Asymmetric Volatility and Performance of Indian Equity Market: Comparison of SENSEX and S&P CNX Nifty

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Abstract

Stock market volatility has its existence from the long time but its complete eradication is not possible, the only thing which can be done is just to know its behavior and pattern that how it behaves. The present study is aimed to understand the nature and different patterns of volatility in Indian equity market. The daily observations comprising of closing data of SENSEX of Bombay Stock Exchange and S&P CNX Nifty of National Stock Exchange for the period of 10 years i.e. from January 2003 to December 2012 is used for analysis. The data was collected from the websites www.bseindia.com and www.nseindia.com. The present study is attempted to examine the volatility of returns in Indian stock market. GARCH models were used to see the volatility of Indian equity market. It was found that there was spillover of information in the Indian stock market and with the significant coefficient of dummy in improved model. It was concluded that negative shocks do have greater impact on conditional volatility compared to positive shocks of the same magnitude in the Indian stock market.

Key words: Asymmetric Volatility, Indian Equity Market, SENSEX, S&P CNX Nifty

Introduction

Prediction of volatility of stock market is always a concern for the researchers, academicians and market analysts. The sensitivity of stock market is measured by different indices which check the health of equity market. Volatility has its connection with different variables which are responsible for its existence such as market information, global factors, market returns, investor sentiments etc. Stock market volatility has its existence from the long time but its complete eradication is not possible, the only thing which can be done is just to know its behavior and pattern that how it behaves. The present paper is a study to understand the nature and different patterns of volatility in Indian equity market.

Literature Review

Kaur (2004) investigated the nature and characteristics of stock market volatility in Indian stock market during 1993-2003 in terms of its time varying nature, presence of certain characteristics such as volatility clustering, day-of-the-week effect and calendar month effect and whether there exists any spillover effect between the domestic and the US stock markets. It was found that asymmetrical GARCH models outperformed the conventional OLS models and symmetrical GARH models. There was mixed evidence of return and volatility spillover between the US and the Indian markets and S&P 500 exhibited significant positive correlation only with Nifty returns, NASDAQ returns exhibited significant albeit weak positive correlation only with SENSEX.

Karmakar (2005) estimated conditional volatility models in an effort to capture the salient features of stock market volatility in India. The various GARCH models provided good forecasts of volatility. Because of the high growth of the economy and increasing interest of foreign investors towards the country, it has become inevitable to see the different stock market volatility patters.

Pandey (2005) believed that there are four possible approaches for estimating and forecasting volatility and there have been many extensions of the basic conditional volatility models to add in experiential characteristics of asset returns.

Karmakar (2007) investigated the heteroscedastic behaviour of the Indian stock market using GARCH models. Different econometric models like EGARCH were used to see whether volatility is asymmetric or not. It was found that the asymmetric volatility occurs because of impact of past information and it generally rise during the period when market declines

Léon (2007) studied the relationship between expected stock market returns and volatility in the regional stock market of the West African Economic and Monetary Union. The study revealed that expected stock return has a positive but not statistically significant relationship with expected volatility and volatility is higher during market booms than when market declines.

Bordoloi and Shankar (2008) explored to develop alternative models from the Autoregressive Conditional Heteroskedasticity (ARCH) or its Generalisation, the Generalised ARCH (G-ARCH) family, to estimate volatility in the Indian equity market return. For this purpose, two indices each from the two widely traded stock exchanges in India – the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) were selected. It was found that these indicators contain information in explaining the stock returns. The Threshold GARCH (T-GARCH) models were found to have explained the volatilities better for both the BSE Indices and S&P-CNX 500, while Exponential GARCH (EGARCH) models for the S&P CNX-Nifty. Evidence of increase in volatility due to certain negative factors has been found in all the equity markets.

Mahajan and Singh (2008) examined the empirical relationship between volume and return, and volume and volatility in the light of competing hypothesis about market structure by using daily data of Sensitive Index of the Bombay Stock Exchange. They emphasized trading volume as an important signal providing critical information that influences both future prices and price volatility. Thus, volume provides information on the precision and dispersion of information signals rather than serving as a proxy for the information signal itself.

Karmakar (2009) conducted Multivariate Co-integration tests on the long-run relation between these two markets and investigated the daily price discovery process by exploring the common stochastic trend between the S&P CNX Nifty and the Nifty future based on vector error correction model (VECM). The bivariate BEKK model showed that although the persistent volatility spills over from one market to another market bi-directionally, past innovations originating in future market have the unidirectional significant effect on the preset volatility of the spot market.

Mehta and Sharma (2011) discussed that Indian stock market has witnessed various confrontations during last two decades resulting into occurrence of alternate phases of the market cycle. They documented that the Indian equity market has witnessed the prevalence of time varying volatility where the past volatility has more significant impact on the current volatility.

Nawazish and Sara (2012) examined the volatility patterns in Karachi Stock Exchange using GARCH framework between 2004 and 2012. This implies that all estimates of risk in this period based on standard deviations must be flawed and would have understated the actual risk. They proposed that higher order moments of returns should be considered for prudent risk assessment.

Research Methodology

In view of above literary work, the study explored the volatility of Indian Stock markets taking sample of SENSEX and S&P CNX Nifty. Following was the objective of the study:

-To analysis the daily returns to monitor volatility changes on the SENSEX of Bombay Stock Exchange and S&P CNX Nifty of National Stock Exchange. The data used in this study consist of the daily closing points of SENSEX and S&P CNX Nifty over a decade for the period from January 2003 to December 2012 compiled from www.bseindia.com and www.nseindia.com. With this data set, we computed the daily returns as follows:

$$R_t = (In\, P_t - In\, P_{t-1}) * 100$$

Where Rt is the return in period t, Pt and Pt-1 are the daily closing prices of the SENSEX and S&P CNX Nifty at time t and t-1 respectively. It is also important to test stationarity of a series lest OLS regression results will be spurious. For testing stationarity, Unit Root Test was made; let us consider an AR (1) model:

$$\gamma_t = p_1\gamma_{t-1} + \varepsilon_t$$

The simple AR (1) model represented in equation (2) is called a *random walk model*. In this AR (1) model if $|p_1|<1$, then the series is I(0) i.e. stationary in level, but if $p_1 = 1$ then there exist what is called unit root problem. In other words, series is non-stationary. Most economists think that differencing is warranted if estimated $p > 0.9$; some would difference when estimated $p > 0.8$. Besides this, there are some formal ways of testing for stationarity of a series.

Daily returns series of SENSEX of Bombay Stock Exchange and S&P CNX Nifty of National Stock Exchange for the sampled period were analyzed in e-views 5. The *Summary of Descriptive Statistics* including Mean, Median, Maximum, Minimum value, Standard Deviation, Skewness, Kurtosis and Jarque-Bera tests etc were studied.

Augmented Dickey-Fuller and Phillips-Perron (PP) tests were applied to test the null hypothesis of a unit root. The *Unit Root Test* is a necessary condition to check the stationarity of the data set used in the study. The results of ADF and PP test for a unit root for SENSEX and S&P CNX Nifty Index were presented in Data Analysis section. The analysis and the results of the first twenty-four orders sample *Autocorrelation Coefficients and Ljung- Box Statistics* on return series of the SENSEX and S&P CNX Nifty for the sampled period were taken for checking the *Serial Correlation.*

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

In this model, the conditional variance is represented as a linear function of its own lags. The simplest model specification is the GARCH (1,1) model:

$$\textit{Mean Equation} \quad r_t = \mu + \varepsilon_t$$

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

$where\ \omega > 0\ and\ \alpha_1 \geq 0\ and\ \beta_1 \geq 0, and$

$r_t = return\ of\ the\ asset\ at\ time\ t$

$\mu = average\ return$

$\varepsilon_t = residual\ returns, defined\ as: \varepsilon_t = \sigma_t z_t$

The Exponential GARCH (E-GARCH) Model

This model captures asymmetric responses of the time-varying variance to shocks and, at the same time, ensures that the variance is always positive. It was developed by Nelson (1991) with the following specification

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

where γ is the asymmetric response parameter or leverage parameter. The sign of γ is expected to be positive in most empirical cases so that a negative shock increases future volatility or uncertainty while a positive shock eases the effect on future uncertainty.

The Threshold GARCH (T-GARCH) Model

Another volatility model commonly used to handle leverage effects is the threshold GARCH (or TGARCH) model. In the TGARCH (1,1) version of the model, the specification of the conditional variance is:

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

Where d_{t-1} $\textit{is a dummy variable, which is as follows}$: $\left\{ \begin{matrix} 1\ if\ \varepsilon_{t-1} \leq 0 & bad\ news \\ 0\ if\ \varepsilon_{t-1} \geq 0, & good\ news \end{matrix} \right\}$

the coefficient γ is known as the asymmetry or leverage term. When $\gamma = 0$, the model collapses to the standard GARCH forms. Otherwise, when the shock is positive (i.e., good news) the effect on volatility is α_1, but when the news is negative (i.e., bad news) the effect on volatility is $\alpha_{1+}\gamma$.

Data Analysis & Interpretation

Descriptive Statistics

A summary of descriptive statistics for returns series of SENSEX of Bombay Stock Exchange and S&P CNX Nifty of National Stock Exchange for the sample period from January 2003 to December 2012 is presented in **Table-1**. It includes various tests i.e. Mean, Median, Maximum, Minimum value, Standard Deviation, Skewness, Kurtosis and Jarque-Bera etc.

Table: 1 Descriptive Statistics of Returns (Sample Period: January 2003 to December 2012)

	SENSEX	S&P CNX Nifty
Mean	0.00071	0.00068
Median	0.00124	0.00136
Maximum	0.1599	0.16334
Minimum	-0.1181	-0.13054
Std. Dev.	0.01634	0.01658
Skewness	-0.0785	-0.25598
Kurtosis	10.8711	11.799
Jarque-Bera	6445.85	8027.86

The *Table-1* depicts the average daily return for SENSEX is found to be at 0.07% and the return for S&P CNX Nifty is .068%. The standard deviation of the return series is 1.6% daily for both SENSEX and S&P CNX Nifty annually. The coefficients of the Skewness are found to be significant and negative for all the returns. The negative Skewness implies that the return distributions of the shares traded in the market in the given period have a higher probability of earning returns greater than the mean. Similarly, the Coefficients of Kurtosis are found to be positive and are significantly higher than 3, indicating highly leptokurtic distribution compared to the normal distribution for all the returns. Kurtosis measures the fat-tail degree of a distribution.

Unit Root Test

The results of ADF and PP test for a unit root for SENSEX and S&P CNX Nifty indices are presented in *Table-2.* The optimal lag length is selected with the Schwartz Info Criterion and maximum lag is set to

12. Augmented Dickey-Fuller and PP unit root test was performed including intercept and intercept and time trend at level and first difference for the sampled period.

Table: 2 Unit Root Testing of Returns for Selected Indices Returns
(Sample Period: January 2003 to December 2012)

		ADF		PP	
		SENSEX	S&P CNX Nifty	SENSEX	S&P CNX Nifty
Level	With Intercept	-1.3408 (0.6125)	-1.31799 (0.6233)	-1.2850 (0.6387)	-1.2991 (0.6321)
	With Trend & Intercept	-2.3013 (0.4325)	-2.4085 (0.3749)	-2.2397 (0.4666)	-2.3496 (0.4062)
First Difference	With Intercept	-46.319 (0.0001)	-47.032 (0.0001)	-46.271 (0.0001)	-47.031 (0.0001)
	With Trend & Intercept	-46.312 (0.0000)	-47.024 (0.0000)	-46.263 (0.0000)	-47.024 (0.0000)

ADF and PP statistics in level series shows presence of unit root in both the stock markets as their Mackinnon's value do not exceed the critical value at 1% level. It suggests that both the price series are non-stationary. It is, therefore, necessary to transform the series to make it stationary by taking its first difference. ADF and PP statistics reported in the *Table-2* show that the null hypothesis of a unit root is rejected. The absolute computed values for the indices are higher than the MacKinnon critical value at 1% level for ADF and PP test. Thus, the results of the indices show that the first difference series are stationary.

Serial Correlation

The results of the first twenty-four orders sample autocorrelation coefficients and Ljung- Box statistics return series of the SENSEX and S&P CNX Nifty for the sample period from January 2003 to are presented in *Table-3*. It presents the Ljung-Box (LB) Q-statistic for high-order serial correlation for the return series of SENSEX up to lag 24. For higher-order return series also show a consistent pattern of positive autocorrelation.

Table 3 Autocorrelation & Ljung-Box Q-statistic for Selected Indices Returns
(Sample Period: January 2003 to December 2012)

	SENSEX			S &P CNX Nifty		
Lag	AC	Q-Stat	Prob	AC	Q-Stat	Prob
1	0.069	11.958	0.001	0.064	10.053	0.002
2	-0.044	16.869	0.000	-0.037	13.511	0.001
3	-0.009	17.077	0.001	-0.003	13.528	0.004
4	0.003	17.096	0.002	0.008	13.691	0.008
5	-0.034	19.904	0.001	-0.029	15.723	0.008
6	-0.043	24.52	0.000	-0.052	22.569	0.001
7	0.013	24.955	0.000	0.012	22.91	0.002
8	0.057	32.983	0.000	0.048	28.695	0.001
9	0.027	34.742	0.000	0.024	30.098	0.001
10	0.025	36.321	0.000	0.028	32.058	0.000
11	-0.02	37.3	0.000	-0.016	32.714	0.001
12	0.001	37.306	0.000	-0.004	32.754	0.001
13	0.035	40.369	0.000	0.034	35.627	0.001
14	0.044	45.287	0.000	0.053	42.742	0.000
15	-0.001	45.292	0.000	-0.008	42.885	0.000
16	0.002	45.303	0.000	-0.003	42.912	0.000
17	0.052	52.025	0.000	0.065	53.522	0.000
18	-0.01	52.261	0.000	-0.019	54.427	0.000
19	-0.023	53.629	0.000	-0.013	54.852	0.000
20	-0.023	54.909	0.000	-0.044	59.753	0.000
21	-0.01	55.176	0.000	0.002	59.761	0.000
22	-0.004	55.21	0.000	-0.017	60.467	0.000
23	0.002	55.22	0.000	-0.004	60.503	0.000
24	0.015	55.787	0.000	0.017	61.264	0.000

The Ljung-Box Q-statistics show that the null hypothesis of no autocorrelation is rejected for all returns on SENSEX and S&P CNX Nifty at lag 1 through 24 at the 1% level of significance. The results show that the independent and identically distributed hypothesis is rejected for all the stock return series in both markets suggesting that equity returns exhibit dependencies on its past behavior.

Volatility Models

The *table 4* reports the results of GARCH (1,1), T-GARCH (1,1) and E-GARCH (1,1) models for the return series of SENSEX and S&P CNX Nifty for the sample period January 2003 to December 2012.

Table-4: Results of GARCH models for SENSEX and NIFTY Returns for Ten Years

(Sample Period: January 2003-December 2012)

Variable	GARCH (1,1)		T-GARCH (1,1)		E-GARCH (1,1)	
	SENSEX	S&P CNX Nifty	SENSEX	S&P CNX Nifty	SENSEX	S&P CNX Nifty
Mean Equation						
ϕ_0	0.001245*	0.001233*	0.000879*	0.000824	0.000801*	0.000785*
ϕ_1	-0.048729	0.078616	0.088419	0.417434	0.085197	0.390596
ϕ_2	0.121581	-0.006114	-0.00702	-0.34011	0.005168	-0.297224
Variance Equation						
ω	0.000004*	0.000004*	0.00000526*	0.000006*	-0.44834*	-0.502955
α	0.11716*	0.1219*	0.053328*	0.04878*	0.235062*	0.238691
Β	0.869632*	0.8635*	0.86429*	0.85696*	0.968946*	0.962669
γ			0.123882*	0.14184*		
δ					-0.08645*	-0.1071
R-squared	0.00462	7069.424	0.00449	-0.001651	0.004357	-0.000114
Adjusted R-squared	0.00262	-5.698608	0.002089	7089.238	0.001956	-0.002541
Log Likelihood	7188.655	-5.684532	7206.968	-5.71378	7203.038	7089.105
Akaike info criterion	-5.75764	2.009863	-5.77152	-5.697364	-5.767797	-5.713679
Schwarz criterion	-5.74364	0.001233*	-5.75518	2.018719	-5.751463	-5.697257
Durbin-Watson stat	1.998305	0.078616	2.016113	0.000824	2.030368	2.048507
Residual Tests						
Q (12) Stats	15.503 (0.115)	15.336 (0.12)	17.42 (0.066)	20.142 (.028)	18.132 (0.053)	22.505 (.013)
Q^2 (12) Stats	12.213 (0.271)	9.5564 (0.48)	10.274 (0.417)	6.0234 (.813)	10.793 (0.374)	5.9648 (.818)
ARCH LM stats						
Lag 5	1.090066 (0.363721)	0.6284 (0.67801)	0.968979 (0.435327)	0.5039 (.7735)	1.099902 (0.358303)	0.5588 (.7316)
Lag 10	1.058599 (0.391122)	0.7571 (0.6705)	0.981202 (0.457458)	0.5612 (.8465)	1.04769 (0.400131)	0.5691 (.8403)
Lag 15	0.8204 (0.655604)	0.7366 (0.7488)	0.711217 (0.775393)	0.5471 (.9149)	0.850962 (0.620441)	0.8143 (.6625)

The *Table-4* shows that in the variance equation, the first three coefficients ω (constant), ARCH term (α) is 0.11716 and GARCH term (β) is 0.8696 for SENSEX and ARCH term (α) is 0.12185 and GARCH term (β) is 0.8635 for the GARCH (1,1) model are statistically significant and exhibit the expected sign.

The α and β indicates that, lagged conditional variance and lagged squared disturbance have an impact on the conditional variance, in other words this means that news about volatility from the previous periods have an explanatory power on current volatility. The coefficient of α is lesser than β which shows that there is more impact of past volatility on the current volatility in comparison to impact of past shocks or news on the conditional volatility. The sum of the two estimated ARCH and GARCH coefficients; $\alpha + \beta$ (persistence coefficients) in the GARCH (1,1) is 0.9868 for SENSEX and 0.9854 for S&P CNX Nifty very close to one which is required to have a mean reverting variance process, indicating that volatility shocks are quite persistent and takes longer time to dissipate. It is an indication of a covariance stationary model with a high degree of persistence and long memory in the conditional variance.

Asymmetric models E-GARCH (1,1) and T-GARCH (1,1) are used to investigate the existence of leverage effect in the returns of the SENSEX and S&P CNX Nifty returns. The result of T-GARCH(1,1) model reveals that asymmetric effect captured by the parameter estimate for SENSEX is γ(0.1239) and for S&P CNX Nifty is γ (0.1418) which is greater than zero suggesting the presence of leverage effect, i.e. the volatility to positive innovations is larger than that of negative innovations. These findings are in consistent with the previous findings. Kaur (2004) proposed good news and bad news have differential effects on the conditional variance. The leverage term is negative indicating the existence of the leverage effect for the stock market returns. Bordoloi and Shankar (2008) supports the results.

The asymmetrical E-GARCH (1,1) model estimated for the returns of the SENSEX and S&P CNX Nifty indicates that all the estimated coefficients are statistically significant at the 1% confidence level. The asymmetric (leverage) effect captured by the parameter estimate δ (-0.08645) for SENSEX and δ (-0.1071) for S&P CNX Nifty is also statistically significant with negative sign, indicating that negative shocks imply a higher next period conditional variance than positive shocks of the same sign, which indicates the existence of leverage effects in the returns of the SENSEX and S&P CNX Nifty during the study period.

The results of the diagnostic tests show that the GARCH models are correctly specified. Ljung-Box test was used to check for any remaining autocorrelations in standardized and squared standardized residuals from the estimated variance equation of GARCH (1,1) model. If the variance equation is specified correctly, two statistics Q(12) and $Q^2(12)$ should not be significant. The Q-statistics for the standardized and squared standardized residuals are insignificant, suggesting the GARCH models are successful at modeling the serial correlation structure in the conditional means and conditional variances. The Lagrange Multiplier (ARCH-LM) test was used to test the presence of remaining ARCH effects in the standardized residuals. ARCH-LM test statistic for all GARCH (1,1) model did not exhibit additional ARCH effects remaining in the residuals of the models. This shows that the variance equations are well specified.

Overall, using the minimum Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC) and the maximum Log Likelihood values as model selection criteria for the GARCH models, the preferred model is the GARCH (1,1) model based on the minimum Akaike Information Criteria and Schwarz Information Criteria. Whereas, the maximum Log Likelihood value shows that the E-GARCH (1,1) is the best model for modeling the volatility of SENSEX and S&P CNX Nifty Indices return. In the presence of an asymmetric response to news, whereby a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude, the symmetric GARCH (1,1) model, as suggested by minimum AIC and SIC, would be biased leading to misleading inferences pertaining to the modeling of volatility of SENSEX Index returns.

Conclusion

The study attempted to estimate volatility of SENSEX of Bombay Stock Exchange and S&P CNX Nifty returns of National Stock Exchange on the basis of sample period of from January 2003 to December 2012. The three volatility models were used GARCH (1,1), E-GARCH (1, 1) and T-GARCH (1, 1). The present paper attempted to examine the volatility of returns in Indian equity market. In the present study, ARCH models were used to detect the volatility in the returns of Indian stock market. With the use of E-GARCH methodology it was found that there was overflow of information in the Indian stock market and with the significant coefficient of dummy in augmented model, it was concluded that negative shocks do have greater impact on conditional volatility compared to positive shocks of the same enormity in the Indian equity market.

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