Modelling Volatility of BSE Realty Index using Conditional Heteroscedasticity Models

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ABSTRACT

This study empirically examines the nature of volatility in BSE Realty Index using daily closing price of BSE Realty Index for five and half years period from January 2011 to June 2016. The study employed conditional heteroscedasticity models, both symmetric and asymmetric, for the analysis. The study found that the volatility is persistent in the Index return indicating the presence of volatility clustering in the series. Further, the study reports the presence of asymmetric or leverage effect in the series as the leverage coefficient $\gamma$ is significant in EGARCH model indicating that negative shocks have significant effect on volatility. However, the study did not find significant risk-return trade-off in the series.

Keywords: Conditional volatility; Volatility clustering; GARCH model; Leverage effect.

1.0 Introduction

To gauge the market performance, and to convey the day to day market movement to the investors, various indices are reported by stock exchanges all over the world. Dow Jones Industrial Average (DJIA) of New York Stock Exchange (NYSE) is one of the earliest stock market indices which appeared in May 26, 1896 which initially reported the simple average of prices of 11 stocks on a particular day. Today, DJIA has become one of the popularly cited indictors of market activity which reports weighted average price of 30 widely traded stocks in NYSE. In India, S&P Sensex and S&P CNX Nifty are the two benchmark indices which report the market movement of Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) respectively.

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While S&P Sensex is an index reported by BSE which is weighted average prices of 30 major stock from various sectors, S&P CNX Nifty is an index reported by NSE which is weighted average price 50 major stock from various sectors. Along with these benchmark indices, both BSE and NSE also report various sectoral indices to track the performance of these sectors thereby enabling more informed investment decisions. Modelling and forecasting of the volatility of these indices has been one of the important issues in the literature of financial economics. This is largely due to the importance of volatility in financial market. Volatility, in simple, denotes the variability of an asset price which is generally expressed in terms of variance or standard deviation of the return of an asset (Gerety and Mulherin, 1991). Because this measure represents the fluctuations in the asset return, it is also used as a simple measure of market risk. Greater volatility is perceived by investors as greater risk in the asset which may threaten investors’ assets and wealth (Karmakar, 2006). This will adversely affect the incentive to save and to invest (Du and Wei, 2004). Higher and persistent variability in the asset return over very short period of time may also result in investors’ loss of confidence in the stock market which may eventually lead to withdrawal of investors from the market. Further, increased volatility will result in higher cost of capital as investors now demand premium for bearing greater risk in the asset (Edwards, 1988). Therefore, estimating and forecasting volatility is critical in various financial activities such as portfolio choice and risk management, derivative pricing and hedging, market making, market timing etc. (Engle and Patton, 2001). This paper aims at examining nature of volatility in BSE Realty return. Specifically, the study attempts understand whether the volatility in the index is time varying, predictable, exhibit volatility clustering, and asymmetry behaviour and risk-return trade off in the series.

2.0 Literature Review

Finance literature documented various features of financial time series such as asset return which led the development of forecasting models. Firstly, as pointed out by Schwert (1989) the variance of financial time series is non-constant or heteroskedastic. Secondly, most of the financial time series exhibit the phenomenon of volatility clustering wherein the large changes in asset price are followed by large changes resulting the persistence of volatility too long in the future leading to connecting periods of volatility and stability. Similarly, small changes are followed by small changes. This results in volatility clustering or pooling in the return series. This phenomenon was first documented by Mandelbrot (1963). Subsequently, it was also reported by Fama (1965) who showed that the distribution of the asset returns tends to be fat-tailed. Thirdly, the
finance literature argued that the volatility caused by a negative shock to financial time series would be more than a positive shock of the same amount. This is called leverage effect in the case of equity returns as debt to equity ratio rises when the value of a stock falls thereby increasing volatility of returns to equity holders (Nelson, 1991, Turner and Weigel, 1992, and Brooks, 2008). However, conventional econometric models assume constant variance or homoscedasticity and hence cannot model the series involving time varying variance. Engle (1982) developed Autoregressive Conditional Heteroscedasticity Models (ARCH) to deal with the time series which exhibits time varying conditional variance in which the conditional variance is modelled to be dependent on the squares of residuals. However, empirically ARCH model was found to be requiring a relatively long lag in the conditional variance equation. Further, a fixed lag is imposed to overcome the problem of negative variance parameters (Goudarzi, 2011).

To overcome these problems of ARCH model, Bollerslev (1986) developed generalized the ARCH (GARCH) Model. In the GARCH model the conditional variance depends not only on past squared errors but also on past conditional variance. To capture the risk return relationship in the financial time series, Engle, Lilien and Robins (1987) developed GARCH in Mean (GARCH-M) Under GARCH-M model the conditional variance is included in the mean equation directly indicating that the return of an asset may depend on the volatility. However, these GARCH models assume that there is symmetric response of volatility to positive and negative shocks. This is because in GARCH equations conditional variance is dependent upon value of the square of lagged residuals which completely disregards the sign of that residuals (Turner and Weigel, 1992). However, the finance literature argued that a volatility caused by negative shock to financial time series would be more than a positive shock of the same amount. This is called leverage effect in the case of equity returns as debt to equity ratio rises when the value of a stock falls thereby increasing volatility of returns to equity holders (Nelson, 1991, Turner and Weigel, 1992, and Brooks, 2008). To capture this asymmetric impact of negative and positive shock on volatility Nelson (1991) developed Exponential GARCH (EGARCH). Besides, allowing possible asymmetry in the series, EGARCH also overcomes the problem of non-negativity constraints which is imposed on symmetric GARCH parameters. Zokoian (1994) introduced alternative model, known as Threshold GARCH, which replaced the quadratic specification of simple GARCH with a piecewise linear function allowing for asymmetric effect of volatility. Glosten, Jagannathan, and Runkle (1993) suggested another alternative asymmetry model, known as GJR model, to allow asymmetric impact of shocks on volatility. The GJR model is a simple extension of GARCH with an additional term added to account for possible asymmetries. Subsequently, several other versions of GARCH such as Power GARCH,
Component GARCH etc. were developed to better capture the characteristics of volatility.

Empirically, many studies have attempted to model the volatility in Indian benchmark indices. For instance, Karmakar (2006) estimated the volatility in Economics Times Index and S&P CNX Nifty over the period 1961 to 2005 and found the evidence of volatility clustering in the series. Karmakar (2006) also reported the presence of asymmetry in volatility. Similarly, Karmakar (2007) examined the nature of volatility in S&P CNX Nifty during July 1990 to December 2004 and found that volatility is time varying, persistent and predictable. He also reported presence of volatility clustering in the series. Similar results were also documented by Banumathy and Ramachandran (2015), Kumar and Singh (2008), Joshi (2010), Banerjee and Sarkar (2006) in the case of CNX Nifty. Goudarzi and Ramanarayanan (2010) studied the nature of volatility of the BSE 500 and found that the volatility is persistent and exhibits clustering. Srinivasan and Ibrahim (2010) examined the volatility in BSE Sensex and reported the presence of leverage effect in the volatility. However, the risk-return tradeoff is not significantly evident in Indian stock market (Banumathy and Ramachandran, 2015, Kumar and Singh, 2008, Karmakar, 2007). Most of the studies in India addressed the volatility of benchmark inducexes like Sensex and Nifty. The volatility of sectoral indices has not been understood. This study intends to partly bridge this research gap by studying the nature of volatility of BSE Realty Index.

3.0 Data Sources and Research Methodology

The study is based on the secondary data that were collected from Bombay Stock Exchange (BSE) Ltd, India. The daily closing prices of BSE Realty Index over the period of five and half years from 1st January 2011 to 30th January 2016 were collected and used for the analysis. Monthly data from January 2015 to June 2016 has been used to understand the performance of Sensex, BSE Realty and companies of BSE Realty Index. Daily data spanning from January 2010 to July 2016 has been used for computing Granger Causality among BSE Realty companies and Sensex and BSE Realty. Further, to understand the behaviour of US Realty, Sensex, and BSE Realty during Global Financial Crisis 2008, daily data from September, 2008 to March 2009 has been used. Data on US Realty has been collected from MSCI Inc.

3.1 Research methods

The study employed descriptive statistics, Granger causality tests and GARCH techniques such as GARCH, GARCH-M, TGARCH and EGARCH to analyse the data.
Data has been analysed using E-views econometrics package. We ran different variants of GARCH as the literature is not conclusive on the efficiency of any single model.

From the index, return series is generated as the first difference of log of daily closing price which is as follows;

$$ r_t = \log \frac{P_t}{P_{t-1}} $$ ...

Equation (1) can be written as;

$$ \log r_t = \log P_t - \log P_{t-1} $$ ...

where $\log r_t$ is the logarithm of daily return on index for time $t$, $P_t$ is the closing price at time $t$, and $P_{t-1}$ is the corresponding price in the period at time $t - 1$. Volatility is measured as the standard deviation of the log return.

3.2 Symmetric GARCH models

As discussed in previous section, symmetric GARCH models assume that there is symmetric response of volatility to both positive and negative shocks. The GARCH model and GARCH-M model are used to study relation between return and volatility.

3.3 Generalized ARCH (GARCH) model

In the GARCH model the conditional variance ($\sigma^2_t$) depends on past squared errors and past conditional variance ($\sigma^2_{t-1}$). So a simple GARCH (1, 1) model can be written as;

**Mean equation:**

$$ r_t = \mu + \varepsilon_t $$ ...

**Variance equation:**

$$ \sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1} $$ ...

3.4 GARCH-in-Mean (GARCH-M) model

Under GARCH-M model the conditional variance is included in the mean equation directly indicating that the return of an asset may depend on the volatility.

A simple GARCH-M (1, 1) model can be shown as:

**Mean equation:**

$$ r_t = \mu + \gamma \sigma^2_{t-1} + \varepsilon_t $$ ...

**Variance equation:**

$$ \sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1} $$ ...

$\gamma$ in equation (5) is interpreted as a risk premium (Brooks, 2008). If $\gamma$ is positive and statistically significant, then it indicates that return is positively related its volatility, i.e. an increase in the conditional variance, leads to an increase in the mean return.

3.5 Asymmetric GARCH Models

To capture this asymmetric impact of negative and positive shock on volatility Nelson (1991) developed EGARCH which can be specified as follows;
\[ \ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[ \frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \frac{2}{\pi} \right] \quad \ldots \quad (7) \]

This model allows for possible asymmetries in the series since if the relationship between volatility and returns is negative, \( \gamma \) will be negative. Another advantage of this GARCH specification is that no artificial non-negativity constraints is required on the model parameters. This is because since \( \log(\sigma_t^2) \) is modelled, even if the parameters are negative, \( \sigma_t^2 \) will be positive (Brooks, 2008).

3.6 Threshold-GARCH

The T-GARCH model is a simple extension of GARCH with an additional term added to account for possible asymmetries. The conditional variance is now given by,

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 I_{t-1} * \varepsilon_{t-1} \quad \ldots \quad (8) \]

where \( I_{t-1} = 1 \) if \( \varepsilon_{t-1} < 0 \)

\[ = 0 \] otherwise

If \( \gamma > 0 \) in equation (8), there is leverage effect in the series.

4.0 BSE Realty Index: Some Stylized Facts

Real estate sector is one of the important sectors in the economy. Besides direct contribution to GDP, it also generates demand in various other sectors like steel, cement, bricks, paints, building materials, consumer durables etc. Construction sector, therefore, has multiplier effect on the economy. Table 1 shows the growth and contribution of construction sector. As shown in the table, during 2010 to 2015 the sector contributed an average of 7.86 per cent to GDP and is expected to reach 13 per cent by 2028 (KPMG, 2014).

| Decade  | GDP (CAGR) | Construction sector (CAGR) | Share of construction sector in GDP |
|---------|------------|----------------------------|------------------------------------|
| 1950-59 | 3.7        | 5.9                        | 5.40                               |
| 1960-69 | 3.3        | 6.9                        | 7.40                               |
| 1970-79 | 3.4        | 3.1                        | 7.35                               |
| 1980-89 | 5.2        | 3.7                        | 6.89                               |
| 1990-99 | 6.1        | 4.8                        | 6.64                               |
| 2000-09 | 7.8        | 10.6                       | 7.46                               |
| 2010-15 | 6.85       | 5.43                       | 7.86                               |

Source: Authors’ construction
The sector is also one of the largest employers in the economy. Recognising the contribution and the importance of real estate sector, BSE introduced BSE Realty Index comprising of 11 scrips representing 95 per cent of real estate companies. The base year is fixed as 2005, with base index value of 1,000. With the introduction of BSE Realty, investors, both domestic and global, now have a benchmark index to track the movement of real estate companies in the stock market which would help them in their investment decision.

Figure 1 presents the movement of Sensex and Realty index during the last 10 years. It is clear from the figure that in the post crisis period, Sensex has experienced upward trend on an average, except for 2011. Until 2012, both Sensex and Realty Index exhibited similar behavior. For instance, after a deep slump in 2008, both the indices came strong in 2009. However, the recovery has been slow in the case of BSE Realty, whereas Sensex reached its pre-crisis value in 2010, BSE Realty never regained its pre-crisis value.

**Figure 1: Movement of Sensex and BSE Realty Index**

In fact after 2012, BSE Realty has witnessed a downward trend with a marginal recovery in 2016. On other hand, Sensex has witnessed a strong upward trend after 2012. As evident from the figure, Sensex and BSE Realty exhibited opposite trend in their movement after 2012 indicating that movement in BSE Realty does not affect the Sensex. This may be due to the fact that none of the companies comprising BSE Realty figures in Sensex.
4.1 Relationship between BSE Realty Index, Sensex and US Realty Index

In order to understand the relationship between US Realty Index and BSE Realty Index and Sensex during US Subprime crisis 2008, we examined the direction of causality between US Realty, BSE Realty Index and Sensex. As shown in the table 2, there was unidirectional causality between US Realty and the causality runs from US Realty. This signifies the deep financial integration of stock markets which becomes more pronounced during economic or financial crisis leading to transmission of shocks from one market to another.

Table 2: Causality Between BSE Realty, US Realty, and Sensex

| Null Hypothesis                                    | F-Statistic | Prob.  | Inference |
|----------------------------------------------------|-------------|--------|-----------|
| US Realty does not Granger Cause BSE Realty        | 4.44105     | 0.0359 | Reject    |
| BSE Realty does not Granger Cause US Realty        | 0.89119     | 0.3459 | Accept    |
| US Realty does not Granger Cause Sensex            | 15.0695     | 0.0001 | Reject    |
| Sensex does not Granger Cause US Realty            | 0.90031     | 0.3434 | Accept    |
| Sensex does not Granger Cause BSE Realty           | 7.88675     | 0.0053 | Reject    |
| BSE Realty does not Granger Cause Sensex           | 1.34363     | 0.2473 | Accept    |

Source: Authors’ computation

4.2 Market performance of BSE Realty and Sensex companies

Performance of BSE Realty Index, Sensex and Index companies in the last 18 months has been presented in Table 3. As shown in Table 3, both BSE Realty and Sensex recorded negative return in the last 18 months. Among BSE Realty companies, Godrej, HDIL, Indiabulls, and Omaxe performed better, whereas NBCC, Oberoi, Prestige, Sobha, and Unitech companies recorded negative return. While HDIL is the best performer in the last 18 months with an average return of 41.4 per cent, NBCC recorded the worst performance with -145.51 per cent. It is clear from the table that real estate companies, on an average experienced poor performance in the stock market.

To understand whether BSE Realty companies move with market return, we ran Granger causality between Sensex and these companies. Table 4 presents the results of Granger causality test. As shown in the table, eight of eleven BSE Realty companies are influenced by market return (Sensex). While no causality was found in the case of DLF, Indiabulls, NBCC, market return was found to cause return of Godrej, HDIL, Oberoi, Omaxe, Phoenix, Prestige, Sobha, and Unitech. Therefore, on an average the performance of BSE Realty companies are influenced by the market return, whereas, none of the BSE Realty companies were found to be causing market return.
Table 3: Return of BSE Realty Companies

| Month          | DLF | Godrej | HDIL | India bulls | NBCC | Oberoi | Omexx | Prestige | Sobha | Unitech | Realty Index | Sensex |
|---------------|-----|--------|------|-------------|------|--------|-------|----------|-------|---------|--------------|-------|
| Jan-Mar -15   | -0.06 | -0.13 | 0.40 | -0.05 | 0.16 | 0.02 | 0.12 | -0.19 | -0.02 | 0.07 | 0.02 | -0.02 | 0.07 |
| Apr-Jun -15   | -0.10 | -0.26 | 0.26 | -0.26 | 0.14 | -0.08 | -0.85 | -1.73 | -0.20 | -0.06 |
| Jul-Sep -15   | -0.17 | 0.03 | 0.05 | 0.00 | 0.03 | -0.02 | 0.01 | -0.10 | 0.11 | 0.08 | -0.04 | 0.00 |
| Oct-Dec -15   | -0.17 | -0.05 | 0.05 | 0.00 | 0.03 | -0.02 | 0.01 | -0.10 | 0.11 | 0.08 | -0.04 | 0.00 |
| Jan-Mar -16   | 0.27 | 0.21 | 0.35 | 0.51 | -1.60 | 0.12 | 0.10 | 0.18 | 0.26 | 0.22 | 0.06 |
| Apr-Jun -16   | 0.43 | 35.35 | 41.40 | 30.17 | -145.5 | -2.58 | 24.63 | -25.9 | -39.1 | -95.1 | -1.44 | -1.83 |

Source: Authors’ construction

Table 4: Granger Causality of BSE Realty Companies’ Return with Market Return (Sensex)

| Null Hypothesis                                      | F-Statistic | Prob. | Inference |
|------------------------------------------------------|-------------|-------|-----------|
| DLF return does not Granger Cause Sensex return       | 0.24        | 0.62  | Accept    |
| Sensex return does not Granger Cause DLF return       | 0.58        | 0.45  | Accept    |
| Godrej return does not Granger Cause Sensex return    | 1.11        | 0.29  | Accept    |
| Sensex return does not Granger Cause Godrej return    | 22.56       | 0.00  | Reject    |
| HDIL return does not Granger Cause Sensex return      | 0.84        | 0.36  | Accept    |
| Sensex return does not Granger Cause HDIL return      | 9.20        | 0.00  | Reject    |
| Indiabulls return does not Granger Cause Sensex return| 1.18        | 0.28  | Accept    |
| Sensex return does not Granger Cause Indiabulls return| 1.23        | 0.27  | Accept    |
| NBCC return does not Granger Cause Sensex return      | 0.26        | 0.61  | Accept    |
| Sensex return does not Granger Cause NBCC return      | 1.93        | 0.16  | Accept    |
| Oberoi return does not Granger Cause Sensex return    | 0.09        | 0.77  | Accept    |
| Sensex return does not Granger Cause Oberoi return    | 21.35       | 0.00  | Reject    |
| Omexx return does not Granger Cause Sensex return     | 0.61        | 0.43  | Accept    |
| Sensex return does not Granger Cause Omexx return     | 8.19        | 0.00  | Reject    |
| Phoenix return does not Granger Cause Sensex return   | 0.03        | 0.87  | Accept    |
| Sensex return does not Granger Cause Phoenix return   | 7.55        | 0.01  | Reject    |
| Prestige return does not Granger Cause Sensex return  | 0.80        | 0.37  | Accept    |
| Sensex return does not Granger Cause Prestige return  | 18.81       | 0.00  | Reject    |
| Sobha return does not Granger Cause Sensex return     | 0.00        | 0.96  | Accept    |
| Sensex return does not Granger Cause Sobha return     | 27.08       | 0.00  | Reject    |
| Unitech return does not Granger Cause Sensex return   | 1.46        | 0.23  | Accept    |
| Sensex return does not Granger Cause Unitech return   | 7.86        | 0.01  | Reject    |

Source: Authors’ Computation
5.0 Results and Discussions of Volatility Modelling

Table 5 summarises the descriptive statistics of the series. The average return of the series is -0.000427 which indicates that the price has decreased over the period. Table also shows that the series is positively skewed. Further, Kurtosis of the series is >3 indicating that the series is fat tailed and does not follow normal distribution which is confirmed by J-B test statistics. The volatility clustering of daily return of BSE Realty return is given in Figure 2. Table 6 presents ADF and Philips-Perron test result for stationarity of the variable. As depicted in the table calculated t statistic is more than critical value at 5% level. So we reject null hypothesis that the series has unit root. Therefore, the return series is stationary which enables us to proceed with the GARCH model. However, one of the important conditions for running GARCH model on the series is the presence of heteroscedasticity or ARCH effect in the residuals of the series. To do this we employ ARCH LM test. Results of ARH LM test depicted in Table 6 confirm that there is ARCH effect in the return series hence this cannot be modelled with the simple ARMA structure.

Table 5: Descriptive Statistics of Daily Return

|        | Mean   | Minimum | Kurtosis | Jarque-Bera |
|--------|--------|---------|----------|-------------|
| Mean   | -0.000427 |         |          |             |
| Median | 0.000168  | Std.dev. | 0.021435 | 114.03      |
| Maximum| 0.076884  | Skewness | 0.210036 | N           |

Source: Authors’ Estimation

Figure 2: Volatility Clustering of Daily Return of BSE Realty Index
Table 6: Result of Unit Root Test and ARCH-LM Test for Residuals

| Value            | ADF    | PP     |
|------------------|--------|--------|
| t-statistics     | -32.89192 | -32.8644 |
| Prob.            | 0.0000 | 0.0000 |
| Critical Value   |        |        |
| 1%               | -3.434924 | -3.434924 |
| 5%               | -2.863447 | -2.863447 |
| 10%              | -2.567834 | -2.567834 |
| ARCH LM test statistics | 10.65268 |        |
| Prob.            | 0.0011 |        |

Source: Authors’ Estimation

Therefore, we employed four variants of GARCH technique, namely Generalized ARCH model, The GARCH in Mean(GARCH-M), Exponential GARCH(E-GARCH), and Threshold GARCH(T-GARCH) models to capture the volatility in the return series.

5.1 Symmetric GARCH Models

Table 7 presents the results of GARCH (1, 1) and GARCH-M (1, 1) Model. The parameters of GARCH model, i.e. constant (ω), ARCH (α) term and GARCH (β) term are statistically significant at 1% level. The estimated value of β is substantially higher than α which indicates that market has longer memory and shows that volatility is persistent. Further, since the sum of α and β is close to unity (0.92) the shock will remain for many future periods.

ARCH LM Test was conducted to know the presence of ARCH effect in residuals. Test results show that there is no further ARCH effect remaining in the residuals of the series which indicates that variance equation is properly specified. As shown in the table, coefficient of conditional variance entered into mean equation is positive, but it is statistically insignificant. Hence one can infer that there is no significant impact of volatility on return the expected return, implying the absence of risk-return tradeoff in the series.

To examine whether risk return tradeoff prevails in the return series, we ran GARCH-M model. The parameters of variance equation in GARCH-M (1, 1) model are statistically significant at 1% level. The sum of α and β is close to unity (0.92) which implies that the shock will persist to many future periods. Further, ARCH LM test on residuals of GARCH-M (1, 1) model shows that there is no ARCH effect implying that the model is well specified.
Table 7: Estimated Results of GARCH(1,1) and GARCH-M(1,1) Models

| Coefficients | GARCH(1,1)        | GARCH-M(1,1)      |
|--------------|-------------------|-------------------|
| Mean         |                   |                   |
| $\mu$ (constant) | -0.000331        | -0.004847        |
| Risk Premium $\lambda$ | 0.000037*   | 0.216924***    |
| Variance     |                   |                   |
| $\omega$ (constant) | 0.068486*    | 0.06896*        |
| $\alpha$ (ARCH effect) | 0.068486*    | 0.06896*        |
| $\beta$ (GARCH Effect) | 0.851096*  | 0.849175*       |
| $\alpha + \beta$ | 0.919582     | 0.918135        |
| Log likelihood | 3339.607       | 3340.077        |
| Akaike info. Criterion (AIC) | -4.876618   | -4.876843       |
| Schwarz info. Criterion(SIC) | -4.861352  | -4.85676        |
| ARCH-LM test heteroscedasticity | 0.736898    | 0.642347        |
| Prob.         | 0.3908            | 0.423             |

Notes: *Significant at 1% level, ***Insignificant
Source: Authors' estimation

5.2 Asymmetric GARCH Models

We employed EGARCH (1, 1) and T-GARCH (1, 1) to capture asymmetries in the return series. Table 8 presents the results of EGARCH and T-GARCH model.

Table 8: Estimated Results of EGARCH (1, 1) and TGARCH (1, 1) Models

| Coefficients | EGARCH(1,1)       | TGARCH-M(1,1)      |
|--------------|-------------------|-------------------|
| Mean         |                   |                   |
| $\mu$ (constant) | -0.000302       | -0.000409        |
| Variance     |                   |                   |
| $\omega$ (constant) | -2.436016*    | 0.0000382*       |
| $\alpha$ (ARCH effect) | 0.710758*    | 0.057733*        |
| $\beta$ (GARCH Effect) | -0.048571*  | 0.845613*        |
| $\gamma$ (leverage effect) | -0.048571** | 0.026576***      |
| $\alpha + \beta$ | 0.662187      | 0.903346         |
| Log likelihood | 3340.224       | 3340.271         |
| Akaike info. Criterion (AIC) | -4.876058    | -4.876127        |
| Schwarz info. Criterion(SIC) | -4.856975  | -4.857044        |
| ARCH-LM test heteroscedasticity | 0.0142       | 0.791731         |
| Prob.         | 0.9052            | 0.3737            |

Notes: *Significant at 1%, **5%, ***Insignificant
Source: Authors’ estimation,
As shown in Table 8, constant (\(\omega\)), ARCH (\(\alpha\)) term and GARCH (\(\beta\)) term of EGARCH (1, 1) model are statistically significant at 1% level. \(\gamma\), the leverage effect is negative and significant at 5% level indicating the presence of leverage effect in the series. This implies that there is negative correlation between past return and future return. Finally, ARCH LM test confirms that there is no further ARCH effect in the return series which shows that EGARCH (1, 1) model is specified properly. We also ran T-GARCH as an alternate model to test for possible asymmetry in volatility in the series. However, the, the leverage effect is found to be statistically insignificant indicating that both positive and negative shock will have same effect on the volatility.

5.3 Summary of findings

The following are the major findings of the above empirical analysis:

- In GARCH (1, 1) model, the sum of the coefficient is \((\alpha + \beta)\) is closer to one which indicates that volatility is persistent.
- In GARCH-M(1,1), the risk premium coefficient is insignificant indicating the absence of risk-return trade off in the series which means that the higher risk does not necessarily lead greater return.
- The leverage effect parameter \(\gamma\) of EGARCH model is significant at 5% level which implies the presence of asymmetry effect in the series. The negative value of \(\gamma\) indicates that there is negative relationship between past variance and future return.
- In the symmetric estimate, GARCH(1,1) model found to be the best fit as it yielded lowest AIC and SIC value and highest log likelihood value when compared to its alternate model GARCH-M(1,1).
- In the asymmetric estimate, T-GARCH seems to be an appropriate model as it produced lowest AIC and SIC value and highest log likelihood value.

6.0 Conclusion

The study tested the volatility of BSE Realty Index with symmetric and asymmetric GARCH models using the daily return of the index for the last five and half years. Four different GARCH models have been employed to understand the volatility clustering. After confirming the stationarity of the series, we employed GARCH (1, 1), GARCH-M (1, 1), EGARCH (1, 1) and TGARCH (1, 1) models. In symmetry estimates, we found that GARCH (1, 1) model is the best fit based on AIC, SIC and log likelihood criteria. Similarly, in asymmetry estimates, EGARCH has been found to be the appropriate model. In nutshell, we found that there is volatility persistence in the series.
resulting volatility clustering. We also found that there is leverage effect in T-GARCH model as $\gamma$ in the model turned out to be statistically significant. However, no risk return trade-off in the series was found as $\gamma$ parameter in GARCH-M (1, 1) model is statistically insignificant.

References

Banerjee, A. & Sahadeb, S. (2006). Modeling daily volatility of the Indian stock market using intra-day data. WPS No. 588, Indian Institute of Management Calcutta, March 2006.

Banumathy, K., & Ramachandran, A. (2015). Modelling stock market volatility: Evidence from India. Managing Global Transitions, 13(1), 27–42.

Brooks, C. (2008). Introductory economics for finance. Second Edition, Cambridge University Press: United Kingdom.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. Journal of Econometrics, 31, 307–327.

Du, J. & Wei, S. (2004). Does insider trading raise market volatility? The Economic Journal, 114, 916-942.

Edwards, R. F. (1988). Does futures trading increase stock market volatility? Financial Analysts Journal, 44(1), 63-69.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987–1007.

Engle, R. F., Lilien, D. M. & Robins, R. P. (1987). Estimating time varying risk premia in the term structure: The ARCH-M model. Econometrica, 55(2), 391-407.

Fama, E. F. (1965). The behavior of stock-market prices. The Journal of Business, 38(1), 34-105.
Glosten, L. R., Jagannathan, R. & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779-1801.

Gerety, M. S. & Mulherin, J. H. (1991). Patterns in intraday stock market volatility, past and present. *Financial Analysts Journal, 47*(5), 71-79.

Goudarzi, H. (2011). Modeling asymmetric volatility in the Indian stock market. *International Journal of Business and Management, 6*(3), 221-231.

Goudarzi, H. & Ramanarayanan, C. S. (2010). Modeling and estimation of volatility in the Indian stock market. *International Journal of Business and Management, 5*(2), 85-92.

Joshi, P. (2010). Modeling volatility in emerging stock markets of India and China. *Journal of Quantitative Economics, 8*(1), 86-94.

Karmakar, M. (2006). Stock market volatility in the long run, 1961-2005. *Economic and Political Weekly, 41*(18), 1796-1802.

Karmakar, M. (2007). Asymmetric volatility and risk –return relationship in the Indian stock market, *South Asia Journal of Economics, 8*(1), 99-116.

KPMG. (2014). Indian real estate-opening doors. Retrieved from https://www.kpmg.com/IN/en/_Issues And Insights/ArticlesPublications/Documents/Indian-real-estate-Opening-doors.pdf.

Kumar, B. & Singh, P. (2008). Volatility modeling, seasonality and risk-return relationship in GARCH-in-Mean framework: The case of Indian stock and commodity markets. *W.P. No.2008-04-04*, Indian Institute of Management, Ahmadabad.

Mandelbrot, B. (1963). The variation of certain speculative prices. *Journal of Business, 36*(3), 394-419.

Nelson, D. B. (1991). Conditional heteroscedasticity in asset returns: A new approach *Econometrica*. 59(2), 347–70.
Schwert, W. G. (1989). Why does stock market volatility change over time? *The Journal Finance*, 44(5), 1115–1153.

Srinivasan, P. & Ibrahim, P. (2010). Forecasting stock market volatility of BSE-30 index using GARCH models. *Asia-Pacific Business Review*, 6(3), 47-60.

Turner, A. L. & Weigel, E. J. (1992). Daily stock market volatility: 1928-1989. *Management Science*, 38(11), 1586-1609.

Zokoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, 18(5), 931-955.