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Comparing the Performance of GARCH Family Models in Capturing Stock Market Volatility in India

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Abstract
In recent times, the prediction of stock market volatility has emerged as a central focus in the domain of financial econometrics. This paper presents an empirical analysis aimed at modelling the volatility of the Indian stock market, particularly focusing on the NSE NIFTY 50, by utilizing various GARCH models. The investigation explores the volatility of stock returns, considering the daily closing prices, and examines the influence of two external factors: Crude oil prices and the INR/USD exchange rate. The inquiry employs data encompassing the period from January 1, 2012, to December 31, 2022, for all three variables. The manuscript delves into an array of univariate GARCH models, encompassing both symmetric and asymmetric models, and assesses their performance by utilizing metrics such as the Akaike Information Criterion, Schwartz Bayesian Information Criterion, and Log Likelihood. To assess the predictive accuracy of these models, statistical error measures such as Mean Squared Error, Root Mean Squared Error, and Mean Absolute Error are employed. The findings strongly suggest that the EGARCH model is the most effective in predicting the variations of the NIFTY index. Furthermore, the research highlights the significant impact of exchange rates and crude oil prices in relation to the volatility of the stock market in India.

Keywords: NIFTY, Returns Volatility, GARCH, EGARCH, TGARCH, MSE, RMSE and MAE
JEL Classification: G17

Introduction

Time-varying volatility is a concept used by financial econometricians to measure fluctuation in an asset's return over time. It is typically defined by the conditional variance of the underlying asset's returns and is employed for quantifying and predicting market fluctuations. (Tsay) opined that understanding the volatility of an asset, investors can better assess the risk and potential rewards associated with it.

Stock market volatility stands as a significant risk factor that exerts an impact on asset prices. Greater fluctuations in stock prices translate to more substantial variations in returns, consequently elevating the level of risk. The relevance of volatility in financial markets has been underscored by the heightened emphasis placed on modelling and scrutinizing stock market returns. (Scott) opined that the government policymakers, market analysts, corporate managers, and economists are all concerned about the volatility in financial markets, particularly stock markets. (Poon and Granger) mentioned that from market participants to policy makers, all those involved in the financial environment have engaged in extensive research on this topic, demonstrating its importance for investment, valuation of securities, risk management, and financial policy making. Volatility forecasting also has become an integral part of risk management, option pricing, portfolio management and capital asset pricing.

The purpose of this study is to conduct a performance comparison between symmetric GARCH and asymmetric GARCH models EGARCH and TGARCH, with the aim of capturing the distinctive characteristics of India's stock market. In pursuit of this goal, the research investigates how the foreign exchange and crude oil factors impact stock movements within India. To facilitate the comparison of these GARCH models, various error measurement techniques, such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), are employed. This analysis is intended to enhance our comprehension of the interplay between exchange rates, crude oil prices, and the behavior of the stock market in India.

Literature Review

(Bollerslev) found that volatility cannot be observed directly, and that financial return volatility shows certain characteristics exclusive to time series, for example volatility clustering and the leverage effect. The econometricians have developed few time-varying volatility models to understand the characteristics of financial markets. Among them, the Autoregressive Conditional Heteroscedastic [ARCH] model by (Engle) and its extension, the Generalized Autoregressive Conditional Heteroscedasticity [GARCH] model by (Bollerslev) are well-known and widely used. Subsequently, these models have been extended into different versions, such as GARCH-M models by (Engle et al.) IGARCH model by (Engle and Bollerslev) Exponential GARCH model by (Nelson) Threshold GARCH model by (Zakoian) and (Glosten et al.), and Power ARCH model by (Ding et al.). These models enable econometricians to model and quantify volatility in financial markets, making them extremely popular. Models designed to explicitly forecast the time-varying volatility of a series by leveraging past unpredictable changes in the returns of that series have been applied in economics, finance, and particularly financial market research.

(Wilhelmsson) utilised GARCH (1,1) model for predicting returns from Standard & Poor's (S&P) 500 index futures.(Tseng et al.) used combination of EGARCH model and a feed forward neural network to estimate the volatility of Taiwan Stock Index option prices.

(Hansen et al.) examined bivariate and multi-realised EGARCH models that support a Constant Conditional Correlation (CCC)- GARCH structure developed for modelling and estimating the Dow Jones Industrial Average (DJIA). The application of bivariate GARCH (Gulzar et al.) confirm the presence of spillover from the NYSE on emerging Asian stock markets before, during, and after the financial crisis using BEKK-GARCH model.

(Aliyev et al.) examined the volatility of the Nasdaq-100 with univariate asymmetric GARCH models confirmed the leveraging effect on the index, and an asymmetric impact of shocks. (Hongwiengjan and Thongtha) examined the analytical approximation of option prices using the TGARCH model provided a new efficient method for pricing in-the-money (ITM) options.

Recent studies have undertaken comparisons of GARCH models to assess their forecasting accuracy, employing error measurement criteria such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). (Wang et al.) by using RMSE of ARIMA (1,1,0)-GARCH (1,1) observed higher accuracy for short term forecasting. (Bragoudakis and Voulgarakis) opined that EGARCH has better in forecasting volatility in comparison with GARCH (1,1), IGARCH, GJR-GARCH models. (Samaila et al.) claimed that GJR-GARCH produced better forecasting result compared to GARCH (1,1) and EGARCH in the study of volatility on the returns of Nigeria exchange rate for period of January2002 to December 2020.

Previous researchers have pioneered a variety of theories and methods to analyze financial market volatility, laying the groundwork for further studies. Of these, GARCH-type models were particularly popular, as they allowed analysts to approach financial market volatility from different angles and ascertain the best model to explain its characteristics. This study applies such models to analyze the fluctuations of the stock market of India. By understanding and grasping the stock market's operation and the law of its price fluctuations, investors can make more informed decisions and reduce the risks of their investments. Additionally, such insight will be beneficial to policymakers, as it will help them to better understand the transmission of monetary policies and make more effective decisions.

Methodology

Data

This study centres its attention on the Indian stock market, specifically focusing on the NIFTY-50 index. The dataset encompasses a total of 2,718 observations of the NIFTY-50 index, spanning from March 1, 2012, to December 30, 2022. To assess the extent of influence on the volatility of the Indian stock market, two additional factors are taken into account: the exchange rate (INR/USD) and crude oil prices. All data sources are verified through cross-referencing with Yahoo Finance (http://finance.yahoo.com), as well as NSE India and MCX. Log returns are calculated and integrated into the analysis to model volatility.

$$R_t = \ln (P_t/P_{t-1})$$

Where R_t = Daily Returns, P_t = price of the current period and $P_{(t-1)}$ = price at the previous period.

Three GARCH type models are applied to capture stock market volatility, i.e., symmetric GARCH (GARCH (1,1)) and asymmetric GARCH (EGARCH, TGARCH). The forecasting performance of these models are evaluated using measures of MSE, RMSE and MAPE for both in sample and out of sample analyses.

ARCH Model

The ARCH model by (Engle) was the first to offer a systematic framework for modelling volatility. The general model of ARCH(q) process is as follows

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \mu_{t-i}^2 \qquad (1)$$

Where σ_t^2conditional volatility, α_0 is mean and μ_t is white noise representing the residuals of the time series. The conditions are:

- $\alpha_0 > 0$ and $\alpha_n > 0$ to guarantee positive variance.
- $0 \leq \sum_{i=1}^{n} \alpha_i < 1$
- $\alpha_0 > \alpha_1 > \ldots \alpha_n$

In accordance with the ARCH model, the variability of the error term in a typical autoregressive process is contingent upon the variances of previous error terms.

GARCH Model

(Bollerslev) developed GARCH model as an improvement to the base model of ARCH modelling, in order to analyse volatility by considering lagged variances.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \mu_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (2)$$

Where i= 0,1,2, … p. σ_t^2 is conditional volatility, α_0 is mean, α_i and μ_{t-i}^2 are ARCH components and β_j and σ_{t-j}^2 are GARCH components. α_0, α_i and β_j are positives. Based on the 2 determinant factors of GARCH Model i.e., Exchange rate and Crude oil prices the modified GARCH (1,1) formula is

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \alpha_1 \text{(exchange rate)} + \alpha_2 \text{(crude oil price)}$$

According to the GARCH (1,1) model, conditional volatility returns depend on the lagged squared residuals, also called ARCH effects, and their own lagged values, or GARCH effects. This measure captures the overall volatility of the time series, i.e., symmetrical volatility in both short and long time periods. ARCH effect states that recent news creates volatility in the time series due to the persistence of short-term volatility. The GARCH effect captures the long-term volatility of stock prices, demonstrating the persistence of old news in the market and its influence on price changes.

These models can identify the volatility when their distribution is symmetric. ARCH and GARCH models assume that shock effects on volatility have symmetric distributions. It is common for asset return series to have skewed distributions, which makes GARCH models asymmetric.

TGARCH

The threshold-GARCH i.e., TARCH (p,q) model shows the leverage effect in a time series. It is the extension of the GARCH(p,q) model by including asymmetric weighting functions in the conditional variance equation. (Glosten et al.; Zakoian) claimed that the weights of the TARCH model depend on the sign of the shock which is incorporated via the use of the absolute value of the shocks. The conditional variance equation for the TARCH model is given below:

$$\sigma_t^2 = \alpha_0 + \alpha_i \mu_{t-i}^2 + \beta_j \sigma_{t-i}^2 + \gamma \mu_{t-i}^2 I_{t-i} \quad (3)$$

γ indicates the asymmetric or leverage effect and I_{t-i} is the variable to differentiate good or bad news. $I_{t-i} = 1$ if $\mu_{t-i} < 0$ indicating the bad news and $I_{t-i} = 0$ if $\mu_{t-i} \geq 0$ indicating good news. The model assumes that the unexpected variations in the market returns will have different effect on stock volatility. If γ is nonzero, it indicates the asymmetric nature of returns and if γ is zero then it indicates symmetric GARCH model. A positive a γ indicates the presence of leverage effect.

By considering the 2 additional variables of the study the formula can be written as below:

$$\sigma_t^2 = \alpha_0 + \alpha_i \mu_{t-i}^2 + \beta_j \sigma_{t-i}^2 + \gamma \mu_{t-i}^2 I_{t-i} + \alpha_1 \text{(exchange rate)} + \alpha_2 \text{(crude oil price)}$$

EGARCH

(Nelson) developed the E-GARCH model to estimate volatility beyond the non-negativity constraint. The GARCH (1,1) assumption was too restrictive, and that asymmetry was present in the time series. As a result, the E-GARCH model, which requires that $\alpha>0$, $\alpha I \geq 0$, and $\beta i \geq 0$, restricts the scope of volatility and may not be able to capture the overall dynamic behavior of volatility in the time series. This model captures the effect of unexpected shocks on the predicted volatility. The formula is as follows.

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i-1}^{q} (\alpha_i |\mu_{t-i}/\sigma_{t-i}| + \gamma_i |\mu_{t-i}/\sigma_{t-i}|) + \sum_{j=1}^{p} \beta_j \ln (\sigma_{t-j}^2) \quad (4)$$

The presence of γ indicate asymmetric effect of shocks on volatility. The positive γ indicate the presence of leverage effect. In order to calculate the impact of independent variables on stock market volatility the model formula can be written as below:

$\ln \sigma_t^2 = \alpha_0 + \alpha_1 |\mu_{t-1}/1| + \gamma_1 | \mu_{t-1}/\sigma_{t-1}| \beta\text{-}1 \ln$ (σ_(t-1)^2) + α_1 (exchange rate) + α_2 (crude oil price)

Information Criterion

Akaike Information Criterion

As per the principle of parsimony, Akaike's information criterion (AIC) attempts to select an appropriate approximating model for inference. Model selection is based upon relative entropy or Kull Black-Libeler (K-L) information in accordance with AIC. It is determined by subtracting twice the maximum likelihood log-likelihood of the model from the total number of estimated parameters in the model. The model with the minimum AIC is judged to be the best fitting model. An appropriate estimator of the K-L relative information is utilized, which consists of two components. The first term is a quantification of the discrepancy between the observed and the predicted values, and the second term is a penalty for increasing the complexity of the model, considering the preference for a smaller number of parameters.

$$AIC(n) = \log(\sigma^2) + 2n/T \quad (5)$$

where n is the dimensionality of the model σ^2 is the maximum likelihood estimate of the white noise variance, and T is the sample size.

Schwartz Bayesian Information Criterion

Swartz initially developed the Bayesian Information Criteria (BIC) in a Bayesian setting, and it is dimensionally consistent when it comes to estimating the true model's dimensions. However, it assumes that the accurate model is included within the array of prospective models, necessitating a substantial sample size for its effectiveness.

$$BIC(n) = \log(\sigma^2) + (n \log(T))/T \quad (6)$$

where n is dimensionality of the model, σ^2 is the maximum likelihood estimate of the white noise variance and T is the sample size.

Model Evaluations

Mean Squared Error (MSE)

The Mean Squared Error (MSE) serves as a metric for quantifying the disparities between a model's predicted values and the actual observed values. It is essentially the average of the squares of the errors incurred by the model in its predictions. MSE plays a pivotal role in assessing a model's performance, offering insights into its capacity to accurately forecast data. It finds extensive utility in regression problems, where the objective is to minimize MSE to achieve the best-fitting model. Computation of MSE involves taking the difference between the predicted and actual values for each data point, squaring this difference, and then computing the average of all these squared differences. In practice, a smaller MSE indicates superior model performance.

$$MSE = \sum_t^n (e_t^2)/n \quad (7)$$

Where $e_t = y_t - \hat{y}_t$ y_t is the observed value in time t and $\hat{y}_t$ is the fitted value in time t.

Root Mean Squared Error (RMSE)

RMSE is calculated by taking the square root of the mean of the squared differences between the actual and predicted values. This is done for each prediction value, and then the mean of the squared errors is taken. By squaring the errors, larger errors are more heavily penalized. RMSE is also often used to compare different models and determine most accurate model

$$RMSE = \sqrt{(\sum_t^n (e_t^2)/n)} \quad (8)$$

Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is a measure of prediction accuracy used in statistics and forecasting. It is a measure of the difference between an actual and predicted value, expressed as a percentage of the actual value. The MAPE is a useful measure of accuracy for forecasting, as it is usually expressed in terms of a percentage. The lower the percentage, the more accurate the forecast.

$$MAPE = \sum_{t=1}^n (|(e_t/y_t)| * 100)/n \quad (9)$$

Where n indicates effective data points, $|(e_t/y_t)| * 100$ defined as the absolute percentage error calculated on fitted values for a particular forecasting method.

Theil Inequality Coefficient (TIC)

The Theil inequality coefficient is a measure of inequality among the values of a given set of data. It is calculated by dividing the variance of the data set by the sum of the absolute differences between each data point and the mean of the data set. The Theil inequality coefficient ranges from 0 to 1, with 0 indicating perfect equality among the data points and 1 indicating perfect inequality. The higher the Theil inequality coefficient, the more unequal the distribution of the data set.

$$U = \sqrt{(1/n \sum_i (X_i - Y_i)^2)} / (\sqrt{(1/n \sum_i (X_i)^2)} + \sqrt{(1/n \sum_i (Y_i)^2)}) \quad (10)$$

Findings

Table 1 Descriptive Statistics

	NIFTY	INR/USD	CRUDEOIL
Mean	0.000502	0.000149	0.000791
Median	0.000720	0.000000	0.001578
Maximum	0.084003	0.060972	0.319634
Minimum	-0.139038	-0.060972	-0.279920
Std. Dev.	0.010732	0.005087	0.026667
Skewness	-1.132852	-0.044862	1.123406
Kurtosis	19.55458	30.32392	24.91254
Jarque-Bera	32339.20	86481.70	56203.20
Probability	0.000000	0.000000	0.000000
Sum	1.395091	0.413510	2.198998
Sum Sq. Dev.	0.320048	0.071905	1.976242
Observations	2780	2780	2780

The descriptive statistics of the daily returns of NIFTY index, exchange rate (INR/USD), and crude oil prices from January 2012 to March 2023 is shown in table 1. It is observed that the mean of all three variables is close to zero and positive, as expected for a time series return. The return of crude oil (31.96%) is higher than the NIFTY and exchange rate (8.4% and 6.09%, respectively). There is negative skewness in the NIFTY and exchange rate returns, indicating that they produce low yields most of the time. This could make investors perceive NIFTY returns as volatile or risky. The crude oil series has positive skewness. All three variables have kurtosis greater than zero (19.55, 30.32, and 24.91), which indicates that the returns are not normally distributed.

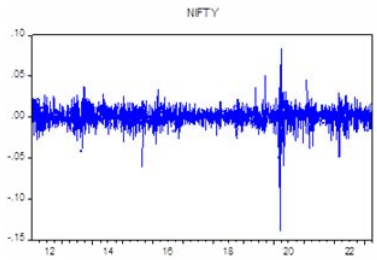

Figure 1 Return Series of NIFTY Index

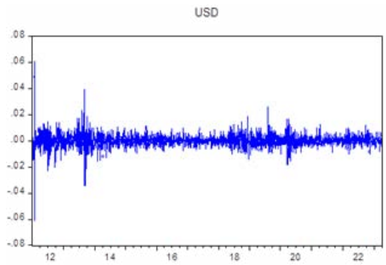

Figure 2 Return Series of Exchange Rate (INR/USD)

The return series volatilities as represented in Figures 1 to 3 change over time and demonstrate positive serial correlation, known as "volatility clustering". It is evident that large changes tend to be followed by large variations and small changes tend to be followed by small variations, confirming the presence of cluster volatility in financial returns data. This contradicts the random walk hypothesis, suggesting instead the presence of a long-memory process.

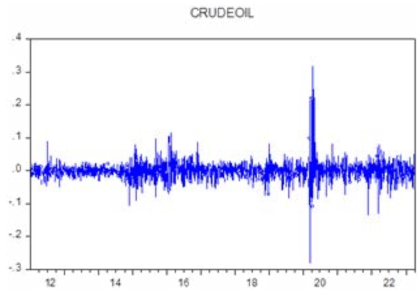

Figure 3 Return Series of Crude Oil

In order test the stationarity of the data series, Augmented Dickey fuller (ADF) unit root test has been applied

$$\Delta y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{n} \mu \Delta Y_{t-i} + \varepsilon_t$$

Y_t represents time series to be tested, α is the intercept term, β is the coefficient of variable in the unite root test, μ is the parameter of the augmented lagged first difference of Y_t to represent nth order autoregressive process, and ε_t is the white noise error term.

Table 2 ADF Unit Root Test Statistics

Variables	Include in Test equation	Test statistics	Probability	Test Critical Values		
				1% level	5% level	10% level
NIFTY	Without constant and linear trend	-18.61703	0.0000	-2.565796	-1.940938	-1.616623
	Constant	-18.75980	0.0000	-3.432517	-2.862383	-2.567263
	With constant and linear trend	-18.76002	0.0000	3.961352	-3.411428	
USD	Without constant and linear trend	-64.53210	0.0001	-2.565794	-1.940938	-1.616623
	Constant	-64.58780	0.0001	-3.432512	-2.862381	-2.567262
	With constant and linear trend	-64.57648	0.0000	-3.961345	-3.411424	-3.127565
Crude oil	Without constant and linear trend	-46.03111	0.0001	-2.565794	-1.940938	-1.616623
	Constant	-46.05701	0.0001	-3.432512	-2.862381	-2.567262
	With constant and linear trend	-46.07324	0.0000	-3.961345	-3.411424	-3.127565

The outcome of the ADF unit root test, as shown in table 2, suggests that the values of the test statistics exceed the critical values determined by Mac Kinnon. As a result, the null hypothesis, which posits the presence of a unit root, is rejected at the 1% significance level. Consequently, the hypothesis of non-stationarity is rejected for all three variables, namely NIFTY, USD, and Crude Oil. This leads to the conclusion that the levels of NIFTY returns, exchange rates, and crude oil returns exhibit stationarity.

ARCH-LM test was applied to inspect the existence of any conditional heteroscedasticity (ARCH effect) within the model. Lagrange

Multiplier test is applied to all data set to check the ARCH effect in NIFTY, Exchange rate and Crude oil returns. The result of ARCH-LM test of Table 3 leads to the rejection of null hypothesis of non-existence of ARCH effect in all 3 variables.

Table 3 Heteroscedasticity test

	F statistics	Prob	Obs. R Squared	Prob
NIFTY	81.03828	0.0000	78.79719	0.0000
USD	1801.434	0.0000	1093.428	0.0000
Crude oil	532.1820	0.0000	446.9182	0.0000

Table 4 Parameter Estimates of GARCH Models, Information Criteria and Log- Likelihood function for GARCH models

Model	C	ARCH (-1)	GARCH (-1)	Leverage effect	AIC	SBC	LL
GARCH (1,1)	2.31E-06	0.089327	0.889145	-	-6.522982	-6.509941	8870.732
TGARCH	2.69E-06	0.004993	0.897202	0.135709	-6.560995	-6.546063	9126.783
EGARCH	-0.350001	0.137656	0.973972	-0.101965	-6.563054	-6.548122	9129.645

All GARCH models have statistically significant coefficients, confirming their validity. Notably, the sum of ARCH and GARCH coefficients is nearly one, except for EGARCH, suggesting persistent volatility as shown in table 4. Asymmetric GARCH models show significant γ parameters, signifying leverage effects. EGARCH and TGARCH models, with normal distribution, outperform the GARCH (1,1) model based on AIC, SBC, and log-likelihood values.

Table 5 Information Criteria and Log-Likelihood Function for GARCH, TGARCH and EGARCH using Student and GED Distributions

Model	Student T Distribution			Ged Distribution		
	AIC	SBC	LL	AIC	SBC	LL
GARCH (1,1)	-6.562217	-6.547002	8925.052	-6.559171	-6.543956	8920.913
TGARCH	-6.592886	-6.575820	9172.111	-6.588804	-6.571739	9166.437
EGARCH	-6.595613	-6.578548	9175.902	-6.590732	-6.573667	9169.118

To compare the GARCH models more accurately, the models were re-estimated with Student t and GED distributions. Table 5 shows AIC, SBC and log likelihood values for all the 3 models. From the table observations, it is confirmed that EGARCH estimates volatility more accurately than GARCH (1,1) with student and GED distributions.

To evaluate the performance of the models, variance is estimated using static forecasts for the full sample period and compared the results using three statistical measures: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Theil's Inequality Coefficient (TIC). The RMSE of all the models is below 1, indicating that the models can be generally acceptable. The Mean Absolute Error (MAE) quantifies the average absolute disparity between forecasted values and their corresponding original values. The goal is to minimize the MAE, and in all the models, the MAE values are notably diminutive. This indicates that the forecasts are of high quality, affirming their accuracy and reliability. The Theil's inequality coefficient, which is a normalized measure of total forecast error and should lie between 0 and 1, is closer to 1 in all the models, again indicating that the forecast is good.

For out of sample analysis, the models are estimated using the full sample with three month shorter, i.e. up to end of December 2022 with 2656 observations. A forecast has been done for the period of 1 month from 1st December 2022 to 30th December 2022 with 22 observations. The highest TIC value and the lower RMSE, MAE, MAPE values indicate the highest forecasting accuracy.

Table 6 Valuation of Out of Sample Volatility Forecasts

	Normal T Distribution			Student T Distribution			GED		
	GARCH	TGARCH	EGARCH	GARCH	TGARCH	EGARCH	GARCH	TGARCH	EGARCH
RMSE	0.007168	0.007111	0.007094	0.007200	0.007153	0.007148	0.007204	0.007162	0.007151
MAE	0.005501	0.005509	0.005498	0.005529	0.005522	0.005517	0.005536	0.005537	0.005528
MAPE	279.9808	230.2650	217.0299	291.0436	251.9480	256.2252	289.7849	254.6203	253.3865
TIC	0.856894	0.880255	0.880656	0.859264	0.871434	0.870443	0.860725	0.875810	0.874977

Using normal distribution, EGARCH model holds best performance in all 4 criteria as shown in table 6. However, TGARCH and EGARCH appear to be more accurate in two criteria respectively. Under Generalised Error Distribution, EGARCH holds best performance in 3 out of 4 criteria. Overall, it can be observed that EGARCH with normal and GED distribution better forecast NSE NIFTY index volatility. However, out of sample forecast uses only one month data, it is not possible to draw clear conclusions about forecasting performance of studied GARCH models.

Discussion

The examination of volatility patterns through the ARCH and GARCH models reveals significant serial correlation in return volatilities, which contradicts the random walk hypothesis and implies a long-memory process. The presence of conditional heteroscedasticity (ARCH effect) in all three variables further emphasizes the importance of using advanced modelling techniques to capture this volatility clustering. In comparing various GARCH models, the EGARCH model consistently outperforms others in estimating volatility, particularly when using both Student t and GED distributions. The models also exhibit strong performance in static forecasts, with RMSE values below 1, low MAE values, and Theil's inequality coefficient close to 1, highlighting the accuracy and reliability of the forecasts. For out-of-sample analysis, the findings suggest that EGARCH with normal and GED distributions provides better forecasts for NIFTY index volatility. However, it's important to note that this analysis only covers a one-month forecast, and further evaluation is needed to draw definitive conclusions about the forecasting accuracy of the studied GARCH models. Investors can use the study's findings to make better trading decisions. For example, they can identify assets that are more or less likely to experience large price swings and adjust their portfolios accordingly. Investors can also use the findings to develop hedging strategies to protect themselves from losses in the event of a sudden market downturn. The study's findings are also relevant for central banks. Central banks can use the information to forecast inflation and asset price volatility. This information can then be used to set interest rates and other policy instruments to maintain price stability and financial stability. Finally, the study's findings can help academics to better understand volatility dynamics in financial markets. Academics can use the findings to develop new models of volatility forecasting, or to investigate the causes of volatility clustering and ARCH effects.

Conclusion

Stock market volatility has a significant impact on the real economy, influencing investment decisions. To better understand and predict the stock market, it is crucial to research how to estimate stock market volatility and its forecasting performance in emerging European capital markets. This paper contributes to the existing literature by expanding on research on stock market volatility using GARCH-type models. It compares the forecasting ability of three GARCH models (GARCH(1,1), TGARCH, and EGARCH) for the volatility of the NIFTY index, exchange rate (INR/USD), and crude oil prices. It also uses three error distributions: the normal distribution, student-t distribution, and generalized error distribution.

The findings demonstrate that the EGARCH model proves to be the most successful in accordance with the information criteria (AIC and SBC) and log-likelihood function. Moreover, the assessment of the models is conducted based on their capability to forecast future returns, and it is determined that the EGARCH model is the most appropriate for capturing the volatility of the NIFTY index. This appropriateness is established through the measurement of root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and their inequality coefficient (TIC).

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