MODELLING VOLATILITY IN EMERGING CAPITAL MARKET: THE CASE OF INDIAN CAPITAL MARKET

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ABSTRACT

This paper investigates the presence and pattern of the volatility clustering in the Nifty index return series using GARCH family of models. In addition, this study examines GARCH family of models with reference to out-of-sample forecast accuracy. Besides, this study evaluates the presence of leverage effect or asymmetric information effect in the Nifty index. Analysis is carried out using the data covering the period from 1st January 1996 to 31st December 2015. The presence of a structural break during the 2008 financial crisis is confirmed by the Chow test. Thus, the study carries out the analysis by dividing the sample period into pre-crisis and post-crisis periods. The result shows that there is volatility clustering and leverage effect during pre- and post-crisis periods. Finally, the forecasting process suggests that GARCH (1,1) model is the most appropriate model for predicting the performance of Nifty index return series.

Keywords: Volatility Clustering, GARCH, Asymmetric GARCH, Leverage Effect.

INTRODUCTION

Peter L Bernstein opined that ‘‘fundamental law of investing is the uncertainty of the future’’. Yet investors (individual and institutional) have no choice, but to forecast the risk and return of individual asset or group of assets. Investors’ incorporates their expectations towards capital market while estimating return and risk of individual asset and group of assets. Both investors and financial authorities place a lot of emphasis on volatility that can be used to measure risk and stock market stability (Yu, 2002). Volatility is a measure of variations in asset prices. Usually, a percentage change in prices or rate of returns is used to measure the volatility of a financial market (Schwert, 1990). According to Pan & Zhang (2006), Modelling volatility in financial markets provides further insight into the data generating process of the returns.

As the volatility of stock market indices varies with time, it is essential to carry out empirical studies to estimate the conditional volatility models of the stock market indices from time to time and compare their forecasting performances. So, there is a need to identify the nature of stock market volatility while constructing the portfolio. In the recent years, Investors prefer to include emerging market in their international portfolio as they are less correlated to developed market. India is one among the important emerging capital market. Understanding the Indian capital market would be useful in constructing an efficient portfolio.

This paper investigates the presence and pattern of the volatility clustering in the Nifty index return series using GARCH family of models. Additionally, the study examines the presence of leverage effect or asymmetric information effect in the Nifty index. Analysis is carried out using the data covering the period from 1st January 1996 to 31st December 2015 by dividing the sample period into pre-crisis and post-crisis periods. The result shows that there is volatility clustering and leverage effect during pre and post crisis periods. Finally, the forecasting process suggests that GARCH (1,1) model is the most appropriate model for predicting the performance of Nifty index return series.

Literature Review

Many scholars have studied the volatility of stock returns in the developed markets. The ground breaking publication of Engle (1982) on Autoregressive Conditional Heteroskedasticity (ARCH) model on UK inflation data and the work of Bollerslev (1986) on GARCH (Generalized ARCH) formed the foundation of much of the empirical work. Research shows that stock market volatility varies with time. Besides, it shows the presence of positive serial correlation (volatility clustering). It means that movements in volatility are not random. In addition, the volatility of returns tends to persist. Consequently, volatility is a long memory process (Bollerslev, Chou & Kroner, 1992).

Baillie and Bollerslev (1990) noted that volatility could be forecasted. It is usually high at the commencement and at the end of the trading period. Akgiray (1989) observed that GARCH (1,1) is a powerful tool to forecast volatility in US stock market. Murinde and Poshakwale (2001) used daily indexes to model volatility in the stock markets of Hungary and Poland. They concluded that ARCH (1,1) was able to explain nonlinearity and volatility clustering. Poon and Granger (2003) provided a precise summary of the volatility literature. They observed that ARCH and GARCH models are very helpful in predicting volatility.

The amount of empirical research on volatility of stock returns in emerging markets is not very high. Karmakar (2009) estimated the conditional volatility models with a view to identify the important characteristics of stock market volatility in India. He found that GARCH models provides good forecast of volatility. He further observed that the swings in the volume of trade in the market have a direct impact on the volatility of assets returns. Pandey (2005) observed that several extensions have been made to the basic conditional volatility models to fit in observed characteristics of stock returns. He found that the extreme value estimators estimate volatility more efficiently than conditional volatility models.

On the other hand, conditional volatility models performed better than the extreme value estimators in terms of bias. Banerjee and Sarkar (2006) observed that the Indian stock market exhibited volatility clustering and so, GARCH models forecast the market volatility better than the simple volatility models such as historical average and moving average. Kumar (2006) assessed the ability of ten statistical and econometric volatility forecasting models in the Indian stock and foreign exchange markets using two types of assessment criteria-symmetric and asymmetric error statistics. He found that GARCH models forecast volatility better in the Indian markets.

Further, Karmakar (2005) studied the heteroscedasticity behaviour of the Indian stock market making use of several GARCH models. First, he used the standard GARCH model to examine whether the stock return volatility changes over time and if so, whether the changes could be predicted. Then, he used the E-GARCH models to examine whether there is asymmetric volatility. It was observed that volatility is an asymmetric function of past innovation, increasing at a higher rate during market decline. Bordoloi and Shankar (2008) made an attempt to build alternative models to forecast volatility in the Indian equity market return. They observed that these models contain information that explains the stock returns. The Threshold GARCH (T-GARCH) models explained the volatilities better for both the BSE Indices and S&P-CNX 500, while Exponential GARCH (E-GARCH) models explained the volatilities better for the S&P

CNX-NIFTY. Srinivasan and Ibrahim (2010) attempted to model and forecast the volatility of the SENSEX returns of Indian stock market. Results showed that the symmetric GARCH model forecasts conditional variance of the SENSEX return better than the asymmetric GARCH models in spite of the existence of leverage effect.

Overall, there is a need to identify the nature of stock market volatility in an emerging market like India, while constructing the portfolio. This paper analyzes the presence and pattern of the volatility clustering in the Nifty index return series using GARCH family of models. Additionally, the study examines the presence of leverage effect or asymmetric information effect in the Nifty index and thus contributes to the existing literature.

METHODOLOGY

This paper studies the presence and pattern of the volatility clustering in the Nifty index return series using GARCH family of models. Specifically, the study uses GARCH model, Exponential GARCH (EGARCH) model and Threshold GARCH (TGARCH) model to examine volatility clustering in the Nifty index return series.

The GARCH Model

ARCH model is designed to model and forecast conditional variances of any time series. The conditional variance of a single series is modelled as a function of its own past values. The ARCH model was introduced by Engle (1982) and generalized by Bollerslev (1986). The generalized model is, known as Generalized ARCH (GARCH) model. The conditional variance of the GARCH (p, q) process is defined as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha_i \varepsilon_{t-i}^2) + \sum_{j=1}^{p}(\beta_j \sigma_{t-j}^2) \quad (1)$$

All the coefficients should be non-zero, that is, $\omega > 0; \alpha_1 \alpha_2 \alpha_3 ... \alpha_q \geq 0; \beta_1 \beta_2 \beta_3 ... \beta_p \geq 0$ in order to ensure the positive conditional variance. If $(\alpha + \beta) < 1$, the series indicates the presence of clustering. The extant literature suggests that the GARCH (1,1) model is empirically adequate to examine the volatility clustering (Diebold, 2012). Therefore, this study employed GARCH (1,1) model. The model is as follows:

$$Y = \mu_t + \varepsilon \quad (2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (3)$$

Where equation 2 is the mean equation; equation 3 is the conditional variance equation; α_1 is a constant term; σ_{t-1}^2 is the previous period volatility; ε_{t-1}^2 is the square of the previous period's error term. α_1 and β are expected to have a positive signs and be statistically significant within the constraint $\alpha_1 + \beta < 1$. In addition, the rate of persistence is expressed by the proximity of the value of $\alpha_1 + \beta$ to unity. High value of β indicates a long memory i.e., the persistence of volatility in the long run.

The Exponential GARCH (EGARCH) Model

GARCH (1, 1) model considers both the good and bad news equally. Thus, it is expected to exert a symmetrical impact on volatility. In reality, this is not the case. To understand the asymmetric effect of information on volatility, Exponential GARCH (EGARCH) was used. Black (1976) propounded this model and was further extended by Nelson (1991). The leverage effect implies that the bad news has a greater impact on volatility than good news of the same magnitude. The equation is as follows:

$$In(\sigma_t^2) = \alpha_0 + \alpha_1 \left\{ \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right\} + \beta In(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (4)$$

Where α_1 and β are interpreted as discussed in the GARCH (1,1); γ is the symmetry coefficient. The inclusion of $\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}$ (standardized residual) allows the EGARCH model to be asymmetric for $\gamma \neq 0$ $\gamma < 0$ it indicates the presence of leverage effect.

The Threshold GARCH (TGARCH) Model

This model is also called GJR GARCH and was developed by Glosten, Jagannathan and Runkle (1993). It is an extension of GARCH model by adding a term that accounts for asymmetries. The equation is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma \mu_{t-1}^2 I_{t-1} \quad (5)$$

Where I_{t-1} if $\mu t-1 < 0$; I is the information asymmetry; γ is information asymmetry coefficient. The effect of good news $\varepsilon_{t-1} > 0$ *and* bad news $\varepsilon_{t-1} < 0$ varies with the conditional variance. The good news affects α_1. The bad news affects $\alpha_1 + \gamma$. Therefore, if the γ is statistically significant, the impact of good news on current volatility varies from the impact of bad news. As observed by Brooks (2014), "The condition for non- negativity will be $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$ and $\alpha_1 + \gamma \geq 0$. That is, the model is still admissible, even if $\gamma < 0$, provided that $\alpha_1 + \gamma \geq 0$.

Data

This study analyses the daily adjusted closing prices of the CNX Nifty which were collected from the official website of the National Stock Exchange of India Limited (www.nseindia.com). The study period is from 1st January 1996 to 31st December 2015. Out of total 4985 observations, the observations relating to the last one year i.e., 251 observations were used to assess the out-of sample predictive ability of the models. The index return has been calculated using continuous compounding method. The study covers 20 years, which is more than the minimum requirement for performing proper GARCH estimation (Engle & Mezrich, 1995). Returns have been estimated at time t as follows:

$$R_t = \ln\left(P_t \div P_{t-1}\right) \quad (6)$$

Where *ln* refers to the natural logarithm, *Pt* and *Pt-1* are the daily-adjusted closing price of NSE Nifty at day's *t* and *t-1* respectively.

To investigate the presence of structural change in the sample period, this study used Chow breakpoint test for NSE daily series. 22nd January 2008 was identified as the breakpoint. The reason for choosing this date as a breakpoint is that Nifty 50 crashed by 630 points on that as a sequel to the US Economic Crisis. The breakpoint was identified by following the procedure advanced by Gil-Alana (2008) in the fractional integration framework. The result of Chow breakpoint test confirms the existence of structural breakpoint (F-statistic: 11615.90, $p<0.00$). This result is similar to those of Gil-Alana and Tripathy (2016) and Tripathy and Gil-Alana (2015). Using breakpoint analysis, the study divides the sample period into two sub-samples, namely pre and post-crisis period. The pre-crisis period extends from 1st January 1996 to 21st January 2008. The post crisis period extends from 22nd January 2008 to 31st December 2015.

Empirical Analysis

Before estimating the volatility model, the study investigated whether the return series meets the preconditions for the use of GARCH, EGARCH and TGARCH. First, the study tested the stationarity of the return series. To examine the degree of stationarity in the Nifty return series, this study used unit root testing procedure. Among the several tests, Augmented Dickey-Fuller (ADF) Test, developed by Dickey and Fuller (1979) and Phillips and Perron (1988) Test (PP Test) are widely used ones. Therefore, three different forms of ADF and PP tests were performed. The results are given in Table 1. The series is stationary in three forms during pre-crisis and post-crisis period at 1 percent level. Thus, the return series can be used for Modelling. In addition, the behaviour of the model could be generalized for other periods.

The second precondition is the presence of volatility clustering or volatility pooling. Volatility clustering refers to the phenomenon that "large changes tend to be followed by large changes, of either sign and small changes tend to be followed by small changes" (Mandelbrot, 1963). As expected, Figure 1 and 2 point out the existence of volatility clustering, as large changes are followed by large changes and small changes are followed by small changes. Third precondition is the presence of ARCH effect. Generally, the time series has heteroscedasticity, which is auto correlated over the period of time. To know the presence of ARCH effect, ARCH-LM Test was performed. Table 2 indicates that there is an ARCH effect in the Nifty returns series during pre and post-crisis period.

Table 1
RESULTS OF ADF TEST AND PP TEST FOR THE RETURN SERIES

Test Equation	Pre-Crisis Period		Post-Crisis Period	
	ADF-test	PP-test	ADF-test	PP-test
Intercept	-50.85*	-50.79*	-42.79*	-42.77*
Intercept and Trend	-50.86*	-50.81*	-42.79*	-42.77*
No intercept and No trend	-50.80*	-50.76*	-42.79*	-42.77*
*Significance at 1 percent level				

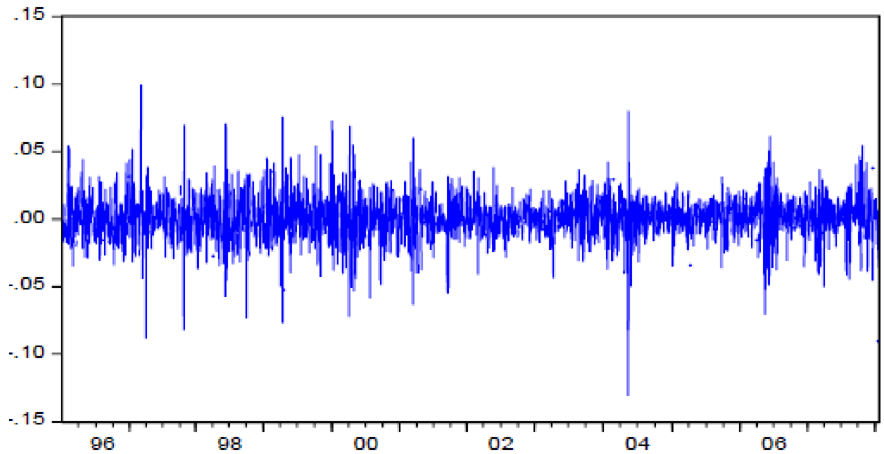

FIGURE 1
PERIOD DAILY RETURNS OF NIFTY DURING PRE-CRISIS PERIOD

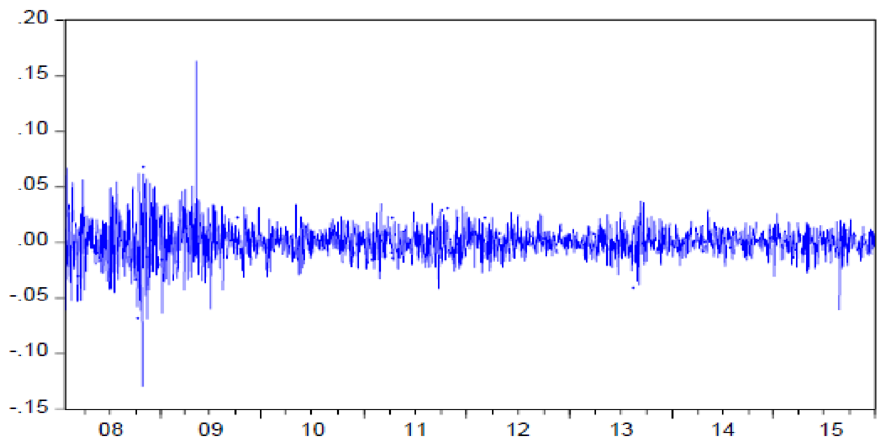

FIGURE 2
DAILY RETURNS OF NIFTY DURING POST CRISIS

Table 2 RESULTS OF ARCH-LM TEST FOR THE RETURN SERIES		
	Pre-Crisis Period	**Post Crisis Period**
F-statistic	349.22*	14.37*
Obs* R-squared	313.18*	14.27*
*Significance at 1 per cent level		
Source: Estimated by the Authors		

After ensuring that the entire preconditions were met, the descriptive statistics were calculated. Table 3 consists of descriptive statistics for the daily returns series of Nifty. The mean return is close to zero with high standard deviations during pre and post crisis period. The distribution of the return series is negatively skewed during pre-crisis and positively skewed during post crisis period. Kurtosis is high during the sample periods. The return series exhibits fatter tails and sharper peaks in comparison with standard normal distribution. The Jarque-Bera test confirms that the Nifty return series is not normally distributed (Table 3). To conclude, the series does not conform to normal distribution and has a leptokurtic distribution. Most financial time series share these features. All the analysis is carried out using EViews software.

Table 3
RESULTS OF DESCRIPTIVE STATISTICS OF RETURN SERIES

	Pre-crisis	Post Crisis
Mean	0.000579	0.00027
Median	0.001113	0.000683
Maximum	0.099339	0.163343
Minimum	-0.130539	-0.130142
Std. Dev.	0.016161	0.015957
Skewness	-0.372791	0.238097
Kurtosis	7.602524	13.80501
Jarque-Bera	2734.601	8373.457
Probability	0	0
Observations	3019	

Note: Post crisis sample period: 22nd January 2016 to 31st December 2016

Table 4
RESULTS OF GARCH MODEL FOR RETURN SERIES

Variable	Pre-Crisis			Post Crisis		
Mean Equation	**Normal**	**Students-**	**GED**	**Normal**	**Students-**	**GED**
Constant	0.0011*	0.0011*	0.0011*	0.0006*	0.0006*	0.0006*
First lag Variance Equation	0.1019*	0.1009*	0.0938*	0.0569*	0.0547*	0.0590*
Constant	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
RESID(−1)^2	0.1368*	0.1356*	0.1328*	0.0754*	0.0709*	0.0728*
GARCH(-1)	0.8292*	0.8260*	0.8289*	0.9169*	0.9194*	0.9188*
AIC	-5.583	-5.6441	-5.6304*	-5.8751	-5.9023	-5.9008
SC	-5.53	-5.6321	-5.6185*	-5.8593	-5.8833	-5.8818
ARCH-LM Test	1.324	1.265	1.45	2.42	2.11	2.24
Correlogram Squared Residuals (pre= Q-17; Post Q36)	14.35	14.12	14.37	19.53	19.5	19.39
Jarque-Bera Test	1048.00*	1060.11*	1051.19*	312.90*	328.62*	317.75*
*Significance at 1 per cent level						
Source: Estimated by the Authors						

Table 4 shows the estimates of GARCH (1,1) model under three different distributions, namely, Normal distribution, Student t distribution and GED distribution. The result indicates that coefficient of first lag is significant at 1 percent level in the mean equation under all the distributions. In addition, the ARCH and GARCH coefficients in conditional variance equations are positive and statistically significance. It indicates the strong support to ARCH and GARCH effects. A large value of (pre-crisis period -0.8292 and post crisis period -0.9169) indicates the presence of volatility clustering. Further, it takes long time for the shocks due to the information to dissipate. A smaller value of *1* (pre-crisis period -0.1368 and post-crisis period -0.0709) indicates the relatively small changes in the volatility due to the large market surprises. The sum of the coefficients of lagged squared error and conditional variance $\alpha_1 + \beta$ are 0.966 and 0.9878 for pre and post-crisis period respectively. It implies that a return of high magnitude (either sign) will cause future forecasts of the variance to be high for a prolonged period.

After fitting the model, it is important to test the specification of mean equation and variance equation. For this purpose, it should be ensured that there is no ARCH effect, no serial correlation among the squared residuals and distribution is non-normal. Although results in table 4 indicate that the distribution is not normal, there is no ARCH effect and variance equation is correctly specified during pre- and post-crisis period.

Table 5
RESULTS OF EGARCH MODEL FOR RETURN SERIES

Variable	**Pre-Crisis**			**Post Crisis**		
	Normal	**Students-**	**GED**	**Normal**	**Students-**	**GED**
Mean Equation						
Constant	0.0007*	0.0008*	0.0008*	0.0004	0.0003	0.0004
First lag	0.1182*	0.1083*	0.1010*	0.0662**	0.0572**	0.0622**
Variance Equation						
C(3)	-0.8483*	-0.8564*	-0.8594*	-0.2222*	-0.2290*	-0.2247*
C(4)	0.2602*	0.2761*	0.2662*	0.1499*	0.1329*	0.1421*
C(5)	-0.1104*	-0.1087*	-0.1087*	-0.0753*	-0.0936*	-0.0861*
C(6)	0.9228*	0.9237*	0.9224*	0.9880*	0.9856*	0.9871*
AIC	-5.5955	-5.6552	-5.6405	-5.8982	-5.9294	-5.9227
SC	-5.5836	-5.6412	-5.6265	-5.8792	-5.9072	-5.9004
ARCH-LM Test	0.277	0.0246	0.1076	1.74	0.9691	1.36
Corre. Squared Residuals (Pre-Q17; Post Q36)	16.68	16.5	17.72	34.77	45.03	36.63
Jarque-Bera Test	1187.10*	1255.65*	1221.79*	546.21*	872.91*	688.43*

*Significance at 1 per cent level
Source: Estimated by the Authors

Table 5 displays the results of EGARCH Model. The value of (pre-crisis= -0.11 and post-crisis= -0.0753) is negative and statistically significant. It indicates the leverage effect on the Nifty return series. It suggests that the bad news has a greater effect on volatility than good news of the same magnitude. The leverage effect is more during the pre-crisis period than post crisis period. Although results in Table 5 indicate that the distribution is not normal, there is no ARCH and variance equation is correctly specified during pre- and post-crisis period.

Table 6 displays the estimates of TGARCH (1,1,1) under three different distributions. The coefficient of asymmetry, γ, is positive and statistically significant. The result indicates the impact of negative information would be higher. Although results in Table 6 indicate that the distribution is not normal, there is no ARCH and variance equation is correctly specified during pre- and post-crisis period.

Table 6
RESULTS OF TGARCH MODEL FOR RETURN SERIES

Variable	Pre-Crisis			Post-Crisis		
	Normal	Students-t	GED	Normal	Students-t	GED
Mean Equation						
Constant	0.0007*	0.0009*	0.0009*	0.0003	0.0002	0.0004
First lag	0.1089*	0.1074*	0.0989*	0.0620**	0.0539**	0.0585*
Variance Equation						
Constant	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*
RESID (-1)^2	0.0666*	0.0697*	0.0663*	0.0283*	0.0087	0.0162
RESID (-1)^2*(RESID (-1)<0)	0.1530*	0.1647*	0.1575*	0.1065*	0.1422*	0.1291*
GARCH (-1)	0.8032*	0.7891*	0.7957*	0.9113*	0.9083*	0.9098*
AIC	-5.5967	-5.6542	-5.6403	-5.8929	-5.9291	-5.8921
SC	-5.5848	-5.6402	-5.6353	-5.8739	-5.9069	-5.8984
ARCH-LM Test	0	0.074	0.015	1.33	0.95	1.33
Corre. Sq. Residuals Pre-Q(17) Post-Q36	13.922	14.15	14.07	32.58	36.91	32.58
Jarque-Bera Test	1048.39*	1100.42*	1068.6*	1147.22*	1489.99*	1147.32*

*Significance at 1 percent level; ** Significance at 5 per cent level
Source: Estimated by the Authors

Forecasting the Market Volatility

The best-fit model is chosen based on the Akaike Information Criterion (AIC). The model that has minimum value of AIC is the best-fit model. The study has chosen the best-fit model from GARCH (1,1), EGARCH (1,1) and TGARCH (1,1,1) and estimated the volatility using out-of-samples. The best-fit model is chosen in terms of its accuracy in forecasting the returns. Four performance measures namely, the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE), the Mean Absolute Percentage Error (MAPE) and the Theil-U-statistic (TU) are used to evaluate the performance of three models. Table 7 provides the results of out-of-sample forecasting for the Nifty return series. The model with the lowest error is the best model. The results show that GARCH (1,1) is the best model in terms of the ability to forecast the volatility of the Nifty return. The EGARCH (1,1,1) and TGARCH (1,1,1) models stand next in terms of the forecasting ability respectively. To conclude, the symmetric GARCH model is better than asymmetric models in predicting conditional variance of the Nifty returns. Figures 1-6 (appearing in the Appendix) show the out-of-sample forecasting. The finding is consistent with those of Banerjee and Sarkar (2006).

Table 7
RESULTS OF FORECAST PERFORMANCE OF ESTIMATED MODELS FOR THE OUT-OF-SAMPLE

Model	GARCH		EGARCH		TGARCH	
	Static	Dynamic	Static	Dynamic	Static	Dynamic
Root Mean Squared Error	0.01531	0.01531	0.01588	0.0159	0.01588	0.0159
Mean Absolute Error	0.01038	0.01039	0.01078	0.0108	0.01078	0.0108
Mean Absolute Percent	132.523	122.963	127.752	111.982	125.101	109.771
Theil Inequality Coefficient	0.93301	0.95831	0.93312	0.97452	0.93753	0.97813
Overall Rank	1	1	2	2	3	3

CONCLUSION

Risk and return are the two sides of a coin. Understanding and measuring the risk plays an important role in making investment decisions. Variance is the simple tool used by investor community to measure risk. The limitation of this tool is that it assumes that variance is constant over time. Such phenomenon is called homoscedasticity (Brooks, 2014). Nonetheless, the extant research suggests that time series data exhibits a volatility clustering. Understanding the volatility clustering would help the investors forecast the volatility in a better manner. As a result, investors can manage their investments optimally. Therefore, this study examined the volatility of Nifty index for the period extending from January 1996 to December 2015. In addition, this study also assessed the impact of financial crisis. The study investigated the volatility pattern of Nifty returns using three variants of GARCH model. Volatility clustering and leverage effect or asymmetric information effect were analysed. The result shows that there is volatility clustering and leverage effect during pre and post crisis period. Finally, the forecasting process suggests that GARCH (1,1) model is the most appropriate one for predicting the performance of Nifty index return series.

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