Article

Time Varying Volatility in the Indian Stock Market

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Abstract

This paper investigates the volatility dynamics of stock market in India by using daily data of the NIFTY index of NSE from Jan 2000 to Dec 2014. The volatility in the Indian stock market exhibits characteristics similar to those found earlier in many of the major developed and emerging stock markets. Various volatility estimators and diagnostic tests indicate volatility clustering, i.e., shocks to the volatility process persist and the response to news arrival is asymmetrical, meaning that the impact of good and bad news is not the same. It is shown that ARCH family models outperform the conventional OLS models. We find that, the TARCH model is better fit, when we compare the GARCH, EGARCH and TARCH models, on the basis of AIC and SC criteria. Moreover, in the GARCH model, ARCH and GARCH effects remain significant, which highlights the inefficiency in the market. In addition, EGARCH and TARCH models indicate the presence of leverage effect and positive impact of volatility on returns.

Keywords

NIFTY, GARCH, EGARCH, TARCH, Causality Test

Introduction

Achieving efficiency in the dynamics of the stock market is very important for any economy. For any stock market return & volume are the two important factors around which the entire stock market revolves. The emergence of information efficient financial markets is an important facet of any country's economic modernization. Moreover, it is observed from the prior literature that stock prices are noisy which can't convey all available information to market dynamics of stock prices and trading volume. Therefore, studying the joint dynamics of stock prices and trading volume is essential to improve the understanding of the microstructure of stock markets.

Volatility of stock returns has been mainly studied in the developed economies. After the seminal work of Engle (1982) on the Autoregressive Conditional Heteroscedasticity (ARCH) model and its generalized form (GARCH) by Bollerslev (1986), much of the empirical work has used these models and their extensions.

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The relationship between the volume & volatility in returns in the stock market are of common interest as they may result in forming base for profitable trading strategies and this has implications for the market efficiency (Chen & Yu, 2004). Karpoff (1987) cited four reasons for discussing price-volume relation. First, it provides insight into the structure of financial markets, such as the rate of information flow to the market, how the information is disseminated, the extent to which market prices convey the information, and the existence of short sales constraints. Second, the relationship between price and volume can be used to examine the usefulness of technical analysis. For example, Murphy (1985) and De Mark (1984) emphasized that both volume and price incorporate valuable information. A technical analyst gives less significance to a price increase with low trading volume than to a similar price increase with substantial volume.

Third, some researchers, such as Garcia et al., (1986) and Weiner (2002) have investigated the role of speculation to price volatility (stabilizing or destabilizing), where speculation is closely related to trading volume. Finally, as Cornell (1981) pointed out, the volume-price variability relationship may have important implications for fashioning new contracts. A positive volume-price variability relationship means that a new futures contract will be successful only to the extent that there is enough price uncertainty associated with the underlying asset.

There is relatively less empirical research on stock return volatility in the emerging markets. In the Indian context, Roy and Karmakar (1995) focused on the measurement of the average level of volatility as the sample standard deviation and examined whether volatility has increased in the early 1990s; Goyal (1995) used conditional volatility estimates as suggested by Schwert (1989) to study the nature and trend of stock return volatility and the impact of carry forward system on the level of volatility; Reddy (1997-98) analysed the effects of market microstructure, e.g., establishment of the National Stock Exchange (NSE) and the introduction of Bombay Stock Exchange Online Trading (BOLT) system on the stock return volatility measured as the sample standard deviation of the closing prices; Kaur (2002) analysed the extent and pattern of stock return volatility during 1990- 2000 and examined the effect of company size, day-ofthe- week, and FII investments on volatility measured as the sample standard deviation. Shenbagaraman (2003) examined the impact of introduction of index futures and options on the volatility of underlying stock index using a GARCH model. Kumar and Mukhopadhyay (2002) applied the GARCH models to examine the co-movement and volatility transmission between the US and Indian stock markets.

Therefore, the current study empirically investigates the pattern of volatility in the Indian stock market during Jan 2000 – Dec 2014 in terms of its time varying nature, presence of certain characteristics such as volatility clustering. It contributes to the body of knowledge by providing a holistic treatment to the subject of stock market volatility in India and providing evidence on its main characteristic features with the help of econometric techniques and employing GARCH models.

The rest of this paper is, organized in following order; Section 2 presents review of literature. Section 3, presents data, methodology and results, whereas Section 4 concludes the study.

Literature Review

A detailed analysis of volatility with relation to return-volume dynamics is important to have knowledge of issues relating to market efficiency and information flow in the market. Table 1 summarizes the previous studies on the contemporaneous relation between volume and return. Table 2 highlights the studies relating to the contemporaneous relation between volume and return volatility/absolute return. efficiency and productivity.

Table 1: Empirical Evidence on the Contemporaneous Relationship between Trading Volume (V) and Return (Δp)

	Author(s)	Year of Study	Sample Data	Sample Period	Differencing Interval	Support Positive (Δp.V) Correlation
1	Granger and Morgenstern	(1963)	Stock market aggregates, 2 common stocks	1939-61	Weekly	No
2	Godfrey et al.,	(1964)	Stock market aggregates, 3 common stocks	1959-62, 1951-53	Weekly, Daily	No
3	Ying	(1966)	S&P 500composite stock price index of NYSE	1957-62	Daily	Yes
4	Epps	(1975)	20 NYSE bonds	Jan, 1971	Transactions	Yes
5	Morgan	(1976)	17 common stocks, 44 common stocks	1962-65 1926-68	4 days, Monthly	Yes
6	Epps	(1976)	20 common stocks	Jan, 1971	Daily	Yes
7	Hanna	(1978)	20 NYSE bonds	May, 1971	Transactions	Yes
8	Rogalski	(1978)	10 common stocks & 10 associated warrants	1968-73	Monthly	Yes
9	James and Edmister	(1983)	500 common stocks	1975, 77-79	Daily	No
10	Comiskey et al.,	(1984)	211 common stocks	1976-79	Yearly	Yes
11	Harris & Gurel	(1984)	50 common stocks	1981-83	Daily	Yes

12	Smirlock and Starks	(1985)	131 common stocks	1981	Transactions	Yes
13	Wood et al.,	(1985)	946 common stocks 1138 common stocks	1971-72 1982	Minutes	No
14	Jain and Joh	(1986)	NYSE	1979-83	Hourly	Yes
15	Richardson et al.,	(1987)	106 common stocks	1973-82	Weekly	Yes
16	Kocagil & Shachmurove	(1998)	16 major U.S. futures contracts	1998-1995	Daily	No
17	Lee & Rui	(2000)	SHSE, SZSE	1990-1997	Daily	Yes
18	Chen et al.,	(2001)	New York, Tokyo, London, Paris, Toronto, Milan, Zurich, Amsterdam and Hong Kong	N.A	Daily	Yes
19	Mcmillan & Speight	(2002)	FTSE-100 Short sterling contracts Long gilt series	1992-1995	Intra day	No
20	Lee and Rui	(2002)	S&P 500, TOPIX, FT-SE 100	1973-1999, 1974-1999, 1986-1999	Daily	Yes
21	Ciner	(2002)	TSE	1990-2002	Daily	No
22	Ciner	(2003)	TSE*-2442 KLSE-2246	1993-2002	Daily	No
23	Mishra	(2004)	7 Co's, CNXIT of NSE	2000-2003	Daily	Yes
24	Otavio and Bernardus	(2006)	Bovespa index	2000-2005	Daily	Yes

25	Mahajan and Singh	(2007)	Nifty index	2001-2006	Daily	Yes
26	Mahajan and Singh	(2008a)	Sensex	1996-2007	Daily	Yes

Where: KLSE= Kuala Lumpur stock exchange, NYSE= New York stock exchange, NSE=National stock exchange, TOPIX= Tokyo stock exchange price Index, TSE= Toronto stock exchange, TSE*= Tokyo stock exchange

Source: Compiled from various studies.

Table 2: Empirical Evidence on the Contemporaneous Relationship between Trading Volume (v) and Absolute Return/Return Volatility (|Δp|)/(Δp) 2

	Author(s)	Year of Study	Sample Data	Sample Period	Differencing Interval	Support Positive (|Δp|.V)
1	Godfrey et al.,	(1964)	Stock market aggregates, 3 common stocks	1959-1962, 1951-1953	Weekly, Daily	No
2	Ying	(1966)	Stock market aggregates	1957-1962	Daily	Yes
3	Crouch	(1970)	5 common stocks	1963-1967	Daily	Yes
4	Clark	(1973)	Cotton futures market	1945-1958	Daily	Yes
5	Epps	(1976)	20 common stocks	Jan, 1971	Transactions	Yes
6	Morgan	(1976)	17 common stocks, 44 common stocks	1962-1965 1926-1968	4 days, Monthly	Yes
7	Westerfield	(1977)	315 common stocks	1968-1969	Daily	Yes
8	Cornell	(1981)	Futures contracts for 17 commodities	1968-1979	Daily	Yes

9	Harris & Gurel	(1984)	16 common stocks	1968-1969	Daily	Yes
10	Tauchen and Pitts	(1983)	T-bill Futures contracts	1976-1979	Daily	Yes
11	Comiskey et al.,	(1984)	211 common stocks	1976-79	Yearly	Yes
12	Harris	(1984)	50 common stocks	1981-83	Daily	Yes
13	Rutledge	(1979)	Futures contracts for 13 commodities	1973-1976	Daily	Yes
14	Wood et al.,	(1985)	946 common stocks 1138comon stocks	1971-72 1982	Minutes	Yes
15	Grammatikos and Saunders	(1986)	Futures contracts for 5 foreign currencies	1978-1983	Daily	Yes
16	Harris	(1986)	479 common stocks	1976-77	Daily	Yes
17	Jain and Joh	(1986)	Stock market aggregates	1979-83	Hourly	Yes
18	Richardson et al.,	(1987)	106 common stocks	1973-82	Weekly	Yes
19	Gallant et al.,	(1992)	S&P 500 index	1928-1987	Daily	Yes
20	Bessembinder and Seguin	(1993)	8 futures contracts	1982-1990	Daily	Yes
21	Jones et al.,	(1994)	NASDAQ	1986-1991	Daily	Yes

22	Brailsford	(1996)	AOI	1989-1993	Daily	Yes
23	Ragunathan	(1997)	Sydney futures exchange	1992-1994	Daily	Yes
24	Kocagil and Shachmurove	(1998)	16 major U.S. futures contracts	1998-1995	Daily	No
25	Daigler and Wiley	(1999)	LDB	1986-1988	Daily	Yes
26	Lee and Rui	(2000)	SHSE, SZSE	1990-1997	Daily	Yes
27	Chan and Fong	(2000)	NYSE, NASDAQ	1993	Daily	Yes
28	Wang and Yau	(2000)	CME, COMEX	1990-1994	Daily	Yes
29	Chen et al.,	(2001)	New York, Tokyo, London, Paris, Toronto, Milan, Zurich, Amsterdam and Hong Kong	N.A	Daily	Yes
30	Ciner	(2002)	TSE	1990-2002	Daily	Yes
31	Ciner	(2003)	TSE*, KLSE	1993-2002	Daily	Yes
32	Darrat et al.,	(2003)	30 DJIA stocks	1998	Intraday	No
33	Gallagher and Kiely	(2005)	14 Irish stocks	2000-2003	Daily	Yes
34	Otavio and Bernardus	(2006)	Bovespa index	2000-2005	Daily	No

35	Long	(2007)	CBOE	1983-1985	Daily	Yes
36	Mahajan and Singh	(2008a)	Sensex	1996-2007	Daily	Yes
37	Mahajan and Singh	(2008b)	Nifty index	2001-2006	Daily	Yes

Where: AOI= All Ordinaries Index, DJIA= Dow Jones Industrial Average, KLSE= Kuala Lumpur Stock Exchange, LDB= Liquidity Data Bank, NYSE= New York Stock Exchange, NSE= National Stock Exchange, TSE= Toronto Stock Exchange, TSE*= Tokyo Stock Exchange, CBOE= Chicago Board of Option Exchange

Source: Compiled from various studies.

In nutshell, on the basis of above-mentioned studies it can be stated that the significant efforts have been made at the international level to evaluate volatility and its relationship with returns and volume, whereas in India this relationship has not been well investigated. Therefore, the current study is an attempt to fill this gap and sheds light on the informational efficiency of Indian stock market. This paper examines the stock market volatility in India during the pre and post derivative period. We use the GARCH models (this model allows for time varying variance in a process and can adequately represent return volatility) in the study. This study further checks the information asymmetry with EGARCH (1, 1) model and TARCH (1, 1) model. Thus, the study will enhance the understanding of market asymmetry, market efficiency and information processing.

Data & Methodology

The aim of this paper is to study the volatility of NIFTY index of National Stock Exchange (NSE). To accomplish the research objective daily data ranging from January-2000 to December-2014 are obtained which comprises 3736 data points for the analysis. The choice of study period is based on the availability of data series. The series of return is computed from daily closing data for the NIFTY Index of National Stock Exchange. The NIFTY index of NSE captures all the events in the most judicial manner. One can identify the booms and busts of the Indian stock market through NIFTY. The daily returns are continuous rates of return, computed as log of ratio of present day's price to previous day's price (i.e. $Rt = \ln (Pt / Pt\text{-}1)$). Descriptions of variables and data sources are presented in Table 3.

Table 3: Description of Variable

Acronyms	Construction of Variable	Data Source
NIFTY	Volatility of the NIFTY Index of Nation al Stock Exchange (NSE)	NSE Website

The present study employs the time series data analysis technique to study the volatility of NIFTY index of NSE. In a time series analysis, the results might provide a spurious if the data series are non-stationary. Thus, the data series must obey the time series properties i.e. the time series data should be stationary, meaning that, the mean and variance should be constant over time and the value of covariance between two time periods depends only on the distance between the two time period and not the actual time at which the covariance is computed. The most popular and widely used test for stationary is the unit root test. The presence of unit root indicates that the data series is non-stationary. The standard procedures of unit root test namely the Augmented Dickey Fuller (ADF) (1979) (1981) is performed to check the stationary nature of the series. Assuming that the series follows an AR (p) process the ADF test makes a parametric correction and controls for the higher order correlation by adding the lagged difference terms of the dependent variable to the right hand side of the regression equation. In the ADF test null hypothesis is that data set being tested has unit root. This provides a robustness check for stationary. The unit root tests also provide the order of integration of the time series variables. In a multivariate context if the variable under consideration are found to be I (1) (i.e. they are non-stationary at level but stationary at first difference), but the linear combination of the integrated variables is I (0), then the variables are said to be co-integrated (Enders, 2004). The Augmented Dickey Fuller (ADF) (1979; 1981) is performed to check the stationary nature of the series. The complete model with deterministic terms such as intercepts and trends is shown in equation (1).

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t, \quad (1)$$

Where, α is a constant, β is the coefficient on a time trend and ρ is the lag order of the autoregressive process.

One of the key assumptions of the ordinary regression model is that the errors have the same variance throughout the sample. This is also called the homoscedasticity model. If the error variance is not constant, the data are said to be heteroscedastic. Findings of heteroscedasticity in stock returns are well documented (Mandelbrot, 1963) (Fama E. , 1965) (Bollerslev, 1986).

In econometric literature, volatility clustering is modeled as an ARCH process. Robert Engle (1982) in his seminal work on inflation in the UK first introduced the idea of ARCH effect.

The ARCH test is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals. However, ignoring ARCH effects may result in loss of efficiency. Engle's (1982) ARCH LM test is a test to assess the significance of ARCH effects. The ARCH LM test statistic is computed from an auxiliary test regression. To test the null hypothesis that there is no ARCH up to order q in the residuals (Engle R. F., 1982), the regression is:

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s e_{t-s}^2 \right) + v_t, \quad (2)$$

Where is e the residual, this is a regression of the squared residuals on a constant and lagged squared residuals up to order q. The F-statistic is an omitted variable test for the joint significance of all lagged squared residuals. The Obs*R-squared statistic is Engle’s LM test statistic, computed as the number of observations times the R2 from the test regression.

The ARCH and the GARCH models assume conditional heteroscedasticity with homoscedastic unconditional error variance. That is, the changes in variance are a function of the realizations of preceding errors and these changes represent temporary and random departures from a constant unconditional variance.

The advantage of GARCH model is that it captures the tendency in financial data for volatility clustering. It, therefore, enables us to make the connection between information and volatility explicit since any change in the rate of informational arrival to the market will change the volatility in the market. Thus, unless information remains constant, which is hardly the case, volatility must be time varying even on a daily basis.

ARCH Models (Engle R. F., 1982) are used whenever there is reason to believe that, at any point in a series, the error terms will have a characteristic size or variance. In particular ARCH models assume the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods' error terms: often the variance is related to the squares of the previous innovations. Higher order GARCH models, (Bollerslev, 1986) (Taylor, 1986) denoted GARCH (q, p) can be estimated by choosing either q or p greater than 1 where q is the order of the autoregressive GARCH terms and p is the order of the moving average ARCH terms. The representation of the GARCH (q, p) variance is:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 \tag{3}$$

However the results based upon GARCH (q, p) may again be doubtful because it doesn't take into account for asymmetry and non-linearity in the conditional variance.

Schwert (1989), French, Schwert and Stambaugh (1987), Christie (1982) and Black (1976) have shown that returns are negatively correlated with volatility. This implies that returns tend to be more volatile in response to bad news and less volatile in response to good news. This kind of differential response to the kind of the news arriving in the market leads to the issue of asymmetric response by stock market returns to various shocks. In the standard GARCH model, it is assumed that only the magnitude of the shock, not the positivity or negativity of the shock, determines the volatility. Hence, GARCH process generates a symmetric response function for the stock returns. This suggests that separate modeling techniques need to be used to capture the asymmetry in the response functions as suggested by Engle and Ng (1993)

Estimating the TARCH (Threshold ARCH) and EGARCH (Exponential GARCH) models and testing the significance of the asymmetric terms is one way to test for asymmetric effects.

Thus it would be more appropriate to apply asymmetric GARCH model. Engle & Ng. (1993) developed an asymmetric GARCH model, which allows for asymmetric shocks to volatility. Thus, among the specifications, which allow for asymmetric shocks to volatility, we estimate the EGARCH (*p, q*) or exponential GARCH (p, q) model, which was proposed by Nelson (1991).

The specification for the conditional variance is: (4)

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left| \frac{\epsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}}.$$

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. The presence of leverage effects can be tested by the hypothesis that , the impact is asymmetric if $\gamma_i \neq 0$

TARCH or Threshold ARCH and Threshold GARCH were introduced independently by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993). The generalized specification for the conditional variance is given by:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \epsilon_{t-k}^2 I_{t-k} \tag{5}$$

Where $I_t = 1$ if $\epsilon_t < 0$ and 0 otherwise. In this model, good news, $\epsilon_{t-i} > 0$, and bad news. $\epsilon_{t-i} > 0$, have differential effects on the conditional variance; good news has an impact of α_i , while bad news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$bad news increases volatility, and we say that there is a leverage effect for the i-th order. If $\gamma_i \neq 0$, the news impact is asymmetric

Empirical Analysis

The volatility study of NIFTY index of National Stock Exchange (NSE) during its pre and post derivative period provides significant information regarding the price discovery efficiency of the asset. The descriptive statistics for all the variables are presented in Table 4. The value of skewness and kurtosis indicate the lack of symmetric in the distribution. Generally, if the value of skewness and kurtosis are 0 and 3 respectively, the observed distribution is said to be normally distributed. Furthermore, if the skewness coefficient is in excess of unity it is considered fairly extreme and the low (high) kurtosis value indicates extreme platykurtic (extreme leptokurtic). From the table it is observed that the frequency distributions of underlying variables normal. The significant coefficient of Jarque-Bera statistics also indicates that the frequency distributions of considered series are normal.

Table 4: Descriptive Statistics of Variable

	NIFTY
Mean	0.0585
Median	0.1102
Maximum	17.7441
Minimum	-12.2377
Std. Dev.	1.5714
Skewness	-0.0200
Kurtosis	11.6051
Jarque-Bera	11526.9400
Probability	0.0000
Sum	218.3801
Sum Sq. Dev.	9222.7870
Observations	3736

Source: Author's Estimation

To check the stationarity of the underlying data series, we follow the standard procedure of unit root testing by employing the Augmented Dickey Fuller (ADF) test. The results are presented in Table 5. On the basis of the ADF test, all the series are found to be non-stationary at level with intercept. However, after taking the first difference these series are found to be stationary at 1, 5 and 10 percent significance level. Thus the stationary test indicates that all series are individually integrated of the order I.

(1)

Table 5: Result of Augmented Dickey-Fuller Unit Root Test

Variable			Trend		Trend & Intercept		None	
			t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*
D(NIFTY)	Augmented Dickey-Fuller test statistic		-27.9140	0.0000	-27.9103	0.0000	-27.9178	0.0000
	Test critical values:	1% level	-3.4319		-3.9605		-2.5656	
		5% level	-2.8621		-3.4110		-1.9409	
		10% level	-2.5671		-3.1273		-1.6166	

*MacKinnon (1996) one-sided p-values.

Source: Author's Estimation

Further, to test for autoregressive conditional heteroskedasticity (ARCH) in the residuals, the ARCH LM test statistic is computed from an auxiliary test regression. The result of the ARCH LM test is presented in Table 6.

Table 6: Result of the ARCH Test

F-statistic	150.7443	Prob. F(1,84)	0.0000
Obs*R-squared	144.9709	Prob. Chi-Square(1)	0.0000

Source: Author's Estimation

The above findings indicate the possible presence of ARCH effect which is confirmed by the computed value of Lagrange Multiplier (LM). This finding shows the clustering effect in returns, i.e. large shocks to the error process are followed by large ones and small shocks by small ones of either sign. This means that our next logical step in modeling exercise should be to express the conditional volatility as an ARCH or GARCH process with the mean return process as an AR (1) process.

Table 7: Result of GARCH Model

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.105012	0.018313	5.734424	0.0000
Variance Equation				
C	0.046999	0.005495	8.553093	0.0000
RESID(-1)^2	0.120395	0.00773	15.57595	0.0000
GARCH(-1)	0.862605	0.007938	108.6739	0.0000
Schwarz criterion	3.427345	Akaike info criterion		3.420679

Source: Author's Estimation

Further, to investigate whether the volatility explains the GARCH effects, GARCH (1, 1) model is estimated and results are shown in table 7. The coefficient of the intercept term in variance equation is (0.046999) positive and statistically insignificant. The coefficients of the ARCH effect is positive (0.120395) statistically significant. GARCH effect in the variance equation is positive (0.862605) and statistically significant. The AIC & SC criteria of the model are 3.420679 & 3.427345 respectively. Further, significant ARCH and GARCH coefficients clearly indicate that conditional variance is predominantly affected by lagged variance, which implies that previous information shocks significantly affect current returns. These evidences imply that Indian stock market is not efficient in weak form.

As significant asymmetry is observed in the returns of Nifty index, thus it would be more informative if we examine the volatility relation through EGARCH (1, 1) model to take into account impact of good and bad news, knowing the fact that both types of news have different kinds of effect on market. The results of EGARCH (1, 1) are shown in Table 8.

Table 8: Result of EGARCH Model

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4) *RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.067256	0.017881	3.761337	0.0002
Variance Equation				
C(2)	-0.161399	0.009346	-17.26848	0.0000
C(3)	0.235658	0.012462	18.91036	0.0000
C(4)	-0.093951	0.007684	-12.22623	0.0000
C(5)	0.964606	0.003268	295.1794	0.0000
Schwarz criterion	3.412089	Akaike info criterion		3.403757

Source: Author's Estimation

The presence of leverage effect can be seen in table 8, coefficient of the C (4) is negative -0.093951) and statistically significant, which implies that every price change responds asymmetrically to the positive and negative news in the market. It also implies that positive news has a less effect on conditional variance as compared to negative news or we can say that good news or shocks creates less variance or volatility than bad news or shocks. Hence, negative news plays important role in volatility in comparison to positive news. This also implies that Indian market is informationally inefficient. The AIC & SC criteria of the model are 3.403757 & 3.412089 respectively.

Table 9: Result of TARCH Model

Further, to test for autoregressive conditional heteroskedasticity (ARCH) in the residuals, the ARCH LM test statistic is computed from an auxiliary test regression. The result of the ARCH LM test is presented in Table 6.

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.071523	0.018823	3.799814	0.0001
Variance Equation				
C	0.056361	0.005813	9.695552	0.0000
RESID(-1)^2	0.050655	0.006483	7.813531	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.130757	0.012588	10.38767	0.0000
GARCH(-1)	0.860178	0.008427	102.0754	0.0000
Schwarz criterion	3.411762	Akaike info criterion		3.403430

Source: Author's Estimation

Further, the leverage effect is been checked with TARCH (1, 1) model and the outcomes of model are shown in Table 9. The C (4) (RESID(-1)^2*(RESID(-1)<0)) is positive (0.130757) and statistically significant. This reinforces the assumption that there is a leverage effect in the model and negative news creates more volatility as compared to positive news or positive and negative shocks have different impact on the volatility of NIFTY. The AIC & SC criteria of the model are 3.403430 & 3.411762 respectively. This is the lowest as compared to GARCH and EGARCH models.

Conclusion

The movement in stock market can't be decided only on the basis of prices. Stock prices without associated with trading volume and volatility in returns convey vague information about market activity. It is well established in the literature that prices react to the arrival of new information and trading volume is viewed as the critical piece of information, which signals where prices will go next. Thus, this paper studies the volatility of NIFTY index of National Stock Exchange (NSE) during its pre and post derivative period by using daily data ranging from January-2000 to December-2014, which comprises 3736 data points for the analysis. The main issue has been whether introduction of derivatives trading have reduce the volatility in the Indian stock market and information about volatility in returns is useful in improving the forecasts of return in dynamic context.

The volatility in the Indian stock market exhibits characteristics similar to those found earlier in many of the major developed and emerging stock markets, viz., autocorrelation and negative asymmetry in daily returns. It is shown that ARCH family models outperform the conventional OLS models. However, when we compare the GARCH, EGARCH and TARCH models, we find that, the TARCH model is better fit. This has been done in accordance with the lowest AIC and SC criteria.

Moreover, in the GARCH model and in contrast to Lamoureux and Lastrapes (1990), ARCH and GARCH effects remain significant as observed in Liam & Daniel (2005), which highlights the inefficiency in the market for pre-derivative, post-derivative and whole period of the NIFTY index under study. This finding leaves the possibility that there may be other variables besides volatility which contribute, to the heteroscedasticity in returns. We can attribute this finding to low level of market depth in India.

Next, in the light of Information asymmetry, the study has used the EGARCH (1, 1) or exponential GARCH (1, 1) model and TARCH (1, 1) model, which allows for asymmetric shocks to volatility. It indicates the presence of leverage effect and positive impact of volatility on returns for pre-derivative, post-derivative and whole period. The differential cost of taking long and short positions is main reason for information asymmetry (leverage effect).

The empirical findings would be useful to investors as it provides evidence of time varying nature of stock market volatility in India. Investors aim at making more profitable and less risky investments. Therefore, they need to study and analyse stock market volatility, among many other factors, before making investment decisions.

In nutshell, it can be stated that volatility provides information on the precision and dispersion of information signals, rather than serving as a proxy for the information signal itself (Blume, Easley and O'Hara (1994)). Moreover, new information is absorbed sequentially and the intermediate informational equilibrium is reached before the final equilibrium is found in Indian stock market. These results might be largely attributed to the existence of substantial speculative trading, low level of market depth and price limits observed in Indian market.

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