Indian Stock Market Volatility using GARCH Models: A Case Study of NSE

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This paper examines volatility of Indian Stock Market returns using GARCH models that capture the volatility clustering and leverage effect. The analyzed data are daily closing prices of Nifty index during 2005 to 2019. GARCH (1, 1), EGARCH (1, 1) and TGARCH (1, 1) models are employed after confirming unit root rest, volatility clustering and ARCH effect. Asymmetric GARCH models reveal a presence of leverage effect and also confirm the effect of conditional volatility. Findings exhibit that the coefficient has a likely indication both in EGARCH (negative, significant) and TGARCH (positive, significant) models. EGARCH (1, 1) model fits better to capture the asymmetric volatility.

Keywords: Nifty, Asymmetric Volatility, GARCH Models, Volatility Clustering and Leverage Effect

1. Introduction

Stock markets experience volatility. Volatility estimates the uncertainty of a security. It replicates the array to which the price of a security rises or declines. If the prices of a security change hastily and unpredictably in a given time span, it is referred as elevated volatility. If the prices of a security vary gradually, it is referred as low volatility. Financial markets are habitually anxious with extend of asset returns which is estimated as standard deviation (Poon, 2005).

Volatility is of quite significant to investors involved in the stock markets. It portrays dispersion from a likely value. Considerable fluctuations in the share market returns result in major unfavourable effects on investors. Fluctuations may also impact on consumption pattern, business resources investment, leverage decisions, business cycle and macro-economic variables (Daly, 2011). A rise in stock market volatility leads to a considerable fluctuation in share prices which was evidenced from 1929 to 1939 during the period of Great Depression (Schwert, 1990).

The volatility of a market tends to be greater when a market is in a downward trend and volatility tends to be lower in an upward trend. This pragmatic experience is termed as asymmetric volatility. The explanation of asymmetric volatility may be attributed to factors like leverage, distress selling, serial correlation etc. The occurrence of such instability is visible during the collapse of stock market when a greater turn down in share price is accompanied by a rise in volatility (Wu.G, 2001).

2. Literature Review

The association of share price and its fluctuation have concerned stock market researchers. Abundant investigations have been embarked on in modelling the movements within the share market. Mandelbrot (1963) and Fama (1965) initiated the assessment on returns from stock market. Stock market returns with time series regularly show signs of volatility clustering. This connotes that large changes in the sequence are usually to be followed by large change and tiny changes are likely to be followed by tiny changes. Engle (1982) termed such movement in the sequence as Autoregressive Conditional Heteroskedasticity (ARCH). Stock market researchers further investigated the fluctuation of rising share markets by applying ARCH models. GARCH model was a generalized and extended version of ARCH technique propounded by Bollerslev (1986). Both the models were a better framework to describe the behaviour of return volatilities. GARCH (1, 1) is regarded as excellent technique to capture conditional volatility from a wide range of financial data. (Matei 2009). GARCH (1, 1) technique has also been successful in predicting the instability in US share market as compared to other techniques (Akgiray, 1989).

Although, the ARCH and the GARCH techniques have been better in capturing the fluctuation of the fiscal time sequence information, they have been unsuccessful in assessing the leverage effect where the conditional variance is likely to react asymmetrically to affirmative and pessimistic market information. Stocks react harshly during the market turn down, showing volatility asymmetry (Bekaert and Wu, 2000). The rising nations exhibit greater asymmetric volatility at the time of financial instability (Jayasuriya and Rossiter, 2008). Several expansions of GARCH techniques have been put forwarded to arrest the leverage effect. An exponential GARCH (EGARCH) technique based on logarithm of the conditional volatility in the financial time series information was applied for further assessing the stock market volatility (Nelson 1991). Thereafter, a number of amendments were put forwarded from this process. Amongst them, is the establishment of Threshold ARCH (TARCH) model for studying the blow of affirmative and pessimistic information (Zakoian 1994). Further research works reflect that the EGARCH and TARCH techniques attained better results in anticipating the stock market information (Chen and Lian, 2005).

A few research initiatives have so far been carried out on fluctuations in share market returns in growing nations. The volatility was examined in the stock market in India and investigated the existence of fluctuation during 1990s (Roy and Karmakar, 1995). A study of Indian market has also revealed the presence of asymmetric volatility (Goudarzi and

Ramanarayanan, 2011). Unexpected shocks cause asymmetric volatility and positive news lead to prominent results than adverse news (Entorf and Darmstadt, 2007). The existence of asymmetry was revealed in the returns of Indian market through the application of TARCH (1, 1) model as well. The research work to predict the fluctuations in Indian stock market was undertaken by comparing the results of unconditional and conditional volatility techniques (Ajay, 2005). GARCH technique was applied in assessing the co-movement and volatility transmission in Indian and US share market (Kumar and Mukhopadhyay, 2002). The effect of introducing index options and futures on fluctuations in stock index was examined by the application of GARCH technique (Shenbagaraman, 2003). The volatility in the daily return of NSE was assessed using GARCH model where this model proved to predict the fluctuations better compared to other techniques (Banerjee and Sarkar, 2006).

3. Objectives of the Study

The objectives of the present study are:

- To estimate the existence of volatility in India stock market by applying the GARCH family of models.
- To investigate the presence of volatility clustering and leverage effect by applying asymmetric models.

4. Research Methodology

4.1 Data Source

The current research work is based on S&P CNX Nifty index value acquired from the website of National Stock Exchange (NSE). The data embodied in the study are Nifty index's daily closing prices. The data spans from April 2005 to March 2019. The study considers closing values on every day basis. S&P CNX Nifty index is considered as a representative sample of share value in India as it is believed to reflect the performance of the entire stock market.

4.2 Investigation Tools

Augmented Dickey Fuller (ADF) test, Philips-Perron (PP) test, Autoregressive Conditional Heteroscedasticity - Lagrange Multiplier (ARCH-LM) tests and GARCH family of models were applied for the present research. The study has employed E-views 10 package for the purpose of investigation.

Volatility is estimated on daily index returns. Hence the difference in the logarithm of Nifty index value for the two following days is first calculated.

4.3 Elementary Measurements of Nifty Index Return

4.3.1 Descriptive Calculation

To categorise the distributional nature of the daily Nifty index return sequence, the descriptive tools like mean, median, skewness, kurtosis and Jarque-Bera statistics tools are applied.

4.3.2 Stationarity Test

To examine the stationarity of the index return time sequence, unit root test has been carried out. A time series of index return is believed to be stationary only when both mean and variance are steady eventually. But a time series which is non stationary and with an existence of unit root will have a changing mean or variance or may be both. Here, the test of stationarity is performed by ADF test (Dickey and Fuller, 1979) and PP test (Phillips and Perron, 1988).

The outcome of a time series which is not static can be calculated for the precise occasion only and assessment cannot be universal. So, a series must be stationary. Moreover, a non-static time sequence cannot give pragmatic results for prediction purpose. As Nifty index return happens to be a time series variable, it must be static in character otherwise movements cannot be predicted. Hence, the index return information used in this paper requires examination to confirm the existence of unit root by using test of Augmented Dickey Fuller.

Null Hypothesis

H_0: There is a unit root; the time series is non stationary.

Alternate hypothesis

H_a: There is no unit root; the time series is stationary.

4.3.3 Heteroscedasticity Test

It is extremely vital to first examine the residuals for the existence of heteroscedasticity before applying the GARCH model. The presence of heteroscedasticity in residual of the return is confirmed by applying the Lagrange Multiplier (LM) test.

4.3.4 Tools for measuring Volatility

In general, it is observed that escalating movement in share market is followed by minor variances when compared to the downward movements with alike nature. This asymmetric moment is termed as the leverage effect. Hence, the Generalized ARCH (GARCH) methodology which is symmetrical in nature will not be suitable to evaluate the unsteadiness in time series.

To capture the asymmetrical data, Exponential GARCH (EGARCH) methodology advocatedby Nelson (1991) and Threshold GARCH (TARCH) advocated by Glosten, Jaganathan, and Runkle (1993) and Zakonian (1994) are applied.

4.3.4.1 GARCH (1, 1)

The GARCH model in which the conditional variance rest on the former lags; specifies the conditional variance equation as:

mean equation : $r_t = \mu + \varepsilon_t$ and
variance equation: $\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$,

Where r_t is the return of the asset at time t, μ is the average return and ε_t is the residual return and where $\omega>0$, $\alpha \geq 0$, $\beta \geq 0$. The degree of factor α and β denote the variability in time series. If $(\alpha + \beta)$ is close to unity, it states that a distress at time t will carry on for future period.

4.3.4.2 EGARCH (1, 1)

The volatility that happens to decline when returns rise and volatility happens to rise when the returns fall is often called the leverage effect (Enders 2004). EGARCH method captures asymmetric reaction of the time changing variance where variance is constantly affirmative. It was developed by Nelson (1991) that υ is the asymmetric response parameter or leverage parameter. If it is below zero it specifies that unfavourable information boosts forthcoming fluctuation while favourable information mitigates the consequence on forthcoming doubts (Kalu 2010). EGARCH (1, 1) is defined as,

$$\log(\sigma^2_t) = \omega + \beta_1 \log(\sigma^2_{t-1}) + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma^2_{t-1}} \right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma^2_{t-1}}$$

4.3.4.3 TGARCH (1, 1)

The equation of the TGARCH for the conditional variance is:

$$\sigma^2_t = \omega + \alpha\, \varepsilon^2_{t-1} + \gamma\, d_{t-1}\, \varepsilon^2_{t-1} + \beta\sigma^2_{t-1},$$

Where γ is termed as the asymmetry or leverage factor. Here, positive facts ($\varepsilon_{t-1} > 0$) and the adverse data ($\varepsilon t-1 < 0$) have variance outcome. α_i connotes positive facts while $\alpha_i+\gamma_i$ connotes adverse information. Thus, in the position where γ is substantial and positive, negative information has more consequence on σ^2_t compared to the positive information.

5. Empirical Results

Table 1 shows descriptive analysis of Nifty index returns during the study period. As reflected in the table, mean returns of Nifty is 0.000216 and a standard deviation of 0.000347. The returns mean is positive which portrays that there is a rise in the share price during that period. Skewness of the distributions of Nifty returns is negative. Negative skewness connotes a higher chance of generating returns that is greater than mean. Kurtosis of the distributions of Nifty index returns is leptokurtic (> 3) depicting fat tail in the return sequence with a normal distribution. It is additionally established by Jarque-Bera test that is significant at 1% level. Thus the null hypothesis of normality is rejected.

Table 1 *Descriptive Statistics of S&P CNX Nifty Returns*

Particulars	Nifty Returns
Mean	0.000216
Median	0.000347
Maximum	0.070939
Minimum	-0.056520
Std. Dev.	0.006075
Skewness	-0.053416
Kurosis	13.74739
Jarque-Bera	16697.12
Probability	0.00000
Sum	0.749875
Sum Sq. Dev.	0.128005
Observation	3469

Figure 1 portrays volatility clustering of S&P CNX Nifty return from April 2005 to March 2019. It is noticed that the stage of low volatility has a tendency to be followed by the stage of low volatility for a longer period and the stage of elevated volatility is followed by the stage of elevated volatility for a longer period. This specifies that the volatility is clustering and the Nifty index return series change about the constant mean but the variance is changeable with time.

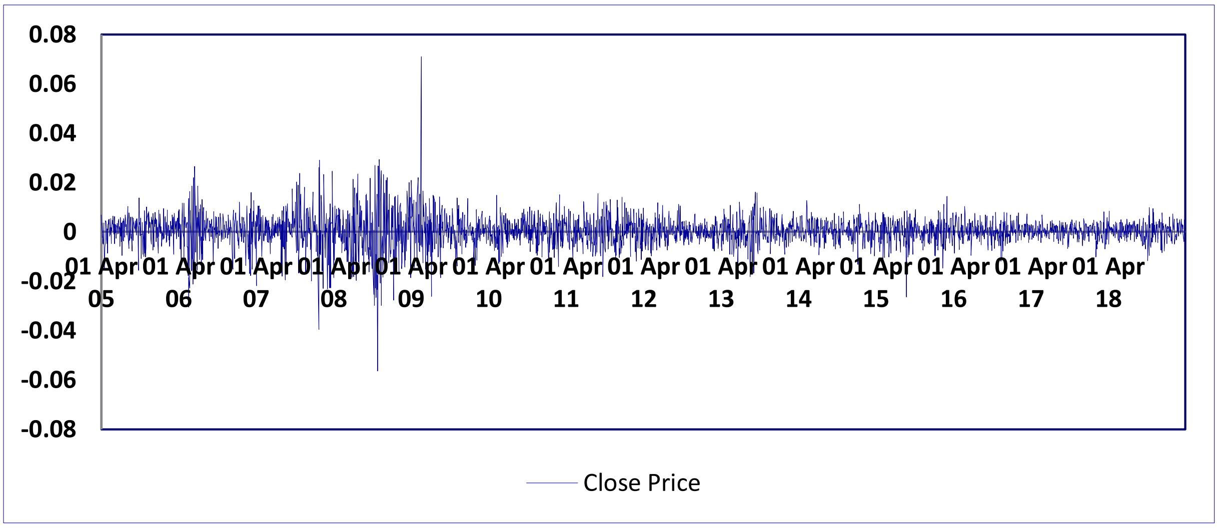

Figure 1 *Volatility Clustering of Daily Return of S&P CNX Nifty*

The test for stationarity is carried out by ADF test and PP test. Table 2 discloses the result of unit root test of index return series using ADF and PP tests. The p values of ADF and PP are less than 0.05 which specify that the index return series during the research period are stationary. ADF test and PP test reject the null hypothesis that there is a presence of a unit root in the index return series in all three levels of significance. Hence, the result of ADF test and PP tests statistics validate that the series is stationary.

Table2 *Unit Root Test*

Value	ADF	PP
t-statistics	-55.43342	-55.41358
Prob.	0.0001	0.0001
Critical Value		
1%	-3.432048	-3.432048
5%	-2.862176	-2.862176
10%	-2.567152	-2.567152

The estimated result of ARCH-LM test is shown in Table 3. ARCH-LM test for heteroskedasticity is considered on residuals estimated by the GARCH model. ARCH-LM test outcome indicates that residuals derived from the regression estimation are free from heteroscedasticity (p>0.05) Therefore, ARCH-LM result does not hold further arch effect residual.

Table 3 *Estimated Result of ARCH-LM Test*

	ARCH-LM test for heteroscedasticity		
F-Statistics	0.431178	Prob. F (1,2969)	0.5126
Obs *R-squared	0.431425	Prob. Chi-Square (1)	0.5122

Table 4 *Estimated Result of GARCH (1, 1) Models*

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4))*GARCH(-1)				
Variance	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.000351	$8.02e^{-5}$	4.336969	0.0000
Variable Equation				
C	$3.27e^{-7}$	$5.99e^{-8}$	5.459731	0.0000
RESID (-1) ^2 (α)	0.087521	0.006619	13.22159	0.0000
GARCH(-1) (β)	0.906711	0.006686	135.6102	0.0000
α + β	0.994232			
Akaike info. Criterion	-7.650418	Schwarz Criterion	-7.642357	

Table 4 represents the estimated outcome of GARCH (1, 1) model. It reflects that the factor of GARCH is noteworthy. In the mean equation, constant value is positive and significant as $p<0.05$. The coefficients on both the lagged squared residual (ARCH) and lagged conditional variance (GARCH) in Variance Equation are highly significant. It reveals that the volatility is frequent. The sum of these coefficients (α and β) is 0.9942, which is close to unity signifying that volatility is quite recurring in nature. This is often noticed in high frequency fiscal information. Thus, the GARCH model proved that conditional variance is repeated in the Indian stock market. The AIC and SC criteria of the model are -7.650418 and -7.642357 respectively.

The volatility through EGARCH (1, 1) methodology is observed to consider the effect of positive or adverse statistical data. The outcome of EGARCH (1, 1) model is shown in Table 5. The outcome reveals the occurrence of leverage effect. C (4) is negative i.e. -0.079592 and statistically significant which specifies that any change in price responds asymmetrically to the positive or adverse information in the market. Further, it can be concluded that affirmative news creates less variance or volatility than bad news. Hence, unfavourable information plays very important part in volatility in comparison to affirmative news. This also denotes that Indian market is inefficient. The AIC and SC criteria of the model are -7.667898 and -7.657812 respectively.

Table 5 *Estimated 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))				
Variance	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.000219	$7.8e^{-5}$	2.760954	0.0062
Variable Equation				
C(2)	-0.335728	0.030573	-10.98363	0.0000
C(3)	0.186781	0.011218	16.66170	0.0000
C(4)	-0.079592	0.007012	-11.36654	0.0000
C(5)	0.981511	0.002398	410.6656	0.0000
Akaike info. Criterion		-7.667898	Schwarz Criterion	-7.657812

The leverage effect is measured through TARCH (1, 1) model and the outcome of the model is shown in Table 6. The C (4)*(RESID (-1) ^2*(RESID (-1) <0) is positive i.e. 0.100242 and statistically significant. This supports the statement that there is a leverage effect in the model and unfavourable information produces more volatility as compared to positive news or positive and adverse shocks have diverse shock on the volatility of Nifty index return. The AIC and SC criteria of the model are -7.665572 and -7.655483 respectively. The TARCH model is believed to have explained the volatility better for Nifty.

Table 6 *Estimated Result of TARCH Model*

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4))*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)				
Variance	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.000242	$8.18e^{-5}$	2.829389	0.0047
Variable Equation				
C	$4.27e^{-7}$	$6.03e^{-8}$	7.077394	0.0000
RESID(-1)^2	0.038461	0.005812	6.625198	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.100238	0.010519	9.533296	0.0000
GARCH(-1)	0.901678	0.006723	134.2142	0.0000
Akaike info. Criterion		-7.665572	Schwarz Criterion	-7.655483

6. Conclusion

This research work examines the volatility of S&P CNX Nifty index returns. The daily closing value of index were gathered from 2005 to 2019 and represented by applying GARCH methods. The methods capture the volatility clustering and leverage effect during the study period. The test of unit root, volatility clustering and ARCH effect are confirmed and established. The Nifty index returns are further analysed by GARCH (1, 1), EGARCH (1, 1) and TGARCH (1, 1) models. The results revealed that the coefficient has the possible indication in the EGARCH (negative and significant) as well as in the TARCH (positive and significant) models. Further, EGARCH (1, 1) model is proved to be the finest model to arrest the asymmetric volatility.

7. References

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