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FORECASTING PERFORMANCE OF SOME GARCH MODELS ON HOLIDAY-INDUCED VOLATILITY IN NIGERIA STOCK EXCHANGE PRICE RETURNS UNDER DIFFERENT ERROR DISTRIBUTIONS

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ABSTRACT

Time series data occasionally depend on factors among which are holidays (such as Mother's days, Children's days, Democracy days, Independent Days, Valentine's days to mention but few) which number of researchers did not put into consideration. This paper aimed at evaluating the forecast performance of some asymmetry GARCH models (EGARCH, GJR-GARCH, and APARCH) on holiday-induced volatility in Nigeria stock exchange price returns under three different error distributions of innovation: Normal, Skewed student's t, and Generalized Error Distribution (GED). Based on minimum value of Root Mean Square Error (RMSE), EGARCH (1,1) model under Skewed student's t is found to be the best model. In addition, there exists consequences of all the holiday's that falls on Thursday's (with effect 0.002803; indicating that for any unit of holiday on Thursday(s), the volatility of NSE price series returns will significantly increase by 0.002803). Volatility clustering and persistence are found in the models. More so, leverage effect is found in EGARCH model under the three error distributions of innovation.

Keywords: EGARCH, GJR-GARCH, APARCH, Holidays Effects, NSE

INTRODUCTION

Within the field of financial econometrics, basically driven by the need for effective risk management and accurate forecasting, volatility has long been a vital statistical variable to be considered. Volatility as a measure of dispersion, described the rate of variation in financial asset returns, which enable investors, policymakers and financial institution alike to make necessary adjustment before jumping into an agreement or business idea. One of the most useful, influential, and widely used methodologies for analyzing financial markets volatility is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, introduced by Bollerslev (1986). The concept of Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982) paved the way for Bollerslev's GARCH model, which extends the ARCH model by incorporating the past conditional volatility into the model. This ARCH extension, allowed more realistic capture of persistence and volatility clustering of financial time series data. Consequently, other GARCH models have been developed to study specific features of financial time series data. Some of these models are Exponential GARCH (EGARCH) introduced by Nelson (1991), in order to capture asymmetric effects of shocks to volatility, Threshold GARCH (TGARCH) introduced by Zakoian (1994), which models threshold effects in volatility, among others.

Numerous empirical studies have shown the robustness and versatility of GARCH models across different economic and financial markets contexts. For instance, Rossetti et al. (2017) applied the EGARCH model to fixed income market volatility across many countries. The result revealed the effectiveness of EGARCH model in capturing volatility influenced by macroeconomic events. Chkili et al. (2021) employed a hybrid model combining Artificial Neural Network (ANN) and Fractional Integrated Asymmetric Power Autoregressive Conditional Heteroskedastic (FIAPARCH) model to study Islamic stock market changes in variance (volatility), describing the forecast accuracy of the adopted approach during the periods of significant financial events; such as 9/11 attacks and the 2008 financial crisis. Due to the significant results shown by GARCH models in literature review, its application extends beyond traditional financial markets to include commodity and macroeconomic indicator. Paolella et al. (2008) studied the consequences of emission allowances on power and gas markets. They emphasized on the importance of understanding the statistical distributions of emission trading returns for hedging strategies. Similarly, Liang (2013) applied GARCH model in reliability forecasting, describing their ability in forecasting failure data for electronic systems.

Despite numerous research on GARCH models, incorporating series returns factor, that is, holidays (such as Sallah day, Christmas day, Id el Maulud among others) has not been given extensive consideration. As such, this paper aimed in exploring GARCH models (EGARCH, GJR-GARCH and APARCH) incorporated with holidays for three error distributions (Normal, Skewed student's t, and GED) to establish their consequences on Nigeria economy.

In fitting and forecasting financial time series returns, GARCH model and its variant have been proven significant. With this regard, number of researchers used GARCH models and elucidate the nuances and applications of it in various contexts, from stock markets to commodity prices, and from macroeconomic impacts to unique industry-specific challenges.

Among the early extensions of the GARCH model, Nelson (1991) established the EGARCH model, which captures the asymmetric effects of shocks on volatility and do not impose any restriction on the parameters in the model. The EGARCH model, Glosten Jakannathan, and Runkle GARCH (GJR-GARCH) introduced by Glosten Jakannathan, and Runkle (1993) and the Non-linear GARCH (NGARCH) model by Bera and Higgins (1993) have been instrumental in fitting and forecasting financial volatility. These models address the need to capture volatility asymmetry, one of the common features in financial markets where negative shocks and positive shocks have different impact on volatility.

Some further extensions include the Asymmetric Power ARCH (APARCH) model introduced by Ding et al. (1993) and the Threshold GARCH (TGARCH) model by Zakoian (1994), where asymmetries and threshold effects will be captured. Bollerslev and Ghysels (1996) came up with Priodic

GARCH (PGARCH) model, which explains the seasonal volatility patterns in high frequency asset returns. These models provide better tools for risk management and forecasting as they have improved our insight on volatility dynamic. Empirical studies, at different time periods explained the strength of these models. For instance, Celik (2020) forecasted the series returns of BIST 100 index between 01st Jan.2020 to 11th Feb.2021. Dummy variables (such as days-of-the-week, dates of holidays and COVID-19 pandemic) were considered in the analysis. Their findings revealed the existence of leverage effect and that EGARCH (3,3) model best fit the series. In addition, holidays, COVID-19 pandemic and Friday's effect caused negative shocks on the volatility of the series returns. Wang et al. (2021) explored many GARCH models in order to study the returns and its dispersion of Bitcoin. The range of data they used was from 1st October, 2013 to 31st July, 2020, where a total of 2496 observations were found. Particularly, GARCH (1,1) revealed volatility clustering characteristic of the series returns. The absence of leverage effect was confirmed by EGARCH and TGARCH models. Sharma et al. (2021) forecasted the volatility for major emerging markets, such as Brazil, Mexico, Indonesia, China and India using GARCH (1,1) and non-linear models. They realized GARCH (1,1) outperformed non-linear models. Gupta (2023) fit and forecast the stock market volatility in emerging nations using symmetric and asymmetric GARCH models, and realized EAGRCH model to be the best. Naidoo et al. (2023) used GARCH (1,1) model to investigate how exchange rate volatility affects South Africa's stock and real estate markets, outlining the interconnectedness of financial markets. Dash (2023) used a year data ranging from Apr. 1, 2018 to Mar. 31, 2019 for twenty major stocks in Indian banking sector and applied AR-GARCH model incorporated with days-of-the-week as dummy variables. The results showed that Tuesday's (with lower returns) and Thursday's effect has higher volatility compared to Monday.

Since little or no research has been done on the factor such as holiday-induced volatility, this paper is aimed at evaluating the forecast performance of some asymmetry GARCH models (EGARCH, GJR-GARCH, and APARCH) on holiday-induced volatility in Nigeria stock exchange price returns under three different error distributions of innovation: Normal, Skewed student's t, and Generalized Error Distribution (GED).

MATERIALS AND METHODS

The study has used the daily stock price returns series of NSE for the period, 16th December 2009 to 6th February 2019 resulting to 2383 of observations in total. The data was obtained from Central Bank of Nigeria (CBN) website on the month of May, 2024.

Log Returns Calculations

Suppose η_t and η_{t-1} represent the present and past day's stock prices respectively. The log returns series, denoted by r_t is:

$$r_t = log\left(\frac{\eta_t}{\eta_{t-1}}\right) \quad (1)$$

The log returns series, r_t will be used as the observing volatility of the Nigeria stock price returns over the period 2009 to 2019.

EGARCH (p,q) Model

In 1991, EGARCH (p,q) model was introduced by Nelson in order to model the volatility and capture the leverage effect of a time series data. It is expressed as follows:

$$log(\sigma_t{}^2) = \omega + \sum_{i=1}^{p}\left[\alpha_i\left(\frac{|\varepsilon_{t-i}|}{\sigma_{t-i}} - \sqrt{\frac{2}{\pi}}\right) + \gamma_i\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right)\right] + \sum_{j=1}^{q}\beta_j\, log(\sigma_{t-j}{}^2) + \sum_{k=1}^{5}\vartheta_k D_{kt} \quad (2)$$

whereγ_i, is the leverage effect. The leverage exists if $\gamma_i > 0$. If $\varepsilon_{t-i} > 0$, good news exists, if $\varepsilon_{t-i} < 0$, bad news exists. If bad news has high impact on volatility,$\gamma_i > 0$. α_i measures the magnitude of the shock $\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) = z_{t-i}$, β_j measures the persistence in conditional volatility of the shocks. D_{kt} is an indicator function such that $D_{1t} = 1$ if t day is a Monday and 0 otherwise; $D_{2t} = 1$ if t day is a Tuesday; $D_{3t} = 1$ if t day is a Wednesday $D_{4t} = 1$ if t day is a Thursday and $D_{5t} = 1$if t day is Friday.

Note:$\varepsilon_t = \sigma_t z_t$ and $z_t \sim N(0,1), \varepsilon_t \sim N(0, \sigma_t{}^2)$ (3)

GJR-GARCH (p,q) Model

The GJR-GARCH(p,q) model is expressed as:

$$\sigma^2{}_t = \omega + \sum_{i=1}^{p}(\alpha_i + \gamma_i I_{t-i})\,\varepsilon^2{}_{t-i} + \sum_{j=1}^{q}\beta_j\sigma^2{}_{t-j} + \sum_{k=1}^{5}\psi_k\, D_{kt} \quad (4)$$

To guarantee the positivity of the conditional variance, the parameters must satisfy $\omega > 0,\ \alpha_i \geq$, and $\beta_j \geq 0$, I_{t-i} is an indicator function taken value 0 or 1. If there is no asymmetric effect, γ is not statistically significant. $D_{kt}$is as explained above.

APARCH (p,q)

The APARCH(p,q) model is expressed as:

$$\sigma^v{}_t = \alpha_o + \sum_{i=1}^{p}\alpha_i\,(|\varepsilon_{t-i}| - \gamma_i\varepsilon_{t-i})^v + \sum_{j=1}^{q}\beta_j\,\sigma^v{}_{t-j} + \sum_{k=1}^{5}\tau_k D_{kt} \quad (5)$$

where $\alpha_o > 0$, $v \geq 0$, $\beta_j \geq 0$, $\alpha_i \geq 0$ and $-1 < \gamma_i < 1$. The asymmetry in the model is captured through the parameter γ_i and the power term υ captures both the conditional standard deviation ($v = 1$) and conditional variance ($v = 2$) as special cases. $D_{kt}$is as explained above.

Diagnostic Test

The diagnostic test conducted to evaluate the adequacy and predictability of NSE price series returns is Root Mean Square Error (RMSE) defined in Equation (6) as follows:

$$RMSE = \sqrt{\frac{1}{k}\sum_{t=T+1}^{T+k}\left(\sigma^2{}_t - \widehat{\sigma^2}_t\right)^2}. \quad (6)$$

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

RESULTS AND DISCUSSION

The analysis of the empirical study on volatility of NSE price series returns using asymmetric GARCH models, EGARCH, GJR-GARCH and APARCH incorporated with holiday's effects reveals insightful findings which are discussed subsequently.

Note that in the subsequent tables, $\delta_1, \delta_2, \delta_3, \delta_4$ and $\delta_5$represents Mondays, Tuesdays,…, Fridays effects in that order.

Table 1: Parameters estimates and persistence of EGARCH (1,1) model with Holiday's Effects

Parameters	Normal Estimates	Skewed student's t Estimates	Generalized Error Distribution Estimates
ω	-0.643349 (0.000036)	-1.209287 (0.000083)	0.325355 (0.000567)
α_1	0.011419 (0.448353)	-0.043284 (0.107527)	-0.023211 (0.361503)
β_1	0.929102 (0.000000)	0.869527 (0.000000)	0.880156 (0.000000)
γ_1	0.322819 (0.000001)	0.491391 (0.000000)	0.433498 (0.000000)
δ_1	0.003175 (0.013614)	0.000987 (0.320139)	0.000017 (0.765090)
δ_2	0.002313 (0.109151)	0.001352 (0.297631)	0.000027 (0.930570)
δ_3	0.003011 (0.058378)	0.002512 (0.058382)	0.001628 (0.621801)
δ_4	0.002312 (0.125238)	0.002803 (0.025774)	0.001597 (0.568911)
δ_5	-0.003270 (0.014848)	0.001232 (0.231335)	0.000017 (0.804289)
Persistence	1.1019305	1.0719385	1.073694
AIC	-6.5380	-6.6281	-6.6408

(The values in the parenthesis represent the p-values)

By table 1, it shows that the parameter, $\delta_1$of Mondays (with effect 0.003175) and $\delta_5$of Fridays (with effect -0.003270) under normal assumptions of innovations are significant (implying that the series returns of Mondays and Fridays will increase and decrease respectively per unit change of the holidays that falls on these days) while the rest of the days are not at 5% level.

The Thursday's parameter, δ_4 (with effect 0.002803) under skewed student's t error distribution of innovations is significance at 5% level while the rest of the days are not.

Under Generalized distributions of innovations, all the parameters of the five days indicated non-significance at 5% level.

On the other hand, α_1(with effects 0.011419, -0.043284, and -0.023211 under Normal, Skewed student's t, and GED respectively) are not statistically significant at 5% level.

β_1, (with effects 0.929102, 0.869527, and 0.880156 under Normal, Skewed student's t and GED respectively) are statistically significant at 5% level. The constant term, ω (has effects, -0.643349, -1.20928, and 0.325355 under Normal, Skewed student's t and GED respectively) are statistically significant at 5% level.

The parameter γ, is the leverage effects (with effects, 0.322819, 0.491391, and 0.433498 under Normal, Skewed student's t, and GED respectively) are statistically significant at 5% level. However, leverage effect will only exist if $\gamma_1 \neq 0$.Therefore, the hypothesis of leverage effect is accepted for EGARCH model.

The persistence (with effects 1.1019305, 1.0719385, and 1.073694 under Normal, Skewed student's t, and GED respectively) exceeds 1, indicating the shocks to volatility are high and the variances are not stationary.

Conclusively, the EGARCH model under generalized error distribution is found to be the best because it has lower AIC.

Table 2: Parameters estimates of GJR-GARCH (1,1) model with Holiday's Effect

Parameters	Normal Estimates	Skewed student's t Estimates	Generalized Error Distribution Estimates
ω	0.000007 (0.000000)	0.000086 (0.000182)	0.000011 (0.000000)
α_1	0.190110 (0.000000)	1.000000 (0.000000)	0.240828 (0.000000)
β_1	0.758207 (0.000000)	0.498154 (0.000147)	0.651225 (0.000000)
γ_1	-0.015757 (0.565375)	-1.000000 (0.000000)	0.064780 (0.24266)
δ_1	0.003239 (0.013001)	0.000827 (0.494195)	0.000010 (0.86500)
δ_2	0.002556 (0.080623)	0.002057 (0.138112)	0.000051 (0.96022)
δ_3	0.003464 (0.027208)	0.002191 (0.130637)	0.001416 (0.62935)
δ_4	0.001255 (0.484108)	0.002869 (0.028864)	0.001054 (0.00000)
δ_5	0.000462 (0.832087)	0.000518 (0.640569)	0.000010 (0.85238)
Persistence	0.9404385	0.998154	0.924443
AIC	-6.5429	-6.5319	-6.6440

(The values in the parenthesis represent the p-values)

By table 2, there exist significance effects of the holidays that falls on Mondays (with effect 0.003239) and Wednesdays (with effect 0.003464) under normal assumptions, while under skewed student's t and GED error assumptions of innovations, only holiday's that falls on Thursdays with effects 0.002869 and 0.001054 are respectively significance at 5%.

On the other hand, α_1(with effects: 0.190110, 1.000000, and 0.240828 under Normal, Skewed student's t, and GED respectively) are statistically significant at 5% level, indicating the presence of volatility clustering in the GJR-GARCH model.

β_1, (with effects: 0.758207, 0.498154, and 0.651225 under Normal Skewed student's t, and GED respectively) are statistically significant at 5%.

The constant term, ω (with effects: 0.000007, 0.000086, and 0.000011 under Normal, Skewed student's t, and GED respectively) are statistically significant at 5% level.

The leverage effects parameter, γ_1 (with effect -1.000000) under skewed student's t assumptions of innovations is statistically significant at 5% level but non-significant under normal (with effect -0.015757) and GED (with effect 0.064780).

The persistence (with effects: 0.9404385, 0.998154 and 0.924443 under Normal, Skewed student's t, and GED respectively) are less than 1, indicating the shocks to volatility are not high. Hence, we can conclude that the GJR-GARCH model under generalized error distribution of innovations to be the best because it has lower AIC.

Table 3: Parameters estimates and persistence of APARCH (1,1) model with Holiday's Effect

Parameters	Normal	Skewed student's t	Generalized Error Distribution
	Estimates	**Estimates**	**Estimates**
ω	0.000000 (0.894060)	0.000000 (0.841765)	0.000000 (0.607480)
α_1	0.152219 (0.000002)	0.180821 (0.000000)	0.199174 (0.000000)
β_1	0.738945 (0.000000)	0.395243 (0.000000)	0.529609 (0.000000)
γ_1	-0.015454 (0.635767)	0.096955 (0.039272)	0.057829 (0.225842)
δ_1	0.003359 (0.016213)	0.001158 (0.356491)	0.000129 (0.891602)
δ_2	0.002325 (0.124918)	0.001275 (0.389665)	0.000235 (0.886418)
δ_3	0.003551 (0.031844)	0.002555 (0.068209)	0.001997 (0.000038)
δ_4	0.000457 (0.801307)	0.002832 (0.048499)	0.001885 (0.469815)
δ_5	0.000130 (0.935652)	0.000395 (0.761869)	-0.000011 (0.984197)
Persistence	0.883437	0.6245415	0.7576975
Delta	2.981832 (0.000000)	3.412847 (0.000000)	3.107898 (0.000000)
AIC	-6.5367	-6.6105	-6.6356

(The values in the parenthesis represent the p-values)

By table 3, it shows that under normal assumptions of innovations, the Mondays parameter, δ_1(with effect 0.003359) and Wednesdays, δ_3(with effect 0.003551) are significance at 5% level (indicating the series return will increase per unit change of the holidays that fall on these days) while the rest of the days are not.
The Thursday's parameter, δ_4(with effect 0.002832) under skewed student's t is statistical significance at 5% level while the rest of the days are not.
Also, there exists only Wednesday's significance effects (with value 0.001997) under generalized error distribution.
Furthermore, α_1, which measures the impact of past squared returns on present volatility (with effects: 0.152219, 0.180821, and 0.199174 under Normal, Skewed student's t, and GED respectively) are statistically significant at 5% level. This indicates the presence of volatility clustering in APARCH (1,1) model.
The coefficient of β_1 (with effects: 0.738945, 0.395243, and 0.529609 under Normal, Skewed student's t, and GED respectively)) are statistically significant at 5% level.
The constant term, ω has zero effects and non-significant at 5% level in the three assumptions of innovations.
The coefficient,γ_1 is positive and statistically significance at the 5% level in the skewed student's t distribution, while for the normal and generalized error distributionγ_1, shows non-significance. Hence, there exist leverage effect in APARCH model under error assumption of skewed student's t.
The sum $\left(\alpha_1 + \beta_1 + \frac{\gamma}{2}\right)$, referred as the persistence (with effects: 0.883437, 0.6245415, and 0.7576975 under Normal, Skewed student's t, and GED respectively) are less than 1, indicating shocks to volatility are not high.
Conclusively, the APARCH model under generalized error distribution is found to be the best because it has lower AIC.

Table 4: Summary of some GARCH models under three different error assumptions with Holiday's effect on NSE

	EGARCH(1,1)			GJR-GARCH(1,1)			APARCH(1,1)		
	Normal	**Skewed t**	**GED**	**Normal**	**Skewed t**	**GED**	**Normal**	**Skewed t**	**GED**
RMSE	0.009574	0.009566776	0.009572434	0.009573327	0.009584331	0.009572166	0.009573645	0.00956811	0.009572979

With the help of forecast performance in Table 4, GJR-GARCH model outperformed EGARCH and APARCH under normal and generalized error distribution of innovations while EGARCH outperformed both GJR-GARCH and APARCH models under skewed student's t. Since the lowest RMSE observed in Table 4 is found in EGARCH model (under skewed student's t), we conclude that EGARCH model performed better than the GJR-GARCH and APARCH models (see Celik (2023), Gupta (2023)).

CONCLUSION

This study provides a thorough analysis of volatility dynamic in Nigeria Stock Exchange (NSE) price series returns using three asymmetric GARCH models: EGARCH(1,1), GJR-GARCH (1,1), and APARCH(1,1). The aim is to assess their performances in capturing holiday's consequences or effects and forecasting volatility over a long period, from 16th December 2009 to 6th February 2019 resulting to 2383 of observations in total. The GARCH model's efficacy to account for these holidays consequences is core for accurate forecast. In determining the performance of the variant GARCH models, GJR-GARCH(1,1) model outperformed both (1,1) and APARCH(1,1) models under normal and GED of innovation, while EGARCH outperformed both GJR-GARCH and APARCH model under skewed student's t.Since EGARCH (1,1) model under skewed student's t is declared to be the best, we can infer that there are consequences of all the holiday's that falls on Thursday's (with 0.002803 effect, indicating that for any unit of holiday on Thursday(s), there will be 0.002803 increase in the volatility of NSE price series returns) at 5% level of significant. This is also consistent with the findings of Mihir (2023). Furthermore, all the three error distributions of innovation considered, Skewed student's t appeared to be better. Hence, considering variant distributions of innovation while analyzing time series data is worth noting.

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