© Apeejay Journal of Management and Technology
January 2016 ,Vol.11 ,No:1

UNFOLDING VOLATILITY AND LEVERAGE EFFECT: A COMPARISON OF S&P BSE SENSEX AND NIFTY50

Vishal Sood*
Harmender Singh Saluja**

Indian stock market in recent years had witnessed an extravagant growth generating interests among foreign as well as domestic investors. This is likely to instigate some inquiry of the market dynamics, particularly of the volatility in the index returns. Volatility might come from within the economy itself in the sense that sectoral volatility or the shocks generated in any sector might be transmitted to the market index, making it volatile. However, in the new era of high trade and financial integration, much of the volatility in any market index could be attributed to the long and short-term dynamic linkages among different markets. The aim of this paper is to identify the volatility and leverage effect caused to BSE SENSEX and NIFTY50, if any for Indian stock market in recent years. The study compares volatility clustering using GARCH (1, 1) and GARCH –M (1, 1) model using Akaike Info Criterion (AIC) and Schwarz Info Criterion (SIC) to judge the authenticity of models. Leverage effects is studied and compared using T-GARCH and E-GARCH models and comparing both on the basis of AIC and SIC criteria.

Keywords: Volatility; Leverage, ARCH Models; Akaike Info Criterion (AIC); Schwarz Info Criterion (SIC); Regression Model.

INTRODUCTION

Indian stock market during the past few years had witnessed a tremendous growth generating interests among various foreign as well as domestic investors. This is likely to instigate some inquiry of the market dynamics with respect to the volatility of index returns. Volatility might come from within the economy and its determinants in the sense that sector wise volatility or the shocks generated in any sector might be transmitted to the market index making the prices and returns volatile. However, in the new era of high trade and financial integration, much of the volatility in any market index could attribute to the long and short-term dynamic linkages among different markets. The discovery of leverage effect is closely relates to the study of stochastic volatility and corrections in the underlying. The "leverage effect" refers to the well-established relationship between stock returns and both implied and realized volatility. It is witnessed that when volatility increases when the stock price falls and vice a versa. A standard explanation ties the phenomenon to the effect a change in market valuation of a firm's equity has on the degree of leverage in its capital structure, with an increase in leverage producing an increase in index volatility (Andersen and Bollerslev, 1998).

Although for very low frequency data, such as monthly or yearly asset returns, the assumption of homogeneity seems not to be entirely unreasonable the increasing frequency of observed data in studies suggests heterogeneity in volatility, in other words, time-varying volatility as pointed out by the returns (Mandelbrot, 1963; Fama, 1965 and Officer, 1973). The other finding had profound implications in both the theory and practice of financial economics and econometrics. It has inspired new model building, such as the emergence of ARCH models and the later Stochastic Volatility models. Modeling volatility as a separate process allows the study of its relation with the associated return process, which leads to the discovery of asymmetric volatility (Engle, 1982, 2000; Bollerslev 1986; Andersen, Bollerslev, Diebold, and Ebens, 2001).

The primary study documented the volatility asymmetry, and gave an explanation based on the Leverage Effect. A drop in the value of the stock has negative return that increases the financial leverage (debt-to-equity ratio), which makes the stock more risky and increases its volatility (Black, 1976 and Christie, 1982). Since then, "Leverage Effect" has been taken to be synonymous with asymmetric volatility. Financial leverage itself, however, seems not enough to explain either the large magnitude of the effect of declines in current price on future volatility, or the phenomenon that the asymmetry of market index returns is generally larger than that for individual stocks (Figlewski; Wang, 2001; Kim and Kon, 1994).

Volatility

Volatility clustering is determined as the observation that, large revision in prices/ returns in stocks tend to be followed by large changes, up or down in prices. The small changes tend to be followed by small changes in prices/ returns. These trends might be caused due to continuous effect of the external shocks (Mandelbrot, 1963). The ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models describe the phenomenon of volatility clustering to be more accurate measure of risk. ARCH model explained the regularity of the return in the time series data. GARCH model explained the heteroscedasticity of the Return Sequence residuals.

Leverage Effect

It was discovered that the current return and future volatility have negative correlation among themselves, which indicates that bad news will cause violent fluctuations as compare to good ones and hence termed as Leverage Effects (Black, 1976). In other words it may be said that, positive and negative information lead to different level of effect to volatility in stock returns. EGARCH model analyzes the effect on stock volatility caused by asymmetric conditional heteroskedasticity on absorbing different information in the market (Nelson, 1991). The use of GJR-GARCH model adds seasonal terms to distinguish the positive and negative shocks (Glosten, Jagannathan and Runkle, 1993).

This paper attempts to study the uncertainty of the financial assets relating to the daily closing index prices of S&P CNX SENSEX and NIFTY50 of the two leading Indian stock markets. The study unfolds the impact of S&P CNX SENSEX on NIFTY50 and vice a versa using regression model. The study also an attempt’s to calculate volatility and leverage effect prevailing in the S&P CNX SENSEX and NIFTY50 indices. The chosen variables estimate mean models and suggest which residuals had white noise and having the ARCH effect among them. ARCH effect indicates the time series variables or the residuals that are produced through the initial models and shows wide swings with respect to center line. The ARCH effect or such influence is evidently persistent for long time in future. The empirical analysis also tried to capture this effect through different GARCH type models as high variability and high volatility has been seen in daily indices returns. The GARCH type models are the better models in describing return series having the property of changing variance level. It has been tested statistically and empirically (Mittal et. al., 2012). A comparison of Volatility clustering is checked using GARCH (1, 1) and GARCH- M (1, 1) models. The Leverage in pricing is checked using T- GARCH and GJR GARCH model. The efficiency of the volatility and leverage model is checked on the basis of Akaike Info Criterion (AIC) and Schwarz Info Criterion (SIC).

REVIEW OF LITERATURE

Volatility and Leverage effect are the two vital terms to study market inconsistencies and trends that prevail for a prolonged period. It is observed that when volatility smiles the markets soars and when markets roar the volatility fades away. Hence volatility hold a key in deciding investor’s destiny and various studies empirical analysis were carried in measuring it. Leverage has a greater role to play in managing volatility when investors tend to shuffle their positions. The study investigated that, the volatility of Athens Stock excess returns over the period 1990-1999 through the comparison of various conditional Heteroskedasticity models. The empirical results indicated that there was significant evidence for asymmetry in stock returns which is captured by a quadratic GARCH specification model (Apergis and Eleptherine, 2001). The study examined the ability of rational economic factors to explain stock market volatility and proposed a simple model of the economy under uncertainty, which identified four determinants of stock market volatility viz. uncertainty about price level, the riskless rate of interest, the risk premium on the equity and the ratio of expected profits to expected revenues. Their results were useful in explaining the past behavior of stock market volatility and in forecasting future volatility (Binder and Merges, 2001).

It was examined through the study that, the time variation in volatility in the Indian stock market during 1979-2003 identified sudden shifts in the stock price volatility and nature of events that cause these shifts in volatility. The study revealed that the period around the BOP crisis and subsequent initiation of the economic reforms in India were the most volatile period in the stock market, it was also concluded that FII entry in particular does not have any direct implication in the stock return volatility. Level of volatility does not show much change during pre and post liberalization (Batra, 2004). The researcher examined the integration behavior and volatility spillover transmission across the stock markets of Sri Lanka, India and Pakistan after liberalization policies initiated in the early 1990's examined the ways in which two issues could relate to movement of stock prices and then investigated the impact of this on the corresponding stock markets using correlation analysis, a multivariate Co-Integration Test and Generalized Impulse Response (GIR) functions based on one factor model (Gunasinghe, 2005).

The empirical analysis investigated the Heteroskedastic behavior of Indian Stock Market by using different GARCH models. The study investigated the asymmetric volatility in Indian Stock Market by employing EGARCH and concluded that, volatility is an asymmetric function of past innovation raising proportionately more during market decline and was evidenced that return is not significantly related to risk (Karmarkar, 2007). Another study used GARCH- class models to two major Stock Exchanges of Indian Stock Market to analyze their characteristics of volatility and found significant ARCH effects. The study also demonstrated the existence of leverage and asymmetric effect in Indian Stock Market (Srivastava, 2008).

The study used GARCH class models ranging from Simple-GARCH (1, 1) to relatively complex GARCH models like EGARCH and TGARCH for modeling the volatility and forecasting the conditional variance of BSE SENSEX-30 demonstrating negative news has long term volatility than good news in the market (Srinivasan and Ibrahim, 2010). The investigation used number of forecasting models like Random Walk, Linear Regression, Moving Average, Autoregressive models on NSE daily returns to evaluate the forecasting performance of the same the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) for testing the return characteristics found that the success or failure of a particular type of forecasting model applied to one type of market carries over to different market are affected by the quality of volatility forecasts and the markets shows high volatility on the basis of information (Srinivasan et. al., 2010).

The study used time varying variance based GARCH process to capture change in volatility and study its impact on Indian Securities Market that compared the change in volatility of Indian Stock Market with U.S.Stock Market (Rastogi and Srivastava, 2011). It was identified using GARCH models that the Indian Stock Market Volatility accounts for asymmetry the study revealed the presence of leverage effect in the stock market and showed the smaller shocks that affect the returns in Indian Stock Market due to news impact (Krishnan and Mukherjee, 2010). The research investigated the stock market volatility in emerging stock markets of India and China using daily closing price and concluded the presence of non-linearity through BDSL test while conditional heteroskedasticity was identified through ARCH-LM test. The findings revealed that the GARCH (1, 1) MODEL successfully captures the non linearity and volatility clustering (Joshi, 2010).

The research estimated the volatility of BSE-500 stock index and its related stylized facts over 10 periods using ARCH models The study concluded that GARCH(1, 1) MODEL explains the volatility of Indian Stock Market and its stylized facts including volatility clustering, fat tail and mean reverting satisfactorily (Goudarzi and Ramanarayan, 2010). An empirical study analyzed the Chinese Stock Market behavior by choosing the data from Shanghai Composite Index and Shenzen Stock Index and used ARIMAEARCH- M (1, 1) and ARIMA-TARCH (1,1) model to analyze the volatility of financial time series with the characteristics of clustering, asymmetry, and peak and fat tails. Another study investigated the asymmetric nature of U.S.Stock Market return and effect of heteroskedasticity on stock return volatility. The research also analysed the relationship between stock return, conditional volatility and standard residuals. GARCH (1, 1) and TGARCH (1, 1) to test the heteroskedasticity and asymmetric nature of stock market returns respectively and concluded the presence of non neariy, heteroskedastic effect and asymmetric nature of stock returns (Kumar and Dhankar, 2011).

In another study it was concluded that, multivariate VAR-EGARCH model to examine the return and volatility dynamics between their traded adjusted equity returns from Ghana, Kenya, Nigeria and South Africa. The findings suggested reciprocal return spill over between Ghan and Kenya and between Nigeria and South Africa (Kuttu, 2014). The study observed that volatility is higher in market downswings that in market upturns. This phenomenon is called asymmetric volatility and has been strongly investigated (Jackwerth and Vilkov, 2014).The study found the impact on the Australian stock market volatility is higher following negative shocks than following positive shocks of the same magnitude. The study concluded the resemblance with the previous findings in the US stock market (Tanha and Dempsey, 2015).

OBJECTIVES

To study Impact, Volatility and Leverage effect caused on S&P BSE SENSEX and NIFTY50.

RESEARCH METHODOLOGY

Hypothesis H_{01}: To study the impact of S&P BSE SENSEX on NIFTY50.

H_{02}: The returns of S&P BSE SENSEX and NIFTY50 are not normally distributed.

H_{03}: The returns of S&P BSE SENSEX and NIFTY50 are non-stationary.

H_{04}: The returns of S&P BSE SENSEX and NIFTY50 are non- heteroscadestic.

H_{05}: There is no volatility caused in the returns of S&P BSE SENSEX and NIFTY50.

H_{06}: There is no leverage effect caused in the returns of S&P BSE SENSEX and NIFTY50.

H_{07}: There is no ARCH effect in the returns of S&P BSE SENSEX and NIFTY50.

The Sample

The daily stocks values of S&P BSE SENSEX and NIFTY50 have been taken from the period 2nd January 2008 to 31st December 2015. There are 3988 observations of the daily closing prices.

The Tools

Descriptive Analysis, Unit Root Test, Regression, Test of Hetroscedasticity, ARCH family test i.e. GARCH (1, 1), GARCH- M (1, 1), E-GARCH (1, 1), and T-GARCH (1, 1), models are used in the study. The tools are applied using E- views 7 statistical software. The time series data is Heteroscedastic and by applying the tool that is: Returns= ln (Pt- Pt-1), we convert data into homoscedastic data.

RESULTS AND ANALYSIS

The Descriptive statistics calculated in Table- 1 using log returns of S&P BSE SENSEX and S&P CNX Nifty have the positive Mean (X) i.e. 0.000125 and 0.000129 indicating that prices has gradually increasing over the period. The skewness in descriptive statistics shows that the returns are positively skewed, indicating that there is a low probability of earning returns as the values are 0.214628 and 0.105996 indices values are >Mean. Standard Deviation is a measure shedding light on historical values of volatility and the calculated values are lower implying low volatility in index returns as the values are 0.015680 for S&P BSE SENSEX and 0.015607 for Nifty50. The Kurtosis of the series is 12.75396 and 14.07636 > 3, indicating that the return series have fat tail and does not follow a normal distribution and is further confirmed by Jarque- Bera test statistics, which is significant at 5% level as p value for all variables are 0. Hence the null hypothesis stating that the variables are not normally distributes is accepted.

Table 1. General statistical tools applied using Descriptive Statistics

DESCRIPTIVE STATISTICS		
	LOGBSE	**LOGNSE**

Mean	0.000125	0.000129
Median	0.000417	0.000419
Maximum	0.159900	0.163343
Minimum	-0.116044	-0.130142
Std. Dev.	0.015680	0.015607
Skewness	0.214628	0.105996
Kurtosis	12.75397	14.07636
Jarque-Bera	7768.920	10002.56
Probability	0.000000	0.000000
Sum	0.243876	0.251492
Sum Sq. Dev.	0.480690	0.476183
Observations	1956	1956

Source: Author's calculation based on Secondary Data using e- Views7.

The Regression Analysis studies the impact of S&P BSE SENSEX on NIFTY50 and vice a versa as shown in Table- 2. It was observed that r^2 in both the cases were 0.978471 indicating 97.85% when NIFTY50 was studied as dependent and independent variable against S&P BSE SENSEX. The p value is smaller than 0.05 indicating that there is a very high impact of dependent variables on independent variables and the null hypothesis of no impact is rejected. Hence it is concluded that both the studied variables complement each other.

Table2. Impact of variables using Regression Model

Regression					**Regression**				
Dependent Variable: LOGBSE					**Dependent Variable: LOGNSE**				
Method: Least Squares					**Method: Least Squares**				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Variable**	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-3.10E-06	5.20E-05	-0.05961	0.9525	**C**	5.82E-06	5.18E-05	0.112415	0.9105
LOGNSE	0.993847	0.003335	298.0047	0	**LOGBSE**	0.984529	0.003304	298.0047	0
R-squared	0.978471	**Mean dependent var**		0.000125	**R-squared**	0.978471	**Mean dependent var**		0.000129
Adjusted R-squared	0.97846	**S.D. dependent var**		0.01568	**Adjusted R-squared**	0.97846	**S.D. dependent var**		0.015607
S.E. of regression	0.002301	**Akaike info criterion**		-9.30962	**S.E. of regression**	0.002291	**Akaike info criterion**		-9.31904
Sum squared resid	0.010349	**Schwarz criterion**		-9.30391	**Sum squared resid**	0.010252	**Schwarz criterion**		-9.31333
Log likelihood	9106.805	**Hannan-Quinn criter.**		-9.30752	**Log likelihood**	9116.018	**Hannan-Quinn criter.**		-9.31694
F-statistic	88806.79	**Durbin-Watson stat**		2.026416	**F-statistic**	88806.79	**Durbin-Watson stat**		2.055365

Prob (F-statistic)	0	**Prob (F-statistic)**	0

Source: Author's calculation based on Secondary Data using e- Views7.

Table 3 below shows the presence of unit root in the series tested using Augmented Dickey Fuller Test (ADF) and the presence of heteroscedasticity tested using ARCH lm test. The p values of ADF for S&P BSE SENSEX and NIFTY50 are 0.000< 0.05 concluding that the data of the time series for the entire study period is stationary. The ADF test statistics reported in table 3 reject the hypothesis at 5% level with the critical value of -41.12783 and -41.72688 for ADF tests of a Unit Root in the return series. Hence, the hypothesis suggesting that the data is non stationary is rejected and the data is stationary.

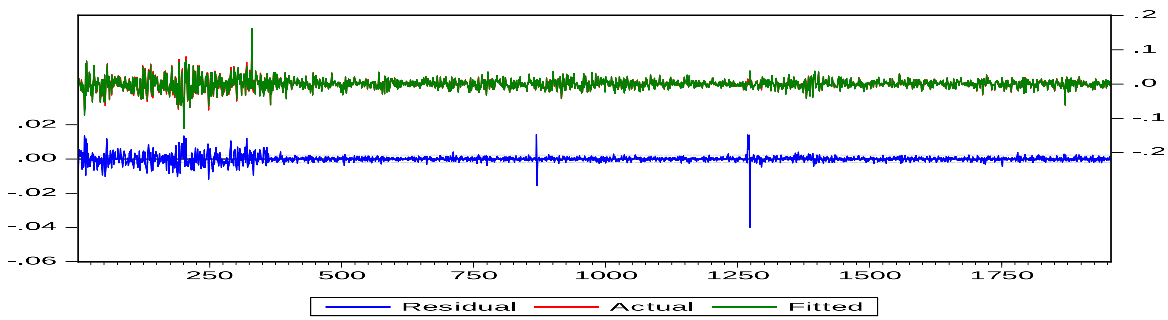
Table3. Result of Unit Root Test and Heteroskedasticity Test: ARCH

Unit Root Test		
	Augmented Dickey-Fuller Test (ADF)	
Value	**BES SENSEX**	**NIFTY50**
t- statististics	-41.12783	-41.72688
Prob.	0	0
	Critical Value	
1%	-3.433495	-3.433495
5%	-2.862816	-2.862816
10%	-2.567496	-2.567496
	Heteroskedasticity Test	
ARCH- LM Test	45.57814	43.45982
Prob.	0.713	0.8122

Source: Author's calculation based on Secondary Data using e- Views7.

Figure 1 shows volatility clustering of return series of the S&P BSE SENSEX and NIFTY50 for the study period ranging from 2nd January 2007 to 31st December 2015. The figures inferred that the period of low volatility tends to be followed by period of low volatility for a prolonged period indicates that, the volatility is clustering and the return series vary around the constant mean but the variance is changing with time at a greater pace. The ARCH- lm test in the table- 3 above confirms the presence of ARCH effect in the residuals of the return series. From the table 3, it is confirmed that the ARCH- lm test statistics is highly significant. Since p values for 0.8130 S&P BSE SENSEX and 0.8122 NIFTY50 are > 0.05, the null hypothesis of 'no arch effect' is rejected at 5% level, confirming the presence of ARCH effects in the residuals of time series models. Hence the results warrant for the estimation of GARCH family models as the data is model fit.

Figure 1. Indicating white noise and trend of prices



© Apeejay Journal of Management and Technology
January 2016 ,Vol.11 ,No:1

Source: Author's calculation based on Secondary Data using e- Views7.

The conformation of volatility clustering is evident in the return series; ADF test suggest the data used in the study is stationary; and non heteroscedasticity effect was confirmed using ARCH-lm test. The study focuses on determining the best fitted GARCH (1, 1) model in the return series. Therefore, GARCH model used for modeling the volatility of return series in the Indian stock market was studied using indices of S&P CNX SENSEX and NIFTY50 in table 4 reveals the parameter of GARCH is statistically significant. In other words, the coefficients viz., constant (ω), ARCH term (α), GARCH term (β) is highly significant at 5% level as p- value 0< 0.05. In the conditional variance equation, the estimated β values are 0.907123 and 0.899505 that is considerably greater than α value 0.084586 and 0.091627 indicating that, the market has long term memory towards reaction of change and the volatility is more sensitive to its lagged values than it is to new surprises in the market values. It shows that, the volatility is persistent and caries for a long period of time in future. The sizes of the parameters α and β determine the volatility in time series. The sum of these coefficients (α and β) are 0.991709 and 0.991132 closer to unity indicating that the shock will persist too many future periods. Since the risk-return parameter is positive and significant at 5% level, it shows that, there is a positive relationship between risk and return. Further, ARCH-lm test is employed to check ARCH effect in residuals and from the results, have p values 0.4467 and 0.5037 > 0.05, stating that the null hypothesis of 'no ARCH effect' is accepted. In other words, the test statistics do not support for any additional ARCH effect remaining in the residuals of the models, which implies that the variance equation is well specified for the market.

Table 4. Volatility and ARCH affect using GARCH (1, 1) Model

GARCH (1,1) Model		
Coefficients	**BES SENSEX**	**NIFTY50**
Mean Equation		
μ (Constant)	0.000547 (0.0287)	0.000615 (0.0141)
□(Risk Premium)	-	-
Variance Equation		
ω (Constant)	2.03E-06 (0)	2.45E-06 (0)
α (ARCH Effect)	0.084586 (0)	0.091627 (0)
β (GARCH Effect)	0.907123 (0)	0.899505 (0)
α+ β	0.991709	0.991132
Log Likelihood	5779.818	5751.928
Akaike Info Criterion (AIC)	-5.905744	-5.877226
Schwarz Info. Criterion (SIC)	-5.894336	-5.865818
Heteroskedasticity Test		
ARCH- LM Test	0.578963	0.447065
Prob. Chi. Square	0.4467	0.5037

Source: Author's calculation based on Secondary Data using e- Views7.

The GARCH- M (1, 1) model is estimated by allowing the mean equation of the return series to depend on a function of the conditional variance and suggesting the presence of volatility in the studied variables. The constant in mean equation is significant at 5% level, indicating that there is an abnormal return for the market. Table 5 inferred that the coefficient of conditional variance (λ) in the mean equation value is positive 0.057567 and 0.000148 respectively. However, it is statistically insignificant, which implies that there is no significant impact of volatility on the expected return, indicating lack of risk-return and trade off over time in the returns of the two indices. In the variance equation of GARCH- M (1, 1), the parameters viz., constant (ω), ARCH term (α), GARCH term (β) are highly significant at 5% level as p values are less than 0.05. The sum of α and β are 0.991553 and 0.991014 suggesting that, shocks will persist in the future period for long time. However, the ARCH-lm test applied on residuals have p values 0.4352 and 0.5016 shows that, the test statistics do not exhibit additional ARCH effect for the entire study period indicating that the variance equation is well specified.

Table5. Volatility and ARCH affect using GARCH M (1, 1) Model

GARCH – M (1,1) Model		
Coefficients	**BSE SENSEX**	**NIFTY50**
	Mean Equation	
μ (Constant)	0.0000607 (0.937)	0.043233 (0.5506)
□(Risk Premium)	0.057567(0.4108)	0.000148 (0.8529)
	Variance Equation	
ω (Constant)	2.07E-06 (0)	2.48E-06 (0)
α (ARCH Effect)	0.085167 (0)	0.092027 (0)
β (GARCH Effect)	0.906386 (0)	0.898987 (0)
α+ β	0.991553	0.991014
Log Likelihood	5780.164	5752.117
Akaike Info Criterion (AIC)	-5.905076	-5.876397
Schwarz Info. Criterion (SIC)	-5.890815	-5.862137
	Heteroskedasticity Test	
ARCH- LM Test	0.608988	0.451501
Prob. Chi. Square	0.4352	0.5016

Source: Author's calculation based on Secondary Data using e- Views7.

In order to capture the asymmetries in the return series, two models have been used viz., EGARCH- M (1, 1) and TGARCH (1, 1). γ captures the asymmetric effect in both EGARCH- M (1, 1) and TGARCH (1, 1) models. TGARCH (1, 1) model is the test for asymmetric volatility in the S&P BSE SENSEX and NIFTY50 returns shown in table 6 and the study estimated the result of coefficient's leverage effect (γ) is positive and significant at 5% level as the p values are less than 0.05. The study implies that negative shocks or bad news have a greater effect on the conditional variance than the positive shocks or good news because γ values are 0.934847 and 0.925047 is statistically significant at 5% level. The ARCH-lm test statistic for TGARCH (1, 1) model does not show any additional ARCH effect present in the residuals of the model as p values are 0.2224 and 0.2145 greater than 0.05concluding that, the variance equation is well specified for the Indian stock market.

Table6. Volatility, Leverage and ARCH affect using TGARCH Model

TGARCH Model		
Coefficients	**BES SENSEX**	**NIFTY50**
	Mean Equation	
μ (Constant)	0.000239 (0.3356)	0.000239(0.3389)
		Variance Equation
ω (Constant)	2.20E-06 (0)	2.54E-06 (0)
α (ARCH Effect)	0.030255 (0)	0.027765 (0)
β (GARCH Effect)	0.904592 (0)	0.897282 (0)
γ (Leverage Effect)	0.113875 (0)	0.134324 (0)

α+ β	0.934847	0.925047
Log Likelihood	5800.395	5777.115
Akaike Info Criterion (AIC)	-5.925761	-5.901958
Schwarz Info. Criterion (SIC)	-5.911501	-5.887698
Heteroskedasticity Test		
ARCH- LM Test	1.488525	1.540972
Prob. Chi. Square	0.2224	0.2145

Source: Author's calculation based on Secondary Data using e- Views7.

The asymmetrical EGARCH (1, 1) model is used to estimate the returns of the S&P BSE SENSEX and NIFTY50 presented in table 7. The results reveal that ARCH (α) and GARCH coefficient (β) are smaller than one i.e. 0.970813 and 0.934458 reporting that conditional variance is not explosive and there is no abnormal increase or decrease in prices but a gradual movement is observed. The estimated coefficients are statistically significant at 5% level as p value is less than 0.05. γ indicating the leverage coefficient, is negative -0.084722 and -0.099528 indicating the study is statistically significant at 5% level and explains the presence of leverage effect in return during the study period. The analysis reveals that there is a negative correlation between past returns and future returns (leverage effect). Hence, EGARCH (1, 1) model supports the presence of leverage effect on the S&P BSE SENSEX and NIFTY50 returns series. Finally, the ARCH-lm test statistics reveals that the null hypothesis of no heteroscedasticity in the residuals is accepted as p values are 0.2847 and 0.2997 > 0.05.

Table- 7: Volatility, Leverage and ARCH affect using E GARCH Model

EGARCH Model		
Coefficients	BES SENSEX	NIFTY50
Mean Equation		
μ (Constant)	0.000244 (0.3079)	0.000255 (0.2684)
Variance Equation		
ω (Constant)	-0.248647 (0)	-0.28047 (0)
α (ARCH Effect)	0.044636 (0)	0.031376 (0)
β (GARCH Effect)	0.926177 (0)	0.903082 (0)
γ (Leverage Effect)	-0.084722 (0)	-0.099528 (0)
α+ β	0.970813	0.934458
Log Likelihood	5806.728	5781.298
Akaike Info Criterion (AIC)	-5.932238	-5.906235
Schwarz Info. Criterion (SIC)	-5.917977	-5.891975
Heteroskedasticity Test		
ARCH- LM Test	1.144462	1.075482
Prob. Chi. Square	0.2847	0.2997

Source: Author's calculation based on Secondary Data using e- Views7.

ANALYSIS AND INTERPRETATION

Based on the results shown in tables, the study reveals that, positive returns of the mean indicates that there is a gradual increase in the returns of S&P BSE SENSEX and NIFY50 by time. As the data is positively skewed there is a low probability of earning returns for investors in shorter period of time. The smaller standard deviation reveals that the prices are tightly bunched around the mean. The lower standard deviation denotes lesser dispersion and lesser risk of investment. Hence the values are indicating that investors should invest their funds in index for shorter time periods instead of long term. There exists low volatility for a prolonged period as indicated in figures and this is indicative for a prolonged period in the years to come. For arbitragers it is good to observe frequent corrections in the prices and the low volatility can help them frame decision to invest in bulk and book profits on small revision at a larger pace. Whereas it was observed that, in the present study the peaks and corrections are not too high resulting in low volatility and investors can make profits on short term investments and revisions.

The studied data are stationary and there is no serial correlation observed in the returns of NSE and BSE Indices. There is an ARCH affect and the prices are showing volatility that can be studied using GARCH family test. There is a strong relation with volatility and market performance. Volatility tends to decline when stock market rises and increases when market falls. In GARCH (1, 1) model, the sum of the coefficient ($\alpha + \beta$) is closer to unity implying that the volatility is highly persistent. This remains for a very short period and the returns have lesser percentage change and low correction in prices but the effect is for a long period of time. In GARCH- M (1, 1) model, the coefficient of conditional variance or risk premium (λ) in the mean equation is positive. This is however insignificant, implying that higher market risk provided by conditional variance will not necessarily lead to higher returns. Hence investors should have a close watch on volatility to identify new bottom and top in terms of price innovation in the market. It can be said that volatility of the market does not stay substantially below mean for a long period of time and as volatility increases the market performance will decrease which is buying signals for the players in the market.

The asymmetric effect captured by TGARCH model infers that the coefficient of leverage effect (γ) is positive and significant at 5% level, providing the presence of leverage effect during the study period. Thus it can be said that, the market is more reluctant to change while absorbing the negative news like inflation, interest rates, currency pricing, unemployment etc. innovate price quickly for long period of time. Leverage effect is a ratio of debt and equity greater risk or volatility or variance of firm when leverage effect is higher. Hence when negative news hit the market investors park there funds in less riskier asset and the shift is observed in the market. The asymmetric effect captured by the parameter (γ) in EGARCH model which is negative and statistically significant at 5% level providing the presence of leverage effect, which reveals that positive shocks have less effect on the conditional variance when compared to the negative shocks. Markets are quick to sense negative information and have competency to change itself and adopt bear run. The best fitted models both in symmetric as well as in asymmetric effect are selected on the basis of minimum AIC and SIC value and the highest log likelihood value. Likewise, the AIC, SIC value between GARCH (1, 1) and GARCH- M model is low in GARCH (1, 1) model log likelihood value is high in GARCH (1, 1) model. Thus GARCH (1, 1) model is found to be the best fitted model in terms of observed volatility. On comparing EGARCH and TGARCH it was concluded that, the AIC, SIC values are low in TGARCH and log likelihood value is also higher than EGARCH. Hence it conforms that, EGARCH (1, 1) model is apparently seems to be an adequate description of asymmetric volatility process.

CONCLUSION

In the study, volatility of S&P BSE SENSEX and NIFTY50 returns were tested using symmetric and asymmetric GARCH models. The regression model states high impact of S&P BSE SENSEX on NIFTY50 returns and vice- versa. It can be inferred that both complement each other and have competency to shape price change. The study confirms the unit root rest and the presence of volatility clustering along with ARCH effect. Higher the volatility that comes with bear market has direct impact on portfolios by pushing the prices of index downward. The study unearthed the facts that, GARCH (1, 1) model has been found to be the best fitted model among all to capture the symmetric effect as per AIC, SIC criterion and likelihood basis. Further, EGARCH (1,1) model is found to be the best fitted model to capture the asymmetric volatility based on the highest log likelihood ratios and minimum AIC and SIC criterion. The overall conclusion of the study supports the findings of previous research studies carried by (Zivanayi and Chinzara, 2012; Zakaria and Winker, 2012) and more particularly the study differs in the way of selecting the appropriate model using diagnostic test. Nevertheless, the results presented in the study in the above tables are in contrary to the research findings of (Karmakar, 2007) where the risk premium is significant. On a whole, the study concludes that increased risk did not increase the returns since the coefficient is insignificant for the selected variables for the study period.

SUGGESTIONS

It is suggested that impact and volatility add to the level of concern and worry on the part of investors as they watch the value of their portfolios move more violently due to price revision. Both the indices complement each other and apparently shape price in the market at large. Index is communicating the average performance of stocks listed so they should also be a part of investment portfolios of investors to create hedging and imparting strength to portfolio. There is decrease in value of indices as volatility smiles and the returns increases as the volatility soars in the markets. This causes irritation in the responses which can increase investor's losses in terms of holdings. Investors can also use volatility to help them buy lower than they might have otherwise in terms of price fixation. Leverage effect can help investors to create a combination of debt and equity where by position can be revised depending on the performance of risky and risk free assets. Investors are recommended to keep a close eye on the changing price dynamics and should react to the signals or indication given by markets on timely basis to reduce losses and overcome frustration of investments.

REFERENCES

Apergis, N. & Eleptheriou, S. (2001). Stock Market Volatility: Evidence from Athens Stock Market Index. *Journal of Economics and Finance, 25(1),* 50- 61.

Andersen, T. G. and T. Bollerslev (1998). Answering the Skeptics: Yes, Standard Volatility Models do Provide Accurate Forecasts. *International Economic Review, 39,* 885-905.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and H. Ebens (2001) The Distribution of Realized Stock Return Volatility. *Journal of Financial Economics, 61,* 43- 76.

Batra, A. (2004). Stock Return Volatility Persistence in India: 1973- 2003. *Working Paper ICRIER, New Delhi, India.* Sited at www.ssrn.com on 20th March 2016.

Binder,J and Merges, M. (2001). Stock Market Volatility and Economic Factors. *Review of Quantitative Finance and Accounting, 17(1)* 5-26.

Black, B. (1976). Studies of Stock Price Volatility Changes. *Proceedings of the 176 Meetings of the American Statistical Association, Business and Economic Statistics,* 177- 181.

Black, F. (1976). Studies of Stock Market Volatility changes. *Proceeding of the American Statistical Association, Business and Economic Statistics Section.* Sited at www.ssrn.com on 20th March 2016.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31,* 307-27.

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics, 10,* 407- 432.

Engle, R. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50,* 987-1007.

Fama, E. F., (1965). The Behavior of Stock-Market Prices. *The Journal of Business, 38, 34,* 105.

Figlewski, S. & X. Wang (2001). Is the 'Leverage Effect' a Leverage Effect? *Review of Financial Studies, 24,* 46- 81.

Goyal, R (1995). Volatility in Stock Market Returns. *Reserve Bank of India Occasional Papers, 16(3),* 175-195.

Gunasinghe, W, (2005). Behavior of Stock Markets in South Asia: An Econometric Investigation. *South Asia Economic Journal, 6,* 165-184.

Glosten, L., Jaganathan, R. & Runkle, D. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Returns on Stocks. *Journal of Finance 48,* 1779-1801.

Jackwerth, J. C., Vilkov, G., (2014). Asymmetric Volatility Risk: Evidence from Option Markets. *Available at SSRN:* http://ssrn.com/abstract=2325380 or http://dx.doi.org/10.2139/ssrn.2325380

Joshi, P. (2010). Modeling Volatility in Emerging Stock Markets of India and China. *Journal of Quantitative Economics, 8(1),* 59-64.

Karmarkar M. (2007). Asymmetric Volatility and Risk Return Relationship in the Indian Stock Market. *South Asian Economic Journal, 8(1),* 99-116.

Kim, D. & S. J. Kon (1994). Alternative Models for the Conditional Heteroscedasticity of Stock Returns. *Journal of Business, 67,* 563- 598.

Krishanan, R. & Mukherjee, C. (2010). Volatility in Indian Stock Market. *Journal of Emerging Market Finance, 9 (1),* 71-93.

Kumar, R. & Dhankar, R. (2011). Non Linearity and Heteroskedasticity Effects on Stock Market Volatility: A Case of U.S. Stock Market. *Global Business Review, 12 (2),* 319-329.

Kuttu, S. (2014). Return and Volatility Dynamics among Four African Equity Markets: A Multivariate VAR-EGARCH Analysis. *Global Finance Journal, 25,* 59-64.

Mandelbrot, B. (1963). The Variation of Certain Speculative Prices. *Journal of Business 36,* 394-419.

Mittal, A.; Arora, D. & Goyal. N. (2012). Modeling the Volatility of Indian Stock Market. *Gitam Journal of Management 10 (1),* 224–43.

Nelson, D. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica, 59,* 347-370.

Officer, R. R. (1973). The Variability of the Market Factor of the New York Stock Exchange. *The Journal of Business, 46,* 434- 453.

Rastogi,S. & Srivastava, V. (2011). A Comparitive Study of Conditional Volatility of Indian and U.S. Stock Markets using GARCH (1, 1) Models. *Asia Pacific Journal of Management Research and Innovation,7 (1),* 92-101.

Srinivasan, P. & Ibrahim, P. (2010). Forecasting Stock Market Volatility of BSE-30 Index Using GARCH Models. *Asia Pacific Journal of Management Research and Innovation, 6, (1),* 47-60.

Srinivasan, K.; Deo, M. & Murugesan, B. (2010). Testin Alternative Models for Forecasting Volatility in Stock Markets. *Asia Pacific Journal of Management Research and Innovation, 6 (4),* 95-104.

Srivastava, A. (2008). Volatility of Indian Stock Market: An Empirical Evidence. *Asia Pacific Journal of Management Research and Innovation, 4 (4)*, 53-61.

Tanha, H. & Dempsey, M., (2015). The asymmetric response of volatility to market changes and the volatility smile: evidence from Australian options. *Research in International Business and Finance, 34(C)*, 164-176.

Zakaria, S. S. A., & Winker, P. (2012). Modelling Stock Market Volatility Using Univariate GARCHModels: Evidence from Sudan and Egypt. *International Journal of Economics and Finance 4 (8)*, 161–176.

Zivanayi, N. M., & Z. Chinzara. (2012). Risk-Return Trade-off and Behaviour of Volatility on the South African Stock Market: Evidence from Both Aggregate and Disaggregate Data. *South African Journal of Economics, 80 (3)*, 345–366.