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ANALYSIS OF VOLATILITY DYNAMICS IN SELECTED SECTORAL INDICES OF NATIONAL STOCK EXCHANGE

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ABSTRACT

This study is based on five consumer specific sectoral indices as Auto, Bank, FMCG, IT and Realty of National Stock Exchange, India especially after recession period.

The main purpose of this study is to examine the dynamics of volatility in these five Sectoral indices. The volatility dynamics such as volatility clustering, volatility persistence and leverage effect in these sectors are investigated by using three GARCH Family models to know the status of these sectors after recession period.

After implementing GARCH family models it is found that Nifty and all five sectors except IT are highly volatile and volatility moves in clusters. Significant ARCH and GARCH terms of these models indicate that current period variance of stock returns is conditional on previous period volatility in all five sectors except IT. Significant Leverage effect is captured in all sectors except FMCG sector in EGARCH model indicating negative shocks have larger impact on volatility than positive shocks. In EGARCH (1, 1) and TGARCH (1, 1) Auto and realty both have shown less volatility persistence means there is faster decay of volatility shocks in these two sectors. So the risk averse investors can invest in IT, auto and Realty sectors by avoiding bank and FMCG sectors stocks where volatility persist for a longer duration. In overall all five sectors are suitable to invest.

Keywords - Sectoral indices, GARCH, EGARCH and TGARCH.

JEL classification –C52, C58, G10

1. INTRODUCTION

Stock market volatility estimation is of great interest for the researchers and academicians because it has its importance in many financial and economic applications. Its knowledge is important for investors because it helps in asset pricing and allocation, portfolio and risk management etc.

Volatility refers to the fluctuation or up and down movement in a stock's price within a period of time. Little movement in stock price would constitute low volatility. Rapid movement in stock price would constitute high volatility. It shows the range to which the price of a security may increase or decrease. It is a measure of risk of a security.

There are two main types of Volatility:

Historical volatility - that measures the stock's price movement based on historical prices.

Implied Volatility - that is implied by the prices of an option on the relevant instrument.

Normally volatility is measured by calculating the standard deviation of the annualized returns over a given period of time. It is generated through various internal and external factors of economy acting as information of positive and negative nature.

Volatility is conditional when today's volatility estimates depends upon an information set derived from previous or future period. To analyse the conditional volatility and to capture the volatility dynamics, ARCH and GARCH models are used, where current period volatility estimates depends on previous period volatility estimates. Robert Engle (1982) introduced ARCH (Autoregressive conditional heteroskedasticity) model to model the time varying volatility which works on the assumption that the variance of the current error term is related to the size of the previous periods' error terms, giving rise to volatility clustering thereby it includes the lags of squared residuals. This model was later generalized by Bollerslev (1986) as GARCH (Generalized ARCH) which includes the lags of conditional variance itself.

The present study examines the conditional volatility and analyses the volatility dynamics (like volatility clustering, persistence and leverage effect) of sectoral indices of NSE. National stock exchange (NSE), India has its major index Nifty. NSE has various sectoral indices like CNX Auto Index, CNX Bank, Energy, Finance, FMCG, IT, Media, Metal, Pharma, PSU Bank and Realty etc. reflecting movement of prices of stocks from different sectors. In present study only 5 sectors (Auto, FMCG, IT, Realty and Bank) along with nifty have been taken. These sectors are consumer specific sectors and directly contribute towards improvement of their standard of living. Reforms in these sectors during study period have impacted the movement of prices and volatility in prices of these sectors's indices. So the volatility levels and persistence study becomes important for these sectors especially for investors and policy makers and regulators.

2. LITERATURE REVIEW

Various studies on analysing the volatility dynamics through volatilities modelling are there in existing literature. Few of them are as follows-

Xu Jiangang (1999) examined the Shanghai stock exchange volatility dynamics from 1992-95. It was conformed that there was no leverage effect found in shanghai stock exchange by using GARCH, EGARCH and GJR GARCH models and GARCH model was the best model for the period of study. **Engle & Patton (2001)** examined the Dow Jones industrial index of New York (US) to check the ability of GARCH type models to illustrate some stylized facts about volatility like persistence, mean reversion, asymmetry, innovation and pre-determined variables. Results were found in support of these characteristics. **Goudarzi & Ramanarayanan (2011)** investigated the asymmetric relation between stock price and its volatility in India by taking log return of BSE500 stock index daily closing price for the period 2000 to 2009. By using EGARCH and TGARCH models it was conformed that return series found to react asymmetrically to good and bad news. Bad news had high impact on volatility than good one. **Ahmed & Suliman (2011)** examined the conditional volatility of returns and its stylized facts like clustering and leverage effect and persistence of Sudanese stock market namely Khartoum stock exchange. GARCH family models as GARCH (1, 1), GARCH-M (1, 1) to capture symmetric effect and EGARCH, TGARCH and PGARCH to capture asymmetric effect were applied. All models explained there was volatility persistence and presence of leverage effect. **Peiris & Peiris (2011)** examined the volatility of different sectors affected by macro-economic factors of Colombo stock exchange for the period 2005-10 by using ARCH and GARCH models and concluded that inflation and interest rates were 2 macro factors influencing stock market volatility of Sri Lanka CSE. **Mahmud & Mirza (2011)** examined the Karachi Stock Exchange before and during financial crisis of 2008 to model and forecast its volatility using GARCH, EGARCH and GJR GARCH Models and concluded that EGARCH model was best at forecasting for both periods and GJR and EGRACH both captured the asymmetric effect of volatility significantly. **Prabakaran & Prabha (2012)** investigated the 6 sectoral indices of NSE to analyse volatility, forecast indices value, correlation and to suggest trading strategies. It was conformed that CNX FMCG was consistent having low volatility and

CNX IT was aggressive index during study period. Few sectors showed perfect positive correlation between them while few sectors showed poor negative correlation. Active strategy suitable for speculators while active strategy for investors. **Ezzat (2012)** examined sector specific volatility to determine sectoral response to shocks of Egyptian market. Study divided in 2 periods, pre revolution (2007-10) and during revolution (2011-12). By taking 12 sectoral indices daily return, GARCH, EGARCH and TGARCH models were used to find out facts like volatility persistence, clustering and leverage effect. It was conformed that TGARCH model was best fitted model in capturing the volatility characteristics. There was strong evidence of heterogeneous responses of different sectors for shocks on volatility. **Nawazish & Sara (2012)** examined the volatility patterns of Karachi Stock Exchange (KSE) using GARCH (1, 1) model by using daily return of index from 2004 to 2012. Index returns were found strongly significant and captured the volatility. It was conformed that conditional volatility changes over time due to volatility clustering. **Kumar (2013)** modelled the volatility of Indian stock market by taking sample of 4 Indices of NSE as CNX Nifty, CNX -100, CNX -200 and CNX -500. Out of GARCH (1, 1), T-GARCH (1, 1) and E-GARCH (1, 1), E-GARCH model was best in explaining the asymmetric effect and volatility persistence. Indian stock market was highly volatile and more sensitive to bad news during study period. **Gupta *et al.* (2013)** examined the volatility of Sensex of BSE and S&P CNX Nifty of NSE by using GARCH (1, 1), E-GARCH (1, 1), T-GARCH (1, 1). GARCH model was found best as per AIC and SIC criteria while Maximum log likelihood values conformed E-GARCH as best model. E-GARCH model captured the leverage effect significantly. **Mohandass & Renukadevi (2013)** modelled the Volatility of BSE sectoral indices. ARMA(1, 1) model was found as best one to model the average return as per akaike information criteria and GARCH (1, 1) model was found as best to model the volatility of return series as per AIC and log likelihood criteria on the basis of various features of indices returns like normality, stationarity and heteroskedasticity. **Alam *et al.* (2013)** investigated the use of ARCH model benchmarked with GARCH, EGARCH, PARCH and TARCH models for forecasting volatility of DSE20 and DSE general indices and conformed that past volatility of returns series had significant influence on current volatility for both indices. **Ramanathan & Gopalakrisnan (2013)** examined the volatility of Indian Stock Market by taking 31 companies from 6 different sectors from Nifty for the pre-recession (2005-2008) and post-recession (2009-2012) periods. Yang-Zhang estimator was used to find out volatility in both periods. Banking sector companies was found more volatile during pre-recession period and few companies stocks were found less volatile. In overall post period volatility was lower than pre-recession period. **Lakshmi P. (2013)** analysed the volatility of NSE CNX Nifty and its 11 sectoral indices. By using unit root test and ARCH Model, lowest and highest volatility sectors as compared to nifty were indentified. Reality sector showed highest volatility while banking sector showed lowest volatility. **Nateson *et al.* (2013)** detected the volatility transmission from BSE Sensex to its 13 sectoral indices from different dates of their existence. By using GARCH (1, 1) model it was conformed that there is volatility transmission from BSE Sensex to 13 sectors (auto, Bankex, capital goods, consumer durables, FMCG, Healthcare, IT, metal, oil & gas, reality & PSU) indices except tech and power. Shocks from Sensex do not transmit to tech and power**. Shanmugasundram & Benedict (2013)** investigated the NSE Nifty and 5 sectoral Indices of NSE to identify the risk factors in them and risk difference in different time intervals. On the basis of two sample T-test and one way ANOVA it was observed that there was no significant difference in risk factors across sectoral indices. One way ANOVA within groups was used and conformed that there was significant difference in risk by taking various time intervals. Both results were suggestive to minimise risk of portfolios. **Rajavat & Joshi (2014)** analysed the volatility of BSE small cap index. With the help of GARCH (1, 1) method GARCH and ARCH effects were analysed and it was conformed that both effects were significant and as family shocks were influencing the index. **Rakesh (2014)** examined the Volatility of FMCG and Auto indices with CNX nifty Index. Descriptive statistics and two samples T-test were used to identify difference between mean and standard deviation. It was found that there was a wide range of difference in return and risk between these indices. **Ramya (2014)** analysed the Volatility of BSE Sensex and its sectoral indices. On the basis of Descriptive analysis, autocorrelation and exponential trend it was found that correlation was significant for most of the sectoral Indices except Auto, power, PSU Bank and reality index. It was also confirmed that all indices have more impact on Sensex during study period. Study was suggestive to reduce risk and increase returns of investments. **Emenike & Ani (2014)** examined the Volatility of Nigerian banking sector indices and All share index. By using GARCH (1, 1) and GJR GARCH (1, 1) results evidenced for volatility clustering and persistence further innovations were insignificantly influencing stock return. **Singhania & Prakash (2014)** examined cross-correlation in stock returns of SAARC countries, conditional and unconditional volatility of stock markets and efficient market hypothesis (EMH) from 2000 to 2011 by using family of GARCH models and indicated presence of serial autocorrelation in stock market returns implying rejection of EMH and there was significant relationship between stock market returns and unconditional volatility. **Srikanth (2014)** modelled the asymmetric volatility of Indian stock market by taking BSE Sensex. By using GJR GARCH and PGARCH and ARCH LM test it was conformed that both models captured the Leverage effect and volatility persistence in Indian stock market. **Akhtar & Khan (2016)** analysed the volatility on the Karachi Stock Exchange (KSE) 100 index of the KSE from 1991 to 2013 by using daily, weekly and monthly returns and GRACH Family models. P-GARCH (1, 1) model was better model for modeling volatility in the case of daily returns, while the GARCH (1, 1) model proved better for weekly data. High persistence and insignificant leverage effect reported in weekly returns. While significant leverage effect was reported regarding the daily returns. Impact of global financial crises upon volatility was low.

Thus there are various studies on analysing volatility dynamics through volatility modelling. But very few studies are there on sectoral volatility. So the present study on sectoral volatility dynamics would be an add-on to the lesser side of existing studies in India.

3. RESEARCH OBJECTIVE AND METHODOLOGY

3.1 Objective-The Main objective of this study to examine the volatility dynamics as volatility clustering, leverage effect and volatility persistence through volatility modelling.

3.2 Data and Its Source- In present study five sectoral indices like Auto, Bank, FMCG, Realty and IT along with Nifty have been taken. Data in form of daily closing prices of these indices have been taken from NSE website from 1st April 2011 to 31 March 2017. Logged returns have been obtained from daily closing prices to use in models.

$$\text{Return Series} = \text{Log}\,(Pt/Pt\text{-}1)*100.$$

3.3 Statistical Tools Used-

3.3.1 Descriptive Statistics is used to find the distribution of returns. Mean, standard deviation, skewness and kurtosis etc. have been used to check the normality of returns distribution.

3.3.2 ARMA Model - ARMA (1, 1) autoregressive moving average model is combination of AR (autoregressive process) and MA (moving average) process to model the mean equations for each index is specified as follows-

AR (p) model – Where current value of variable X depends linearly on its own previous values and a stochastic (unpredicted) term.

$$X_t = \alpha_0 + \sum_{i=1}^{p} \alpha_1 X_{t-i} + u_t (1)$$

Where α_0 is a constant, α_1 to α_p is parameter of model, u_t is white noise error term with 0 mean and same variance.

MA (q) model – Where current value of variable X depends linearly on previous values of white noise terms.

$$X_t = \alpha_0 + \sum_{i=1}^{q} \alpha_1 u_{t-i} + u_t \qquad (2)$$

Where α_0 is a constant, α_1 to α_q is parameter of model, u_t is white noise error term with 0 mean and same variance

AR (p) is a pth order autoregressive process while MA (q) is a linear combination of qth order white noise error terms.

ARMA (1, 1) model – This the combination of AR and MA process upto order one.

$$Xt = \alpha_0 + \alpha_1 X_{t-1} + \beta_0 u_t + \beta_1 u_{t-1} \qquad (3)$$

Through linear regression, residuals are obtained from the above AR, MA or ARMA models to check serial correlation between them and then ARCH effect of order 1 is tested on squared residuals.

3.3.3 ARCH Model- Autoregressive Conditional Heteroskedasticity model introduced by Engle (1982) specifically to model and forecast conditional variances of error terms of time series. ARCH effect means heteroskedasticity[1] that is modelled as conditional variance of squared residuals obtained from mean equation of ARMA model. ARCH (q) specification for conditional variance $\sigma_t^2$of error terms is as follows-

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots\cdots\cdots + \alpha_q u_{t-q}^2 \qquad (4)$$

Null hypothesis $\mathbf{H_0} = \alpha_0 = \alpha_1 = \alpha_2 \cdots\cdots\cdots = \alpha_q = 0$ (No ARCH Effect)

Against alternate hypothesis $H_1 = \alpha_0 \neq \alpha_1 \neq \alpha_2 \cdots\cdots\cdots \alpha_q \neq 0$ (ARCH Effect)

If value of test statistic is greater than critical value from chi square distribution or coefficient of α is statistically significant then null hypothesis is rejected.

3.3.4 Serial Correlation is also checked before applying GARCH model. There should be serial correlation in squared residuals. To check the serial correlation Ljung-Box Q* statistic is as follows:

$$LB = N(N+2)\sum_{k-1}^{m}\left(\frac{\hat{\rho}_k^2}{N-K}\right) \quad (5)$$

Where N is the sample size, $\hat{\rho}_k$ is the sample autocorrelation at lag k, and m is the number of lags being tested. Here N+2 and N-K terms are cancelled out as the samples size increases towards infinity and statistics becomes equal to Box pierce statistics.

$$Q = n\sum_{k=1}^{m}\hat{\rho}_k^2$$

Where n = sample size and m= maximum lag length.

In large samples Q statistics is approximately distributed as chi square distribution with m degree of freedom.

H0 = There is no autocorrelation in return series.

We can test joint hypothesis that all $\hat{\rho}_k$ at different lags are simultaneously equal to zero. If Q statistics > χ_m^2distribution at any lag or non zero at any lag than joint null hypothesis get rejected. Null hypothesis of no autocorrelation get rejected if coefficient lies outside the ±1.96 range.

4. **VOLATILITY MODELS** may be symmetric and asymmetric. In symmetric models conditional variance is dependent on only magnitude of shocks of returns while in asymmetric models it responds differently according to positivity and negativity of shocks of returns. Volatility model pre-condition of no autocorrelation have been checked through AR (1) and ARMA (1, 1) model that has been satisfied at order 1 so in GARCH models we have used order one.

4.1 GARCH (1, 1) Model developed by Bollerslev and Taylor (1986) is popular to capture the volatility dynamics it is consistent with volatility clustering. In GARCH models variance is taken as dependent on its own past values and lags of squared error terms means current volatility of returns is based on last period's squared returns and last period volatility. The model has two equations mean and variance equations.

Mean Equation –It was taken any of the three equations (1, 2 and 3) specified above as per suited to the model.

Variance Equation - $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon^2{}_{t-1} + \beta_1 \sigma_{t-1}^2$ (6)

Where α_0 is the constant, $\sigma_t^2$is conditional variance or one period ahead forecast of variance,$\varepsilon^2{}_{t-1}$(ARCH term) is one period lagged squared residual returns that indicates news about volatility from previous period, σ_{t-1}^2(GARCH term) is one period lagged variance, α_1 is the arch term coefficient and $\beta_1$is the coefficient of GARCH term at lag one.

These coefficients can be upto p and q lags where p would be the order of moving average arch terms and q would be the order of autoregressive GRACH terms.

Significant positive values of α and β indicates news on volatility from past have an impact on current volatility. Sum of α+β close to 1 indicates volatility persistence and clustering α+β<1 indicates GARCH process is mean reverting and volatility shocks decay

This model produces the symmetric response for stock returns means only shocks magnitude determines volatility irrespective of their positivity or negativity.

4.2 EGARCH (1, 1) Model developed by Nelson (1991) is popular to capture the asymmetric volatility. There is some relation between current returns and future volatility. Volatility may rise when returns fall and volatility may decline when returns rise. This type of tendency is called leverage effect. So EGARCH model is developed to capture such asymmetric effect (positive or negative) of volatility shocks.

The model has two equations mean and variance equations.

Mean Equation – It was taken any of the three equations (1, 2 and 3) specified above as per suited to the model.

Variance Equation - $log\sigma_t^2 = \alpha_0 + \alpha_1 |\varepsilon_{t-1}/\sigma_{t-1}| + \beta_1 log\sigma_{t-1}^2 + \gamma_1(\varepsilon_{t-1}/\sigma_{t-1})$ (7)

Where,α_0 is the constant α_1 is the arch term coefficient and β_1 is the coefficient of GARCH term. γ is asymmetric response or leverage parameter. If γ≠0 it means there is asymmetric impact. γ <0 (negative and statistically significant) indicates presence of leverage effect means negative shocks have larger impact on next period conditional variance as compared to positive shocks visa versa.

Log of conditional variances ensures non negative forecasts of variance.

4.3 TGARCH (1, 1) Model Threshold GARCHmodel developed by Zakoian (1994) and Glosten, Jaganathan and Runkle (1993), is popular to capture the asymmetric volatility including impact of good and bad news.

The model has two equations mean and variance equations.

Mean Equation – It was taken any of the three equations (1, 2 and 3) specified above as per suited to the model.

Variance Equation - $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \sigma_{t-1}^{2} + \gamma_1 \varepsilon_{t-1}^{2} * d_{t-1}$ (8)

Where, α_0 is the constant implying unconditional volatility, α_1 is the arch term coefficient and $\beta_1$is the coefficient of GARCH term. $d_{t-1}$is a dummy variable. γ is leverage term coefficient.

d_{t-1} =1 if $\varepsilon_{t-1}<0$ indicating bad news and d_{t-1}= 0 if $\varepsilon_{t-1} \geq 0$ indicating good news. If $\gamma=0$ model converts to standard GARCH model.

If this $\gamma \neq 0$ means asymmetric news impact is conformed and $\gamma>0$ (positive and statistically significant) indicates presence of Leverage effect means negative shocks increases the volatility more as compared to positive shocks.

A positive shock (good news) has an impact of α_1 on volatility or conditional variance, and a negative shock (bad news) has an impact of $\alpha_1+\gamma_1$ on volatility.

5. THE FINDINGS

5.1 Descriptive Statistics:

From descriptive statistics shown in **Table I** given in appendix we can see that average returns of 4 sectors and Nifty is positive while reality sector is showing negative returns. FMCG and Auto sectors are showing highest returns. In standard deviation we can see that realty sector is showing highest volatility followed by bank, IT, Auto and FMCG. Nifty is also lowest volatile. Nifty and all sectors except bank are negatively skewed. Kurtosis is also more than 3 in all indices indicating more peakedness in distribution of returns. Jarque bera test P-value is also less than 0.05 indicating variability of distribution from normality. Return series data is not normal and have fat tails. If we see the graph of these indices returns movement in **Figure 1** we can observe that all indices are highly volatile and sometimes spikes can be seen indicating high movement downward or upward. We can see volatility clustering in all indices. Nifty, Realty, auto, FMCG and bank are showing more volatility. In IT sector there is less volatility in overall period while spikes in it are showing more volatility, increasing its overall effect during the period.

5.2 Modelling of Mean Equation:

We have used AR (1) for Auto and realty and for remaining ARMA (1, 1) model to model the mean equations and used their residuals and squared residuals to check the serial correlation in them and then ARCH effect is also checked at lag 1 and 2 to find out the return series suitability to model the volatility through GARCH models. We can see in **Table II** the residuals diagnostics of ARMA model. Ljung box Q-statistics is used to find the serial correlation in residuals and squared residuals series. In residual series and squared residual series Q statistics have been checked up to 36 lags. But here in table 2 up to lag 5 this statistics have been shown. We can see that in all sectoral indices along with Nifty residual series Q statistics is statistically insignificant because P value is more than 0.05 except realty at lag 3 after that it is also more than 0.05. Thus all P values are showing more than 0.05 values indicating Null hypothesis of No serial correlation is accepted in residual series. While if we see the squared residual series Q-statistics then we can found that all p values are less than 0.05 except IT sector. It means null hypothesis of no autocorrelation get rejected here and there is serial correlation in squared residual series. Further we have checked for ARCH effect of heteroskedasticity up to lag 2. At lag 2 all p values are less than 0.05 in nifty and all 5 sectors except IT so there is ARCH effect in Nifty and all sectors except IT sector. So we can find that **our volatility model pre conditions like**- No Auto correlation in residual series, Serial correlation in Squared residual series or ARCH effect in residual series have been met in Nifty and all sectors except IT. Now we can fit GARCH family models to model the volatility in Nifty and 4 sectors. IT sector can't be used for volatility models because there is no ARCH effect found.

5.3 GARCH Family Models-

Symmetric GARCH and Asymmetric GARCH models are used assuming student-t distribution[2] to capture the volatility and its dynamics for these indices. GARCH (1, 1) is a symmetric model while EGARCH and TGARCH are Asymmetric models. All models have been applied by assuming student t distribution because data was not normally distributed. **Table III** is showing the results of all GARCH models. We can see that arch term (α_1) coefficients of variance equation in GARCH (1, 1) model are positive and statistical significant at 5% level indicating news about previous period positive and statistical significant at 5% level indicating news about previous period volatility is significantly impacting current period returns. All GARCH term (β_1) Coefficients are also positive and statistical significant at 5% indicating volatility clustering and conditional variance is significantly affected by previous period volatility. $\alpha_1+\beta_1$values in it are close to 1 in all indices indicating volatility persistence means it takes time to decay volatility shocks. In EGARCH (1, 1) model also we can see that arch term (α_1) coefficients of variance equation are positive and statistical significant at 5% indicating news about previous period volatility is significantly impacting current period volatility. All GARCH term (β_1) Coefficients are positive and statistical significant indicating volatility clustering and that conditional variance of current period is significantly affected by previous period volatility. $\beta_1$values can be seen for volatility persistence values close to 1 indicates higher persistence and $\alpha_1+\beta_1$values are slight more than 1 in all sectors indicating volatility increases with time and conditional variance is explosive, all γvalues are negative so this slight more than 1 value is not making model estimation incorrect. Leverage effect is shown by γ all values of γ are negative and statistically significant except FMCG indicating negative shocks have greater impact on volatility than positive shocks. Leverage effect γ in Realty sector is significant at 10% but in FMCG sector it is insignificant indicating less effect of shocks on volatility. Likewise in TGARCH (1, 1) model we can see that arch term (α_1) coefficients of variance equation are negative in nifty and auto while positive in FMCG and bank but insignificant in all four at 5% indicating news about previous period volatility is not impacting current period volatility so arch term unable to predict volatility. In realty sector arch term is significantly predicting volatility. All GARCH term (β_1) Coefficients are positive and statistical significant indicating conditional variance of current period is significantly affected by previous period volatility. $\alpha_1+\beta_1$values are close to 1 in Nifty, Bank and FMCG indicating higher persistence of volatility shocks as compared to realty and auto because these 2 sectors are showing low persistence with their low values. Leverage effect is shown by γ all values of γ are positive and statistically significant except FMCG and Realty indicating negative shocks have greater impact on volatility than positive shocks. We can see that GARCH (1, 1) and EGARCH (1, 1) are best fitted as compared to TGARCH (1, 1). Durbin Watson statistics given in all three models is close to 2 indicating autocorrelation in residuals indicating best fitting of models. Further model diagnostics are also done to best fit the models.

From **Table IV** we can see that log likelihood values are higher in all GARCH models while Akaike's information criterion (AIC) and Schwarz information criterion (SIC) values are lower in all GARCH models as compared to ARMA models so all GARCH models are fitted best. Further EGARCH model is best fitted as compared to GARCH and TGARCH for Nifty, Auto, Bank and Realty sectors on the basis of these information criteria.

5.4 GARCH Models Residual Diagnostic of ARCH Effect-

GARCH models residuals have been checked after applying GARCH models to check the ARCH effect. In **Table V, VI and VII** ARCH effect of these 3 tests have been shown and it was found that all p values in Nifty and 4 sectors are more than 0.05 so Null hypothesis of No ARCH effect have been accepted means there is no further ARCH effect remained in residual series. So our implemented models have captured the ARCH effect found at pre stage of these models and all models are fitted best to capture the volatility dynamics like volatility persistence, leverage effect and clustering as explained above. GARCH (1, 1) model and EGARCH (1, 1) model is best as compared to TGARCH (1, 1) in predicting the volatility.

6. CONCLUSION

In this paper conditional volatility and its dynamics such as volatility persistence, leverage effect and volatility clustering of five sectoral indices along with nifty from April 2011 to march 2017 is analysed. It is concluded that Nifty and 5 sectors like Auto, Bank, FMCG, and Realty are showing volatility clustering in their return. Only four sectors are found suitable to implement GARCH family models and IT sector is not found suitable to implement GARCH models after implementing AR (1) and ARMA (1, 1) model and their residuals diagnostics. GARCH (1, 1) model and EGARCH (1, 1) are found best fit as compared to TGARCH (1, 1) to capture the volatility dynamics as volatility clustering and persistence. All ARCH term and GARCH term coefficient are positive and statistically significant in GARCH (1, 1) model and EGARCH (1, 1). But in EGARCH (1, 1) Leverage effect in FMCG sector is not found significant means FMCG sector is less impacted by previous period shocks on volatility. While in all other sectors its leverage effect shown that negative shocks have larger impact on volatility than positive shocks. Leverage effect in

TGARCH model has shown that negative shocks have larger impact on volatility than positive shocks except FMCG and Realty. TGARCH model ARCH term significantly predicted only realty sector volatility not rest of the sectors along with nifty. While its GARCH term is significant for all sectors indicating that previous period volatility has impact on conditional variance. Volatility persistence is close to 1 in GARCH (1, 1) indicating more persistence and slower decay of shocks to volatility. EGARCH model shows beta value as persistence, volatility persistence is more in all sectors. It also shows that volatility is exponential in all sectors. Shocks will continue to persist. In TGARCH (1, 1) Auto and realty both have shown less volatility persistence. So the risk aversive investors can invest in IT, Auto and realty sectors and can avoid these two bank and FMCG sectors stocks in which volatility persist for a longer duration while risk taker investors can invest in them because more volatile stocks can generate more returns also. They can consider the positive or negative news coming in the market impacting the volatility of stocks. In overall all four sectors are suitable to invest for investors. Government can take some measures to control the high volatility of these two sectors.

Notes

1. Heteroskedasticity refers to the expected value of all error terms obtained from least square method to be unequal. Data in which the variances of the error terms are not equal, in which the error terms may reasonably be expected to be larger for some points or ranges of the data than for others, are said to suffer from heteroskedasticity. (Engle, Robert. 2001)

2. Data in this paper is deviated from normality and have fat tails so we take student t distribution while GARCH modelling. Zivot, E. (2009) explains in his paper Practical issues in the analysis of univariate GARCH models, that financial time series have well known fat tails so the most common fat-tailed error distributions for fitting GARCH models are: the Student's t distribution; the double exponential distribution; and the generalized error distribution.

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Appendix

Table I

Descriptive statistics

Description	NIFTY	AUTO	BANK	FMCG	IT	REALTY
Mean	0.013	0.027	0.018	0.027	0.012	-0.011
Median	0.012	0.041	0.018	0.046	0.014	0.032
Maximum	1.623	2.523	3.925	2.277	3.875	3.515
Minimum	-2.648	-3.272	-3.104	-2.067	-5.424	-5.357
Std. Dev.	0.442	0.536	0.647	0.467	0.568	0.961
Skewness	-0.181	-0.149	0.103	-0.241	-0.857	-0.366
Kurtosis	4.771	4.688	5.147	5.103	13.365	4.963
Jarque-Bera	202.417	182.156	288.208	288.455	6838.640	271.885
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Sum	19.660	40.791	26.292	40.861	17.533	-16.362
Sum Sq. Dev.	289.733	426.801	622.875	324.557	478.886	1373.740
Observations	1487	1487	1487	1487	1487	1487

Figure 1

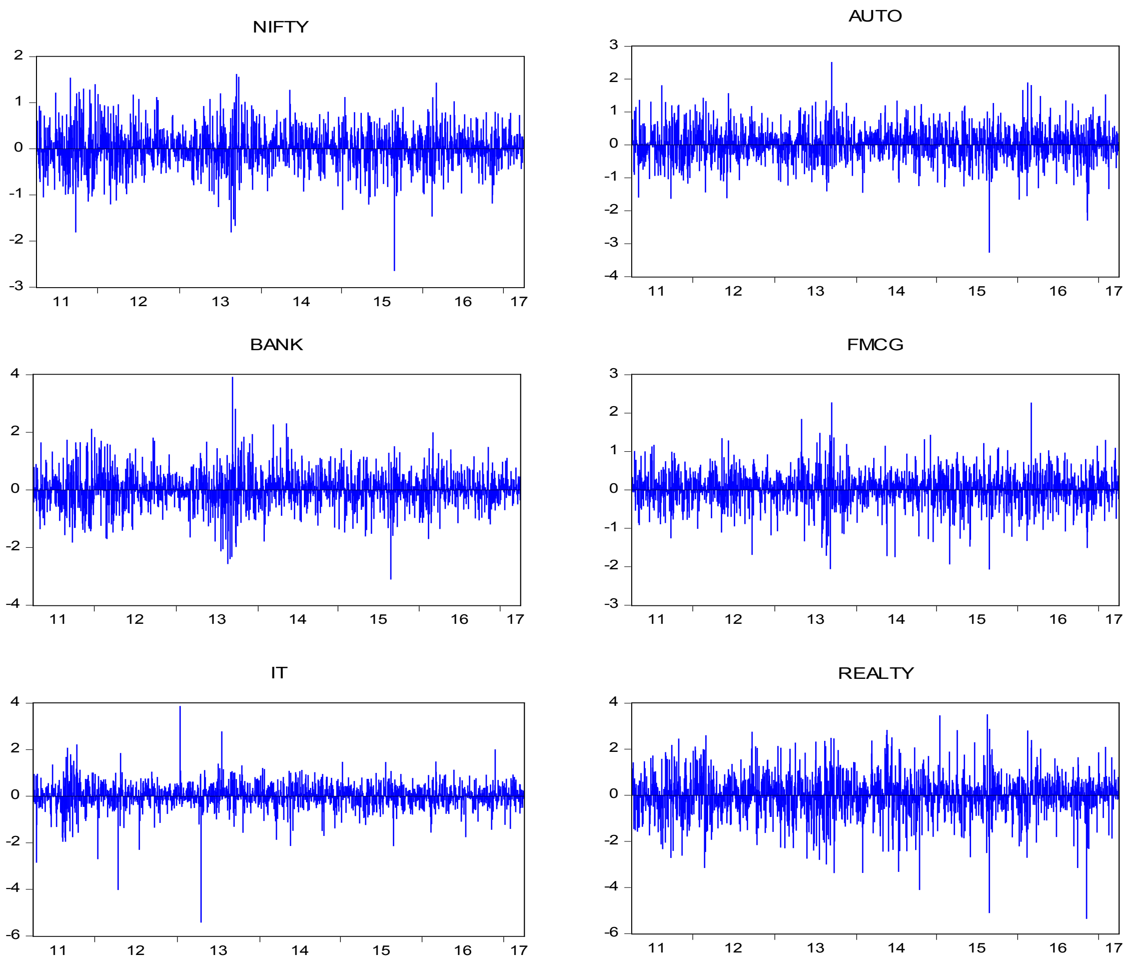

Table II

AR(1), ARMA (1,1) MODEL RESIDUAL DIAGNOSTICS																
Sectors	Residual series					Squared residual series						ARCH LM Test				
	lags	AC	PAC	Q-stat	P-value	lags	AC	PAC	Q-stat	P-value	lags	F-statistics	P-value	obs R-squared	P-value	Inference
Nifty	1	0.007	0.007	0.067	-	1	0.030	0.030	1.328	0.249	1	1.324	0.250	1.325	0.250	NO ARCH
	2	0.008	0.008	0.164	-	2	0.098	0.098	15.760	0.000						
	3	-0.031	-0.031	1.562	0.211	3	0.110	0.105	33.768	0.000	2	7.795	0.000	15.460	0.000	ARCH
	4	-0.034	-0.034	3.302	0.192	4	0.060	0.047	39.202	0.000						
	5	0.001	0.002	3.302	0.347	5	0.035	0.013	41.023	0.000						
Auto AR (1)	1	0.002	0.002	0.008		1	0.107	0.107	17.146	0.000	1	17.281	0.000	17.105	0.000	ARCH
	2	-0.026	-0.026	1.036	0.309	2	0.044	0.033	20.057	0.000						
	3	-0.014	-0.014	1.326	0.515	3	0.027	0.019	21.173	0.000	2	9.479	0.000	18.757	0.000	ARCH
	4	-0.030	-0.031	2.664	0.446	4	0.020	0.014	21.773	0.000						
	5	-0.033	-0.033	4.264	0.372	5	0.042	0.037	24.351	0.000						
Bank	1	0.000	0.000	0.000	-	1	0.082	0.082	10.018	0.002	1	10.046	0.002	9.992	0.002	ARCH
	2	-0.002	-0.002	0.005	-	2	0.131	0.125	35.700	0.000						
	3	-0.006	-0.006	0.061	0.805	3	0.038	0.019	37.883	0.000	2	16.924	0.000	33.159	0.000	ARCH
	4	-0.016	-0.016	0.446	0.800	4	0.028	0.008	39.072	0.000						
	5	-0.016	-0.016	0.850	0.838	5	0.038	0.029	41.248	0.000						
FMCG	1	0.032	0.032	1.527	-	1	0.049	0.049	3.510	0.061	1	3.504	0.061	3.501	0.061	NO ARCH
	2	-0.011	-0.012	1.714	-	2	0.053	0.051	7.725	0.021						
	3	-0.006	-0.005	1.767	0.184	3	0.034	0.030	9.485	0.023	2	3.674	0.026	7.327	0.026	ARCH
	4	-0.053	-0.052	5.899	0.052	4	0.083	0.078	19.753	0.001						
	5	0.016	0.019	6.278	0.099	5	0.045	0.035	22.749	0.000						
IT	1	-0.008	-0.008	0.095	-	1	0.030	0.030	1.361	**0.243**	1	1.357	0.244	1.357	**0.244**	NO ARCH

	2	-0.031	-0.031	1.563	-	2	0.020	0.020	1.986	**0.370**						
	3	-0.027	-0.028	2.661	0.103	3	-0.001	-0.002	1.989	**0.575**	2	0.963	0.382	1.927	**0.382**	
	4	0.016	0.014	3.020	0.221	4	0.009	0.009	2.123	**0.713**						
	5	0.029	0.028	4.290	0.232	5	0.005	0.005	2.162	**0.826**						
Realty AR (1)	1	0.001	0.001	0.001		1	0.110	0.110	18.036	0.000	1	18.186	0.000	17.990	0.000	ARCH
	2	-0.009	-0.009	0.133	0.715	2	0.084	0.073	28.677	0.000						
	3	0.033	0.033	1.775	0.412	3	0.078	0.062	37.744	0.000	2	13.111	0.000	25.818	0.000	ARCH
	4	-0.034	-0.034	3.529	0.317	4	0.004	-0.016	37.773	0.000						
	5	-0.005	-0.004	3.569	0.467	5	0.021	0.012	38.419	0.000						

Table III

GARCH models results

Models	**Sectors**	**Mean Equation**			**Variance Equation**			**α1+β1 of Variance Equation**	**γ (leverage effect)**	**Durbin Watson Stat.**
		α_0	**α_1 (AR Term)**	**β_1 (MA Term)**	**α_0**	**α_1 (ARCH Term)**	**β_1 (GARCH Term)**			
GARCH(1,1)	Nifty	0.0222	-0.6511	0.7240	0.0026	0.0471	0.9400	0.9871	-	1.9818
	P-value	0.0342	0.0000	0.0000	0.0628**	0.0001*	0.0000*			
	Auto	0.0377	0.0911		0.0133	0.0454	0.9073	0.9527		1.9882
	P-value	0.0085	0.0004		0.0583**	0.0035*	0.0000*			
	Bank	0.0247	-0.5259	0.6143	0.0064	0.0528	0.9335	0.9863		1.9519
	P-value	0.1052	0.0010	0.0000	0.0409*	0.0000*	0.0000*			
	FMCG	0.0408	-0.8480	0.8553	0.0086	0.0368	0.9265	0.9634		1.9529
	P-value	0.0002	0.0000	0.0000	0.0378*	0.0048*	0.0000*			
	Realty	0.0161	0.0828		0.0901	0.0904	0.8165	0.9069		1.9795
	P-value	0.5066	0.0018		0.0143*	0.0004*	0.0000*			

EGARCH(1,1)	Nifty	0.0134	-0.6713	0.7441	-0.1017	0.0767	0.9757	1.0524	-0.0957	1.9828
	P-value	0.1949	0.0000	0.0000	0.0000*	0.0005*	0.0000*		0.0000*	
	Auto	0.0258	0.0970		-0.2130	0.1079	0.9022	1.0101	-0.1196	2.0003
	P-value	0.0715	0.0002		0.0001*	0.0031*	0.0000*		0.0000*	
	Bank	0.0112	-0.4865	0.5734	-0.0730	0.0790	0.9851	1.0641	-0.0670	1.9492
	P-value	0.4582	0.0047	0.0004	0.0001*	0.0002*	0.0000*		0.0000*	
	FMCG	0.0396	0.4451	-0.4419	-0.1320	0.0900	0.9561	1.0461	-0.0280	1.9476
	P-value	0.0002	0.7144	0.7169	0.0037*	0.0030*	0.0000*		**0.1754**	
	Realty	0.0138	0.0777		-0.1264	0.1581	0.9277	1.0859	-0.0391	1.9695
	P-value	0.5614	0.0028		0.0000*	0.0000*	0.0000*		0.0623**	
TGARCH(1,1)	Nifty	0.0140	-0.6628	0.7375	0.0052	-0.0080	0.9227	0.9147	0.1171	1.9866
	P-value	0.1792	0.0000	0.0000	0.0007*	**0.4943**	0.0000*		0.0000*	
	Auto	0.0281	0.0952		0.0305	-0.0156	0.8286	0.8130	0.1592	1.9968
	P-value	0.0501	0.0002		0.0011*	**0.3048**	0.0000*		0.0000*	
	Bank	0.0146	-0.5078	0.5946	0.0058	0.0071	0.9426	0.9497	0.0781	1.9490
	P-value	0.3332	0.0023	0.0001	0.0137*	**0.4456**	0.0000*		0.0000*	
	FMCG	0.0375	0.9451	-0.9593	0.0103	0.0286	0.9179	0.9465	0.0171	1.9178
	P-value	0.0000	0.0000	0.0000	0.0445*	**0.1057**	0.0000*		**0.4235**	
	Realty	0.0118	0.0850		0.1008	0.0709	0.8001	0.8709	0.0461	1.9843
	P-value	0.6288	0.0015		0.0089*	0.0141*	0.0000*		**0.1980**	

(Note- Values with * means statistically significant at 5% because p values are <0.05 and values with ** indicates statistically significant at 10% because p values are <0.10)

Table IV

Model diagnostics

Models	**Sectors**	**AR and ARMA Models diagnostics**			**GARCH Models diagnostics**		
		Log likelihood	**AIC**	**SIC**	**Log likelihood**	**AIC**	**SIC**
GARCH(1,1)	Nifty	-888.124	1.199	1.210	-808.450	1.098	1.122
	Auto	-1175.324	1.583	1.591	-1138.073	1.539	1.560
	Bank	-1450.203	1.956	1.967	-1361.529	1.842	1.867
	FMCG	-974.362	1.315	1.326	-910.011	1.234	1.259
	Realty	-2044.432	2.752	2.760	-1977.757	2.668	2.690
EGARCH(1,1)	**Nifty**	-888.124	1.199	1.210	-786.444	1.069	1.098
	Auto	-1175.324	1.583	1.591	-1121.500	1.518	1.543
	Bank	-1450.203	1.956	1.967	-1348.832	1.826	1.855
	FMCG	-974.362	1.315	1.326	-910.937	1.237	1.265
	Realty	-2044.432	2.752	2.760	-1976.846	2.668	2.693
TGARCH(1,1)	Nifty	-888.124	1.199	1.210	-792.286	1.077	1.106
	Auto	-1175.324	1.583	1.591	-1124.404	1.522	1.547
	Bank	-1450.203	1.956	1.967	-1348.861	1.826	1.855
	FMCG	-974.362	1.315	1.326	-909.579	1.235	1.264
	Realty	-2044.432	2.752	2.760	-1976.915	2.668	2.693

Table V

ARCH Test for EGARCH(1,1)						
Indices	**lags**	**F- statistics**	**P-value**	**obs R-squared**	**P-value**	**Inference**
Nifty	1	2.4837	0.1152	2.4829	0.1151	No ARCH
	2	1.3258	0.2659	2.6522	0.2659	No ARCH
Auto	1	0.4464	0.5042	0.4468	0.5038	No ARCH
	2	0.2277	0.7964	0.4562	0.7960	No ARCH
Bank	1	0.1105	0.7396	0.1107	0.7394	No ARCH
	2	0.0556	0.9459	0.1114	0.9458	No ARCH
FMCG	1	0.0041	0.9491	0.0041	0.9491	No ARCH
	2	0.1410	0.8685	0.2824	0.8683	No ARCH
Realty	1	0.4740	0.4912	0.4745	0.4909	No ARCH
	2	0.5575	0.5728	1.1164	0.5722	No ARCH

Table VI

ARCH Test for GARCH(1,1)						
Indices	**lags**	**F-statistics**	**P-value**	**obs R-squared**	**P-value**	**Inference**
Nifty	1	2.7148	0.0996	2.7135	0.0995	No ARCH
	2	1.9403	0.1440	3.8782	0.1438	No ARCH
Auto	1	2.2660	0.1325	2.2656	0.1323	No ARCH
	2	1.2175	0.2963	2.4360	0.2958	No ARCH
Bank	1	1.4955	0.2216	1.4960	0.2213	No ARCH
	2	0.7623	0.4668	1.5262	0.4662	No ARCH
FMCG	1	0.0000	0.9968	0.0000	0.9968	No ARCH
	2	0.1564	0.8552	0.3134	0.8550	No ARCH
Realty	1	0.0002	0.9888	0.0002	0.9888	No ARCH
	2	0.0428	0.9581	0.0857	0.9581	No ARCH

Table VII

ARCH Test for TGARCH(1,1)						
Indices	**lags**	**F- statistics**	**P-value**	**obs R-squared**	**P-value**	**Inference**
Nifty	1	2.7241	0.0991	2.7228	0.0989	No ARCH
	2	1.4201	0.2420	2.8404	0.2417	No ARCH
Auto	1	0.2053	0.6505	0.2056	0.6502	No ARCH
	2	0.1424	0.8673	0.2852	0.8671	No ARCH
Bank	1	0.7436	0.3886	0.7442	0.3883	No ARCH
	2	0.5652	0.5684	1.1318	0.5679	No ARCH
FMCG	1	0.0073	0.9319	0.0073	0.9318	No ARCH
	2	0.1958	0.8222	0.3922	0.8219	No ARCH
Realty	1	0.0004	0.9844	0.0004	0.9844	No ARCH
	2	0.0090	0.9910	0.0181	0.9910	No ARCH