Forecasting Performance Of Various Volatility Models On Intra-Day Equity Price In The Indian Stock Market

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INTRODUCTION

The Indian financial markets are exhibiting significant changes after the commencement of derivative trading, and the subsequent changes are being observed in terms of money supply and growth, liquidity and volatility. Financial derivative is a contract defined in terms of some underlying asset, whose value is paid by traders today to exercise the contract at the time and/or before of maturity. Estimation and forecasting of volatility play a key role in the pricing of derivatives, which has a wider impact on financial regulation, monetary policy and macro-economy. The boom in the Indian financial markets after the introduction of derivative trading (in 2000), and the recent financial crisis are good reminders of this fact. Numerous research works have been carried out to investigate the relationship between stock returns and volatility for developed markets. Black (1976) and Christie (1982) suggested that decline of stock prices of an individual firm raises the financial leverage and volatility. Koulakiotis et.al.(2006) concluded that the GARCH(1,1) and EGARCH(1,1) models provide the relationship between stock market volatility and stock returns for Australia, Canada, France, Japan, U.S., Germany and Italy. Akgiray (1989) found that the GARCH model is superior than the ARCH model, forecasting future volatility of New York stock exchange. Pagan and Schwert (1990), Lee (1991), Tse (1991), Cumby et. al.(1993) Cao and Tsay (1992) found that EGARCH gave better forecasting than linear GARCH. Brailsford and Faff (1996), Brooks (1998) , Bali (2000) and Taylor (2004) studied EWMA, GARCH, EGARCH and GJR-GARCH and found that GJR-GARCH is better than the other. Koulakiotis et.al. (2006), Taufiq and Hao (2009) and Abdullah and Guven (2008) also found that the GJR-GARCH model appears to be a more accurate forecaster than other bivariate GARCH models.

In the Indian context, Rajan (2011) and Panandikar (2007) discussed the volatility of the Indian Stock Exchange. Varma (1999) observed that the GARCH models performed better in a range of common risk (ranging from 0.25% to 10%), and EWMA does well at 10% and 5% risk levels, but breaks down at the 1% and lower than 1% level of risk. Pandey (2002) and Singh and Prabakaran (2008) explored the extreme value estimators focused on the time-varying characteristic of volatility. Later on, Kaur (2004) discussed the nature of stock market volatility and concluded that the asymmetric GARCH models outperform the conventional linear or symmetric GARCH models. Recently, the GARCH and EWMA model were discussed by Kumar (2006) and Banerjee and Sarkar (2006).

In this paper, the researchers have selected the three most popular stocks of smooth liquidity, which substantially influence the financial market, as depicted in the Table 1 given below.

Table 1 : High Liquidity Stocks In NSE/BSE (Nifty/Sensex)

			Weightage	
Stock Code	No. of Equity	Market Capitalization	NIFTY50	SENSEX30
HDFC	284453318	36250 (in Crores ₹)	2.11	4.65
INFOSYS	2863207515	70506 (in Crores ₹)	4.10	12.73
RELIANCE	15737980330	199251(in Crores ₹)	11.58	10.99

The daily intra-day data of 2310 points, which tends boom to burst, of these three stocks from 1st Jan 2000 to 31st March 2009 listed in National Stock Exchange, India. Daily previous closing, opening, high, and low prices are considered of these stocks during the period of study. These prices are converted into daily returns using logarithmic

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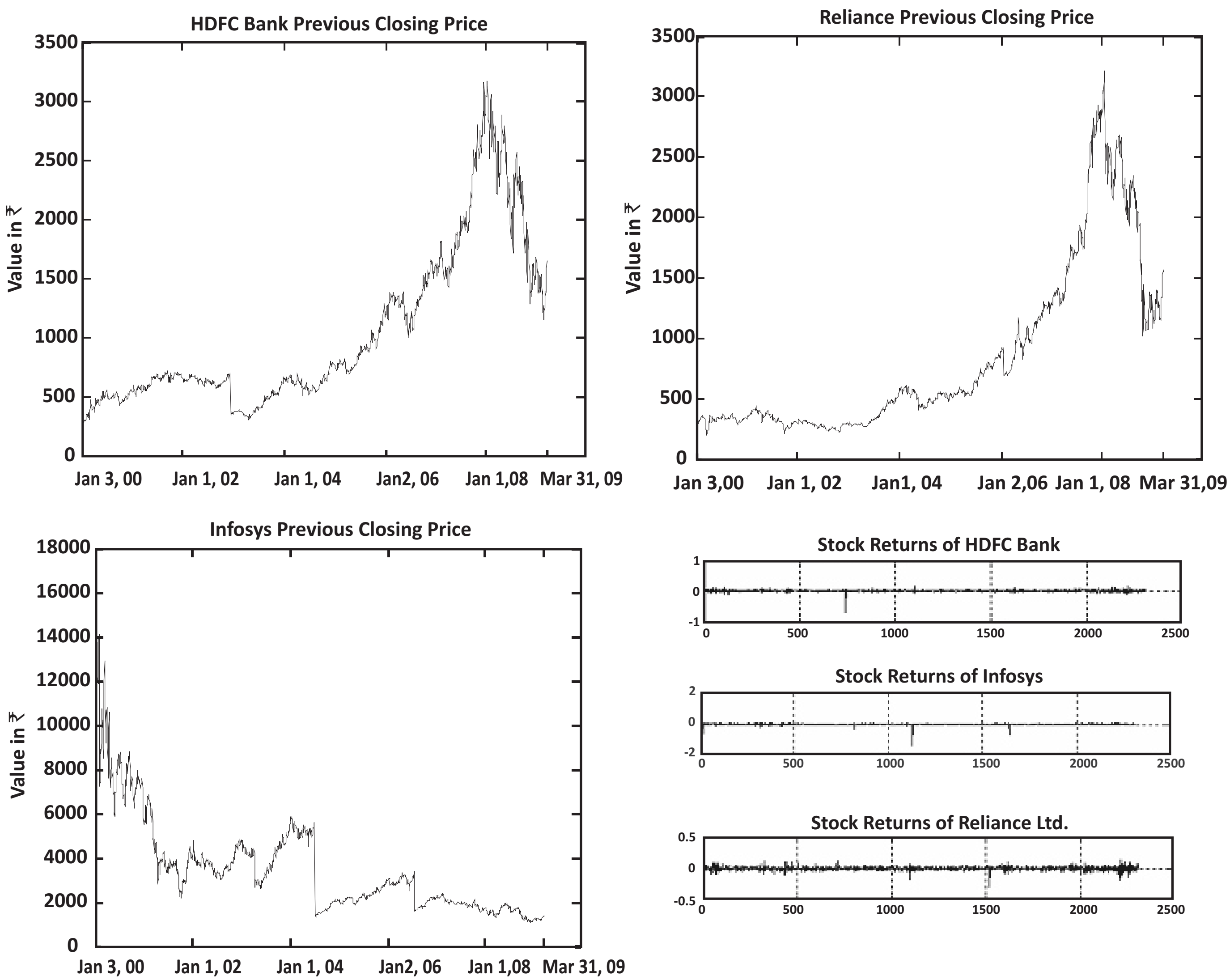
difference of prices of successive periods as :

$$r = \ln\left(\frac{S_t}{S_{t-1}}\right)$$

where, S_t is stock price at time.
The data of the various stocks and its returns are represented through the following Figure 1.

Figure 1 : Data of Various Stocks and Their Returns



THE EXPONENTIALLY WEIGHTED MOVING AVERAGE MODEL (EWMA MODEL)

The exponentially weighted average (EWMA) model is an adaptive forecasting method that gives greater weight to the more recent observation so that the finite recent memory of the market is required. It turns out that this weighting scheme leads to a particularly simple formula for updating volatility estimates. The formula is :

$$\sigma^2_n = \lambda\sigma^2_{n-1} + (1-\lambda)\,u^2_{n-1} \quad \text{Where, } \lambda \text{ is a scalar} \qquad \text{.................................} (1)$$

The estimate σ_n of the volatility for n days is calculated from σ_{n-1} (the estimate that was made at the end of day n-2 of volatility for n-1) and u^2_{n-1} is the most recent daily percentage change in the market variables. To understand, why eq. (1) corresponds to weights that decrease exponentially, we substitute for σ^2_{n-1} to get

$$\sigma^2_n = \lambda [\lambda\sigma^2_{n-1} + (1-\lambda)u^2_{n-1}]$$
$$\sigma^2_n = (1-\lambda)[u^2_{n-1} + u^2_{n-2}]\ \lambda^2\sigma^2_{n-2}$$
$$\sigma^2_n = (1-\lambda)[u^2_{n-1} + \lambda u^2_{n-2} + \lambda u^2_{n-3}] + \lambda^3\sigma^2_{n-3}$$

Continuing in this way to obtain :

$$\sigma^2_n = (1-\lambda)\Sigma^m_{i=1}\lambda^{i-1}u^2_{n-i} + \lambda^m\sigma^2_{n-m} \qquad \text{.................................. (2)}$$

For large m, the term $\lambda^m\sigma^2_{n-m}$ is sufficiently small and we can take it equal to zero.

The EWMA Model has an attractive feature that relatively little data is needed to store. At any given time, we need to remember only the current estimate of the variance rate and the most-recent observation on the value of the market variable. Risk Metrics software, developed by J. P. Morgan based on EWMA model with $\lambda = 0.94$ was used for updating the daily volatility estimates.

GARCH (P, Q) MODEL

The GARCH (p, q) was introduced by Bollerslev (1986), with two conditional mean equations :

$$y_t = bx_t + \varepsilon_t \text{ and } y_t = \varepsilon_t\sigma_t \qquad \text{where } \varepsilon_t \sim N(0, \sigma^2) \qquad \text{.................................. (3)}$$

and conditional variance equation is :

$$\sigma^2_t = \alpha_0 + \Sigma^q_{i=1}\alpha_i y^2_{t-i} + \Sigma^p_{i=1}\beta_i\sigma^2_{t-i} \qquad \text{.................................. (4)}$$

where y_t is the dependent variable, and x_t is a vector of explanatory variables, b is a vector of unknown parameters, $p \geq 0, q > 0, \alpha_0 > 0, \alpha_1 \geq 0$ for $i = 1, 2, ... q$ and $\beta_i \geq 0$ for $i = 1, 2, ... p$

For $p = 0$, the process reduces to the ARCH (q) process. In the ARCH (q) process, the conditional variance is specified as a linear function of sample variance only, whereas the GARCH (p, q) process allows lagged conditional variance to enter as new information.

Then GARCH (1,1) define with conditional mean equation as :

$$y_t = \varepsilon_t\sigma_t \qquad \text{where } \varepsilon_t \sim N(0, \sigma^2) \qquad \text{.................................. (5)}$$

and conditional variance equation is :

$$\sigma^2_t = \alpha_0 + \alpha_1 y^2_{t-1} + \beta_1\sigma^2_{t-1} \qquad \text{where } \alpha_0 > 0, \alpha_1 \geq 0, \beta_1 \geq 0 \qquad \text{.................................. (6)}$$

The GARCH (1,1) process as defined in Eqs. (5) and (6) is wide-sense stationary with :

$$E(y_t) = 0,\ var(y_t) = \frac{\alpha_0}{1 - \alpha_1 - \beta_1}$$

and cov $(y_t, y_s) = 0$ for $t \neq s$ if and only if $\alpha_1 + \beta_1 < 1$ i.e. roots of characteristic equation associated GARCH (1,1) process lie outside the unit circle. The likelihood function for GARCH (1,1) process is defined as :

$$\iota_\theta = -\frac{r}{2}\ln(2\pi) - \frac{1}{2}\Sigma^m_{t=1}\ln(\sigma^2_t) - \frac{1}{2}\Sigma^m_{t=1}\frac{y^2_t}{\sigma^2_t} \qquad \text{.................................. (7)}$$

EXPONENTIAL GARCH (EGARCH)

In 1991, Nelson suggested that the GARCH model has drawbacks concerning interpretation of *"persistence"* of shocks to conditional variance, non-negativity of conditional variance and asymmetrical behavior and developed the exponential GARCH (EGARCH) model incorporating these drawbacks by appropriately weighting innovation ε_t :

$$g(\varepsilon_t) = \theta\,\varepsilon_t + \gamma[|\varepsilon_t| - E(|\varepsilon_t|)] \qquad \text{.................................. (8)}$$

$$y_t = \varepsilon_t\sigma_t, \text{ and } \ln(\sigma^2_t) = \alpha_0 + \left(\frac{1 + \beta_1 B + ... + \beta_q B^q}{1 - \alpha_1 B - ... - \alpha_1 B^p}\right) g(\varepsilon_{t-1}) \qquad \text{.................................. (9)}$$

where α_0 is a constant, B is the back-shift or lag operator such that $B(g(\varepsilon_t)) = g(\varepsilon_t)$, $(1 + \beta_1 B + ... + \beta_q B^q)$ and

$(1-\alpha_1 B - ... - \alpha_1 B^p)$ are polynomials in B.

The alternative representation for EGARCH (p, q) model is given by $y_t = \varepsilon_t \sigma_t$ and

$$\ln(\sigma^2_t) = \alpha_0 + \Sigma^p_{i=1} \alpha_i \, (|\varepsilon_{t-1}| + \gamma_i \varepsilon_{t-1}) + \Sigma^q_{j=1} \beta_j \ln(\sigma^2_{t-j}) \quad ....(10)$$

where $\alpha_0 > 0$, $\alpha_1 \geq 0$ for $i = 1, 2,... q$ and $\beta_j \geq 0$ for j = 1, 2, ... p and γ_i's are the leverage parameters. A fact of financial volatility is that the bad news tends to cause a larger impact on volatility than good news. At t = 0 , good and bad news exhibit the same effect on volatility. The sufficient condition for process ε_t to be stationary is $\Sigma^q_{j=1} \beta_j < 1$.

GJR-GARCH

In 1993, Glosten et.al developed a GJR-GARCH model incorporating asymmetric effect of asset price returns with conditional mean equation :

$$y_t = \varepsilon_t \sigma_t \qquad \text{where } \varepsilon_t \sim N(0, \sigma^2)$$

and conditional variance equation is :

$$\sigma^2_t = \alpha_0 + \Sigma^p_{i=1} (\alpha_i \varepsilon^2_{t-i} + \gamma S^-_{t-i} \varepsilon^2_{t=i}) + \Sigma^q_{j=1} \beta_j \sigma^2_{t-i} \quad ....(11)$$

where S^-_t dummy variable, which takes values 1 and 0 as $\varepsilon_{t-i} < 0$ and $\varepsilon_{t-i} \geq 0$ respectively. The conditional volatility is positive if $\alpha_0 > 0$, $\alpha_i \geq 0$, $\alpha_i + \gamma \geq 0$ and $\beta_j \geq 0$ for $i = 1, 2, ... p$ and $j = 1, 2, ...q$. The process of covariance is stationary if and only if :

$$\Sigma^p_{i=1} (\alpha_i + \gamma) + \Sigma^q_{j=1} \beta_j < 1 \quad ....(12)$$

The term $\gamma S^-_{t-i} \varepsilon^2_{t-i}$ represents asymmetric effect asset price returns. The effect of shock on volatility is α_i and $\alpha_i + \gamma$ as shock is negative and positive respectively.

Table 2: Estimated Parameters For GARCH (1,1) Model

NSE Code for Company	Intra-day Price	α_0	β_1	α_1
HDFC	Previous Closing	0.00055844	0.65766	0.1056
	Open Price	0.0013465	0.48459	0.16409
	High Price	0.00063775	0.26698	0.092607
	Low Price	0.00029449	0.84047	0.15811
INFOSYS	Previous Closing	-0.00018862	0	0.32183
	Open Price	-0.0010694	0.23969	0
	High Price	-0.00074755	0	0.16938
	Low Price	-0.00072763	0.27591	0.18156
RELIANCE	Previous Closing	0.0012989	0.60058	0.30372
	Open Price	0.0014683	0.53334	0.36482
	High Price	0.0015801	0.5533	0.29377
	Low Price	0.0018411	0.61598	0.35168

Table 3 : Estimated Parameters For EGARCH (1,1) Model

NSE Code for Company		α_0	β_1	α_1	γ_1
HDFC	Previous Closing	0.00096587	0.84751	0.17636	0.051035
	Open Price	0.0010096	0.75588	0.22825	-0.12868
	High Price	0.00074508	0.96184	0.015452	0.042258
	Low Price	-0.0005592	0.96566	0.32077	-0.14893
INFOSYS	Previous Closing	0.0015321	1	0.013781	0.076642
	Open Price	-0.0015478	0.88711	0.63019	0.28584

	High Price	-0.0025944	0.89476	0.19792	0.31033
	Low Price	-0.0018583	0.87295	0.80474	0.36213
RELIANCE	Previous Closing	0.0012596	0.84844	0.50279	-0.0019875
	Open Price	0.0012101	0.81153	0.47907	-0.059009
	High Price	0.0021299	0.79049	0.44959	0.07199
	Low Price	0.00073266	0.84878	0.41836	-0.12853

Table 4 : Estimated Parameters For GJR-GARCH (1,1) Model

NSE Code for		α_0	MA(1)	ε_t	β_1	α_1	γ_1
Company HDFC	Previous Closing	0.00096587	-0.010564	-1.0475	0.84751	0.17636	0.051035
	Open Price	0.0010096	-0.16605	-1.6565	0.75588	0.22825	-0.12868
	High Price	0.00074508	-0.034351	-0.26915	0.96184	0.015452	0.042258
	Low Price	-0.0005592	-0.017287	-0.19942	0.96566	0.32077	-0.14893
INFOSYS	Previous Closing	0.0015321	-0.013134	0.0069222	1	0.013781	0.076642
	Open Price	-0.0015478	-0.57171	-0.56486	0.88711	0.63019	0.28584
	High Price	-0.0025944	-0.011602	-0.61483	0.89476	0.19792	0.31033
	Low Price	-0.0018583	-0.57925	-0.62481	0.87295	0.80474	0.36213
RELIANCE	Previous Closing	0.0012596	0.031426	-1.124	0.84844	0.50279	-0.001987
	Open Price	0.0012101	-0.11776	-1.2717	0.81153	0.47907	-0.059009
	High Price	0.0021299	-0.003756	-1.4983	0.79049	0.44959	0.07199
	Low Price	0.00073266	0.12298	-1.0681	0.84878	0.41836	-0.12853

PARAMETERS ESTIMATION FOR VARIOUS METHODS

The process of coding of the estimation of GARCH parameters is as:

First, guess the value of the parameters b, α_0, α_i and β_1. The guess of b can be taken from Least Square (LS) estimation of Eq. (5) and guess α_0, α_i and β_1 from LS estimation of $\alpha_t^2 = \alpha_0 + \alpha_1 y^2_{t-1} + \beta_1 \sigma^2_{t-1}$, where σ^2_t are fitted residuals from the LS estimation of Eq. (5).

Second, loop over the sample (first t =1 then t =2 and so on) and calculate σ^2_t from Eq.(6) and b from Eq.(5). Plug in

Table 5 : Forecasted Volatility For HDFC Bank's Stock Through EWMA, GARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1)

No. of	HDFC Previous Closing				HDFC Open Price			
Days	EWMA (%)	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)
1	3.04	3.29	3.78	3.20	3.76	3.47	3.01	3.17
2	2.87	3.24	3.69	3.17	3.54	3.44	3.09	3.23
3	2.70	3.21	3.61	3.15	3.34	3.43	3.15	3.27
4	2.71	3.18	3.55	3.14	3.35	3.41	3.20	3.30
5	2.71	3.16	3.50	3.13	3.35	3.41	3.24	3.33
6	2.71	3.15	3.46	3.12	3.35	3.40	3.27	3.35
7	2.71	3.13	3.42	3.11	3.55	3.40	3.29	3.36
8	2.71	3.13	3.39	3.10	3.55	3.40	3.31	3.37
9	2.71	3.12	3.36	3.10	3.55	3.40	3.32	3.38
10	2.71	3.11	3.34	3.10	3.55	3.40	3.33	3.38

Table 5 (contd.): Forecasted Volatility For HDFC Bank's Stock Through EWMA, GARCH(1,1), EGARCH(1,1) And GJR-GARCH(1,1)								
No. of	HDFC High Price				HDFC Low Price			
Days	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)
1	3.50	2.77	3.25	2.72	3.41	4.35	3.52	3.55
2	3.30	2.84	3.24	2.85	3.21	4.39	3.58	3.59
3	3.11	2.86	3.23	2.86	3.03	4.42	3.63	3.62
4	3.12	2.87	3.22	2.86	3.04	4.45	3.68	3.66
5	3.12	2.88	3.21	2.86	3.04	4.48	3.73	3.69
6	3.12	2.88	3.20	2.86	3.04	4.51	3.78	3.72
7	3.12	2.88	3.19	2.86	3.04	4.54	3.83	3.76
8	3.12	2.88	3.18	2.86	3.04	4.57	3.88	3.79
9	3.12	2.88	3.17	2.86	3.04	4.60	3.93	3.82
10	3.12	2.88	3.16	2.86	3.04	4.63	3.97	3.85

Table 6 : Forecasted Volatility For Infosys's Stock Through EWMA, GARCH (1,1), EGARCH (1,1) And GJR - GARCH(1,1)								
No. of	INFOSYS Previous Closing				INFOSYS Open Price			
Days	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)
1	4.46	4.46	3.41	4.40	4.86	4.91	5.02	4.85
2	4.21	4.92	3.43	4.67	4.59	4.91	5.31	5.29
3	3.97	5.06	3.44	4.89	4.32	4.91	5.57	5.70
4	3.99	5.11	3.45	5.06	4.34	4.91	5.82	6.08
5	3.98	5.12	3.46	5.20	4.34	4.91	6.05	6.43
6	3.98	5.13	3.47	5.32	4.34	4.91	6.26	6.77
7	3.98	5.13	3.49	5.41	4.34	4.91	6.46	7.09
8	3.98	5.13	3.50	5.49	4.34	4.91	6.63	7.40
9	3.98	5.13	3.51	5.56	4.34	4.91	6.79	7.69
10	3.98	5.13	3.52	5.62	4.34	4.91	6.94	7.98

Table 6 (contd.) : Forecasted Volatility For Infosys's Stock Through EWMA, GARCH(1,1), EGARCH(1,1) And GJR-GARCH(1,1)								
No. of	INFOSYS High Price				INFOSYS Low Price			
Days	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)
1	4.49	4.68	4.31	3.31	4.82	4.94	4.74	7.87
2	4.24	4.77	4.42	3.39	4.54	5.06	5.11	8.66
3	3.99	4.78	4.51	3.47	4.28	5.12	5.45	9.38
4	4.01	4.78	4.59	3.55	4.30	5.14	5.77	10.05
5	4.01	4.78	4.67	3.63	4.30	5.15	6.07	10.68
6	4.01	4.78	4.74	3.70	4.30	5.16	6.34	11.27
7	4.01	4.78	4.81	3.78	4.30	5.16	6.59	11.84
8	4.01	4.78	4.86	3.85	4.30	5.16	6.81	12.37
9	4.01	4.78	4.92	3.92	4.30	5.16	7.01	12.89
10	4.01	4.78	4.96	3.99	4.30	5.16	7.19	13.39

Table 7 : Forecasted Volatility For Reliance Ltd. Stock Through EWMA, GARCH(1,1), EGARCH(1,1) And GJR-GARCH(1,1)								
No. of	Reliance Previous losing				Reliance Open Price			
Days	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)
1	2.49	2.88	2.83	2.78	3.27	3.44	2.90	2.82
2	2.34	2.87	2.77	2.78	3.08	3.54	2.88	2.85
3	2.20	2.86	2.72	2.78	2.90	3.63	2.86	2.87
4	2.21	2.86	2.68	2.78	2.92	3.71	2.85	2.90
5	2.21	2.85	2.64	2.78	2.91	3.78	2.84	2.91
6	2.21	2.85	2.61	2.79	2.91	3.84	2.83	2.93
7	2.21	2.84	2.59	2.79	2.91	3.90	2.83	2.94
8	2.21	2.84	2.57	2.79	2.91	3.95	2.82	2.95
9	2.21	2.83	2.55	2.79	2.91	3.99	2.82	2.96
10	2.21	2.83	2.53	2.79	2.91	4.03	2.81	2.96

Table 7 (Contd) : Forecasted Volatility For Reliance Ltd. Stock Through EWMA, GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1)								
No. of	Reliance High Price				Reliance Low Price			
Days	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)
1	2.78	2.89	2.90	2.82	2.88	3.23	2.85	2.89
2	2.62	2.91	2.88	2.85	2.72	3.32	2.86	3.02
3	2.46	2.92	2.86	2.87	2.56	3.40	2.87	3.14
4	2.47	2.94	2.85	2.90	2.57	3.48	2.88	3.26
5	2.47	2.95	2.84	2.91	2.57	3.56	2.89	3.37
6	2.47	2.96	2.83	2.93	2.56	3.63	2.89	3.47
7	2.47	2.97	2.83	2.94	2.56	3.70	2.90	3.57
8	2.47	2.97	2.82	2.95	2.56	3.77	2.90	3.66
9	2.47	2.98	2.82	2.96	2.56	3.83	2.91	3.75
10	2.47	2.98	2.81	2.96	2.56	3.89	2.91	3.84

these numbers in Eq.(7) to find the likelihood value. Third, make better guesses of parameters b, α_0, α_i and β_1. The second step is reiterated until the likelihood value converges.

Thirdly, the whole process of estimation of parameter will be performed with the help of MATLAB programming. The code for EGARCH (1,1) would be the same except the equations of models. Tables 2-4 represent the estimated parameters of GARCH (1,1) , EGARCH (1,1) and GJR-GARCH (1,1) respectively.

TEN DAYS FORECASTING OF PRICE VOLATILITY

After estimation of parameters of various volatility forecasting models, the work remains to forecast the price volatility in terms of % for convenience (see Tables 5 - 7).

EVALUATION MEASURES

The various models give different price volatility ,therefore, analysis of error to assess the performance of the forecasting is essential. Hence, the researchers have computed four measures - namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Theil's U (TU) and MAPE. These are defined as follows :

$$\text{MAE} = \frac{1}{n}\ \Sigma^{n}_{i=1}|\hat{\sigma}_i - \sigma_i| \qquad \text{MSE} = \sqrt{\frac{1}{n}\Sigma^{n}_{i=1}(\hat{\sigma}_i - \sigma_i)^2}$$

Table 8 : Error Measure For EWMA, GARCH(1,1), EGARCH(1,1) And GJR-GARCH(1,1)								
	MAE				RMSE			
	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)
HDFC (P.C)	0.0008	0.0008	0.0009	0.0008	0.0010	0.0010	0.0010	0.0010
HDFC (O.P)	0.0012	0.0011	0.0011	0.0011	0.0015	0.0015	0.0015	0.0015
HDFC (H.P)	0.0008	0.0007	0.0008	0.0007	0.0009	0.0009	0.0009	0.0009
HDFC (L.P)	0.0011	0.0017	0.0014	0.0013	0.0016	0.0018	0.0016	0.0016
INFOSYS (P.C)	0.0011	0.0020	0.0007	0.0022	0.0012	0.0021	0.0008	0.0023
INFOSYS (O.P)	0.0014	0.0017	0.0027	0.0033	0.0015	0.0018	0.0030	0.0037
INFOSYS (H.P)	0.0013	0.0017	0.0016	0.0016	0.0014	0.0018	0.0017	0.0503
INFOSYS (L.P)	0.0015	0.0019	0.0029	0.0011	0.0016	0.0021	0.0032	0.0118
RELIANCE (P.C)	0.0008	0.0008	0.0008	0.0008	0.0011	0.0010	0.0010	0.0010
RELIANCE (O.P)	0.0012	0.0012	0.0012	0.0012	0.0016	0.0014	0.0016	0.0015
RELIANCE (H.P)	0.0006	0.0007	0.0006	0.0007	0.0008	0.0008	0.0008	0.0008
RELIANCE (L.P)	0.0011	0.0014	0.0011	0.0014	0.0016	0.0016	0.0016	0.0016
	Theil-U				MAPE			
	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)	EWMA	GARCH (1,1)	EGARCH (1,1)	GJR-GARCH(1,1)
HDFC(P.C)	0.5413	0.5262	0.6238	0.5116	0.0351	0.0270	0.0325	0.0274
HDFC(O.P)	0.3834	0.3400	0.3258	0.3278	0.0413	0.0307	0.0400	0.0391
HDFC (H.P)	0.9616	1.1095	1.0330	1.0795	0.0233	0.0223	0.0226	0.0222
HDFC (L.P)	1.0981	0.9409	1.0331	1.0395	0.0397	0.0412	0.0398	0.0396
INFOSYS (P.C.)	1.0399	1.0370	1.0605	1.0301	0.0278	0.0398	0.0208	0.0412
INFOSYS (O.P)	1.2145	1.1459	1.1029	1.0876	0.0309	0.0336	0.0436	0.0492
INFOSYS (H.P.)	1.1923	1.1302	1.1296	0.9994	0.0308	0.0364	0.0348	0.0640
INFOSYS (L.P)	1.1637	1.1000	1.0594	1.0223	0.0354	0.0378	0.0465	0.0994
RELIANCE (P.C.)	1.9142	1.6592	1.7890	1.7006	0.0350	0.0267	0.0294	0.0272
RELIANCE (O.P)	1.0068	0.9867	0.9993	1.0028	0.0418	0.0330	0.0427	0.0410
RELIANCE (H.P)	1.0446	1.0046	1.0126	1.0032	0.0249	0.0225	0.0224	0.0225
RELIANCE (L.P)	1.0210	1.0708	1.0247	1.034	0.0410	0.0398	0.0392	0.0387

*(P.C.)= Previous day closing prices , (O.P)= Open price , (H.P)=Highest price, (L.P)= lowest price of a stock in a trading day

$$\text{Theil} - U = \frac{\Sigma^{n}_{i=1}(\hat{\sigma}_i - \sigma_i)^2}{\Sigma^{n}_{i=1}(\hat{\sigma}_{i-1} - \sigma_i)^2} \qquad MAPE = \frac{1}{n}\Sigma^{n}_{i=1}\left|\frac{(\hat{\sigma}_i - \sigma_i)}{\sigma_i}\right|$$

In all the above statistics, $'n'$ stand for number out of sample forecasts.

RESULTS AND CONCLUSIONS

The Table 8 presents the result of the error statistics in the earlier section. From the results, the researchers have made the following observations:

1) The Theil-U statistics is a poor evaluator of performance in our case except Reliance Ltd. But the MAE and RMSE give the best error statistics.

2) The error statistics MAE, EWMA (1,1) give the best forecasting for HDFC Bank only, while the error statistic RMSE shows that all three methods performs similarly. But the EGARCH (1,1) gives the best forecasting performance in each case, which support the observation of Koulakiotis et. al.(2006).

3) The volatility forecasting for open and previous closing price are very closed through each of the methods, which shows that the overnight effect is insignificant.

4) Lastly, the volatility, of high price of stocks has less errors and of low price of stocks has more errors, which implies that the good news (positive shock) has less effect on volatility, while the bad news has more effect on volatility. It is concluded that one of the causes of failure of numerous banks and non-financial corporation at the end of 2008 may be due to persistence of high volatility for a long-run in the stock markets.

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