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A Study on Unfolding Volatility and Leverage Effect in Indian Stock Market

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Abstract

Return is the major attribute of an investment asset that can be considered as a random variable. The variability in return can be expressed as volatility. Forecasting volatility and modelling are the most prolific areas for the research. Volatility and leverage effect are the two crucial stipulations to study market contradictions and trends that prevail for a drawn-out period. It is observed that when volatility beams the markets soar and when markets roar the volatility fades away. Leverage has a larger scope in managing volatility when investors tend to shuffle their positions. This literature aims to identify the volatility clustering and leverage effect caused to NSE NIFTY 50 index. The study contrasts volatility clustering using symmetric model of, i.e., GARCH (1,1). Leverage effects are studied and compared using TGARCH and EGARCH models.

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

JEL Classification: C01, C22, C5, E22, E27, G1, G14

Introduction

Volatility

Volatility (Conditional Variance) is a key structure for pricing of financial instruments. Volatility forecasting and modelling are decisive for option pricing, management of risk and portfolio management. Volatility refers to the spread of all likely outcomes of an uncertain variable (Poon, 2005). Statistically, volatility is frequently measured as the sample standard deviation

$$\hat{\sigma} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \mu)^2}$$

where r_t is the return on day t, and μ is the average return over the T-day period. Sometimes, variance, σ^2, can also be used as a volatility measure. As variance is simply the square of standard deviation, there is no difference that measures which we use for comparing volatility of two investment assets. However, variance is much less invariable and less enviable than standard deviation as an object for volatility forecasting and modelling. Hence, standard deviation is more expedient and instinctive when we talk about volatility. The ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) models portray the phenomenon of volatility clustering to be more accurate measure of risk. ARCH model elucidated the constancy of the return in the time series data. GARCH model explained the heteroskedasticity of the return sequence residuals.

Leverage Effect

The existing return and potential volatility have negative correlation between themselves, which designates that bad news will cause aggressive fluctuations as compare to good news and hence called as Leverage Effects (Black, 1976). In other words, positive and negative information lead to a diverse level of effect to volatility in stock returns. Asymmetric models like EGARCH, TGARCH and PGARCH EGARCH analyze the effect on stock volatility caused by asymmetric conditional heteroskedasticity on absorbing different information in the market.

Review of Literature

Modelling volatility of a financial time series has become an important area for research. The time series are found to depend on their own past value (autoregressive), depending on past information (conditional) and exhibit non-constant variance (heteroskedasticity). It has been found that the stock market volatility changes with time (i.e., it is ‘time-varying’) and exhibits ‘volatility

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clustering'. A series with some periods of low volatility and some periods of high volatility is said to exhibit volatility clustering (Banumathy & Azhagaiah, 2015).

The empirical results specified that there was noteworthy evidence for asymmetry in stock returns which is confined by GARCH specification model (Apergis & Eleptherine, 2001). The study scrutinized the ability of economic factors to describe stock market volatility and proposed a model of the economy under uncertainty, which recognized four determinants of stock market volatility viz. uncertainty about price level, the riskless rate of interest, the risk premium on the equity and the ratio of expected profits to expected revenues. Their results were useful in explaining the past behaviour of stock market volatility and in forecasting future volatility (Binder & Merges, 2001). The empirical analysis examined the heteroskedastic behaviour of Indian Stock Market employing different GARCH models. The study observed the asymmetric volatility in Indian Stock Market by employing EGARCH and concluded the volatility is an asymmetric function of past innovation raising proportionately more during market decline and was evidenced that return is not significantly related to risk (Karmarkar, 2007). Another study used GARCH family models viz., GARCH (1, 1), EGARCH and TGARCH for modelling the volatility and forecasting the conditional variance of BSE SENSEX-30 representing negative news has long-term volatility than good news in the market (Srinivasan & Ibrahim, 2010).

Data and Statistics

Data for Analysis

For the purpose of investigating volatility clustering and checking the presence of leverage effect in Indian Stock Market (NSE CNX Nifty 50), financial time series were used, i.e., daily closing prices of the selected market index for a period of 10 years ranging from April 2006 to March 2016 resulting in 2,474 observations. Return estimation is essential in volatility estimation and hence, daily returns (r_t) were calculated as continuously compounded returns that are the difference in log of closing prices of the market index of consecutive days by using the formula;

$$r_t = \log\left[\frac{P_t}{P_{t-1}}\right]$$

where r_t is the logarithmic daily return on NSE CNX Nifty 50 market index for time t, P_t is the closing price at time t and P_{t-1} is the corresponding price in the period at time $t-1$.

Summary of Basic Statistics

In order to state the distributional properties of the daily return series (r_t) during the period of study, different descriptive statistics were calculated and reported. A stationary time series can be defined as its statistical properties viz., mean, variance and autocorrelation are stable over time. One of the major reasons for stationarised a time series is to attain significant sample statistics such as mean, variance and autocorrelations with other variables. Such statistics are constructive as descriptors of potential behaviour only if the series are stationary. It is essential to check that whether the data are stationary or non-stationary. Hence, to check Stationarity, Augmented Dicky-Fuller Test is applied. Before applying the GARCH methodology, it is essential to first scrutinize the residuals for confirmation of heteroskedasticity. In order to test for existence of heteroskedasticity in residuals of NSE CNX Nifty 50 market index return series, the Lagrange Multiplier (LM) test for ARCH effects propounded by Engle (1982) is applied.

Methodology

The following are the research hypotheses:

H_{01}: The returns of NSE NIFTY 50 are not normally distributed.

H_{02}: The returns of NSE NIFTY 50 are non-stationary.

H_{03}: The returns of NSE NIFTY 50 are homoskedastic.

H_{04}: There is no volatility caused in the returns of NSE NIFTY 50.

H_{05}: There is no leverage effect caused in the returns of NSE NIFTY 50.

H07: There is no ARCH effect in the returns of S&P BSE SENSEX and NIFTY50.

The Sample

The daily stocks values of NSE NIFTY 50 have been taken for 10 years' period ranging from April 2006 to March 2016. There are 2,473 observations of the daily closing prices.

In order to measure the volatility clustering and to model leverage effect in Indian Stock Market, both symmetric and asymmetric models viz., GARCH(1,1) and EGARCH (1,1) and TGARCH (1,1) are used.

Symmetric Measurement

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

Under this model, the conditional variance is corresponding to a linear function of its own lags. The simplest model specification is the GARCH (1,1) model;

Where the mean function and variance equation are represented as:

$$r_t = \mu + \varepsilon_t$$

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

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

r_t = return of the asset at time t.

μ = average return

ε_t = residual return, which is defined as,

$$\varepsilon_t = \sigma_t z_t$$

Where z_t is standardized residual returns (i.e., random variable with zero mean and variance 1), and σ_t^2 is conditional variance. For GARCH(1,1), the constraints $\alpha_1 \geq 0$ and $\beta_1 \geq 0$ are needed to ensure σ_t^2 should be positive (Poon, 2005).

In GARCH (1,1), the mean equation is written as a function of constant with an error term. Since σ_t^2 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 (ARCH term), Last period forecast variance = σ_{t-1}^2 (GARCH term). The general specification of GARCH is, GARCH (p, q) is as:

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

where, p is the number of lagged σ^2 terms and q is the number of lagged ε^2 terms.

Asymmetric Measurement

The Exponential GARCH (EGARCH) Model

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

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

The left-hand side is the log of the conditional variance. The coefficient γ is known as the asymmetry or leverage term. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. The impact is symmetric if $\gamma \neq 0$.

The Threshold GARCH (TGARCH) Model

The generalized specification of the Threshold GARCH (TGARCH) for the conditional variance developed by Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994) is given by:

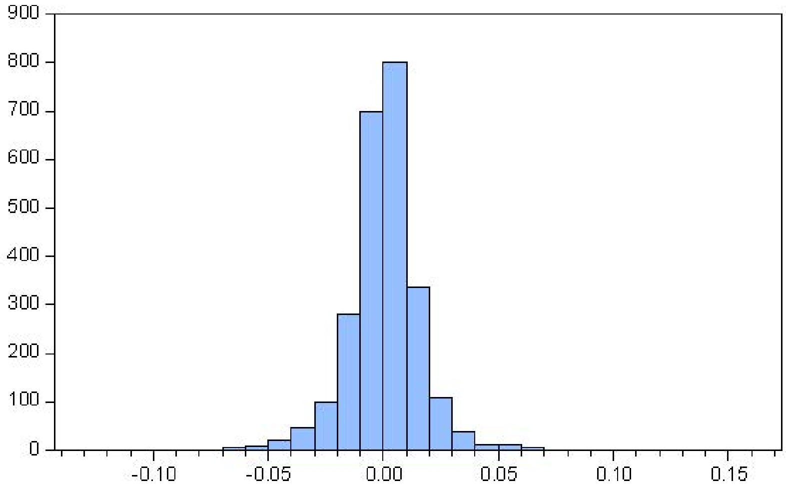
$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Where, γ is known as the asymmetry or leverage parameter and d_{t-1} is dummy variable. Under TGARCH model, good news (ε_{t-1}>0) and the bad news (ε_{t-1}< 0) have differential effect on the conditional variance. Good news has an impact of α_i, while bad news has impact on $\alpha_i + \gamma_i$. Hence, if γ is significant and positive, negative shocks have a larger effect on σ_t^2 than the positive shocks.

Results and Analysis

The descriptive statistics of NSE CNX Nifty 50 returns during the study period is shown in Table 1. As shown in the table, mean return of the index is positive 0.000324% with a high standard deviation of 0.015720% that indicates NSE CNX Nifty 50 index offer high average returns but these returns are also subject to high volatility. Skewness of the distribution of the index returns is negative that indicates longer left tail of the distribution showing large number of high values in the distribution. The value of kurtosis is higher than 10 which mean that the index return has a heavier tail than a standard normal distribution. Hence, the index returns are non-normally distributed. It is further evidenced through Jarque-Bera test statistics that is significant at 1% level and hence the null hypothesis of normality is rejected.

Table 1: Descriptive Statistics for Log Returns of NSE CNX Nifty 50



Series: LOG_RETURNS	
Sample 4/03/2006 3/30/2016	
Observations 2473	
Mean	0.000324
Median	0.000758
Maximum	0.163343
Minimum	-0.130142
Std. Dev.	0.015720
Skewness	-0.007332
Kurtosis	11.97149
Jarque-Bera	8293.610
Probability	0.000000

Source: Authors Calculated

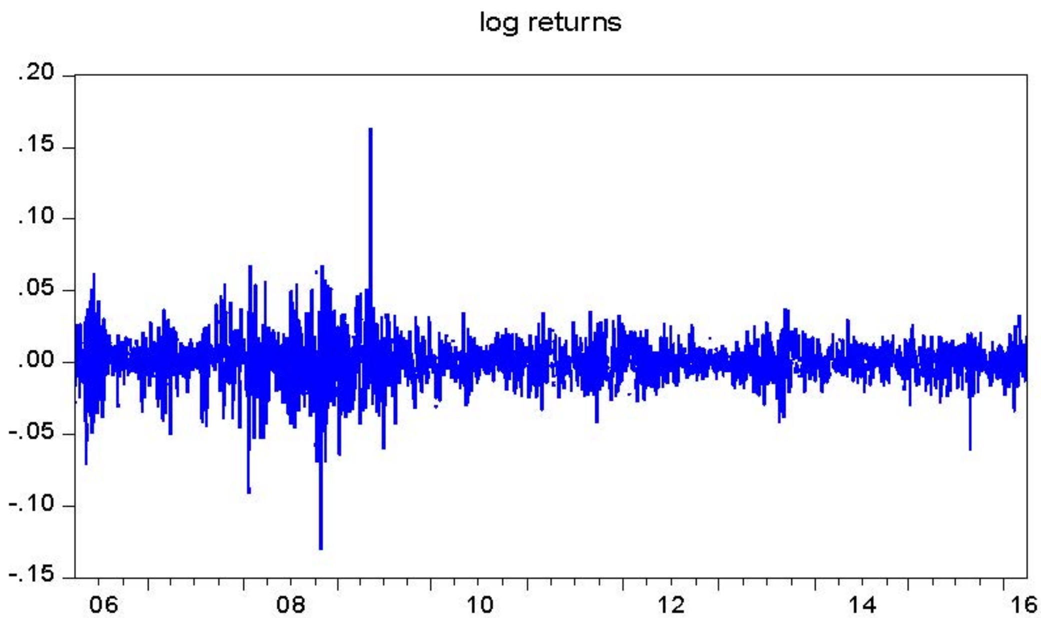


Fig. 1: Volatility Clustering of NSE CNX Nifty 50 Returns

Fig. 1 shows that Volatility Clustering of NSE CNX Nifty 50 returns that explains large price fluctuations are followed by large price fluctuations and small price fluctuations are followed by small price fluctuations of both signs (positive and negative). This phenomenon implies that stock index return volatility changes over a time period. Volatility clustering is explained by heterogeneous expectations theory. According to this theory, returns on stock fall as market participants learn from their past trading strategies. As a result, the markets have a propensity to stay in a condition of partial equilibrium till new information hits the market. In other words, volatility clustering stands for sturdy autocorrelation in squared returns. This proved in Table 1. Since all the probability values are significant, we reject the null hypothesis of no autocorrelation.

To examine whether the daily index price and its mean returns are stationary series, the Augmented Dickey–Fuller (ADF) test has been applied. The test results are reported in Table 2. It shows that the presence of unit root in the series. The probability (p-value) of ADF test is less than 0.05; hence, the data of the time series for the study period are stationary.

Table 2: Augmented Dickey-Fuller Test Results

		t-Statistic	*Prob.**
Augmented Dickey-Fuller Test Statistic		*-46.86379*	*0.0001*
Test critical values:	1% level	-3.432801	
	5% level	-2.862509	
	10% level	-2.567331	

Source: Authors Calculated

To investigate the ARCH effect or heteroskedasticity, ARCH-LM test was applied. The test results are shown in Table 3. From the table, it is clear that ARCH-LM test statistics is highly significant. Since probability value (p-value) is less than 0.05 the null hypothesis of no ARCH effect is not accepted at 1% level of significance. This evidenced the presence of ARCH effects in the residuals of the time series models in the stock index returns. Since, the presence of ARCH effects in the residuals of times series models in the index returns, GARCH family models can be proceeded further.

Table 3: ARCH-LM Test Results

F-statistic	785.2888	Prob. F(1,2470)	0.0000
Obs*R-squared	596.3323	Prob. Chi-Square(1)	0.0000

Source: Authors Calculated

The study spotlights on determining the best fitted GARCH (1,1) model in the return series. Hence, GARCH model is used for modelling the volatility of return series in NSE NIFTY 50 index. Table 4 reveals the parameter of GARCH is statistically significant. In other words, the coefficients viz., constant (ω), ARCH term (α), GARCH term (β) is highly significant at 5% level as p-value 0.0000 < 0.05. In the conditional variance equation, the estimated β value is 0.895291 that is considerably greater than α value 0.094990 indicating that, the market has long-term memory towards reaction of change and the volatility is more sensitive to its lagged values than it is to new surprises in the market values. It shows that the volatility is persistent and caries for a long period of time in future. The sizes of the parameters α and β determine the volatility in time series. The sum of these coefficients (α and β) is 0.990281 closer to unity indicating that the shock will persist too many future periods. Since the risk-return parameter is positive and significant at 5% level, it shows that there is a positive relationship between risk and return.

Table 4: Conditional Standard Deviation [GARCH (1,1)]

*GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)*				
Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
C	0.000643	0.000226	2.848022	0.0044
	Variance Equation			
C (Constant)	2.83E-06	4.60E-07	6.148380	0.0000
RESID(-1)^2 (α ARCH effect)	0.094990	0.007961	11.93190	0.0000
GARCH(-1) (β GARCH effect)	0.895291	0.008065	111.0106	0.0000
(α+ β)	0.990281			
R-squared	-0.000413	Mean dependent var		0.000324
Adjusted R-squared	-0.000413	S.D. dependent var		0.015720
S.E. of regression	0.015723	Akaike info criterion		-5.830441
Sum squared resid	0.611099	Schwarz criterion		-5.821039
Log likelihood	7213.341	Hannan-Quinn criter.		-5.827026
Durbin-Watson stat	1.881915			

Source: Authors Calculated

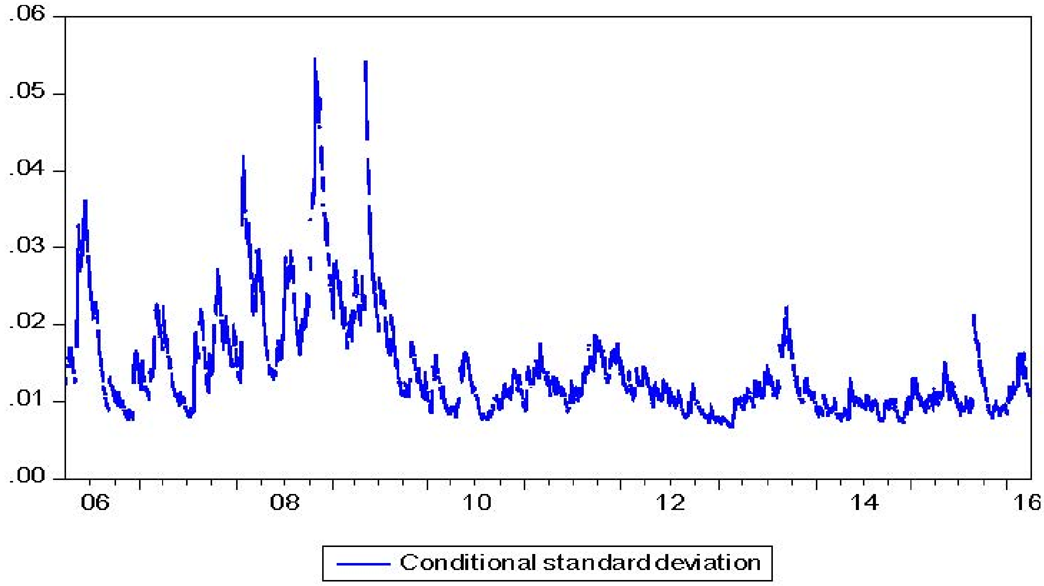


Fig. 2: Conditional Standard Deviation Graph GARCH (1,1)

In order to capture the asymmetries in the return series, two models have been used viz., EGARCH (1,1) and TGARCH (1,1). γ captures the asymmetric effect in both EGARCH (1,1) and TGARCH (1,1) models. The asymmetrical EGARCH (1,1) model is used to estimate the returns of NSE NIFTY50 index presented in Table 5. The results show that ARCH (α) and GARCH coefficient (β) are smaller than one, i.e., 0.183598 and -0.098094 stating that conditional variance is not volatile and there is no atypical increase or decrease in prices but a gradual movement is observed. The estimated coefficients are statistically significant at 5% level as p-value is less than 0.05. γ indicating the leverage coefficient, is negative -0.097629 representing the study is statistically significant at 5% level and explains the presence of leverage effect in return during the study period. The analysis reveals that there is a negative correlation between past returns and future returns (leverage effect). Hence, EGARCH (1, 1) model supports the presence of leverage effect on the NSE NIFTY50 index returns series.

Table 5: Conditional Standard Deviation EGARCH (1,1)

Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
C	-0.000164	0.000586	-0.279116	0.7802
	Variance Equation			
C(1) (ω)	-0.347843	0.049915	-6.968751	0.0000
C(2) (α)	0.183598	0.020427	8.988216	0.0000
C(3) (β)	-0.098094	0.012997	-7.547587	0.0000
C(4) (γ)	-0.097629	0.004906	198.9945	0.0000
R-squared	-0.001239	Mean dependent var		0.000324
Adjusted R-squared	-0.001645	S.D. dependent var		0.015720
S.E. of regression	0.015733	Akaike info criterion		-5.891197
Sum squared resid	0.611604	Schwarz criterion		-5.874742
Log likelihood	7291.465	Hannan-Quinn criter.		-5.885220
Durbin-Watson stat	1.873270			

Source: Authors Calculated

Further, TGARCH (1, 1) model is the used to test for asymmetric volatility in the NSE NIFTY50 index returns shown in Table 6 and the study estimated the result of coefficient's leverage effect (γ) is positive and significant at 5% level as the p-values are less than 0.05. The study implies that negative shocks or bad news have a greater effect on the conditional variance than the positive shocks or good news because γ values 0.891248, which is statistically significant at 5% level.

Table 6: Conditional Standard Deviation TGARCH (1,1)

Variable	*Coefficient*	*Std. Error*	*z-Statistic*	*Prob.*
C	0.000336	0.000226	1.484818	0.1376
	Variance Equation			
C(1) (ω)	3.28E-06	4.50E-07	7.305500	0.0000
RESID(-1)^2 (α)	0.038158	0.006428	5.936224	0.0000
RESID(-1)^2*(RESID(-1)<0) (β)	0.116796	0.012784	9.136038	0.0000
GARCH(-1) (γ)	0.891248	0.007838	113.7071	0.0000
R-squared	-0.000001	Mean dependent var		0.000324
Adjusted R-squared	-0.000001	S.D. dependent var		0.015720
S.E. of regression	0.015720	Akaike info criterion		-5.848278
Sum squared resid	0.610847	Schwarz criterion		-5.836525
Log likelihood	7236.396	Hannan-Quinn criter.		-5.844009
Durbin-Watson stat	1.882691			

Source: Authors Calculated

Conclusion

In the present study, volatility of NSE NIFTY50 index returns was tested using symmetric and asymmetric GARCH models. The data used for the study are stationary and there is no serial correlation observed in the returns of NSE Index. There is presence of ARCH affect in the data set. There is a sturdy relation between volatility and market performance. Volatility tends to turn down when stock market rises and amplify when market falls. In GARCH (1,1) model, the sum of the coefficient (α + β) is closer to unity mean that the volatility is highly constant. The asymmetric effect captured by TGARCH model deduce that the coefficient of leverage effect (γ) is positive and significant at 5% level, states presence of leverage effect during the study period. Hence, the market is more averse to change while captivating the negative news. When negative news hit the market, investors deploy their funds in less riskier asset and the swing is experiential in the market. The asymmetric effect is captured by the parameter (γ) in EGARCH model, which is negative and statistically significant at 5% level providing the presence of leverage effect, which reveals that positive shocks have less effect on the conditional variance when compared to the negative shocks.

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