Modelling Stock Return Volatility in India

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ABSTRACT

This paper empirically estimates the clustering volatility of the Indian stock market by considering twelve indicators of BSE SENSEX. The cluster volatility has been estimated through ARCH family models such as ARCH, GARCH, IGARCH, GARCH-M, EGARCH, TARCH, GJR TARCH, SAARCH, PARCH, NARCH, NARCHK, APARCH, and NPARCH.

KEYWORDS: Clustering Volatility, BSE SENSEX, ARCH Effects, asymmetric information.

Section -1

1.1. INTRODUCTION

Volatility is defined as the conditional heteroscedasticity, which explains the conditional standard deviations of the underlying asset return. It is an important factor in trading system in the stock market. Volatility has various application in financial institutions. In the modern financial econometrics, the ARCH (Autoregressive Conditional Heteroscedasticity) model was introduced by Engel (1982). It has been observed that stock market volatility changes with time or we can say that it is time – varying and exhibits volatility clustering, which is nothing but the variance (standard deviation) measures as the risk and elements of uncertainty. Volatility changes occur because of time – varying, which requires more empirical estimation of financial time series over the period of time. In financial time series analysis, all the statistical theory and methods plays an important role. There are specials features which tells about the volatility of stock return, which is not directly observable.

There are certain characteristics that are common in asset returns. Firstly, it has a volatility clusters, it means that volatility may be high for the certain period and low for the others periods. Secondly, volatility evolves over time in a continuous manner. Thirdly, volatility doesn't diverge to infinity that is volatility varies within a fixed range. Fourthly, volatility seems to react in a different manner to a big price increase or a big price drop, that is called as leverage effect.

The rest of the paper is follows as; introduction is followed by literature review in section 2 which discusses both theoretical understanding of the model applied in the present study as well as empirical studies. Section 3 and 4, discuss the empirical estimation and findings and conclusion.

Section II- Literature Review

2.1. Theoretical Modelling

The univariate volatility models, which is discussed in the paper are the autoregressive conditional heteroscedastic (ARCH) model of Engel (1982) , the generalized ARCH (GARCH) model of Bollerslev (1986) the Integrated GARCH (1990) and exponential GARCH (EGARCH) model of Nelson (1991) Threshold ARCH (TARCH) model of Zakoian (1994) , GJR , from threshold ARCH Glosten , Jagannathan and Runkel (1993) , Simple Asymmetric ARCH (SAARCH) model(1990) of Engel, Power ARCH (PARCH) model (1992) of Higgins and Bera, Nonlinear ARCH (NARCH) model, Nonlinear with one shift (NARCHK) Asymmetric power ARCH (APARCH) model (1993) of Ding , Granger and Engel and the last model is Nonlinear power ARCH (NPARCH) model .

Structure of a Model

Let's consider mean and variance of r_t is given as;

$$\mu_t = \mathrm{E}(r_t/F_{t-1}) \text{ and } \mathrm{E}\ [(r_t - \mu_t)^2/F_{t-1}]$$

$$\sigma_t^2 = \mathrm{var}\ (r_t/F_{t-1}) \tag{1}$$

Where,

F_{t-1} denotes the information set available at one lag period. Typically, F_{t-1} consists of all linear function of the past returns. Here, r_t follows a simple time series model such as stationary ARMA (p , q) model with explanatory variables and shocks or error terms. In other words, we entertain the model as;

$$r_t = \mu_t + a_t\ ,$$

Where, $\mu_t = \emptyset_0 + \sum_{i=1}^{k} \beta_i x_{it} + \sum_{i=1}^{P} \emptyset_i r_{t-1} - \sum_{i=1}^{q} \theta_i a_{t-i}$ (2)

Equation (2) illustrates the financial application of the time series model, where k ,p , q are non – negative integers and x_{it} is the explanatory variables . The explanatory variables x_t in equation (2) are flexible. We can take an example about the daily returns of market index, which often shows serial correlation and if we talk about monthly returns of markets index there is no serial correlation.

Combining equation (1) and (2), we have

$$\sigma_t{}^2 = \text{var}\left({r_t}/{F_{t-1}}\right) = \text{var}\left({a_t}/{F_{t-1}}\right) \tag{3}$$

The conditional heteroscedastic model is concerned with the evolution of $\sigma_t{}^2$. The manner under which $\sigma_t{}^2$ evolves over time distinguishes one volatility model from another. Where, a_t is the shock or innovation of an asset return at time t and σ_t is the positive square root of $\sigma_t{}^2$. Therefore, modelling conditional heteroscedasticity, explains the time evolution of the conditional variance of an asset return. This paper discusses the modelling of the volatility of stock return with the following time series models, is discussed as below.

1. Arch Model

Autoregressive conditional heteroscedasticity (ARCH) model was introduced by Engel (1982) that provides a systematic framework for volatility modelling. The basic idea of ARCH model is that (a) the stock a_t of an asset return should be serially uncorrelated and (b) the dependence of a_t can be shown by a simple quadratic function with its lagged values . Specifically, an ARCH (m) model take the form as,

$$a_t = \sigma_t \epsilon_t \text{ , } \sigma_t{}^2 = \alpha_0 + \alpha_1 a_{t-1}{}^2 + \text{----------} + \alpha_m a_{t-m}{}^2 \tag{4}$$

Where,

$\{\epsilon_t\}$ is a sequence of independent and identically distributed random variables with mean zero and variance constant and where, $\alpha_0 > 0$. The coefficients of the regressors must satisfy some regularity conditions to ensure that the unconditional variance of a_t is finite. ϵ_t is assumed to follow the standard normal or a standardized student t- distribution or a generalized error distribution. From the structure of the model, it is seen that large past squared shocks imply a large conditional variance $\sigma_t{}^2$ for the innovation a_t, which means that , under the ARCH model framework , large shocks tend to be followed by another large shocks . This features are similar to the volatility clustering's observed in asset returns.

Properties of Arch Model

First , the unconditional mean of a_t remains zero because

$$E(a_t) = \text{E}\left[E\left({a_t}/{F_{t-1}}\right)\right] = \text{E}[\sigma_t E(\epsilon_t)] = 0$$

Second , the unconditional variance of a_t can be obtained as

Var (a_t) = E $(a_t{}^2)$ = E $\left[E\left({a_t{}^2}/{F_{t-1}}\right)\right]$ = E $(\alpha_0 + \alpha_1 a_{t-1}{}^2)$ $= \alpha_0 + \alpha_1 E(a_{t-1}{}^2)$, is a stationary process.

2. Garch Model

Bollerslev (1986) proposes this model, which is an extension of ARCH model popularly known as the generalized ARCH (GARCH).

For a log return series r_t , let $a_t = r_t - \mu_t$ be the innovation at time t . Then a_t follows a GARCH (m ,s) model IGARC

$$\text{If } a_t = \sigma_t \epsilon_t \ , \ \sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}{}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}{}^2 \qquad (5)$$

where,

$\{\epsilon_t\}$ is a sequence of independent and identity distributed random variables with mean zero and variance constant. Here, $\alpha_i = 0$ for i > m and $\beta_j = 0$ for j > s . We observed that the constraint on $\alpha_i + \beta_i$ shows that the unconditional variance of a_t is finite, where as its conditional variance $\sigma_t{}^2$ evolves overtime. ϵ_t is often assumed to be a standard normal or standardized student – t distribution or generalized error distribution.

The strength and weaknesses of GARCH models can be easily seen by focusing on the simplest GARCH model with

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

$$\text{where}, \alpha_1 \leq 0,\ \beta_1 \leq 1 \text{ and } (\alpha_1 + \beta_1) < 1 \qquad (7)$$

This model investigates the weaknesses of the ARCH Model. It follows both positive and negative shocks.

3. The Integrated Garch Model

$$a_t{}^2 = \alpha_0 + \sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i)\, a_t{}^2 + \eta_t - \sum_{j=1}^{s} \beta_j\, \eta_{t-j} \qquad (8)$$

Above equation is the AR polynomial GARCH representation, has unit root, also represented as unit root IGARCH models. It is similar to ARIMA model ,the key feature of IGARCH models is that the impact of past squared shocks $\eta_{t-i} = a_{t-i}{}^2 - \sigma_{t-i}{}^2\ for\ i > 0\ on\ a_t{}^2$ is persistent.

An IGARCH model can be written as

$$a_t = \sigma_t \epsilon_t , \quad \sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + (1-\beta_1)\, a_{t-1}^2 \tag{9}$$

The unconditional variance of a_t is not defined under the above IGARCH model .It is difficult to justify for an excess return series . From a theoretical point of view, the IGARCH phenomenon has been caused by occasional level shifts in volatility. Exponential smoothing methods which is used to estimate such an IGARCH model.

4. The Garch-M Model

GARCH-M, where "M" stand for GARCH in mean. A simple GARCH – M model can be written as

$$r_t = \mu + C\sigma_t^2 + a_t \ , \ a_t = \sigma_t \epsilon_t$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 , \tag{10}$$

Where

, μ and C are constants . The parameter C is called the risk premium parameter.Positive C indicates that the return is positively related to its volatility.

5. The exponential GARCH (EGARCH) model

This EGARCH model was introduced by Nelson (1991), this Exponential GARCH model explains that asymmetric effects between positive and negative of asset returns.

$$g(\epsilon_t) = \theta\epsilon_t + \gamma[\ |\epsilon_t| - E(\ |\epsilon_t|)] , \tag{11}$$

Where θ *and* γ *are denoted as real constants . Both* ϵ_t *and* $|\epsilon_t| - E(\ |\epsilon_t|)$ *are zero* mean iid sequence with continuous distributions . Therefore , E $[g(\epsilon_t)] = 0$. The asymmetry of $[g(\epsilon_t)]$ can easily be shown by rewriting it as

$$g\epsilon_t = \begin{cases} (\theta+\gamma)\,\epsilon_t - \gamma E\ (\ |\epsilon_t|)\ if\ \ \epsilon_t \geq 0 \\ \quad (\theta-\gamma)\epsilon_t - \gamma E\ (\ |\epsilon_t|) < 0 \end{cases}$$

6. THE THRESOLD GARCH (TGARCH) model

TGARCH model was developed by Zakoian (1994), Glosten , Jagannathan and Runkle (1993). TGARCH (m , s)model takes the form as;

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{s}(\alpha_i + \gamma_i N_{t-i}) a_{t-i}^2 + \sum_{j-1}^{m} \beta_j\, \sigma_{t-j}^2 \tag{12}$$

Where , N_{t-i} is an indicate for negative a_{t-i} , that is , $N_{t-i} = \begin{cases} 1\ if a_{t-i}\ < 0 , \\ 0\ if\ a_{t-i}\ \geq 0 , \end{cases}$

and $\alpha_i, \gamma_i, and\ \beta_j$ are known as non-negative parameters , which is satisfying conditions as similar to those of GARCH models . From this model , we observed that a positive a_{t-1} contributes $\alpha_i a_{t-i}{}^2\ to\ \sigma_t{}^2,\ where\ a\ negative\ a_{t-i}$ has a larger impact $(\alpha_i + \gamma_i) + a_{t-i}{}^2$ with $\gamma_i > 0$. This model uses zero as its Threshold

7. GJR Form of Threshold Garch Model

This model GJR- TGARCH was framed by Glosten, Jagannathan and Runkle (1993) which relaxed the restrictions of conditional variance dynamics. Above equation (12) shows the same. where r_t is the series of demeaned returns and $\sigma_t{}^2$ is the conditional variance of returns given time t information . We assume that the sequence of innovations ϵ_t follow independent and identical distribution with mean 0 and variance 1: ϵ_t ~ iidD (0, 1) . GJR-TGARCH reveals leverage effect which is that good news has an impact on volatility greater than bad news.

8. Simple Asymmetric ARCH model

This (SAARCH) simple asymmetric ARCH model (1990) of Granger Engel, which follows above two models, such as –(EGARCH) Exponential GARCH model of Nelson (1991) and (TGARCH) and GJR-TGARCH model by Zakoian (1994), Glosten, Jagannathan and Runkle (1993) and power GARCH (PGARCH) model. These models are describing the asymmetric volatility process. This characteristic in the financial market has become known as "Leverage effects ". Which is actually meaning is that it follows the symmetric response of volatility negative and positive shocks, this is the primary restrictions of GARCH model. In this model a negative sock in the financial time series, that is the cause of volatility to increase the positive shocks in the same magnitude. Basically it shows the relationship between asymmetric volatility and return.

9. Power arch (parch) model

This model PARCH was given by Higgins and Bera (1992). Nelson (1990a, b) and Gannon (1996) have reformed the relationship between the estimation of ARCH models and the identification of the mean equation. Their general conclusion drawn from their work i.e., the identification of the mean equation creates small impact on the ARCH model when it's estimated in continuous time. In the mean equation should be identified as an expected mean reverting equation in the form of $r_t = \epsilon_t$ "t where , r_t is the returns to the market index. This error term may be decomposed into $a_t = \sigma_t \epsilon_t$ is normally distributed with a zero mean and a variance of one . The general power ARCH model introduced by Ding et al. (1993), identifies σ_t as a form ,

$$\sigma_t{}^d = \alpha_0 + \sum_{t-i}^{p} \alpha_i \left(|\epsilon_{t-1}| + \gamma_i \epsilon_{t-i}\right)^d + \sum_{i=1}^{q} \beta_i \sigma_{t-i}{}^d \tag{13}$$

Where , in the above equation (13) shows as α_i *and* β_i called as the standard ARCH and GARCH parameters , γ_i is the leverage parameter and d is the parameter for the power term.

10. Nonlinear arch (narch) model

Non-linear ARCH (NARCH) model was also developed by Higgins and Bera (1990) ,which was obtained same as the above PARCH model equation (13) , shows that d and α_i are free ($\alpha_i = 0$, $\beta_i = 0$) . If this NARCH model allows to free to β_i is equal to zero then the PGARCH will give specified is the results .

11. Nonlinear arch with one shift model

It is also called as NARCHK , which means that there is specifying lags between two parameters term , such as $\alpha_i(\epsilon_t - k)^2$ this is nothing as the variations of the nonlinear arch model , where ‘ k ‘ is constant for all lags . there is difference between two models NARCH and NARCH with one shift, which tells about past lags. It is not collinear with other models ARCH, SAARCH, NARCH, NAPARCHK and NAPARCH.

12. Asymmetric power arch (aparch) model

This model was decorated by Ding, Granger, Engle (1993), identified the generalise asymmetric Power ARCH model, in financial time series this model plays important role for stock market. The important purpose of this model is that to identified the variance of error term in a regression equation, of its square past errors. This APARCH model satisfies in the above given model PARCH and its equation (13), restrictions is to require to produce for each of the models, which given within APARCH model. The power term provided by this model which is generated above given models NARCH, PARCH and APARCH. This term asymmetric which is include in generated Ding et al power ARCH models, which measuring all the positive and negative in equal magnitude shocks of the return in the financial markets.

13. Nonlinear power arch (nparch) model

This also measures the asymmetric impacts on shocks or innovations in a specified form in the financial markets. In this model there is a minimum conditional variance when the all lagged innovations or shocks are all zero, and on the other hand that the symmetric response to lagged innovations or shocks but all are not zero. If there is conditional variance is small, then there is no "NO NEWS ARE GOODS NEWS ". This model as similar to others models, NARCH, NARCHK, NPARCH. All these models have responded the symmetric innovations. There is minimum variance which lies at positive and negative value for innovations or shocks.

2.2. Empirical reviews of literature

There is literature based on modelling and measuring stock return volatilities in India. Ahmed et al. (2011) investigated the volatility using daily data from two Middle East stock indices viz., the Egyptian cma index and the Israeli tase-100 index and used ARCH, GARCH, EGARCH, TGARCH, Asymmetric Component GARCH (AGARCH) and Power GARCH (PGARCH). Their study showed that EGARCH is the best fit model among the other models for measuring volatility. Few models have been limited to at studies only symmetric models. Karmakar (2005) estimated volatility model which is the feature of Indian stock market. Emenike Kalu O et al. (2012) who analysed the effects of response of positive and negative shocks of volatility stock returns of the daily closing price of Nigeria Stock Market Exchange (NSE) from January 2nd 1996 to December 30th 2011. Suliman Zakaria (2012) developed a model which measure the volatility in the Saudi Stock Market (TASI INDEX). He introduced many types of asymmetric GARCH models, such models are EGARCH, TGARCH and PGARCH. His studies explained that the positive correlation hypothesis which is the positive relation between the expected stock return and volatility has favour towards the conditional volatility. Hojatallah Goudarzi (2009) studied asymmetric effects which occurred in the stock market, they used ARCH model measured the effects of good and bad news on volatility in the India stock markets during the period of global financial crisis of 2008-09. There are two models EGARCH and TGARCH which are estimated asymmetric volatility. The BSE500 stock index was used as a proxy to the Indian stock market to study the asymmetric volatility over 10 year's period. They investigated a growing and increasingly complex market-oriented economy, and the global finance will need more efficient deep and in well – regulated financial markets. Saurabh Singh and Dr. L.K Tripathi (2013) have study the symmetric and asymmetric GARCH models which are estimated for the daily closing prices of Nifty index for fifteen years are collected and estimated by four different GARCH models that capture the conditional volatility and leverage effects. Their study shows the relationship between positive and negative shocks or innovations but asymmetric negative effect is greater than the positive. In this study, volatility of Nifty index return has been tested by using the symmetric and asymmetric GARCH models. The study period i.e. from 1st March 2001 to April 2016. Potharla Srikanth, in his paper studied about estimation of volatility which helps to risk management of portfolios. Their study mentioned two modelled measured asymmetric nature of volatility i.e. GJR-TGARCH and PGARCH. GJR-TGARCH results concludes that shocks due to negative or bad news have greater effect on conditional volatility than the good or positive news and findings under GJR-TGARCH model.

Section -III

Objective of study

Our main objective is to estimate ARCH effects or conditional volatility of SENSEX indices of BSE market and to investigate the 'Leverage Effects "through using all ARCH models.

Section -IV

Data description and Methodology

The study is based daily stock prices covering the sample period of 1st January 2011 to 1st January 2017. Bombay stock market (BSE) indices are used as proxy of Indian stock market. With the availability of high frequency data being compiled by Bombay stock exchange (BSE), under this index, there are 12 sub-groups such as: 1) BSE SENSEX(BSESN), 2) BSE PUBLIC SECTOR UNDERTAKING (BSEPSU), 3) BSEPOWER, 4) BSEOIL, 5) BSE REAL ESTATE (BSEREAL), 6) BSE TECHNOLOGY (BSETECK), 7) BSE MATERIALS (BSEMET), 8) BSEBANK, 9) BSE CAPITAL GOODS (BSECG), 10) S&P BSE HEALTH CARE(SPBSEHC), 11) S&P BSE FAST MOVING CONSUMER GOODS (SPBSEFMCG), 12) S&P BSE INFORMATION TECHNOLOGY (SPBSEIT). The stock price data is collected from the data base of www.investing.com.

In our studying processes, we have used both statistical calculations and econometrics analysis to analyse the volatility of this daily stock returns to can identify how these ARCH models check errors of volatility returns in the financial markets. The econometric analysis is based on the ARCH family model, analysed through STATA. The volatility of the price indices estimates on return (r_t), hence before proceeding with the econometric test, we have to calculate the Sensex returns series, which is calculated as a one period of closing daily price .

Section -IV

Empirical Analysis

Descriptive statistics; i.e. Mean, Standard deviation, Variance, Skewness and Kurtosis are given in table-1

Skewness is negatively skewed, indicating that the distribution of stock prices is more left skewed or distribution will have greater variations towards lower value for all indicators. Similarly, kurtosis is greater than 3, indicating that the distribution of stock price is leptokurtic

Table 1: Descriptive Statistics

Indicator	Mean	Std.Dev	Variance	skewness	Kurtosis
BSESN	-8.75	218.12	47578.34	0.34	5.62
BSEPSU	-5.48	225.41	50811.31	-30.91	1125.21
BSEPOWER	-1.42	69.33	4806.26	-31.29	1144.56
BSEOIL	-8.86	267.93	71783.89	-27.77	976.91
BSEREAL	-1.28	60.45	3653.92	-21.62	701.45
BSETECK	-3.63	105.01	11027.38	-25.50	873.63
BSEMET	2.55	166.66	27776.61	-0.07	4.29
BSEBANK	-9.76	227.69	51840.60	0.07	5.00
BSECG	-3.41	189.60	35948.35	0.00	6.46
SPBSEHC	-9.13	197.10	38849.73	-15.21	453.40
SPBSEFMCG	-6.51	107.87	11635.53	-16.81	504.23
SPBSEIT	-6.48	188.96	35705.29	-21.98	719.56

Stationarity Test

The stationarity test for each price indices is done through Augmented Dickey – Fuller Test (ADF Test). The price indices are stationary and statically significant at 1 percent, after first.

Indicator	Without Intercept		With Intercept And Trend	
	T-STATISTICS	P-VALUE	T-STATISTICS	P-VALUE
BSEBANK	-36.425	0.000	-36.438	0.000
BSECG	-34.798	0.000	-34.808	0.000
BSEMET	-37.024	0.000	-37.068	0.000
BSEOIL	-17.213	0.000	-17.167	0.000
BSEPOWER	-13.907	0.000	-13.864	0.000
BSEPSU	-13.42	0.000	-13.382	0.000
BSEREAL	-20.378	0.000	-20.350	0.000
BSESN	-36.441	0.000	-36.439	0.000
BSETECK	-19.217	0.000	-19.239	0.000
SPBSEIT	-21.592	0.000	-21.615	0.000
SPBSEHC	-24.144	0.000	-24.202	0.000
SPBSEFMCG	-23.767	0.000	-23.769	0.000

Clustering Volatility test.

ARCH models

After that, we ran all ARCH models to checked the ARCH effects (i.e. conditional volatility) for subgroups of the BSE SENSEX Indices through Z- statistics.

For test of heteroscedasticity, ARCH-LM test is used. A statistically significant coefficient indicates the presence of ARCH effect in the residuals of mean equation of BSE SENSEX. The ARCH-Test is a portmanteau test. It tests a number of lags (lag 1 through lag q) at once as a group and indicates whether the average ARCH effect within the group is large. The maximum lag q governs the trade-off between power and generality. One of the most important issues before applying the ARCH methodology is to first examine the residuals for the evidence of heteroscedasticity. Therefore, to test the presence of heteroscedasticity in residual of the return series, Lagrange Multiplier (LM) test is used.

Table 3. explains about the conditional variance of the series of BSE SENSEX. We have estimated the ARCH effects for all indices at 5% significant level. We found that in BSEOIL index, there is ARCH effect of other indices like stocks of BSEREAL, BSETECK, SPBSEFMCG and BSECG in the BSE market. There are various reasons behind high clustering volatility. If the returns of BSEOIL increases or decreases its means that oil shocks have impacts on various goods and services and other indices in the financial market because oil is a tradable commodity. Some factors are really affecting to financial market, for example, if the exchange rate variation and any types of policies changes also affects BSE SENSEX index.

Table 3: Arch effects

Indicator	Arch effects	Standard error	z-statistics	P – value
BSEBANK	0.078	0.016	4.87	0.000
BSECG	0.117	0.021	5.59	0.000
BSEMET	0.081	0.011	7.63	0.000
BSEOIL	0.350	0.053	6.61	0.000
BSEPOWER	0.172	0.029	5.84	0.000
BSEPSU	0.220	0.036	6.06	0.000
BSEREAL	0.218	0.036	6.08	0.000
BSETECK	0.120	0.025	4.77	0.000
SPBSEIT	0.107	0.024	4.50	0.000
SPBSEHC	0.149	0.035	4.26	0.000
SPBSEFMCG	0.260	0.042	6.25	0.000

GARCH Model

Another model we used for the forecasting is the GARCH model, which measured the unconditional variance of the shocks or innovations in the financial market. It has estimated the volatility of unobservable series returns. We estimated the GARCH effects for all respective indices. We found the GARCH effect which is described in the table 4.

The null hypothesis of 'no arch effect' is rejected at 1% level, which estimates the presence of arch effects in the errors terms of time series models in the stocks returns and hence the results require for the estimation of GARCH family models.

Table 4: Garch effects

Indicator	Garch effects	Standard error	z-statistics	P – value
BSEBANK	0.819	0.042	19.52	0.000
BSECG	0.621	0.074	8.43	0.000
BSEMET	0.887	0.018	49.47	0.000
BSEOIL	0.461	0.075	6.12	0.000
BSEPOWER	0.543	0.101	5.36	0.000
BSEPSU	0.531	0.091	5.86	0.000
BSEREAL	0.510	0.093	5.46	0.000
BSETECK	0.558	0.129	4.33	0.000
SPBSEIT	0.552	0.142	3.88	0.000
SPBSEHC	0.529	0.124	4.26	0.000
SPBSEFMCG	0.543	0.086	6.30	0.000

EGARCH Model

Our next model is the EGARCH model, which tells about asymmetric information's of stock's returns in the financial market. But it unable to capture the conditional variance of stocks. Table 5 represents EGARCH effect is positive in BSEPOWER and BSEMET, but in BSEOIL there is negative effects. EGARCH effect is greater in BSEPOWER (0.89) followed by BSEMET (0.96), but in the case of BSEOIL (-0.95) it is negative. In the BSE market get influenced because oil is a tradable goods and services. Its impacts will create imbalances in BSE SENSEX

Table 5: EGARCH Effects

Indicator	Egarch effects	Standard error	z-statistics	P – value
BSEBANK	0.910	0.027	33.70	0.000
BSECG	0.740	0.073	10.11	0.000
BSEMET	0.967	0.013	77.30	0.000
BSEOIL	-0.953	0.016	-60.79	0.000
BSEPOWER	0.893	0.011	78.08	0.000
BSEPSU	0.783	0.052	15.08	0.000
BSEREAL	0.143	0.057	2.52	0.012
BSETECK	0.694	0.096	7.24	0.000
SPBSEIT	-0.779	0.111	-7.03	0.000
SPBSEHC	0.661	0.109	6.06	0.000
SPBSEFMCG	0.747	0.063	11.81	0.000

TGARCH Model

TGARCH and GJR TGARCH captures the "Leverage effect "of series returns. There is a relationship between the negative and positive shocks or innovations. The asymmetrical TGARCH model which is used to estimate the returns of BSE SENSEX which is presented in the table 6. Our analysis revealed that there is a negative correlation between past return and future return (leverage effect). The EGARCH model supports for the presence of leverage effect BSE SENSEX return series.

Table 6: TGARCH Effects

Indicator	Tgarch effects	Standard error	z-statistics	P – value
BSEBANK	-0.116	0.034	-3.45	0.001
BSECG	-0.129	0.031	-4.23	0.000
BSEMET	-0.077	0.034	-2.24	0.025
BSEOIL	0.169	0.037	4.63	0.000
BSEPOWER	0.126	0.033	3.78	0.000
BSEPSU	0.156	0.035	4.51	0.000
BSEREAL	0.335	0.051	6.57	0.000
BSETECK	0.117	0.033	3.51	0.000
SPBSEIT	0.095	0.032	2.91	0.004
SPBSEHC	0.099	0.032	3.11	0.002
SPBSEFMCG	0.120	0.035	3.46	0.001

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GJR TGARCH Model

It is also showing the same GJR TARCH effects in BSEREAL (0.98) and in BSETECK (0.67), here the positive shocks or innovations are greater than the negative shocks or returns in the markets. The booms which is occurred in the BSE SENSEX. It is the drawbacks of GRACH model, which has shown in our table 7.

Table 7: GJR TARCH Effects

Indicator	GJR Tarch effects	Standard error	z-statistics	P – value
BSEBANK	-0.151	0.051	-2.97	0.003
BSECG	-0.088	0.030	-2.88	0.004
BSEMET	-0.123	0.048	-2.55	0.011
BSEOIL	0.174	0.054	3.24	0.001
BSEPOWER	0.135	0.049	2.73	0.006
BSEPSU	0.167	0.052	3.19	0.001
BSEREAL	0.986	0.165	5.99	0.000
BSETECK	0.678	0.119	5.69	0.000
SPBSEIT	0.335	0.069	4.85	0.000
SPBSEHC	0.400	0.081	4.92	0.000
SPBSEFMCG	0.158	0.052	3.03	0.002

SAARCH Model

In table 8, the negative shocks or innovations highly from BSEOIL (-0.90) which have negative impacts on other goods and services markets. Because it is a tradable commodity from other exportable country which affects most of the other price indices BSEPSU (- 0.90) BSEREAL (-0.87) SPBSEFMCG (-0.89) and BSETECK (-0.82) there is SAARCH effects in the BSE markets. It is the main important cause to variation in stocks. Which shows the relationship between asymmetric volatility and return.

Table 8. SAARCH Effects

Indicator	Simple asymmetric Arch effects	Standard error	z-statistics	P – value
BSEBANK	-0.821	0.309	-2.65	0.008
BSECG	-0.717	0.191	-3.75	0.000
BSEMET	-0.544	0.452	-1.20	0.229
BSEOIL	-0.910	0.067	-13.56	0.000
BSEPOWER	-0.912	0.078	-11.70	0.000
BSEPSU	-0.905	0.070	-13.01	0.000
BSEREAL	-0.870	0.069	-12.68	0.000
BSETECK	-0.820	0.098	-8.41	0.000
SPBSEIT	-0.795	0.106	-7.50	0.000
SPBSEHC	-0.748	0.117	-6.38	0.000
SPBSEFMCG	-0.894	0.082	-10.91	0.000

PARCH Model

There are alternate models to measure asymmetric information’s like goods news and bad news of the return series. Such models are GJR TARCH, SAARCH, PARCH, these models are actually the drawbacks of the GARCH model. PARCH model which is estimating the ARCH effect through the power asymmetric returns series.

We observed from the given above Table 9, that is the POWER ARCH effect which is nothing as the “Leverage effect” through power. It follows GARCH models, the PARCH effects found in SPBSEFMCG (0.22) which positively affect to other indices, BSEBANK (0.09) and in BSECG (0.11).

Table 9. PARCH Effects

Indicator	Parch effects	Standard error	z-statistics	P – value
BSEBANK	0.092	0.016	5.78	0.000
BSECG	0.118	0.021	5.61	0.000
BSEMET	0.080	0.011	7.13	0.000

BSEOIL	0.116	0.023	5.06	0.000
BSEPOWER	0.132	0.028	4.76	0.000
BSEPSU	0.142	0.030	4.74	0.000
BSEREAL	0.188	0.035	5.43	0.000
BSETECK	0.137	0.026	5.19	0.000
SPBSEIT	0.138	0.025	5.48	0.000
SPBSEHC	-0.043	0.021	-2.00	0.046
SPBSEFMCG	0.222	0.034	6.45	0.000

NARCH Model

Others models like NARCH, NARCH with one shift, APARCH and NAPARCH, these models are measuring all those asymmetric volatility and symmetric relationship between of negative and positive shocks or innovations in the BSE SENSEX. Our study found that implies the negative shocks or bad news have a greater effect on the conditional volatility than the positive shocks or good news, which shows that the variance equation is well recognised for the Indian stock (BSE) markets. From table 10, NARCH effects found mostly in BSEOIL (0.35) and its followed by other indices as SPBSEFMCG (0.26) BSEREAL (0.22) and BSEPSU (0.22).

Table 10. NARCH Effects

Indicator	Narch effects	Standard error	z-statistics	P – value
BSEBANK	0.100	0.022	4.47	0.000
BSECG	0.117	0.021	5.47	0.000
BSEMET	0.077	0.012	6.40	0.000
BSEOIL	0.352	0.053	6.69	0.000
BSEPOWER	0.177	0.032	5.58	0.000
BSEPSU	0.227	0.038	6.02	0.000
BSEREAL	0.221	0.036	6.20	0.000
BSETECK	0.125	0.027	4.54	0.000
SPBSEIT	0.111	0.026	4.24	0.000
SPBSEHC	0.148	0.034	4.30	0.000
SPBSEFMCG	0.263	0.043	6.16	0.000

Nonlinear arch with one shift Model (NARCHK)

Nonlinear arch with one shift effects means unobservable variation, which is the asymmetric volatility of its past one period lag shocks. Mostly we found negative arch effects in BSEREAL (-92) BSEOIL (-105) and positive in SPBSEFMCG (80. 05) and BSETECK (- 76.39). Which is shown under the given table 11.

Table 11. NARCH Model with one shift effect				
Indicator	**Narch model with one shift effects**	**Standard error**	**z-statistics**	**P – value**
BSEBANK	35.624	12.539	2.84	0.004
BSECG	-46.844	22.699	-2.06	0.039
BSEMET	-31.378	13.645	-2.30	0.021
BSEOIL	-105.007	25.545	-4.11	0.000
BSEPOWER	-93.215	16.581	-5.62	0.000
BSEPSU	-95.407	24.725	-3.86	0.000
BSEREAL	-92.294	15.041	-6.14	0.000
BSETECK	-76.398	26.051	-2.93	0.003
SPBSEIT	-59.842	25.097	-2.38	0.017
SPBSEHC	-121.626	44.287	-2.75	0.006
SPBSEFMCG	80.058	16.928	4.73	0.000

APARCH Model

APARCH effect shown in table 12, the positive and negative have equal magnitudes.

Table 12. APARCH Effects				
Indicator	**Aparch effects**	**Standard error**	**z- statistics**	**P – value**
BSEBANK	0.062	0.016	3.94	0.000
BSECG	0.121	0.021	5.64	0.000
BSEMET	0.073	0.012	6.11	0.000
BSEOIL	0.530	0.074	7.15	0.000
BSEPOWER	0.135	0.029	4.70	0.000
BSEPSU	0.105	0.017	6.27	0.000
BSEREAL	0.059	0.019	3.03	0.002
BSETECK	0.133	0.027	4.86	0.000
SPBSEIT	0.136	0.026	5.19	0.000
SPBSEHC	0.167	0.027	6.16	0.000
SPBSEFMCG	0.367	0.049	7.44	0.000

NPARCH Model

NPARCH effects which shows in the indices like more in BSEPSU (0.45) its followed BSEREAL (0.30) BSETECK (0.25) and SPBSEIT (0.20). There is minimum variance which lies between positive and negative value of shocks and innovations.

Given below table 14. We studied about the correlation between the indices and its returns also to calculated the deviations. Our ARCH model measure the regularity of conditional variance and our drawbacks of GARCH, EGARCH and TGARCH model which are best model to find out the asymmetric volatility clustering. Above that shown the negative correlation coefficient in BSEPOWER (-0.694) and BSEPSU (-0.782).

Table 13. NPARCH Effects				
Indicator	**Nparch effect**	**Standard error**	**z-statistics**	**P – value**
BSEBANK	0.084	0.014	6.08	0.000
BSECG	0.118	0.021	5.52	0.000
BSEMET	0.092	0.011	8.74	0.000
BSEOIL	0.225	0.021	10.48	0.000
BSEPOWER	0.042	0.008	5.16	0.000
BSEPSU	0.459	0.064	7.23	0.000
BSEREAL	0.304	0.030	9.99	0.000
BSETECK	0.254	0.028	9.00	0.000
SPBSEIT	0.208	0.026	8.04	0.000
SPBSEHC	0.185	0.029	6.36	0.000
SPBSEFMCG	0.187	0.02	8.68	0.000

Conclusions

One an important objective of our paper is that to investigate volatility clustering of the BSE SENSEX returns series through using various ARCH FAMILY models**.** The study is based on the secondary data sources that were collected from the data base of Bombay stock market. (BSE) indices are used as proxy of Indian stock market. With the availability of high frequency data being compiled by Bombay stock exchange (BSE). The data is collected on the daily prices of BSE SENSEX indices over the period of seven years from 1st January 2011 to 1st January 2017. Our data set is the time series, which is daily data of the closing price of stock market. GARCH, EGARCH and TGARCH models have been employed for this study after confirming the unit root test, volatility clustering and ARCH effect. Modelling and forecasting volatility of stock markets, it is an important field to analysis and research in financial economics time series.

Various Conditional volatility models (ARCH/GARCH) asymmetric responded volatility to movement of stock markets and investigate the ARCH effects. Our results show that while conditional volatility models estimating volatility for the past series, extreme value estimators based on trading range perform well on efficiency. This value estimators act well to forecast the daily or our data is five-days we can say weekend effect and one month (30 days) volatility ahead much best than the conditional volatility models.

There is an ARCH effect in BSEOIL found which is affecting all the indices in the BSE SENSEX market. We also found in our study that the BSEREAL also have volatility clustering in the stock markets because the price of real estate differs according its forms of land and we can see in the case of BSEBANK and SPBSEIT both are performing as an important dominants indicator in the BSE market.

PGARCH model results shows significant influence in terms of power on the conditional volatility. If we see in our present era of global integration of emerging stock markets like India with other world major stock markets, there is leverage effect which is present in the Indian stock market indicates that negative shocks have greater impacts on the International markets can easily external or spill over effect on our Indian stock markets, which clearly shows that it affects adversely to the Indian stock markets and it was proved from global financial crisis in 2008. The volatility of BSE stock returns has estimated and modelled two models which is asymmetric nonlinear models EGARCH and TGARCH and news impact curve. The results represent that the volatility in the Indian stock market exhibits the persistence of volatility and mean reverting behaviour. In our study we found that BSE Sensex returns series responded leverage effects and to summed of others stylized facts such as volatility clustering and leptokurtosis represented as a stock returns on International stock markets. Our ARCH model measure the regularity of conditional variance and our drawbacks of GARCH, EGARCH and TGARCH model which are best model to find out the asymmetric volatility clustering. We studied about the correlation between the indices and its returns also to calculated the deviations You can see the appendix, the indicators are BSEBANK, BSECG, BSEMET and BSEOIL have positive impact on BSE SENSE and other hand the negative in BSEPOWER (-0.694) and BSEPSU (-0.782).

Appendix

INDICATORS	BSE BANK	BSE CG	BSE MET	BSE OIL	BSE POWER	BSE PSU	BSE REAL	BSE TECK	SPBSE IT	SPBSE HC	SPBSE FMCG
ARCH MODEL	0.533	0.273	0.329	0.399	-0.694	-0.781	-0.224	0.590	0.117	0.085	0.553
EGARCH MODEL	0.536	0.271	0.330	0.399	-0.685	-0.782	-0.230	0.590	0.115	0.083	0.553
TARCH MODEL	0.536	0.271	0.330	0.399	-0.685	-0.782	-0.230	0.590	0.115	0.083	0.553
Standard error	0.009	0.009	0.010	0.019	0.100	0.037	0.056	0.117	0.055	0.012	0.020

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