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Stock Market Volatility and Returns: A Study of NSE & BSE in India

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Abstract

The paper examines the relationship between returns and volatility, volatility clustering, leverage effect and the persistence of volatility for the Indian stock markets viz. National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) for the financial year 2005-06 to 2013-14. The GARCH-M model is used to examine the volatility clustering and persistence of volatility and the relationship between returns and volatility. The EGARCH model is used to capture the asymmetric effect. The study reveals that the volatility in both the markets exhibits the characteristics like volatility clustering, asymmetry effect and persistence of volatility in their daily returns. The study finds that the recent news as well as past news both has an impact on volatility. The study also finds the existence of leverage effect indicating that the negative shocks or bad news have more impact on volatility than that of positive shocks or good news. The relationship between returns and volatility is not significant for both the markets.

Key Words: *Stock returns, Volatility clustering, Leverage Effect, GARCH-M and EGARCH model.*

JEL Classification: G10, G11, G12, G20¹.

1. Introduction: Economic growth is essential for improving the quality of life. Standard classical and neo-classical theories emphasize the role of investment in enhancing economic growth. Monetary and financial sectors play a key role in mobilizing resources. Financial stability is crucial for promoting investment. In a situation of financial stability, financial institutions and markets are able to efficiently mobilize savings, provide liquidity and allocate investment. The growing role of the financial sector in the efficient allocation of resources at appropriate prices could significantly enhance the efficiency with which our economy functions. If financial markets work well, they will direct resources to their most productive uses. Risks will be more accurately priced and will be borne by those who have appetite for absorbing risks. Real economic activity with higher investments, in both quantity as well as quality, would result in growth with macroeconomic stability and fewer financial uncertainties. A stable financial system facilitates efficient transmission of monetary policy initiatives.

Financial sector reforms constitute the core of the New Economic Policy initiated in India in early 1990s. Because of this, Indian stock market has witnessed metamorphic changes and transition from a dull to an emerging stock market in international arena. Improved market surveillance, trading mechanism and introduction of new financial instruments have made it a centre of attraction for the international investors. Entry of Foreign Institutional Investors (FIIs) and at the domestic level spectacular growth of the corporate sector and mutual fund industry have further added to the depth and width of the Indian stock market. Introduction of screen based trading depository system; derivative instruments, rolling settlements etc. have changed the very complexion of the stock market. The market has witnessed substantial increase in the number of listed companies, greater reliance on market for resource mobilization, remarkable increase in number of brokers and investors are some of the developments that have taken place in Indian stock markets. In such an emerging market, investment analysts, institutional investors, fund managers and other market players continuously search for investment strategies that can outperform the market.

2. Review of Literature:

There are many literatures on the financial market. Some literatures are reviewed in the following:

Gahan et al. (2012) examine the volatility pattern of BSE Sensex and NSE Nifty during the pre and post derivative period. They estimate volatility by recognizing the stylist features of volatility like persistence, asymmetry etc. for both pre and post derivative period. They use daily closing index levels of BSE Sensex and NSE Nifty over a period of 1992-2012 and 1995-2012 respectively. They find that volatility is lower in the post derivative period as compared to the pre derivative period. They also find that recent news has more impact on volatility in the post derivative period in comparison to the pre derivative period. They further find that introduction of derivatives has increased the asymmetric effect on volatility.

Nicholas et al (2011) examine the relationship between stock returns and volatility for the three largest stock markets in Europe. They find that volatility changes for majority of the stocks rapidly during the crisis period with changes being persistent. They also find that before the crisis more investors are rewarded for market wide risk and during the crisis less stocks exhibit a positive relationship between stock returns and volatility. Finally, they find that most stocks don't exhibit positive and statistically significant leverage effects.

Tripathy et al. (2009) investigate the relationship between leverage effect and daily stock returns, volume and volatility in the BSE Sensex index in India during the period January 2005 to June 2009. They find that there exist substantial ARCH effects in the residuals and the volatility shocks are quite persistent in the market. They also find that both the recent news and the old news have an impact on the volatility of the stock. They find the evidence of leverage and asymmetric effect on stock market. They find that bad news generate more impact on change in trading volumes and volatility of the market. They also observed that asymmetric GARCH models provide a better fit than the symmetric GARCH model suggesting that systematic variations in trading volume are assumed to be caused only by the arrival of new information.

Sarkar and Banerjee (2006) measure the volatility in the daily return at five-minute intervals of the Indian National Stock Exchange from June 1, 2000 through January 30, 2004. They find that the Indian stock market experiences volatility clustering and hence GARCH model predict the market volatility better than simple volatility models like historical average, moving average etc. They also

observe that the asymmetric GARCH models provide better fit than the symmetric GARCH model, confirming the presence of leverage effect. Finally, the study reveals that the change in volume of trade in the market directly affects the volatility of asset returns. Further, the presence of FII in the Indian stock market does not appear to increase the overall market volatility.

Balaban and Bayar (2005) examine relationship between stock market returns and their forecast volatility derived from the daily observations of stock market indices of 14 countries covering the period December 1987 to December 1997 are used. Both weekly and monthly returns and their volatility are investigated. Expected volatility is derived from the ARCH (p), GARCH (1, 1), GJR-GARCH (1, 1) and EGARCH (1, 1) forecast models. Expected volatility is found to have a significant negative or positive effect on country returns in a few cases. Unexpected volatility has a negative effect on weekly stock returns in six to seven countries and on monthly returns in nine to eleven countries depending on the volatility-forecasting model.

Chang-Jin Kim et al. (2004) investigate whether evidence for a positive relationship between stock market volatility and the equity premium is more decisive when the volatility feedback effects of large and persistent changes in market volatility are taken into account for the period from January 1926 to December 2000. They derive and estimate a formal model of volatility feedback under the assumption of Markov-switching market volatility. They find that a negative and significant volatility feedback effect, supporting a positive relationship between stock market volatility and the equity premium.

Samanta (2003) examines the roles of stock market on excess return and volatility in predicting future output growth of Indian economy for the period April 1993 to December 2002. He finds that past values pointing to the presence of significant volatility-feedback effects in the stock market. The volatility is also quite strongly related to excess return in recent years. However, roles of stock market return and volatility in predicting future output growth are not clear. Thus, there is a need to undertake further in-depth research for understanding the relationship between stock market return / volatility and future output growth in the context of Indian economy.

Song et al. (1998) examine the relationship between returns and volatility of the Shanghai and Shenzhen Stock Exchanges in China over a period from May 1992 to February 1996. They use GARCH models to analyses the relationship between returns and volatility. They find that there is a positive relationship between returns and volatility. Volatility transmission between the two markets (the volatility spill-over effect) is also found to exist. The results of one month ahead ex ante forecasts show that the conditional variances of the returns of the two stock markets exhibit a similar pattern.

French et al (1987) examine the relationship between stock returns and stock market volatility. They use daily values of the Standard and Poor's (S&P) composite portfolio for the period from January 1928 through December 1984. They use auto regressive integrated moving average (ARIMA), auto regressive conditional heteroscedasticity (ARCH) and generalized auto regressive conditional heteroscedasticity (GARCH) model. They find that the expected market risk premium is positively related to the predictable volatility of stock returns. They also find that unexpected stock market returns are negatively related to the unexpected change in the volatility of stock returns.

3: Objectives:

The study is based on the following objectives.

- To examine the nature of volatility clustering of the NSE and BSE stock Exchange.

- To examine whether the asymmetric effect or leverage effect exist in the NSE and BSE stock Exchange
- To examine the relationship between returns and volatility of the NSE and BSE stock Exchange.

1.5 Data Source and Methodology:

Data Source: The study is based on the closing index value of the S&P Sensex of Bombay Stock Exchange and S&P CNX Nifty of National Stock Exchange in India. The period of the study is from April 1, 2005 to April 1, 2014. The sample size comprises of daily closing price is of 2241 observations for both the indices. The data is collected from the NSE and BSE website, www.nseindia.com and www.bseindia.Com .

Methodology:

The stock return is calculated using the following formula

$$r_t = \ln\left(\frac{c_t}{c_{t-1}}\right) * 100$$

$$r_t = [\ln(c_t) - \ln(c_{t-1})] * 100 \dots\dots\dots (1)$$

Where; r_t = stock market return
 c_t = closing index value at time period t
 c_{t-1} = closing index value at time period t-1.
 ln = natural logarithm

The data is first tested for normality by using JB (Jarque-Bera) test and to test unit root, Augmented Dickey Fuller test is used.

To examine the nature of volatility and the relationship between returns and volatility GARCH-M (Generalized Auto Regressive Conditional Heteroscedasticity) model is used. Engle (1982) introduced the ARCH model in his study “Autoregressive Conditional Heteroscedasticity with estimates of the Variance of United Kingdom Inflation” as the first formal model, which seemed to capture the phenomena of changing variance in time series data. Bollerslev (1986) extends Engle’s (1982) ARCH process by allowing the conditional variance to follow an ARMA process. This model is known as a generalized ARCH model, or GARCH model. Engle, Lilien and Robins (1987) extend the basic ARCH framework to allow the mean of a sequence to depend on its own conditional variance. This class of model, called the ARCH in mean (ARCH –M) model, is particularly suited to the study of asset markets. The basic insight is that risk-averse agents will require compensation for holding a risky asset. The GARCH –M model form as follows:

$$r_t = \omega + \theta h_t + \sum_{i=1}^p \phi_i r_{t-i} + \varepsilon_t + \sum_{i=1}^q \delta_i \varepsilon_{t-i} \dots\dots\dots (2)$$

Where r_t is the daily returns on equity and r_{t-i} represents lag returns and h_t represents conditional variance which are considered as regressors and ε_t represent random shocks.

The conditional variance equation is formed as:

$$\varepsilon_t = v_t \sqrt{h_t} \quad v_t \sim iid(0, 1)$$

$$h_t = \alpha_0 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j h_{t-j} \quad \text{GARCH (p, q)} \quad \dots (3)$$

Where, $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$ and $\alpha_i + \beta_j < 0$.

A significant ARCH coefficient (α_1) indicates that there is significant impact of previous period shocks on current period volatility. The ARCH coefficient (α_i) is also treated as recent “news” component which explains that recent news has a significant impact on price changes which implies the impact of yesterday’s news on today’s volatility.

The GARCH coefficient (β_i) measures the impact of last period variance on current period volatility. A significant GARCH coefficient (β_i) indicates the presence of volatility clustering. A positive β_i indicates that positive stock price changes are associated with further positive changes and vice versa. A relatively higher values of β_1 implies a larger memory for shocks. The GARCH coefficient (β_1) also treated as old “news” component, which implies that the news, which is old by more than one day, plays a significant role in volatility. The sum of the ARCH and GARCH coefficients i.e. ($\alpha_i + \beta_i$) indicates the extent to which a volatility shock is persistent over time. A persistent volatility shock raises the asset price volatility. A positive θ indicates that the return is positively related to volatility process. In other words, higher value of θ represents greater the impact of conditional variance on returns.

To examine the leverage effect EGARCH (Exponential Generalised Auto Regressive Conditional Heteroscedasticity) model can be used. Though ARCH and GARCH models respond to good and bad news or positive and negative shocks and quite useful in forecasting and measuring volatility but these models are unable to capture the “leverage effect” or asymmetric information. The rational and underlying logic of asymmetric or “leverage effect is that the distribution of stock return is highly asymmetric. An interesting future of asset prices is that “bad news” (negative shocks) seems to have a more pronounced effect on volatility than that of “good news” (positive shocks) of the same magnitude, that is, bad news is followed by larger increase in price volatility than good news of the same magnitude. It is known that the magnitude of the response of asset prices to shocks depends on whether the shock is negative or positive. To demonstrate this point Engle and Ng (1990) mapped the relationship between the conditional variance of asset returns to exogenous shocks, which resulted in what they termed a news impact curve. Nelson (1991) proposed an exponential GARCH model or EGARCH model that is the earliest extension of the GARCH model that incorporates asymmetric effects in returns from speculative prices based on a logarithmic expression of the conditional variability of variable under analysis. The conditional variance equation in the EGARCH (1, 1) model is

$$\ln(h_t) = \alpha_0 + \alpha_1 \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \lambda_1 \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + \beta_1 \ln(h_{t-1})$$

Where, h_t is an asymmetric function of past ε_t and $\alpha_0, \alpha_1, \lambda_1$ and β_1 re constant parameters.

Note that the left hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic and that forecasts of the conditional variance are guaranteed to be nonnegative. In this model specification, β_1 is the GARCH term that measures the impact of last period’s forecast variance. A positive β_1 indicates volatility clustering implying that positive stock price changes are associated with further positive changes and vice versa. If $\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$ is positive the effect of the shock on the log of the conditional variance is $(\alpha_1 + \lambda_1)$. If $\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$ is negative, the effect of the shock on the log of conditional variance is $(-\alpha_1 + \lambda_1)$. λ_1 measures the leverage or asymmetric effect. λ_1 is expected to be negative implying that bad news has a bigger impact on volatility than that of good news of the same magnitude.

4: Result and Discussion:

Table 1: Descriptive Statistics of Returns

Indices	Mean	Max.	Min.	SD	Skewness	Kurtosis	Jarque-Bera	Prob.	Obs.
BSE Sensex	0.055	15.99	-11.60	1.622	0.094	10.647	5462	0.00	2241
NSE Nifty	0.053	16.33	-13.01	1.624	-0.020	11.479	6713	0.00	2241

Source: Calculated by author, data collected from www.nseindia.com and www.bseindia.com .

The descriptive statistics of the daily returns of BSE Sensex and NSE Nifty indices are reported in the Table 1. The mean return of BSE Sensex (0.055) is higher than that of NSE Nifty (0.053). However, the volatility of the BSE Sensex is lower than that of NSE Nifty. However, there is little difference but the mean returns and risk in both the market are almost same. NSE Nifty series is negatively skewed (-0.020) and that of BSE is positively skewed (0.094). It indicates that BSE has larger possibilities to generate positive returns while NSE has higher probability to generate negative returns. The Kurtosis for both the indices are more than 3 (excess kurtosis), thus they are leptokurtic, i.e., the frequency distribution assigns a higher probability to returns around zero as well as very high positive and high negative returns. Likewise, a highly significant large JB statistic confirms that the return series are not normally distributed and indicate the presence of heteroscedasticity. Hence, GARCH model is suitable for testing of hypothesis.

Table 2: Augmented Dickey-Fuller Unit Root Test

Indices	Coefficient	Std. Error	t-Statistic	Prob.
BSE Sensex	-0.93	0.02	-44.04	0.00
NSE Nifty	-0.94	0.02	-44.67	0.00

Source: Estimated by author, data collected from www.nseindia.com and www.bseindia.com

The study here employs the unit root test to examine the time series properties of concerned variables. Unit root test describes whether a series is stationary or non-stationary. For the test of unit root the present study employs the Augmented Dickey-Fuller test. ADF is used to measure the stationarity of time series data, which in turn tells whether regression can be done on the data, or not. From Table 2 it is observed that the Augmented Dickey-Fuller test statistic for both the indices are greater than the critical values at less than one per cent level of significance.

Table 3 Ljung-Box (Q) Statistics for ARCH Effect

Lags	BSE				NSE			
	AC	PAC	Q-Stat	Prob.	AC	PAC	Q-Stat	Prob.
1	0.14	0.14	41.72	0.00	0.13	0.13	39.92	0.00
2	0.19	0.17	119.19	0.00	0.18	0.17	114.65	0.00
3	0.16	0.12	174.75	0.00	0.14	0.10	156.02	0.00
4	0.24	0.19	299.22	0.00	0.19	0.14	235.31	0.00
5	0.15	0.08	351.24	0.00	0.15	0.08	283.15	0.00
6	0.14	0.05	393.05	0.00	0.11	0.04	311.84	0.00
7	0.19	0.11	478.06	0.00	0.17	0.10	374.05	0.00
8	0.12	0.02	511.79	0.00	0.10	0.01	394.31	0.00

9	0.17	0.07	575.64	0.00	0.14	0.06	437.42	0.00
10	0.20	0.12	666.16	0.00	0.17	0.11	505.93	0.00
11	0.17	0.06	733.56	0.00	0.15	0.06	557.15	0.00
12	0.12	0.00	763.74	0.00	0.10	0.00	577.95	0.00
13	0.13	0.02	803.75	0.00	0.12	0.03	609.06	0.00
14	0.13	0.00	841.06	0.00	0.09	-0.01	628.56	0.00
15	0.13	0.02	879.30	0.00	0.13	0.04	663.55	0.00

Source: Estimated by author, data collected from www.nseindia.com and www.bseindia.com

To test whether there is ARCH effect or not Ljung-Box Q statistic is used on squared residual series of the mean model (ε_t^2). In the Ljung-Box Q test the null hypothesis is that, the first 36th lags of autocorrelation function (ACF) of the squared residual series are zero that implies there is no ARCH effect (McLeod and Li 1983). Hence, the result of 15th lags is reported in the above table. From the Ljung-Box Q statistics it is observed that the null hypothesis is rejected at less than one per cent level of significance for both the market indices indicating that the ARCH effect exists.

The final GARCH specification is decided by looking at the properties of standardized residuals, which are the conventional residuals divided by their conditional standard deviation. The best specification of GARCH model is GARCH (1, 1) for both the indices with the mean equations of AR (1). Other model such as GARCH (p, q) for p = 1, 2, 3 and q = 1, 2, 3 were also tried but there were no significant improvement in goodness of fit.

Table 4: Result of GARCH-M Model

Model	Coefficients	BSE Sensex		NSE Nifty	
		Coefficient	P-Value.	Coefficient	P-value
GARCH-M	w	0.094	0.005	0.085	0.014
	θ	0.010	0.583	0.013	0.460
	φ_1	0.070	0.001	0.055	0.013
	α_1	0.097	0.000	0.097	0.000
	β_1	0.895	0.000	0.894	0.000
	α_0	0.097	0.000	0.028	0.002
Log Likelihood		-3789.118		-3817.429	
AIC		3.389		3.415	
SBIC		3.407		3.433	
Q(12)		9.55 (0.57)		10.87 (0.45)	
Q(24)		24.4 (0.38)		25.83 (0.31)	
Q ² (12)		10.69 (0.47)		8.49 (0.66)	
Q ² (24)		12.59 (0.96)		10.75 (0.98)	

Source: Estimated by author, data collected from www.nseindia.com and www.bseindia.com

The value in the parenthesis is p – value

Table 4 shows the result of GARCH-M model. The result shows that the coefficients α_1 and β_1 are statistically significant and are within parametric restriction, thus implying a greater impact of shocks on volatility. A significant ARCH coefficient (α_1) indicates that there is significant impact of

previous period shocks on current period volatility. The ARCH coefficient (α_1) is also treated as recent “news” component which explains that recent news has a significant impact on price changes which implies the impact of yesterday’s news on today’s volatility.

The GARCH coefficient (β_1) measures the impact of last period variance on current period volatility. A significant GARCH coefficient (β_1) indicates the presence of volatility clustering. A positive β_1 indicates that positive stock price changes are associated with further positive changes and vice versa. A relatively higher values of β_1 implies a larger memory for shocks. The GARCH coefficient (β_1) also treated as old “news” component, which implies that the news that is old by more than one day plays a significant role in volatility. The sum of the ARCH and GARCH coefficients i.e. ($\alpha_1 + \beta_1$) indicates the extent to which a volatility shock is persistent over time. A persistent volatility shock raises the asset price volatility. From table 4 it is observed that the degree of volatility persistent is very high as the sum of α_1 and β_1 are approach to one.

Here θ is the risk parameter. A significant positive θ indicates that there is direct relationship between return and volatility. If volatility increases then return will also increase and vice versa. Here the θ coefficient is insignificant for both the indices. The mean return is higher in BSE Sensex than that of NSE Nifty. However, the risk (conditional variance) is higher in NSE Nifty than BSE Sensex which is inconsistent with the theory of asset pricing.

To check the adequacy of the mean equation the Ljung-Box (Q) statistics of standardized residual is used and that of square standardized residual is used to check for adequacy of volatility equation. The diagnostic test for model adequacy as shown in table 4 suggests that the Ljung-Box (Q) statistics and their probability values are highly insignificant indicating that there is no further serial correlation in standardized residuals and square standardized residuals. It means that both the mean and variance models fit the data well. That is the GARCH-M (1, 1) model is suitable for both the indices.

Table5: The Result of EGARCH Model

Indices	Coefficients	Value of Coefficients	Standard Error	Z-statistic	P value			
BSE Sensex	α_1	0.194133	0.021934	8.850929	0.00			
	λ_1	-0.09297	0.015236	-6.1024	0,00			
	β_1	0.978862	0.004589	213.3122	0,00			
	α_0	-0.13806	0.016349	-8.44459	0.00			
	GED	1.419357	0.048634	29.18469	0,00			
NSE Nifty	α_1	0.199398	0.022575	8.832531	0.00			
	λ_1	-0.10102	0.015495	-6.51964	0.00			
	β_1	0.976386	0.005066	192.7298	0.00			
	α_0	-0.14022	0.016883	-8.30532	0.00			
	GED	1.404577	0.044094	31.85409	0.00			
	Log likelihood	AIC	BIC	Q(12)	Q(24)	Q ² (12)	Q ² (24)	
NSE Nifty	-3800.52	3.399569	3.417426	10.47 (0.49)	16.63 (0.83)	12.12 (0.36)	27.56 (0.23)	
BSE Sensex	-3774.18	3.376052	3.393909	14.68 (0.20)	17.73 (0.77)	10.39 (0.50)	25.73 (0.31)	

Source: Estimated by author, data collected from www.nseindia.com and www.bseindia.com

The value in the parenthesis is p – value

Table 5 presents the result of EGARCH (1, 1) model for both the indices. The EGARCH model takes the leverage effect into account. The presence of leverage effect implies that every price changes are responding asymmetrically to the positive and negative shocks in the market. In the conditional variance equation; the ARCH coefficient and the GARCH coefficient are statistically significant for both the indices implying a greater impact of shocks on volatility. The asymmetric term is negative and statistically significant indicating that the volatility is high when there is negative shocks in the market than that of positive shocks for both the indices. From table 5 it is revealed that leverage effect is higher in NSE Nifty.

To check the adequacy of the mean equation the Ljung-Box (Q) statistics of standardized residual is used and that of square standardized residual is used to check for adequacy of volatility equation. The diagnostic test for model adequacy suggest that the Ljung-Box (Q) statistics and their probability values are highly insignificant indicating that there is no further serial correlation in standardized residuals and square standardised residuals. It means that both the mean and variance models fit the data well. That is the EGARCH (1, 1) model is suitable for both the indices.

1.7 Conclusions: The study reveals that the volatility in the BSE Sensex and NSE Nifty return series exhibits the characteristics like volatility clustering, asymmetry effect and persistence of volatility in their daily return. The study finds that there exists a significant presence of volatility clustering and degree of volatility is persistent which implies the recent news as well as past news both has an impact on volatility. The study also finds the existence of leverage effect indicating that the negative shocks or bad news have more impact on volatility than that of positive shocks or good news. The study further examines the relation between returns and volatility and it is found that the relation between returns and volatility for both the return series are statistically insignificant.

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