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An Assessment on the Impact of Holidays on Nigeria Stock Exchange Price Returns using EGARCH and Prophet Models under Two Different Distributions of Innovations

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Abstract
In this study, the aim is to investigate the forecast performance of EGARCH and Prophet models on holidays effect of Nigeria Stock Exchange (NSE) price returns. The holidays effect are incorporated into EGARCH model to investigate whether the volatility of the series returns will decrease or increase thereby increasing the accuracy of results than using ordinary EGARCH model. On the other hand, Prophet model also called Facebook Prophet model was used to investigate whether including functions such as trend, seasonality, and holidays could accurately forecast the return series. Based on the evaluation criteria, EGARCH (under skew student's t distribution of innovation) performed better than the Facebook Prophet model as well as EGARCH (with normality assumptions of innovations) model. Furthermore, the results revealed a positive return series for holidays that falls on Thursdays.

Keywords: EGARCH, Prophet model, NSE, Holidays effect, Skew t distribution

INTRODUCTION

Generally, information is power; as such information plays a vital role in a financial market. Research has shown that a well-developed economy will lead to complete and reliable information about a financial market. Nowadays, information is not shared equally between the parties, as such economy effectiveness, especially that of financial market is reduced. The lack of this complete information on the financial market(s) led to the revelation of concept of asymmetric GARCH models. Mishkin (1996, 1998) pointed out that asymmetric information affects the financial market series returns. Development in financial market(s) did not only affects themselves but also, significantly affects the overall economy. However, if a market is real or financial, the smooth function of it is of great importance for a stable economy system. Though, for developing countries, it is not always possible to ensure and maintain the stability of a market due to the financial market of those countries characterized by some factors such as a high fragility, risk and uncertainty (Mishkin, 2004). It could also be due to some holidays (Id el Kabbir, Christmas day, Valentine's Day, Happy Maulud among others). As such, testing the volatility of financial assets returns is crucial as it plays a vital role and provide access to market information and predictability.

In the theory of finance, there exist a direct relationship between risk and volatility of a series returns. Volatility (variance) distribution is a measure of financial market's risk (Mazibaş,

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2005). Heteroskedasticity exist when the variance of a series returns varies over time. Symmetric conditional heteroskedasticity such as ARCH and GARCH models and asymmetric conditional heteroskedasticity such as EGARCH, GJR-GARCH models etc. provides a solution in fitting and forecasting a series with heteroskedasticity problem. These symmetric and asymmetric models are not the same as symmetric models assumed positive and negative shocks to have the same effects over the variance of series returns while asymmetric models assumed positive and negative shocks have different effects on the volatility of series returns. With this regard, it is assumed that asymmetric models provide more realistic information and results than the symmetric models.

Özden (2008) calculated daily return values using the Istanbul Stock Exchange-100 closing index from January 04-2000 to September 20-2008. In the analysis, the author employed GARCH, EGARCH and TGARCH to test the volatility of Istanbul Stock Exchange-100 closing index series returns and found TGARCH (1, 1) to be the best model. Olowe (2009) determined the relationship between stock market returns and changes in variance (volatility) by applying EGARCH-M model. The study revealed the existence of relationship between stock returns and changes in variance (volatility). The suspected impact of banking reforms and market crash was seen to be negative. In addition, insurance reforms and financial crisis was found to be of no effect on stock returns.

Ade and Dallah (2010) used asymmetric GARCH models to fit and forecast the daily stock returns of the Nigeria's insurance stocks by considering twenty six insurance companies daily data for the estimation. In their study, EGARCH (1,1) was found to fit and forecast better compared to ARCH(1), GARCH(1,1) and TGARCH(1,1). Bala and Asemota (2013) investigated the volatility of exchange rate using different GARCH models with and without volatility break. They recommended the inclusion of important events in the estimation of the GARCH models.

Babatunde (2013) applied EGARCH model to determine the contribution of Nigeria stock market volatility on economic growth. The studied gives evidenced of volatility persistent. Lama *et al.* (2015) used ARIMA, GARCH, and EGARCH models to fit and forecast volatility in table oil and international cotton price index over the period of April, 1982 to March, 2012. They realized EGARCH model to be the best. Accordingly, the asymmetric conditional heteroskedasticity described the volatility in the international cotton price index. Asemota *et al.* (2017) applied asymmetric GARCH models on volatility of banks equity using weekly returns for six banks (coded as B1 to B6) in Nigeria's Stock Market. Their studied revealed the presence of ARCH effect in B2 and B3 equity returns. Furthermore, they realized non-existence of leverage effect in the fitted models. On evaluating the fitted models, EGARCH (1,1) and CGARCH(1,1) models using student's t distribution of innovation provided better realistic results on B2 and B3 equity returns respectively.

On the other hand, Güleryüz and Özden (2020) assessed the accuracy of Long-Short Term Memory (LSTM) and Facebook Prophet models in crude oil price series. Based on the loss function used, they realized LSTM performed better than Facebook Prophet model in forecasting the crude oil price series. Saxena *et al.* (2022) applied Facebook Prophet model to prophecies (forecast) future stock market prices and how they varies from previous stock market. The considered data for the studied ranged from year 2012 to 2022. They revealed that the analysis has the potential for further investigation. Gaur (2022) prophecies covid-19 using ARIMA based Facebook Prophet model. The forecasted period covered from 22-01-2020 to 20-06-2020 and revealed very near recorded confirmed cases (indicating the forecast error less than 5 thousand cases at the end of every 30-days period). The results revealed a slowing down trend of covid-19, leading to the conclusion of covid-19 extinction if proper lockdown and social distances are maintained thoroughly. Aziz *et al.* (2022) examined the forecast performance of Facebook Prophet and hybrid ARIMA models on crude oil prices. They applied Savitzky–Golay smoothing filter to realize a better diagnosing forecast performance. The loss function used were RMSE and MAPE which supported ARIMA based on machine learning to outperform the Facebook Prophet model.

Little or no research has been done on Nigeria stock exchange price returns using GARCH model(s) incorporated with holiday's effects such as (Children days, Christmas days, Id el Kabbir among others). As such, this paper aimed to fill this gap so that more realistic results will be obtained.

METHODOLOGY

This section described the method of data transformation and methodology used in analyzing the Nigeria stock exchange price returns.

Materials and Method

The daily stock exchange price returns data over the period 2009 to 2019 of Nigeria Stock Exchange (NSE) resulting to a total of 2384 observations is used for the analysis (the only available data in internet). Suppose η_t and η_{t-1} denotes the present and past day's stock exchange prices returns respectively. Let the log return series be r_t, then:

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

EGARCH (1,1) model

The EGARCH(1,1) is expressed in equation (2) as:

$$\log\left(\sigma_t^{\ 2}\right) = \omega_0 + \varpi_1\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right) + \gamma_1\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \varpi_2 \log\left(\sigma_{t-1}^2\right) + \sum_{m=1}^{5}\beta_m D_{mt} \tag{2}$$

as ϖ_1 determines the volatility clustering, ϖ_2 determines the volatility persistence and γ_1 determines whether leverage effect exist or not while σ_t and σ_{t-1} denotes the present and past volatility of the series returns. D_{mt} is a variable taken value 0 or 1. When $D_{1t} = 1$, day *t* is said to be Monday and 0 otherwise; $D_{2t} = 1$, day *t* is said to be Tuesday; $D_{3t} = 1$, day *t* is said to be Wednesday $D_{4t} = 1$, day *t* is said to be Thursday and $D_{5t} = 1$, day t is said to be Friday.
The shock of the series returns is expressed as:

$$\varepsilon_t = \sigma_t z_t \ and \ \mathrm{z}_t \sim N(0,1) \tag{3}$$

Prophet model

The Prophet model was developed by the Core Data Science team at Facebook (Taylor & Letham 2017). The model is capable enough to take care of missing value(s) problem, shifts in the trend and outliers (Rodriguez et al. 2018). In forecasting a trend series, this Prophet model considered two models (saturated growth and piece-wise linear). A model related to population growth models used to forecast growth in natural ecosystem (the interconnectedness of organism, being plants, animals, microbes with each other and their environment), when nonlinear growth at a carrying capacity has reached a saturating point. When saturating point never reached, a piece-wise model with a constant growth-rate gives an efficient and beneficial solution forecasting application.

Suppose $y(t)$, $G(t)$, $S(t)$, $H(t)$, and ε_t are the series returns, trend function, seasonality function, holidays function and error term respectively. Then the Prophet model is given by:

$$y(t) = G(t) + S(t) + H(t) + \varepsilon_t. \tag{4}$$

Where $$G(t) = \frac{c(t)}{1 + e^{\left(-\left(k + \mathbf{a}_j(t)^{\mathrm{T}}\delta\right)\left(t - \left(\mathrm{m} + \mathbf{a}_j(t)^{\mathrm{T}}\gamma_j\right)\right)\right)}}. \tag{5}$$

And $$a_j(t) = \begin{cases} 1, \text{ if t} \geq \text{s} \\ 0, \text{ otherwise} \end{cases} \tag{6}$$

$$\gamma_j = \left(s_j - m - \sum_{i<j}\gamma_i\right)\left(1 - \frac{k + \sum_{i<j}\delta i}{k + \sum_{i \leq j}\delta i}\right). \tag{7}$$

where $c(t)$ is a carrying capacity varying with time, k is the growth rate, m an offset parameter, $\delta \in R^S$ (a vector rate of adjustment) and δi is the change in rate that occurs at time s_j.

$$s(t) = X(t)\beta = \sum_{n=1}^{N}\left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)\right) \tag{8}$$

Where:

$X(t)$ is a matrix of seasonality vectors for each value of t in a historical and future data, a_n and b_n are parameters to be estimated , $\beta = \left[a_1, b_1, ..., a_N, b_N\right]^T$.

$$H(t) = Z(t)\kappa_i. \tag{9}$$

where κ_i is a respective holiday's effect, $Z(t)$ is a matrix of regressors and it is expressed by:

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

Evaluation criteria

In measuring the forecast performance of the two models, two criteria are used, the Root Mean Square Error (RMSE) and Mean Absolut Scale Error (MASE). RMSE is an evaluation criteria which provides an amount of differences between the forecasted series and the actual series. It is expressed as:

$$RMSE = \sqrt{\frac{1}{k}\sum_{t=T+1}^{T+k}\left(\sigma_t^2 - \hat{\sigma}_t^2\right)^2}. \tag{11}$$

While MASE is usually used when there exist zero value(s) in a series. It measures the accuracy of a model. It is expressed as:

$$MASE = \frac{\frac{1}{j}\sum_j |e_j|}{\frac{1}{k}\sum_{t=T+1}^{T+k}\left|\sigma_t^2 - \hat{\sigma}_t^2\right|} \tag{12}$$

As $\sigma^2{}_t$ denotes the actual volatility of the series, $\hat{\sigma}_t^2$ denotes the forecasted volatility at time t , e_t is the error term and k predictions are taking from $t = T + 1$ to $T + K$.

RESULTS AND DISCUSSION

The parameters estimate of EGARCH model with holiday's effect under normal and student's t assumptions of innovations is explained in table 1.

Table1: Parameters estimate of EGARCH (1,1) Model with holidays effect: under Normal and Skew Student's t assumptions of innovation

Parameters	ERROR DISTRIBUTION: NORMAL	ERROR DISTRIBUTION: Skew student's t Distribution
δ_1	0.003175 (0.013614)	0.000987 (0.320139)
δ_2	0.002313 (0.109151)	0.001352 (0.297631)
δ_3	0.003011 (0.058378)	0.002512 (0.058382)
δ_4	0.002312 (0.125238)	0.002803 (0.025774)
δ_5	0.003270 (0.014848)	0.001232 (0.231335)
α_1	0.011419 (0.448353)	-0.043284 (0.107527)
β_1	0.929102 (0.000000)	0.869527 (0.000000)
ω	-0.643349 (0.000036)	-1.209287 (0.000083)
γ_1	0.322819 (0.000001)	0.491391 (0.000000)
Persistence	1.1019305	1.0719385

According to table 1, it shows that the parameter, δ_1 of Mondays and δ_5 of Fridays under normal assumptions of innovation are all positive and significant (implying that the series returns of Mondays and Fridays will increase per unit change of the holidays that falls on these days) while the rest are not significant at 5% level of significant.

The parameter of Thursdays effects, δ_4 under skew student's is positive and significant at 5% level (implying the series returns will increase per unit change of the holidays that falls on Thursdays) while the rest of the days are not significant.

Furthermore, α_1 (in both the error assumptions of innovation) is not statistically significant at 5% level. This indicates that the presence of volatility clustering in EGARCH (1, 1) model can be ignored even though it exist.

β_1, (in both the error assumptions of innovation) are statistically significant at 5% level.

The persistence, $\left(\alpha_1 + \beta_1 + \frac{\gamma}{2}\right)$, of the EGARCH model under the two assumptions of innovation exceed 1, implying the shocks to volatility are high and the variances are not stationary.

The parameter, γ_1 are positive and statistically significant at the 5% level in all the two error assumptions of innovation. Therefore, the hypothesis of leverage effect is rejected for all the two error assumptions of innovation.

The forecast evaluation of the EGARCH model with holiday's effect under normal and skew student's t distribution of innovations is explained in table 2.

Table 2: Forecast evaluation of the EGARCH (with normal assumptions) and EGARCH (with skew student's t assumptions) models

Forecast Measures	ERROR DISTRIBUTION: NORMAL	ERROR DISTRIBUTION: Skew student's Distribution
RMSE	0.009574458	0.009566776
MASE	0.829656	0.8304276

Based on table 2, it is clear to see that EGARCH (with skew student's distribution of innovation) slightly forecast better than EGARCH (with normal assumptions).
The parameters estimate of EGARCH model and Prophet model with holiday's effect under normal assumptions of innovations is described in table 3.

Table 3: Parameters estimate of EGARCH (1,1) Model and Prophet model

Parameters	EGARCH	PROPHET
δ_1	0.000987 (0.320139)	0.037166 (0.6777)
δ_2	0.001352 (0.297631)	0.019149 (0.6418)
δ_3	0.002512 (0.058382)	0.050025 (0.6539)
δ_4	0.002803 (0.025774)	-0.064744 (0.6539)
δ_5	0.001232 (0.231335)	-0.066770 (0.6836)
α_1	-0.043284 (0.107527)	
β_1	0.869527 (0.000000)	
ω	-1.209287 (0.000083)	
γ_1	0.491391 (0.000000)	
Persistence	1.0719385	

By table 3, Prophet model shows non-significant effects of all the holiday's parameters while EGARCH shows only significant effects of Thursday parameter, indicating the series returns will increase per unit change of the holidays that falls on Thursdays while the rest of the days are not at 5% level.
Furthermore, α_1 is not statistically significant at 5% level. This implies that the presence of volatility clustering in EGARCH (1, 1) model can be ignored even though it exist.
β_1, is statistically significant at 5% level.
The persistence, $\left(\alpha_1+\beta_1+\frac{\gamma}{2}\right)$, of the EGARCH model exceed 1, implying the shocks to volatility are high and the variances of Nigeria stock exchange price returns are not stationary. The parameter, γ_1 is positive and statistically significant at the 5% level. Therefore, the hypothesis of leverage effect is rejected.

The forecast evaluation between EGARCH and Facebook Prophet model is discussed in table 4.

Table 4: Forecast evaluation between EGARCH(1,1) and Facebook Prophet models

Forecast Measures	EGARCH	PROPHET
RMSE	0.009566776	0.009855862
MASE	0.8304276	0.8658212

According to table 4, EGARCH (with skew student's t distribution assumptions of innovation) performed better than Prophet model because it has smaller forecast error. This better performance is in line with some literatures reviewed (see, Ade and Dallah, 2010; Lema *et al.*, 2015; and Asemota *et al.* 2017). With this regard, all the holidays that falls on Thursdays (with value 0.002803) are significant at 5% level; indicating for a unit change of these holidays, there will be an increment of returns on Nigeria stock price. Hence, it is worth noting that incorporating holidays effect on EGARCH(1,1) model will reduce the forecast error, thereby revealing more realistic results (see Bala and Asemota, (2013)).

CONCLUSION

According to the findings, the parameter, δ_1 of Mondays and δ_5 of Fridays under normal assumptions of is positive and negative respectively and 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 are not significant at 5% level.

The parameter of Thursdays effects, δ_4 under skew student's is positive and significant at 5% level (implying the series returns will increase per unit change of the holidays that falls on Thursdays) while the rest of the days are not significant. Furthermore, the volatility clustering of the EGARCH model (in both the two error distribution of innovation) shows non-significant at 5% level. β_1, (in both the error assumptions of innovation) are statistically significant at 5% level. In comparing the persistent of the EGARCH model (under Normal and Skew student's t), that of skew student's t has lower persistent.

On the other hand, Facebook Prophet model shows non-significant of the holidays that falls on Mondays down to Fridays, describing the holidays effects can be ignored even though they exists.

In addition, EGARCH (with skew student's assumptions of innovation) outperformed EGARCH (with normal assumptions) and Facebook Prophet models. Hence, including other variant distribution of innovation is quite crucial in analyzing series returns of financial markets. Furthermore, we can conclude that there is a positive series returns price of holiday's that falls on Thursdays compared to other days of the week.

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