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Modelling Stock Market Return Volatility: Evidence from India

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Abstract
This paper empirically investigates the volatility pattern of Indian stock market based on time series data which comprises of daily closing prices of the S&P CNX Nifty Index for a fifteen year period from 1st April 2001 to 31st March 2016. For this study the analysis has been done using both symmetric and asymmetric models of Generalized Autoregressive Conditional Heteroscedastic (GARCH). For capturing the symmetric and asymmetric volatility GARCH-M (1, 1) and EGARCH (1, 1) estimations are found to be the most appropriate model as per the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Log Likelihood ratios. The study also provides evidence for the existence of a positive and insignificant risk premium as per GARCH-M (1, 1) model. The asymmetric leverage effect captured by the parameter of EGARCH (1, 1) and TGARCH (1, 1) models show that negative shocks have a significant effect on conditional variance (volatility).
Keywords: ARCH Effects, GARCH Models, Leverage Effect, Stock Returns, Volatility.

Introduction

Over the past few years, modelling and forecasting volatility of a financial time series has become a popular area of research and has gained a great deal of attention from academicians, researchers and others, this is because volatility is considered as an important concept for many economic and financial applications, like risk management, portfolio optimization and asset pricing. Volatility refers to the amount of risk or uncertainty about the size of changes in a security's value. A higher volatility means a security's value can potentially be spread out over a larger range of values, whereas, a lower volatility means a security's value does not fluctuate drastically, but changes in value over a period of time. A special feature of the volatility is that it is not directly visible, so the financial analysts are especially eager to find a precise estimate of this conditional variance process. Consequently, a number of models have been developed that are especially suited to estimate the conditional volatility of financial instruments, of which the most well-known and often applied model for this volatility is the conditional heteroscedastic models. The main aim of building these models was to make a good forecast of future volatility that would be helpful in obtaining a more efficient portfolio allocation, having a better risk management and more precise derivative prices of a certain financial instrument.

The time series observations are found to depend on their own past value (autoregressive), depending on past information (conditional) and exhibit non-constant variance (heteroskedasticity). It has been found that the stock market volatility changes with time (i.e., it is 'time-varying') and exhibits 'volatility clustering'. A series with some periods of high volatility and some periods of low volatility is said to exhibit volatility clustering.

Variance or standard deviation is often used as the risk measure in risk management. Engle (1982) introduced Autoregressive Conditional Heteroskedasticity (ARCH) model to the world to model financial time series that exhibit time varying conditional variance. A generalized arch (GARCH) model extended by Bollerslev (1986) is another popular model for estimating stochastic volatility. These models are generally used in various branches of econometrics, especially in financial time series analysis. Besides, with the introduction of models of ARCH and GARCH, there have been number of empirical applications of modelling variance (volatility) of financial time series. Though, the GARCH cannot account for leverage effect, however they account for volatility clustering and leptokurtosis in a series, this necessitated to develop new and extended models over GARCH that resulted in to new models viz., GARCH-M, EGARCH, TGARCH and PGARCH.

This paper is organised as follows: after this introductory section, Section 2 is devoted to the Literature Review. Section 3 presents the methodology, while Section 4 is based on the discussion of the empirical results. Finally, Section 5 contains the conclusion of the study. This paper adopted the approach of Banumathy and Azhagaiah (2015) in arranging the methodology, with slight modification.

Literature Review

Jorge (2007) modeled the volatility for daily and weekly returns of the Portuguese Stock Index PSI-20 by using simple GARCH-M, GARCH, Threshold ARCH (TARCH) and Exponential GARCH (EGARCH) models & found that there have been significant asymmetric shocks to volatility in the daily stock returns, but not in the weekly stock returns. They also reported that some weekly returns time series properties have been substantially different from properties of daily returns, and the persistence in conditional volatility has been different for some of the sub-periods referred. Lastly, they have compared the forecasting performance of the various volatility models in the sample periods before and after the terrorist attack on September 11, 2001.

Floros (2008) employed the GARCH model, as well as EGARCH, TGARCH, the component GARCH , asymmetric component GARCH and the PGARCH model using daily data from Egypt (CMA General index) and Israel (TASE-100 index) to model the Stock Market Volatility and concluded that increased risk has not been found to necessarily lead to a higher return.

Tripathy, Rao and Kanagaraj (2009) investigated the impact of introduction of the derivative instruments and leverage and asymmetric effect on spot market volatility using NSE Nifty as a proxy for Indian stock market during the period October 1995 to December 2006 by using EGARCH, TARCH, GARCH, and component ARCH model. The results have suggested a decline in spot market volatility and market efficiency has improved after introduction of index futures, stock futures, stock options and index options on the spot market due to increased impact of recent news. This research study has also found evidence of leverage and asymmetric effect on spot market where the conditional variance is an asymmetric function of past innovation, rising proportionately more during market declines. The research study has also reported that asymmetric GARCH models provide better fit than the symmetric GARCH models.

Goudarzi and Ramanarayanan (2010) examined the volatility of Indian stock market using BSE 500 stock index as the proxy for ten years. ARCH and GARCH models were estimated and the best model was selected using the model selection criterion viz., Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). The study found that GARCH (1, 1) was the most appropriate model for explaining volatility clustering and mean reverting in the series for the study period.

Ahmed and Suliman (2011) tried to estimate volatility (conditional variance) in the daily returns of the principal stock exchange of Sudan namely, Khartoum Stock Exchange (KSE) over the period from January 2006 to November 2010. They used symmetric and asymmetric models that capture the volatility clustering and leverage effect and found that conditional variance process is highly persistent (explosive process), and provide evidence on the existence of risk premium for the KSE index return series which support the positive correlation hypothesis between volatility and the expected stock returns. They also suggested that the asymmetric models provide better fit than the symmetric models, which confirms the presence of leverage effect.

Elsayeda (2011) employed EGARCH and TGARCH models to examine the existence of asymmetric volatility and leverage effect for the Egyptian stock market index. The results indicated that there is existence of the leverage effect for daily EGX30 index returns.

Goudarzi and Ramanarayanan (2011) in another study, they investigated the volatility of BSE 500 stock index and modelled two non-linear asymmetric model viz., EGARCH (1, 1) and TGARCH (1, 1) and found that TGARCH (1, 1) model was found to be the best preferred model as per Akaike Information Criterion (AIC), Schwarz Information Criterion (SBIC) and Log Likelihood (LL) criteria.

Mittal, Arora, and Goyal (2012) examined the behaviour of Indian stock price and investigated to test whether volatility is asymmetric using daily returns from 2000 to 2010. As per the study GARCH and PGARCH models were found to be best fitted models to capture symmetric and asymmetric effect respectively.

Adesina (2013) used symmetric and asymmetric GARCH models to estimate the stock return volatility and the persistence of shocks to volatility of the Nigerian Stock Exchange (NSE). He used monthly data from January 1985 to December 2011 of the NSE all share-index. His study revealed high persistent volatility for the NSE return series found no asymmetric shock phenomenon (leverage effect) for the return series.

Vijayalakshmi and Gaur (2013) used eight different models to forecast volatility in Indian and international stock markets. NSE and BSE index were considered as a proxy for Indian stock market and the exchange rate data for Indian rupee and foreign currency over the period from 2000 to 2013. Based on the forecast statistics the study found that TARCH and parch models lead to better volatility forecast for BSE and NSE return series for the stock market evaluation and ARMA (1, 1), ARCH (5), EGARCH for the foreign exchange market.

Banumathy and Azhagaiah (2015) examined the volatility pattern of Indian stock market. The study used both symmetric and asymmetric models of Generalized Autoregressive conditional Heteroscedastic (GARCH) using daily returns from 2003 to 2012. As per the study GARCH and GARCH and TGARCH models were found to be best fitted models to capture symmetric and asymmetric effect respectively. The study also provides evidence for the existence of a positive and insignificant risk premium as per GARCH-M (1, 1) model. The asymmetric effect (leverage) captured by the parameter of EGARCH (1, 1) and TGARCH (1, 1) models show that negative shocks have significant effect on conditional variance (volatility).

Most of the Indian studies attempted on modelling volatility found that the GARCH (1, 1) is considered the best model to capture the symmetric effect and for leverage effects, EGARCH-M and PGARCH models have been found to be appropriate by the previous studies. However, the choice of best fitted and adequate model depends on the model that is included for the evaluation in the study. Hence, this study used different GARCH family models, both in symmetric as well as asymmetric effect to capture the facts of return and to study the most appropriate model in the volatility estimation.

Research Methodology

Data source

The study is based on the secondary data that were collected from official website of National Stock Exchange www.nseindia.com. S&P CNX Nifty indices were used as proxy to the stock market. The daily closing prices of Nifty indices over the period of fifteen years from 1st April 2001 to 31st March 2016 were collected and used for analysis.

Research methods

Volatility has been estimated on return (R_t) and hence before going for all these tests, first the daily returns were calculated. The Nifty return series is calculated as a natural log of first difference of daily closing price, which is as follows:

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

where R_t is the natural log daily return on Nifty index for time t, Pt is the closing price at time t, and P_{t-1} is the corresponding price in the period at time t − 1.

Test for Stationarity

Before estimating the models, the unit root properties for the time series data have been tested individually for Nifty series using ADF and Phillips-Perron test statistic.

Test for Heteroscedasticity

One of the most important issues before applying the GARCH methodology is to first examine the residuals for the evidence of heteroscedasticity. To test the presence of heteroscedasticity in residual of the return series of Nifty index returns, Lagrange Multiplier (LM) test for Autoregressive conditional heteroscedasticity (ARCH) is used. The test procedure is performed by first obtaining the residuals e_t from the ordinary least squares regression of the conditional mean equation which might be an autoregressive (AR) process, moving average (MA) process or a combination of AR and MA processes; (ARMA) process (Suliman, 2012).

In this study, an autoregressive moving average ARMA (1, 1) model for the conditional mean in the return series as an auxiliary regression is employed. The conditional mean equation is as:

$$R_t = \emptyset_1 R_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

It is sensible to compute the Engle (1982) test for arch effect to ensure that there is no arch effect.

Volatility Measurement Technique

GARCH models represent the main methodologies that are applied in modeling the stock market volatility. The present study employed GARCH (1, 1) and GARCH-M (1, 1) for modeling conditional volatility and for modeling asymmetric volatility EGARCH (1, 1) and TGARCH (1, 1) were applied.

The following GARCH techniques are applied to capture the volatility in the return series.

Symmetric Measurement

To study the relation between asymmetric volatility and return, the GARCH (1, 1) and GARCH-M (1, 1) models are used in the study.

The Generalized ARCH Model (GARCH)

The GARCH model (Bollerslev[1] 1986), which allows the conditional variance to be dependent upon previous own lags; conform to the conditional variance equation in the simplest form as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$.

The size of parameters α_1 and β_1 determine the short-run dynamics of the volatility time series. If the sum of the coefficient is equal to one, then any shock will lead to a permanent change in all future values. Hence, shock to the conditional variance is 'persistence.'

The GARCH-in-Mean (GARCH-M Model)

In GARCH model, the conditional variance enters the mean equation directly, which is generally known as a

[1] T. Bollerslev, "Generalized Autoregressive Conditional Heteroscedasticity," *Journal of Econometrics,* vol. 31, 1986, pp. 307–326.

GARCH-M model. The return of a security may depend on its volatility and hence a simple GARCH-M (1, 1) model can be written as:

Mean Equation $R_t = \mu + \lambda_1 \sigma_t^2 + \varepsilon_t$

where, r_t is the return of the asset at time t, μ is the average return, and ε_t is the residual return.

Variance Equation $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

The parameter λ in the mean equation is called the risk premium. A positive λ indicates that the return is positively related to its volatility, i.e. a rise in mean return is caused by an increase in conditional variance as a proxy of increased risk.

Asymmetric Measurement

The main drawback of symmetric GARCH is that the conditional variance is not able to respond asymmetrically to rise and fall in the stock returns. Hence, a number of models have been introduced to deal with the issue and are called asymmetric models viz., EGARCH, TGARCH and PGARCH, which are used for capturing the asymmetric phenomena. To study the relation between asymmetric volatility and return, the EGARCH (1, 1) and TGARCH (1, 1) models are used in the study.

The Exponential GARCH Model

This model is based on the logarithmic expression of the conditional variability. The presence of leverage effect can be tested and this model enables to find out the best model, which capture the symmetries of the Indian stock market (Nelson 1991) and hence the following equation:

$$Ln(\sigma_t^2) = \alpha_0 + \beta_1 Ln(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

The left-hand side is the log of the conditional variance. The coefficient γ is known as the asymmetry or leverage term. The termγ, accounts for the presence of the leverage effects, which makes the model asymmetric. If γ = 0, then the model is symmetric. If γ is negative and statistically different from zero, it indicates the existence of the leverage effect.

Threshold GARCH Model

The generalized specification of the threshold GARCH for the conditional variance (Zakoian 1994) is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

The γ is known as the asymmetry or leverage parameter. In this model, good news ($\varepsilon t-1 > 0$) and the bad news ($\varepsilon t-1 < 0$) have differential effect on the conditional variance. Good news has an impact of αi, while bad news has impact on αi + γi. Hence, if γ is significant and positive, negative shocks have a larger effect on σ_t^2 than the positive shocks.

The criteria to accept the null hypothesis of no leverage effect in TGARCH model is that γ coefficient must be negative. In other words, if the γ coefficient is not negative ($\gamma \neq 0$) the news impact is asymmetric.

Results and Discussion

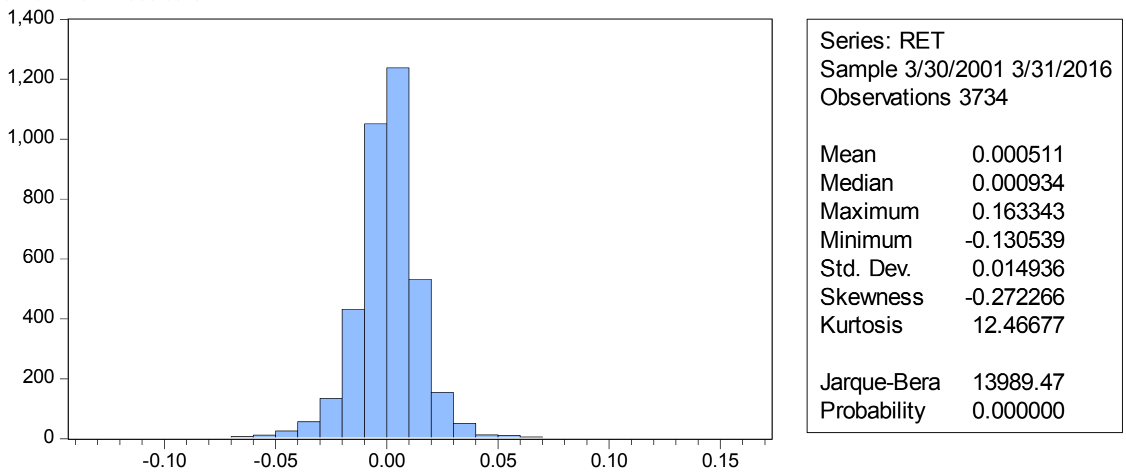


Fig. 1 Descriptive Statistics

The mean of the Nifty returns is positive, indicating the fact that price has increased over the period. The descriptive statistics shows that the returns are negatively skewed, indicating that there is a high probability of earning returns which is greater than the mean. The K of the series is greater than 3, which implies that the return series is fat tailed and does not follow a normal distribution and it was further confirmed by Jarque-Bera test statistics, which is significant at 1% level and hence the null hypothesis of normality is rejected.

To make the series stationary, the closing price of the Nifty index is converted into daily natural logarithmic return series. Figure 2 shows volatility clustering of return series of the S&P CNX Nifty for the study period from 1st April 2003 to 31st March 2016. From the figure 2, it can be inferred that the period of low volatility tends to be followed by period of low volatility for a prolonged period and the period of high volatility is followed by period of high volatility for a prolonged period, which means the volatility is clustering and the return series vary around the constant mean but the variance is changing with time.

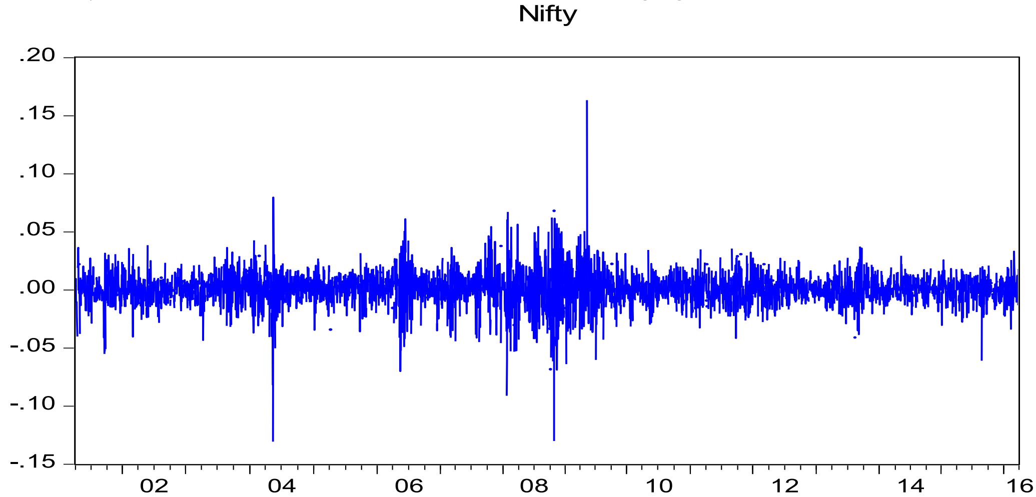


Fig. 2 Nifty Returns

Table 1 shows the presence of unit root in the series tested using ADF and PP tests. Both the ADF and PP test statistics reported in table 1 reject the hypothesis at 1% level as the critical value of –3.43 for both ADF and PP tests of a unit root in the return series. Also the p values of ADF and PP are less than 0.05. Hence, the results of both the tests confirm that the series are stationary.

Table 1 Stationarity Test

Value	ADF	PP
t-Statistic	-56.69278	-56.70007
Prob.*	0.0001	0.0001
Critical Value		
1%	-3.431916	-3.431916
5%	-2.862117	-2.862117
10%	-2.567121	-2.567121

As a prior step for estimating ARCH family model equation, a mean equation needs to be formulated. The mean equation for ARCH family model has been formulated as ARMA (1, 1) model using Box Jenkins methodology. The results for mean equation have been enumerated in the table below:

Table 2 Mean Equation ARMA (1, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000513	0.000258	1.988394	0.0468
AR(1)	-0.352298	0.158833	-2.218035	0.0266
MA(1)	0.432098	0.153069	2.822905	0.0048

The coefficients of constant, AR & MA terms are significant at 5% level.

After obtaining the residuals from the ARMA (1, 1) model the ARCH-LM test is applied to find out the presence of arch effect in the residuals of the Nifty return series. From the table 3, it is inferred that the ARCH-LM test statistics is highly significant. Since p value is less than 0.05, the null hypothesis of 'no ARCH effect' is rejected at 1% level, which confirms the presence of ARCH effects in the residuals of time series models in the Nifty returns.

Table 3 ARCH-LM Test

Heteroskedasticity Test: ARCH

F-statistic	188.9328	Prob. F(1,3730)	0.0000
Obs*R-squared	179.9207	Prob. Chi-Square(1)	0.0000

The Ljung-Box Q-statistics is used to check the validity of autoregressive conditional heteroskedasticity (ARCH) in the residuals. If there is no ARCH in the residuals, the autocorrelations and partial autocorrelations should be zero at all lags and the Q-statistics should not be significant. Looking at Table 4, there is clear evidence that the return series exhibit ARCH effect. The squared residuals of Nifty returns revealed significant correlation among the error terms with all Q statistics being significant as is evident from low p values reported in the last column of the table 4.

Table 4 Correlogram of Residuals Squared

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|** |	|** |	1	0.220	0.220	180.11	
|* |	|* |	2	0.177	0.136	297.76	
|* |	| |	3	0.118	0.059	350.11	0.000
|* |	|* |	4	0.178	0.131	468.79	0.000
|* |	| |	5	0.135	0.061	536.71	0.000
|* |	| |	6	0.099	0.021	573.17	0.000
|* |	|* |	7	0.133	0.076	639.66	0.000
|* |	| |	8	0.082	0.003	664.75	0.000
|* |	|* |	9	0.136	0.075	734.26	0.000
|* |	|* |	10	0.147	0.082	814.79	0.000
|* |	| |	11	0.124	0.034	872.33	0.000
| |	| |	12	0.073	-0.009	892.33	0.000

From the ARCH-LM test and squared residuals of Nifty returns there is a sufficient evidence for using ARCH family models has been generated. For mean equation ARMA (1, 1) model can be used.

Symmetric GARCH Models

The result of GARCH (1, 1) and GARCH-M (1, 1) models is shown in table 5, which reveals that the parameter of GARCH is statistically significant. In other words, the coefficients viz., constant (α_0), ARCH term (α_1) and GARCH term (β_1) are highly significant at 1% level. In the conditional variance equation, the estimated β_1 coefficient (0.864563) is considerably greater than α_1 coefficient (0.114001) which resembles that the market has a memory longer than one period and that volatility is more sensitive to its lagged values than it is to new surprises in the market values. It shows that the volatility is persistent. The sizes of the parameters α_1 and β_1 determine the volatility in time series. The sum of these coefficients (α_1 and β_1) is 0.978564, which is close to unity indicating that the shock will persist for many future periods.

Since the risk-return parameter is positive and significant at 1% level, it shows that there is a positive relationship between risk and return. Further, ARCH-LM test is employed to check ARCH effect in residuals and from the results, it was found that the p is greater than 0.05, which led to the conclusion that the null hypothesis of 'no arch effect' is accepted. In other words, the test statistics does not support for any additional arch effect remaining in the residuals of the models, which implies that the variance equation was well specified for the market.

The GARCH-M (1, 1) model is estimated by allowing the mean equation of the return series to depend on a function of the conditional variance. The constant in mean equation is significant at 5% level, indicating that there is an abnormal return for the market. From the table 5, it is inferred that the coefficient of conditional variance (λ) in the mean equation value is positive however, it is statistically insignificant, which implies that there is no significant impact of volatility on the expected return, indicating lack of risk-return trade off over time. This outcome was in consensus of the previous findings of Goudarzi and Ramanarayanan (2010). In the variance equation of GARCH-M (1, 1), the parameters viz., constant (α_0), ARCH term (α_1) and GARCH term (β_1) are highly significant at 1% level. The sum of α_1 and β_1 is 0.9783, which infers that shocks will persist in the future period. The ARCH-LM test was applied on Nifty residuals to check the presence of additional arch effect and the results showed that the test statistics do not exhibit additional arch effect for the whole study period indicating that the variance equation is well specified.

The best fitted models both in symmetric as well as in asymmetric effect are selected based on the minimum AIC and SIC value and the highest log likelihood value. Likewise, the AIC value (–5.892580) is low and Log Likelihood value (11005.50) is high for GARCH-M (1, 1) when compared to its alternate symmetric model, called GARCH (1, 1) but the SIC value (-5.882552) is low for GARCH (1, 1) model. Hence GARCH-M (1, 1) model is found to be the best fitted model for this study. This outcome was not in consensus with the previous studies, as per Goudarzi and Ramanarayanan (2010), Mittal, Arora, and Goyal (2012) and Banumathy and Azhagaiah (2015) GARCH (1, 1) model is best fitted model to describe the symmetric volatility process.

Table 5 Results of GARCH (1, 1) and GARCH-M (1, 1) models

Coefficient	GARCH (1, 1)	GARCH-M (1, 1)
Mean		
μ (Constant)	0.000877*	0.000563
λ Risk Premium	–	2.416465
Variance		
(α_0) Constant	4.86E-06*	4.90E-06*
(α_1) ARCH effect	0.114001*	0.114313*
(β_1) GARCH effect	0.864563*	0.864054*
$\alpha_1 + \beta_1$	0.978564	0.978367
Log likelihood	11004.46	11005.50
Akaike Info. Criterion (AIC)	-5.892557	-5.892580
Schwarz Info. Criterion (SIC)	-5.882552	-5.880907
ARCH-LM test for heteroscedasticity		
ARCH-LM test statistics	0.008072	0.020140
Prob. Chi-Square (1)	0.928400	0.887100

Notes Source: Computed from the compiled and edited data by using EVIEWS 8.
* Significant at 1% level.

Asymmetric GARCH Models

In order to capture the asymmetries in the return series, two models have been used viz., EGARCH-M (1, 1) and TGARCH (1, 1). γ captures the asymmetric effect in both EGARCH-M (1, 1) and TGARCH (1, 1) models. The asymmetrical EGARCH (1, 1) model is used to estimate the returns of the Nifty index and the result is presented in table 6. The table reveals that the sum of ARCH (α_1) and GARCH coefficient (β_1) are greater than one, reporting that conditional variance is explosive; the estimated coefficients are statistically significant at 1% level. γ, the leverage coefficient, is negative and is statistically significant at 1% level, exhibiting the leverage effect in the Nifty return during the study period. The analysis revealed that there is a negative correlation between past return and future return (leverage effect); hence, EGARCH (1, 1) model supports for the presence of leverage effect on the Nifty return series. Finally, the ARCH-LM test statistics for EGARCH (1, 1) reveals that the null hypothesis of no heteroscedasticity in the residuals is accepted.

An alternate model to test for asymmetric volatility in the Nifty return is TGARCH, which shows (see table 6) the estimated result of TGARCH (1, 1) model. In it, the coefficient of leverage effect (γ) is positive and significant at 1% level, which implies that negative shocks or bad news have a greater effect on the conditional variance than the positive shocks or good news. The diagnostic test is performed to test the presence of additional arch effect in the residuals. The ARCH-LM test statistic for TGARCH (1, 1) model does not show any additional arch effect present in the residuals of the model, which implies that the variance equation is well specified for the Indian stock market.

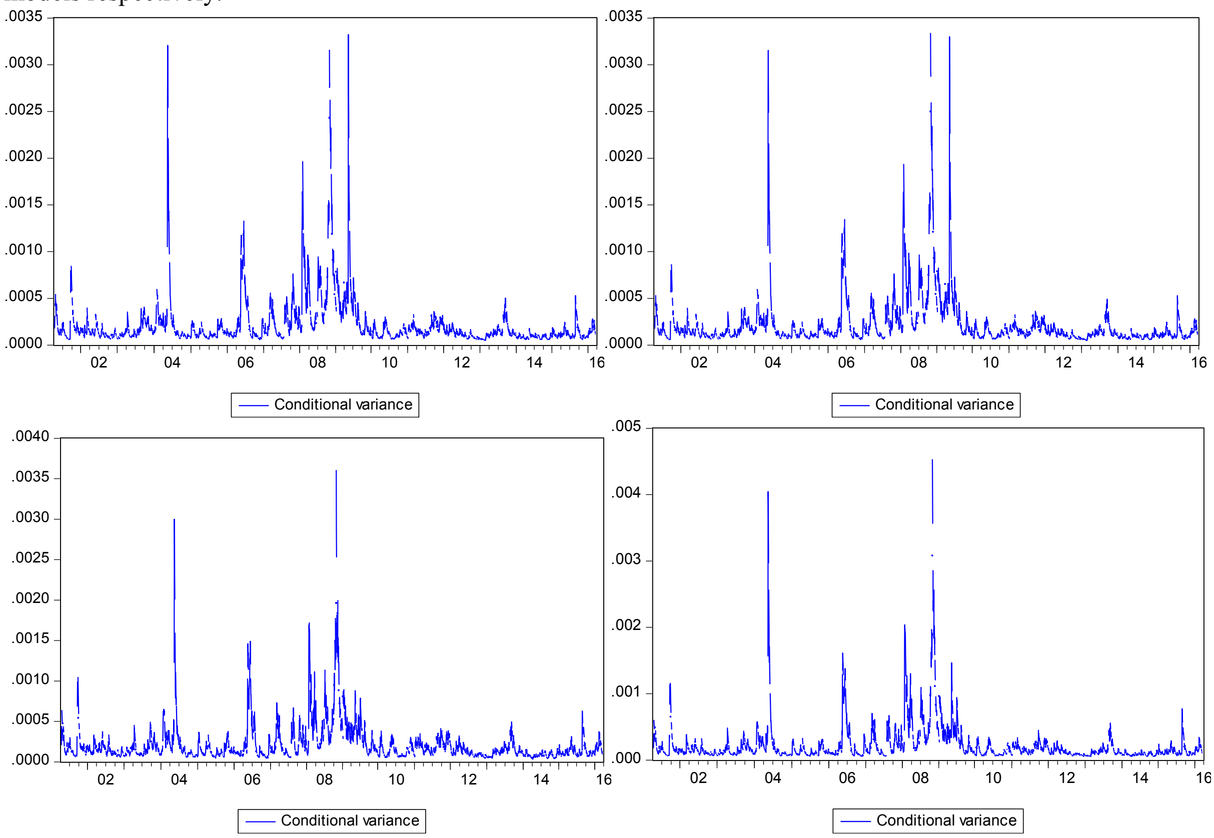
The AIC, SIC (–5.909726; –5.898053) and Log Likelihood value (11037.50) for EGARCH (1, 1) conforms the norms and hence EGARCH (1, 1) model is apparently seems to be an adequate description of asymmetric volatility process. This was not in consensus with the previous findings of Goudarzi and Ramanarayanan (2010), Mittal, Arora, and Goyal (2012) and Banumathy and Azhagaiah (2015), as per their findings TGARCH and PGARCH is best fitted model to describe the asymmetric volatility process.

Table 6 Results of EGARCH (1, 1) and TGARCH (1, 1) models

Coefficient	EGARCH (1, 1)	TGARCH (1, 1)
Mean		
μ (Constant)	0.000524*	0.000517*
Variance		
(α_0) Constant	-0.482467*	5.66E-06*
(α_1) ARCH effect	0.225247*	0.045500*
(β_1) GARCH effect	0.964569*	0.861108*
(γ) Leverage effect	-0.100739*	0.132785*
$\alpha_1 + \beta_1$	0.978564	0.978367
Log Likelihood	11037.50	11036.85
Akaike Info. Criterion (AIC)	-5.909726	-5.909375
Schwarz Info. Criterion (SIC)	-5.898053	-5.897703
ARCH-LM test for heteroscedasticity		
ARCH-LM test statistics	0.468391	1.471138
Prob. Chi-Square (1)	0.493700	0.225200

Notes Source: Computed from the compiled and edited data by using EVIEWS 8.
* Significant at 1% level.

Conditional Variance of GARCH (1, 1), GARCH-M (1, 1), EGARCH (1, 1) and TGARCH (1, 1) models respectively.



Conclusion

In this study, volatility of Nifty index return has been tested by using the symmetric and asymmetric GARCH models. The daily closing prices of Nifty index for fifteen years are collected and modelled using four different GARCH models that capture the volatility clustering and leverage effect for the study period i.e. from 1st March 2001 to 31st April 2016. GARCH (1, 1), GARCH-M (1, 1), EGARCH (1, 1), and TGARCH (1, 1) models have been employed for this study after confirming the unit root rest, volatility clustering and arch effect. The results show that the leverage coefficient has the expected sign in both the models i.e. EGARCH (negative and significant) and TARCH (positive and significant). To identify the best fitted model among the different specifications of GARCH models, Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) were used, which proved that GARCH-M (1, 1) model found to be the best fitted model among all to capture the symmetric effect as per AIC criterion and Log Likelihood ratio. Further, EGARCH (1, 1) model is found to be the best fitted model to capture the asymmetric volatility based on the highest Log Likelihood ratios and minimum AIC and SIC criterion.

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