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On the Hybrid of Arima and Garch Model in Modelling Volatilities in Nigeria Stock Exchange

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ABSTRACT

This work examined the implementation of combination of the most effective univariate time series model, ARIMA models with the superior volatility models GARCH, in examining the daily stocks returns of 2910 observations. Augmented dickey Fuller and Phillips Perron test were used to check the stationarity of the series. The series were confirmed stationary after the first difference. Comparison of forecasting accuracy of the hybridization between ARIMA Model and Generalized Autoregressive Conditional Heteroscedastic (GARCH) processes was done using the secondary data of All share Index of Nigeria Stock Exchange series obtained from National Bureau of Statistics and World Bank Statistics Database dated, from January 2012 to October 2023.The empirical results of 2910 daily series monthly revealed that the ARIMA (1,1,1)-GARCH (1,1) model gives the optimum results in modelling the Nigeria Stock exchange returns compared to conditional mean model ARIMA (1,1,1).

Keywords: ARIMA GARCH, Hybrid, Stock Exchange, Forecasting and Volatilities.

INTRODUCTION

The ARIMA-GARCH model combines the application of ARIMA and GARCH models in modeling times series data. ARIMA is a model that studies the mean behavior of a time series and GARCH is a variance model that employ the residual series from the fitted ARIMA to model the variance behavior (Yaziz *et al.*, 2013). ARIMA model introduced by Box and Jerkins (1976) is known to be among the utmost statistical procedures broadly used for model forecasting, it has the characteristics of applying simple applications for forecasting exactness and accordingly entails only the endogenous variables without necessarily requires other exogenous variables (Xiajuan Zhang etal. 2007, Adewole (2023)).

Autoregressive Integrated Moving Average (ARIMA), efficiently considered serial linear correlation amongst observations, the concept of ARIMA model is highly relevant in volatility modeling which give room for the generalized autoregressive conditional heteroskedaticity (GARCH) model to be regarded as ARIMA model. Tsay *(2002).* The generalized autoregressive conditional heteroskedasticity (GARCH) introduced by Bollerslev *(1986)* was designed to capture the dynamic pattern of conditional variance.

The square volatility modelling was assumed to relate to its past values and errors in estimating the parameters involved. Several studies had been conducted on modelling and forecasting times series model applying the outline of ARIMA and ARIMA- GARCH. Qasim et al (2021) erected a suitable model for the conditional mean and conditional variance for forecasting the rate of inflation in Pakistan by reviewing the properties of the series. GARCH (2,2) model was selected as the best variance model for the series, their results revealed that the asymmetric effect invariance is not so essential for the rate of inflation in Pakistan.

Uwilingiyimana (2015) developed empirical ARIMA-GARCH models for forecasting rates of inflation Kenya inflation using the historical monthly data ranging from 2000 to 2014. The research employs time series analysis, ordinary least square and auto-regressive conditional heteroscedastic to detect the estimators. They concluded that combination between ARIMA(1,1,12)-GARCH(1,2) model yields the optimum results and effectively improved estimating and prediction accuracy when compared to the other preceding methods of forecasting. Also, Ghani and Rahim (2019) worked on detecting the best ARMA-GARCH model in modeling and forecasting of volatility of Malaysia natural rubber prices by using different specifications structures of times series models and to forecast the daily price for 20 days ahead. 20 models were produced from different specifications in ARMA(r,m) and GARCH(p,q) models in their work. Their results shows that ARMA(1,0)-GARCH(1,2) model is the best volatility modeling in S.M.R 20 rubber price.

Isenah et al (2013) employed ARMA GARCH models to predict future values of Nigerian Stock Market's percentage nominal returns and volatility. They used times series data of monthly All share Index from the interval of January 1990 to December 2012. Results from their study shows that the asymmetry of the stock market returns is characterized with kurtosis exceeding that of normal distribution. Their results yield an ARMA (1,2) GARCH (1,1) model characterized with skewed normal error distributions.

Jokosenumi and Adesete (2018) employed panel ARDL estimation approach to examine the long run and short run effects of stock market volatility on FDI in using a secondary data ranging from 1990 to 2016. ARCH/ GARCH methods was used to estimate the exchange rate volatility and GARCH(1,1) was employed to estimate stock market volatility.

Stock market volatility is the degree of variation in the prices of stocks overtime. It reflects the uncertainty and risk associated with investing in stock market.

Masoud *(2013*) defined stock market is defined as a very sophisticated market state where the traded commodities are stocks and shares Stock market is paramount in making decisions on business investment, since financing investment spending is impacted by share prices. According to Bodie et al (1998), stock market indexes give guidance regarding the performance of the overall stock market. Stock market volatility measures the variation of price of a financial asset over time at the same time, it is central to the creation and development of a strong and competitive economy. Information on stock market provides investors with the status of the market value of their assets, and this serve as guide to businessmen on their investments.

Ibrahim (2017) ascertain the record of market capitalization is declining regarding the performance of the Nigeria Stock Exchange (NSE). It is therefore of high priority to postulate ideas based on research to investors and policy makers with adequate prediction on stock market index in order to avert risk of acquiring unnecessary loss in their imminent investments and safe guiding them in trading in the Nigeria stock market.

The All Share Index (ASI) on the Nigeria Stock Exchange (NSE) is used as proxy for stock market prices in order to assess volatility by measuring the trends and thereby examining the forecasting performance of the Nigeria Stock Exchange

Researchers have extensively developed

various times series model in literatures to enhance the efficiency of modelling and forecasting returns of stock exchange trade. (Wang etal (2012) Adebiyi et al (2014), Badge (2013), Kuhe & Chiawa (2017), Ibrahim (2019)) among others,

The Nigeria stock exchange (NSE) has experienced periods of high volatility in recent years, due to various contributing factors such as oil, price stocks, political wavering, security disputes, instability in exchange rate and COVID-19 pandemic. Understanding the dynamics and impact of stock market volatility on economic growth is crucial for formulating effective financial and economic policies.

However, in existing literature, there have not been consistency in the results of techniques for modeling and forecasting volatility in the Nigeria stock market prices that is superior. Therefore, this research contributes to existing knowledge by investigating the application of ARMA-GARCH models for estimating and predicting both conditional means as well as conditional variance of the returns. and hence selecting the most efficient model for volatility forecast of the Nigerian stock market prices.

The objective of this research focus mainly on reexamining and proposing a hybrid model that depict the temporal behavior in forms of serial dependence and time varying volatility in daily returns of NSE All Share Index. Three different criteria that includes Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE) respectively was employed to evaluate the performance of the models.

MATERIAL AND METHODS

ARIMA Modelling.

The ARIMA modelling constitute three main parts which include; autoregressive, integrated (I) and moving-average. The autoregressive part represents the autocorrelation between current and previous data, In contrast, the MA narrate the autocorrelation framework of the residuals in the model. The integrated (I) part indicates the number of differences needed to achieve a stationarity series from a non-stationarity data Hasmida (2009).

The ARIMA model usually takes the form (*p*, *d*, *q*) where the p signifies AR fragment of the model which is represents no. of lag observations in the model (known as the lag order), d signify the level of appropriate differencing and q describes the size of moving average section. the MA operator in ARIMA model is expressed as;

$$\emptyset(U) = 1 - \emptyset_1 U - \emptyset_2 U^2 - \dots, - \emptyset_q U^q \quad (1)$$

q is the size of the MA operator $\emptyset_p, p = 1, 2, \dots, q$ is the Moving Average parameters and M is the backward shift operator in such a way that

$$UY_t = Y_{t-1} \quad (2)$$

The Autoregressive operator is expressed in form of;

$$\theta(U) = 1 - \theta_1 U - \theta_2 U^2 - \dots, - \emptyset_p U^p \quad (3)$$

p denotes the order of Autoregressive operators and θ_i is the non- seasonal AR parameters, $i = 1, 2, \dots, n$

ARIMA model defined for an average data size can be defined in form of

$Y = (Y_1, Y_2, \dots, Y_n)$

written as;

$$\theta(U)(1 - U)^d (Y_t) = \theta(U) e_t \quad (4)$$

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d represent the level of modifications; t denotes the definite time and e_t denotes the residual.
The general form of Autoregressive Integrated Moving Average with the order p, d, q (notated as ARIMA(p,d,q)) is stated as follows

$$X_t = \theta_1 X_{t-1} + \theta_2 X_{t-2} + , ..., \theta_p X_{t-p} + \epsilon_t - \emptyset_1 \epsilon_{t-1} - \emptyset_2 \epsilon_{t-2} - , ..., \emptyset_q \epsilon_{t-q} \quad (5)$$

$$X_t = Y_t - Y_{t-d} \quad (6)$$

θ_p is the autoregressive parameter; ϵ_t denotes the white noise or residual while $\emptyset_q$ is the moving average parameter and Y_t is the dependent variable; X_t is the dth difference of the dependable variable. ARIMA modeling is in stages.
The process is illustrated in the flow chart below as designed by Box and Jerkins(1976)

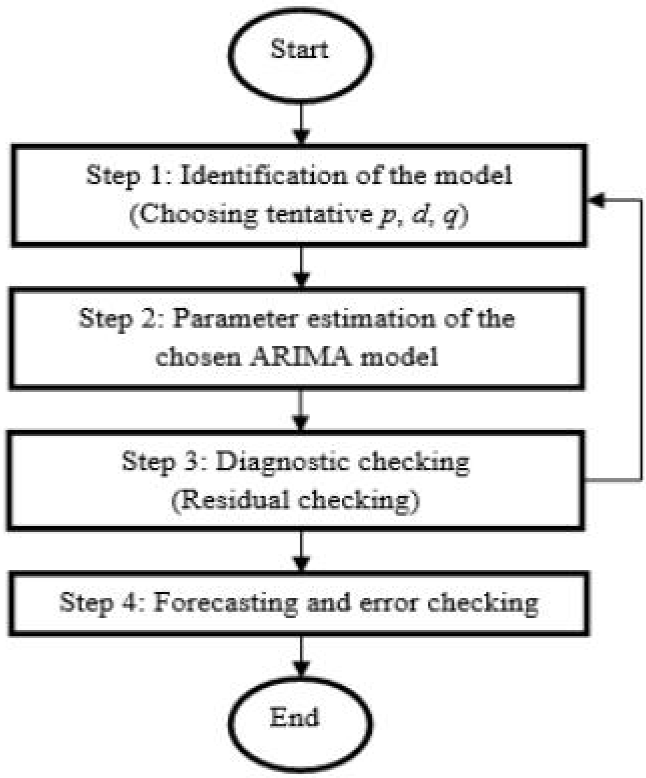

Figure 1: Flow chart of the ARIMA modeling.

GARCH Model

The variance equation of GARCH(u,v) model can expressed as;

$$\sigma_t^2 = \omega + \sum_{t=1}^{u} \alpha_i \varepsilon_{t-1}^2 + \sum_{t=1}^{v} \beta_j \sigma_{t-j}^2 \quad (7)$$

The model parameter to be estimated according to GARCH(u,v) models are σ_t^2 which represent the volatility at day t-j, $\omega > 0$, for i= 1…,u and $\beta_j \geq 0$, for j = 1,…,v.

represent the parameter determining the effect of previous residualε_{t-1}^2while measures the effect of change in its lagged value σ_{t-j}^2..

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From equation (7), it can be deduced that the conditional variance, $\sigma_{t.}^2\ \varepsilon_t$ at time tI dependent on the occurrence of the lagged squared errors in the preceding past periods and also on the conditional variance over the past periods.

In general, Bolerslev (1986) has established that the GARCH (*u, v*) process is stationary if there is satisfactory of the following conditions,

$$E(\varepsilon_t) = 0 \quad (8)$$

$$Var(\varepsilon_t) = \frac{\omega}{(1-\alpha(1)-\beta(1))} \quad (9)$$

$Cov(\varepsilon_t, \varepsilon_s), t \neq s,\ provided\ \alpha(1) + \beta(1)$ is less than 1

The GARCH models applies the assumption of conditional mean of the time series equal to zero. The conditional variance structure of GARCH can be augmented by a conditional mean that is modeled by some ARMA model. GARCH models can further be extended as;

Considering $\{X_t\}$ be a time series of the returns in ARIMA (p,q) format:

$$X_t = \emptyset_1 X_{t-1} + , ..., + \emptyset_u X_{t-p}\theta_0 + \epsilon_t + \theta_1\epsilon_{t-1} + , ..., + \theta_v\epsilon_{t-q}$$

(10)

$$\epsilon_t = \sigma_t|_{t-1}\varepsilon_t \quad (11)$$

$$\sigma_t^2|_{t-1} = \omega + \beta_1\sigma_{t-1}^2|_{t-1} +,\ldots,+ \beta_1\sigma_{t-u}^2|_{t-u} + \alpha_1\epsilon_{t-1}^2 +,\ldots,\alpha_v\epsilon_{t-v}^2 \quad (12)$$

The identification of ARMA order depends on the given time series, while GARCH orders depends on the squared residuals from the fitted ARMA model. After identifying the order, full maximum likelihood estimation for the ARMA + GARCH model can be implemented by maximizing the log-likelihood function numerically which is similar to maximizing GARCH function

$$L(\omega, \alpha, \beta) = -\frac{n}{2}\ log2\pi - \frac{1}{2}\ \sum_{i=1}^{n} \log\left(\sigma_{t-1}^2|_{t-2} + \frac{\epsilon_{t-1}^2}{\sigma_{t-1}^2}\right) \quad (13)$$

GARCH models are sufficient are sufficient tools in establishing a suitable model for financial times data.

The ARIMA-GARCH Model

The ARIMA-GARCH model is employed to examine trend and volatility of a time series concurrently. ARIMA (p,d,q) and GARCH(u,v) is generally defined as

$$\emptyset(B)(1-U)^d Y_t = \emptyset(U)\varepsilon_t \quad (14)$$

$$\varepsilon_t\ /Y_{t-1} \sim N(\mu, \sigma_t^2) \quad (15)$$

The ARIMA-GARCH method has been established to handle the serial correlated residuals encountered in ARIMA models. ARIMA-GARCH model permits concurrent modeling of both the conditional means and the volatility of the series. Moreover, this method of modelling times series yields more precise estimate values and higher forecast performance compared to ARIMA models.

The estimation of the ARIMA-GARCH model parameters is done by first creating the GARCH model for the series. Parameters of mean and conditional variance is estimated by estimating the parameters $\omega, \alpha_i\ and\ \beta_j$ employing the regression model

$$X_t = \emptyset_0 + \emptyset_1 X_t + \epsilon_t \qquad t = 1,\ldots,T$$

$$X_t = Z_t\sqrt{h_t} \quad (16)$$

$$h_t = \omega + \emptyset_i X_{t-1}^2 + \beta_j h_{t-1} \quad (17)$$

Simplifying the hybrid of ARIMA and GARCH model, we have,

$$\hat{\theta}\,(\emptyset_0, \emptyset_1, \omega, \alpha_i, \beta_j)' = (\hat{\emptyset}', \delta') \quad (18)$$

Where the vectors of the parameter $\hat{\theta}$ is

$$\hat{\delta} = \begin{pmatrix} \omega \\ \alpha_i \\ \beta_j \end{pmatrix} \quad and \quad \hat{\emptyset} = \begin{pmatrix} \emptyset_0 \\ \emptyset_1 \end{pmatrix} \quad (19)$$

The estimates of the parameters are obtained by maximizing likelihood method.

Stationarity Test and Volatility Presence

In estimating ARIMA GARCH models, it is necessary to check whether the data exhibit the presence of ARCH effect and also to test for stationarity of the data. This is to certify appropriate choice of the estimation method for the data. A series is assumed to be stationary if the mean and variance remain constant over time and a non-stationary series is characterized by features of a unit root.

Stationarity test was conducted using Augmented Dickey Fuller (ADF) and Philipp Pherron methods were used to ascertain the stationarity of the NSE All Share Index. The Autoregressive Conditional Heteroscedastic-Lagrange Multiplier (ARCH –LM) Test was employed to assess volatility in the series after ascertaining that the variable is stationary.

Model selection criteria

The Akaike Information Criterion (AIC): it measures the relative goodness of fit of a statistical model and also the order of the model. It is expressed as;

$$= 2 \quad - 2\ln(\quad), \quad (20)$$

where signifies the number of parameters in the model, and represent the maximized value of the likelihood function for the estimated model.

Schwarz Information Criterion**:** The SIC employed a likelihood function for choosing the least complex probability model among multiple options. The SIC is expressed by:

$$SIC = Kln\,(n) - 2\ln\hat{L} \quad (21)$$

where the likelihood $\hat{L}$ is defined as

$$\hat{L} = Prob\,(x \mid \hat{\theta}m) \quad (22)$$

where m signifies the model x are the data and $\hat{\theta}$ represents the estimate parameters of the model.

Hannan-Quinn Information Criterion**:** The HQIC is a measure of the goodness of fit defined by:

$$HQIC = -2\,L_{max} + 2\,Kln[\ln(n)] \quad (23)$$

where L_{max} is the log-likelihood, k represents the number of parameters and n is the number of observations

Model Diagnostics

Test for serial correlation and presence of heteroscedasticity after model's estimation is highly essential for a mean and hybrid modeling. Adequacy of the selected models was validated employing the residual normality test, the Portmanteau test and Autoregressive Conditional Heteroscedasticity Lagrange Multiplier (ARCH-LM) test to examine the white noise, serial correlation and the heteroscedasticity test respectively.

Residual Normality Test.

Lung box test for the residual examination is given by;

$$Q = n(n+2)\sum_{k=1}^{k} n - k^{-1}\hat{\rho}_k^2 \quad (24)$$

If $Q > \chi^2$ or the ρ- value is less than the Significant value, then there will be rejection of the null hypothesis of no residual with white noise property.

Portmanteau Test

The Portmanteau test examines the existence of autocorrelation in the residuals of a fitted model.

Let the autocorrelation between ε_t and ε_{t-k} be defined as ρ_k = Corr(ε_t, ε_{t-k})

Then, the null hypothesis states that all lags correlation are zero,

0: 1 = 2 = ⋯ = 0.

The test statistic is given by:

$$Q_1 = n(n+2)\sum_{j=1}^{K}(n-j)^{-1}\,\hat{\rho}_{\hat{\varepsilon}(j)}^2 \quad (25)$$

The Q_1 statistic follows an approximation of χ^2 distribution with − − degrees of freedom.

Autoregressive Conditional Heteroscedastic-Lagrange Multiplier (ARCH –LM) Test

ARCH-LM test proposed by Engle (1982) accommodate issues of conditional heteroscedasticity in squared residuals with the null hypothesis that there is no heteroscedasticity in the model residuals. The test statistic is given by;

$$Q = M(M+2)\sum_{i=1}^{M}\frac{\rho_i}{(M-1)}, \quad (26)$$

where the statistic follows an asymptotic χ^2 distribution with degrees of freedom provided the squared residuals is uncorrelated. M signifies the number of observation and ρ_i represent the sample correlation coefficient between squared residuals $\hat{\varepsilon}_t^2$ *and* $\hat{\varepsilon}_{t-1}^2$. The null hypothesis of squared residuals states that $\hat{\varepsilon}_t^2$ are not correlated.

Model Forecasting and Performance Evaluation

The forecasts accuracy of the model is evaluated employing the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE),) and the Mean Absolute Percentage Error (MAPE) respectively.

MAE is the absolute value of the difference between the forecasted value and the actual value. It calculates the average absolute deviation of predicted values from real values. MAE is estimated as follow:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} /\hat{y}_f - y_t / \quad (27)$$

MAPE is projected as the computation of the percentage of mean absolute error occurred in the model formation. It is given by;

$$MAPE = \frac{100}{n}\sum_{t}^{n} /\frac{\hat{y}_f - y_t}{y_t}/ \quad (28)$$

RMSE illustrate the absolute fit of the model to the observed data, it is estimated as:

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$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\widehat{y}_f - y_t} \quad (29)$$

where: $\widehat{y}_f$ and y_t are the estimated and the real values respectively; n is the sample size. Model with lesser value is likely to have the best precision power of forecast.

Data Collection and Description

The data for this study is a secondary data obtained from Nigeria Stock exchange website. The data comprises of daily data of All Share Index on the Nigeria Stock Exchange is in unit, ranging from first day in January 2012 to last day in October 2023.

RESULTS AND DISCUSSION

Table 1: Summary Statistics

Mean	Median	Max	Min	St. dev.	Skewness	Kurtosis	Jarque B.	Prob.	No. of Obs.
0.0414	0.0055	7.9848	-5.032	0.9632	0.3376	8.7176	407.723	0.0000	2909

Table 1 gives the summary statistics of the daily returns of the stock series ranging from the period of January 2012 to October 2023.

Stationarity Test

Table 2: ADF and PP Test Result of NSE at level

Test	t- statistic	Probability	Test	t- statistic	Probability
ADF	-15.143	0.2804	Phillips Perron	16.218	0.3115
Test Critical Values 1%	-2.9418		Test Critical Values 1%	-3.1618	
5%	-3.004		5%	-3.2103	
10%	-3.2819		10%	-2.9603	

Note - ADF is the Augmented Dickey Fuller

The various stationarity tests at level are presented in Table 2. The tests shows that the data series exhibits non-stationary characteristics respectively

Table 3: ADF and PP Test Result of NSE at first difference.

Test	t- statistic	Probability	Test	t- statistic	Probability
ADF	-39.132	0.000	Phillips Perron	-38.982	0.000
Test Critical Values 1%	-3.5381		Test Critical Values 1%	-3.5339	
5%	-3.2750		5%	-3.2684	
10%	-3.1562		10%	-3.1602	

Table 3 shows the unit root tests using ADF and PP at first difference. The p-values of ADF and PP are less than 0.01, thus, reject the null hypothesis that the series has a unit root at 1%, 5% and 10% and this leads to conclude that the market returns series is stationary.

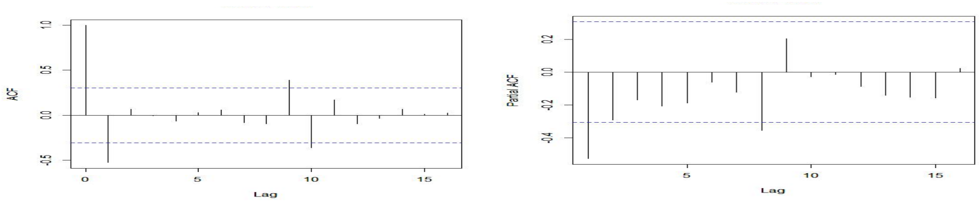

Fig 2: correlogram of the stock returns

From the correlogram presented in fig 2, the model with the lowest value of AIC, SIC and HQIC was selected as the best model amidst the competitors.

Table 4: Tentative ARIMA models of the daily stock returns**.**

Model	Specification(p,d,q)	AIC	SIC	H QIC
Model 1	**ARIMA (1,1,1)**	**182.4159**	**183.0026**	**179.2679**
Model 2	ARIMA (1,1,8)	184.3697	184.7056	183.1260
Model 3	ARIMA (7,1,1)	184.6289	185.2247	185.1962

Note- ARIMA is Autoregressive Integrated Moving Average

The competitive models and their respective values for the selection criteria are tabulated in Table 4 above.

Table 5: Parameter Estimation of ARIMA(1,1,1) model

Parameter	Coefficient	Standard Error	Prob.
C	0.0552	0.6125	0.0075
θ_1	0.1103	0.3631	0.0032
$\emptyset_1$	-0.0571	0.0491	0.0000

where Θ_1 is the autoregressive parameters of seasonal component and Φ_1 is the moving average parameters of the ARIMA component. From the results shown in Table 5, the parameter estimation adopted from Box and Jenkins procedures engaging maximum likelihood method of estimations which relied on asymptotic condition for any time series observation in line with Brockwell et al, 2013.

The equation of the selected ARIMA (1,1,1) model is expressed;

$$ASI_t = 0.0552 + 0.1103ASI_{t-1} - 0.0571\varepsilon_{t-1} \quad (30)$$

Table 6: Diagnostic Check for the ARIMA Model.

Times series	ARIMA(p,d,q)	Autocorrelation Test		Normality test	
	Model	Lung Box Q p- value	Portmanteau p- value	Jarque Bera Test p-value	Shapiro Wiki p-value
Stock R.	ARIMA(1,1,1)	0.1825	0.1904	0.3328	0.3715
α		0.05	0.05	0.05	0.05

Table 6 presents results of serial correlation and Heteroskedacity check for the selected ARIMA models. The Ljung-Box and the Durbin Watson p value for the series exceeds 0.05(the significant level) which indicates there is no autocorrelation among the residual of the model's forecast errors and the residual is normally distributed. .

GARCH Model Estimation.

Heteroscedasticity Test

To model the volatility of a time series variable, it is mandatory to test for the presence of ARCH Effect in the residuals of the series.

Table 7: Results of test for Arch effect on Daily Data

	Test statistic value	Probability
F Statistic	127.8196	0.0000**
Observed R^2	121.2779	0.0000

From Table 7, it was deduced that there is an ARCH effect in the ARIMA(1,1,1) residual model since the probability value of Obs * R-squared is smaller than the significance level of 0.05.

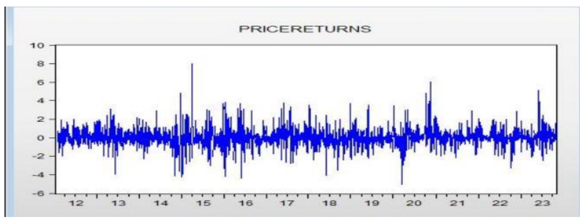

Figure 3: Volatility clustering of the series

The GARCH model was identified by examining the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the squared residual data correlogram. From the squared residual data correlogram, the tentative GARCH models were presented in Table 8 below. GARCH models for variables were fitted to the series and the model with the lowest value of AIC and SIC was chosen as the best amidst the competitors.

Table 8: Tentative GARCH Models

GARCH MODEL	AIC	SIC	S. Error	Log likelihood
GARCH(0,1)	3.7169	3.7243	2.9652	- 285.11
GARCH(1,1)	**3.5194***	**3.5530***	**3.1966**	**-277.34**
GARCH(1,2)	3.6552	3.6502	3,5075	-288.06

Note- GARCH is Generalized Autoregressive Conditional Heteroscedastic

ARIMA-GARCH model combines the ARIMA model that considered the mean behavior of the time series and the GARCH model which is employed to model the variance behavior (ARCH effect). Applying the residual series obtained from the fitted ARIMA models, suitable GARCH models were built. The results of the combined models are presented in Table 9 below,

Table 9: Estimate of ARIMA GARCH.

Parameter	Coefficient	Std. Error	t- value	Prob.
θ	0.1103	0.3631	-2.4458	-2.4458
ω	0.0004	0.0006	2.1270	0.0005
α	0.1126	0.0247	4.3345	0.0000
β	0.4938	0.0159	7.3492	0.0000

Table 10: Diagnostics check for the ARIMA GARCH Model.

Times series	Model	Portmanteau Test	ARCH LMTest
All Share Index	ARIMA(1,1,1) GARCH(1,1)	(13.258) 0.2046	(15.287) 0.4721

Table 10 above present the serial correlation and heteroscedascity diagnostics for the ARIMA-GARCH models

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Table 11: Measurement of Forecast Accuracy

Preferred Model	MAE	MAPE	RMSE
ARIMA(1,1,1)	0.6824	0.9025	1.2926
ARIMA(1,1,1) GARCH(1,1)	0.7352	0.7962	0.8157

Table 11 present the summary of forecast accuracy of selected ARIMA and ARIMA GARCH model. ARIMA/GARCH models outperform ARIMA models in modeling returns of Nigeria stock exchange in terms of MAPE and RMSE validation criteria but ARIMA yields a better precision than ARIMA GARCH Model with MAE.

CONCLUSION

The complete combination of powerful and flexibility of ARIMA and the strength of GARCH models in handling volatility and risk in the data series as well as to overcome the linear and data limitation in the ARIMA models made the combination of ARIMA-GARCH as a new potential approach in analyzing and forecasting the returns of Nigeria stock exchange. The stages in the model building strategy such as identification, estimation and model evaluation has been explored and utilized in erecting adequate model for forecasting stock returns of Nigeria stock exchange, from the result of the research, ARIMA-GARCH model outperform ARIMA of Nigeria stock market volatility with the aid of validation criteria, ARIMA (1,1) GARCH (1,1) was selected as best forecast model. The result justifies the result of Emenyonu, et al., (2023) that works on estimating Volatility of Daily Price Returns of Nigerian Stock Market.

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