Volatility Clustering and Leverage Effect in Indian Stock Market

Nisha Jindal*

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Abstract

Leverage effect plays a very importan role in Indian stock market. It refers that negative returns lead to more volatility in the market as compared to postive retuns. The present study is examining the presence of leverage effect in the Indain stock market. The index of National Stock Exchange, NIFTY was used in the study to represent the Indian stock market. The daily closing prices were taken for the sample period of ten years from January 2009 to January 2019. The data was collected from the official website of National stock exchange i.e. www.nseindia.com. *Different statistical tools like E-Garch and GJR-GARCH were used to analyze the data with the help of software Eviews5. The results indicated that leverage effect is presented in Indian stock market as negative news are creating more panic in the stock market as compared to the postive news.*

Keywords: *National Stock Exchange, NIFTY, Leverage effect, Volatility Clustering, Indian stock market.*

Introduction

Leverage effect means the volatility in stock market is negatively corelated with the stock returns. Risk in the market reuslts into uncertainty of returns. Returns may vary due to presence of risk. Due to risk, returns may move upward or downward resulting into fluctuations. Returns are the main driving force to invest in the stock market. So, investor has keen interest in understanding the patterns of stock market volatility behavior. It is

* Faculty, Maharaja Agrasen Institute of Management Studies, New Delhi
Email id: njindal144@gmail.com

genearlly seen that negative news in the market resulted into more volatility as compared to positive news i.e. asymmetric volatility.

Literature Review

Karmakar (2007) investigated the heteroscedastic behaviour of the Indian stock market using different GARCH models. First, the standard GARCH approach was used to investigate whether stock return volatility changes over time and if so, whether it was predictable. Then, the E-GARCH models were applied to investigate whether there is asymmetric volatility. It was found that the volatility is an asymmetric function of past innovation, rising proportionately more during market decline.

Bordoloi and Shankar (2010) explored to develop alternative models from the Autoregressive Conditional Heteroskedasticity (ARCH) or its Generalization, the Generalized ARCH (GARCH) family, to estimate volatility in the Indian equity market return. It was found that these indicators contain information in explaining the stock returns. The Threshold GARCH (T-GARCH) models explained the volatilities better for both the BSE Indices and S&P-CNX 500, while Exponential GARCH (E-GARCH) models for the S&P CNX-NIFTY.

Srinivasan and Ibrahim (2010) attempted to model and forecast the volatility of the SENSEX Index returns of Indian stock market. Results showed that the symmetric GARCH model performed better in forecasting conditional variance of the SENSEX Index return rather than the asymmetric GARCH models, despite the presence of leverage effect.

Mehta and Sharma (2011) focused to examine the time varying volatility of Indian stock market specifically in equity market. The findings of the study 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.

Joshi (2010) investigated the stock market volatility in the emerging stock markets of India and China. The findings revealed that the persistence of volatility in Chinese stock market is more than Indian stock market.

Gupta et. al. (2013) aimed to understand the nature and different patterns of volatility in Indian stock market on the basis of comparison of two indices which are BSE index, SENSEX and NSE index, NIFTY. GARCH models were used to see the volatility of Indian equity market and it was concluded that negative shocks do have greater impact on conditional volatility compared to positive shocks of the same magnitude in both indices i.e. SENSEX and NIFTY of the Bombay Stock Exchange and National Stock Exchange.

Herbert et. Al. (2019) investigated whether leverage effect and volatility clustering is in existence in the Nigerian stock market. The data was taken for the time period of 7 years. GARCH (1,1) and GJR-GARCH (1,1) models were applied to understand the market behavior. It was found that volatility clustering and leverage effect is present in the Nigerin Stock Market.

Chu et al. (2020) employed the Baidu Index as the novel proxy for unexpected information demand and shows that this novel proxy can explain the volatility clustering of Chinese stock returns. They suggested that investors in China could take advantage of the Baidu Index to obtain information and then improve their investment decision.

Dufitinema (2020) examined whether the house prices in Finland share financial characteristics with assets such as stocks. Results revealed that clustering effects exist in over half of the cities and sub–areas in all studied types of apartments. He found mixed results on the sign of the significant risk–return relationship are observed across cities and sub–areas in all three apartment types. Furthermore, the evidence of the asymmetric impact of shocks on housing volatility is noted in almost all the cities and sub–areas housing markets.

Inoua (2020) found long-run investors' valuations of an asset were assumed to follow a news-driven random walk, thus capturing the investors' persistent, long memory of fundamental news. Short-term speculators' anticipated returns, on the other hand, were assumed to follow a news-driven autoregressive process, capturing their shorter memory of fundamental news, and, by the same token, the feedback intrinsic to the short-sighted, trend-following (or herding) mindset of speculators.

Research Methodology

The study explored the various studies relating to the asymmetric volatility of Indian stock market. According the following objective of the study was developed:

-To analyze the asymmetric volatility of Indian Stock market taking sample of NIFTY of NSE.

The data used in this study consist of the daily closing points of NIFTY for the period of ten years from January 2009 to January 2019. The data was collected from the website www.yahoofiance.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 at time t and t-1 respectively. **Augmented Dickey-Fuller** was 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 were presented in Data Analysis section.

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:

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

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

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

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

$\mu = average\ return$

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

$\varepsilon_t = \sigma_t z_t$

Where z_t is standardized residual returns (i.e. *iid* random variable with zero mean and variance 1), and α^2_t is conditional variance. For GARCH (1,1), the constraints $\alpha \geq 0$ and $\beta_1 \geq 0$ are needed to ensure α^2_t is strictly positive. In this model, the mean equation is written as a function of constant with an error term. Since α^2_t is the one –period ahead forecast variance based on past information, it is called the conditional variance. The conditional variance equation specified as a function of three terms:

- *A constant term :* ω
- *News about volatility from the previous period, measured as the lag of the squared residual from the mean equation:* ε_{t-1}^2 *(the ARCH term)*
- *Last period forecast variance:* σ_{t-1}^2 *(the GARCH term)*

The conditional variance equation models the time varying nature of volatility of the residuals generated from the mean equation. This specification is often interpreted in a financial context, where an agent or trader predicts this period's variance by forming a weighted average of a long term average (the constant), the forecast variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). If the asset return was unexpectedly large in either the upward or the downward direction, then the trader will increase the estimate of the variance for the next period. The general specification of GARCH is, GARCH (p, q) is as:

$$\boldsymbol{\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \ \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_i \ \sigma_{t-1}^2}$$

where, p is the number of lagged α^2 terms and q is the number of lagged ε^2 term

GJR-GARCH Model

Asymmetric GARCH models due to the leverage effect with asset prices, where a positive shock has less effect on the conditional variance compared to a negative shock. This can be incorporated into the GARCH model using a dummy variable. This was introduced by Glosten, Jangathann and Runkle (GJR), and showed that asymmetric adjustment was an important consideration with asset prices. The model is of the form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \lambda u_{t-1}^2 I_{t-1}$$

Where *I* is a dummy variable that takes the value of 1 when the shock is less than 0 (negative) and 0 otherwise. To determine if there is asymmetric adjustment, depends on the significance of the last term, which can be determined using the t-statistic

Data Analysis & Interpretation

I. Descriptive Statistics of NIFTY

A summary of descriptive statistics for returns series of NIFTY of National Stock Exchange is presented in Table 1. This includes mean, maximum, minimum value, standard deviation, skewness, kurtosis and jarque-bera test.

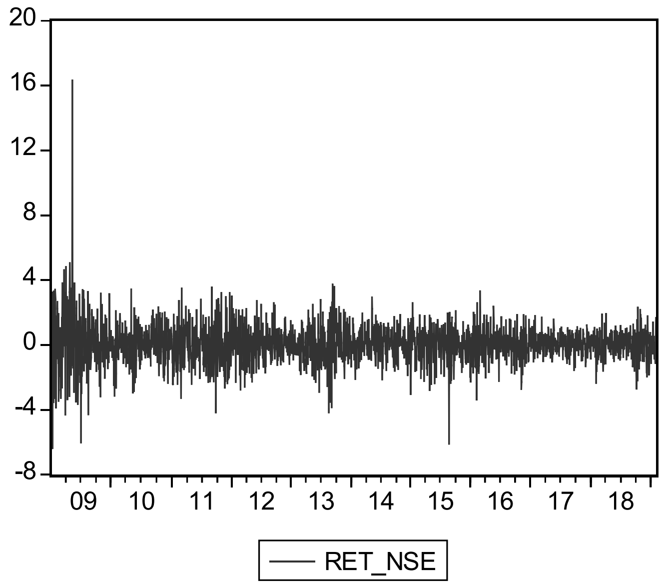

Table 1: Descriptive Statistics of NIFTY
(January 2009 to January 2019)

	NIFTY
Mean	0.0514
Median	0.0563
Maximum	16.3343
Minimum	-6.3802
Std. Dev.	1.1501
Skewness	0.9698
Kurtosis	20.965
Jarque-Bera	33549.12
Probability	0.0000
Sum	126.833
Sum Sq. Dev.	3260.308
Observations	2466

The above Table 1 showed that NIFTY has a sign of positive average daily returns. The average daily return was shown by NIFTY with .051. As far as volatility is concerned the standard deviation of NIFTY was 1.15%. The coefficients of the skewness were found to be significant and positive for all the returns. It is within acceptable limits but however it is heavily tailed. The coefficient of kurtosis was found to be positive and was significantly higher than 3, indicating highly leptokurtic distribution compared to the normal distribution for all the returns. The jarque- bera test was applied to know whether the return series is normally distributed or not. The null hypothesis was that the series is normally distributed. The above table showed that the p-value (0.0000) was less that .01 at 1% significance level so null hypothesis was rejected and hence the return series of NIFTY was not normally distributed.

II. Analysis of Unit Root Test

Table 2: Unit Root Test of NIFTY
(January 2009 to January 2019)

Unit Root Test	**ADF**	
Index	**t-Statistic**	**Prob.***
With Intercept at level	-0.95892	0.7695
With Trend & Intercept at level	-2.7609	0.2122
With Intercept at first difference	-46.378	0.0001*
With Trend & Intercept at first difference	-46.3686	0.0000*

*Indicates significance at 1% level of significance

The results of ADF test for a unit root for NIFTY of National Stock Exchange are presented in Table 2. The above table showed that the p-value NIFTY was significant at 1% level, so null hypothesis that series has a unit root problem was rejected. It means the series was stationary and therefore it was concluded that this market does not have random walk and was not weak form of efficient.

Table 3: Analysis of GARCH (1, 1) Model for NIFTY Returns for Ten Years
(January 2009 to January 2019)

	Coefficient	Std. Error	z-Statistic	Prob.
ϕ_0	0.063142	0.019742	3.198264	0.0014
ϕ_1	0.067971	0.022115	3.073525	0.0021
Variance Equation				
C	0.009491	0.002169	4.376676	0.0000
RESID(-1)^2	0.057417	0.007213	7.960136	0.0000
GARCH(-1)	0.934704	0.007839	119.2428	0.0000
R-squared	0.002929	Mean dependent var	0.050471	

Adjusted R-squared	0.001308	S.D. dependent var	1.149302	
S.E. of regression	1.14855	Akaike info criterion	2.850012	
Sum squared resid	3245.152	Schwarz criterion	2.861797	
Log likelihood	-3507.64	F-statistic	1.80651	
Durbin-Watson stat	2.018415	Prob(F-statistic)	0.124788	

*indicates significant at 1% and 5% level.

Table 4: Analysis of GJR-GARCH (1, 1) Model for NIFTY Returns for Ten Years

(Period: January 2009 to January 2019)

	Coefficient	Std. Error	z-Statistic	Prob.
ϕ_0	0.040019	0.01961	2.040709	0.0413
ϕ_1	0.078079	0.022854	3.416441	0.0006
C	0.011885	0.002531	4.696275	0.0000
RESID(-1)^2	0.022835	0.006288	3.631216	0.0003
RESID(-1)^2*(RESID(-1)<0)	0.091813	0.012483	7.354998	0.0000
GARCH(-1)	0.923027	0.008814	104.7221	0.0000
R-squared	0.002626	Mean dependent var	0.050471	
Adjusted R-squared	0.000598	S.D. dependent var	1.149302	
S.E. of regression	1.148958	Akaike info criterion	2.835455	
Sum squared resid	3246.137	Schwarz criterion	2.849597	
Log likelihood	-3488.7	F-statistic	1.294956	
Durbin-Watson stat	2.038158	Prob(F-statistic)	0.263114	

indicates significant at 1% and 5% level.

The Table no 3 represents the vale of ARCH is 0.0574 which is significant and more than zero which means the impact of past historical news in the stock market. The vale of GARCH is 0.934 which is again more than zero and significant represents the presence of conditional volatility in the market. The sum total of (ARCH and GARCH) is 0.98 which is near to one which means volatility clustering means large changes results into large changes and small changes results into small changes, is persisten in the indian stock market.

The leverage effect of the stock market is shown with the help of model GJR-GARCH (1,1), the results of which are shown in table no. 4. The asymmetric coefficient value is 0.06. This is positive and significant as well which implies that negative information in the market is followed by higher volatility as compared to positive information of the same magnitude. The T-value of the same is 7.35 whereas the table value is 1.98. It measn t-value is greater than the table value. On the other hand, p-value is 0.00 which is lesser than the table value 0.05 so it shows the results are highly significant at 5% significant level.

The coefficients of ARCH and GARCH (0.02 & 0.92) imply that impact of both past news (ARCH) and present news (GARCH) responds asymmetrical to the stock retruns of the Indian stock market at 5% level.

Conclusions

Arbitrators are the person who always wants to take benefit out of stock market price differentials because of lack of information. As a result they have keen interest in knowing the volatility of the stock market. Volatility clustering and leverage effect are very important variables of the stock market as these can help in understanding the behavior and pattern of stock market which is helpful for taking investment decision. The index selected for the purpose was NIFTY of the National Stock Exchange. The data was taken for the sample period of ten years from January 2009 to January 2019. The data was collected from the official website of National stock exchange i.e. www.nseindia.com. Different statistical tools like E-Garch and GJR-GARCH were used to analyze the data with the help of software Eviews5. It is concluded that volatility clustering means large changes results into large changes and small changes results into small changes, is persisten in the Indian stock market. Also, the coefficients of ARCH and GARCH (0.02 & 0.92) imply that impact of both past news (ARCH) and present news (GARCH) responds asymmetrical to the stock retruns of the Indian stock market at 5% level. So, it is found that volatility clustering and leverage effect is present in the Indian stock market.

There is a general belief that volatility clustering is the result of increasing interdependence among different economies. The interdependece means shock can be transmitted globally or domestic due to the financial linkages of different ecomomies resuled into volatility clustering. Leverage effect is the result of fixed costs in the capital structure. So, an investor is required to keep a close eye on the changing prices dynamics of the market so to prevent the losses.

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