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Comparing the Forecasting Performance of GARCH type Models: Evidence from FMCG Sector of NSE

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ABSTRACT

Nowadays, forecasting ability and stock market volatility has created a huge demand for researchers to target their analysis on market fluctuations of stock market returns. This paper conducts an empirical analysis for understanding the forecasting ability of symmetric and asymmetric GARCH models. Research study utilize the daily return data of FMCG sector index from National Stock Exchange covering the time period from April 2003 to March 2019. Forecasting ability of the data series was compared in terms of in sample data fit and out sample data. Three conventional GARCH family models explains the characteristics of conditional variance, volatility clustering and leverage effect under normal Gaussian distribution. The results reveals that both EGARCH and TGARCH model performed well in modelling of return series confirming the presence of leverage effect. Among linear and non-linear GARCH class model, EGARCH and TGARCH model proves better fitted for in-sample forecasting analysis (from April 2003 to March 2017). Moreover, EGARCH model provides a bit higher accurate performance in comparison to TGARCH model under error measure evaluation. Finally, out-of-sample data (from April 2017 to March 2019) analyse that EGARCH model is best fitted model. Subsequently, asymmetric GARCH model outperforms well for Nifty FMCG sector, in comparison to symmetric GARCH model.

Keywords: ***Symmetric, Asymmetric, Forecasting, Volatility, GARCH Model, Stock Market Returns***

INTRODUCTION

In the field of financial and economic research, volatility is an important issue. It is a centralized approach for a financial market, indicating its diversified uses in risk based areas such as portfolio management, pricing of options and derivatives. Fluctuating stock prices are serving different level of risk among all the investors, speculators and financial players. A highly liquid stock market indicates presence of volatile market. Being an integral part of stock market, volatility shows both bull and bear phase. Increase in share price explains a bullish market while decrease in share price refers to bearish market. Prices of securities are dependent on volatility of a particular asset.

Li & Hong (2011) stated that traditional measures of volatility were computed using constant volatility and standard deviation of close price referred as historical volatility. Computing the fluctuation in rate of return directs towards an appropriate portfolio selection, risk management and asset pricing. Therefore, volatility is considered as a time varying concept. Though volatility is very puzzling concept and act as wide challenging issue for investors to purely understand this area of knowledge. Hence, market returns and volatility forecasting is a complex concept.

All researchers have made many efforts to identify an appropriate technique for volatility measurement with the help of varied GARCH family models. Results of these models can either lead to success or failure, but it depends on ability to compute accurate volatility forecast. Tripathy & Gil-Alana (2010) explained a wide range of ARIMA models used for forecasting future stock prices and measuring volatility in equity market. Conditional volatility can be appropriately analysed by GARCH models as it captures time varying volatilities. A GARCH model is a function of lagged squared variables and lagged conditional variances by providing appropriate forecasting performance. It is a return based model which acts as an important tool for analysing movement of stock prices in future. Gokbulut & Pekkaya (2014) stated that Random Walk (RW) and Ordinary Linear Square (OLS) regression models are linear models and unable tocapture the characteristics of variance. Later, Engle (1982) introduced ARCH (Autoregressive Conditional Heteroskedasticity) modelshowing its effect on conditional variance using lag difference. But ARCH model has some limitations which leads to extension by developing a high order model that captures dynamic behaviour of conditional variance. Thus, Bollerslev (1986) developed an extension model referred as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The stochastic models, ARCH and GARCH shows stylized characteristics with symmetric nature but they fail to capture leverage effect. Non-linear extension of GARCH models are referred as asymmetric models such as EGARCH, TGARCH, GJR-GARCH, PGARCH and many more. These models make a clear distinguish between good and bad news and later creating an impact on volatility. Hence, variation in volatility and return rate indicates negative impact expressed as leverage effect (Devi, 2018).

Forecasting of a data is mathematically a technique of computing future values by using both past and present values of a particular time series. For estimating future stock prices, a data set is gathered and analysed by appropriate fitted model and future forecast technique is applied at each time point. Forecasting accuracy of different fitted models are compared and evaluated by statistical error functions. Error functions acts as a relative measure for comparing forecast of same data set of time series under different models. The measures of forecast error are Mean Squared Errors (MSE), Root Mean Squared Errors (RMSE), Mean Absolute Percentage Error (MAPE) and Thiele's U Test. Results analysed at time point states that smaller the error, better is the forecasting ability (Korir, 2018).

REVIEW OF LITERATURE

Over the last decade, lot many studies are conducted on forecasting volatility in Indian stock market and its performance on future stock prices. Comparison on forecasting performance is a booming subject and many researchers have shared lots of new information in this area.

A comprehensive empirical analysis was performed on data gathered from different sectors of Indian stock market. Lakshmi P (2013) investigate 11 sectoral indices of NSE considering sectors with high turnover and measures volatility using ARCH model. ARCH LM test was performed on return series data and later on residuals after application of ARCH model. Results indicate that realty sector has high volatility in comparison to CNX NIFTY and other sectors.

In a similar study, Yilmaz, Sensoy, Ozturk and Hacihasanoglu (2015) evaluate the performance of 10 major sectors of Islamic equity indices by implementing correlation of standard methodology as dynamic conditional correlation (DCC) and dynamic equicorrelation (DECO). Findings indicates that Islamic equity indices are affecting world financial system and investors have to be more cautious while making investment.

For instance, Tanty & Patjoshi (2016) focused on measurement of sectoral indices of BSE considering 19 sectors for studying the data of 11 years. This study also explains the risk return relationship at different time intervals, creating a base for portfolio trading with active participation of investors. Conclusion derived from the research study indicates that linear model is more appropriate in comparison to linear model.

A study on significant relationship between Indian volatility index (VIX) and returns of sectoral indices was discussed by Singh, Singh & Singh (2019). This study utilizes return data from major sectors of NSE such as Auto, Metal, Bank and IT, where Indian volatility index express its impact on these sectors. The study also targets on comparing volatility trend of manufacturing and service sector. Data of 8 years' duration concludes that sectoral indices and Indian volatility index shows a reciprocal relation, while NSE IT sector did not provide a significant impact of VIX.

Studies based on GARCH family models including both symmetric and asymmetric models are utilized to capture stock market volatility. Both type of models has different volatility based stylized characteristics such as leverage effect, stationarity, volatility clustering and mean reversion.

Researchers can earn benefit from the studies done by Monday & Abdulkadir (2020), Yelamanchili (2020),Kumari & Tan (2018) and many more.

Table 1: Different literature reviews on symmetric and asymmetric generalized autoregressive conditional heteroskedasticity (GARCH)models.

Authors & Year	**Data Set**	**Econometric Models**	**Study Results**
Monday & Abdulkadir (2020)	Monthly data, Crude oil price of Nigerian Economy, from May 1989 to April 2019	GARCH & GARCH-M model	Findings revealed that asymmetric model ARCH-M outperforms in comparison to symmetric models ARCH
Yelamanchili (2020)	Monthly returns data of BSE SENSEX, January 1991 to December 2019	GARCH (1, 1), GJR-GARCH, EGARCH, APARCH	GARCH model had better information criterion values, LL function and lowest standard error values but only GJR-GARCH model exhibits leverage effect.
Kumari & Tan (2018)	Daily price of Gold traded on COMEX, January 1990 to June 2014.	GARCH, EGARCH, APARCH, TARCH, FIGARCH & FIEGARCH	Linear GARCH model provides higher accuracy predictions while EGARCH and FIEGARCH models are superior in terms of forecasting accuracy.
Kandora & Hamdi (2016)	Monthly return data from stock exchange of Sudan, January 1999 to December 2013	GARCH (1, 1), GARCH-M(1, 1), EGARCH (1, 1), TGARCH (1, 1) PGARCH (1, 1)	Results concluded that data indicates presence of leverage effect supported with a better fitted asymmetric model in comparison to symmetric model. Hence, confirms the presence of high volatility in return series.

Miah & Rahman (2016)	Data from 4 Bangladeshi companies listed under Dhaka Stock Exchange, for period January 2001 to November 2014	All symmetric GARCH models for different lag order	Finding concluded that GARCH (1, 1) model is best fitted that other model of different lag order.
Alam, Siddikee & Masukujjaman (2013)	Daily returns data of DSE20 and DSE general indices from Dhaka Stock Exchange, December 2001 to September 2011	ARCH, GARCH, EGARCH, PARCH AND TGARCH	Outputs for DSE20 index proves EGARCH model was best performing while ARCH and GARCH model outperforms in case of DSE general index.
Tripathy & Garg (2013)	Six emerging countries i.e. China, India, Brazil, Mexico, Russia and South Africa. The daily observations of indices for period January 1999 to May 2010.	GARCH family models including ARCH, GARCH, GARCH-M, EGARCH, and TGARCH.	GARCH (1, 1) model helps in predicting future behaviour of market volatility. The Brazilian, Russian, South African and Mexican stock market show a positive relation with volatility but Indian stock market shows negative relation.
Gabriel (2012)	Daily stock return data from BET index of Romania, September 2001 to February 2012	GARCH, EGARCH, TGARCH, PGARCH (1,1,1), PGARCH (1,2,1), IGARCH	TGARCH and PGARCH (1,2,1) model was most appropriate for modelling in terms of AIC, SBC and LL function while only TGARCH model is fitted for forecasting ability.

Most of the studies concluded that GARCH (1, 1) model is appropriate for capturing symmetric effect while asymmetric models indicated leverage effect. According to empirical literature review, both symmetric and asymmetric models plays an important role in volatility estimation of a time series. Hence, both linear and non-linear model must be selected for comparing volatility forecasting performance.

OBJECTIVES

- To model the volatility of Nifty FMCG of Indian Stock market
- To compare forecasting performance of Nifty FMCG index using symmetric and asymmetric GARCH models.

RESEARCH METHODOLOGY

Study Area: The aim of this paper was to evaluate the forecasting performance of different GARCH family models using the data from Nifty FMCG index. The study is descriptive in nature and provides appropriate future forecasting models. The study compares symmetric and asymmetric GARCH models for ensuring forecasting future returns.

Sample: A secondary data was gathered from official website of National Stock exchange (NSE), India, with daily closing price of Nifty FMCG index from the period of April 2003 to March 2019.The data of 3980 daily observations was divided in two data set samples including in-sample forecasting data from 1st April 2003 to 31st March 2017 while out-of-sample forecasting data from 1st April 2017 to 31st March 2019. Nifty FMCG index comprises of 15 stock reflecting the behaviour and performance of fast moving consumer goods including non-durable, mass consumption products and available off the shelf.

Model Estimation and Model Selection Criteria: The study involves comparison of symmetric and asymmetric models including GARCH (1, 1) of linear model category and TGARCH (1, 1) and EGARCH (1, 1) model of non-linear category. Parameters of these models are estimated using robust method of Bollerslev-Woodridge’s Quasi Maximum Likelihood Estimator (QMLE) approach considering data of Nifty FMCG sectoral index to be Gaussian standard normal distribution.

Table 2 Overview of GARCH family models

Model	Short Explanation	Equation
Symmetric Model	These models are symmetric in modelling conditional volatility.	
GARCH	GARCH model was proposed by Bollerslev (1986). This model provides the time varying conditional volatility as a function of its own first lag value and past innovations.	$\alpha_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ Where σ_t is the conditional standard deviation of return at time t.
Asymmetric Model	Ensures asymmetric properties of asset returns volatility	
TGARCH	Threshold GARCH was also known as GJR model and developed by Glosten, Jagannathan and Runkle in 1993. This model ensures analysis on the effect of positive and negative return shocks (good and bad news).	$\sigma^2_t = \omega + \alpha_1\varepsilon^2_{t-1} + \beta_1\sigma^2_{t-1} + \gamma d_{t-1}\varepsilon^2_{t-1}$ Where d_{t-1} is a dummy variable and elaborated as: If $\varepsilon_{t-1} < 0$, indicates bad news, showing $d_{t-1} = 1$ If $\varepsilon_{t-1} \geq 0$, indicates good news, showing $d_{t-1} = 0$ Here γ is referred as asymmetry or leverage term.
EGARCH	Nelson (1991) proposed the concept of Exponential GARCH. This model captures external unexpected shocks on the predicted volatility.	$\ln(\sigma_t^2) = \omega + \alpha_1 \left\lvert \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right\rvert + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_t ln\sigma_{t-1}^2$ Where, γ is referred as asymmetric response parameter or leverage effect parameter. If value of γ is zero, then this model will be stated as symmetric.

For model selection procedure, information criteria including values of AIC and SC were computed and Log Likelihood function. Akaike Information Criteria (AIC) is a measure for analysing statistical quality of a model using given set of data. AIC and SC measures effectiveness of a model, where lower the values of information criteria, better is the model. Log Likelihood function indicates that higher LL value, proves best fitted model.

Diagnostic testing: For diagnostic testing of a model, presence of heteroskedasticity in the residuals is checked. For particular estimation, ARCH LM test is performed after the application of appropriate models. Analysis directs the rejection of null hypothesis and confirms the presence of ARCH effect in the residuals.

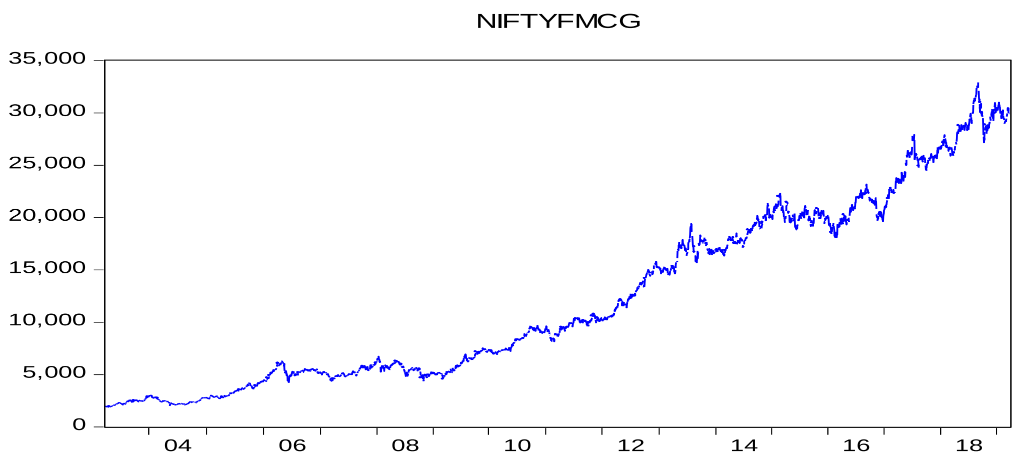
Forecasting Evaluation: For model evaluation, forecasting is a technique which estimates future values with the use of present and past historical value of the time series. Forecasting of the future values was computed by selecting best fitted model using common statistical error measures and functions. Error measures used for evaluation of GARCH family models are root mean square error (RMSE), mean square error (MSE), Mean absolute error (MAE) and Mean absolute percentage error (MAPE). Error measures yields that lower the error measures, better is the model.

RESULT AND DISCUSSION

Transformation of time series and Graphical Depiction: For volatility estimation, data set of Nifty FMCG index are computed as logarithmic price relatives: R_t = log [(close price)/close price (-1)], where R_t refers to Nifty FMCG return series.Both the data series of Nifty FMCG index and Nifty FMCG return series was plotted on figure 1. The figure below provides the association between the return and volatility which change with respect to time and other related factors. Figure 1(a) is upward trending indicating a continuous growth in Nifty FMCG, but in year 2004 stock market faced a sudden crash. Figure 1(b) clearly depicts higher volatility on 18th May 2009, when Nifty FMCG stock hiked by 700 points and this indicates 20% breach and hence trading on particular day was suspended. Thus, return series depicts some periods of low volatility and some periods of high volatility exhibiting the phenomena of volatility clustering.

Preliminary Investigations and Summary Statistics: The descriptive and inferential measure of statistics was applied on daily return data of Nifty FMCG for further analysis of data. Table 3 below provides the results on descriptive statistics, unit root analysis and ARCH LM Test.

Figure 1: Daily returns of Nifty FMCG Index - (a) and Nifty FMCG return series - (b)



(b)

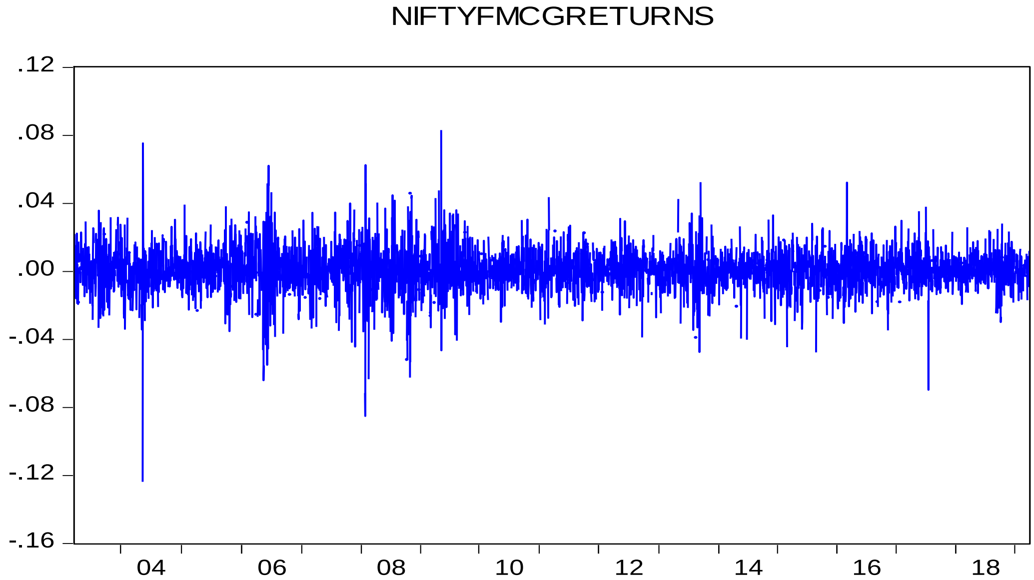


Table 3: Preliminary investigation for daily return series

(a) Descriptive Statistics

Mean	Min	Max	Std. Dev	Skewness	Kurtosis	Jarque Bera Statistics
0.000693	-0.123824	0.083038	0.012911	-0.402051	8.456136	5042.719 (0.000)

(b) Unit Root Analysis

Variables	ADF Value	t-stat 1%
Returns of Nifty FMCG	-61.37577	-3.43

*: values statistically significant at all critical levels of 1%, 5% and 10%.

(c) Heteroskedasticity Test

Variables	F-statistic	Obs*R-squared
Returns of Nifty FMCG	115.6488 (0.00)	505.4594 (0.00)

Daily return analysis of Nifty FMCG had a mean value of 0.0693% during the considered time period, while its volatility is measured by standard deviation of 1.29%. The return series shows negative skewness, which directs the flatter graph towards left. And kurtosis value is higher than 3, refers to positive kurtosis values of 8.456 naming it as leptokurtic distribution. Jarque-Bera test is a test for checking normality and rejection of null hypothesis in the series indicates that series is not normally distributed (values mentioned in Table 3 (a)).

Table 3 (b) investigates stationarity of returns series by using Augmented Dickey Fuller (ADF) test. The results of ADF test concludes that null hypothesis of a unit root test was rejected and thus return series is stationary at level and hence modelling of conditional volatility can be proceeded using GARCH class models.

To analyse the presence of heteroskedasticity in the residuals of time series, Lagrange Multiplier (LM) test is applied. Presence of heteroskedastic effect in the daily return series leads to GARCH model application. Table 3 (c) reveals results of ARCH LM test providing a strong evidence for rejecting null hypothesis. Hence, the residual series confirms the presence of ARCH effect.

Model Estimation: For model estimation and evaluation, GARCH family models belonging to both symmetric and asymmetric category are selected. GARCH models chosen for analysis are GARCH (1, 1), TGARCH (1, 1) and EGARCH (1, 1) under normal distribution.Table 4 explains the parameter estimates of all the conditional volatility models selected for analysis purpose on the basis of information criteria and log-likelihood function.

Table 4: Comparative study of GARCH family models

Coefficient	GARCH (1, 1)	TGARCH (1, 1)	EGARCH (1, 1)
C (μ)	0.000907	0.000735	0.000718
α (ARCH effect)	0.114428	0.071242	0.211602
β (GARCH effect)	0.828232	0.818911	0.937985
γ (Leverage Effect)		0.082650	-0.058439
AIC	-6.025949	-6.031227	-6.026828
SIC	-6.019627	-6.023324	-6.018925
LL	11992.63	12004.13	11995.37
SSR	0.663288	0.663112	0.663107
ARS	-0.000276	-0.000011	-0.000004
Durbin Watson (DW) Statistic	1.944124	1.944640	1.944653
ARCH LM Test	0.914448 (0.4704)	0.810773 (0.5418)	1.646226 (0.1442)

From Table 4, the GARCH (1, 1) model reports that α and β coefficients in the variance equation are statistically significant. Both α and β coefficients indicates that news generated from past volatility period pose a high impact on the current volatility.

Both asymmetric GARCH model coefficients are significant and proves a strong validity of these models. For both EGARCH and TGARCH model, value of leverage effect coefficient is significantly variant from zero and this indicates that series are not symmetric and even leverage effect is present in series. The positive value of leverage effect in case of TGARCH that future volatility increases because of “good news” rather than “bad news”. As EGARCH model has significant and negative value of leverage (γ) explains that this model has leverage effect. Hence, it indicates that leverage effect is a negative correlation between the past return and future volatility of return.

On comparative analysis, model with least AIC, SC criteria and maximum Log Likelihood function is chosen as best model. TGARCH model possess least value of AIC and SC values and highest LL value in comparison to EGARCH and GARCH (1, 1) model. Another factor for model selection that lowest value for SSR respectively the highest value for ARS is of EGARCH, followed closely by TGARCH. Hence, these criteria reveals that TGARCH and EGARCH models under normal distribution shows better estimate for series in comparison to GARCH (1, 1) model.

For diagnostic testing purpose, ARCH LM test is performed which checks the presence of ARCH effect in the data series. This testing confirms the presence heteroskedasticity in the data. Under null hypothesis, ARCH LM test analyse the residuals of the fitted models. Results in Table 4 indicates that all three models has p value greater than 0.05, rejecting the null hypothesis of no ARCH effect present in the residuals. Therefore, confirms the presence of heteroskedasticity.

In Sample Forecasting analysis: For ensuring forecasting analysis of data series error measures used for evaluation purpose are mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).The performance of model is measured as lower the error, best is the model. For in sample forecasting analysis, the data set chosen from 1st April 2003 to 31st March 2017 with 3843 observations. Table 5 provides a comparative study of forecasting measures on three models i.e. GARCH, TGARCH and EGARCH model. Performance of model is ranked on the basis of lower the error, better is the rank. Finally, results are concluded by summation values of rank derived from error measurements. On ranking analysis, RMSE and MSE statistic suggest that EGARCH and TGARCH models have similar ranking and lowest value, while MAE statistic provides GARCH model as least ranked. Forecasting analysis through MAPE statistic indicates that EGARCH shows better results. Comparing the performance of both symmetric and asymmetric GARCH models, total ranking results show that EGARCH and TGARCH model has similar results and superior to GARCH (1, 1) model. Thus, concluding that asymmetric models are superior to symmetric model.

Table 5: Comparison of In-sample forecasting performance

Model Selection Criteria						
Model	**GARCH (1, 1)**	**Rank**	**TGARCH (1, 1)**	**Rank**	**EGARCH (1, 1)**	**Rank**
RMSE	0.013316	2	0.013315	1	**0.013315**	1
MSE	0.00017732	2	0.00017730	1	**0.00017730**	1
MAE	**0.009564**	1	0.009568	2	0.009569	3
MAPE	125.5281	3	119.5962	2	**119.0175**	1
Total Rank		**8**		**6**		**6**

Out of Sample Forecasting analysis: For out-of-sample forecasting data of 5 years was chosen from 1st April 2017 to 31st March 2019 with 494 observations. Table 6 provides an evaluation for forecasting performance using different error measures. RMSE, MSE, MAE and MAPE statistic explains that EGARCH model provides best forecast accuracy with least rank. On overall ranking of statistic measures, it proves out that for Nifty FMCG returns index, EGARCH model has lowest ranking and hence a best performance model.

Table 6: Comparison of out-of-sample forecasting performance

Model Selection Criteria						
Model	**GARCH (1, 1)**	**Rank**	**TGARCH (1, 1)**	**Rank**	**EGARCH (1, 1)**	**Rank**
RMSE	0.009613	2	0.009607	1	**0.009607**	1
MSE	0.00009241	2	0.00009230	1	**0.00009230**	1
MAE	0.00708	2	0.007073	1	**0.007073**	1
MAPE	117.2999	3	112.6915	2	**112.254**	1
Total Rank		**9**		**5**		**4**

CONCLUSION

The paper conducted a comparative forecasting performance of symmetric and asymmetric GARCH models and also captures stock market volatility at different point of time for daily return data obtained from Nifty FMCG of National Stock Exchange. Study ensures modelling and forecasting the effectiveness of various volatility models by evaluating market based risk and return analysis. A long span of data was selected for studying forecasting in more appropriate manner, thus complete was divided in two sets of in-sample forecasting data and out of sample forecasting data. Initially volatility estimation of data was performed by three linear and non-linear models i.e. GARCH (1, 1), TGARCH and EGARCH model. Analysis concludes that both TGARCH and EGARCH model provides best result for the conditional returns. Moreover, findings are supported by Alam, Siddikee & Masukujjaman (2013), that both TGARCH and EGARCH model are appropriate for modelling purpose in comparison to GARCH (1, 1) model. Hence, asymmetric model is superior for modelling and confirms the presence of leverage effect.

After that, future price volatilities of Nifty FMCG index are forecasted using error measures for in-sample and out-sample data. Forecasting of in-sample data concluded that EGARCH and TGARCH modelare superior in comparison GARCH (1, 1) model. Therefore, critical literature analysis of Devi (2018) also signifies that non-linear models are best fitted for forecasting. In addition, empirical performance of out-of-sample forecasting results that EGARCH model is superior to TGARCH and GARCH model.

Summing up the results, study confirms that non-linear modelsare superior and return series demonstrates volatility clustering effect. Therefore, asymmetric models explainpresence of conditional volatility as it allows different responses in relation to varied past shocks andeven the current data has asymmetric effect.

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