarterly stock exchange rate.

**Table 3.6: Table showing the Forecast for the next four years**

| Month | Forecast | LCL | UCL |
|---|---|---|---|
| Jan-20 | 26623 | 22581 | 30664 |
| Feb-20 | 27061 | 21011 | 33110 |
| Mar-20 | 26780 | 18775 | 34785 |
| Apr-20 | 27048 | 16980 | 37116 |
| May-20 | 27048 | 15486 | 38610 |
| Jun-20 | 27178 | 14202 | 40155 |
| Jul-20 | 27245 | 13035 | 41454 |
| Aug-20 | 27343 | 11980 | 42705 |
| Sep-20 | 27425 | 10999 | 43852 |
| Oct-20 | 27516 | 10086 | 44945 |
| Nov-20 | 27602 | 9227 | 45977 |
| Dec-20 | 27690 | 8414 | 46967 |
| Jan-21 | 27778 | 7641 | 47914 |
| Feb-21 | 27865 | 6904 | 48827 |
| Mar-21 | 27953 | 6198 | 49708 |
| Apr-21 | 28041 | 5519 | 50562 |
| May-21 | 28128 | 4866 | 51390 |
| Jun-21 | 28216 | 4236 | 52195 |
| Jul-21 | 28304 | 3627 | 52980 |
| Aug-21 | 28391 | 3037 | 53745 |
| Sep-21 | 28479 | 2465 | 54493 |
| Oct-21 | 28566 | 1908 | 55224 |
| Nov-21 | 28654 | 1368 | 55941 |
| Dec-21 | 28742 | 841 | 56643 |
| Jan-22 | 28829 | 327 | 57332 |
| Feb-22 | 28917 | -174 | 58008 |
| Mar-22 | 29005 | -663 | 58673 |
| Apr-22 | 29092 | -1142 | 59326 |
| May-22 | 29180 | -1610 | 59970 |
| Jun-22 | 29268 | -2068 | 60603 |
| Jul-22 | 29355 | -2517 | 61227 |
| Aug-22 | 29443 | -2957 | 61842 |
| Sep-22 | 29531 | -3388 | 62449 |

| | | | |
|---|---|---|---|
| Oct-22 | 29618 | -3811 | 63048 |
| Nov-22 | 29706 | -4227 | 63639 |
| Dec-22 | 29794 | -4635 | 64223 |
| Jan-23 | 29881 | -5037 | 64799 |
| Feb-23 | 29969 | -5431 | 65369 |
| Mar-23 | 30056 | -5819 | 65932 |
| Apr-23 | 30144 | -6201 | 66489 |
| May-23 | 30232 | -6577 | 67041 |
| Jun-23 | 30319 | -6947 | 67586 |
| Jul-23 | 30407 | -7312 | 68126 |
| Aug-23 | 30495 | -7671 | 68660 |
| Sep-23 | 30582 | -8025 | 69190 |
| Oct-23 | 30670 | -8374 | 69714 |
| Nov-23 | 30758 | -8718 | 70233 |
| Dec-23 | 30845 | -9058 | 70748 |

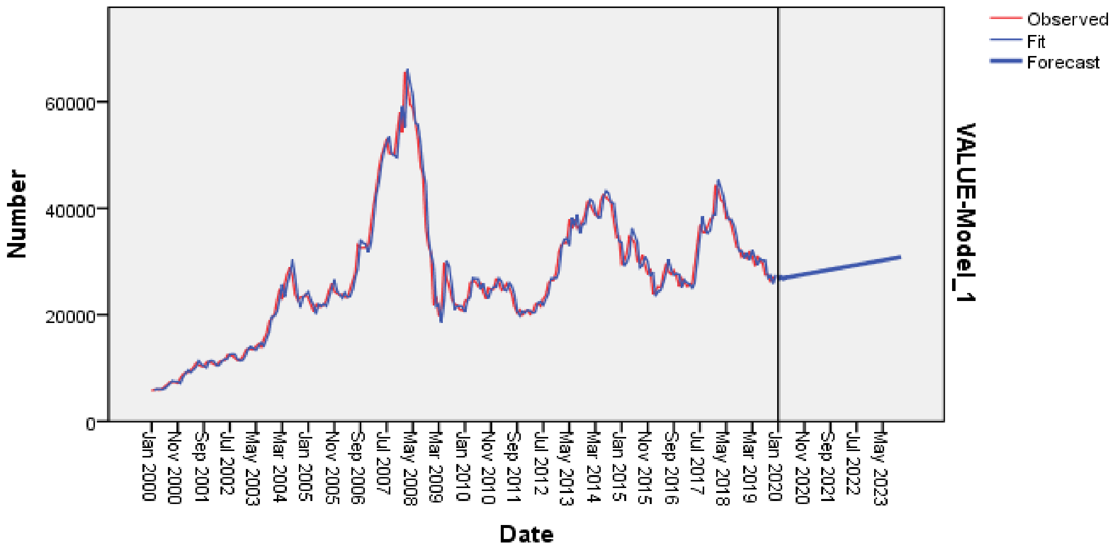


**Fig 3.5 Time plot of the Forecast for the next four years**

The figure above depicts the time plot of the Forecast of the All Share Index of the Nigeria Stock Exchange for the next four years.

## IV. Conclusion

This study examined the time series analysis on the All Share index of the Nigeria Stock Exchange rate between 2000 and 2019 using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model.

An upwards trend was observed from the time plot of the original series from the quarters along the years. The autocorrelation function plot of the original data was plotted to confirm the presence of seasonal variation in the data, the ACF plot indicated that the data is seasonal since there is significant spikes at equal interval in the plots.

The modeling cycle was in three stages, the first stage was model identification stage, where the series was not non-stationary at level from base on the result provided by ADF test on the coefficient of AR(1) model and time plot. It was found out that the series was not stationary at the initial stage. Base on the selection criteria AIC, reports show that ARIMA, report show that ARIMA (1, 1, 3) was selected and to be the best model to fit the data. The second stage was the GARCH model estimation, GARCH term - the coefficient of GARCH (-1): is positive and statistically significant.

As the GARCH coefficient value is higher than the ARCH coefficient value, we can conclude that the volatility is highly persistent and clustering.

An out sample forecast for period of four years of four Quarters term was made, and this shows that there will be increase in All Share index of the Nigeria Stock Exchange.

The current and past value of real interest has a positive relationship with the Stock Exchange.

The selected model was found to be adequate for short term forecast of the monthly stock market returns from Nigeria Stock Exchange. The forecast from the market showed a future bearish market to persist and investor are advised to weigh the risks before investing. The All Share Index of the Nigerian Stock Exchange is non-random. The investigations show that the series is void of seasonal component.

Hence, the result obtained indicate that the forecast show an upward movement along the along the months of the year. Also, both developing and developed economics, stock exchange management plays a very important role in economic performance and hence serves as an anchor for the determination of both domestic and foreign trade balance.

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