

## Does Holidays affect the Returns of Stock Markets Prices? An Application of some GARCH and Prophet Models under Varying Error Distributions

<sup>1</sup>M. Tasi'u, <sup>2</sup>A.A. Umar and <sup>3</sup>\*U. Abdulaziz

<sup>1,2,3</sup>Department of Statistics, Ahmadu Bello University Zaria, Kaduna State, Nigeria.

\*Corresponding Author's Email & Phone No.: rabdulazizusman@gmail.com, +2347064164622

Received on: October, 2024

Revised and Accepted on: November, 2024

Published on: December, 2024

### ABSTRACT

Logically speaking, financial time series data such as stock price returns is directly or indirectly affected by some factors such as holidays (Valentine's Day, Father's Day, etc.). These effects have not been fully studied by researchers. This paper utilizes GJR-GARCH (with dummy variables as holidays) and Prophet models on Nigeria and Chinese stock price returns so that more realistic results and information on how the holidays affect the returns of stock markets will be obtained. Results of the analysis reveal the existence of holiday's effects on Thursdays (for NSE) and Mondays and Fridays (for CSE) both under Generalized Error Distribution (GED) assumption of innovations. Additionally, no leverage effect was found in the two returns series. Furthermore, the GJR-GARCH model under all the three considered distributions of innovations on the two data sets shows volatility clustering and persistence. Thereafter, evidence from the minimum RMSE and MAE, the GJR-GARCH model under NSE slightly outperformed the Prophet model, while under CSE, the Prophet model performed better than the GJR-GARCH model.

**Keywords:** Holidays Effects, GJR-GARCH, Prophet model, NSE, CSE.

### 1.0 INTRODUCTION

A linear time series model, named, Autoregressive Integrated Moving Average (ARIMA) is useful in assessing linear dynamics of financial time series data, but failed to address some properties such as volatility. Volatility is a measure of unexpected dispersion of a financial time series returns, and it accounts for the nonlinear component. The volatility of a series returns may be affected by many factors which include holidays (such as Valentine Day, Father's Day, and many more), weather abnormalities, natural disaster, unfixed government policies, among others. Fitting and forecasting volatility of a series returns is of great important as it aids investors in making good decision about time of entering and exit in a business. ARIMA model (i.e. the mean model) along sides with Autoregressive Conditional Heteroskedastic (ARCH) and Generalized Autoregressive Conditional Heteroskedastic (GARCH) models (as a volatility model) are mostly used in fitting and forecasting financial time series returns.

Financial time series characteristics such as volatility clustering and leptokurtosis are commonly seen (Mandelbrot, 1963). Another element usually encountered is the so called 'leverage effects' (Black, 1976), which occurs when stock price changes are negatively correlated with changes in variance. With

these reasons, different volatility models have been established in order to estimate and forecast the volatility of a series returns. Fitting and forecasting volatility of time series is a crucial element in risk and portfolio management as well as equity pricing. Stock price returns reflect all available information and the faster the absorbing new information they are, the better the efficient market is the stock market in allocating resources.

The conventional GARCH model is well-known in capturing stylized facts such as volatility clustering and leptokurtosis but due to the symmetric assumptions of innovations of series returns, it failed to capture the leverage effect. Another problem encountered when using said GARCH model is the inability to fully embrace the thickness tails property of high frequency financial time series returns. To overcome this problems, Bollerslev (1987), Baillie and Bollerslev (1989), and Beine et al. (2002) used the Student's t-distribution. Similarly, to capture skewness, Liu and Brorsen (1995) used an asymmetric stable density. In order to fit both skewness and kurtosis, Fernandez and Steel (1998) used the skewed Student's t-distribution which was later extended to the GARCH framework by Lambert and Laurent (2000, 2001).

The financial series return is a variable and usually unstable by volatility, which is typically not constant. As such, ARCH-type models must be used instead of the traditional models with constant variance. The ARCH model, established by Engle (1982) has the advantage of taking the conditional volatility into account in the model, but requires a large number of parameters to be estimated, which may lead to over-parameterization. Considering that the conditional variance depends on both the squares of the series returns and the conditional variances of just the past periods, the GARCH model introduced by Bollerslev's (1986) has an advantage over the ARCH model. Though, it does not provide the variant signs (negative or positive). The GJR-GARCH model solves this problem as it makes it possible to examine whether price changes are positive or negative. Similarly, one of the statistical models, the EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) model can as well assist in explaining the time-varying changes in variance (volatility) patterns of a series returns, (Yahaya *et al.* 2022; Mohammed *et al.* 2022; Adams *et al.*, 2023; Tasi'u *et al.*, 2024).

Fitting and forecasting of stock price series returns using time varying GARCH models established by Engle (1982), Bollerslev (1986), by adding additional term in the Engle (1982) ARCH model and extended by Nelson (1991), Ding *et al.* (1993), Glosten *et al.*, (1993), Zakoian (1994), among others, has been recently gaining attention by investors, financial analysts, academics and researcher. This is as a result of the ability GARCH model in capturing statistical regularities (stylized facts) of time series returns such as volatility clustering, persistence, mean reversion and asymmetric (leverage effect). The price series and other financial assets depends on the expected key measure of dispersion (volatility) of returns.

Numerous scholars have released evidence relating to variance model (GARCH) in the presence of structural break across emerging and developed economies. Lamoureux and Lastrapes (1990) revealed that not incorporating structural breakpoints in the conditional variance while fitting and forecasting volatility increased persistence of volatility shocks whereas incorporating the sudden shifts in conditional variance mitigated the persistence of shocks in volatility models.

Yu *et al.* (2018) compared the forecast performance of GARCH and LSTM models in forecasting the fluctuations of China's equity market. Huang *et al.* (2019) respectively constructs time series models and deep learning model, and compared the forecasted results

of the two kinds of models from the perspective of dynamic and static prediction based on SSE index data. Their analysis revealed that GARCH model has more average forecasting accuracy in static forecasting, while the LSTM model accurately forecasted most in dynamic forecasting, with a Root Mean Square Error (RMSE) value of 0.0632. Shaik and Aditya (2020) studied the strength of GARCH and artificial neural networks (ANN) models in forecasting the volatility of Indian stock market indexes. Their results revealed that GARCH outperformed the ANN model. Nasrin *et al.* (2020) employed the Autoregressive Conditionally Heteroskedastic time-series (ARCH) model to accurately forecast the data-driven models for monthly stream flow in the Urmia Lake basin. Their analysis indicated that ARCH-CHAID models outperformed all other models in the two stations. Shen *et al.* (2021) investigated risk management efficiency forecasting accuracy using RNN, GARCH and EWMA models. The results showed that RNN outperformed GARCH and EWMA on average forecasting performance. However, it performed poorly in Value at Risk forecasting, indicating that it may not work well as econometric model in explaining severe volatility. Furthermore, in capturing the Bitcoin market's extreme occurrences, RNN is less effective.

In a similar manner, Zhou and Rui (2021) compared the performance of GARCH and deep learning models to forecast the volatility of SSE50 ETF options, and realized the GARCH model to performed better. Zahid *et al.* (2022) applied hybrid GARCH models and machine learning to forecast Bitcoin changes in variance (volatility). Their studied revealed that both the in-sample and out-sample indicated the hybrid GARCH models can accurately forecast how Bitcoin prices will disperse. Chatterjee *et al.* (2022) applied time series variance models (GARCH, EGARCH, and GJR-GARCH) and LSTM model to forecast stock volatility in three distinct industries. The studied revealed that the LSTM model beats the considered GARCH models in forecasting volatility in the pharmaceutical sector than in the IT and banking sectors. Cai *et al.* (2023) studied stock price prediction using GARCH, RNN and LSTM models with the aimed of comparing their forecast performances and advantages. The results revealed that RNN and LSTM models outperformed GARCH model. Goel *et al.* (2023) applied GARCH and Multilayer Perceptron Neural Network models to forecast monthly returns series and concluded that Multilayer Perceptron Neural Network performed better than GARCH model. Tasi'u *et al.* (2024) applied EGARCH and Prophet models to assess the impact of holidays on Nigeria stock exchange price returns using two different distributions of innovations. With the help of RMSE, their studied

revealed that EGARCH (1,1) under skewed student's  $t$  outperformed both EGARCH (1,1) and Prophet models under normal assumptions of innovations. Furthermore, they revealed there exist a positive and significant effects of all the holidays that falls on Thursdays. Adams and Uchema (2024) compared the efficacy of EGARCH(1,1) and Recurrent Neural Network (RNN) based on long short term memory (LSTM) models to fit and forecast the volatility of Nigeria naira exchange rate with pounds, Euro and US dollars. The results revealed that EGARCH(1,1) outperformed LSTM model. Furthermore, they found the existence of leverage effect. Adams et al. (2024) applied EGARCH, TGARCH and LSTM models to study the characteristics volatility of Nigeria stock exchange returns. They considered monthly data ranging from January, 1985 to December 2023. With the help of EGARCH(1,1) and TGARCH(1,1), the volatility persistence was found and realized that EGARCH(1,1) outperformed LSTM (160-80-5) model.

Based on the reviewed literature so far, little or no studies had empirically evaluated the effects of Holidays on the returns of stock markets prices. Research shows that the impacts of the holidays on the stock markets is enormous and it should not be ignored. This paper is therefore aimed to address this challenge.

## 2.0 MATERIALS AND METHODS

### 2.1 Material

The used data in this research are daily data of the Nigerian Stock Exchange (NSE) price returns ranging from 2016 to 2019 obtained from the Central Bank of Nigeria, and Chinese Stock Exchange (CSE) price returns from 2017 to 2022 obtained from Federal Reserve Bank of St Lius, USA.

### 2.2 Method

Most studies on finance used the returns instead of asset prices because returns are scale free and easier to handle than prices, Bruno *et.al* (2023). Let's assume  $p_t$  and  $p_{t-1}$  be the present and past day's price returns or asset prices respectively. The log returns  $y_t$  is expressed as:

$$y_t = \log \left( \frac{p_t}{p_{t-1}} \right) \quad (1)$$

#### 2.3.1 GJR-GARCH (1,1) model with Holiday's

GJR-GARCH model was introduced by Glosten, Jagannathan and Runkle (1993) as a variance model. The conditional volatility of a series returns is defined as:

$$\sigma_t^2 = \omega + \sum_{i=1}^p (\alpha_i + \gamma_i I_{t-i}) \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{k=1}^5 \psi_k D_{kt} \quad (2)$$

The parameters must satisfy  $\alpha_o > 0$ ,  $\alpha_i \geq 0$ , and  $\beta_j \geq 0$ , to guarantee the positivity of the conditional variance ( $\sigma_t^2 \geq 0$ ),  $\alpha_i + \gamma_i \geq 0$ . Leverage effect exists when  $\gamma_i > 0$ . If there are no asymmetries effects,  $\gamma$  is not statistically significant and the volatility equation is nothing but the equation of a GARCH model.  $D_{kt}$  is an indicator function implying  $D_{1t} = 1$  if day  $t$  is a Monday and 0 otherwise;  $D_{2t} = 1$  if day  $t$  is a Tuesday;  $D_{3t} = 1$  if day  $t$  is a Wednesday,  $D_{4t} = 1$  if day  $t$  is a Thursday and  $D_{5t} = 1$  if day  $t$  is Friday.

#### 2.3.2 Prophet model

Prophet model (also called Facebook Prophet model) was introduced by the Core Data Science organization (Taylor and Letham 2017) in order to capture trend, seasonality and holidays effects of financial time series data. It is expressed as follows:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (3)$$

As,  $g(t)$  model the trend function of non-periodic changes in the value of the series returns,  $s(t)$  accounts for periodic changes (*e.g.*, weekly and yearly seasonality), and  $h(t)$  explain the effects of holidays which take place on potentially irregular schedules over one or more days. The error term  $\varepsilon_t$  represents any idiosyncratic changes which are not explained by the equation,  $y(t)$ , represents the series returns. The three functions  $g(t)$ ,  $s(t)$  and  $h(t)$  are statistically defined as follows:

$$G(t) = \frac{c(t)}{1 + e^{-(k + a_j(t)^T \delta)(t - (m + a_j(t)^T \gamma_j))}} \quad (4)$$

Where  $c(t)$  is a carrying capacity changing with time,  $k$  is the rate of growth,  $m$  an offset parameter,  $\delta \in \mathbb{R}^s$  is a rate of vector adjustment,  $\delta_j$  is the varying rate that occurs at time  $s_j$ . An indicator function,  $a_j(t)$ , is defined as:

$$a_j(t) = \begin{cases} 1, & \text{if } t \geq s \\ 0, & \text{otherwise} \end{cases} \quad (5)$$



$$\gamma_j = \left( s_j - m - \sum_{i < j} \gamma_i \right) \left( 1 - \frac{k + \sum_{i < j} \delta_i}{k + \sum_{i \leq j} \delta_i} \right) \tag{6}$$

The seasonality function is defined as:

$$s(t) = \sum_{n=1}^N \left( a_n \cos \left( \frac{2\pi nt}{P} \right) + b_n \sin \left( \frac{2\pi nt}{P} \right) \right) = X(t)\beta \tag{7}$$

Where  $X(t)$ , is a seasonality vectors matrix for each value of  $t$  in the historical and future data,  $a_n$  and  $b_n$  are parameters to be estimated,  $\beta$  is defined as;

$$\beta = [a_1, b_1, \dots, a_N, b_N]^T \tag{8}$$

The holidays function is given by:

$$h(t) = Z(t)K_i \tag{9}$$

where  $K_i$  is an individual holiday's impact,  $Z(t)$  is a regression matrix given as:

$$Z(t) = [1(t \in D_1), \dots, 1(t \in D_L)] \tag{10}$$

**2.4 Measure of accuracy**

The best model will be selected based on Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). They are defined as follows:

$$MAE = \frac{1}{k} \sum_{t=T+1}^{T+k} \left| \sigma_t^2 - \hat{\sigma}_t^2 \right| \tag{11}$$

$$RMSE = \sqrt{\frac{1}{k} \sum_{t=T+1}^{T+k} \left( \sigma_t^2 - \hat{\sigma}_t^2 \right)^2} \tag{12}$$

where  $\sigma_t^2$  and  $\hat{\sigma}_t^2$  are the actual and predicted volatilities of the exchange rate returns at time  $t$ ,  $k$  forecasts are carried out from  $t = T + 1$  to  $T + k$ .

**3.0 RESULTS AND DISCUSSION**

The used data in this research are daily data of the Nigerian Stock Exchange (NSE) price returns ranging from 2016 to 2019 obtained from the Central Bank of Nigeria, and Chinese Stock Exchange (CSE) price returns from 2017 to 2022 obtained from Federal Reserve Bank of St Lius, USA. The analysis done on these two data sets are GJR-GARCH (1,1) and Prophet models.

**3.1 Statistics and Data Analysis**

The parameter estimates of GJR-GARCH model alongside with holidays effects on Nigeria and Chinese stock exchange price returns data under normal, skewed student's t and Generalized Error distributions (GED) of innovations are explain in table 1.

**Table1: Parameter Estimates Of GJR-GARCH (1,1) Model with Holiday's Effects Under Normal, Skewed t And GED Of Innovations On Nigeria And Chinese Stock Exchange Price Returns**

Parameters	GJR-GARCH (1,1)					
	Nigeria			Chinese		
	Estimate: Normal	Estimate: Skewed student's t	Estimate: GED	Estimate: Normal	Estimate: Skewed student's t	Estimate: GED
$\delta_1$	0.003239 (0.013001)	0.000827 (0.494195)	0.000010 (0.86500)	0.008527 (0.44948)	0.011939 (0.08383)	0.007078 (0.02076)
$\delta_2$	0.002556 (0.080623)	0.002057 (0.138112)	0.000051 (0.96022)	0.001650 (0.85268)	0.000282 (0.96739)	0.000109 (0.97164)
$\delta_3$	0.003464 (0.027208)	0.002191 (0.130637)	0.001416 (0.62935)	0.013778 (0.18976)	-0.000164 (0.98751)	0.000121 (0.97050)
$\delta_4$	0.001255 (0.484108)	0.002869 (0.028864)	0.001054 (0.000000)	-0.001929 (0.85572)	-0.003276 (0.71114)	0.002651 (0.00000)
$\delta_5$	0.000462 (0.832087)	0.000518 (0.640569)	0.000010 (0.85238)	0.013906 (0.13764)	0.009840 (0.19657)	0.000005 (0.96783)
$\alpha_1$	0.190110 (0.000000)	1.000000 (0.000000)	0.240828 (0.000000)	0.377758 (0.00000)	0.570104 (0.00000)	0.508447 (0.00000)
$\beta_1$	0.758207 (0.000000)	0.498154 (0.000147)	0.651225 (0.000000)	0.650724 (0.00000)	0.635606(0.0000)	0.610713 (0.00000)
$\omega$	0.000007 (0.000000)	0.000086 (0.000182)	0.000011 (0.000000)	0.000520 (0.00000)	0.000590 (0.00000)	0.000552 (0.00000)
$\gamma_1$	-0.015757 (0.565375)	-1.000000 (0.000000)	0.064780 (0.24266)	-0.285865 (0.00000)	-0.521883 (0.00000)	-0.427234 (0.00003)

<b>Persistence</b>	0.9404385	0.998154	0.924443	0.885549	0.9447685	0.905543
<b>AIC</b>	-6.5429	-6.5319	-6.6440	-2.8825	-3.0680	-3.0636
<b>Shibata</b>	-6.5430	-6.5320	-6.6441	-2.8826	-3.0682	-3.0638
<b>RMSE</b>	0.009573327	0.009584331	0.009572166	0.1130218	0.1130101	0.1130112
<b>MAE</b>	0.006763846	0.006779455	0.00676212	0.05896728	0.05890874	0.05892409

Table 1 under Nigeria, depicts that the coefficient of Mondays,  $\delta_1$  and Wednesdays,  $\delta_3$ , under normal are positive and significant (indicating the series returns will increase per unit change of the holidays that fall on these days) while the rest are not significant. The coefficient of Thursdays,  $\delta_4$  under skew student's t is positive and significant (implying the series returns will increase per unit change of the holidays that fall on Thursdays) while the rest are not significant. In the case of generalized error distribution, the Thursdays coefficient,  $\delta_4$  is also positive and significant, implying the series returns will increase per unit change of the holidays that falls on Thursdays, while the rest are not significant. On the other hand,  $\alpha_1$  coefficient is statistically significant at 5% level of significant in the three-error distribution of innovation. This appears to show the presence of volatility clustering in GJR-GARCH model. The coefficient of  $\beta_1$  are statistically significant in all the three error assumptions. This appears to show that shocks to volatility are very high. The persistence in the three error assumptions of innovations is less than 1, indicating shocks to volatility are not high. The coefficient,  $\gamma_1$  is negative and statistically significant at the 5% level in skew student's t while for the normal and generalized error distribution  $\gamma_1$ , is negative and positive respectively and shows non-significant.

Conclusively, the GJR-GARCH model under generalized error distribution is found to be the best because it has lower forecast measures.

While under Chinese stock exchange price returns, all the holidays that falls on Mondays down to Fridays under normal and skewed student's t distributions of innovations shows non-significant effects at 5% level while for the GED of innovations, all the holidays that falls on Mondays (with effect 0.007078) and Fridays (with effect 0.002654) are significant. Additionally, the constant term of the GJR-GARCH model under the three error assumptions are all positive and significant.  $\alpha_1$  are statistically significant in the three error assumptions. This indicates the presence of volatility clustering in GJR-GARCH model.  $\beta_1$ , are statistically significant in all the three error assumptions. The persistence of the GJR-GARCH model under the three assumptions are less than 1, indicating the shocks to volatility are not high and the variances are not stationary. The coefficient,  $\gamma_1$  are negative and statistically significant at the 5% level in all the three error assumptions.

Conclusively, the GJR-GARCH model under skewed student's t distribution of innovations is found to be the best based on lower forecast measures observed.

The parameter estimates of Prophet model on Nigeria and Chinese stock price returns are explain in table 2 as follows:

**Table 2: Parameter Estimates Of Prophet Model On Nigeria And Chinese Stock Exchange Price Returns**

Parameters	Prophet	
	Nigeria	Chinese
$\delta_1$	0.037166(0.6777)	0.000019325(0.7514)
$\delta_2$	0.019149(0.6418)	0.000019821(0.6983)
$\delta_3$	0.050025(0.6539)	0.000017172(0.6629)
$\delta_4$	-0.064744(0.6539)	0.000013141(0.6983)
$\delta_5$	-0.066770(0.6836)	0.000019264(0.7188)

From table 2, it shows that the effect of holidays of Mondays down to Wednesdays on Nigeria price returns is positive (indicating the increment of the price returns per unit changes of the holidays that falls on Mondays down to Wednesdays) while for the Thursdays and Fridays is negative (indicating the decrement of the price returns per unit changes of the holidays that fall on Thursdays and Fridays). In addition, the parameter estimates are all insignificant at 5% level.

While for the Chinese price returns, the effect of holidays of Mondays down to Fridays are positive (indicating the increment of the price returns per unit changes of the holidays that falls on Mondays down to Fridays), though they are all insignificant at 5% level.

Since GJR-GARCH model under GED is seen to be the best, table 3 will explain the comparison of GJR-GARCH under Generalized Error Distribution of innovations and Prophet models forecast performance as follows:

**Table 3: Summary Of GJR-GARCH Under GED And Prophet Models Forecast Performance On Nigeria Stock Exchange Price Returns**

Loss Functions	GJR-GARCH (1,1): GED	Prophet
RMSE	0.009572166	0.009855862
MAE	0.00676212	0.007060411

With the help of RMSE and MAE in table 3, GJR-GARCH(1,1) model under GED of innovations slightly outperformed Prophet model. Hence, considering different distributions of innovations to study the effects of holiday's on Nigeria stock exchange price returns is worth noting.

Since GJR-GARCH model under Skewed student's t is seen to be the best on Chinese stock exchange price returns, table 4 will compare GJR-GARCH under Skewed student's t distributions of innovations and Prophet models forecast performance as follows:

**Table 4: Summary Of GJR-GARCH Under Skewed Student's t And Prophet Models Forecast Performance On Chinese Stock Exchange Price Returns**

Loss Functions	GJR-GARCH (1,1): Skewed student's t	Prophet
RMSE	0.1130101	0.07326395
MAE	0.05890874	0.04370841

Evidence from table 4, shows that RMSE and MAE have value of 11.30% and 5.89% respectively under GJR-GARCH (1,1) model, while under Prophet model, the RMSE and MAE have value of 7.3% and 4.37% respectively. Hence, we can conclude that Prophet model outperformed GJR-GARCH (1,1) model (under GED of innovations).

#### 4.0 CONCLUSION

For NSE price returns, results revealed the existence of holiday's effects of Mondays and Wednesdays to be positive and significant (under normal assumptions of innovations) while under skewed student's t and generalized error distribution of innovations, only holiday's that falls on Thursdays that are positive and significant. Furthermore,  $\alpha_1$  and  $\beta_1$  revealed the volatility clustering and persistence as they are all positive and significant. Leverage effect exist only under GED, though, non-significant at 5% level. In addition, among the three distributions assumptions of innovations considered, generalized error distribution is found to be the best based on the forecast measures.

For CSE price returns, all the holidays that falls on Mondays down to Fridays under normal and skewed student's t distributions of innovations shows non-significant effects at 5% level while for the GED of innovations, all the holidays that falls on Mondays (with effect 0.007078) and Fridays (with effect 0.002654) are

significant. Furthermore, volatility clustering and persistence are observed and significant. The exist no leverage effect in the three error distributions of innovations considered. Additionally, based on the forecast measured considered, the best distribution among the three considered is the skewed student's t distribution.

GJR-GARCH(1,1) model slightly defeated Prophet model under NSE price returns data, while under CSE price returns data, Prophet model defeated GJR-GARCH(1,1) model.

With this regard, it is worth noting that considering series returns factor (such as holiday's: Valentine's day, Father's day, etc.) in time series model (GJR-GARCH) and applying different distributions assumptions of innovations when analyzing financial series returns is important as it will provide more realistic information.

#### ACKNOWLEDGEMENTS

I acknowledge my supervisors for helping me through writing of this paper. I also acknowledge Central Bank of Nigeria and Federal Reserve Bank of St Lius, USA for sharing data with the public.

#### REFERENCES

- Adams, O. U., Asemota, O. J. & Ibrahim, A. A. (2024). Asymmetric GARCH Type Models and LSTM for Volatility Characteristics Analysis of Nigeria Stock

## IJS GS FUGUSAU VOL. 10(2)

WEBSITE: <https://fugus-ijsgs.com.ng>

- Exchange Returns, *American Journal of Mathematics and Statistics*, 14(2): 17-32.
- Adams, S. O., & Uchema, J. I. (2024). Nigeria Exchange Rate Volatility: A Comparative Study of Recurrent Neural Network LSTM and Exponential Generalized Autoregressive Conditional Heteroskedasticity Models, *Journal of Artificial Intelligence and Big Data*, 4(2), 61–73. <https://doi.org/0.31586/jaibd.2024.983>.
- Adams, S.O., Zubair, M.A. & Ezike, M.F. (2023). Mathematical Modeling of the Price Volatility of Maize and Sorghum between 1960 and 2022, *Journal of Mathematical Letters*, 1(1), 1–19. <https://doi.org/10.31586/jml.2023.801>.
- Attar, N. F., Pham, Q. B., Nowbandegani, S. F., Rezaie-Balf, M., Fai, C. M., Ahmed, A. N., ... & El-Shafie, A. (2020). Enhancing the prediction accuracy of data-driven models for monthly streamflow in Urmia Lake basin based upon the autoregressive conditionally heteroskedastic time-series model. *Applied Sciences*, 10(2), 571. <https://doi.org/10.3390/app10020571>.
- Beine, M., Laurent, S. & Lecourt, C. (2002) Accounting for conditional leptokurtosis and closing days effects in FIGARCH models of daily exchange rates, *Applied Financial Economics*, 12, 589–601.
- Black, F. (1976). Studies of stock price volatility changes, *Proceedings of the 1976 Business Meeting of the Business and Economics Statistics Section. American Statistical Association, Washington, DC* 177181.
- Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroscedasticity, *Journal of Econometrics*, 31, 307-327.
- Bollerslev, T. (1987) A conditionally heteroskedastic time series model for speculative prices and rates of return, *Review of Economics and Statistics*, 69, 542–7.
- Bollerslev, T. (1987). A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. *The Review of Economics and Statistics*, 69(3): pp. 542 547.
- Brorsen, B & Liu, S. (1995) Maximum likelihood estimation of a GARCH-stable model, *Journal of Applied Econometrics*, 10, 273–85.
- Bruno, D., J.H., Claver, K.K., Cletus, & S.F., elix-che. (2023). Modeling and Predicting Exchange Rate Volatility: Application of Symmetric GARCH and Asymmetric EGARCH and GJR-GARCH Models. *Journal of the Cameroon Academy of Sciences*, 19(2) (July 2023).
- Cai, W., Liu, K. & Lu, K. (2023). Forecasting Daily Stock Volatility: A Comparison between GARCH and Recurrent Neuro-networks, *BCP Business & Management*, 38, 427-438.
- Chatterjee, A., Bhowmick, H. & Sen, J. (2022). Stock Volatility Prediction using Time Series and Deep Learning Approach, *Computational Finance*, <https://doi.org/10.48550/arXiv:2210.02126>.
- Ding, Z., Granger, C.W.J. & Engle, R. F. (1993). A Long Memory Property of Stock Market Returns and a New Model, *Journal of Empirical Finance*, 1(1), 83 – 106. [https://doi.org/10.1016/0927-5398\(93\)90006-D](https://doi.org/10.1016/0927-5398(93)90006-D).
- Engle R. F. (1982). Autoregressive Conditional Heteroscedasticity with estimates of the Variance of the United Kingdom inflation, *Econometrics* 50, 987-1008.
- Fernandez, C. & Steel, M. (1998) On Bayesian modeling of fat tails and skewness, *Journal of the American Statistical Association*, 93, 359–71.
- Glosten, L., Jagannathan, R. & Runkle, D. (1993) On the relation between expected return on stocks, *Journal of Finance*, 48, 1779–801.
- Goel, A., Goel, A.K. & A. Kumar, A. (2023). The Role of Artificial Neural Network and Machine Learning in Utilizing Spatial Information, *Spatial Information Research*, 31, 275–285, 2023. <https://doi.org/10.1007/s41324-022-00494-x>
- Huang, X., You, P., Gao, X. & Cheng, D. (2019). Stock Price Prediction Based on ARIMA-GARCH and LSTM, *J. ICBIS*, 14, pp. 438–448. [https://doi.org/10.2991/978-94-6463-198-2\\_45](https://doi.org/10.2991/978-94-6463-198-2_45).
- Lambert, P. & Laurent, S. (2000) Modelling skewness dynamics in series of financial data, *Discussion Paper, Institut de Statistique, Louvain-la-Neuve*.
- Lambert, P. & Laurent, S. (2001) Modelling financial time series using GARCH-type models and a skewed student density, mimeo, Université de Lie`ge.
- Mandelbrot, B. (1963). The variation of certain speculative prices. *Journal of Business*, 36:394-414.
- Mohammed, T., Yahaya, H.U. & Adams, S.O. (2022). Modeling the Volatility for Some Selected Beverages Stock Returns in Nigeria (2012-2021): A GARCH Model Approach. *Matrix, Science Mathematic (MSMK)*, 6(2), 41-50.
- Nasrin, F.A., Quoc, B.P., Sajad, F.N., Mohammad, R., Chow, M., Ali, N.A. & E. Ahmed, E. (2020). Enhancing the Prediction Accuracy of Data-Driven Models for Monthly
- Nelson D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica* 59, 347–370.
- Shaik, M. & Aditya. (2020). The Comparison of GARCH and ANN Model for Forecasting Volatility: Evidence based on Indian Stock Markets: Predicting Volatility using GARCH and ANN, *The Journal of Prediction Markets*, 14(2), 103-121. <https://doi.org/10.5750/jpm.v14i2.1843>.



- Shen, Z., Wan, Q. & Leatham, D.J. (2021). Bitcoin Return Volatility Forecasting: A Comparative Study between GARCH and RNN. *Journal of Risk and Financial Management*, 14(337), 1-28. <https://doi.org/10.3390/jrfm14070337>.
- Tasi'u, M., Adamu, U.A. & Abdulaziz, U. (2024). An assessment on the impact of Holidays on Nigeria Stock Exchange Price Returns using EGAERCH and Prophet models under two different distributions of innovations, *Dutse Journal of Pure and Applied Sciences*, 10(3c): pp. 180-187. <https://dx.doi.org/10.4314/dujopas.v10i3c.17>
- Taylor, S. J. & Benjamin, L.,(2007) "Forecasting at Scale," *PeerJ Preprints*, 2017,doi: 10.7287/peerj.preprints.3190v2.
- Yahaya, H. U., Oyinloye, J. S., & Adams, S. O. (2022). Modeling and Forecasting Cryptocurrency Returns and Volatility: An Application of GARCH Models, *Universal Journal of Finance and Economics*, 2(1), 71–90. <https://doi.org/10.31586/ujfe.2022.497>.
- Yu, S., & Li, Z. (2018). Forecasting Stock Price Index Volatility with LSTM Deep Neural Network. In: Tavana, M., Patnaik, S. (eds) *Recent Developments in Data Science and Business Analytics*. Springer, 265–272. [https://doi.org/10.1007/978-3-319-72745-5\\_29](https://doi.org/10.1007/978-3-319-72745-5_29).
- Zahid, M., Iqbal, F. & D. Koutmos, D. (2022). Forecasting Bitcoin Volatility Using Hybrid GARCH Models with Machine Learning, *Risks*, 10, 237-244. <https://doi.org/10.3390/risks10120237>.
- Zakoian, J. M. (1994). Threshold Heteroscedastic Models, *Journal of Economic Dynamics and Control*, 18, 931-955.
- Zhou A, & Rui G. (2021). Research on Volatility Prediction Based on Deep Learning Algorithm Example of SSE 50ETF Option, *Huabei Finance*, 09 (07).