Modelling Conditional Volatility in Stock Returns and Trading Volume of Indian Stock Market

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Abstract: *The role of information releases in asset pricing has created enormous interest among researchers, academics and practitioners. The general perspective of the market is that higher the level of trading volume, the greater the movement in share prices and vice-versa. But, this may not hold true every time. Lower trading volume may also induce the larger jumps in prices. The study aimed at modelling conditional volatility in stock returns and trading volume of 30 stocks of S&P BSE Sensex by using two asymmetric volatility models EGARCH and TGARCH with and without trading volume effects. Further, the study explores the impact of information flow on volatility with the inclusion of trading activity. The volatility persistence for individual stocks seems to be mixed. The results support that trading volume is an important variable in explaining conditional volatility in stock returns.*

Key Words: *Heteroskedasticity, Information releases, Trading Volume, Volatility*

1. Introduction

Stock prices and trading volume are induced by information releases and the role of information in asset pricing has created enormous interest among researchers, academics and practitioners. The general perspective of the market is that higher the level of trading volume, the greater the movement in share prices and vice-versa. But, this may not hold true every time. Lower trading volume may also induce the larger jumps in prices.

A number of studies have addressed the role of trading volume as an important variable in price formation models. The relationship between price changes and trading volume is investigated by Karpoff (1987), Schwert (1989), Hiemstra and Jones (1994), Wang (1994), Chordia and Swaminathan (2000), Ghysels et al (2000), Ranter and Leal (2001), Ciner (2002), Darrat et al. (2003), Gagnon and Karolyi (2009), Ederington and Guan (2010), Sabbaghi (2011),Chen (2012), Asai and Brugal (2013), Bagchi (2014), Hsieh (2014), Shahzada et al. (2014) among others. The use of conditional volatility models have been proved successful in modeling the conditional volatility of equity stocks and the markets in which they trade (Lamoureux and Lastrapes, 1990; Gallant et al., 1992; Srinivasan and Ibrahim, 2010; Sabbaghi, 2011; among others).

There has been a very little research done in this context as far as Indian markets are concerned (see Karmakar, 2005; Srinivasan and Ibrahim, 2010; Tripathy, 2010; Tripathy and Gil-Alana, 2010). The objective of this study is to model conditional volatility in stock returns and trading volume of Indian stock market by using a reasonably more recent database post financial crisis. The contribution of this paper is three fold: Firstly, this study helps to identify the internal dynamics of widely traded Sensex stocks. Secondly, it models the conditional volatility between stock returns and trading volume by using EGARCH and TARCH models with and without trading volume effects. Thirdly, there is no study using emerging market data in this field. Therefore, the present study seeks to extend the existing knowledge base and literature.

The organization of this paper is as follows. Section 2 reviews the previous literature. Section 3 discusses the data and methodology. Section 4 presents the empirical results, and Section 5 concludes the paper.

2. Literature Review

Several studies have been conducted to examine the linkages between trading volume and stock return volatility by using econometric models. Augmenting GARCH models with trading volume, Lamoureux and Lastrapes (1990) found that trading volume considered as a proxy for information flow helps to explain conditional volatility. They provided evidence that GARCH effects and persistence levels disappeared once trading volume is incorporated into the conditional variance equation. Blume et al. (1994) showed the relationship between trading volume, information precision, and price fluctuations. They found that traders who use the information contained in volume obtained higher-quality private signals than traders who do not. The finding that average trade size contains no information would seem to be inconsistent with the volume-based technical trading activities observed in security markets. Jones et al. (1994) reported striking evidence for the role of the frequency of trades in determining the volatility of returns. They found that the positive relation between volatility and volume actually reflects the positive relation between volatility and the frequency of transactions. Brailsford (1996) investigated the effect of information arrivals on the volatility persistence in the Australian stock market and found that the inclusion of contemporaneous trading volume in the conditional variance equation dramatically reduced volatility persistence of stock returns.

Ragunathan and Peker (1997) found a strong contemporaneous effect of trading volume on volatility in the Sydney Futures Exchange. Chordia and Swaminathan (2000) studied the interaction between trading volume and predictability of short-term stock returns and found that daily returns of stocks with high trading volume lead daily returns of stocks with low trading volume. They concluded that trading volume plays a significant role in the dissemination of market wide information. Ghysels et al. (2000) investigated the causality between the series of returns and transaction volumes in high frequency data of the Alcatel stock on the Paris Stock Exchange. They found co-movements between volumes and transaction prices. Using standard Granger causality test, they reported that there is a causal relation between stock returns and volume. Chordia, Subrahmanyam, and Anshuman (2001) found that the volatility of trading activity is negatively associated with stock returns in the cross-section, after controlling for size, book-to-market, momentum, and the level of share turnover. Bohl and Henke (2003) investigated the relationship between daily returns and trading volume for 20 Polish stocks. The results indicated that in the majority of cases volatility persistence tends to disappear when trading volume is included in the conditional variance equation.

Darrat et al. (2003) examined the contemporaneous correlation and lead–lag relation between trading volume and return volatility in all constituent stocks of Dow Jones industrial average (DJIA) using individual and pooled Granger-causality tests. Majority of the DJIA stock failed to show contemporaneous correlation between volume and volatility. Significant lead–lag relationship was evident. Kim (2005) studied the stock market linkages in the advanced Asia–Pacific stock markets of Australia, Hong Kong, Japan and Singapore with the US. The study found significant contemporaneous return and volatility linkages. Dynamic information spillover effects in terms of returns, volatility and trading volume from the US and Japan did not produce time-varying influence. Significant dynamic information spillover effects from the US were found in all the Asia–Pacific markets, but the Japanese information flows were relatively weak and the effects were country specific. Karmakar (2005) estimated conditional volatility models to capture the features of stock market volatility of India and evaluated the models in terms of out-of-sample forecast accuracy. Besides, the presence of leverage effect in Indian companies was also investigated. The study found that the GARCH (1, 1) model provided good forecast of market volatility. Xu et al. (2006) examined volume and volatility dynamics of Dow Jones 30 stocks. Time-consistent VAR model was used to identify the informed and uninformed components of return volatility and to estimate the speed of price adjustment to new information. The study found that volatility and volume are persistent and highly correlated with past volatility and volume. Girard and Biswas (2007) examined the relationship between volatility and trading volume in some developed and emerging markets. They found that emerging markets showed a greater response to large information shocks as compared to developed markets. In addition, emerging markets also exhibited greater sensitivity to unexpected volume.

Rashid (2007) investigated the dynamic association between daily stock index returns and percentage trading volume changes using the data set from Karachi Stock Exchange (KSE). The results showed the presence of linear unidirectional Granger causality from stock returns to volume, nonlinear Granger causality from volume to stock returns and linear Granger causality from percentage volume change to percentage in stock prices depends on the direction of the stock returns. Engle and Rangel (2008) estimated variant of GARCH models across 50 different countries and found that equity volatilities are higher when output growth, inflation, and short-term interest rates are more volatile. Chuang et al. (2009) used quantile regressions to investigate the causal relationship between stock return and volume, and showed that causal effects of volume on return are usually heterogeneous across quantiles and those of return on volume are more stable. Pati (2008) investigated the asymmetric impact of shocks on volatility and provided evidence of predictable time varying volatility, high persistence and leverage effect in Indian stock market. Fenghua and Xiaoguang (2009) indicated that the persistence-free trading volume can explain the hetroscedasticity of the return better than the unexpected trading volume.

Park (2010) employed the mixture of distribution hypothesis (MDH) and demonstrated that the effect of surprising information on the relationship between volatility and trading volume contrasts with that of general information. The results supported the use modified version of the MDH with surprising information. Srinivasan and Ibrahim (2010) attempted to model and forecast conditional variance of the SENSEX by using daily data. The result showed that the symmetric GARCH model performed better in forecasting conditional variance of the SENSEX Index return rather than the asymmetric GARCH models, despite the presence of leverage effect. Tripathy (2010) investigated the relationship between trading volume and stock returns volatility in Indian stock market and found evidence of leverage and asymmetric effect of trading volume in stock market. The results showed that bad news generated more impact on the volatility of share prices. Tripathy and Gil-Alana (2010) compared the different volatility models by taking daily closing, high, low and open values of the NSE returns from 2005-2008. The models were compared on the basis of their ability in explaining the ex-post volatility. The study concluded that the AGARCH and VIX models proved to be the best methods while Extreme Value Indicators (EVIs) gave the best forecasting performance followed by the GARCH and VIX models.

Sabbaghi (2011) investigated asymmetric volatility–trading volume relationship during global financial crisis of 2008. By employing EGARCH analysis for data from the G5 stock markets, the study suggested that trading volume is an important variable in explaining conditional volatility. Trading volume captured a significant fraction of asymmetric volatility effects during financial crisis period. Chen (2012) investigated empirical linkages between stock returns and trading volume during bull and bear markets using S&P 500 price index data. The study found strong evidence of asymmetry in contemporaneous correlation. Based on a joint two-state Markov-switching model, the results indicated strong evidence that the stock return is able to forecast volume in both bear and bull markets. There is weaker evidence regarding the information content of trading volume to forecast stock returns. The forecastability is found only in bear markets. Asai and Brugal (2013) examined the interdependence of stock markets in Brazil and the US, based on information of daily return, range and trading volume. They used heterogeneous VAR model for forecasting volatility. They reported strong evidence for spillover effects. Kaizoji (2013) investigated the statistical properties of the returns and the trading volume. The study showed that as the interaction among the interacting traders strengthens both the returns and the trading volume present power-law behaviour.

Bagchi (2014) found both positive and negative relationship for return-volatility dynamics and showed that cognitive dissonance is responsible for return-volatility relationship. The study confirmed that volatility feedback theory is always not tenable for explaining return-volatility relationship. Hsieh (2014) examined the contemporaneous and causal relationship between stock returns, trading volume and volatility in Asian listed real estate companies and found that there are positive contemporaneous relationship between trading volume and both returns and absolute returns. The study found that current trading volume help to explain the returns indirectly by leading return volatility but trading volume does not explain future returns directly. Shahzada et al. (2014) studied the volume–volatility relationship in Australian stock market for the period between 2006 and 2010. The results indicated that the number of trades is the main driving factor for the volume–volatility relation. The average trade size played a role in explaining volatility but has a lower impact on volatility than the number of trades.

3. Data and Methodology

The dataset used for this study consists of daily closing prices and trading volume from January 4, 2010 to June 30, 2014[1] on the 30 stocks of S&P BSE Sensex. The rationale for selecting these stocks is that they represent the largest, most liquid and financially sound companies across key sectors of the Indian economy. They are very actively traded and experience most frequent flow of information into the market.

The data is extracted from the Prowess database maintained by Centre for Monitoring Indian Economy (CMIE). The daily closing prices are transformed to a time series of continuously compounded return by using the equation $R_t = (P_t / P_{t-1}) * 100$ where R_t is the logarithmic daily return at time and P_{t-1} and P_t are daily closing share prices at two successive days $t-1$ and t respectively.

Daily squared return, R_t^2 is used as a proxy for volatility is stock returns2 while, one day lagged trading volume in its logarithmic form, $\ln V_{t-1}$ is used as a proxy for trading volume.

The study uses two asymmetric volatility models EGARCH and TGARCH with and without trading volume effects. A brief description of these models is presented below:

[1] *The closing share prices and trading volume data for Coal India were available only from November 4, 2010. There are 1123 data points in the final dataset for all the stocks except for Coal India which included 911 data points.*

[2] *Daily squared return is used as a proxy for return volatility in earlier studies such as Bluhm and Yu (2000), Balaban et al. (2002), Vilasuso (2002), Yu (2002), Taylor (2004) and Ederington and Guan (2005).*

EGARCH model without trading volume effect

Proposed by Nelson (1991), Exponential GARCH (EGARCH) models the logarithmic of the conditional variance and has an additional leverage term to capture asymmetry in volatility clustering. It does not impose the non-negative constraints on the parameters.
The specification of conditional variance equation is expressed as:

$$\log(\sigma^2{}_t)=\omega+\sum_{j=1}^{q}\beta_j\log(\sigma^2{}_{t-j})+\sum_{i=1}^{p}\alpha\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|+\sum_{k=1}^{r}\gamma_k\frac{\varepsilon_{t-k}}{\sigma_{t-k}} \qquad \text{...............} \ (1)$$

In the model specification, β captures the volatility clustering effect, α measures the effect of news about volatility from the previous period on current period volatility and γ measures the leverage effect. The impact is asymmetric if $\gamma \neq 0$. If γ =0, positive and negative shocks have the same effect on volatility, while $\gamma < 0$ indicates that the bad news has a bigger impact on volatility than good news of same magnitude.

TGARCH model without trading volume effect

Pioneered by Glosten et al. (1993) TGARCH model incorporates a dichotomous variable to check whether there is statistically significant difference when shocks are negative. Unlike EGARCH model, the leverage effect is quadratic in TGARCH model. The conditional variance equation can be represented as follows:

$$\sigma_t^2=\gamma+\omega\varepsilon_{t-1}^2+\eta\varepsilon_{t-1}^2 d_{t-1}+\psi\sigma_{t-1}^2 \qquad \text{...............} \ (2)$$

Where $d_t=1$ if $\varepsilon_{t-1}<0$ and $d_t=0$ otherwise. The parameter η captures the asymmetrical effect of positive news and negative news. ω and ψ are the ARCH and GARCH terms respectively. Good news $(\varepsilon_{t-1}<0)$ and bad news $(\varepsilon_{t-1}>0)$ have differential impact on the conditional variance. Good news has an impact on ω , while bad news has an impact on $\omega+\eta$. If $\eta>0$, bad news increases volatility, and we say that there is a leverage effect for the i-th order. The impact is asymmetric if $\eta \neq 0$. Negative η estimates shows that positive return shocks generate less volatility than negative shocks.

EGARCH model with trading volume effect

The conditional variance equation (Eq. 1 above) of EGARCH model is extended to include the effects of trading volume. The EGARCH model with trading volume effect is formally given by:

$$\log(\sigma^2{}_t)=\omega+\sum_{j=1}^{q}\beta_j\log(\sigma^2{}_{t-j})+\sum_{i=1}^{p}\alpha\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|+\sum_{k=1}^{r}\gamma_k\frac{\varepsilon_{t-k}}{\sigma_{t-k}}+\zeta\ln V_{t-1} \qquad \text{...............} \ (3)$$

The coefficient on the trading volume variable, denoted by $\ln V_{t-1}$, captures the effect of the instantaneous rate of information arrival on conditional volatility.

TGARCH model with trading volume effect

The conditional variance equation (Eq. 3 above) of TGARCH model is extended to include the effects of trading volume. The TGARCH model with trading volume effect is formally given by:

$$\sigma_t^2 = \gamma + \omega\varepsilon_{t-1}^2 + \eta\varepsilon_{t-1}^2 d_{t-1} + \psi\sigma_{t-1}^2 + \zeta \ln V_{t-1} \quad \text{............... (4)}$$

The coefficient on the trading volume variable, denoted by $\ln V_{t-1}$, captures the effect of the instantaneous rate of information arrival on conditional volatility.

4. Empirical Results and Analysis

Table 1 exhibit the descriptive statistics and diagnostic checks on daily returns. The daily returns of Sensex stocks vary between -0.228% to 0.104% during the study period. The highest mean return is posted by TCS. Tata power, on the other hand, reported the lowest return during the sample period. Majority of the return series have shown evidence of significant negative skewness. Excess kurtosis implies that the return distribution has fat tails, i.e. leptokurtic, relative to the normal distribution. Further, the significant Lilliefors test statistics reject the null hypothesis of normality at 1% significance level. All these findings show the existence of strong ARCH effects. ADF test was employed to test the stationarity of return series. The results strongly support the rejection of the hypothesis of non-stationarity at 1% significance level both on level and at first difference.

Table 2 reports the descriptive statistics of daily squared returns, used as proxy for return volatility. The squared return series are positively skewed and are leptokurtic. The non-normality in the return distribution is confirmed by Lilliefors test statistics. The series were found to be stationary on both levels and at first difference.

Table 3 presents the empirical results of EGARCH (1, 1) model. Of the 27 stocks reporting statistically significant beta estimates, 15 stocks have posted positive and statistically significant beta coefficient suggesting volatility clustering. Positive beta signals that positive stock return changes are associated with further positive changes and vice versa. The impact of news about volatility from the previous period on current period volatility is also found to significant at 1% level for all the stocks except Heromotocorp, ITC and TCS. The results negate the existence of leverage effect and the news impact is asymmetric. The gamma estimates were positive and statistically significant for 14 stocks indicating that bad news has a smaller impact on volatility of these stocks than good news of same magnitude.

Followed by this, TGARCH (1,1) model estimation in the absence of trading volume effect were run. The estimated coefficients for ψ are statistically significant for all the stocks at 1% level of significance except for Cipla, Coal India and SBI. The ψ coefficients are larger than ω suggesting that large market surprises induce small revisions in future volatility. The ω coefficients ranged from -12.364 to 3.227 while the ψ ranged from -0.006 to 1.727. The persistence in volatility is measured by $\omega+\psi$. Since $(\omega+\psi)<0$, it indicates that the shocks decay with time. Further, the study explores the impact of information flow on volatility with the inclusion of trading activity. The ζ coefficients for 15 stocks were statistically significant (Table 6). The volatility persistence for individual stocks seems to be mixed. The results support that trading volume is an important variable in explaining conditional volatility in stock returns.

5. Conclusion

The study aimed at modeling conditional volatility in stock returns and trading volume. on the 30 stocks of S&P BSE Sensex. The study uses two asymmetric volatility models EGARCH and TGARCH with and without trading volume effects. The return series showed the presence of strong ARCH effects. The results of EGARCH (1, 1) indicated the phenomenon of volatility clustering while the TGARCH (1,1) model results suggested that large market surprises induce small revisions in future volatility. Further, the study explores the impact of information flow on volatility with the inclusion of trading activity. The volatility persistence for individual stocks seems to be mixed.

The results support that trading volume is an important variable in explaining conditional volatility in stock returns.

References:

1. Asai, M., & Brugalb, I. (2013). Forecasting volatility via stock return, range, trading Forecasting volatility via stock return, range, trading. *North American Journal of Economics and Finance*, *25*, 202-213.
2. Bagchi, D. (2014). Application of the concept of dissonance to explain the phenomenon of return-volatility relationship. *The IUP Journal of Applied Finance*, *20* (2), 5-17.
3. Blume, L., Easley, D., & O'Hara, M. (1994). Market statistics and technical analysis: the role of volume. *Journal of Finance*, *49*, 153–181.
4. Bohl, M. T., & Henke, H. (2003). Trading volume and stock market volatility: The Polish case. *International Review of Financial Analysis*, *12*, 513–525.
5. Brailsford, T. J. (1996). The empirical relationship between trading volume, returns, and volatility. *Accounting and Finance*, *35*, 89-111.
6. Chen, S.-S. (2012). Revisiting the empirical linkages between stock returns and trading volume. *Journal of Banking and Finance*, *36*, 1781-1788.
7. Chordia, T., & Swaminathan, B. (2000). Trading volume and cross-autocorrelation in stock returns. *Journal of Finance*, *55*, 913–935.
8. Chordia, T., Subrahmanyam, A., & Anshuman, R. (2001). Trading activity and expected stock returns. *59*, 3-32.
9. Chuang, C.-C., Kuan, C.-M., & Lin, H.-Y. (2009). Causality in quantiles and dynamic stock return-volume relations. *Journal of Banking and Finance*, *33*, 1351-1360.
10. Darrat, A. F., Rahman, S., & Zhong, M. (2003). Intraday trading volume and return volatility of the DJIA stocks: A note. *Journal of Banking and Finance*, *27*, 2035-2043.
11. Engle, R. F., & Gonzalo, R. J. (2008). The Spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *Review of Financial Studies*, *21*, 1187-1222.
12. Fenghua, W., & Xiaoguang, Y. (2009). Empirical study on relationship between persistence-free trading volume and stock return volatility. *Global Finance Journal*, *20*, 119-127.
13. Ghysels, E., Gourierous, C., & Jasiak, J. (2000). Causality between returns and trading volumes. *Annales, D'Economie Et De Statistique*, *60*, 191–206.
14. Girard, E., & Biswas, R. (2007). Trading volume and market volatility: Developed versus emerging stock markets. *The Financial Review*, *42*, 429–459.
15. Hsieh, H.-C. S. (2014). The causal relationships betwen stock returns, trading volume and volatility: Empirical evidence from Asian listed real estate companies. *International Journal of Managerial Finance*, *10* (2), 218-240.
16. Jones, M. J., Kaul, G., & Lipson, M. L. (1994). Transactions, volume, and volatility. *Review of Financial Studies*, *7*, 631–651.
17. Kaizoji, T. (2013). Modelling of stock returns and trading volume. *IIM Kozhikode Society and Management Review*, *2* (2), 147-155.
18. Karmakar, M. (2005). Modeling Conditional Volatility in the Indian Stock Markets. *Vikalpa*, Vol. 30(3), pp.21-37.
19. Kim, S.-J. (2005). Information leadership in the advanced Asia–Pacific stock markets: Return, volatility and volume information spillovers from the US and Japan. *Journal of the Japanese and International Economies*, *19*, 338–365.
20. Lamoureux, C. G., & Lastrapes, W. D. (1990). Heteroskedasticity in stock return data: Volume versus GARCH effects. *Journal of Finance*, *45*, 221-229.
21. Park, B.-J. (2010). Surprising information,the MDH,and the relationship between volatility and trading volume. *Journal ofFinancia lMarkets*, *13*, 344–366.
22. Pati, P. C. (2008). Econometric modeling of time varying conditional heteroscedasticity and assymetry in volatility using GARCH and non-normal distribution: The case of

National Stock Exchange of India. *Indian Journal of Business and Economics , 7* (1), 129-143.
23. Raghunathan, V., & Peker, A. (1997). Price variability, trading volume, and market depth: evidence from the Australian futures market. *Applied Financial Economics , 7,* 447-454.
24. Rashid, A. (2007). Stock prices and trading volume: An assessment for linear and nonlinear Granger causality. *Journal of Asian Economics , 18,* 595-612.
25. Sabbaghi, O. (2011). Asymmetric volatility and trading volume: The G5 evidence. *Global Finance Journal , 22,* 169-181.
26. Shahzada, H., Duonga, H. N., Kalev, P. S., & Singh, H. (2014). Trading volume, realized volatility and jumps in the Australian stock market. *International FInancial Markets, Institutions and Money , 31,* 414-430.
27. Srinivasan, P., & Ibrahim, P. (2010). Forecasting Stock Market Volatility of BSE 30 Index Using Garch Models. *Asia-Pacific Journal of Management Research and Innovation ,* Vol. 6 (3), pp.47-60.
28. Tripathy, N. (2010). The empirical relationship between trading columes and stock return volatility in Indian stock market. *European Journal of Economics, Finance and Administrative Sciences , 24,* 59-75.
29. Tripathy, T., & Gil-Alana, L. A. (2010). Suitability of Volatility Models for Forecasting Stock Market Returns: A Study on the Indian National Stock Exchange. *American Journal of Applied Sciences ,* Vol. 7 (11), pp.1487-1494.
30. Xu, X. E., Chen, P., & Wu, C. (2006). Time and dynamic volume–volatility relation. *Journal of Banking and Finance , 30,* 1535–1558.

Table I Descriptive statistics and diagnostic checks on daily returns

Sl.No.	Stocks	Mean	Std. Dev	Skewness	Kurtosis	N	Lilliefors test		Unit root test (ADF)			
									Levels		First Difference	
							t- statistic	p-value	t- statistic	p-value	t- statistic	p-value
1	AXIS	0.0588	2.2395	0.1897	5.2313	1122	0.0447	0.0000	-29.972	0.000	-19.228	0.000
2	BAJAJAUTO	0.0258	2.6665	-16.4281	436.3464	1122	0.1483	0.0000	-32.098	0.000	-16.841	0.000
3	BHAAIRT	0.0032	2.0306	0.0826	4.5572	1122	0.0478	0.0000	-34.177	0.000	-16.805	0.000
4	BHEL	-0.2024	5.3794	-24.6920	746.5562	1122	0.2336	0.0000	-32.326	0.000	-18.497	0.000
5	CIPLA	0.0234	1.4529	0.0133	5.2942	1122	0.0441	0.0000	-34.571	0.000	-16.727	0.000
6	COAL	0.0130	1.8927	0.2993	8.1212	910	0.0558	0.000	-29.9625	0.000	-16.188	0.000
7	DRREDDY	0.0737	1.4308	-0.1559	4.2523	1122	0.0454	0.0000	-33.336	0.000	-17.391	0.000
8	GAIL	0.0096	1.6078	-0.0052	4.1312	1122	0.0307	0.0146	-33.316	0.000	-17.391	0.000
9	HDFC	-0.0885	4.9982	-28.0564	886.3105	1122	0.2606	0.0000	-34.384	0.000	-18.087	0.000
10	HDFCBANK	-0.0651	5.0319	-28.8571	920.2650	1122	0.2838	0.0000	-31.891	0.000	-16.428	0.000
11	HEROMOT	0.0381	1.8302	0.5646	10.0922	1122	0.0585	0.0000	-33.166	0.000	-15.070	0.000
12	HINDALCO	0.0005	2.4796	0.2065	3.8103	1122	0.0332	0.0055	-33.166	0.000	-17.071	0.000
13	HUL	0.0758	1.5356	1.5056	15.6230	1122	0.0685	0.0000	-31.951	0.000	-17.177	0.000
14	ICICIBK	0.0427	2.0567	0.2985	3.9727	1122	0.0440	0.0000	-31.842	0.000	-16.893	0.000
15	INFOS	0.0193	1.8148	-2.1846	40.2307	1122	0.0997	0.0000	-32.792	0.000	-18.959	0.000
16	ITC	0.0221	2.5718	-18.6431	513.4080	1122	0.1651	0.0000	-34.411	0.000	-16.882	0.000
17	LT	0.0005	2.2470	-4.1969	74.3555	1122	0.0742	0.0000	-31.127	0.000	-18.793	0.000
18	MM	0.0014	2.7162	-13.1627	324.6994	1122	0.1257	0.0000	-33.945	0.000	-16.797	0.000
19	MARUTI	0.0403	1.8575	-0.0041	7.3224	1122	0.0511	0.0000	-33.538	0.000	-16.882	0.000
20	NTPC	-0.0354	1.5880	-0.4700	10.1407	1122	0.0523	0.0000	-33.948	0.000	-14.632	0.000
21	ONGC	-0.0918	4.6740	-26.2107	810.8889	1122	0.2478	0.0000	-32.948	0.000	-18.070	0.000
22	RIL	-0.0052	1.6637	0.0442	3.6461	1122	0.0320	0.0089	-32.785	0.000	-17.013	0.000
23	SBI	0.0142	1.9809	0.0694	4.7771	1122	0.0437	0.0000	-29.197	0.000	-15.721	0.000
24	SESGOA	-0.0310	2.5416	0.5278	6.0715	1122	0.0562	0.0000	-21.646	0.000	-19.443	0.000
25	SUNPHAR	-0.0702	5.4348	-24.6621	699.7792	1122	0.2884	0.0000	-33.379	0.000	-17.910	0.000
26	TATAMOT	-0.0581	5.4717	-24.5027	740.4626	1122	0.2165	0.0000	-31.817	0.000	-15.846	0.000
27	TATAPOW	-0.2279	7.1900	-29.9215	965.3283	1122	0.3033	0.0000	-34.223	0.000	-17.605	0.000
28	TATASTEEL	-0.0163	2.1960	0.1647	3.9686	1122	0.0342	0.0037	-32.172	0.000	-22.166	0.000
29	TCS	0.1042	1.6764	0.3720	6.7453	1122	0.0542	0.0000	-33.576	0.000	-17.432	0.000
30	WIPRO	-0.0215	2.2889	-9.5303	205.3730	1122	0.0454	0.0000	-35.265	0.000	-17.784	0.000

Table 2 Descriptive statistics and diagnostic checks on daily squared returns

Sl.No.	Stocks	Mean	Std. Dev	Skewness	Kurtosis	N	Lilliefors test		Unit root test (ADF)			
									Levels		First Difference	
							t- statistic	p-value	t- statistic	p-value	t- statistic	p-value
1	AXIS	5.0141	10.3393	9.0922	151.9978	1122	0.3139	0.0000	-17.9197	0.0000	-16.7482	0.0000
2	BAJAJAUTO	7.1046	148.1816	33.3985	1117.6350	1122	0.4809	0.0000	-33.5327	0.0000	-17.2871	0.0000
3	BHAAIRT	4.1196	7.7738	5.1001	42.3764	1122	0.2981	0.0000	-29.5865	0.0000	-17.2655	0.0000
4	BHEL	28.9535	791.7741	33.4254	1118.8320	1122	0.4854	0.0000	-33.4751	0.0000	-17.2929	0.0000
5	CIPLA	2.1095	4.3732	6.3823	64.1120	1122	0.3148	0.0000	-33.0640	0.0000	-18.4308	0.0000
6	COAL	3.5787	9.5604	9.0914	114.0331	910	0.3541	0.0000	-27.6395	0.0000	-21.4805	0.0000
7	DRREDDY	2.0507	3.6779	4.3412	32.7193	1122	0.2886	0.0000	-31.5428	0.0000	-18.3361	0.0000
8	GAIL	2.5829	4.5724	5.3045	50.1205	1122	0.2861	0.0000	-30.2789	0.0000	-25.0850	0.0000
9	HDFC	24.9675	743.8185	33.4493	1119.9050	1122	0.4927	0.0000	-33.5003	0.0000	-17.2949	0.0000
10	HDFCBANK	25.3021	767.9824	33.4497	1119.9240	1122	0.4965	0.0000	-33.4781	0.0000	-17.2983	0.0000
11	HEROMOT	3.3479	10.1223	18.0219	458.9142	1122	0.3704	0.0000	-31.7706	0.0000	-18.8398	0.0000
12	HINDALCO	6.1428	10.3028	3.9306	26.6499	1122	0.2755	0.0000	-31.7706	0.0000	-21.0794	0.0000
13	HUL	2.3618	9.1077	20.3506	532.1927	1122	0.3977	0.0000	-28.5913	0.0000	-16.4121	0.0000
14	ICICIBK	4.2281	7.3225	3.7088	22.5949	1122	0.2818	0.0000	-28.8517	0.0000	-17.0093	0.0000
15	INFOS	3.2910	20.5956	21.5341	555.6456	1122	0.4365	0.0000	-32.7802	0.0000	-17.1611	0.0000
16	ITC	6.6090	149.5663	33.4072	1118.0200	1122	0.4824	0.0000	-33.5268	0.0000	-17.3101	0.0000
17	LT	5.0444	43.2222	32.3376	1070.1260	1122	0.4535	0.0000	-33.3967	0.0000	-18.0444	0.0000
18	MM	7.3714	132.6763	33.3590	1115.8700	1122	0.4778	0.0000	-33.5593	0.0000	-17.2664	0.0000
19	MARUTI	3.4489	8.6729	10.1578	158.0670	1122	0.3454	0.0000	-31.3887	0.0000	-16.1931	0.0000
20	NTPC	2.5208	7.6390	13.6840	238.2078	1122	0.3707	0.0000	-32.9763	0.0000	-20.2251	0.0000
21	ONGC	21.8348	622.2149	33.4454	1119.7310	1122	0.4860	0.0000	-33.4865	0.0000	-17.3026	0.0000
22	RIL	2.7654	4.4999	3.3333	18.2249	1122	0.2694	0.0000	-30.1501	0.0000	-15.8053	0.0000
23	SBI	3.9207	7.6250	5.3443	44.1704	1122	0.3036	0.0000	-31.4771	0.0000	-18.6381	0.0000
24	SESGOA	6.4549	14.5046	7.0704	74.5954	1122	0.3282	0.0000	-16.6454	0.0000	-23.7665	0.0000
25	SUNPHAR	29.5156	781.1581	32.1205	1054.3900	1122	0.4957	0.0000	-33.4978	0.0000	-17.2944	0.0000
26	TATAMOT	29.9163	814.3582	33.4427	1119.6080	1122	0.4853	0.0000	-33.4454	0.0000	-17.2912	0.0000
27	TATAPOW	51.7021	1607.7990	33.4496	1119.9180	1122	0.4986	0.0000	-33.4646	0.0000	-17.2976	0.0000
28	TATASTEEL	4.8183	8.2984	4.0677	28.3631	1122	0.2807	0.0000	-8.4341	0.0000	-21.2649	0.0000
29	TCS	2.8187	6.7961	10.5483	188.5193	1122	0.3392	0.0000	-31.1473	0.0000	-19.5718	0.0000
30	WIPRO	5.2347	74.9267	32.9632	1097.7820	1122	0.4722	0.0000	-33.3671	0.0000	-17.2943	0.0000

Table 3 Estimates of EGARCH (1, 1) restricted model

Sl. No.	Stocks	ω	Prob.	β	Prob.	α	Prob.	γ	Prob.	Diagnostics			
										AIC	SIC	LL	DW
1	AXIS	0.074	0.002	0.143	0.000	0.124	0.000	0.956	0.000	6.815	6.837	-3818.071	1.815
2	BAJAJAUTO	3.351	0.000	5.354	0.000	-5.801	0.000	0.000	0.984	7.099	7.122	-3977.688	2.000
3	BHAAIRT	4.553	0.000	0.068	0.056	0.300	0.000	-0.139	0.001	6.881	6.903	-3855.167	1.755
4	BHEL	8.699	0.000	2.561	0.000	-2.213	0.000	-0.146	0.000	13.388	13.410	-7505.680	2.002
5	CIPLA	5.752	0.000	-0.464	0.000	0.249	0.000	-0.896	0.000	5.762	5.785	-3227.570	1.972
6	COAL	7.272	0.000	-2.656	0.000	2.750	0.000	-0.582	0.000	7.076	7.103	-3214.798	1.785
7	DRREDDY	0.436	0.000	-0.091	0.000	0.252	0.000	0.842	0.000	5.331	5.353	-2985.527	1.867
8	GAIL	2.635	0.000	0.184	0.000	0.489	0.000	0.028	0.244	5.682	5.704	-3182.426	1.785
9	HDFC	12.957	0.000	10.824	0.001	-11.244	0.000	0.004	0.983	16.051	16.074	-8999.754	2.000
10	HDFCBANK	13.114	0.000	-1.879	0.000	1.592	0.000	0.030	0.000	16.110	16.132	-9032.605	2.002
11	HEROMOT	-0.027	0.298	0.431	0.000	0.027	0.264	0.953	0.000	6.792	6.814	-3805.278	1.886
12	HINDALCO	0.221	0.000	0.025	0.044	0.082	0.000	0.947	0.000	7.421	7.443	-4158.124	1.808
13	HUL	3.623	0.000	-4.871	0.000	5.496	0.000	-0.101	0.000	6.106	6.129	-3420.580	1.617
14	ICICIBK	0.577	0.000	-0.127	0.000	0.239	0.000	0.867	0.000	6.687	6.709	-3746.212	1.695
15	INFOS	4.459	0.000	20.792	0.000	-17.773	0.000	-0.090	0.000	7.985	8.007	-4474.404	1.918
16	ITC	9.984	0.000	-1.043	0.481	0.721	0.661	0.007	0.979	12.841	12.863	-7198.654	2.000
17	LT	3.899	0.000	3.373	0.000	-2.891	0.000	-0.121	0.000	8.088	8.110	-4532.148	1.994
18	MM	9.807	0.000	-2.588	0.000	2.379	0.000	0.005	0.000	12.487	12.509	-7000.245	2.002
19	MARUTI	2.889	0.000	2.720	0.000	-1.760	0.000	0.157	0.000	7.108	7.130	-3982.454	1.805
20	NTPC	0.881	0.000	2.991	0.000	-1.846	0.000	0.621	0.000	6.828	6.850	-3825.409	1.882
21	ONGC	7.883	0.000	5.457	0.000	-5.463	0.000	-0.232	0.000	12.136	12.158	-6803.325	2.001
22	RIL	0.299	0.000	-0.011	0.627	0.111	0.000	0.899	0.000	5.765	5.787	-3228.907	1.786
23	SBI	2.739	0.000	-0.862	0.000	0.765	0.000	0.431	0.000	6.844	6.867	-3834.621	1.874
24	SESGOA	1.282	0.000	-0.164	0.000	0.490	0.000	0.751	0.000	7.729	7.752	-4331.034	1.680
25	SUNPHAR	12.256	0.000	22.492	0.000	-22.541	0.000	-0.063	0.117	15.640	15.662	-8768.797	2.002

26	TATAMOT	13.189	0.000	-9.608	0.001	9.340	0.000	0.023	0.921	16.050	16.072	-8998.789	1.999
27	TATAPOW	13.931	0.000	19.390	0.000	-19.399	0.000	-0.057	0.474	17.465	17.487	-9792.854	2.001
28	TATASTEEL	0.950	0.000	-0.243	0.000	0.368	0.000	0.794	0.000	6.823	6.846	-3822.908	1.742
29	TCS	-0.143	0.000	0.694	0.000	0.008	0.770	0.937	0.000	6.283	6.305	-3519.773	1.832
30	WIPRO	8.622	0.000	-3.068	0.000	3.278	0.000	0.009	0.875	10.444	10.467	-5854.239	1.986

Table 4 Estimates of EGARCH (1, 1) unrestricted model

Sl. No.	Stocks	ω	Prob.	β	Prob.	α	Prob.	γ	Prob.	ς	Prob.	Diagnostics			
												AIC	SIC	LL	DW
1	AXIS	0.124	0.062	0.145	0.000	0.124	0.000	0.958	0.000	-0.005	0.467	6.816	6.843	-3818.021	1.814
2	BAJAJAUTO	3.867	0.000	2.204	0.000	-2.511	0.000	0.098	0.000	-0.135	0.000	7.062	7.089	-3955.669	2.002
3	BHAAIRT	-1.462	0.000	0.204	0.000	0.096	0.001	0.460	0.000	0.274	0.000	6.843	6.870	-3833.129	1.755
4	BHEL	21.152	0.000	10.976	0.000	-11.198	0.000	0.432	0.000	-1.200	0.000	13.807	13.834	-7739.907	1.999
5	CIPLA	-5.251	0.000	-0.043	0.295	-0.296	0.000	0.107	0.000	0.659	0.000	5.671	5.697	-3175.216	1.975
6	COAL	-2.949	0.000	-1.542	0.000	1.560	0.000	-0.396	0.000	0.727	0.000	6.917	6.949	-3141.353	1.806
7	DRREDDY	0.166	0.003	-0.122	0.000	0.262	0.000	0.806	0.000	0.038	0.000	5.329	5.355	-2983.361	1.867
8	GAIL	3.759	0.000	0.076	0.125	0.583	0.000	0.000	0.998	-0.088	0.000	5.679	5.706	-3179.835	1.784
9	HDFC	15.570	0.000	-4.705	0.000	4.205	0.002	0.301	0.003	-0.559	0.000	15.275	15.302	-8563.491	2.001
10	HDFCBANK	14.781	0.000	-3.064	0.153	2.860	0.182	0.728	0.000	-1.012	0.000	13.557	13.583	-7599.262	1.997
11	HEROMOT	-6.573	0.000	0.350	0.000	-0.270	0.000	0.162	0.000	0.900	0.000	6.505	6.532	-3643.458	1.891
12	HINDALCO	0.892	0.000	0.075	0.000	0.052	0.000	0.987	0.000	-0.064	0.000	7.377	7.404	-4132.680	1.800
13	HUL	-1.121	0.000	-2.811	0.000	2.846	0.000	-0.273	0.000	0.455	0.000	6.377	6.404	-3571.600	1.639
14	ICICIBK	0.105	0.181	-0.063	0.012	0.170	0.000	0.892	0.000	0.026	0.000	6.684	6.711	-3743.688	1.696
15	INFOS	1.379	0.000	-1.694	0.000	1.705	0.000	-1.061	0.000	0.899	0.000	7.951	7.977	-4454.274	1.946
16	ITC	9.457	0.000	-3.866	0.000	3.690	0.000	-0.044	0.000	0.100	0.000	12.757	12.784	-7150.677	2.002
17	LT	-12.802	0.000	2.799	0.000	-2.711	0.000	-0.158	0.000	1.352	0.000	7.478	7.505	-4189.151	1.992
18	MM	9.789	0.000	-2.883	0.000	2.629	0.000	0.010	0.949	0.001	0.985	12.489	12.516	-7000.210	2.001

19	MARUTI	-5.810	0.000	-0.249	0.000	0.250	0.000	-0.765	0.000	1.163	0.000	6.766	6.793	-3789.885	1.860
20	NTPC	2.965	0.000	-0.807	0.000	0.733	0.000	0.616	0.000	-0.093	0.000	6.789	6.816	-3802.855	1.945
21	ONGC	9.927	0.000	16.466	0.000	-16.515	0.000	-0.129	0.000	-0.083	0.033	12.432	12.459	-6968.579	2.001
22	RIL	0.792	0.000	-0.041	0.042	0.144	0.000	0.901	0.000	-0.037	0.000	5.747	5.774	-3218.347	1.787
23	SBI	2.568	0.000	-0.740	0.000	0.677	0.000	0.546	0.000	-0.030	0.000	6.850	6.877	-3836.674	1.870
24	SESGOA	-10.524	0.000	0.920	0.000	-0.926	0.000	0.051	0.017	1.114	0.000	7.847	7.874	-4396.345	1.684
25	SUNPHAR	7.288	0.000	6.466	0.000	-6.425	0.000	0.042	0.000	-0.255	0.000	12.590	12.617	-7057.029	2.001
26	TATAMOT	14.199	0.000	-6.653	0.000	6.230	0.000	0.074	0.000	-0.129	0.000	15.944	15.971	-8938.680	2.000
27	TATAPOW	37.917	0.000	-2.213	0.000	2.018	0.000	-0.324	0.000	-1.606	0.000	16.426	16.453	-9208.942	2.001
28	TATASTEEL	-0.488	0.000	-0.344	0.000	0.411	0.000	0.695	0.000	0.132	0.000	6.879	6.906	-3853.356	1.727
29	TCS	-8.195	0.000	0.991	0.000	0.170	0.042	0.185	0.000	0.891	0.000	6.289	6.316	-3522.362	1.826
30	WIPRO	8.598	0.000	-2.425	0.100	2.640	0.074	0.006	0.975	0.004	0.964	11.199	11.226	-6276.856	1.993

Table 5 Estimates of TGARCH (1, 1) restricted model

Sl. No.	Stocks									Diagnostics			
		ω	Prob.	β	Prob.	α	Prob.	γ	Prob.	AIC	SIC	LL	DW
1	AXIS	6.624	0.000	0.105	0.000	-0.744	0.000	0.872	0.000	6.812	6.835	-3816.652	1.817
2	BAJAJAUTO	14259.630	0.311	-0.001	0.000	-1.363	0.982	0.599	0.124	12.931	12.953	-7249.251	2.002
3	BHAAIRT	77.436	0.000	0.124	0.000	-0.547	0.000	-0.081	0.008	6.917	6.940	-3875.595	1.754
4	BHEL	407125.900	0.308	-0.001	0.000	-1.077	0.995	0.598	0.125	16.284	16.306	-9130.263	2.002
5	CIPLA	9.302	0.000	-0.004	0.098	0.741	0.000	0.439	0.000	5.788	5.811	-3242.271	1.975
6	COAL	146.916	0.000	0.005	0.341	-12.364	0.000	-0.163	0.000	7.082	7.109	-3217.485	1.823
7	DRREDDY	2.670	0.000	0.061	0.000	-1.159	0.000	0.847	0.000	5.333	5.356	-2987.089	1.855
8	GAIL	2.423	0.000	0.213	0.000	0.025	0.757	0.710	0.000	5.665	5.688	-3173.213	1.782
9	HDFC	359302.400	0.307	-0.001	0.000	-0.713	0.998	0.598	0.151	16.158	16.181	-9059.778	2.001
10	HDFCBANK	383026.300	0.311	-0.001	0.000	-1.074	0.997	0.598	0.133	16.223	16.245	-9096.050	2.002
11	HEROMOT	19.153	0.000	1.721	0.000	-1.494	0.000	0.292	0.000	6.719	6.742	-3764.633	1.887

12	HINDALCO	7.939	0.000	0.036	0.000	-0.289	0.000	0.924	0.000	7.432	7.454	-4164.312	1.808
13	HUL	41.227	0.000	0.280	0.000	-8.472	0.000	-0.002	0.000	5.998	6.021	-3360.082	1.686
14	ICICIBK	8.327	0.000	0.032	0.000	-0.882	0.000	0.903	0.000	6.683	6.706	-3744.253	1.695
15	INFOS	278.386	0.011	-0.002	0.403	-3.664	0.066	0.605	0.001	8.783	8.806	-4922.440	1.928
16	ITC	14527.340	0.310	-0.001	0.000	-0.483	0.995	0.598	0.129	12.952	12.974	-7261.030	2.002
17	LT	1212.768	0.315	-0.001	0.000	-0.005	1.000	0.599	0.136	10.470	10.492	-5868.562	1.994
18	MM	11431.520	0.305	-0.001	0.000	-1.188	0.979	0.599	0.127	12.711	12.733	-7125.884	2.002
19	MARUTI	3.982	0.000	0.011	0.000	3.227	0.000	0.749	0.000	7.094	7.117	-3974.853	1.868
20	NTPC	150.469	0.000	-0.004	0.000	-5.379	0.000	-0.657	0.000	6.801	6.824	-3810.594	1.930
21	ONGC	251424.100	0.307	-0.001	0.000	-0.404	0.998	0.598	0.143	15.802	15.825	-8860.052	2.002
22	RIL	2.870	0.000	0.035	0.000	-0.480	0.000	0.882	0.000	5.767	5.789	-3230.253	1.786
23	SBI	36.784	0.000	-0.006	0.113	-2.368	0.000	0.631	0.000	6.869	6.892	-3848.747	1.876
24	SESGOA	49.329	0.000	0.530	0.000	-1.863	0.000	0.560	0.000	7.711	7.733	-4320.722	1.671
25	SUNPHAR	396281.700	0.307	-0.001	0.000	-0.695	0.998	0.598	0.138	16.257	16.279	-9115.170	2.002
26	TATAMOT	430682.400	0.307	-0.001	0.000	-1.966	0.995	0.599	0.131	16.338	16.360	-9160.551	2.000
27	TATAPOW	1678764.000	0.308	-0.001	0.000	-1.003	0.998	0.599	0.145	17.700	17.723	-9924.968	2.001
28	TATASTEEL	17.791	0.000	0.027	0.000	-1.136	0.000	0.843	0.000	6.876	6.899	-3852.659	1.761
29	TCS	6.905	0.000	0.446	0.000	-1.503	0.000	0.727	0.000	6.331	6.353	-3546.502	1.849
30	WIPRO	3645.771	0.303	-0.001	0.000	-1.734	0.923	0.600	0.126	11.562	11.584	-6481.188	1.990

Table 6 Estimates of TGARCH (1, 1) unrestricted model

Sl. No.	Stocks										Prob.	Diagnostics			
		ω	Prob.		Prob.		Prob.		Prob.			AIC	SIC	LL	DW
1	AXIS	67.718	0.000	0.142	0.000	-2.124	0.000	0.707	0.000	-2.699	0.000	6.963	6.990	-3900.145	1.847
2	BAJAJAUTO	21937.790	0.447	-0.002	0.000	-4.016	0.967	0.597	0.142	-1.966	0.999	13.126	13.153	-7357.713	1.996
3	BHAAIRT	-107.218	0.000	0.249	0.000	0.007	0.941	0.292	0.000	10.966	0.000	6.857	6.884	-3840.748	1.754
4	BHEL	626347.500	0.419	-0.002	0.000	-4.763	0.994	0.594	0.136	-0.298	1.000	16.492	16.518	-9245.730	2.002

5	CIPLA	-59.786	0.000	-0.006	0.277	1.356	0.000	0.121	0.000	6.182	0.000	5.706	5.733	-3194.968	1.975
6	COAL	-42.137	0.062	0.073	0.052	-8.558	0.000	0.400	0.000	11.311	0.000	7.219	7.251	-3278.546	1.823
7	DRREDDY	-8.350	0.000	0.047	0.000	-1.432	0.000	0.704	0.000	1.448	0.000	5.340	5.367	-2989.861	1.868
8	GAIL	11.286	0.000	0.217	0.000	-0.315	0.000	0.710	0.000	-0.724	0.000	5.663	5.690	-3170.927	1.782
9	HDFC	552772.900	0.455	-0.002	0.284	-3.878	0.994	0.594	0.001	-0.327	1.000	16.366	16.393	-9175.467	2.001
10	HDFCBANK	589271.200	0.534	-0.002	0.000	-4.791	0.995	0.594	0.146	-0.295	1.000	16.430	16.457	-9211.121	2.002
11	HEROMOT	-51.536	0.000	1.474	0.000	-1.476	0.000	0.300	0.000	6.867	0.000	6.652	6.679	-3725.607	1.888
12	HINDALCO	92.574	0.000	0.041	0.000	-0.404	0.000	0.940	0.000	-6.258	0.000	7.395	7.422	-4142.616	1.795
13	HUL	26.490	0.000	0.572	0.000	-10.430	0.000	-0.001	0.717	1.202	0.005	5.957	5.984	-3335.940	1.683
14	ICICIBK	24.254	0.160	0.133	0.000	-1.816	0.000	0.210	0.001	1.784	0.218	6.729	6.756	-3769.195	1.703
15	INFOS	422.577	0.222	-0.003	0.070	-8.673	0.339	0.599	0.002	-0.080	0.997	8.931	8.958	-5004.543	1.948
16	ITC	22349.610	0.530	-0.002	0.000	-2.089	0.985	0.595	0.155	-4.007	0.999	13.159	13.185	-7375.928	2.000
17	LT	1863.209	0.658	-0.002	0.000	-0.382	0.980	0.596	0.143	-1.173	0.997	10.673	10.700	-5981.433	1.992
18	MM	17586.800	0.563	-0.002	0.000	-3.332	0.967	0.596	0.142	-3.337	0.999	12.913	12.940	-7238.202	1.999
19	MARUTI	-217.535	0.000	1.125	0.000	2.068	0.000	-0.003	0.129	23.569	0.000	6.996	7.023	-3918.925	1.851
20	NTPC	65.617	0.000	-0.004	0.116	-4.624	0.001	0.738	0.000	-1.448	0.193	6.878	6.904	-3852.333	1.927
21	ONGC	386806.200	0.526	-0.002	0.000	-3.011	0.989	0.594	0.154	-0.440	1.000	16.010	16.037	-8975.828	2.002
22	RIL	18.538	0.000	0.050	0.000	-0.775	0.000	0.842	0.000	-1.094	0.000	5.761	5.787	-3225.671	1.784
23	SBI	90.886	0.000	-0.002	0.538	-2.496	0.000	0.758	0.000	-4.719	0.000	6.870	6.897	-3847.884	1.876
24	SESGOA	-79.926	0.000	0.297	0.000	-1.726	0.000	0.642	0.000	9.800	0.000	7.674	7.701	-4299.140	1.672
25	SUNPHAR	609664.100	0.356	-0.002	0.002	-2.846	0.994	0.596	0.161	-0.158	1.000	16.468	16.495	-9232.530	2.002
26	TATAMOT	662588.200	0.487	-0.002	0.000	-6.933	0.994	0.594	0.159	-0.281	1.000	16.544	16.571	-9275.387	2.000
27	TATAPOW	2582714.000	0.407	-0.002	0.000	-4.666	0.995	0.594	0.154	-0.070	1.000	17.908	17.935	-10040.310	2.001
28	TATASTEEL	32.298	0.000	0.041	0.000	-1.926	0.000	0.746	0.000	0.231	0.000	6.949	6.976	-3892.397	1.764
29	TCS	-9.877	0.000	0.485	0.000	-1.303	0.000	0.709	0.000	1.398	0.000	6.326	6.353	-3542.939	1.847
30	WIPRO	5608.316	0.544	-0.002	0.000	-5.881	0.903	0.599	0.130	-0.939	0.999	11.733	11.760	-6576.175	1.985