Modelling Stock Market Volatility: Evidence from India

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This study empirically investigates the volatility pattern of Indian stock market based on time series data which consists of daily closing prices of s&p cnx Nifty Index for ten years period from 1st January 2003 to 31st December 2012. The analysis has been done using both symmetric and asymmetric models of Generalized Autoregressive Conditional Heteroscedastic (garch). As per Akaike Information Criterion (aic) and Schwarz Information Criterion (sic), the study proves that garch (1,1) and tgarch (1,1) estimations are found to be most appropriate model to capture the symmetric and asymmetric volatility respectively. The study also provides evidence for the existence of a positive and insignificant risk premium as per garch-m (1,1) model. The asymmetric effect (leverage) captured by the parameter of egarch (1,1) and tgarch (1,1) models show that negative shocks have significant effect on conditional variance (volatility).

Key Words: asymmetric volatility, conditional volatility, garch models and leverage effect
jel Classification: c32, c53

Introduction

Volatility refers to the amount of uncertainty or risk about the size of changes in a security's value. A higher volatility means a security's value can potentially be spread out over a larger range of values whereas, lower volatility means a security's value does not fluctuate dramatically, but changes in value over a period of time. Over the last few years, modelling volatility of a financial time series has become an important area and has gained a great deal of attention from academics, researchers and others. 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 clustering.' A series with some periods of low volatility and some periods of high volatility is said to exhibit volatility clustering.

Variance (or standard deviation) is often used as the risk measure in risk management. Engle (1982) introduced Autoregressive Conditional Heteroskedasticity (ARCH) model to the world to model financial time series that exhibit time varying conditional variance. A generalized ARCH (GARCH) model extended by Bollerslev (1986) is another popular model for estimating stochastic volatility. These models are widely used in various branches of econometrics, especially in financial time series analysis. Besides, with the introduction of models of ARCH and GARCH, there have been number of empirical applications of modelling variance (volatility) of financial time series. However, the GARCH cannot account for leverage effect, however they account for volatility clustering and leptokurtosis in a series, this necessitated to develop new and extended models over GARCH that resulted in to new models viz., GARCH-M, EGARCH, TGARCH and PGARCH.

GARCH-in-Mean model (GARCH-M), a variation under GARCH model is used to identify the risk return relationship (Engle, Lilien, and Robins 1987). Further, Nelson (1991) proposed an Exponential GARCH model, which is the logarithmic expression of the conditional volatility used to capture the asymmetric effects. Later, a number of different specifications of these models and extensions were derived. One of them is Threshold GARCH (TGARCH) model (Zakoian 1994), which was used to identify the relation between asymmetric volatility and return. It is also known as the GJR model (Glosten, Jagannathan, and Runkle 1993). In addition, Schwert (1989) introduced the standard deviation GARCH model, whereby the standard deviation is modelled rather than the variance. This model, along with several other models, is generalized (Ding, Engle, and Graange 1993) with the Power ARCH specification.

All these models were designed to explicitly model and forecast the time-varying conditional variance of a series. Hence, the present paper aims at modelling the volatility of Indian stock market by the use of different GARCH family models and provides empirical evidence on the fit of conditional volatility for the Indian stock market.

Review of Literature

Several studies were made in modelling the stock market volatility both in developed and in developing countries. Many researchers investigated

the performance of GARCH models in explaining volatility of emerging stock markets (French, Schwert, and Stambaugh 1987; Chou 1988; Baillie and DeGennaro 1990; Bekaert and Wu 2000; Chand, Kamal, and Ali 2012; Kenneth 2013). Besides, few studies were attempted on Egyptian market too. Zakaria and Winker (2012) examined the return volatility using daily prices of Khartoum Stock Exchange (KSE) and Cairo and Alexandria Stock Exchange (CASE) and found that GARCH-M model described conditional variance with statistically significant for both the markets; there existed a leverage effect in the returns of KSE and CASE with positive sign.

Further, Floros (2008) investigated the volatility using daily data from two Middle East stock indices viz., the Egyptian CMA index and the Israeli TASE-100 index and used GARCH, EGARCH, TGARCH, Component GARCH (CGARCH), Asymmetric Component GARCH (AGARCH) and Power GARCH (PGARCH). The study found that the coefficient of EGARCH model showed a negative and significant value for both the indices, indicating the existence of the leverage effect. AGARCH model showed weak transitory leverage effects in the conditional variances and the study showed that increased risk would not necessarily lead to an increase in returns. Ahmed and Aal (2011) examined Egyptian stock market return volatility from 1998 to 2009 and his study showed that EGARCH is the best fit model among the other models for measuring volatility. The study showed that there is no significant asymmetry in the conditional volatility of returns captured by GARCH (1,1) and GARCH (1,1) and it was found to be the appropriate model for volatility forecasting in Nepalese stock market (Bahadur 2008).

Although many research studies were undertaken on modelling the volatility of the developed stock markets, only few studies has been done on Indian context. Recently, few studies have been done on modelling the stock market volatility of Indian market but most of the studies are limited to only symmetric model of the market. Karmakar (2005) estimated volatility model to capture the feature of stock market volatility in India. The study also investigated the presence of leverage effect in Indian stock market and the study showed that the GARCH (1,1) model provided reasonably good forecasts of market volatility. Whereas, in his another study he (Karmakar 2007) found that the conditional variance was asymmetric during the study period and the EGARCH-M was found to be an adequate model that reveals a positive relation between risk and return.

Goudarzi and Ramanarayanan (2010) examined the volatility of Indian stock market using BSE 500 stock index as the proxy for ten years. ARCH

and GARCH models were estimated and the best model was selected using the model selection criterion viz., Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). The study found that GARCH (1,1) was the most appropriate model for explaining volatility clustering and mean reverting in the series for the study period. Further, in their (Goudarzi and Ramanarayanan 2011) another study, they investigated the volatility of BSE 500 stock index and modelled two non-linear asymmetric model viz., EGARCH (1,1) and TGARCH (1,1) and found that TGARCH (1,1) model was found to be the best preferred model as per AIC, Schwarz Information Criterion (SBIC) and Log Likelihood (LL) criteria.

Mittal, Arora, and Goyal (2012) examined the behaviour of Indian stock price and investigated to test whether volatility is asymmetric using daily returns from 2000 to 2010. The study reported that GARCH and PGARCH models were found to be best fitted models to capture symmetric and asymmetric effect respectively. Vijayalakshmi and Gaur (2013) used eight different models to forecast volatility in Indian and foreign stock markets. NSE and BSE index were considered as a proxy for Indian stock market and the exchange rate data for Indian rupee and foreign currency over the period from 2000 to 2013. Based on the forecast statistics the study found that TARCH and PARCH models lead to better volatility forecast for BSE and NSE return series for the stock market evaluation and ARMA (1,1), ARCH (5), EGARCH for the foreign exchange market.

Most of the Indian studies attempted on modelling volatility found that the GARCH (1,1) is considered the best model to capture the symmetric effect and for leverage effects, EGARCH-M and PGARCH models have been found to be appropriate by the previous studies. However, the choice of best fitted and adequate model depends on the model that is included for the evaluation in the study. Hence, the present study used different GARCH family models both in symmetric as well as asymmetric effect to capture the facts of return and to study the most appropriate model in the volatility estimation.

Objectives of the Study

The primary objective of the study is to fit appropriate GARCH model to estimate market volatility based on Nifty index. The paper aims at:

- To investigate the volatility pattern of emerging Indian stock market using symmetric and asymmetric models.

- To identify the presence of leverage effect in daily return series of stock market using asymmetric models.
- To analyse the appropriateness of Generalized Autoregressive Conditional Heteroscedastic (GARCH) family models that capture the important facts about the index returns and fits more appropriate.

Research Methodology

DATA SOURCE

The study is based on the secondary data that were collected from Centre for Monitoring Indian Economy (CMIE), Prowess database. S&P CNX Nifty indices were used as proxy to the stock market. The daily closing prices of Nifty indices over the period of ten years from 1st January 2003 to 31st December 2012 were collected and used for analysis.

RESEARCH METHODS

Various statistical tools viz., ADF, PP, and ARCH-LM tests and GARCH family models were applied and analysed using E-views 7 Econometrics package. Volatility has been estimated on return (r_t) and hence before going for all these tests, first the daily returns were calculated. The Nifty return series is calculated as a log of first difference of daily closing price, which is as follows:

$$r_t = log \frac{P_t}{P_{t-1}}, \tag{1}$$

where r_t is the logarithmic daily return on Nifty 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 $t - 1$.

BASIC STATISTICS OF NIFTY RETURN

Descriptive Statistics

To specify the distributional properties of the daily return series of Nifty market index during the study period, the descriptive statistics are reported in table 1. It shows mean ($\overline{X}$), standard deviation (σ), skewness (S), kurtosis (K) and Jarque-Bera statistics.

Test for Stationarity

First of all, there is a need for testing whether the data are stationary or non-stationary and it is found out by unit root test, which is conducted

by Augmented Dickey-Fuller Test (ADF) (Dickey and Fuller 1979) and Philips-Perron Test (PP) (Phillips and Perron 1988).

Test for Heteroscedasticity

One of the most important issues before applying the GARCH methodology is to first examine the residuals for the evidence of heteroscedasticity. To test the presence of heteroscedasticity in residual of the return series, Lagrange Multiplier (LM) test for Autoregressive conditional heteroscedasticity (ARCH) is used. It is sensible to compute the Engle (1982) test for ARCH effect to ensure that there is no ARCH effect.

Volatility Measurement Technique

GARCH models represent the main methodologies that are applied in modelling the stock market volatility. The present study employed GARCH (1,1) and GARCH-M (1,1) for modelling conditional volatility and for modelling asymmetric volatility EGARCH (1,1) and TGARCH (1,1) were applied.

The following GARCH techniques are applied to capture the volatility in the return series.

Symmetric Measurement

To study the relation between asymmetric volatility and return, the GARCH (1,1) and GARCH-M (1,1) models are used in the study.

The Generalized ARCH Model

The GARCH model (Bollerslev 1986), which allows the conditional variance to be dependent upon previous own lags, conform to the conditional variance equation in the simplest form as:

mean equation: $r_t = \mu + \varepsilon_t$ and $\qquad\qquad$ (2)

variance equation: $\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2,$ $\qquad\qquad$ (3)

where $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and r_t is the return of the asset at time t, μ is the average return, and ε_t is the residual return.

The size of parameters α and β determine the short-run dynamics of the volatility time series. If the sum of the coefficient is equal to one, then any shock will lead to a permanent change in all future values. Hence, shock to the conditional variance is 'persistence.'

The GARCH-in-Mean (GARCH-M) Model

In GARCH model, the conditional variance enters the mean equation directly, which is known generally as a GARCH-M model. The return of a security may depend on its volatility and hence a simple GARCH-M (1,1) model can be written as:

mean equation: $r_t = \mu + \lambda \sigma t_\tau^2 + \varepsilon_t$ and (4)

variance equation: $\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2.$ (5)

The parameter λ in the mean equation is called the risk premium. A positive λ indicates that the return is positively related to its volatility, i. e. a rise in mean return is caused by an increase in conditional variance as a proxy of increased risk.

Asymmetric Measurement

The main drawback of symmetric GARCH is that the conditional variance is unable to respond asymmetrically to rise and fall in the stock returns. Hence, number of models have been introduced to deal with the issue and are called asymmetric models viz., EGARCH, TGARCH and PGARCH, which are used for capturing the asymmetric phenomena. To study the relation between asymmetric volatility and return, the EGARCH (1,1) and TGARCH (1,1) models are used in the study.

The Exponential GARCH Model

This model is based on the logarithmic expression of the conditional variability. The presence of leverage effect can be tested and this model enables to find out the best model, which capture the symmetries of the Indian stock market (Nelson 1991) and hence the following equation:

$$\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{\pi}{2}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}.$$ (6)

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 $\gamma \neq 0$.

Threshold GARCH Model

The generalized specification of the threshold GARCH for the conditional variance (Zakoian 1994) is given by:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{7}$$

The γ is known as the asymmetry or leverage parameter. In this model, good news ($\varepsilon_{t-1} > 0$) and the bad news ($\varepsilon_{t-1} < 0$) 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 Discussion

Descriptive statistics on Nifty return are summarized in table 1.

The $\overline{X}$ of the returns is positive, indicating the fact that price has increased over the period. The descriptive statistics shows that the returns are negatively skewed, indicating that there is a high probability of earning returns which is $>\overline{X}$. The K of the series is > 3, which implies that the return series is fat tailed and does not follow a normal distribution and is further confirmed by Jarque-Bera test statistics, which is significant at 1% level and hence the null hypothesis of normality is rejected.

To make the series stationary, the closing price of the Nifty index is converted into daily logarithmic return series. Figure 1 shows volatility clustering of return series of the s&p cnx Nifty for the study period from 1st January 2003 to 31st December 2012. From the figure 1, it is inferred that the period of low volatility tends to be followed by period of low volatility for a prolonged period and the period of high volatility is

TABLE 1   Descriptive Statistics of Daily Return

Mean	0.000673	Minimum	−0.130142	Kurtosis	11.87825
Median	0.001372	Std. dev.	0.016528	Jarque-Bera	8225.742
Maximum	0.163343	Skewness	−0.259137	N	2496
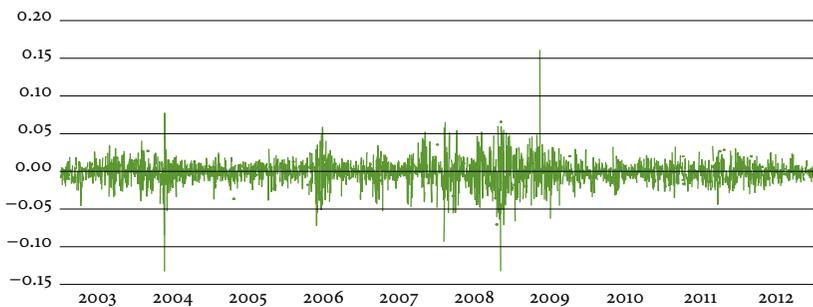
FIGURE 1   Volatility Clustering of Daily Return of s&p cnx Nifty

TABLE 2   Result of Unit Root Test and ARCH-LM Test for Residuals

Value	ADF	PP
t-statistics	−10.5260	−46.7430
Prob.	0.000	0.000
Critical Value		
1%	−3.4327	−3.4327
5%	−2.8625	−2.8625
10%	−2.5673	−2.5673
ARCH-LM test statistics		122.79
Prob. (1)		0.0000

followed by period of high volatility for a prolonged period, which means the volatility is clustering and the return series vary around the constant mean but the variance is changing with time.

Table 2 shows the presence of unit root in the series tested using ADF and PP tests and the presence of heteroscedasticity tested using ARCH-LM test. The p values of ADF and PP are < 0.05, which lead to conclude that the data of the time series for the entire study period is stationary. Both the ADF and PP test statistics reported in table 2 reject the hypothesis at 1% level with the critical value of −3.43 for both ADF and PP tests of a unit root in the return series. Hence, the results of both the tests confirm that the series are stationary. The ARCH-LM test is applied to find out the presence of ARCH effect in the residuals of the return series. From the table 2, it is inferred that the ARCH-LM test statistics is highly significant. Since $p < 0.05$, the null hypothesis of 'no ARCH effect' is rejected at 1% level, which confirms the presence of ARCH effects in the residuals of time series models in the returns and hence the results warrant for the estimation of GARCH family models.

After volatility clustering is confirmed with return series and stationarity using ADF and PP test, heteroscedasticity effect using ARCH-LM test, the study focuses on determining the best fitted GARCH model to the return series. Therefore, GARCH model is used for modelling the volatility of return series in the Indian stock market.

The result of GARCH (1,1) and GARCH-M (1,1) models is shown in table 3, which reveals the parameter of GARCH is statistically significant. In other words, the coefficients viz., constant (ω), ARCH term (α), GARCH term (β) are highly significant at 1% level. In the conditional variance equation, the estimated β coefficient is considerably greater than α co-

TABLE 3   Estimated result of GARCH (1,1) and GARCH-M (1,1) Models

Coefficients	GARCH (1,1)	GARCH-M (1,1)
Mean		
μ (constant)	0.001206*	0.001105**
Risk premium λ	—	0.636885
Variance		
ω (constant)	$4.73e^{-6}$*	$4.73e^{-6}$*
α (ARCH effect)	0.121501*	0.121586*
β (GARCH effect)	0.864800*	0.864757*
$\alpha + \beta$	0.986301	0.986343
Log likelihood	7123.909	7123.986
Akaike info. criterion (AIC)	−5.705056	−5.704315
Schwarz info. criterion (SIC)	−5.695725	−5.692652
ARCH-LM test for heteroscedasticity		
ARCH-LM test statistics	0.4726	0.4961
Prob. Chi-square (1)	0.4917	0.4811

NOTES   Source: Computed from the compiled and edited data from the CMIE data source. * Significant at 1% level.

efficient which resembles that the market has a memory longer than one period and that 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. The sizes of the parameters α and β determine the volatility in time series. The sum of these coefficients (α and β) is 0.978, which is close to unity indicating that the shock will persist to many future periods. Since the risk-return parameter is positive and significant at 1% level, it shows that there is a positive relationship between risk and return. Further, ARCH-LM test is employed to check ARCH effect in residuals and from the results, it is inferred that the $p > 0.05$, which led to conclude that the null hypothesis of 'no ARCH effect' is accepted. In other words, the test statistics do not support for any additional ARCH effect remaining in the residuals of the models, which implies that the variance equation is well specified for the market.

The GARCH-M (1,1) model is estimated by allowing the mean equation of the return series to depend on a function of the conditional variance. The constant in mean equation is significant at 5% level, indicating that there is an abnormal return for the market. From the table 3, it is in-

ferred that the coefficient of conditional variance (λ) in the mean equation value is positive however, it is statistically insignificant, which implies that there is no significant impact of volatility on the expected return, indicating lack of risk-return trade off over time. In the variance equation of GARCH-M (1,1), the parameters viz., ω, α and β are highly significant at 1% level. The sum of α and β is 0.986, which infers that shocks will persist in the future period. However, the ARCH-LM test is applied on residuals and shows that the test statistics do not exhibit additional ARCH effect for the entire study period indicating that the variance equation is well specified.

In order to capture the asymmetries in the return series, two models have been used viz., EGARCH-M (1,1) and TGARCH (1,1). γ captures the asymmetric effect in both EGARCH-M (1,1) and TGARCH (1,1) models. The asymmetrical EGARCH (1,1) model is used to estimate the returns of the Nifty index and the result is presented in table 4. The table reveals that ARCH (α) and GARCH coefficient (β) are greater than one, reporting that conditional variance is explosive; the estimated coefficients are statistically significant at 1% level. γ, the leverage coefficient, is negative and is statistically significant at 1% level, exhibiting the leverage effect in return during the study period. The analysis reveals that there is a negative correlation between past return and future return (leverage effect); hence, EGARCH (1,1) model supports for the presence of leverage effect on the Nifty return series. Finally, the ARCH-LM test statistics reveals that the null hypothesis of no heteroscedasticity in the residuals is accepted.

An alternate model to test for asymmetric volatility in the Nifty return is TGARCH, which shows (see table 4) the estimated result of TGARCH (1,1) model. In it, the coefficient of leverage effect (γ) is positive and significant at 1% level, which implies that negative shocks or bad news have a greater effect on the conditional variance than the positive shocks or good news. The diagnostic test is performed to test whether the residuals are normally distributed. The ARCH-LM test statistic for TGARCH (1,1) model does not show any additional ARCH effect present in the residuals of the model, which implies that the variance equation is well specified for the Indian stock market.

Summary of Findings of the Study

Based on the empirical analysis, the following are the findings of the study:

TABLE 4   Estimated result of EGARCH (1,1) and TGARCH (1,1) Models

Coefficients	EGARCH (1,1)	TGARCH (1,1)
Mean		
μ (constant)	0.000902*	0.000897*
Variance		
ω (constant)	−0.496798*	$6.18e^{-6}$*
α (ARCH effect)	0.241448*	0.055275*
β (GARCH effect)	0.963610*	0.859030*
γ (leverage effect)	−0.090619*	0.124030*
$\alpha + \beta$	1.205058	0.914305
Log likelihood	7139.688	7142.083
Akaike info. criterion (AIC)	−5.716879	5.718817
Schwarz info. criterion (SIC)	−5.705234	5.707153
ARCH-LM test for heteroscedasticity		
ARCH-LM test statistics	0.0527	0.5299
Prob. Chi-square (1)	0.8182	0.4665

NOTES   Source: Computed from the compiled and edited data from the CMIE data source. * Significant at 1% level.

- In GARCH (1,1) model, the sum of the coefficient ($\alpha + \beta$) is 0.9863, which implies that the volatility is highly persistent.
- In GARCH-M (1,1) model, the coefficient of conditional variance or risk premium (λ) in the mean equation is positive however, insignificant, which implies that higher market risk provided by conditional variance will not necessarily lead to higher returns.
- The asymmetric effect captured by the parameter (γ) in EGARCH model is negative and statistically significant at 1% 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.
- The asymmetric effect captured by the coefficient of leverage effect (γ) is positive and significant at 1% level, providing the presence of leverage effect during the study period.
- The best fitted models both in symmetric as well as in asymmetric effect are selected based on the minimum AIC and SIC value and the highest log likelihood value. Likewise, the AIC, SIC value (−5.7050; −5.695) is low and log likelihood value (7123.909) is high

for GARCH (1,1) when compared to its alternate symmetric model, called GARCH-M (1,1). Hence GARCH (1,1) model is found to be the best fitted model.

- The AIC, SIC (−5.7188; −5.7071) and log likelihood value (7142.08) for TGARCH (1,1) conforms the norms and hence TGARCH (1,1) model is apparently seems to be an adequate description of asymmetric volatility process.

Concluding Remarks

In this study, volatility of Nifty index return is tested using the symmetric and asymmetric GARCH models. The daily closing prices of Nifty index for ten years are collected and modelled using four different GARCH models that capture the volatility clustering and leverage effect for the study period i. e. from 1st January 2003 to 31st December 2012. GARCH (1,1), GARCH-M (1,1), EGARCH (1,1), and TGARCH (1,1) models are employed in the study after confirming the unit root rest, volatility clustering and ARCH effect. The results show that the coefficient has the expected sign both in the EGARCH (negative and significant) and in the TARCH (positive and significant) models. Finally, to identify the best fitted model among the different specifications of GARCH models, Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) are used, which prove that GARCH (1,1) model has been found to be the best fitted model among all to capture the symmetric effect as per AIC and SIC criterion. Further, TGARCH (1,1) model is found to be the best fitted model to capture the asymmetric volatility based on the highest log likelihood ratios and minimum AIC and SIC criterion.

The overall conclusion of the study supports the findings of previous research studies of Karmakar (2007), Zakaria and Winker (2012) and Zivanayi and Chinzara (2012); and more particularly the study differs in the way of selecting the appropriate model using diagnostic test. Nevertheless, the results presented in the study (in the said tables) are in contrary to the research findings of Karmakar (2007) where the risk premium is significant. On a whole, the study concludes that increased risk did not increase the returns since the coefficient is insignificant for the selected variables for the study period.

LIMITATIONS OF THE STUDY

1. The study suffers from the limitation of non-calculation of intraday volatility.

2. The study used only ten years data of s&p cnx Nifty Index from 1st January 2003 to 31st December 2012.

SCOPE FOR FURTHER STUDIES

The study aims at modelling the volatility of an emerging stock market and investigated if there is any asymmetric volatility in its return structure. The study tried to address three issues. First, does stock return volatility have long term impact? Second, is there asymmetric volatility in Indian stock market? Finally, what is the relationship between risk and return? The investigation has been made on market index s&p cnx Nifty Index. In addition to these three issues, the study can also be extended using intra-day volatility with the help of high frequency data. The present study focused on modelling volatility on Indian stock market, therefore the study can also be done comparing the volatility of Indian stock market with other stock exchanges of developed countries.

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