A Study of the NSE's Volatility for Very Small Period using Asymmetric GARCH Models*

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Abstract

The prediction of volatility in financial markets has been of immense interest among financial econometricians. Using data collected at five-minute intervals, the present paper attempts to model the volatility in the daily return of National Stock Exchange (NSE). This paper shows that the Indian Stock Market experiences volatility clustering and hence GARCH-type models predict the market volatility better than simple volatility models, like historical average, moving average etc. It is also observed that the asymmetric GARCH models provide better fit than the symmetric GARCH model, confirming the presence of leverage effect. Finally, the results show that the change in volume of trade in the market directly affects the volatility of asset returns.

Key Words: GARCH, ARCH, E-ARCH, T-GARCH, P-GARCH, GARCH Volume, E-GARCH Volume, T- GARCH Volume, P-GARCH Volume H, EWMA, MA, Volatility, Indian Stock Market.

1.0 INTRODUCTION

The magnitude of fluctuations in the return of an asset is called its volatility. The prediction of volatility in financial markets has been of immense interest among financial econometricians. This interest is further rekindled by Bollerslev et al. (1994) when they established that financial asset return volatilities are highly predictable. It is true that unlike prices, Volatilities are not directly observable in the market, and it can only be estimated in the context of a model. However, Andersen et al. (2004) concluded that by sampling intraday returns sufficiently frequently, the realized volatility (measured by simply summing intra-day squared returns) can be treated as the observed volatility. This observation has profound implication for financial markets since,

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(a) The realized volatility provides a better measure of total risk (value at risk) of financial assets.

(b) It can lead to better pricing of various traded options.

Later popular models of volatility clustering were developed by Engle (1982) and Bollerslev (1986). The autoregressive conditional heteroskedastic (ARCH) models (Engle, 1982) and generalized ARCH (GARCH) models (Bollerslev, 1986) have been extensively used in capturing volatility clusters in financial time series. Bollerslev et al., (1996) have confirmed the superiority of GARCH-type models in volatility predictions over models such as the naïve historical average, moving average and exponentially weighted moving average (EWMA). GARCH models can replicate the fat tails observed in many high frequency financial asset return series, where large changes occur more often than a normal distribution would imply.

The Threshold GARCH model (TGARCH) (Glosten et al., 1993) and Exponential GARCH (EGARCH) model (Nelson, 1991) are used to predict conditional variance. Both E GARCH and T GARCH give relatively steady models as they do not explicitly assume the conditional distribution. Hence, it becomes useful in the absence of user specific pre-sample data. We have used all these three models in the present study to predict conditional variance.

Karmakar (2005) used conditional volatility models to estimate volatility of fifty individual stocks and observed that the GARCH (1,1) model provides reasonably good forecast. The present paper determines the best-fit mean model for the index return, which is then used in GARCH model specifications. Krishnan (2010) in a working paper used high frequency data for Indian stock market and autoregressive conditional hetroscedasticty models in order to observe how larger and smaller errors cluster together. In his study he used SBI stock tick prices and studied the cluster and there after used SBI and TATA stocks tick price to observe the volatility cluster. However, none of the studies, based on Indian stock markets, attempted to fit a mean equation for the stock return series before modeling volatility of stock returns. Apart from that, there was a need to study the tick values of the index, which serves as the aggregate volatility estimator of the market. This study has used the index and tried to find out the microstructure effect, half life period of the volatility with TGARCH and EGARCH to find the effect of asymmetry of the higher frequency data.

2.0 DATA AND METHODOLOGY

The Indian capital market has witnessed significant regulatory changes since 1992 with the creation of an independent capital market regulator, the Securities and Exchange Board of India (SEBI). Subsequent changes (e.g., screen based trading, derivatives trading, cycles etc.) have further developed the market and brought it in line with international capital markets. Presently only two exchanges in India, the NSE and the BSE (Stock Exchange, Mumbai) provide trading in the security derivatives. We have used the most popular index of the National Stock Exchange in India, called S&P CNX NIFTY (Nifty) to model the volatility in the Indian capital market. The Nifty, a market capitalization weighted index, is an index of 50 scrips accounting for 23 sectors of the Indian economy.

The BSE, the oldest stock exchange in India (and also in Asia), being in existence for more than 100 years, has been chosen for the study. In the study, the sample contains a total of 56,32,500 data points consisting of the Nifty values at five-minute intervals from 01 June 2000 through 30 January 2004. The choice of the period is guided by the fact that a lot of policy reforms in the Indian securities market have been implemented during this period. For example, trading on index futures was allowed in India since June 2000. High-frequency data have now become a popular experimental bench for analyzing financial markets (Dacorogna et al., 2001).

High frequency data are direct information from the market and are a recent entrant to the world of statistics. With a tick to tick data we get the microstructure of the markets and are better able to see how they vary from the traditional portrayal. Traditional tools generally used daily or weekly variability but were not very useful in studying variability in the time scales of seconds and minutes. Hence, instead of using the daily closing value of the index, this paper uses the directly observable data. It cannot be denied that very high frequency data have microstructure effect (e.g., how the data are transmitted and recorded in the data base). In order to avoid serious microstructure biases and at the same time reduce the measurement error due to data generation at low frequency; we have used data at regularly spaced five-minute intervals (Andersen et al., 2001). The present papers uses index values rather than stock prices and thus there are no bid and ask prices. We have used the last quoted value of the index at five-minute intervals. The daily index return is estimated using these five-minute interval values. A large part of the data set, from June 01, 2000 through December 16, 2003, is used to model volatility using various established volatility models. The remaining data set, from December 17, 2003 through January 30, 2004, is used to test the efficacy of various models using one-ahead volatility forecasts.

Let,

$r_{\pi}, i = 1, \ldots, m_t$

denote log of price relatives at an intra-day time-point i on day t, where m_t is the number of return observations obtained by using prices m times per day. Then daily return on day t is calculated as

$$r_t = \sum_{i-1}^{m_1} r_{ti}$$

Following Andersen et al,

(2001), we define the daily *realized volatility* $({}_tV^2)$as the sum of squares of returns collected at 5-minute intervals:

$$V_t^2 = \sum_{i=1}^{m_t} r_{ti}^2$$

Let δ_t^2 denote volatility forecast. One can assess the accuracy of the daily volatility forecasts under a model by considering the simple linear regressions (Andersen et al., 2005) of y_t on δ_t^2:

$$y_t = a + b\delta_t^2 + \varepsilon_t$$

Where $y_t = V_t^2$ or r_t^2 and then computing the coefficient of determination R^2. The model with the highest R^2 value may be treated as the best model for predicting y_t. On the other hand, if the R^2 Value turns out to be generally higher for one choice of y_t, then that choice $(V_t^2 \text{ or } r_t^2,)$ may be considered to be a better measure of observed volatility.

In addition to the regression-based framework, we have used the standard measures of predictive power of a model-the root mean square error (RMSE), the mean absolute error (MAE), and the Theil-U statistic. These are defined as follows:

$$RMSE = \sqrt{\frac{1}{k}\sum_{k=1}^{K} \delta_k^2 - V_k^2)^2}, \; MAE = \frac{1}{k}\sum_{k=1}^{k} \delta_k^2 - V_k^2, \; Theil-U = \frac{\frac{1}{k}\sum_{k=1}^{k}(\delta_k^2 - V_k^2)^2}{\frac{1}{k}\sum_{k=1}^{k}(V_{k-1}^2 - V_k^2)^2}$$

3.0 VOLATILITY MODELS

Random walk: The random walk model is the simplest of the models considered and it is given by $\delta_r^2 = \delta_{t-1}^2 + \varepsilon_t$, where ε_t is a white noise series.

Historical Average: The historical average model (Yu, 2002) is given by:

$$\delta_r^2 = \frac{1}{t-1}\sum_{i=1}^{t-1} \delta_t^2$$

GARCH: The volatility model for the r_r or a_t is said to follow a GARCH (m, s) model (Bollerslev, 1986, Bollerslev et al., 1994) if

$$a_t = \delta_t \varepsilon_t, \delta_t^2 = \alpha_0 + \sum_{i-1}^{m} \alpha_i \alpha_{t-t}^2 + \sum_{j=1}^{s} \beta_t \delta_{t-j}^2 \quad \text{........(5)}$$

Where $\alpha_0 > 0, \alpha_j \geq 0, \beta_j \geq 0,$

$\sum_{i=i}^{\max(m.s)} (\alpha_i + \beta_t) < 1,$

with $\alpha_i = 0$ for $i > m$ and

$B_j = 0$ for $j > s,$

And $\{\varepsilon_t\}$ is a sequence of random variables with mean 0 and variance 1, which is often assumed to have a standard normal or standardized student-*t* distribution.

An exogenous explanatory variable X_k may be included in the GARCH *model.* For example, the GARCH(1,1) model can be augmented as

$$a_t = \delta_t \varepsilon_t, \delta_t^2 = a_0 + a_1 a_{t-1}^2 + \beta_1 \delta_{t-1}^2 + \eta_1 X_{kt} \quad \text{........(6)}$$

GARCH (1,1) process $\delta_t^2 = a_0 + a_1 a_{t-1}^2 + \beta_1 \delta_{t-1}^2$ is done as follows. For this model the mean-reverting form is given by

$$(a_t^2 - \delta^2) = (a_1 + \beta_1)(a_{t-1}^2 - \delta^2) + u_t - \beta_1 u_{t-1}$$

Where $\delta^2 = a_0 / (1 - \alpha_1 - \beta_1)$ is the unconditional long-run level of volatility and $u_t = (a_t^2 - \delta_t^2)$ is the volatility shock. The half-life of the volatility is given by the formula (Zivot and Wang, 2002):

$$L_{half} = \text{In}(\frac{1}{2}) / \text{In}\,(a_1 + \beta_1).$$

4.0 RESULTS AND ANALYSIS

The sample kurtosis of 70.08 and skewness of 6.92 indicate that the distribution of daily volatility is not a normal distribution. This is further supported by the normality test statistics in Table 2. The constructed daily return series has an insignificant mean (Table 1) of around 6.30% per annum, using a standard 250-trading days in a year. The negative skewness of the return series usually indicates that there is at least one very large negative return in the data, which is what we observe in our case with the minimum daily return being -6.15%. The existence of excess kurtosis also indicates that the daily return series is not normal.

To test whether the daily return and realized volatility series is stationary, the augmented Dickey-Fuller (ADF) statistic is calculated on the entire sample and the results (Table 1) fail to accept the unit root null hypothesis at 1% level. The autocorrelation test (Ljung-Box) for the realized volatility series shows that (Table 2) the first-order autocorrelation of volatility is quite high, although we observed the higher-order autocorrelations to generally diminishing (the numerical results not presented here, for brevity). However, autocorrelations up to order four are statistically significantly different from zero. This demonstrates the evidence of volatility clustering and hence any autoregressive heteroskedastic volatility model should be a better fit.

Table 1: Descriptive Statistics for the data

Series	Mean	Median	Maximum	Minimum	Skewness	Excess	ADF
Return	0.0252%	0.1045%	5.2994%	-6.1585%	-0.04670	1.6596	-12.01*
Volatility	0.0222%	0.0126%	0.5757%	0.0014%	6.9179	70.0842	-9.623*

**Significant at 1% level.*

Table 2: Normality and Autocorrelation Test for Unconditional Volatility series

Test	Model	Test-statistic	P-Value
Normality	Jarque-Bera	192038.4	0.0000
	Shapiro-Wilks	0.4471	0.0000
Autocorrelation	Ljung-Box	302.6835	0.0000

In order to apply the GARCH-type models, one needs to first identify the best model for the mean equation and then fit a model for variance equation. We have applied various models on daily returns to identify the best-fit mean model. We have used first 883 daily returns to model the return series. A random walk mean model without a drift shows that the return series is non-normal (Table 3, panel A). We have also used a random walk model with a drift. However, the intercept coefficient is not different from zero. In order to test whether the return series is autocorrelated, we have used a higher-order autoregressive model, namely AR (25):

$$r_t = \phi_0 + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \ldots + \phi_{25} r_{t-25} + a_t$$

We observed that the Nifty series is largely uncorrelated. However, we find, from the AIC (Akaike Information Criterion) values that a moving average model, namely [MA (1)], is a better fit. It may be noted that neither the autoregressive nor the moving average models contain an intercept term.

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Table 3: Statistics for Mean Model

Panel A: Normality and Autocorrelation Tests for in-sample Mean Return Series

Test	Model	Test-statistic	p-value
Normality	Jarque-Bera	155.01179	0.0000
	Shapiro-Wilks	0.9684	0.0000
Autocorrelation	Ljung-Box	27.0563	0.3531
Panel B: Test Results of Various mean Models			
Model	Coefficient	tstatistic	p-value AIC
Random walk with Drift	0.0002	0.4561	0.648
AR(25)			-4843.07
AR(1): AR term	0.0743	2.2135	0.0271
			-5009.63
MA(1):MA-term	-0.0755	-2.2499	0.0245
			-5013.73
ARMA(1,1)			-5009.21
AR-term	-0.2527	-0.6122	0.5404
MA-term	-0.3251	-0.8059	0.4203

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After modeling the mean of the Nifty return series, the Nifty volatility series is modeled using various competing GARCH models as described above. The parameter estimates of various GARCH models are given in Tables 4.1 and 4.2. The sizes of *ARCH* and *GARCH* parameters determine the short-run dynamics of the resulting volatility time series. Large GARCH coefficient normally indicates persistence of volatility and large arch coefficient implies that volatility is les persistent and more 'spiky'. The sum of arch and GARCH coefficients in GARCH (1,1) model for the Nifty is less than one indicating that the variance process is stationary. In fact, the GARCH coefficient, though significant, is relatively low and ARCH coefficient high. This indicates that volatilities do not 'persist' for long.

Table 4. 1 Parameter Estimates of Various GARCH Models
Panel A Parameter Estimates

Model	Coefficient	Value	t-value	p-valu	AIC	BIC
GARCH (1,1)					-5121.92	-5102.78
	MA	0.1005	2.595	0.0048		
	Intercept	0.0000	4.589	0.0000		
	ARCH	0. 2338	6.306	0.0000		
	GARCH	0.6053	10.199	0.0000		
E-GARCH (1,1)					-5137.22	-5112.31
	MA	0.1146	3.053	0.0012		
	Intercept	-2.2207	-5.594	0.0000		
	ARCH	0.3852	7.838	0.0000		
	GARCH	0.7780	17.905	0.0000		
	Gamma	(y)-0.3717	-5.293	0.0000		
T-GARCH (1,1)					-5135.49	-5111.60
	MA	0.1079	2.749	0.0030		
	Intercept	0.0004	4.906	0.0000		
	ARCH	0.1122	4.063	0.0000		
	GARCH	0.5740	8.975	0.0000		
	Gamma(y)	0.2528	3.954	0.0000		

P-GARCH (1,1)					- 5137.25	-5113.33
	MA	0.1052	2.92	0.0018		
	Intercept	0.0031	5.030	0.0000		
	ARCH	0.2065	7.13	0.0000		
	GARCH	0.6172	10.51	0.0000		
	Gamma (y)	-0.4449	-5.906	0.0000		
GARCH (1,1) With Volume					-5133.13	-5109.21
	MA	0.0954	2.388	0.0086		
	Intercept	0.0000	4.946	0.0000		
	ARCH	0.2524	6.918	0.0000		
	GARCH	0.5635	10.54	0.0000		
	Volume	0.0001	5.015	0.0000		
E-GARCH (1,1) with Volume					-5137.85	-5109.15
	MA	0.1090	2.873	0.0021		
	Intercept	-2.4359	-6. 148	0.0000		
	ARCH	0.4012	7.831	0.0000		
	GARCH	0.7562	17.449	0.0000		
	Lev	-0.3820	-5.441	0.0000		
	Volume	0.2345	2.339	0.0098		
T-GARCH (1,1) With Volume					-5149.39	-5120.69
	MA	0.1063	2.622	0.0044		
	Intercept	0.0000	5.258	0.0000		
	ARCH	0.1138	4.457	0.0000		
	GARCH	0.5405	9.279	0.0000		
	Gamma(y)	0.2753	4.339	0.0000		
	Volume	0.0001	4.548	0.0000		
p-GARCH (1,1) With Volume					-5147.05	-5118.35
	MA	0.0932	2.479	0.0067		
	Intercept	0.0033	6.022	0.0000		
	ARCH	0.2340	7.546	0.0000		
	GARCH	0.5565	10.226	0.0000		
	Gamma	(y)-0.4550	-6.485	0.0000		
	Volume	0.0044	4.041	0.0000		

Table 4.2 Pannel B Normality and Autocorrelation Test

Model	JB Statistic	p-value	SW-Statistic	p-value	LB Statistic*	p-value
GARCH(1,1)	38.48	0.0000	0.9849	0.2704	13.38	0.3420
E-GARCH(1,1)	35.27	0.0000	0.9864	0.5093	17.93	0.1177
T GARCH(1,1)	35.56	0.0000	0.9848	0.2643	17.40	0.1351
P-GARCH (1-1)	34.74	0.0000	0.9866	0.5498	19.46	0.07801
GARCH (1,1) with volume	40.04	0.0000	0.982	0.0325	14.69	0.2586
E-GARCH (1,1) with volume	37.32	0.0000	0.9859	0.4198	19.55	0.07613
T-GARCH (1,1) With Volume	36.86	0.0000	0.9829	0.07067	19.21	0.0836
P- GARCH 1,1) with Volume	38.67	0.0000	0.9845	0.2178	23.25	0.0256

Note: JB stands for Jarque –Bera; SW for Shapiro-Wilk and LB stands for Ljung-Box. LB statistics is for squared standard residuals.

In symmetric GARCH models, the signs of the residuals (estimated shocks) have no impact as we consider only squared residuals (a_{t-i}^2) in the GARCH equation. The negative skewness in the return series (Table1) indicates the existence of leverage effect and hence any asymmetric GARCH model would be capable of capturing such effect. The negative (and significant) coefficient of leverage in EGARCH confirms the leverage effect.

However, when GARCH models are augmented with exogenous variables in the variance equation, TGARCH (1,1) with volume as the exogenous variable has given a better fit than PGARCH(1,1). It may be noted that all versions of the GARCH model use only first-order autoregressive variance and squared error terms. We have tried with higher-order GARCH models, but the results did not improve.. The normality (Shapiro-Wilk) and autocorrelation (Ljung-Box) tests show that the conditional variances (Table 4, Panel B) are normal and uncorrelated. In other words, the effect of hetroscedasticty in the residuals has been controlled.

The GARCH(1,1) model in Table 4 (Panel A) reports that the conditional volatility is stationary. Using the

ARCH coefficient (0.2338) and the GARCH coefficient (0.6053) of the symmetric GARCH(1,1) model, the half-life of variance is estimated as 4 days. This implies that volatility would not persist for a long period. It may be conjectured that frequent regulatory interventions in the Indian capital markets have not allowed market volatility to persist for long. Thus, moving average model of volatility prediction uses realized volatility of the immediately past four days. These results are presented in Table 5. Results show that (Table 5, Panel A) conditional volatility models better

Table 5: Evaluation Measures for Volatility prediction

Panel A: Correlation (r^2) of general volatility forecast evaluation regression

Model	r_t^2	v_t^2
Random Walk	0.5007	0.3651
Historical Average	0.1413	0.2314
Moving Average	0.2170	0.3054
EWMA	0.3341	0.3515
GARCH	0.1464	0.3092
E-ARCH	0.3979	0.6074
T-GARCH	0.3685	0.5667
P-GARCH	0.3973	0.5667
GARCH Volume	0.1524	0.3163
E-GARCH Volume	0.3820	0.6189
T- GARCH Volume	0.3792	0.5859
P-GARCH Volume	0.4289	0.6026

Pannel B: Standard Evaluation Measures

Model	RMSE ($\times 10^1$)	MAE ($\times 10^2$)	Theil - U
Random Walk	0.5318		
Historical Average	0.8378	0.5268	1.00
Moving Average	0.5137	0.5841	1.57
EWMA	0.4619	0.4507	0.96
GARCH(1,1)	0.5738	0.4161	0.86
E- GARCH (1,1)	0.3310	0.4448	1.07
T-GARCH (1,1)	0.3292	0.3757	0.62
P-GARCH (1,1)	0.3252	0.3509	0.61
GARCH Volume	0.5686	0.3758	0.61
E- GARCH Volume	0.3377	0.4322	1.06
T-GARCH Volume	0.3204	0.3788	0.63
P- GARCH Volume	0.3144	0.3446	0.60
		0.3788	0.59

predict actual volatility. In fact, EGARCH (1,1) with volume as exogenous variable has the best predictive power. It can also be observed that R^2 has significantly improved for the same volatility forecast when realized volatility v_t^2 is used in place of its poor cousin of r_t^2. This result reiterates that even if a researcher is interested in predicting volatility over daily horizon, it is always better to use v_t^2 as the proxy for latent daily volatility (Andersen et al., 2005).

Other standard measures (Table 5, Panel B) show the superiority of asymmetric GARCH models for predicting volatility as compared to historical average, moving average and EWMA models. The prediction error measures RMSE and Theil-U show that the forecast error is minimum when the PGARCH (1,1) model containing the volume as an exogenous variable in the variance equation model is used. However, the MAE measure of forecast error reports that the TGARCH (1,1) model with volume as an exogenous variable in variance equation is a better predictor of one-day ahead volatility. The Theil-U statistic is a poor evaluator of performance in our case as it treats the random walk model as a benchmark to compare the forecast performance of other volatility models. The poor forecasting ability of the random walk model implies that the market volatility is not a random walk and hence can be conveniently modeled. Results in Table 5 confirm two distinct features of the Nifty: (a) the 28 stylized fact of leverage effect in volatility clustering, and (b) the empirical evidence that greater the volume of trade in the market, larger is the market volatility.

It has been further observed that where there is no asymmetric effect, the standard GARCH models dominate EGARCH, TGARCH and non parametric models. The estimators with t-distribution errors perform slightly better than the normal fittings. However, the non parametric models provide the nearly identical results, which disregard the innovation distribution.

5.0 CONCLUSION AND FUTURE COURSE OF ACTION

There have been attempts to model and forecast stock return volatilities in emerging markets. The present paper attempted to model the volatility in the index returns of the NSE, using high frequency intra-day data covering a period from June 2000 through January 2004. This paper has four main findings:

(a) Existence of volatility clustering in the Indian stock market;

(b) Evidence of leverage effect on volatility;

(c) The change in volume of trade positively affecting market volatility.

The study has used intra-day data over a period of about three and half years. A longer period of study could lead to different results. The paper has not attempted to travel beyond GARCH-type models to predict the market volatility. The forecasting performance of various volatility models is gauged using standard evaluation measures. It was observed (Brooks and Persand, 2003) that relative accuracies of the various volatility models are highly sensitive to the measure used to evaluate them. While the parametric methods model the persistent, smoother aspects of volatility, the nonparametric methods model the highly nonlinear response to large return shocks (Pagan and Schwert, 1990). We intend to use nonparametric methods in our future research for modeling volatility.

From the study the following can be the managerial learning (which have been discussed earlier but put here for better focus)

1. The empirical evidence points at the fact that greater the volume of trade in the market, larger is the market volatility.
2. Half life of variance is 4 days which implies that volatility does not persist for a long period. This may be due to the fact that there is frequent regulatory intervention in the market; hence, market volatility is not allowed to persist for a long term. This may influence the technical prediction done in the market as most of them Q depend on moving average smoothing.

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