MODELING THE VOLATILITY OF INDIAN STOCK MARKET

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ABSTRACT

This article aims at studying the stock price behavior & modeling the volatility of an emerging stock market, the Indian Stock Market and investigates if there is any asymmetric volatility in its return structure. It also finds out the best model for unfolding the asymmetric effects. S&P CNX Nifty returns have been used to proxy the Indian Stock Market over the ten years period starting from April 1st, 2000- June 30th, 2010. The return series exhibit heteroskedasticity, volatility clustering & has fat tails. GARCH (1, 1) model has been found to be most appropriate model to capture the symmetric effects and among the asymmetric models, PARCH (1, 1) has been found to be the best as per AIC & LL criterion. The ARCH in Mean model reported that Indian markets do not offer risk premium. Apart from the presence of leverage effect, we also found volatility persistence over the period considered.

Keywords: *Volatility; GARCH; EGARCH; PARCH; TARCH; ARCH in Mean.*

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INTRODUCTION

Volatility is a key parameter used in many financial applications, from derivatives valuation to asset management and risk management. Volatility refers to the ups and downs in the stock prices. Volatility in the stock return is an integral part of stock market with the alternating bull and bear phases. Without volatility superior returns cannot be earned. However, too much volatility is considered as a symptom of an inefficient stock market. Higher the volatility, higher the risk. Volatility of returns in financial markets can be a major stumbling block for attracting investment in small developing economies. It has an impact on business investment spending and economic growth through a number of channels. Moderate returns, high liquidity & low level of volatility is taken to be a symptom of a developed market. Low volatility is preferred as it reduces unnecessary risk borne by investors thus enables market traders to liquidate their assets without large price movements.

The rise and the fall of shares are linked to a number of reasons such as political climate, economic cycle, economic growth, international trends, budget, general business conditions, company profits, product demand etc. Investment decisions are governed significantly by this volatility apart from other interdependent factors like price, volume traded, stock liquidity, among many others.

Volatility estimation is important for several reasons: Investment decisions, as characterized by asset pricing models, strongly depend on the assessment of future returns and risk of various assets. The pricing of options is based on expected volatility of a security. Various linear and nonlinear methods by which volatility can be modeled have been developed in the literature and extensively applied in practice to describe the stock return volatility.

The distribution of financial time series shows certain characteristics such as:

1. Leptokurtosis: i.e. fat tails as compared to normal distribution.
2. Volatility clustering: Statistically, volatility clustering implies a strong autocorrelation in returns. Large changes tend to be followed by large changes and small changes tend to be followed by small changes
3. Heteroskedasticity: i.e. non constant variance.

Economic time series have been found to exhibit periods of unusually large volatility followed by periods of relative tranquility (Engle, 1982). In such circumstances, the assumption of constant variance (homoskedasticity) is inappropriate (Nelson, 1991).

This requires models that are capable of dealing with the volatility of the market (and the series). One of the most prominent tools for capturing such changing variance was the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) models developed by Engle (1982), and Bollerslev (1986) respectively.

Following the introduction of models of ARCH by Engle (1982) and their generalization by Bollerslev (1986), there have been numerous refinements of the approach to modelling conditional volatility to better capture the stylized characteristics of the data. **The GARCH (1, 1) is often considered by most investigators to be an excellent model for estimating conditional volatility for a wide range of financial data (Bollerslev, Ray and Kenneth, 1992).**

However, there are some features of the financial time series data which cannot be captured by symmetric ARCH and GARCH models. The most interesting feature not addressed by these models is the “leverage effect” where the conditional variance tends to respond asymmetrically to positive and negative shocks in returns.

These asymmetric effects are captured by models such as the Exponential GARCH (EGARCH) of Nelson (1991), the so-called GJR model of Glosten, Jagannathan, and Runkle (1993). Asymmetric effects were discovered by Black (1976) and confirmed by the findings of French, Schwert, and Stambaugh (1987); Schwert (1990); and Nelson (1991), among others.

This so called Leverage Effect appears firstly in Black (1976), who noted that:

``a drop in the value of the firm will cause a negative return on its stock, and will usually increase the leverage of the stock which ill cause a rise in the debt-equity ratio which will surely mean a rise in the volatility of the stock".

A very simple but plausible explanation for the leverage effect: Negative returns imply a larger proportion of debt through a reduced market value of the firm, which leads to a higher volatility. The risk, i.e. the volatility reacts first to larger changes of the market value; nevertheless it is empirically shown that there is a high volatility after smaller changes. On the other hand, Black said nothing about the effect of positive returns on the volatility. Although the positive returns cause smaller increases, they do cause an increase in the volatility.

The characteristics of the Nifty return series are consistent with the above characteristics of financial time series.

The aim of this article is to track and model the volatility of Indian stock Market by exploring the features of its return structure.

REVIEW OF LITERATURE

Much of the literature is present on modeling the volatility of the developed markets but no sufficient literature is available on modeling the volatility of the emerging economies. However, recently few studies have been made on the modelling the stock market volatility of Indian market but most of the studies are limited to modeling the symmetries of the market.

Madhusudan Karmakar (2003), explained the heteroskedastic behavior of the Indian stock market using 'vanilla' GARCH (1, 1) model for a period of about 24 years from January 1980 to June 2003.

Madhusudan Karmakar (2005), estimated conditional volatility models in an effort to capture the salient features of stock market volatility in India and evaluated them in terms of out-of sample forecast accuracy. The paper also investigated whether there is any leverage effect in Indian stock market. The results reported the presence of leverage effect but which model can best capture the leverage effect has been left for further research.

Rousan Raya, AL-Khouri, Ritab (2005), attempted to investigate the volatility of the Jordanian emerging stock market using daily observations from Amman Stock Exchange Composite Index (ASE) for the period from January 1, 1992 through December 31, 2004. The nature of the time series suggested ARCH and GARCH models as the best to capture the characteristics of ASE. Also no asymmetry was found in the returns and hence, both good and bad news of the same magnitude have the same impact on the volatility level. Moreover, the volatility persists in the market for a long period of time, which makes ASE market inefficient; therefore, returns can be easily predicted and forecasted.

Alberg et al. (2006) estimated stock market volatility of Tel Aviv Stock Exchange indices, for the period 1992-2005, using asymmetric GARCH models. They reported that the EGARCH model is most successful in forecasting the TASE indices.

Banerjee Ashok & Sahadeb Sarkar (2006), attempted to model the volatility in the daily return in the Indian stock market. They found that the Indian stock market experience volatility clustering and hence GARCH-type models predict the market volatility better than simple volatility models, like historical average, moving average etc. They also observed that the asymmetric GARCH models provide better fit than the symmetric GARCH model, confirming the presence of leverage effect. They also found that the change in volume of trade in the market directly affects the volatility of asset returns & the presence of FII in the Indian stock market does not appear to increase the overall market volatility.

Bhaskkar Sinha(2006) in an attempt to model stock market volatility of Indian markets and to capture the asymmetric effects found EGARCH model best for modeling volatility clustering and persistence of shock at BSE sensex and GJR-GARCH for NSE nifty.

Caiado, Jorge (2007),modelled the volatility for daily and weekly returns of the Portuguese Stock Index PSI-20 by using simple GARCH, GARCH-M, Exponential GARCH (EGARCH) and Threshold ARCH (TARCH) models & found that there are significant asymmetric shocks to volatility in the daily stock returns, but not in the weekly stock returns. They also found that some weekly returns time series properties were substantially different from properties of daily returns, and the persistence in conditional volatility is different for some of the sub-periods referred. Finally, they compared the forecasting performance of the various volatility models in the sample periods before and after the terrorist attack on September 11, 2001

Jordaan, Grové, Jooste A & Z G Alemu(2007), modelled the volatility of daily spot prices of the crops traded on the South African Futures Exchange (yellow maize, white maize, wheat, sunflower seed and soybeans). The volatility in the prices of white maize, yellow maize and sunflower seed have been found to vary over time, suggesting the use of the GARCH approach in these cases. The volatility in the prices of wheat and soybeans was found to be constant over time; hence the standard error of the ARIMA process was used.

Karmakar Madhusudan(2007) investigated the heteroscedastic behaviour of the Indian stock market through market index S&P CNX Nifty for 14.5 years from July 1990 to December 2004 using different GARCH models. First, the standard GARCH approach has been used to investigate whether stock return volatility changes over time and if so, whether it is predictable. Then, the EGARCH models were applied to investigate whether there is asymmetric volatility. Finally, (E) GARCH in the mean extension had been used to examine the relation between market risk and expected return.The study reports an evidence of time varying volatility which exhibits clustering, high persistence and predictability. It is found that the volatility is an asymmetric function of past innovation, rising proportionately more during market decline. It is also evidenced that return is not significantly related to risk.

Rajni Mala & Mahendra Reddy(2007) modeled the stock market volatility of Fiji's stock market , an emerging economy using ARCH/GARCH techniques for a period of 5 years from 2001-2005.

Marta Casas & Cepeda Edilberto(2008), explained the ARCH, GARCH, and EGARCH models and the estimation of their parameters using maximum likelihood. The study concluded based on AIC & BIC criterion that GARCH (1,2) best explains the performance of stock prices and EGARCH (2,1) best explains the returns series.

Khedhiri Sami, Muhammad Naeem (2008) investigated the volatility characteristics of the UAE stock markets measured by fat tail, volatility clustering, and leverage effects, in order to explore a parsimonious model for the UAE stock market and predict its future performance. He used EGAECH, TGARCH and other class of ARCH techniques to model the volatility.

Surya Bahadur G.C. (2008) modeled the volatility of the Nepalese stock market using daily returns from July 2003 to Feb 2009 and different classes of estimators and volatility models. The empirical findings did not report any significant asymmetry in the returns and thus suggests GARCH (1,1) model as most appropriate for modeling the heteroskedasticity and volatility clustering in the Nepalese stock market . It also reported high persistence of volatility in the Nepalese stock market.

Floros Christos (2008), employed the simple GARCH model, as well as exponential GARCH, threshold GARCH, asymmetric component GARCH, the component GARCH and the power GARCH model using daily data from Egypt (CMA General index) and Israel (TASE-100) index to model the stock market volatility and concluded that increased risk will not necessarily lead to a rise in the returns. The most volatile series is CMA index from Egypt, because of the uncertainty in prices (and economy) over the examined period.

Yalama Abdullah & Guven Sevil (2008) attempted to forecast world's stock market volatility by employing seven different GARCH class models to forecast in-sample of daily stock market volatility in 10 different countries. The results of the study emphasized that the class of asymmetric volatility models perform better in forecasting stock market volatility than the historical models.

Hakim Ali Kanasro, Chandan Lal Rohra, Mumtaz Ali Junejo (2009), examined the presence of volatility at the Karachi Stock Exchange (KSE) by analyzing two Indexes namely;'KSE-100 Index' and 'All shares index through the use GARCH family models introduced by Engle (1982), Bollerslev (1986) and Nelson (1991). The empirical results confirmed the presence of high volatility at Karachi Stock Exchange throughout the study period.

K.N Badhani (2009) analysed the closing values of S&P 500 index and S&P CNX Nifty from Jan 1996 to Sept. 2008 in order to find out the impact of return & volatility in US on Indian stock market using AR (1)-TGARCH (1, 1) process. Among other objectives, the study aimed at finding out whether the Indian stock market reacts differently towards positive and negative shocks from the US market, He concluded that the returns in the Indian stock market are more sensitive to negative shocks in the US market rather than the positive shocks

Marius Matei (2009) evaluated the main forecasting techniques with the motive to offer support for the rationale behind of the idea: GARCH is the most appropriate model to use when one has to evaluate the volatility of the returns of groups of stocks with large amounts (thousands) of observations. The appropriateness of the model was seen through a unidirectional perspective of the quality of volatility forecast provided by GARCH when compared to any other alternative model, without considering any cost component.

Hojatallah Goudarzi & C. S. Ramanarayanan (2010), examined the volatility of the Indian stock markets and its related stylized facts using ARCH models. The BSE500 stock index was used to study the volatility in the Indian stock market over a 10 years period. Two commonly used symmetric volatility models, ARCH and GARCH were estimated and the fitted model of the data, selected using the model selection criterion such as SBIC and AIC. The adequacy of selected model was tested using ARCH-LM test and LB statistics. The study concluded that GARCH (1, 1) model explains volatility of the Indian stock markets and its stylized facts including volatility clustering, fat tails and mean reverting satisfactorily

Majority of studies on modeling volatility have found non- linear models such as ARCH & GARCH as the best. The return series exhibit all the characteristics of financial time series data appropriate for using GARCH class models. Most of the studies on modeling volatility related to Indian markets have found GARCH (1, 1) model as the best to capture the symmetric effects. Indian markets show leverage effects for which EGARCH model has been found as most appropriate by the earlier studies. However, the choice of the best model also depends on the models included for evaluation. Volatility persistence has also been found in the emerging economies by the studies under consideration.

Even in evaluating the forecasting performance of different models, many competing studies have found ARCH class of models as most appropriate. For example, Akgiray (1989), Pagan and Schwert (1990), Brailsford and Faff (1996), and Brooks (1998) used the US stock data and found that the GARCH models outperformed most competitors.

RESEARCH METHODOLOGY:

Traditionally volatility modeling techniques were based on the assumption of homoskedasticity and were not able to capture the changing variance i.e. heteroskedasticity found in the returns. So more sophisticated models needed to be developed to capture such effects and leave the errors white noise. Thus non linear models such as ARCH/GARCH were developed to capture the features of the financial time series.

The following GARCH techniques to capture the volatility have been used:

GARCH (1, 1)

The GARCH specification, firstly proposed by Bollerslev (1986), formulates the serial dependence of volatility and incorporates the past observations into the future volatility (Bollerslev et al. (1994)

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

News about volatility from the previous period can be measured as the lag of the squared residual from the mean equation (ARCH term). Also, the estimate of β shows the persistence of volatility to a shock or, alternatively, the impact of old news on volatility.

EGARCH (1, 1):

Proposed by Nelson (1991) & is given by the following equation:

$$\ln (\sigma_t^2) = \alpha_0 + \alpha_1 ln(\sigma_{t-1}^2 \ ) + \beta_1 \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}}$$

The logarithmic form of the conditional variance implies that the leverage effect is exponential (so the variance is non-negative). The leverage effect is denoted by γ and is present if γ is significantly negative.

TARCH (1, 1):

The Threshold-GARCH model was introduced by Zakoian (1994) and Glosten, Jaganathan and Runkle (1993). The TGARCH specification for the conditional variance is given by:

$$\sigma_2^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}$$

Where:

Where leverage effect is captured by γ. For a leverage effect, we would see γ>0 i.e. γ is significantly positive.

PARCH (1, 1):

Power-GARCH model was proposed by Ding *et al.* (1993). In the Power-GARCH model, the power parameter β of the standard deviation can be estimated rather than imposed, and the optional γ parameters are added to capture asymmetry.

$$\sigma_t^{\beta} = u + \beta \sigma_{t-1}^{\beta} + \gamma(|e_{t-1}| - \gamma e_{t-1})^{\beta}$$

Leverage effect is present if γ≠0

DATA & PRELIMINARY STATISTICS

To model the volatility of the Indian stock Market, we have used daily closing prices of the most popular stock index i.e. S&P CNX Nifty as proxy to the Indian stock market. The data ranges for a period of ten years and two months starting from 1st April 2000 to30th June, 2010. The data has been collected from the official website of NSE of India i.e. www.nseindia.com and has been analysed using Eviews 5 software.

ANALYSIS OF DATA:

Table 1 provides the descriptive statistics of the return series. Fig. 1 and fig. 2 are graphs of the non stationary and stationary return series. Table 3 reports the consolidated results of the various GARCH family models used in our analysis. Table 2 & Table 4 are given in the appendix. Table 2 reports the results of squared residuals of GARCH (1, 1) using LJUNG BOX Q statistic and Table 4 relates to the descriptive statistics of the residuals of GARCH (1, 1) model.

T he Graph of the closing price series is shown in fig 1 below. The graph of the series does not show a constant mean and thus reports non stationarity of the data.

Fig.1

To make the series stationary, daily logarithmic returns have been calculated from the closing price series as follows:

$$r_t = \log(p_t - p_{t-1})$$

Where

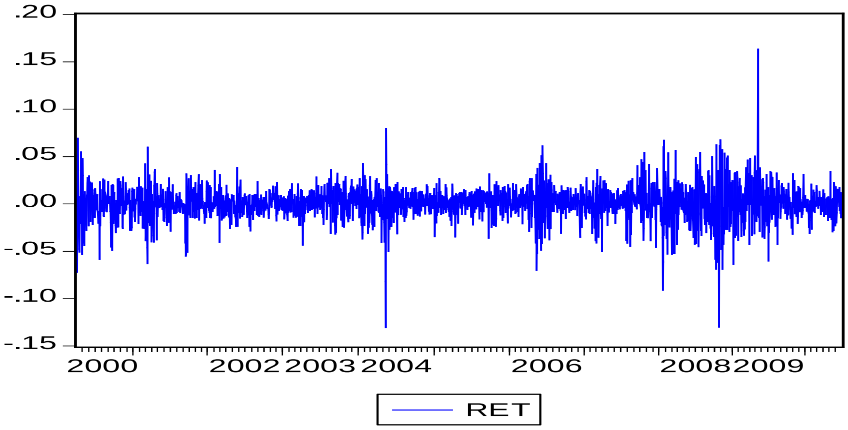
r_t = continuously compounded logarithmic return

p_t =daily closing value of index at day t and

p_{t-1} =closing value of index at day t-1

Thus, the closing value of the index is converted into continuously compounded daily logarithmic return series. Logarithmic returns are calculated since it improves the statistical properties of the data.

Graph of the return series: fig 2



The stationarity of the series can also be confirmed using the Augmented Dickey Test statistic assuming H_o of non stationarity.

The result of the ADF Test is as follows:

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.30163	0.0000
Test critical values:	1% level	-3.432717	
	5% level	-2.862472	
	10% level	-2.567311	

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

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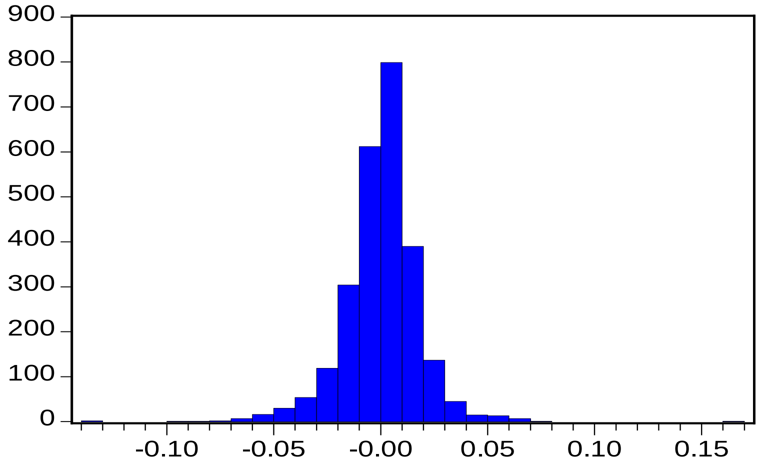
The low p value of the t statistic calls for rejecting the null hypothesis of unit root and accepting the alternate of stationarity.

The graph of the return series is shown in fig 2 above which shows a constant mean which shows stationarity of the data. The series has a non constant variance i.e. heteroskedasticity, which is the typical feature of the time series data. Also volatility clustering in the returns can also be easily seen. If we look at the fig. 2 above, we can easily see that the large changes tend to be followed by large changes and small changes tend to be followed by small changes, which mean that volatility is clustering and the series vary around the constant mean but the variance is changing with time. Thus the return series follow the characteristics of the time series data i.e. heteroskedasticity, leptokurtosis & volatility clustering which means linear model will not be able to capture the volatility of the series therefore non linear models such as ARCH/GARCH need to be used for modelling the volatility of the Indian stock market.

Descriptive Statistics:

Table 1 gives the descriptive statistics of the return series.

Table1



Series: RET
Sample 4/03/2000 6/30/2010
Observations 2556

Mean	0.000486
Median	0.001468
Maximum	0.163343
Minimum	-0.130539
Std. Dev.	0.017371
Skewness	-0.303005
Kurtosis	10.38834
Jarque-Bera	5852.687
Probability	0.000000

A return of series is around 0.04% with a standard deviation of 1.73% which indicated large variability in the returns.

The skewness of the series is negative which means that there is more probability of earning a negative return and also is indicative of the presence of asymmetries in the returns. There is also a lot of variation between the maximum & the minimum return values. The kurtosis of the series is greater than 3, which means that the return series is fat tailed & does not follow a normal distribution which is further confirmed by Jarque Bera Test statistic.

Modelling the Mean:

We use Box Jenkins methodology to model the conditional mean equation. The correlogram of the series reflects a dynamic pattern suggestive of an ARMA model to be used. AC & PAC coefficients are significant at the order of lag 1 & lag 2.

ARMA (1, 1) model seems to be the best fit according to the Akaike Information Criterion to capture the dynamics of the series.

The residuals of the equation when tested using LJUNG BOX Q Statistic showed no correlation upto 13th lag but the squared residuals showed high degree of significant correlation.

Correlogram: Residuals of Returns

Q-statistic probabilities

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.005	-0.005	0.0773	
| |	| |	2	-0.020	-0.020	1.1021	
| |	| |	3	-0.012	-0.012	1.4837	0.223
| |	| |	4	0.019	0.018	2.3851	0.303
| |	| |	5	-0.008	-0.008	2.5376	0.469
| |	| |	6	-0.051	-0.051	9.2815	0.054
| |	| |	7	0.010	0.010	9.5379	0.089
| |	| |	8	0.042	0.040	14.074	0.029
| |	| |	9	0.018	0.017	14.868	0.038
| |	| |	10	0.023	0.027	16.204	0.040
| |	| |	11	-0.012	-0.011	16.546	0.056
| |	| |	12	-0.013	-0.016	16.990	0.075
| |	| |	13	0.022	0.023	18.198	0.077

Correlogram: Squared Residuals of Returns

Q statisticprobabilities

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|** |	|** |	1	0.218	0.218	122.09	
|* |	|* |	2	0.170	0.128	195.72	
|* |	| |	3	0.105	0.048	223.96	0.000
|* |	|* |	4	0.170	0.128	297.92	0.000
|* |	| |	5	0.128	0.060	339.92	0.000
|* |	| |	6	0.087	0.014	359.29	0.000
|* |	|* |	7	0.126	0.077	400.31	0.000
|* |	| |	8	0.066	-0.007	411.64	0.000
|* |	|* |	9	0.121	0.068	449.29	0.000
|* |	|* |	10	0.132	0.077	494.06	0.000
|* |	| |	11	0.115	0.033	527.88	0.000
| |	| |	12	0.061	-0.012	537.31	0.000
|* |	| |	13	0.090	0.035	557.92	0.000
|* |	| |	14	0.082	0.012	575.22	0.000
|* |	| |	15	0.089	0.028	595.65	0.000
|* |	| |	16	0.070	0.010	608.14	0.000
| |	| |	17	0.056	-0.004	616.29	0.000
|* |	| |	18	0.075	0.026	630.89	0.000
| |	| |	19	0.042	-0.016	635.35	0.000
|* |	| |	20	0.071	0.019	648.29	0.000
| |	| |	21	0.056	0.012	656.52	0.000
| |	| |	22	0.049	-0.003	662.64	0.000
| |	| |	23	0.060	0.021	671.80	0.000
| |	| |	24	0.039	-0.011	675.63	0.000
| |	| |	25	0.029	-0.018	677.80	0.000

The residuals were further tested for ARCH effects using ARCH LM Test. The F statistic reported by ARCH LM Test is significant and thus rejects the null hypothesis of no heteroskedasticity, necessitating the use of non linear models for capturing the volatility.

ARCH LM test at lag 5

F-statistic	47.10262	Prob. F(5,2544)	0.000000
Obs*R-squared	216.0660	Prob. Chi-Square(5)	0.000000

Modeling the Conditional variance:

Since the ARCH LM test confirms the presence of ARCH effects, we use GARCH (1, 1) model to capture the conditional variance of the series. GARCH (1, 1) is the most popular model amongst all GARCH class models.

The result of the GARCH (1, 1) model is as follows:

GARCH (1, 1)

Variance Equation

C	7.73E-06	1.71E-06	4.522861	0.0000
RESID(-1)^2	0.144366	0.017974	8.031799	0.0000
GARCH(-1)	0.831624	0.018623	44.65501	0.0000
T-DIST. DOF	7.432659	0.897940	8.277458	0.0000

The consolidated results of different models are given in table 3 below. All the coefficients of the variance equation are highly significant and a careful look at Table 2 which represents the correlogram of the squared GARCH residuals suggests GARCH (1, 1) model as the most appropriate for modeling the variance of the return series. The AIC criterion of the model is also least as compared to other ARCH models

The sum of $\sigma+\ \beta= 0.97599$ which shows high persistence in volatility. i.e. a shock in the present will have a lost lasting effect on the future returns and will die out slowly in around 29 days. The persistence in volatility has been calculated by using the following formula: $\ln 0.5/\ln(\alpha+\beta)$, kashifsaleem, (2007).

The residuals of the GARCH(1, 1) model does not show any correlation but the normality test of standardized residuals(as given in table 4 in appendix below) shows that the returns are negatively skewed with a standard deviation of 0.999431 & a mean of -0.049286. This skewness could be attributed due to the presence of asymmetric effects in returns which calls for using model such as EGARCH, TGARCH and PARCH.

Before we model the asymmetries, let's take a look at another feature of the return in the Indian market.

ARCH in MEAN:

To capture another feature of the Indian stock market, i.e to know if greater risk allows for greater return, we included standard deviation in the mean equation. The results are as follows:

	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.041733	0.060398	0.690964	0.4896
C	0.000940	0.000777	1.209110	0.2266
AR(1)	-0.334207	0.149728	-2.232089	0.0256
MA(1)	0.427080	0.143808	2.969784	0.0030
		Variance Equation		
C	7.77E-06	1.72E-06	4.516856	0.0000
RESID(-1)^2	0.144607	0.018028	8.021354	0.0000
GARCH(-1)	0.831242	0.018702	44.44773	0.0000
T-DIST. DOF	7.412073	0.894386	8.287330	0.0000

R-squared	0.006145	Mean dependent var	0.000514
Adjusted R-squared	0.003413	S.D. dependent var	0.017315
S.E. of regression	0.017286	Akaike info criterion	-5.642917
Sum squared resid	0.761045	Schwarz criterion	-5.624613
Log likelihood	7216.826	F-statistic	2.249585
Durbin-Watson stat	1.991718	Prob(F-statistic)	0.027862

The risk term incorporated into the mean equation (as GARCH coefficient) , is highly insignificant, which means that increased risk does not necessarily lead to rise in mean return. I.e. it does not allow for risk premium.

Modeling the Asymmetries:

The limitation of symmetric models is that they variance is not affected by the sign of the past error terms.

In order to capture the asymmetries three competing models have been used –TARCH (1, 1), EGARCH (1, 1) and PARCH (1, 1) models using t distribution. Our aim is to find out the best model out of the three which can capture the asymmetries of the Indian Stock Exchange.

The result of the TARCH model is as follows:

TARCH (1, 1):

Variance Equation

C	1.03E-05	1.75E-06	5.872139	0.0000
RESID(-1)^2	0.039383	0.017371	2.267231	0.0234
RESID(-1)^2*(RESID(-1)<0)	0.196401	0.028875	6.801811	0.0000
GARCH(-1)	0.820410	0.018799	43.64065	0.0000
T-DIST. DOF	7.880724	0.915183	8.611091	0.0000

The coefficients of the variance equation are significant. The asymmetric factor γ is significant and is positive suggestive of the presence of leverage effect. The σ+β=0.859793 i.e. the sum of ARCH & GARCH terms shows high persistence in volatility.

EGARCH (1, 1):

Variance Equation

C(4)	-0.623330	0.077025	-8.092533	0.0000
C(5)	0.257483	0.028193	9.132812	0.0000
C(6)	-0.129089	0.017010	-7.588880	0.0000
C(7)	0.950360	0.007993	118.8975	0.0000
T-DIST. DOF	7.879343	0.955050	8.250193	0.0000

Here also the coefficients of the variance equation are significant. The asymmetric factor is significantly negative indicating the presence of the leverage effect. The ARCH & GARCH coefficients sum up to more than 1 suggestive of an integrated process and shows high persistence in volatility. (results consistent with finding of Bhaskkar Sinha , 2006)

PARCH (1, 1):

	Variance Equation			
C(4)	0.000176	0.000160	1.099342	0.2716
C(5)	0.136851	0.019594	6.984245	0.0000
C(6)	0.512481	0.094504	5.422840	0.0000
C(7)	0.830178	0.017966	46.20920	0.0000
C(8)	1.351433	0.207597	6.509893	0.0000
T-DIST. DOF	7.938086	0.960215	8.266988	0.0000

The significance of the coefficients of the variance equation of the asymmetric models point towards the leverage effect in the Indian stock market In PARCH (1, 1) model as well, we can see that the sum of alpha & beta coefficients turn up around 96% percent which shows a high persistence in volatility and the effect of shocks on returns die out slowly. The high persistence in volatility is indicative of inefficiency of the Indian stock market.

The coefficient of the constant term is however insignificant but the insignificance of constant term does not affect much as the constant term has no natural interpretation. It captures the mean of the dependent variable as well as the average effects of the omitted variables. Therefore the general rule is to ignore the insignificance of constant term.

TABLE 3:

	Garch(1,1)	EGARCH(1,1)	TGARCH(1,1)	PARCH(1,1)
MEAN	0.001454*	0.001051*	0.001096*	0.001060*
AR(1)	-0.336171*	-0.299356*	-0.314748*	-0.308907*
MA(1)	0.428703 *	0.404997*	0.413923*	0.412063*
CONSTANT	7.73E-0.6*	-0.623330*	1.03E-05*	0.000176**
ARCH TERM	0.144366*	0.257483*	0.039383*	0.136851

GARCH T[1]ERM	0.831624*	0.950360*	0.820410*	0.830178
ASSYMETRIC TERM	-	-0.129089*	0.196401*	0.512481
AIC	-5.643522	-5.660890	-5.661771	-5.663507
LL	7216.599	7239.787	7240.912	7244.131

The results of table 3 indicate that PARCH (1, 1) model is the best in modeling the conditional variance of the Indian market as per Akaike Criterion & Log Likelihood Method. AIC is least for this model and Log Likelihood is highest.

Summary:

The returns series in Indian stock market exhibit characteristics such as volatility clustering , heteroskedasticity & excess peakedness which can be best captured by using non linear models. GARCH (1, 1) model has been found to be best for modeling the symmetric volatility. The study shows that return reacts differently to different news. Bad news increase volatility more than good news. So the return series show 'leverage effect' and amongst asymmetric models, Parch (1, 1) model has been found as best as per AIC & LL criterion. The long persistence in volatility indicates that Indian market is inefficient and information is not reflected in stock prices quickly. The result of the ARCH-in-mean model shows that Indian market does not offer any risk premium. I.e. investors taking higher risk are not compensated by high returns in the short run.

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[1] *IMPLIES SIGNIFICANCE OF COEFFICIENTS AT 5% LEVEL

** IMPLIES INSIGNIFICANCE

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APPENDIX:

Table 2:

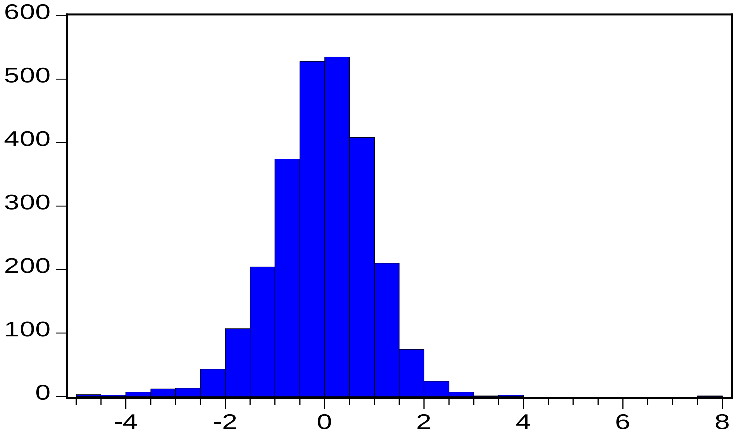
Correlogram of squared GARCH residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.005	0.005	0.0646	
| |	| |	2	-0.000	-0.000	0.0648	
| |	| |	3	0.007	0.007	0.1739	0.677
| |	| |	4	0.019	0.018	1.0516	0.591
| |	| |	5	-0.007	-0.007	1.1670	0.761
| |	| |	6	-0.017	-0.017	1.8789	0.758
| |	| |	7	-0.010	-0.010	2.1223	0.832
| |	| |	8	-0.025	-0.025	3.7194	0.715

						9	-0.031	-0.030	6.1391	0.524
						10	0.015	0.016	6.7186	0.567
						11	-0.016	-0.015	7.3425	0.602
						12	-0.022	-0.021	8.5776	0.573
						13	0.024	0.024	10.022	0.528
						14	-0.004	-0.006	10.058	0.611
						15	0.003	0.003	10.085	0.687
						16	0.011	0.011	10.389	0.733
						17	-0.015	-0.018	10.966	0.755
						18	-0.022	-0.022	12.181	0.731
						19	-0.006	-0.005	12.269	0.784

Table 4

Descriptive statistics of GARCH (1, 1) RESIDUALS:



Series: Standardized Residuals
Sample 4/05/2000 6/30/2010
Observations 2555

Mean	-0.060063
Median	-0.014315
Maximum	7.655843
Minimum	-4.534083
Std. Dev.	1.003642
Skewness	-0.258034
Kurtosis	5.417257
Jarque-Bera	650.4027
Probability	0.000000