



Modeling and Comparison of the Nigerian All Share Index Using ARIMA and Hybrid ARIMA-GARCH Models

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ABSTRACT

In this Paper, the performance of the Autoregressive Integrated Moving Average (ARIMA) and hybrid Autoregressive Integrated Moving Average Generalized Autoregressive Conditional Heteroscedastic (ARIMA-GARCH) models was compared using daily data (Five working days) of the Nigeria stock exchange data stream. There are 4610 share price index between the 14th January 2005 and 14th September 2023. An attempt was made to make the share price index data stationary. The ARIMA model's residuals and squared residuals were subjected to the Box-Ljung, Box-Pierce, and McLeod-Li tests. These tests demonstrated that the ARIMA model's residuals possessed a conditional variance, or volatility. The volatility was then modeled using the GARCH model. The fitted ARIMA model was obtained using the Box-Jenkins technique, and the hybrid ARIMA-GARCH model was utilized to capture the sequences' volatilities. The results indicate that in terms of the lowermost Akaike information criteria (AIC) and Mean absolute error (MAE), the best ARIMA out of the ARIMA models verified was ARIMA (2, 1, 2). The comparison of ARIMA (2, 1, 2) with hybrid (ARIMA-GARCH) in terms of the uppermost maximum likelihood (ML), lowermost AIC and MAE indicates that the hybrid model is the best. Therefore, the study recommends that the Nigerian financial markets should replace the application of ARIMA only with ARIMA-GARCH in modelling Nigeria all share price index data.

Keywords: ADF, AIC, ARIMA, GARCH, ARIMA-GARCH

1.0 INTRODUCTION

A stock exchange or securities market has been defined by (Shah et al., 2019) as market places where securities may be bought and sold for either investment or speculation. Stock market forecast stresses on developing an effective modeling approach for projecting index values or stock values (Ghezolbash and Keynia, 2014). The vital key to positive stock market forecast is realizing desired outcomes and also to reduce the imprecise prediction of stock value. However, nowadays, in developing countries, growth of the fiscal system is considered an exceptional way to funding economic growth and holds the progress of monetary institutions and economic markets (Bonga & Ozili, 2025).

The stock index as it forms and represents the significant part of every financial institutions and economy is the mirror that reflect the hope, strength and future of most economy (Zhang, 2024). The index also inform the policy makers any improvement or otherwise in the economy. Therefore, as one of the determinants of most developing economy, the learning of the performance of stock index is imperative. Nigeria stock index was dominated by period deterministic trends, regime switching, long memory and volatility. Therefore, these create uncertainties in the mind of market participants and investors (Francq & Zakoian, 2022). In Nigeria, however, some published studies on stock index and

prices focuses on the mean models like (Aribisala, 2014). In time series analysis, studying only the mean components is inadequate in estimating a reliable model for forecasting stock index (Qiu, et al., 2025). This paper therefore, improve and extends the existing application of ARIMA model on the Nigeria financial markets by combining the ARIMA and GARCH models using the ARIMA model to study the trend and GARCH model to cover heteroscedasticity for policy making and other decisions.

Babu and Reddy (2014) examined highly volatile time series data from investment market. They emphasized that one of the fundamental research challenges in time series literature is accurately predicting stock market data. The majority of prediction issues focus on one-step forward forecasting, using linear models such as Generalized Auto Regressive Conditional Heteroscedastic (GARCH) and Auto Regressive Integrated Moving Average (ARIMA). When this model's effectiveness is compared to other models, it is shown that the one being proposed performs better than the others in terms of stabilizing data drift and prediction accuracy for multi-step forward forecast.

Sun (2017) examined the highly volatile time series data from the investment market. They highlighted that one of the main challenges in time series literature is correctly anticipating stock market data. The majority of prediction-related problems focus on one-step forward forecasting, using linear models such as



Generalized Auto Regressive Conditional Heteroscedastic (GARCH) and Auto Regressive Integrated Moving Average (ARIMA). When this model's performance is compared to previous models, it is shown that the proposed model performs better than the others in terms of stabilizing data drift and prediction accuracy for multi-step forward forecast (Ayoade, 2024).

Mustapha and Ismail (2019) estimated the ARIMA model that best suited the monthly stock price of the S&P 500 for a period of 17 years, 2001–2017. Their study involved a two-step procedure that involved first identifying the ARIMA model and then fitting GARCH (1, 1) into it. Consequently, it has been discovered that the ARIMA (2, 1, 2)-GARCH (1, 1) model is the best model for anticipating the S&P 500 stock values. According to the study's findings, the hybrid model outperformed the single ARIMA in this regard.

This study aimed to estimate a composite model capable of capturing the properties of Nigerian All Share index. The objectives for achieving our aim was to observe properties of Nigerian All Share index, develop a trend model for the Nigerian All Share index data, incorporate GARCH family to capture volatility in it and examine how well the two models perform.

2.0 MATERIALS AND METHOD(S)

The data for current research was acquired from the Nigeria Stock Exchange data stream. There was 4610 observations between 14th January 2006 and 14th September 2023. Inspired by the works of (Kilani et al., 2025), R statistical software was employed for the data analysis (R Core Team, 2025). The technique creates a nonlinear hybrid time series model through integrating conditional heteroscedasticity GARCH with linear ARIMA. It is critical to do a stationary test prior to model estimations when modeling non-stationary time series. This is crucial because it serve to give a clue picture for selecting the right model for the time series data used in the research. We examine the Augmented Dickey Fuller for stationary test in this work. The unit root test is another name for it.

2.1 Augmented Dickey Fuller (ADF) Test

The ADF test has been suggested by (Dickey & Fuller 1981) with the null hypothesis that the data created in the process is stationary and tested in contradiction of a unit root. The ADF check is conducted by initially considering autoregressive model of order one as follows:

$$y_t = c + \gamma_t + \phi_1 y_{t-1} + \varepsilon_t. \quad (1)$$

The ADF add lagged differences to these models hence

$$\Delta y_t = c + \gamma_t + \phi_1 y_{t-1} + \sum_{i=1}^p \delta_i \Delta y_{t-i} + \varepsilon_t \quad (2)$$

Where c stands as constant, γ the coefficient on a time trend, p the lag order of the autoregressive model and $\varepsilon_t \sim i. i. d(0, \sigma_\varepsilon^2)$ the error (white noise).

2.2 Box-Jenkins Models

The original data collected from time series is investigated and evaluated using time series models called Box-Jenkins models. The Box-Jenkins models presented in the paper are the Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA) models.

2.2.1 Autoregressive (AR) Model

The universal symbol of Yule (1924) autoregressive model of order p , AR (p) is written as:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots + \phi_p X_{t-p} + \varepsilon_t, \quad (3)$$

Where ε_t is the source of randomness and is named white noise. The $\phi_1, \phi_2, \dots, \phi_p$ are unknown constraints relating X_t to X_{t-1}, \dots, X_{t-p} .

2.2.2 Moving Average (MA) Model

Slutzky (1927) introduced the MA model and the representation MA (q) also denotes moving average model of order q is express as:

$$X_t = \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \quad (4)$$

Where $\theta_1, \dots, \theta_q$ are the constraints of the model, and $\varepsilon_t, \varepsilon_{t-1}, \dots, \varepsilon_{t-q}$ are white noise (error terms).

2.2.3 Autoregressive Moving Average (ARMA) Model

The universal ARMA model was designated by Whittle (1951) and it was interpreted in the book of (Box & Jenkins, 1976) as;

$$X_t = \phi_1 X_{t-1} + \dots + \phi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q}. \quad (5)$$

Similarly, it can be written as:

$$\phi(L)X_t = \theta(L)\varepsilon_t, \quad (6)$$

Where $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \dots - \phi_p L^p$ and $\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \dots - \theta_q L^q$. It is well identified that for (6) to be stationary and invertible, the zeros of $\phi(L)$ and $\theta(L)$ must be outer the unit circle respectively.

2.2.4 Autoregressive Integrated Moving Average (ARIMA) Model

Consider non-stationary time series Y_t and supposing the stationary d^{th} order difference of Y_t is represented by $\Delta^d = (1 - L)^d$. Putting Δ^d in (6) yields an ARIMA

model of order p , d and q , represented by ARIMA (p , d , q):

$$\phi(L)(1-L)^d Y_t = \theta(L)\varepsilon_t, d = 1. \quad (7)$$

2.3 Model Diagnostic Checking for ARIMA Model

The graphs for the Auto correlation Function (ACF) and Partial Auto correlation Function (PACF) of the ARIMA residuals, accompanied by a line showing two standard errors on either side of zero, serve as diagnostic checks for the ARIMA model. Box-Ljung Test for assessing the distribution's normality and the Autoregressive Conditional Heteroskedastic (ARCH) effect Testing for serial correlation and heteroscedasticity after model estimate is important for mean and hybrid modeling.. Autocorrelation are determined by the formula:

$$\phi = \sqrt{1 + \frac{2}{\sqrt{n}} \sum_{k=1}^{i-1} r_k^2} \quad (8)$$

Where, n is the number of observations in the series, r_k is the k_i autocorrelation and $\frac{2}{\sqrt{n}}$ is the distance between the lines and zero for all partial autocorrelation.

2.4 GARCH Model

The ARCH model was introduced by (Engle, 1982). Bollerslev (1986) developed an extended model that generalizes the ARCH model called the Generalized Autoregressive Conditional Heteroskedastic model (GARCH). The word "conditional" refers to the degree of interaction with previous observations, while "auto regressive" refers to the response instrument that integrates previous observations into the current. The GARCH(r , s) model's variance equation can be written as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^r \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2, \quad (9)$$

where σ_{t-j}^2 is the volatility at day $t-j$, $\omega > 0$, $\alpha_i \geq 0$ for $i = 1, \dots, r$, and $\beta_j \geq 0$ for $j = 1, \dots, s$, are constraints of the model to be assessed. Under the GARCH(r , s) model, the conditional variance of ε_t , and σ_t^2 , depends on the squared innovations in the previous r periods, and the conditional variance in the preceding s periods.

2.5 ARIMA-GARCH Models

The ARIMA-GARCH models are applied to study concurrently the trend and volatility of a time series. The ARIMA (p , d , q)-GARCH(r , s) model can be defined as follows:

$$\phi(L)(1-L)^d Y_t = \theta(L)\varepsilon_t, d = 1 \quad (10)$$

$$\varepsilon_t | \psi_{t-1} \sim N(0, \sigma_t^2), \quad (11)$$

Where σ_t^2 can be represented as (9) and

$$\psi_{t-1} = Y_1, Y_2, \dots, Y_{t-1}. \quad (12)$$

2.6 Information Criterion

The Akaike Information Criterion (AIC) measures a statistical approach's relative quality of fit just as much as the model's hierarchy. According to (Akaike, 1974), a model's goodness of fit can be assessed by integrating both the number of components in the model and the fit error. It shows how much information is overlooked when using a particular paradigm to establish reality. One might suggest that it clarifies the association between bias and differences in model construction. Although AIC values are utilized specifically for model selection, they are unable to convey the models' goodness of fit. If the all-inclusive candidate models fit poorly, the AIC won't issue any notifications. The AIC formula is:

$$AIC = 2k - 2 \ln(L), \quad (13)$$

Where, L is the maximum value of the likelihood function for the projected model and k is the number of parameters in the statistical model.

2.7 Diagnostic Checking of Hybrid ARIMA-GARCH Model

The diagnostic tests for the hybrid ARIMA-GARCH models are based on residuals. The Jarque-Bera test developed by (Jarque & Bera, 1980) is use in conjunction with the residuals' normality test. The Ljung-Box Q-statistic by (Ljung & Box, 1978)) is used to determine whether autocorrelation exists in the residuals. Similarly, the squared residuals of the autocorrelation function are used for the conditional heteroscedasticity test.

2.7.1 Conditional Heteroscedastic-Lagrange Multiplier Test

According to (McLeod & Li, 1983), the ARCH-Lagrange Multiplier (ARCH-LM) test determines if the residuals produced from fit exhibit a significant reliance. The residual's sequential association was determined using the Ljung-Box statistic, which is expressed as:

$$Q = N(N+2) \sum_{i=1}^N \frac{\rho_i}{(N-i)}, \quad (14)$$

Where the Q statistic has an asymptotic distribution of χ^2 with n degrees of freedom if square residuals is uncorrelated. N is the number of observations and ρ_i is the sample correlation coefficient between squared residuals $\hat{\varepsilon}_t^2$ and $\hat{\varepsilon}_{t-1}^2$. The null hypothesis of square residuals is that: the $\{\hat{\varepsilon}_t^2\}$ are uncorrelated.

2.7.2 Root Mean Square Error (RMSE)

The computation of deviation of forecasting mistakes provides a clear definition of the RMSE. It is computed by taking the square root of the difference between previous and expected data that are averaged over the sample. A better model estimate is indicated

by a less significant RMSE. The RMSE can be obtained using:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t)^2} \quad (15)$$

2.7.3 Mean Absolute Error (MAE)

When evaluating a time series model's accuracy fit, the MAE is typically employed. It can be presented as:

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i| \quad (16)$$

3.0 RESULTS AND DISCUSSION

This section presents the results of the study and discussion of the main findings.

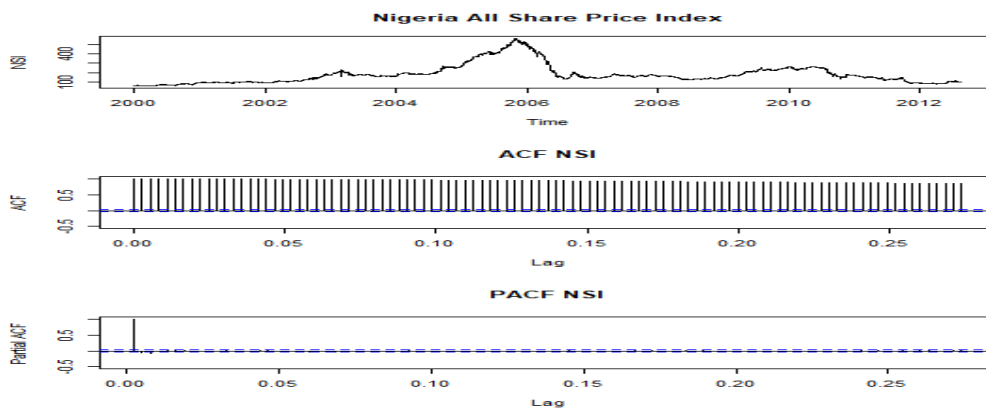


Figure 1. ACF and PACF Plot for Daily NSI

Figure 1 shows evidence of high rising and falling of share price that portends that the share prices is highly volatile. The series displays long-term drifts that are rising and falling, as the plot demonstrates. A non-stationary series is suggested. We can see that the variance and mean change over time. Strong correlations from earlier values are suggested, even though the ACF plot shows that the trend is steadily declining. It is necessary to test the time series' stationarity. The series is trending and non-stationary when the ACF plot tails off extremely slowly in a linear fashion.

3.1 The Diagnostic Tests of ARIMA Models

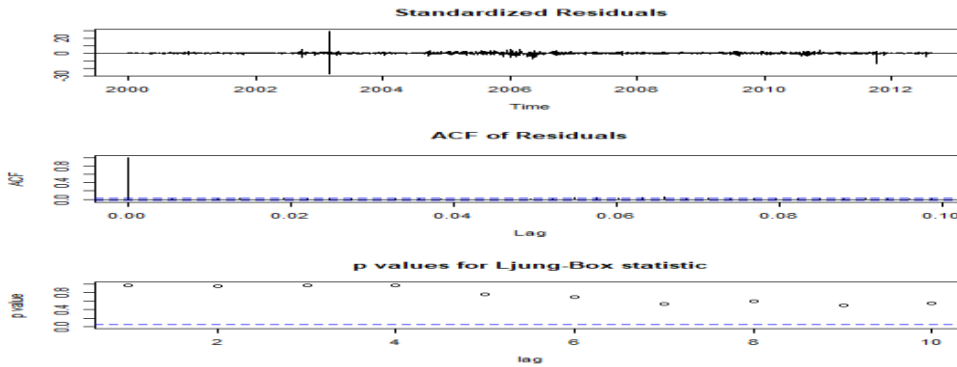


Figure 2. Standardized Residuals, ACF of Residuals and p-values for Ljung-Box statistic for the First Difference of Daily NSI

To verify the assumption of independence of error terms, Figure 2 plots the standardized residuals, the sample ACF of the residuals, and p-values for the Ljung-Box test statistic. Independent mistakes were deduced from randomized, non-pattern residuals. The ARIMA models were suitable for the variables since there was no significant autocorrelation in the residual plot, ACF, or PACF at any lag. Prior to building the GARCH model, we must use the Ljung-Box test to determine the ARCH influence (heteroscedasticity) in the fitted ARIMA model's standardized prediction error (ϵ).

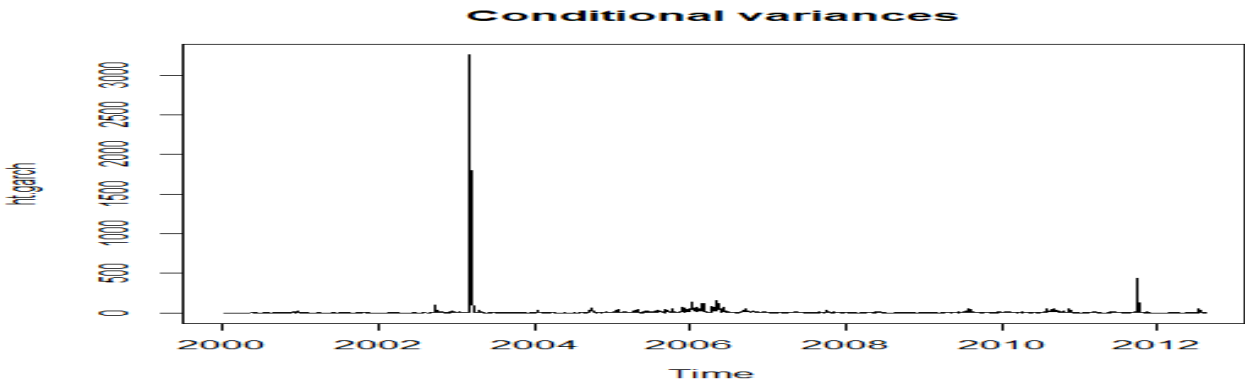


Figure 3: Conditional Variances

Figure 3 shows the constant variances which is the indication of normality of the Distribution.

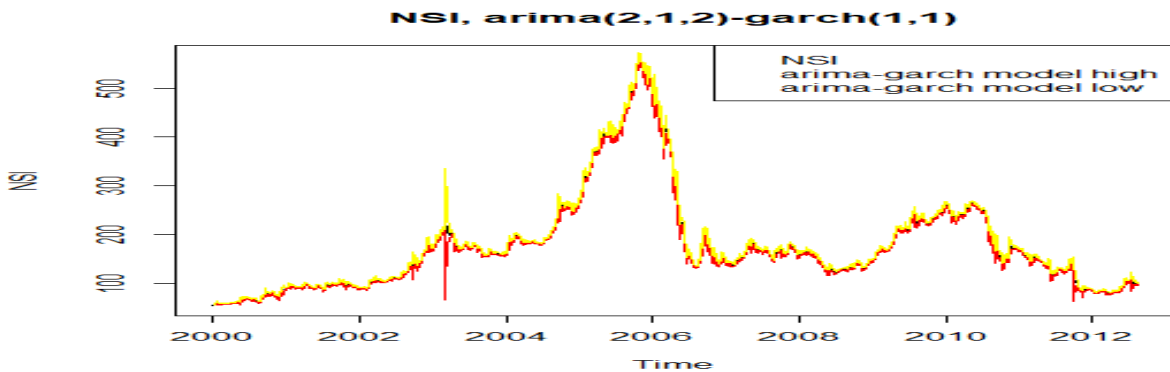


Figure 4. ARIMA (2, 1, 2) - GARCH(1,1) of Daily NSI

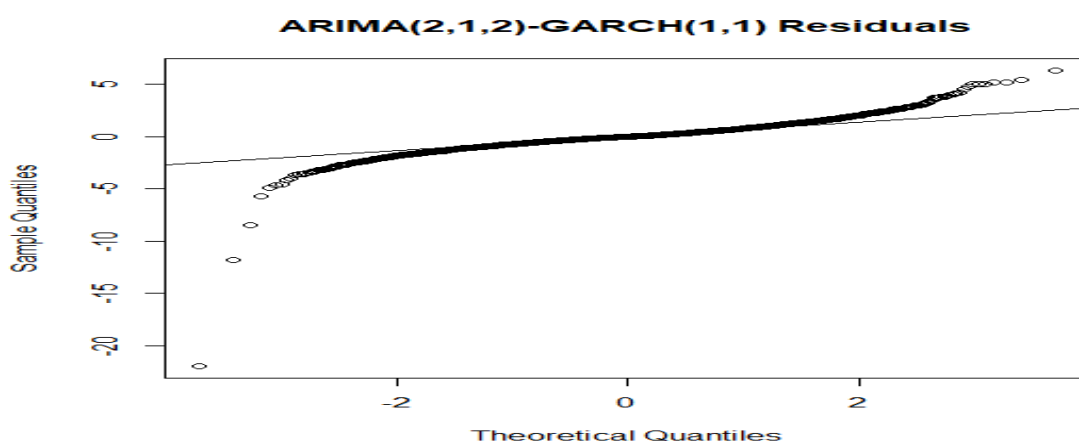


Figure 5. ARIMA (2, 1, 2)-GARCH (1, 1) Residuals for Daily NSI

From Figure 5, the standardized residuals of model essentially fulfil normality. Only a rare front end of points diverge the line.

Table 1: ADF test for Daily Nigeria all share index

Test	Statistic	P-Value	Decision	Remark
ADF	-1.2256	0.9024	Accept	Nonstationary

From Table 1, the ADF test outcome shows the p-value of 0.9024 which is larger than significance level, we fail to reject the null hypothesis so we can accomplish that the time series is non stationary (has a unit root).

Table 2: ADF test of daily Nigeria all share index for the first difference

Test	Statistic	p-Value	Decision	Remark
ADF	-15.501	0.01	Fail to accept	Stationary

From Table 2, the ADF test outcome displays the p-value of 0.01 which is fewer than significance level (0.05). We fail to accept the null hypothesis and conclude that the time series is stationary.

Table 3: AIC values for ARIMA (p, d, q) models

S/N	ARIMA(p,d,q)	AIC
1	ARIMA(2,1,2)	22336.09
2	ARIMA(2,1,3)	22338.05
3	ARIMA(3,1,2)	22338.05

In Table 3, the three ARIMA models specifications are identified; ARIMA (2, 1, 2), ARIMA (2, 1, 3) and ARIMA (3, 1, 2). The AIC of the recognized ARIMA models are presented. The values are compared and ARIMA (2, 1, 2) that is autoregressive order AR (2) and MA (2) by means of first order term of integration is the model with the minimum AIC is most appropriate to forecast the future NIS.

Table 4: Parameters estimation for ARIMA (2, 1, 2) model

Estimate	AR1	AR2	MA1	MA2
	0.7819	-0.4381	-0.6931	0.5017
S.E.	0.1022	0.0963	0.1000	0.0867

Table 4 presents the parameters estimates for ARIMA (2, 1, 2). The standard errors of AR1, AR2, MA1 and MA2 are 0.1022, 0.0963, 0.1000 and 0.0867 respectively.

Table 5: ML method and MAE parameters estimation for ARIMA models.

S/N	MODEL	PARAMETER	sigma2	MAE
1	ARIMA(2,1,2)	Θ- 11163.04	7.434	1.362723
2	ARIMA(2,1,3)	Θ- 11163.03	7.434	1.362852



3 ARIMA(3,1,2) Θ- 11163.03 7.434 1.362796

Table 5 displays the likely parameters for ARIMA models by the maximum likelihood method. From the parameter estimation outcomes in the Table 5, the ARIMA (2, 1, 2) has a largest value of maximum likelihood. The value of MAE of ARIMA (2, 1, 2) is the model with smallest MAE which indicate it has the best forecasting accuracy.

Table 6: ARIMA (2, 1, 2)-GARCH (1,1) error analysis:

Parameter	Estimate	Standard error	t-value	Pr(> t)
ω	0.052524	0.003833	13.70	<2e-16 ***
α	0.305837	0.006729	45.45	<2e-16 ***
β_j	0.780798	0.004437	175.99	<2e-16 ***

Table 6 is the error analysis displaying the implication of all the terms at 5% Significance level.

Table 7: ARIMA (2, 1, 2) GARCH (1, 1)

Test	Distribution	Statistic	p-value
JarqueBera	Chi-Square	653112	2.2e-16
Box-Ljung	Chi-Square	0.020838	0.8852

In Table 7, The Jarque-Bera test P-value is close to zero which indicates that the data has a normal distribution. Also the p value of the Box–Ljung test overdid 0.05. Consequently, the hypothesis in which

the autocorrelation of residuals is dissimilar from 0 can be accepted, and it implied that the GARCH model is suitable.

Table 8: Comparison between ARIMA and ARIMA-GARCH models

Statistic	ARIMA(2,1,2)	ARIMA(2,1,2)+Garch(1,1)
AIC	22336.09	18229.06
ML	- 11163.04	-9111.53
MAE	1.362723	0.5230086

The results in table 8 shows that the hybrid model (ARIMA, (2, 1, 2) + GARCH (1, 1)) perform better than ARIMA (2, 1, 2). Due to smaller AIC of 18229.06, the hybrid model is smaller than that of ARIMA which was 22336.09. Additionally, ML of the Crossbreed model is Greater than that of ARIMA that is -9111.53 > - 11163.04. The MAE of the hybrid model is also lower than that of ARIMA that is 0.5230086<1.362723.

22336.09 and MLvalue of -9111.53 greater than - 11163.04 of ARIMA. Thus, the hybrid ARIMA-GARCH is more robust and effective in dealing with time series behavior on Nigeria stock exchange data. In forecasting performance also the hybrid model is better. Because, the MAE of the hybrid model is lower than that of ARIMA, that is 0.5230086<1.362723.

4.0 CONCLUSION

This research modeled and compared the efficacy of two time series models on Nigeria stock exchange data. The finding indicates that the hybrid ARIMA-GARCH shows outstanding performance in dealing with volatility over the standard ARIMA (2, 1, 2) alone, which do not adequately capture the behavior of the series.

Based on the AIC and ML outputs, the hybrid ARIMA-GARCH performed better than ARIMA with AIC of 18229.06 smaller than that of ARIMA

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CONFLICT OF INTEREST

The authors declare no conflict of interest

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