CHAPTER-VI

HEDGING EFFECTIVENESS OF CONSTANT AND TIME-VARYING HEDGE RATIO IN INDIAN EQUITY FUTURES MARKET: EVIDENCE FROM THE NATIONAL STOCK EXCHANGE

6.1 Introduction

In an emerging market context like India, derivatives are mainly introduced with a view to curb the increasing volatility of the asset prices in financial markets and to introduce sophisticated risk management tools leading to higher returns by reducing risk and transaction costs as compared to individual financial assets. Futures markets provide opportunities to hedge the risks associated with holding diversified equity portfolios. The effective use of futures contract in hedging decisions has become focus and center of debate on finding out an optimal hedge ratio and hedging effectiveness in empirical financial research. Hedging with futures contracts is perhaps the simplest method for managing market risk arising from adverse price movements of various assets. For managing risk, understanding optimal hedge ratio is critical for devising effective hedging strategy. Hedgers usually short an amount of futures contracts if they hold the long position of the underlying assets and vice versa. An important question is how many futures contracts are needed. In other words, investors have to decide on the optimal hedge ratio, that is how many futures contracts should be held for each unit of the underlying assets, as well as the effectiveness measure of that ratio. The hedge ratio is defined by Hull (2003, p.750) as "the ratio of the size of the portfolio taken in futures contracts to the size of the exposure'. The hedge ratio provides information on how many futures contracts should be held, whereas its effectiveness evaluates the hedging performance and the usefulness of the strategy. In addition, the hedgers may use the effectiveness measure to compare the benefits of hedging a given position from many alternative futures contracts. The detailed theoretical explanation of hedging is provided in Chapter-II.

Hedging strategy is measured by the extent to which it reduces risk and may techniques have been developed and applied to find the optimal hedge ratio (OHR). The earlier form of hedge ratio is the 1:1 hedge or the naïve strategy. This strategy suggests that an investor who has a long position in the spot market should sell a unit of futures today and buy it back when he sells the spot. Hence, the optimal hedge ratios (OHRs) of the naïve model are always one. This strategy represents the perfect hedge since it assumes that both spot and futures prices change by the same amount at all time. However, the strategy failed due to the existence of market frictions such as transaction costs, margin requirements, short-sale constraints, liquidity differences and non-synchronous trading effects which may induces the futures and spot prices to behave differently. This has brought a renewed interest at the theoretical level by the works of Working (1953), Johnson (1960), Stein (1961) and Ederington (1979)[9]. It postulates that the objective of hedging is to minimize the variance of spot portfolio held by the investor. Therefore, the hedge ratio that generates the minimum portfolio variance should be the hedge ratio, which is also known as minimum variance hedge ratio.

Several empirical studies have been carried out in the estimation of optimal hedging strategies in perpetuating the return and the variance reduction. In this area, the

[9] For details see the hedging theory of Working (1953), Johnson (1960), Stein (1961) and Ederington (1979) provided in chapter-II.

hedge ratio varies according to the conditioning information adopted[10]. The existing literature concluded that the conventional regression approach to optimal hedge ratio estimation fails to take proper account of all of the relevant conditioning information available to hedgers when they make hedging decision and it implicitly assumes that the covariance matrix of spot and futures prices and hence optimal hedge ratios are constant over time (Myer, 1991) which was supported by Park Switzer (1995a, 1995b), Lypny and Powalla (1998), Koutmos and Pericli (1998), Lien and Tse (1999), Floros and Vougas (2004), and Bhaduri and Durai (2007). Also vector autoregressive model and vector error correction model ignore the time varying nature of hedge ratios. They concluded that the constant hedge ratio do not consider the joint distribution of the spot and futures varies over time and multivariate GARCH model provides a flexible and consistent framework for estimating time-varying hedge ratio by considering the conditional variance and covariance of the spot and futures returns. The present study compares the effectiveness of hedge ratio for the stock futures market derived from the constant conditional covariance models and time-varying hedge ratio model. This will be immensely useful for the market participants, investors and hedgers to identify the suitable model for hedging their market risk and maximizing their absolute risk aversion utility.

Against this background, the present chapter aims to examine the hedging efficiency of the Indian equity futures in terms of eighty-three individual stock portfolios that belong to eleven sectors of the economy. The remaining part of this chapter is

[10]For details see chapter-III for related literature pertaining to Hedging Effectiveness of futures market.

organized as follows: Section–6.2 presents the methodology of the study. Section–6.3 offers empirical results and discussion. Concluding remarks are presented in Section–6.4.

6.2 Methodology

The present study employs OLS regression, VECM and time-varying MGARCH model to determine optimal hedge ratios of Indian equity futures. Then, the performance of the hedge ratios is compared to assess whether the more advanced time-varying hedge ratios calculated from Bollerslev, Engle and Wooldridge's (1988) Multivariate-GARCH model can provide more efficiency than other constant hedge ratios from the regression model, and the Vector Error Correction Model. This study focuses on three different methods for estimating the hedge ratios and testing it effectiveness for both forecasted in-sample and out-of-sample data.

Model-1: The Conventional Regression Method

The conventional approach in estimating minimum variance hedge ratio (MVHR) relies upon the linear of changes in spot prices on changes in futures prices. Let S_t and F_t be the logged spot and futures prices respectively. The one period minimum variance hedge ratio can be estimated from the expression:

$$\Delta S_t = \alpha + \beta \Delta F_t + \varepsilon_t \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (6.1)$$

where ε_t is the error term from OLS estimation, and ΔS_t and ΔF_t represent changes in the spot and futures prices. β is the estimated optimal hedge ratio.

Model-3: The Vector Error Correction Model (VECM)

Engle and Granger (1987) stated that if sets of series are cointegrated, then there exists a valid Error Correction Representation of the data. Besides, Ghosh (1993), Lien and Luo (1994) and Lien (1996) argue that if the two price series are found to be cointegrated, then there exist valid error correction representations of the price series that includes short-term dynamics and long-run information. Thus, if S_t represents the spot price series and F_t the futures price series and if both series are I(1), there exists an error correction representation of the following form:

$$\Delta S_t = \alpha_s + \sum_{i=1}^{n} \beta_{si} \Delta S_{t-i} + \sum_{i=1}^{n} \theta_{si} \Delta F_{t-i} + \gamma_s Z_{t-1} + \varepsilon_{st} \quad \ldots\ldots\ldots\ldots\ldots\ldots \ (6.2)$$

$$\Delta F_t = \alpha_f + \sum_{i=1}^{n} \beta_{fi} \Delta S_{t-i} + \sum_{i=1}^{n} \theta_{fi} \Delta F_{t-i} + \gamma_f Z_{t-1} + \varepsilon_{ft} \quad \ldots\ldots\ldots\ldots\ldots\ldots \ (6.3)$$

where α_s and α_f are intercepts and ε_{st}, ε_{ft} are white-noise disturbance terms. β_s, β_f, θ_s, θ_f, γ_s and γ_f are parameters. Z_{t-1} is the error-correction term, which measures how the dependent variable adjusts to the previous period's deviation from long-run equilibrium:

$$Z_{t-1} = S_{t-1} - \alpha - \delta F_{t-1} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (6.4)$$

where δ is the cointegration vector and α is the intercept. The two-variable error correction model expressed in equation (6.2) and (6.3) is a bivariate VAR (n) model in first difference augmented by the error-correction term $\gamma_s Z_{t-1}$ and $\gamma_f Z_{t-1}$. The coefficients γ_s and γ_f are interpreted as the speed of adjustment parameters. The larger γ_s is, the greater the response of S_t to the previous period's deviation from long-run equilibrium. Let Var (ε_{st}) = σ_{ss}, Var (ε_{ft}) = σ_{ff} and Cov (ε_{st}, ε_{ft}) = σ_{sf}. The minimum variance hedge ratio is $\sigma_{sf} / \sigma_{ff}$, which is called the VECM hedge ratio.

Model-3: The Multivariate GARCH Model

The above conventional models assume that the residuals have constant variances and covariances. In general, GARCH models assume that the conditional variance is affected by its own history and history of the squared innovations. The advantage of GARCH models is that they have been able to capture the behaviour of financial time series, such as serial correlation in volatility and co-movements in volatilities. The substantial amounts of literature on optimal hedging have been extensively used multivariate GARCH models to generate minimum variance hedge ratios. Those studies include Myers (1991), Kroner and Sultan (1993), Park and Switzer (1995a, 1995b), Koutmos and Pericli (1998), Lypny and Powalla (1998), Lien and Tse (1999), Floros and Vougas (2004), Bhaduri and Durai (2007), Kavussanos and Visvikis (2008), and Kenourgios et al. (2008), etc. From hedging point of view, the multivariate GARCH models are suitable because they can estimate jointly the conditional variances and coivariances required for minimum variance hedge ratio. Thus, the multivariate GARCH model is applied to calculate the dynamic hedge ratios that vary over time based on the conditional variance and covariance of the spot and futures prices and generalized from GARCH (1,1). A standard M-GARCH (1,1) is expressed as:

$$\begin{bmatrix} h_{ss,t} \\ h_{sf,t} \\ h_{ff,t} \end{bmatrix} = \begin{bmatrix} c_{ss,t} \\ c_{sf,t} \\ c_{ff,t} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{s,t-1}^{2} \\ \varepsilon_{s,t-1}, \varepsilon_{f,t-1} \\ \varepsilon_{f,t-1}^{2} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} h_{ss,t-1} \\ h_{sf,t-1} \\ h_{ff,t-1} \end{bmatrix} \quad \ldots\ldots \textit{(6.5)}$$

where h_{ss}, h_{ff} are the conditional variance of the errors (ε_{st}, ε_{ft}) from the mean equations. In this paper, the mean equation is the bivariate vector error correction model. As the model has large number of parameters to be estimated, Bollerslev, Engle and Wooldridge (1988) proposed a restricted version of the above model with α and β matrixes have only diagonal elements which allow for a time-varying conditional variance. The diagonal representation of the conditional variance elements h_{ss} and h_{ff} and the covariance element h_{sf} can be expressed as:

$$h_{ss,t} = c_{ss} + \alpha_{11}\,\varepsilon^2_{s,t-1} + \beta_{11}\, h_{ss,t-1} \qquad \text{………………..} \; (6.6)$$

$$h_{sf,t} = c_{sf} + \alpha_{22}\;\varepsilon_{s,t-1}, \varepsilon_{f,t-1} + \beta_{22}\, h_{sf,t-1} \qquad \text{……………..} \; (6.7)$$

$$h_{ff,t} = c_{ff} + \alpha_{33}\;\varepsilon^2_{f,t-1} + \beta_{33}\, h_{ff,t-1} \qquad \text{…………………..} \; (6.8)$$

The time-varying hedge ratio has been estimated as the ratio between covariance of spot and futures price with variance of futures price. So $h_{sf,t}$ / $h_{ff,t}$ will be the time-varying hedge ratio and hence generates more realistic time-varying hedge.

Estimating Hedging Effectiveness

The performance of the hedging strategies developed in the previous section has been examined by finding the hedging effectiveness of each strategy. To compare, the un-hedged portfolio is constructed as the composition of shares with same proportion held in the spot price index. The hedged portfolio is constructed with the combination of both the spot and the futures contract held. The hedge ratios estimated from each strategy determines the number of futures contract. The hedging effectiveness is calculated by the variance reduction in the hedged portfolio compared to that of un-hedged portfolio. The returns of un-hedged and hedged portfolios are simply expressed as follows:

$$R_{unhedged} = S_{t+1} - S_t \text{ ……………………………..} \; (6.9)$$

$$R_{hedged} = (S_{t+1} - S_t) - h^*(F_{t+1} - F_t) \text{ ……………….} \; (6.10)$$

where, $R_{unhedged}$ and R_{hedged} are return on un-hedged and hedged portfolio. S_t and F_t are logged spot and futures prices at time t with h* is optimal hedge ratio. Similarly the variance of the un-hedged and hedged portfolio is expressed as:

$$Var_{unhedged} = \sigma^2_s \text{ ……………………………....} \; (6.11)$$

$$Var_{hedged} = \sigma^2_s + h^{*2}\, \sigma^2_f - 2h^*\, \sigma_{sf} \text{ ……..………} \; (6.12)$$

where $Var_{unhedged}$ and Var_{hedged} are variance of un-hedged and hedged portfolios with σ_s, σ_f and σ_{sf} are standard deviations of spot and futures price and covariance between them respectively. The effectiveness of hedging (HE) can be measured by the percentage reduction in the variance of a hedged portfolio as compared with the variance of an un-hedged portfolio (Ederington, 1979). The variance reduction can be calculated as:

$$HE = 1- \left[\frac{Var_{HedgedPortfolio}}{Var_{UnhedgedPortfolio}} \right] \text{…………………} \quad (6.13)$$

This gives us the percentage reduction in the variance of the hedged portfolio as compared with the unhedged portfolio. When the futures contract completely eliminates risk, we obtain HE = 1 which indicates a 100% reduction in the variance, whereas we obtain HE = 0 when hedging with the futures contract does not reduce risk. Therefore, a larger number indicates better hedging performance. As proposed by Lien and Tse (1998), the hedging performance of the models may vary over different hedge periods. Therefore, the present study compares the hedging effectiveness of three types of hedge ratios over in-sample and out-of-sample periods.

The data for the study consist of daily closing prices of spot and futures markets of eighty-three underlying stocks that are traded in the National Stock Exchange (NSE). The selected underlying stocks belong to 11 sectors of the economy. The sectors in the study comprise of automobiles, bank, cement, electrical equipments, fertilizers, information technology (IT), oil & gas, pharmaceuticals, power, steel and textiles. The list of the selected stocks considered for the study is presented in Appendix-4.1. The data span for the study considered is from 27th May, 2005 to 26th March, 2009. Out of total observations of the respective stocks, the last 30 observations were used to facilitate out-of-sample hedge ratio performance comparison. The near month contract of equity futures contract has been considered for the study as they are most heavily traded as compared to next month and far month future contracts. All the required data information for the study has been retrieved from the website of National Stock Exchange (NSE), Mumbai.

6.3 Empirical Results and Discussions

6.3.1 Results of Unit Roots and Cointegration

The standard Augmented Dickey – Fuller (ADF) and Phillips – Perron (PP) tests were employed to examine stationary property of the selected data series. This is important from a hedging perspective as non-stationary series may lead to spurious regressions and therefore invalidate the estimation of optimal hedge ratios. The results of Augmented Dickey-Fuller and Phillips-Perron tests for the spot and futures markets price series of the respective underlying stocks are presented in the Chapter-IV (Table-4.1). Both the unit root test results of each individual stock show that the price series are stationary at their first difference, indicating that the spot and futures price series of each respective stocks are integrated at order one, i.e., I(1). Johansen's Cointegration test was performed to examine the presence of long-run relationship between spot and futures market prices of underlying stocks of different sector and its results are presented in the Chapter-IV (Table-4.2). The table result of Johansen's maximum Eigen (λ_{max}) and Trace (λ_{trace}) statistics indicates the presence of one cointegrating vector between the futures and spot market prices at 5 % level in case of each selected individual stocks of different sector respectively. The Johansen's cointegration test confirms the existence of long-run relationship between the spot and futures prices of each underlying stocks in India.

6.3.2 Results of Optimal Hedge Ratio

First, the optimal hedge ratio was derived from the OLS regression (*6.1*) where the spot return is regressed on the futures return for each individual stock. Second, since the spot and futures prices of each respective underlying stock are cointegrated, then according to Engle and Granger (1987), an error correction representation of the data series must exist as presented in equations (*6.2*) & (*6.3*). Therefore, the optimal hedge ratios from the VEC Model are estimated. Based on the standardized squared residuals, the study also examined the efficiency of VEC Model. In order to examine the efficiency of the VEC Model, it could be useful to verify the features of the residuals. According to McLeod and Li (1983), a causal examination of the sample autocorrelation functions of the mean equation squared residuals for a significant Q-statistic at a given lag can be used to infer the presence of ARCH effects. The Ljung-Box Q-Statistics at a given lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k. It is common to test serial correlation within squared values of a distribution as it can be indicative of the presence of conditional heteroskedasticity (Bollerslev, 1986). Also, examining absolute returns can be of assistance for the same reason (see Ding et al., 1993). For standardized squared residuals, the autocorrelation functions (ACF) and partial autocorrelation functions (PACF) from equation (6.2) & (6.3) are presented in Table-6.2. Table-6.2 reports the tenth and twenty-fourth orders of serial correlations from squared normalized residuals of equations (6.2) & equation (6.3) for the each underlying stocks. They are highly significant confirming the presence of ARCH effects. This indicates the existence of heteroscedasticity in the VEC Model. Therefore, it confirms the necessity of an M-GARCH modeling to estimate the conditional variance and covariance for calculating time-varying hedge ratios. The study estimated the multivariate GARCH model of Bollerslev, Engle and Wooldridge's (1988) that provides a flexible and consistent framework for estimating time-varying hedge ratio by considering the conditional variance and covariance of the spot and futures returns. The estimation from variances and covariances and a time-varying hedge ratios based on a GARCH model are expected to give better results. The estimated results are presented in Table-6.3. The table results show that all the parameter estimates are positive definite and statistically significant in the case of almost all underlying stocks that belong to 11 respective industry groups of the economy. This shows that current information in the market is essential for predicting conditional variances. Besides, the estimated significant parameters imply that the GARCH error is proficient to capture the dynamics in the variances of the joint distribution of spot and futures returns of the underlying stocks of respective industry groups. Furthermore, the sum of the coefficients ($c_{ss}+ \alpha_{ss}+ \beta_{ss}$, $c_{sf}+ \alpha_{sf}+ \beta_{sf}$, $c_{ff}+ \alpha_{ff}+ \beta_{ff}$) in the case of almost all underlying stocks of 11 respective industry groups is close to unity, implying the persistence of ARCH effects in the data sets.

This chapter employs conventional regression method, Vector Error Correction Model and time-varying MGARCH model for evaluating hedge ratios. Table-6.1 presents the optimal hedge ratios derived from the OLS, VECM and MGARCH models for the eighty-three underlying stocks that belong to 11 sectors of the economy. The table result reveals that the hedge ratio estimated from the time-varying MGARCH model was found to be greater than that obtained from other models in case of four underlying stocks of automobile industry such as ESCORTS, HEROHONDA, TATAMOTORS and TVSMOTOR. This is followed by the hedge ratio obtained from VEC Model that yields the highest in the case of rest of the three selected automobile stocks, viz., ASHOKLEY, M&M and MARUTI. Besides, the table result indicates that OLS regression method provides the lowest hedge ratios in majority of the cases as compared to other models.

In the case of banking industry stocks, the hedge ratio estimated from the time-varying conditional variance and covariance between spot and futures returns are higher than other methods for the majority of the cases. Besides, the conventional OLS regression method provides the lowest hedge ratios in majority of the banking stocks as compared to other models. This implies that hedge ratio estimated by time-varying MGARCH was more efficient in reducing risk of spot prices.

The hedge ratio from the estimates of VECM was found to be higher for ACC and GRASIM, and that from the estimate of OLS was higher in the case of INDIACEM. Similarly, in the case of fertilizer industry stocks, the table results show that VECM hedge ratios are found to be greater for the three stocks – CHAMBLFERT, GNFC and TATACHEM – and OLS hedge ratio greater for NAGARFERT. As far as the electrical equipments industry is concerned, Table-6.3 shows that the time-varying hedge ratio is higher in the two stocks of BHEL and SIEMENS. For ABB and SUZLON, the result supports the VECM and OLS hedge ratios that generate the minimum portfolio variance respectively.

For the stocks of IT industry, the hedge ratio estimated from the time-varying MGARCH model was found to be superior than that obtained from other models in the case of five underlying stocks, such as HCLTECH, OFSS, PATNI, POLARIS and TCS. This is followed by the hedge ratio obtained from VEC Model that yields the highest in case of rest of the selected automobile stocks, viz. INFOSYSTCH and WIPRO. Besides, the table result indicates that OLS hedge ratio underperforms in majority of the cases as compared to other models.

Moreover, the table results reveal that the hedge ratio estimated by the error-correction model was greater than that obtained from other models for five underlying Oil and Gas industry stocks, viz. BONGAIREFN, BPCL, ESSAROIL, GAIL and ONGC. This is followed by OLS hedge ratios that are greater in the case of IOC and MRPL and MGARCH hedge ratios that are higher in HINDPETRO and RELIANCE. Besides, the empirical results of the pharmaceutical industry stocks reveal that optimal hedge ratio from VEC model was greater as compared to hedge ratios from other models for most of the cases, such as AUROPHARMA, DABUR, DIVISLAB, GLAXO, ORCHIDCHEM, PIRHEALTH, RANBAXY and SUNPHARMA. Moreover, the table result suggests the time-varying MGARCH hedge ratio that generates the minimum portfolio variance for rest of the stocks such as CIPLA, MATRIXLABS, DRREDDY, STAR and WOCKPHARMA. The table result also confirms that the OLS hedge ratio underperforms in most of the cases as compared to other models.

For the power industry stocks, the analysis reveals that hedge ratio estimated by the error-correction model was greater than that obtained from other models for four underlying stocks, viz. JPHYDRO, NTPC, RELINFRA and TATAPOWER. This is followed by OLS hedge ratios that are superior in the case of CESC and NEYVELILIG and MGARCH hedge ratios that are higher in CUMMINSIND. For steel industry, the analysis shows that VEC Model yields greater hedge ratio for the stocks, such as JINDALSTEL, MAHSEAMLES and TATASTEEL and time-varying MGARCH model for JSL. Moreover, the analysis confirms that conventional regression method provides greater hedge ratio for textile stocks, viz. ARVIND and SRF. This is followed by the hedge ratios obtained from VEC Model for CENTURYTEX and time-varying MGARCH model favours ALOKTEXT.

From the table result, it was clear that the hedge ratios estimated from error correction model was found to be greater than that obtained from other models in majority of the underlying stocks that belonging industry groups such as cement, fertilizers, oil and gas, pharmaceuticals, power and steel. This result is consistent with those from Ghosh (1993) and Lien (1996) where it is noted that the hedge ratio results biased downward in size when the cointegrating relationship is ignored. Following this, it can be seen that the hedge ratio obtained from the time-varying MGARCH model was slightly greater than those obtained from the OLS and VEC models in the case of majority of the underlying stocks that belongs to automobiles, bank, electrical equipments, and IT. It is noted that the OLS hedge ratio was found to be slightly greater as compared to hedge ratio obtained from other models only in the majority cases of textiles. Besides, the table result indicates that OLS regression method provides the lowest hedge ratios in majority of the stocks in the industry groups such as automobiles, bank, electrical equipments, IT, pharmaceutical and steel.

6.3.3 Results of In-Sample Hedging Effectiveness

The performance of the hedging strategies developed in the previous section has been examined by finding the hedging effectiveness of each strategy. The effectiveness of hedging (HE) can be measured by the percentage reduction in the variance of a hedged portfolio as compared with the variance of an un-hedged portfolio (Ederington, 1979). As proposed by Lien and Tse (1998), the hedging performance of the models may vary over different hedge periods. Therefore, the present study compares the hedging effectiveness of three types of hedge ratios over in-sample and out-of-sample periods. For in the sample estimation, the study considered the daily closing prices of spot and futures markets of eighty-three underlying stocks that are traded in National Stock Exchange (NSE). The selected underlying stocks belong to 11 sectors of the economy. The data span for the study is from 27th May, 2005 to 26th March, 2009. Out of total observations of the respective stocks, the last 30 observations were used to facilitate out-of-sample hedge ratio performance comparison. The present chapter evaluates and compares the in-sample hedging performances of the three hedging models considered in the study. Table-6.4 displays the in-sample hedging performances of the various models for eighty-three underlying individual stocks under examination. The table result reveals the time-varying hedge ratios computed from MGARCH model for the underlying stocks of automobile industry showed better in-sample performance except for ASHOKLEY in terms of variance reduction than the other models. Similarly, the table provides evidence for most of the banking sector stocks that a time-varying MGARCH was economically and statistically superior to other models in terms of minimizing the variance of hedged portfolios with respect to its unhedged portfolios. For ALBK and KTKBANK, the result supports the OLS and VECM hedging performances that generate the minimum portfolio variance respectively.

The performances of the hedge ratios from the estimates of OLS and MGARCH models in the in-sample period was found to dominate for the two cement industry stocks, GRASIM and INDIACEM, while MGARCH model dominates for ACC. Similarly, in the case of fertilizer industry stocks, the table results show that VECM hedge outperforms the other models for the three stocks – CHAMBLFERT, TATACHEM and NAGARFERT – and OLS hedge for GNFC. As far as the electrical equipments industry is concerned, the in-sample hedging effectiveness of MGARCH hedge ratios is superior to the OLS and VECM hedge ratios for three stocks, viz. BHEL, SIEMENS and SUZLON. For ABB, the result supports the VECM hedge performances that generate the minimum portfolio variance.

For IT industry, the in-sample hedging effectiveness of the time-varying MGARCH hedge ratios outperform OLS and VECM hedge ratio in most of the underlying scrips such as HCLTECH, OFSS, PATNI, POLARIS, TCS and WIPRO. For INFOSYSTCH, the result supports the OLS hedge performances that generate the minimum portfolio variance. Moreover, the hedging effectiveness from OLS hedge ratio which minimizes the unconditional variance performs better than the VECM and time-varying MGARCH hedge ratio for the majority of the underlying stocks of Oil and Gas industry, namely, BONGAIREFN, ESSAROIL, GAIL, IOC, MRPL and RELIANCE. This is followed by the hedging performances obtained from time-varying model outperforms the other models in case of rest of the stocks, viz. BPCL, HINDPETRO and ONGC. Besides, the in-sample hedging effectiveness of the pharmaceutical industry stocks shows that MGARCH model provides substantial reductions in variance except for DIVISLAB.

For the power industry stocks, the in-sample analysis reveals that OLS hedges outperform hedging strategies obtained from other models for five underlying stocks, viz. JPHYDRO, NEYVELILIG, NTPC, RELINFRA and TATAPOWER. This is followed by MGARCH hedges perform better in the case of CESC and CUMMINSIND. For steel industry, the analysis shows that hedging strategies obtained from OLS model yields greater performance in terms of variance reduction for the stocks, such as JINDALSTEL, JSL and MAHSEAMLES and VEC model for TATASTEEL. Moreover, the analysis for the textile industry confirms that time-varying hedge strategy which minimizes the conditional variance of hedged portfolio with respect to unhedged outperforms the OLS and VECM hedge strategies.

From the table result, it was clear that the dynamic M-GARCH hedging strategy does seem to outperform the simple constant conventional OLS and error correction hedge strategies in majority of the underlying stocks belonging to industry groups such as automobiles, bank, electrical equipments, IT, pharmaceuticals and textiles. This implies that risk aversion is the major goal of an investor, the dynamic M-GARCH model hedging strategy performs the best in reducing the conditional variance of the hedged portfolio. The investor's degree of risk aversion, in these cases, plays an important role in selecting the hedging method. This is consistent with most of the previous studies of Myers (1991), Baillie and Myers (1991) and Park and Switzer (1995a, 1995b) on US commodity and financial markets. Following this, another striking feature of the in-sample results is that the OLS hedge strategy performs better in reducing the risk of the hedged portfolio relative to other alternatives in most cases of industry groups such as cement, fertilizers, oil and gas, power and steel. This finding suggests that, in terms of risk reduction, a hedge strategy based on an unconditional variance hedge ratio estimated through OLS outperforms a strategy based on a minimum variance hedge ratio estimated using more advanced techniques such as the VECM and the M-GARCH approach. This is consistent with the findings of previous studies such as Holmes (1995), Chakrabothy and Barkoulas (1999) and Miffre (2001).

6.3.4 Results of Out-of-Sample Hedging Effectiveness

The in-sample performance of the alternative hedging strategies provides an indication of their historical performance, but the investors are more concerned about how well they can do in the future. The more reliable measure of hedging effectiveness is the hedging performance of the post-sample periods. Since investors need to predict all about the future, the study use an out-of-sample (post-sample) performance measure, which represents a way to evaluate effectiveness of hedge ratios. Brook and Chong (2001) suggest that out-of-sample evaluation of models is more appropriate because traders are more concerned with future performance. Therefore, the present study compares the hedging effectiveness of three types of hedge ratios over out-of-sample periods. The present chapter evaluates and compares the out-of-sample hedging performances of the three hedging models with in-sample hedging performances. Out of total observations of the respective stocks under examination, the last 30 observations were used to facilitate out-of-sample hedge ratio performance comparison. Table-6.5 displays the out-of-sample hedging performances of the various models for eighty-three underlying individual stocks under examination. The table result reveals the time-varying hedge ratios computed from M-GARCH model for five underlying stocks of automobile industry showed better out-of-sample performance in terms of variance reduction than the other models. This is followed by the out-of-sample hedging effectiveness of the TATAMOTOR and TVSMOTORS stocks shows that M-GARCH model provides substantial reductions in variances. Similarly, the table provides evidence that a time-varying MGARCH was economically and statistically superior to other models in terms of minimizing the variance of hedged portfolios with respect to its unhedged portfolios for most of the banking sector stocks such as BANKINDIA, CORPBANK, HDFCBANK, ICICIBANK, IDBI, INDUSINDBK, J&KBANK, SBIN and VIJAYABANK. This is followed by the result that supports the OLS hedging performances that generate the minimum portfolio variance in the seven cases, viz. ANDHRABANK, AXISBANK, BANKBARODA, CANBK, ORIENTBANK, PNB and UNIONBANK. Besides, it can be seen that the hedge strategy obtained from the VEC model was performs better than those obtained from the OLS and M-GARCH models in the case of five stocks, such as ALBK, FEDERALBNK, IOB, KTKBANK and SYNDIBANK.

The performances of the hedge ratios from the estimates of VEC model in the out-of-sample period was found to be dominate than the others for the cement industry stocks. In the case of fertilizer industry stocks, the table results show that time-varying M-GARCH hedging strategy outperforms the other models for TATACHEM, NAGARFERT and GNFC and VECM hedging strategy for CHAMBLFERT. As far as the electrical equipments industry is concerned, the out-of-sample hedging effectiveness of MGARCH hedge ratios is superior to the OLS and VECM hedge ratios for three stocks – BHEL, SIEMENS and SUZLON. For ABB, the result supports the VECM hedge performances that generate the minimum portfolio variance. This is consistent with the findings offered by the in-sample hedging performances.

For IT industry, the out-of-sample hedging effectiveness of the time-varying MGARCH hedge ratios outperform OLS and VECM hedge ratio in most of the underlying scrips such as HCLTECH, OFSS, PATNI, POLARIS and TCS. For INFOSYSTCH and WIPRO, the result supports the VECM hedge performances that generate the minimum portfolio variance. Moreover, the hedging effectiveness from time-varying hedge ratio that minimizes the conditional variance performs better than the other models for majority of the underlying stocks of oil and gas industry, namely, BPCL, ESSAROIL, HINDPETRO, IOC and RELIANCE. This is followed by the hedging performances obtained from VEC model outperforms the other models in case of rest of the stocks, viz. BONGAIREFN, GAIL, MRPL and ONGC. Besides, the out-of-sample hedging effectiveness of the pharmaceutical industry stocks shows that VEC model provides substantial reductions in variance for most of the stocks such as AUROPHARMA, DIVISLAB, DRREDDY, MATRIXLABS, ORCHIDCHEM, RANBAXY, STAR and SUNPHARMA. This is followed by the hedging performances obtained from OLS model outperforms the other models in the case of GLAXO, PIRHEALTH and WOCKPHARMA and dynamic M-GARCH model for CIPLA and DABUR.

For the power industry stocks, the out-of-sample analysis reveals that dynamic M-GARCH hedges outperform hedging strategies obtained from other models for five underlying stocks, viz. CESC, CUMMINSIND, NEYVELILIG, RELINFRA and TATAPOWER. This is followed by VECM hedges perform better in the case of JPHYDRO and NTPC.

For steel industry, the analysis shows that hedging strategies obtained from VEC model yields greater performance in terms of variance reduction for the stocks, such as JINDALSTEL, JSL and MAHSEAMLES and OLS model for TATASTEEL. This was quite contradictory with the findings offered by the in-sample hedging performances. Moreover, the analysis for the textile industry confirms that OLS hedge strategy which minimizes the unconditional variance of hedged portfolio with respect to unhedged outperforms the VECM and M-GARCH hedge strategies. This finding was too quite contradictory with the result offered by the in-sample hedging performances.

From the table result, it was clear that the dynamic M-GARCH hedging strategy outperform the other alternatives in majority of the underlying stocks that belongs to industry groups such as automobiles, bank, cement, electrical equipments, fertilizer, IT, oil & gas and power. This implies that risk aversion is the major goal of an investor, the dynamic M-GARCH model hedging strategy performs the best in reducing the conditional variance of the hedged portfolio. The investor's degree of risk aversion, in these cases, plays an important role in selecting the hedging method. This is consistent with most of the previous studies of Myers (1991), Baillie and Myers (1991) and Park and Switzer (1995a, 1995b) on US commodity and financial markets. Following this, another striking feature of the out-of-sample results is that the VEC hedge strategy performs better in reducing the risk of the hedged portfolio relative to other alternatives in most cases of industry groups such as pharmaceuticals and steel. This finding suggests that, in terms of risk reduction, a hedge strategy based on an unconditional variance hedge ratio estimated through VEC outperforms a strategy based on a minimum variance hedge ratio estimated using conventional OLS regression and the M-GARCH approach. Following this, the OLS hedge dominates the other alternative models in the case of textiles industry.

This study has important implications for hedgers in that their performance criteria indicate which hedging model would be most appropriate in a given hedging context. Where hedgers have a variety of performance aims they should, therefore, consider a variety of measures of hedging effectiveness. By and large, the comparison of both in-sample and out-of-sample hedging performances tell the conflict story in most of the industry groups such as cement, fertilizer, oil & gas (except ONGC), pharmaceuticals (except CIPLA and DABUR), power (CESC and CUMMINSIND), steel and textiles respectively. This finding is consistent with the evidences of earlier studies such as Chou et al. (1996) for Japan's Nikkei Stock Average (NSA) index, Lee et al. (2007) for six emerging country's stock index futures markets and Kenourgious et al. (2008) for Greece stock index futures markets. Following this, the comparisons of in-sample and out-of-sample hedging effectiveness in the study indicates that the hedging strategies obtained from time-varying hedge ratio which minimizes the conditional variance performs better than the alternative models for majority of the underlying stocks of industry groups such as automobiles, oil and gas, electrical equipments and IT respectively. This finding indicates that in selecting the most appropriate hedge ratio, the investor's degree of risk aversion, in these industry groups' cases play a relatively important role. This suggests that that risk aversion is the major goal of an investor, the dynamic M-GARCH model hedging strategy performs the best in reducing the conditional variance of the hedged portfolio. This is consistent with most of the previous studies of Myers (1991), Baillie and Myers (1991) and Park and Switzer (1995a, 1995b) on US commodity and financial markets.

6.4 Conclusion

The present study examines the performance of various hedge ratios estimated under different econometric models and compared in terms of variance minimization criterion over the in-sample and out-of-sample periods for the eighty-three underlying stocks of National Stock Exchange (NSE) belonging to eleven sectors of the economy. This study has important implications for hedgers in that their performance criteria indicate which hedging model would be most appropriate in a given hedging context. Where hedgers have a variety of performance aims they should, therefore, consider a variety of measures of hedging effectiveness. From the in-sample estimations, it was clear that the dynamic M-GARCH hedging strategy does seem to outperform the simple constant conventional OLS and error correction hedge strategies in majority of the underlying stocks that belongs to industry groups such as automobiles, bank, electrical equipments, IT, pharmaceuticals and textiles. This implies that risk aversion is the major goal of an investor, the dynamic M-GARCH model hedging strategy performs the best in reducing the conditional variance of the hedged portfolio. The investor's degree of risk aversion, in these cases, plays an important role in selecting the hedging method. This is consistent with most of the previous studies of Myers (1991), Baillie and Myers (1991) and Park and Switzer (1995a, 1995b) on US commodity and financial markets. Following this, another striking feature of the in-sample results is that the OLS hedge strategy performs better in reducing the risk of the hedged portfolio relative to other alternatives in most cases of industry groups such as cement, fertilizers, oil and gas, power and steel. This finding indicates that, in terms of risk reduction, a hedge strategy based on an unconditional variance hedge ratio estimated through OLS outperforms a strategy based on a minimum variance hedge ratio estimated using more advanced techniques such as the VECM and the M-GARCH approach. This is consistent with the findings of previous studies such as Myers (1991), Holmes (1995), Chakrabothy and Barkoulas (1999) and Miffre (2001).

Besides, it was clear that the dynamic M-GARCH hedging strategy outperforms the other alternatives in majority of the underlying stocks belonging to industry groups such as automobiles, bank, cement, electrical equipments, fertilizer, IT, oil & gas and power. This implies that risk aversion is the major goal of an investor, the dynamic M-GARCH model hedging strategy performs the best in reducing the conditional variance of the hedged portfolio. The investor's degree of risk aversion, in these cases, plays an important role in selecting the hedging method. This is consistent with most of the previous studies of Myers (1991), Baillie and Myers (1991) and Park and Switzer (1995a, 1995b) on US commodity and financial markets. Following this, another striking feature of the out-of-sample results is that the VEC hedge strategy performs better in reducing the risk of the hedged portfolio relative to other alternatives in most cases of industry groups such as pharmaceuticals and steel. This finding suggests that, in terms of risk reduction, a hedge strategy based on an unconditional variance hedge ratio estimated through VEC outperforms a strategy based on a minimum variance hedge ratio estimated using conventional OLS regression and the M-GARCH approach. Following this, the OLS hedge dominates the other alternative models in the case of textiles industry.

By and large, the comparison of both in-sample and out-of-sample hedging performances tell the conflicting story in most of the industry groups such as cement, fertilizer, oil & gas (except ONGC), pharmaceuticals (except CIPLA and DABUR), power (CESC and CUMMINSIND), steel and textiles. This finding is consistent with the evidences of earlier studies such as Chou et al. (1996) for Japan's Nikkei Stock Average (NSA) index, Lee et al. (2007) for six emerging country's stock index futures markets and Kenourgious et al. (2008) for Greece stock index futures markets. Following this, the comparison of in-sample and out-of-sample hedging effectiveness in the study indicates consistent evidence that the hedging strategies obtained from time-varying hedge ratio which minimizes the conditional variance performs better than the alternative models for majority of the underlying stocks of industry groups such as automobiles, oil and gas, electrical equipments and IT respectively. This finding implies that in selecting the most appropriate hedge ratio, the investor's degree of risk aversion, in these industry groups' cases plays a relatively important role. This suggests that that risk aversion is the major goal of an investor, the dynamic M-GARCH model hedging strategy performs the best in reducing the conditional variance of the hedged portfolio. This is consistent with most of the previous studies of Myers (1991), Baillie and Myers (1991) and Park and Switzer (1995a, 1995b) on US commodity and financial markets.

Table 6.1
Estimates of Optimal Hedge Ratio for the In-Sample Period

S. No.	Name of the Stocks	OLS	VECM	MGARCH
1. Industry Group: Automobiles				
1.	ASHOKLEY	0.958486 ^{L}	0.968896 ^{H}	0.96328
2.	ESCORTS	0.954202 ^{L}	0.9613027	0.99191 ^{H}
3.	HEROHONDA	0.967813	0.950512 ^{L}	0.97380 ^{H}
4.	M&M	0.985232	0.993858 ^{H}	0.98506 ^{L}
5.	MARUTI	0.973596 ^{L}	0.988751 ^{H}	0.98853
6.	TATAMOTORS	0.957258 ^{L}	0.962808	0.96856 ^{H}
7.	TVSMOTOR	0.965063 ^{L}	0.9658679	1.01046 ^{H}
2. Industry Group: Bank				
8.	ALBK	0.965181	0.97168 ^{H}	0.96304 ^{L}
9.	ANDHRABANK	0.950548 ^{L}	0.973154 ^{H}	0.96008
10.	AXISBANK	0.987193 ^{L}	0.987768	1.00484 ^{H}
11.	BANKBARODA	0.957409	0.954264 ^{L}	0.96425 ^{H}
12.	BANKINDIA	0.993618 ^{L}	1.000588	1.00500 ^{H}
13.	CANBK	0.978866 ^{L}	0.985452	0.99037 ^{H}
14.	CORPBANK	0.919424 ^{L}	0.954280	0.98221 ^{H}
15.	FEDERALBNK	0.913704 ^{L}	0.955312	0.96645 ^{H}
16.	HDFCBANK	0.989483 ^{H}	0.986789	0.97754 ^{L}
17.	ICICIBANK	0.981167 ^{L}	0.989388 ^{H}	0.98503
18.	IDBI	0.868477 ^{L}	0.875523	0.89607 ^{H}
19.	INDUSINDBK	0.962620 ^{L}	0.963198	0.96822 ^{H}
20.	IOB	0.970303	0.964163 ^{L}	0.97079 ^{H}
21.	J&KBANK	0.754001 ^{L}	0.847288	0.89595 ^{H}
22.	KTKBANK	0.920641 ^{L}	0.932519 ^{H}	0.92989
23.	ORIENTBANK	0.977727 ^{H}	0.973222	0.96878 ^{L}
24.	PNB	0.957230	0.957118 ^{L}	0.96084 ^{H}
25.	SBIN	0.952710 ^{L}	0.960784	0.96587 ^{H}
26.	SYNDIBANK	0.971947 ^{L}	0.972447	0.98126 ^{H}
27.	UNIONBANK	0.966135 ^{L}	0.979366	0.98148 ^{H}
28.	VIJAYABANK	0.590941 ^{L}	0.776911	0.77932 ^{H}
3. Industry Group: Cement				
29.	ACC	0.962695 ^{L}	0.968266 ^{H}	0.96478
30.	GRASIM	0.953417	0.958154 ^{H}	0.95175 ^{L}
31.	INDIACEM	0.980320 ^{H}	0.978322	0.96204 ^{L}
4. Industry Group: Electrical Equipments				
32.	ABB	0.978047 ^{L}	0.982545 ^{H}	0.97994
33.	BHEL	0.979272 ^{L}	0.97933	0.97997 ^{H}
34.	SIEMENS	0.982731 ^{L}	0.982954	0.99609 ^{H}
35.	SUZLON	0.991754 ^{H}	0.991544	0.99124 ^{L}
5. Industry Group: Fertilizers				
36.	CHAMBLFERT	0.967850	0.96935 ^{H}	0.95481 ^{L}

37.	GNFC	0.950298 L	0.956505 H	0.95416
38.	NAGARFERT	0.963189 H	0.96227	0.96221 L
39.	TATACHEM	0.913730	0.931126 H	0.92180
6. Industry Group: Information Technology (IT)				
40.	HCLTECH	0.967437 L	0.982081	0.98476 H
41.	OFSS	0.950457 L	0.951267	0.97062 H
42.	INFOSYSTCH	0.953240	0.957072 H	0.93607 L
43.	PATNI	0.175894	0.175734 L	0.18300 H
44.	POLARIS	0.951556 L	0.959393	0.96018 H
45.	TCS	0.988655 L	0.995255	0.99979 H
46.	WIPRO	0.963443 L	0.975556 H	0.97384
7. Industry Group: Oil & Gas				
47.	BONGAIREFN	0.928628	0.961377 H	0.91337 L
48.	BPCL	0.976608 L	0.994146 H	0.98788
49.	ESSAROIL	0.962200	0.966087 H	0.96086 L
50.	GAIL	0.949056 L	0.957111 H	0.95341
51.	HINDPETRO	0.923827 L	0.959184	0.96872 H
52.	IOC	0.984483 H	0.984026	0.98076 L
53.	MRPL	0.957011 H	0.954089	0.95054 L
54.	ONGC	0.931753 L	0.952014 H	0.94343
55.	RELIANCE	0.988315	0.988285 L	0.99052 H
8. Industry Group: Pharmaceuticals				
56.	AUROPHARMA	0.966669	0.967638 H	0.95407 L
57.	CIPLA	0.979728 L	0.98377	0.98483 H
58.	DABUR	0.980727 L	0.994028 H	0.98770
59.	DIVISLAB	0.245580 L	0.290192 H	0.28723
60.	DRREDDY	0.982255 L	0.983859	0.98572 H
61.	GLAXO	0.809912 L	0.883882 H	0.88297
62.	MATRIXLABS	0.868530 L	0.8976921	0.91201 H
63.	ORCHIDCHEM	0.964615 L	0.971532 H	0.96835
64.	PIRHEALTH	0.214939 L	0.252149 H	0.23558
65.	RANBAXY	0.943811	0.963402 H	0.93991 L
66.	STAR	0.889379 L	0.9135844	0.94058 H
67.	SUNPHARMA	0.970968 L	0.990071 H	0.97962
68.	WOCKPHARMA	0.936550	0.9333526 L	0.95531 H
9. Industry Group: Power				
69.	CESC	0.965507 H	0.958463 L	0.95936
70.	CUMMINSIND	0.916495 L	0.962898	0.96447 H
71.	JPHYDRO	0.958510	0.961826 H	0.95742 L
72.	NEYVELILIG	0.962870 H	0.961629	0.95780 L
73.	NTPC	0.944904 L	0.949931 H	0.94866
74.	RELINFRA	0.976001	0.976727 H	0.96905 L
75.	TATAPOWER	0.953999	0.966962 H	0.94404 L
10. Industry Group: Steel				
76.	JINDALSTEL	0.98346 L	0.987369 H	0.984428

77.	JSL	0.097739^{L}	0.103452	0.15480^{H}
78.	MAHSEAMLES	0.930739^{L}	0.95932^{H}	0.940424
79.	TATASTEEL	0.974714	0.976094^{H}	0.97370^{L}
11. Industry Group: Textiles				
80.	ALOKTEXT	0.973128^{L}	0.973281	0.99384^{H}
81.	ARVIND	0.968722^{H}	0.962893^{L}	0.96657
82.	CENTURYTEX	0.971318	0.973002^{H}	0.97050^{L}
83.	SRF	0.957643^{H}	0.952509	0.95173^{L}
Note: ^{H}Highest hedge ratio and ^{L}Lowest hedge ratio				

Table 6.2
Autocorrelation Function of the Standardized Squared Residuals from VEC Model

Name of the Stocks	Spot Equation *(6.2)*					Futures Equation *(6.3)*			
	Lags	AC	PAC	Q-Statistics	Prob.	AC	PAC	Q-Statistics	Prob.
1. Industry Group: Automobiles									
ASHOKLEY	10	0.000	-0.026	123.79	0.000	0.005	-0.021	121.57	0.000
	24	-0.012	-0.020	138.72	0.000	-0.013	-0.023	139.53	0.000
ESCORTS	10	0.015	-0.009	138.25	0.000	0.019	-0.007	162.51	0.000
	24	-0.017	-0.031	148.81	0.000	-0.010	-0.023	174.83	0.000
HEROHONDA	10	0.021	0.010	115.38	0.000	0.025	0.018	107.24	0.000
	24	-0.014	-0.013	121.06	0.000	-0.008	-0.008	114.64	0.000
M&M	10	-0.003	-0.003	50.122	0.000	-0.004	-0.004	49.783	0.000
	24	0.007	0.009	50.286	0.001	0.005	0.007	49.942	0.001
MARUTI	10	0.047	-0.005	132.04	0.000	0.045	-0.018	160.89	0.000
	24	0.013	-0.038	201.27	0.000	0.029	-0.017	241.17	0.000
TATAMOTORS	10	0.068	-0.049	330.19	0.000	0.076	-0.061	385.94	0.000
	24	0.132	0.077	459.04	0.000	0.131	0.058	596.44	0.000
TVSMOTOR	10	0.011	-0.008	124.92	0.000	0.015	-0.003	132.10	0.000
	24	0.031	0.023	137.24	0.000	0.019	0.009	147.77	0.000
2. Industry Group: Bank									
ALBK	10	0.046	0.027	50.073	0.000	0.028	0.009	55.998	0.000
	24	0.013	0.002	74.249	0.000	0.016	0.002	83.218	0.000
ANDHRABANK	10	0.006	-0.004	124.04	0.000	0.012	-0.003	138.48	0.000
	24	-0.006	-0.006	133.03	0.000	-0.006	-0.001	150.44	0.000
AXISBANK	10	0.113	0.045	124.07	0.000	0.118	0.045	134.35	0.000
	24	0.012	-0.018	201.66	0.000	0.010	-0.026	213.35	0.000
BANKBARODA	10	0.042	0.033	45.995	0.000	0.038	0.031	42.934	0.000
	24	-0.024	-0.040	68.575	0.000	-0.023	-0.035	63.805	0.000
BANKINDIA	10	0.055	0.026	95.205	0.000	0.041	0.020	108.15	0.000
	24	-0.016	-0.009	105.42	0.000	-0.018	-0.012	118.87	0.000
CANBK	10	-0.010	-0.017	29.500	0.001	0.002	-0.009	64.455	0.000
	24	0.001	-0.010	50.533	0.001	-0.001	-0.017	91.493	0.000
	10	-0.009	0.001	50.956	0.000	-0.012	-0.006	67.792	0.000

CORPBANK	24	-0.015	-0.068	124.39	0.000	-0.009	-0.080	162.69	0.000
FEDERALBNK	10	0.035	0.030	45.506	0.000	0.018	0.011	50.512	0.000
	24	-0.022	-0.011	51.123	0.001	-0.028	-0.016	56.145	0.000
HDFCBANK	10	0.054	-0.006	127.88	0.000	0.143	0.079	165.85	0.000
	24	0.087	0.048	232.52	0.000	0.079	0.036	231.34	0.000
ICICIBANK	10	0.209	0.116	339.51	0.000	0.194	0.102	322.15	0.000
	24	0.041	-0.059	544.16	0.000	0.035	-0.060	519.01	0.000
IDBI	10	0.001	-0.013	134.92	0.000	-0.012	-0.014	65.931	0.000
	24	-0.037	-0.026	147.95	0.000	-0.031	-0.030	83.366	0.000
INDUSINDBK	10	0.033	0.020	84.425	0.000	0.036	0.021	97.918	0.000
	24	0.010	0.011	136.88	0.000	0.006	0.010	148.59	0.000
IOB	10	0.014	-0.044	114.74	0.000	-0.011	-0.065	100.99	0.000
	24	-0.004	-0.018	167.62	0.000	-0.005	-0.024	153.11	0.000
J&KBANK	10	-0.024	-0.016	62.587	0.000	0.016	-0.002	94.359	0.000
	24	0.098	0.075	85.616	0.000	0.086	0.071	114.19	0.000
KTKBANK	10	0.063	0.048	109.68	0.000	0.054	0.039	124.94	0.000
	24	-0.017	-0.020	134.97	0.000	-0.015	-0.014	153.36	0.000
ORIENTBANK	10	0.030	0.021	51.020	0.000	0.031	0.009	63.442	0.000
	24	0.029	0.016	67.132	0.000	0.034	0.018	81.410	0.000
PNB	10	0.035	0.026	39.868	0.000	0.037	0.028	38.284	0.000
	24	0.018	-0.015	83.685	0.000	0.010	-0.026	81.070	0.000
SBIN	10	0.097	0.025	185.54	0.000	0.103	0.033	193.00	0.000
	24	0.034	-0.004	311.33	0.000	0.029	-0.009	325.30	0.000
SYNDIBANK	10	-0.006	-0.019	68.662	0.000	-0.007	-0.024	78.901	0.000
	24	-0.005	-0.007	108.37	0.000	-0.014	-0.019	118.19	0.000
UNIONBANK	10	0.029	0.021	32.557	0.000	0.035	0.026	33.616	0.000
	24	-0.017	-0.020	37.614	0.007	-0.005	-0.006	39.001	0.007
VIJAYABANK	10	0.004	-0.007	49.397	0.000	0.011	-0.020	203.96	0.000
	24	-0.000	0.002	60.773	0.000	0.007	-0.010	211.47	0.000
3. Industry Group: Cement									
ACC	10	0.012	-0.029	118.45	0.000	0.010	-0.032	118.85	0.000
	24	0.041	0.004	182.27	0.000	0.043	0.006	182.41	0.000
GRASIM	10	0.033	-0.024	169.38	0.000	0.032	-0.031	176.43	0.000
	24	0.022	-0.016	285.16	0.000	0.024	-0.020	308.83	0.000
INDIACEM	10	-0.001	-0.009	85.602	0.000	0.006	0.006	82.664	0.000
	24	-0.004	-0.006	103.28	0.000	-0.002	-0.004	105.32	0.000
4. Industry Group: Electrical Equipments									
ABB	10	-0.002	-0.001	53.454	0.000	-0.002	-0.001	53.215	0.000
	24	-0.001	-0.001	53.493	0.000	-0.001	-0.001	53.256	0.001
BHEL	10	-0.003	-0.001	54.156	0.000	-0.003	-0.002	55.867	0.000
	24	-0.005	-0.003	54.354	0.000	-0.005	-0.003	56.066	0.000
SIEMENS	10	0.002	0.002	62.564	0.000	-0.003	-0.004	64.711	0.000
	24	-0.003	-0.002	62.974	0.000	-0.003	-0.002	65.149	0.000
SUZLON	10	0.000	0.001	42.185	0.000	0.001	0.001	41.389	0.000
	24	-0.002	-0.001	42.269	0.008	-0.003	-0.002	41.468	0.007

5. Industry Group: Fertilizers									
CHAMBLFERT	10	0.040	-0.003	199.60	0.000	0.039	0.001	199.16	0.000
	24	0.035	0.024	226.56	0.000	0.030	0.021	225.95	0.000
GNFC	10	-0.011	-0.017	63.676	0.000	0.019	-0.004	63.354	0.000
	24	0.036	0.001	139.30	0.000	0.025	-0.012	137.67	0.000
NAGARFERT	10	0.012	-0.037	186.36	0.000	0.015	-0.037	206.19	0.000
	24	0.014	0.017	210.76	0.000	0.013	0.015	233.61	0.000
TATACHEM	10	0.046	-0.038	437.45	0.000	0.066	0.026	375.72	0.000
	24	0.068	0.004	606.70	0.000	0.046	0.015	457.41	0.000
6. Industry Group: Information Technology (IT)									
HCLTECH	10	0.014	0.012	39.266	0.000	0.012	0.010	50.042	0.000
	24	-0.001	-0.002	39.894	0.002	-0.001	-0.001	50.905	0.001
OFSS	10	0.113	0.054	310.37	0.000	0.118	0.042	342.22	0.000
	24	0.001	-0.014	325.81	0.000	-0.002	-0.017	358.00	0.000
INFOSYSTCH	10	-0.003	-0.003	29.649	0.001	-0.001	0.000	27.741	0.001
	24	0.002	-0.002	30.414	0.005	0.001	-0.005	28.456	0.002
PATNI	10	0.223	0.150	454.60	0.000	0.118	0.080	173.38	0.000
	24	0.151	0.081	687.43	0.000	0.051	0.018	211.23	0.000
POLARIS	10	0.038	-0.030	186.62	0.000	0.037	-0.030	206.01	0.000
	24	-0.005	-0.017	194.12	0.000	-0.008	-0.027	212.89	0.000
TCS	10	-0.003	-0.003	40.405	0.000	-0.003	-0.004	38.362	0.000
	24	-0.004	-0.003	40.504	0.003	-0.004	-0.003	38.452	0.005
WIPRO	10	-0.005	-0.006	49.232	0.000	-0.005	-0.006	50.664	0.000
	24	0.003	0.005	49.423	0.002	0.003	0.004	50.867	0.001
7. Industry Group: Oil & Gas									
BONGAIREFN	10	0.033	-0.020	265.68	0.000	0.035	-0.001	229.68	0.000
	24	0.003	0.014	277.02	0.000	0.105	0.041	178.43	0.000
BPCL	10	0.096	0.044	142.38	0.000	0.015	-0.041	273.52	0.000
	24	0.020	-0.037	228.84	0.000	0.015	-0.041	273.52	0.000
ESSAROIL	10	0.048	0.036	208.10	0.000	0.049	0.034	210.01	0.000
	24	0.053	0.046	249.30	0.000	0.052	0.042	256.16	0.000
GAIL	10	0.016	0.015	38.997	0.000	0.016	0.016	46.049	0.000
	24	0.002	-0.020	88.515	0.000	0.005	-0.018	96.639	0.000
HINDPETRO	10	0.047	0.003	140.82	0.000	0.066	0.012	174.17	0.000
	24	0.043	0.022	205.93	0.000	0.049	0.010	280.46	0.000
IOC	10	0.051	0.007	214.81	0.000	0.064	0.011	252.93	0.000
	24	0.032	-0.026	269.70	0.000	0.024	-0.045	337.42	0.000
MRPL	10	0.007	-0.024	162.17	0.000	0.007	-0.026	176.57	0.000
	24	0.019	0.011	183.99	0.000	0.026	0.016	203.92	0.000
ONGC	10	-0.001	-0.000	44.937	0.000	-0.004	-0.003	37.950	0.000
	24	-0.013	-0.012	46.165	0.004	-0.003	-0.002	38.362	0.001
RELIANCE	10	0.048	0.034	30.358	0.001	0.046	0.034	28.605	0.001
	24	0.020	0.006	36.521	0.006	0.012	0.000	36.531	0.003
8. Industry Group: Pharmaceuticals									
	10	0.036	-0.024	270.48	0.000	0.056	-0.000	273.20	0.000

AUROPHARMA	24	0.008	-0.082	391.93	0.000	-0.007	-0.110	395.41	0.000
CIPLA	10	-0.000	-0.001	45.007	0.000	-0.000	-0.001	43.595	0.000
	24	0.002	0.003	45.058	0.006	0.002	0.002	43.652	0.008
DABUR	10	-0.004	-0.004	38.476	0.000	-0.004	-0.004	38.476	0.000
	24	-0.007	-0.006	38.736	0.007	-0.002	0.001	45.831	0.005
DIVISLAB	10	-0.002	-0.002	41.406	0.000	0.444	0.444	198.85	0.000
	24	0.001	0.002	41.436	0.002	-0.002	0.001	198.90	0.000
DRREDDY	10	-0.001	-0.001	42.112	0.000	-0.001	0.000	42.098	0.000
	24	-0.003	-0.001	42.222	0.002	-0.004	-0.003	42.239	0.006
GLAXO	10	0.044	-0.027	206.78	0.000	0.051	-0.038	204.17	0.000
	24	-0.008	-0.014	299.13	0.000	-0.007	-0.029	293.02	0.000
MATRIXLABS	10	0.027	-0.010	149.17	0.000	0.002	-0.017	164.32	0.000
	24	0.007	0.008	219.40	0.000	0.008	0.014	239.82	0.000
ORCHIDCHEM	10	0.021	0.016	51.849	0.000	0.026	0.021	47.800	0.000
	24	0.058	0.048	91.326	0.000	0.069	0.057	76.912	0.000
PIRHEALTH	10	0.227	-0.012	51.066	0.000	-0.001	-0.159	41.003	0.000
	24	0.060	0.053	53.843	0.000	0.002	-0.083	41.009	0.008
RANBAXY	10	-0.003	-0.002	28.260	0.002	0.020	0.006	21.502	0.000
	24	-0.005	-0.004	28.411	0.005	0.001	-0.008	21.503	0.001
STAR	10	0.036	0.028	96.401	0.000	0.034	0.028	144.51	0.000
	24	-0.004	0.009	99.234	0.000	-0.008	0.006	148.10	0.000
SUNPHARMA	10	0.003	-0.045	158.43	0.000	0.019	-0.016	118.11	0.000
	24	0.025	0.007	171.25	0.000	0.041	-0.006	153.79	0.000
WOCKPHARMA	10	0.108	0.093	194.91	0.000	0.072	0.053	213.28	0.000
	24	0.138	0.145	262.24	0.000	0.099	0.105	268.11	0.000
9. Industry Group: Power									
CESC	10	0.087	0.074	149.37	0.000	0.086	0.070	130.98	0.000
	24	0.010	0.010	210.32	0.000	0.012	0.008	191.04	0.000
CUMMINSIND	10	0.004	-0.002	77.127	0.000	-0.029	-0.034	76.781	0.000
	24	-0.005	0.010	88.223	0.000	-0.004	0.016	94.566	0.000
JPHYDRO	10	0.023	-0.016	135.28	0.000	0.024	-0.017	133.95	0.000
	24	-0.001	-0.017	172.06	0.000	0.005	-0.014	177.17	0.000
NEYVELILIG	10	0.003	-0.029	234.42	0.000	0.006	-0.034	257.81	0.000
	24	0.030	0.032	261.54	0.000	0.030	0.030	288.01	0.000
NTPC	10	0.103	0.015	268.02	0.000	0.108	0.021	265.25	0.000
	24	0.045	0.010	374.47	0.000	0.058	0.013	404.51	0.000
RELINFRA	10	0.116	0.054	229.01	0.000	0.127	0.059	256.13	0.000
	24	0.047	-0.032	441.23	0.000	0.053	-0.030	493.28	0.000
TATAPOWER	10	0.079	-0.009	436.75	0.000	0.089	0.001	443.92	0.000
	24	-0.010	-0.020	486.98	0.000	-0.017	-0.022	501.69	0.000
10. Industry Group: Steel									
JINDALSTEL	10	-0.003	-0.002	47.263	0.000	-0.003	-0.002	45.138	0.000
	24	-0.003	-0.002	47.365	0.003	-0.003	-0.002	45.235	0.005
JSL	10	-0.033	-0.084	274.60	0.000	-0.000	-0.085	251.38	0.000
	24	-0.001	-0.016	303.12	0.000	-0.004	-0.076	567.96	0.000

MAHSEAMLES	10	-0.005	-0.004	57.121	0.000	0.003	0.000	55.970	0.000
	24	-0.000	-0.005	57.483	0.000	0.007	-0.009	57.818	0.000
TATASTEEL	10	0.156	0.018	570.47	0.000	0.164	0.019	638.68	0.000
	24	0.063	-0.033	876.75	0.000	0.062	-0.031	946.87	0.000
11. Industry Group: Textiles									
ALOKTEXT	10	0.062	0.020	142.38	0.000	0.077	0.023	156.12	0.000
	24	0.044	-0.013	241.55	0.000	0.047	-0.017	238.07	0.000
ARVIND	10	0.002	-0.016	251.90	0.000	0.005	-0.010	276.86	0.000
	24	0.044	0.053	278.37	0.000	0.040	0.049	300.95	0.000
CENTURYTEX	10	0.043	-0.010	175.31	0.000	0.042	-0.003	167.65	0.000
	24	0.053	0.004	322.19	0.000	0.046	0.005	307.74	0.000
SRF	10	-0.003	0.017	165.22	0.000	-0.008	0.005	166.70	0.000
	24	-0.006	0.003	184.47	0.000	-0.007	0.001	185.72	0.000

Notes: Q(10) and Q(24) represents Ljung-Box (1978) Q-statistics for the Standardized Squared Residuals obtained from VEC Model. They test for existence of autocorrelation in Standardized Squared Residual up to 10 and 24 lags respectively. L-Jung-Box test statistic tests the null hypothesis of absence of autocorrelation.

Table 6.3
Estimates of the DVEC-GARCH Model

Name of the Stocks		c_{ss}	c_{sf}	c_{ff}	α_{ss}	α_{sf}	α_{ff}	β_{ss}	β_{sf}	β_{ff}
Industry Group: Automobiles										
ASHOKLEY	Coefficient	0.00015	0.000152	0.000160	0.69701	0.69058	0.68205	0.15295	0.15998	0.16776
	Std. Error	0.000008*	0.000007*	0.000007*	0.005566*	0.003083*	0.003833*	0.001731*	0.000390*	0.001780*
ESCORTS	Coefficient	0.00199	0.00202	0.00207	0.42043	0.41124	0.40113	0.25176	0.25507	0.26093
	Std. Error	0.00003*	0.000041*	0.000049*	0.009948*	0.00973*	0.010031*	0.03935*	0.038944*	0.039086*
HEROHONDA	Coefficient	0.00003	0.00002	0.00002	0.87478	0.88099	0.89064	0.06473	0.06799	0.07147
	Std. Error	0.000006*	0.000004*	0.000003*	0.01690*	0.01320*	0.01035*	0.00903*	0.00859*	0.00822*
M&M	Coefficient	0.00111	0.00094	0.00068	0.15099	0.27399	0.47313	0.06349	0.06023	0.05714
	Std. Error	0.000094*	0.000069*	0.000046*	0.068711**	0.051528*	0.035510*	0.011482*	0.011158*	0.011779*
MARUTI	Coefficient	0.00019	0.00022	0.00026	0.58352	0.51283	0.44104	0.12548	0.14406	0.17051
	Std. Error	0.000023*	0.000023*	0.000024*	0.042566*	0.041158*	0.040502*	0.019880*	0.021137*	0.023055*
TATAMOTORS	Coefficient	0.00003	0.00003	0.00003	0.85977	0.86370	0.86708	0.10058	0.09904	0.09920
	Std. Error	0.000005*	0.000005*	0.000004*	0.011722*	0.011014*	0.010536*	0.010378*	0.009766*	0.009588*
TVSMOTOR	Coefficient	0.00199	0.00202	0.00207	0.42043	0.41124	0.40113	0.25176	0.25507	0.26093
	Std. Error	0.000034*	0.000041*	0.000049*	0.009948*	0.009733*	0.010031*	0.039353*	0.038944*	0.039086*
Industry Group: Bank										
ALBK	Coefficient	0.00003	0.00003	0.00003	0.87199	0.87324	0.87627	0.08723	0.08390	0.08097
	Std. Error	0.000004*	0.000003*	0.000003*	0.009181*	0.008942*	0.009058*	0.006821*	0.006925*	0.007121*
ANDHRABANK	Coefficient	0.000073	0.000075	0.000078	0.79625	0.79291	0.79082	0.11434	0.11445	0.11547
	Std. Error	0.000009*	0.000010*	0.000011*	0.018716*	0.019380*	0.020305*	0.012582*	0.012733*	0.013121*
AXISBANK	Coefficient	0.00599	0.00597	0.00591	0.01236	0.01018	0.01386	0.07457	0.07550	0.07644
	Std. Error	0.000034*	0.000013*	0.000031*	0.001581*	0.001204*	0.001476*	0.002832*	0.000195*	0.002902*
BANKBARODA	Coefficient	0.000069	0.000068	0.000068	0.84026	0.84337	0.84603	0.09705	0.09509	0.09401
	Std. Error	0.000011*	0.0000111*	0.000010*	0.018526*	0.017219*	0.016172*	0.013646*	0.013237*	0.013057*
BANKINDIA	Coefficient	0.00027	0.00026	0.00025	0.630803	0.63356	0.63552	0.16612	0.16683	0.16872
	Std. Error	0.000033*	0.0000336*	0.0000338*	0.032294*	0.033626*	0.035141*	0.019198*	0.019746*	0.020542*

CANBK	Coefficient	0.00019	0.00018	0.00017	0.66228	0.67930	0.69017	0.18022	0.17172	0.16941
	Std. Error	0.000021*	0.000020*	0.0000206*	0.022449*	0.022263*	0.022145*	0.016943*	0.016527*	0.016368*
CORPBANK	Coefficient	0.00011	0.000115	0.00012	0.74889	0.74268	0.73361	0.18678	0.18713	0.19239
	Std. Error	0.000012*	0.0000126*	0.000013*	0.013424*	0.013344*	0.014258*	0.012124*	0.010742*	0.010720*
FEDERALBNK	Coefficient	0.00053	0.00052	0.00054	0.10179	0.12001	0.12413	0.39653	0.34024	0.32769
	Std. Error	0.000023*	0.000025*	0.000030*	0.011692*	0.017477*	0.023916*	0.026710*	0.024289*	0.022948*
HDFCBANK	Coefficient	0.00759	0.00192	0.00016	0.99061	0.49519	0.95624	0.00020	0.00119	0.00001
	Std. Error	0.00002*	0.00095**	0.00003*	0.003923*	0.249653**	0.008543*	0.000107**	0.000556*	0.000164
ICICIBANK	Coefficient	0.00057	0.00063	0.00071	0.53310	0.51020	0.48561	0.37111	0.39038	0.41291
	Std. Error	0.000027*	0.000028*	0.000029*	0.006499*	0.006889*	0.007846*	0.008715*	0.009692*	0.011446*
IDBI	Coefficient	0.00189	0.00207	0.00252	0.17466	0.08909	0.03909	0.03666	0.04336	0.04768
	Std. Error	0.000235*	0.000135*	0.000158*	0.101245	0.053428	0.047208	0.011239*	0.010556*	0.010762*
INDUSINDBK	Coefficient	0.00053	0.000536	0.00054	0.49938	0.50036	0.50025	0.15988	0.16298	0.16752
	Std. Error	0.000094*	0.000093*	0.000092*	0.073407*	0.070760*	0.068406*	0.023323*	0.023244*	0.023408*
IOB	Coefficient	0.00139	0.00133	0.00128	0.05180	0.06403	0.08426	0.50403	0.48230	0.46441
	Std. Error	0.000048*	0.000051*	0.000054*	0.025521**	0.025843**	0.027033*	0.056043*	0.054387*	0.053183*
J&KBANK	Coefficient	0.00332	0.00317	0.00309	0.40077	0.43079	0.45350	0.21000	0.17888	0.16658
	Std. Error	0.000054*	0.000036*	0.000077*	0.009647*	0.001183*	0.007248*	0.013433*	0.008928*	0.007093*
KTKBANK	Coefficient	0.00052	0.00053	0.00056	0.27866	0.27649	0.27069	0.47053	0.44326	0.43077
	Std. Error	0.000034*	0.0000341*	0.000035*	0.026200*	0.024640*	0.024589*	0.042070*	0.040326*	0.037792*
ORIENTBANK	Coefficient	0.00037	0.00043	0.00050	0.52127	0.46282	0.39341	0.11610	0.12716	0.14480
	Std. Error	0.000026*	0.000028*	0.000032*	0.025426*	0.025702*	0.026494*	0.018902*	0.019397*	0.020136*
PNB	Coefficient	0.00005	0.00006	0.00007	0.86192	0.85520	0.84782	0.18435	0.18418	0.18438
	Std. Error	0.000009*	0.000010*	0.000011*	0.008574*	0.008783*	0.009258*	0.016901*	0.016803*	0.016908*
SBIN	Coefficient	0.00005	0.000050	0.00004	0.82206	0.82628	0.82990	0.15797	0.15502	0.1528
	Std. Error	0.000007*	0.000006*	0.0000069*	0.013366*	0.012569*	0.012104*	0.017073*	0.016311*	0.015805*
SYNDIBANK	Coefficient	0.00189	0.00184	0.00181	0.59920	0.60962	0.61789	0.26040	0.25087	0.24460
	Std. Error	0.000144*	0.000141*	0.0001418*	0.027819*	0.027528*	0.027968*	0.030652*	0.029393*	0.028551*
UNIONBANK	Coefficient	0.00022	0.00023	0.00024	0.62725	0.62146	0.62134	0.17327	0.16849	0.16296
	Std. Error	0.000007*	0.000008*	0.000009*	0.003277*	0.000194*	0.003828*	0.001448*	0.000390*	0.001708*
	Coefficient	0.00033	0.00027	0.00043	0.39903	0.38450	0.30037	0.24548	0.21780	0.24542

VIJAYABANK	Std. Error	0.000030*	0.000020*	0.000033*	0.044102*	0.034098*	0.041644*	0.027259*	0.024868*	0.028092*
Industry Group: Cement										
ACC	Coefficient	0.000041	0.000042	0.000045	0.84720	0.84530	0.842549	0.11025	0.11194	0.114281
	Std. Error	0.0000037*	0.0000034*	0.0000035*	0.00946*	0.00853*	0.008195*	0.010259*	0.010077*	0.010264*
GRASIM	Coefficient	0.000055	0.000054	0.000056	0.795871	0.798565	0.799988	0.112144	0.110866	0.110398
	Std. Error	0.0000081*	0.0000080*	0.0000083*	0.019915*	0.018884*	0.018386*	0.013356*	0.012641*	0.012261*
INDIACEM	Coefficient	0.000458	0.000452	0.000449	0.53258	0.545481	0.558944	0.172128	0.164211	0.157300
	Std. Error	0.000058*	0.000056*	0.000055*	0.042665*	0.042076*	0.041492*	0.024277*	0.023822*	0.023518*
Industry Group: Electrical Equipments										
ABB	Coefficient	0.002824	0.002676	0.002379	0.029940	0.084293	0.192616	0.091681	0.103641	0.121783
	Std. Error	0.000022*	0.000041*	0.000071*	0.007622*	0.01363*	0.024708*	0.029984*	0.030008*	0.030490*
BHEL	Coefficient	0.000519	0.000529	0.000547	0.26106	0.24055	0.220985	0.383494	0.413795	0.447734
	Std. Error	0.0000097*	0.0000094*	0.000011*	0.017416*	0.015411*	0.014055*	0.02664*	0.02590*	0.02533*
SIEMENS	Coefficient	0.000550	0.000568	0.000590	0.39879	0.39731	0.395546	0.905430	0.856616	0.81273
	Std. Error	0.000030*	0.000033*	0.000036*	0.005368*	0.003235*	0.003867*	0.046617*	0.04571*	0.045901*
SUZLON	Coefficient	0.003586	0.003391	0.003196	0.229308	0.273783	0.319679	0.107502	0.10488	0.104798
	Std. Error	0.000058*	0.000053*	0.000087*	0.012194*	0.013508*	0.020880*	0.015159*	0.015407*	0.01604*
Industry Group: Fertilizers										
CHAMBLFERT	Coefficient	0.000117	0.000114	0.000118	0.687744	0.69017	0.691207	0.243696	0.242465	0.242317
	Std. Error	0.0000123*	0.0000122*	0.0000126*	0.015290*	0.015414*	0.015849*	0.016468*	0.016816*	0.01730*
GNFC	Coefficient	0.000256	0.000283	0.000318	0.504147	0.478213	0.450815	0.287371	0.295183	0.304584
	Std. Error	0.000022*	0.000023*	0.000024*	0.028645*	0.027743*	0.026885*	0.022234*	0.023177*	0.024554*
NAGARFERT	Coefficient	0.000025	0.000024	0.000026	0.895766	0.891518	0.886626	0.078102	0.083356	0.088809
	Std. Error	0.0000049*	0.0000044*	0.0000043*	0.01066*	0.01082*	0.011401*	0.008974*	0.009469*	0.010234*
TATACHEM	Coefficient	0.0000301	0.0000309	0.0000339	0.837635	0.831628	0.821890	0.12761	0.134729	0.146797
	Std. Error	0.0000043*	0.0000042*	0.0000046*	0.011033*	0.010239*	0.010050*	0.0114864*	0.011026*	0.010992*
Industry Group: Information Technology (IT)										
HCLTECH	Coefficient	0.000648	0.000654	0.000669	0.545722	0.524633	0.501064	0.144775	0.173895	0.21442
	Std. Error	0.000029*	0.000025*	0.000026*	0.019136*	0.016339*	0.016193*	0.016963*	0.017700*	0.018681*
OFSS	Coefficient	0.000338	0.000334	0.000336	0.465719	0.46100	0.45436	0.23642	0.23874	0.24355
	Std. Error	0.000038*	0.000037*	0.000036*	0.046471*	0.045436*	0.044472*	0.022992*	0.022838*	0.023062*

INFOSYSTCH	Coefficient	0.000013	0.000014	0.000017	0.71396	0.709680	0.705026	0.34792	0.338369	0.330106
	Std. Error	0.0000023*	0.0000022*	0.0000024*	0.00118*	0.00053*	0.00148*	0.01377*	0.01469*	0.015490*
PATNI	Coefficient	1.37929e-06	1.50396e-06	8.98433e-06	0.87479	0.87683	0.87155	0.14018	0.13827	0.14142
	Std. Error	3.00720e-07*	4.98422e-07*	1.73203e-06*	0.00875*	0.00751*	0.00810*	0.01221*	0.01017*	0.01105*
POLARIS	Coefficient	0.000369	0.000390	0.000412	0.60942	0.59974	0.59323	0.14985	0.15458	0.15959
	Std. Error	0.000032*	0.000034*	0.000037*	0.02071*	0.02159*	0.02242*	0.01479*	0.01503*	0.01539*
TCS	Coefficient	0.00081	0.00076	0.00071	0.23922	0.28620	0.34196	0.16366	0.129426	0.102414
	Std. Error	0.000058*	0.000063*	0.000074*	0.05253*	0.05801*	0.06792*	0.03282*	0.02969*	0.026593*
WIPRO	Coefficient	0.00056	0.00057	0.00059	0.53523	0.52363	0.51145	0.12949	0.14864	0.17112
	Std. Error	0.000015*	0.000013*	0.000015*	0.01283*	0.01115*	0.01259*	0.020293*	0.020773*	0.02153*
Industry Group: Oil & Gas										
BONGAIREFN	Coefficient	0.000724	0.000659	0.000612	0.18915	0.23530	0.29070	0.69706	0.619099	0.552831
	Std. Error	0.000020*	0.000018*	0.000017*	0.014262*	0.014050*	0.013578*	0.035083*	0.029911*	0.026052*
BPCL	Coefficient	0.000027	0.000025	0.000026	0.89576	0.891518	0.886626	0.078102	0.083356	0.088809
	Std. Error	0.0000049*	0.0000044*	0.0000043*	0.010666*	0.01082*	0.011401*	0.008974*	0.009469*	0.010234*
ESSAROIL	Coefficient	0.000355	0.000365	0.000379	0.54767	0.54834	0.54682	0.333519	0.330059	0.331070
	Std. Error	0.000025*	0.000026*	0.000027*	0.01404*	0.01314*	0.01243*	0.01727*	0.01656*	0.01620*
GAIL	Coefficient	0.000127	0.000129	0.000136	0.67575	0.66928	0.66264	0.21326	0.21876	0.22454
	Std. Error	0.0000097*	0.0000098*	0.000010*	0.01258*	0.01323*	0.01512*	0.01053*	0.01093*	0.01255*
HINDPETRO	Coefficient	0.000109	0.000107	0.000108	0.69683	0.695843	0.692840	0.199604	0.201239	0.204188
	Std. Error	0.000015*	0.000014*	0.000013*	0.023603*	0.02281*	0.02278*	0.01511*	0.01480*	0.01504*
IOC	Coefficient	0.000109	0.000107	0.000109	0.69683	0.695843	0.692840	0.199604	0.20123	0.20418
	Std. Error	0.000015*	0.000014*	0.000014*	0.023603*	0.022815*	0.022785*	0.015115*	0.01480*	0.015044*
MRPL	Coefficient	0.000239	0.000251	0.000268	0.579801	0.574892	0.56962	0.233040	0.23385	0.23519
	Std. Error	0.000024*	0.000025*	0.000027*	0.02648*	0.02583*	0.02544*	0.02019*	0.019399*	0.01869*
ONGC	Coefficient	0.000213	0.000208	0.000215	0.68244	0.69280	0.697560	0.08145	0.07915	0.08070
	Std. Error	0.000034*	0.000036*	0.000041*	0.05086*	0.05308*	0.056212*	0.013627*	0.01436*	0.01604*
RELIANCE	Coefficient	0.000121	0.000120	0.000120	0.60062	0.60049	0.600543	0.21879	0.22043	0.22210
	Std. Error	0.0000134*	0.0000132*	0.0000133*	0.021310*	0.020621*	0.020286*	0.008781*	0.008076*	0.007648*
Industry Group: Pharmaceuticals										
	Coefficient	0.000051	0.000057	0.000062	0.82820	0.81988	0.815958	0.12711	0.128875	0.13093

AUROPHARMA	Std. Error	0.0000071*	0.0000077*	0.0000086*	0.013317*	0.014682*	0.016124*	0.011191*	0.011926*	0.012985*
	Coefficient	0.000436	0.000498	0.000560	0.72406	0.68692	0.652262	0.053229	0.066228	0.082276
CIPLA	Std. Error	0.000038*	0.000044*	0.000051*	0.02162*	0.024218*	0.027594*	0.00461*	0.004148*	0.003883*
	Coefficient	0.000495	0.000561	0.000635	0.63345	0.567750	0.50437	0.08212	0.105074	0.13705
DABUR	Std. Error	0.000011*	0.000004*	0.000011*	0.008102*	0.003858*	0.00642*	0.00892*	0.01077*	0.014227*
	Coefficient	0.0001003	0.000102	0.000109	0.691458	0.680836	0.667850	0.170205	0.17556	0.183182
DIVISLAB	Std. Error	0.0000124*	0.0000125*	0.0000133*	0.028711*	0.028310*	0.028312*	0.020025*	0.019197*	0.018359*
	Coefficient	0.000055	0.000063	0.000072	0.86192	0.855200	0.84782	0.18435	0.18418	0.184388
DRREDDY	Std. Error	0.0000091*	0.0000101*	0.0000109*	0.00857*	0.008783*	0.009258*	0.016901*	0.016803*	0.016908*
	Coefficient	0.000034	0.000038	0.000044	0.754377	0.735601	0.72177	0.181039	0.192453	0.209574
GLAXO	Std. Error	0.0000037*	0.0000038*	0.0000046*	0.01412*	0.01419*	0.01660*	0.01297*	0.012064*	0.014168*
	Coefficient	0.000338	0.000344	0.000356	0.465719	0.461000	0.454366	0.236420	0.238749	0.243558
MATRIXLABS	Std. Error	0.000038*	0.000037*	0.000036*	0.046471*	0.04543*	0.04447*	0.022992*	0.022838*	0.02306*
	Coefficient	0.000595	0.000590	0.000592	0.382431	0.393473	0.403221	0.421834	0.41717	0.415778
ORCHIDCHEM	Std. Error	0.000015*	0.000014*	0.000015*	0.01372*	0.01240*	0.01169*	0.02202*	0.02105*	0.02053*
	Coefficient	0.002197	0.00223	0.00305	0.36735	0.33068	0.30064	0.12309	0.09612	0.07457
PIRHEALTH	Std. Error	0.00022*	0.00018*	0.00029*	0.06419*	0.04419*	0.04205*	0.02868*	0.01234*	0.00514*
	Coefficient	0.000398	0.000388	0.000412	0.71833	0.72465	0.724991	0.01542	0.01514	0.01478
RANBAXY	Std. Error	0.000132*	0.000077*	0.000083*	0.093511*	0.055938*	0.058928*	0.005529*	0.004903*	0.006159**
	Coefficient	0.000109	0.000107	0.000109	0.696833	0.695843	0.692840	0.199604	0.201239	0.204188
STAR	Std. Error	0.000015*	0.000014*	0.000014*	0.023603*	0.022815*	0.02278*	0.015115*	0.014809*	0.015044*
	Coefficient	0.000114	0.000100	0.000099	0.550985	0.587463	0.601125	0.271122	0.227407	0.213249
SUNPHARMA	Std. Error	0.000010*	0.000007*	0.000007*	0.007542*	0.000304*	0.008502*	0.026094*	0.021503*	0.019225*
	Coefficient	0.005740	0.005854	0.006365	0.183543	0.16298	0.08622	0.05694	0.052311	0.128719
WOCKPHARMA	Std. Error	0.00023*	0.00019*	0.00013*	0.03131*	0.02618*	0.01543*	0.01888*	0.01484*	0.013111*
Industry Group: Power										
	Coefficient	0.000562	0.000573	0.000591	0.53523	0.523630	0.511453	0.12949	0.148648	0.171125
CESC	Std. Error	0.000015*	0.000013*	0.000015*	0.012837*	0.011150*	0.012597*	0.020293*	0.020773*	0.021535*
	Coefficient	0.000655	0.000726	0.000804	0.70322	0.67724	0.649525	0.282648	0.30050	0.32340
CUMMINSIND	Std. Error	0.000033*	0.000032*	0.000033*	0.014847*	0.014358*	0.014744*	0.019563*	0.019596*	0.020403*
	Coefficient	0.000033	0.000027	0.000022	0.874786	0.880997	0.890645	0.064732	0.067998	0.071472

JPHYDRO	Std. Error	0.000006*	0.000004*	0.000003*	0.01690*	0.013208*	0.01035*	0.00903*	0.00859*	0.008220*
NEYVELILIG	Coefficient	0.001948	0.002012	0.002073	0.60784	0.59650	0.586247	0.25587	0.258133	0.260526
	Std. Error	0.000267*	0.000265*	0.000266*	0.044526*	0.044042*	0.043992*	0.040892*	0.040061*	0.03946*
NTPC	Coefficient	0.000073	0.000075	0.000079	0.79569	0.79237	0.790312	0.11462	0.11471	0.11572
	Std. Error	0.000009*	0.0000010*	0.0000011*	0.01875*	0.01941*	0.02033*	0.01259*	0.01274*	0.01313*
RELINFRA	Coefficient	0.000469	0.000479	0.000495	0.28899	0.272451	0.255652	0.082328	0.089269	0.096910
	Std. Error	0.0000158*	0.0000162*	0.0000199*	0.02847*	0.02711*	0.029333*	0.009512*	0.010337*	0.011470*
TATAPOWER	Coefficient	0.000611	0.000609	0.000619	0.51217	0.513512	0.509994	0.269135	0.279921	0.295125
	Std. Error	0.000011*	0.000005*	0.000010*	0.005732*	0.003541*	0.007629*	0.022669*	0.022590*	0.022772*
Industry Group: Steel										
JINDALSTEL	Coefficient	0.001314	0.001334	0.001361	0.10369	0.09431	0.085491	0.492932	0.498711	0.506497
	Std. Error	0.000057*	0.000057*	0.000059*	0.003986*	0.00152*	0.002358*	0.018260*	0.014553*	0.011324*
JSL	Coefficient	0.001119	0.000940	0.000680	0.150996	0.273992	0.473131	0.063493	0.060237	0.057146
	Std. Error	0.00009*	0.00006*	0.00004*	0.06871**	0.05152*	0.03551*	0.01148*	0.011158*	0.011779*
MAHSEAMLES	Coefficient	0.000149	0.000136	0.000124	0.793279	0.80956	0.823059	0.412483	0.392802	0.380504
	Std. Error	0.0000078*	0.0000076*	0.0000077*	0.002007*	0.001137*	0.001341*	0.010231*	0.007283*	0.00620*
TATASTEEL	Coefficient	0.0000165	0.0000170	0.0000174	0.85506	0.85583	0.85611	0.201491	0.19962	0.199286
	Std. Error	0.0000038*	0.0000037*	0.0000037*	0.00630*	0.00602*	0.00612*	0.012456*	0.012176*	0.01237*
Industry Group: Textiles										
ALOKTEXT	Coefficient	0.015669	0.014801	0.013713	0.15113	0.196407	0.254274	0.342250	0.348293	0.35836
	Std. Error	0.000333*	0.000305*	0.000313*	0.01596*	0.015968*	0.015685*	0.01676*	0.036722*	0.03634*
ARVIND	Coefficient	0.018293	0.021223	0.022329	0.13486	0.32481	0.401325	0.07084	0.06783	0.07716
	Std. Error	0.000317*	0.000072*	0.000253*	0.025354*	0.023433*	0.031791*	0.011917*	0.012844*	0.01470*
CENTURYTEX	Coefficient	0.000325	0.000336	0.000349	0.540071	0.534392	0.52890	0.39090	0.397397	0.40418
	Std. Error	0.000036*	0.000037*	0.000038*	0.025139*	0.024774*	0.024693*	0.020015*	0.019485*	0.01924*
SRF	Coefficient	0.000325	0.000336	0.000349	0.540071	0.534392	0.528902	0.390904	0.397397	0.404182
	Std. Error	0.000036*	0.000037*	0.000038*	0.025139*	0.024774*	0.024693*	0.020015*	0.019485*	0.019247*
Notes: * (**) – indicates significance at one and five per cent level, respectively.										

Table 6.4
Optimal Hedging Effectiveness Comparison for the In-Sample Period

S. No.	Name of the Stocks	OLS	VECM	MGARCH
1. Industry Group: Automobiles				
1.	ASHOKLEY	0.959695 [H]	0.959582178	0.95916 [L]
2.	ESCORTS	0.978138 [L]	0.998101894	0.99217 [H]
3.	HEROHONDA	0.885323	0.874840539 [L]	0.89573 [H]
4.	M&M	0.961968	0.961894076 [L]	0.97054 [H]
5.	MARUTI	0.944199	0.943970048 [L]	0.95920 [H]
6.	TATAMOTORS	0.948746	0.948596803 [L]	0.95284 [H]
7.	TVSMOTOR	0.971959 [L]	0.972612544	0.98821 [H]
2. Industry Group: Bank				
8.	ALBK	0.958705 [H]	0.958661075	0.95326 [L]
9.	ANDHRABANK	0.954276	0.953736774 [L]	0.95722 [H]
10.	AXISBANK	0.9636457	0.963646096 [L]	0.99124 [H]
11.	BANKBARODA	0.959782	0.959771959 [L]	0.96957 [H]
12.	BANKINDIA	0.975156	0.97510849 [L]	0.98121 [H]
13.	CANBK	0.946557	0.94651407 [L]	0.96223 [H]
14.	CORPBANK	0.873815	0.87128427 [L]	0.94421 [H]
15.	FEDERALBNK	0.905606	0.903728283 [L]	0.94453 [H]
16.	HDFCBANK	0.958925	0.958918202 [L]	0.96842 [H]
17.	ICICIBANK	0.967100	0.967032041 [L]	0.96934 [H]
18.	IDBI	0.862522	0.862464792 [L]	0.89724 [H]
19.	INDUSINDBK	0.982918	0.982884219 [L]	0.98702 [H]
20.	IOB	0.962618	0.962579561 [L]	0.96567 [H]
21.	J&KBANK	0.696556	0.490744499 [L]	0.82789 [H]
22.	KTKBANK	0.950258 [L]	0.996124768 [H]	0.96329
23.	ORIENTBANK	0.963148	0.963127238 [L]	0.97455 [H]
24.	PNB	0.9688691	0.96886929 [L]	0.97897 [H]
25.	SBIN	0.977846	0.977776089 [L]	0.98372 [H]
26.	SYNDIBANK	0.959882	0.959881626 [L]	0.97587 [H]
27.	UNIONBANK	0.966135	0.966130102 [L]	0.97197 [H]
28.	VIJAYABANK	0.491955	0.476184845 [L]	0.55831 [H]
3. Industry Group: Cement				
29.	ACC	0.960301	0.959414599 [L]	0.96173 [H]
30.	GRASIM	0.968585 [H]	0.96735212	0.96268 [L]
31.	INDIACEM	0.983840 [H]	0.983635942	0.97377 [L]
4. Industry Group: Electrical Equipments				
32.	ABB	0.985696	0.986227598 [H]	0.97918 [L]
33.	BHEL	0.979252	0.978966032 [L]	0.98305 [H]
34.	SIEMENS	0.994079	0.993146126 [L]	0.99432 [H]
35.	SUZLON	0.993832	0.993780975 [L]	0.99623 [H]
5. Industry Group: Fertilizers				
36.	CHAMBLFERT	0.980591 [H]	0.976956724	0.95095 [L]

37.	GNFC	0.968998	0.951603088 L	0.97216 H
38.	NAGARFERT	0.988010 H	0.98789166	0.987689 L
39.	TATACHEM	0.920205 H	0.917514376	0.91057 L
6. Industry Group: Information Technology (IT)				
40.	HCLTECH	0.951744	0.951351197 L	0.96983 H
41.	OFSS	0.950244	0.9502429 L	0.97032 H
42.	INFOSYSTCH	0.883644 H	0.883629236	0.76094 L
43.	PATNI	0.175894	0.175698825 L	0.18501 H
44.	POLARIS	0.988317	0.988249814 L	0.99026 H
45.	TCS	0.982477	0.982433574 L	0.98598 H
46.	WIPRO	0.971188	0.971034796 L	0.98349 H
7. Industry Group: Oil & Gas				
47.	BONGAIREFN	0.939397 H	0.936916221	0.90686 L
48.	BPCL	0.943713	0.943408786 L	0.95086 H
49.	ESSAROIL	0.983307 H	0.983290813	0.98255 L
50.	GAIL	0.940330 H	0.940262691	0.93557 L
51.	HINDPETRO	0.883138	0.881844687 L	0.93260 H
52.	IOC	0.959455 H	0.959454141	0.95820 L
53.	MRPL	0.986196 H	0.986186695	0.98350 L
54.	ONGC	0.929830	0.929390774 L	0.94913 H
55.	RELIANCE	0.988637 H	0.988614522	0.98371 L
8. Industry Group: Pharmaceuticals				
56.	AUROPHARMA	0.937095	0.937093668 L	0.95432 H
57.	CIPLA	0.980178	0.980161622 L	0.98869 H
58.	DABUR	0.935021	0.934848942 L	0.95985 H
59.	DIVISLAB	0.242409 H	0.234409366	0.10642 L
60.	DRREDDY	0.962984	0.962981261 L	0.97259 H
61.	GLAXO	0.749745	0.743491091 L	0.84288 H
62.	MATRIXLABS	0.861440	0.820429498 L	0.90690 H
63.	PIRHEALTH	0.162185	0.161071 L	0.17042 H
64.	ORCHIDCHEM	0.962854	0.96280416 L	0.97605 H
65.	RANBAXY	0.928330	0.927930209 L	0.93854 H
66.	STAR	0.885300	0.880951905 L	0.93260 H
67.	SUNPHARMA	0.884924	0.884755845 L	0.90596 H
68.	WOCKPHARMA	0.944938	0.941423969 L	0.96428 H
9. Industry Group: Power				
69.	CESC	0.958977	0.956770915 L	0.96441 H
70.	CUMMINSIND	0.888852	0.878082677 L	0.94628 H
71.	JPHYDRO	0.987127 H	0.985880719	0.98374 L
72.	NEYVELILIG	0.985355 H	0.985132652	0.98474 L
73.	NTPC	0.964125 H	0.963280557	0.95892 L
74.	RELINFRA	0.985178 H	0.984436452	0.98286 L
75.	TATAPOWER	0.946228 H	0.944664148	0.93767 L
10. Industry Group: Steel				
76.	JINDALSTEL	0.996705 H	0.994913195	0.98468 L

77.	JSL	0.102432[H]	0.099072561	0.04780[L]
78.	MAHSEAMLES	0.990837[H]	0.943442[L]	0.95209
79.	TATASTEEL	0.980646[L]	0.998781245[H]	0.98130
11. Industry Group: Textiles				
80.	ALOKTEXT	0.958308	0.956495738[L]	0.95942[H]
81.	ARVIND	0.983422	0.983231678[L]	0.98619[H]
82.	CENTURYTEX	0.989596	0.989479685[L]	0.99069[H]
83.	SRF	0.975464[L]	0.975515993	0.97731[H]
Note: [H] Highest variance reduction and [L] Lowest variance reduction				

Table 6.5
Optimal Hedging Effectiveness Comparison for the Out-of-Sample Period

S. No.	Name of the Stocks	OLS	VECM	MGARCH
1. Industry Group: Automobiles				
1.	ASHOKLEY	0.959695[L]	0.96886163	0.968971954[H]
2.	ESCORTS	0.978138[L]	0.99997827	0.999979744[H]
3.	HEROHONDA	0.885323[L]	0.979242154	0.981981936[H]
4.	M&M	0.961968[L]	0.983210338	0.98358329[H]
5.	MARUTI	0.944199[L]	0.981407575	0.981408759[H]
6.	TATAMOTORS	0.948746[L]	0.969989526[H]	0.96998647
7.	TVSMOTOR	0.971959[L]	0.999912582[H]	0.999893452
2. Industry Group: Bank				
8.	ALBK	0.958705[L]	0.987676417[H]	0.987182139
9.	ANDHRABANK	0.954276[H]	0.924964731[L]	0.925051691
10.	AXISBANK	0.963646[H]	0.987285854	0.986567342[L]
11.	BANKBARODA	0.959782[H]	0.957329356[L]	0.957632948
12.	BANKINDIA	0.975156[L]	0.980738113	0.980752149[H]
13.	CANBK	0.946557[H]	0.939471179[L]	0.939868889
14.	CORPBANK	0.873815[L]	0.999102087	0.999683199[H]
15.	FEDERALBNK	0.905606[L]	0.931591584[H]	0.930855918
16.	HDFCBANK	0.958925[L]	0.971173466	0.971381597[H]
17.	ICICIBANK	0.967100[L]	0.985355978	0.985516166[H]
18.	IDBI	0.862522[L]	0.982625797	0.98605543[H]
19.	INDUSINDBK	0.982918[L]	0.993681751	0.993682965[H]
20.	IOB	0.962618[L]	0.985178659[H]	0.985151213
21.	J&KBANK	0.696556[L]	0.71408439	0.719562156[H]
22.	KTKBANK	0.950258[L]	0.99770653[H]	0.993831926
23.	ORIENTBANK	0.963148[H]	0.958025838[L]	0.95813956
24.	PNB	0.968869[H]	0.960072847	0.960068994[L]
25.	SBIN	0.977846[L]	0.980693793	0.980977782[H]
26.	SYNDIBANK	0.959882[L]	0.976646863[H]	0.975656508
27.	UNIONBANK	0.966135[H]	0.929481225[L]	0.929512835
28.	VIJAYABANK	0.491955[L]	0.943330839	0.944239293[H]

3. Industry Group: Cement				
29.	ACC	0.960301 ^{L}	0.970349086 ^{H}	0.967008287
30.	GRASIM	0.968585 ^{L}	0.977829419 ^{H}	0.977795024
31.	INDIACEM	0.983840 ^{L}	0.988362124 ^{H}	0.987334624
4. Industry Group: Electrical Equipments				
32.	ABB	0.965696 ^{L}	0.986843203 ^{H}	0.986722949
33.	BHEL	0.979252 ^{L}	0.991083629	0.991085299 ^{H}
34.	SIEMENS	0.984079 ^{L}	0.985319302	0.986239823 ^{H}
35.	SUZLON	0.993832 ^{L}	0.996457092	0.996457948 ^{H}
5. Industry Group: Fertilizers				
36.	CHAMBLFERT	0.980591 ^{L}	0.990188365 ^{H}	0.989305001
37.	GNFC	0.968998 ^{L}	0.975114402	0.975359207 ^{H}
38.	NAGARFERT	0.988010 ^{L}	0.988610528	0.988613233 ^{H}
39.	TATACHEM	0.920205 ^{L}	0.930596282	0.930678065 ^{H}
6. Industry Group: Information Technology (IT)				
40.	HCLTECH	0.951744 ^{L}	0.988611334	0.988669902 ^{H}
41.	OFSS	0.950244 ^{L}	0.979362221	0.979810932 ^{H}
42.	INFOSYSTCH	0.883644 ^{L}	0.973538741 ^{H}	0.971129407
43.	PATNI	0.175894 ^{L}	0.330615416	0.333917982 ^{H}
44.	POLARIS	0.978317 ^{L}	0.985984427	0.985990278 ^{H}
45.	TCS	0.982477 ^{L}	0.998675597	0.998732083 ^{H}
46.	WIPRO	0.971188 ^{L}	0.974757128 ^{H}	0.974737442
7. Industry Group: Oil & Gas				
47.	BONGAIREFN	0.939397 ^{L}	0.971695142 ^{H}	0.970848333
48.	BPCL	0.943713 ^{L}	0.979327356	0.979418761 ^{H}
49.	ESSAROIL	0.983307 ^{L}	0.988240335	0.988464011 ^{H}
50.	GAIL	0.940330 ^{L}	0.98014737 ^{H}	0.979840105
51.	HINDPETRO	0.883138 ^{L}	0.9825737	0.982649206 ^{H}
52.	IOC	0.959454 ^{L}	0.967971946	0.967919477 ^{H}
53.	MRPL	0.986196 ^{L}	0.992121402 ^{H}	0.991923378
54.	ONGC	0.929830 ^{L}	0.982979435 ^{H}	0.982110199
55.	RELIANCE	0.988637 ^{L}	0.988684671	0.988726215 ^{H}
8. Industry Group: Pharmaceuticals				
56.	AUROPHARMA	0.937095 ^{L}	0.960457968 ^{H}	0.960164065
57.	CIPLA	0.980178 ^{L}	0.980557859	0.980583859 ^{H}
58.	DABUR	0.935021 ^{L}	0.965836181	0.974194065 ^{H}
59.	DIVISLAB	0.242409 ^{L}	0.497534458 ^{H}	0.493314806
60.	DRREDDY	0.962984 ^{L}	0.969757531 ^{H}	0.96974465
61.	GLAXO	0.749745 ^{H}	0.66210466 ^{L}	0.662485866
62.	MATRIXLABS	0.861440 ^{L}	0.8714257 ^{H}	0.87129765
63.	ORCHIDCHEM	0.962854 ^{L}	0.995084179 ^{H}	0.995017969
64.	PIRHEALTH	0.162185 ^{H}	0.09676	0.07945 ^{L}
65.	RANBAXY	0.928330 ^{L}	0.987079314 ^{H}	0.986263223
66.	STAR	0.885300 ^{L}	0.974985441 ^{H}	0.974228725
67.	SUNPHARMA	0.884924 ^{L}	0.976071241 ^{H}	0.975821252

68.	WOCKPHARMA	0.944938 ^{H}	0.893991588 ^{L}	0.900503116
9. Industry Group: Power				
69.	CESC	0.958977 ^{L}	0.983844116	0.983898485 ^{H}
70.	CUMMINSIND	0.888852 ^{L}	0.979165637	0.979272935 ^{H}
71.	JPHYDRO	0.987127 ^{L}	0.994868532 ^{H}	0.994833761
72.	NEYVELILIG	0.985355 ^{L}	0.986771452	0.986855673 ^{H}
73.	NTPC	0.964125 ^{L}	0.975310316 ^{H}	0.975243311
74.	RELINFRA	0.985178 ^{L}	0.994091166	0.994367652 ^{H}
75.	TATAPOWER	0.946228 ^{L}	0.965369251	0.96672604 ^{H}
10. Industry Group: Steel				
76.	JINDALSTEL	0.996705 ^{L}	0.99962685 ^{H}	0.999536544
77.	JSL	0.102432 ^{L}	0.213152014 ^{H}	0.207523989
78.	MAHSEAMLES	0.900837 ^{L}	0.908407355 ^{H}	0.901064435 ^{L}
79.	TATASTEEL	0.980646 ^{H}	0.972321949	0.972289227 ^{L}
11. Industry Group: Textiles				
80.	ALOKTEXT	0.958308 ^{H}	0.997331772	0.996516008 ^{L}
81.	ARVIND	0.983422 ^{H}	0.982805315	0.982733163 ^{L}
82.	CENTURYTEX	0.989596 ^{H}	0.970300199	0.970183591 ^{L}
83.	SRF	0.975464 ^{H}	0.962830588 ^{L}	0.96294448
Note: ^{H} Highest variance reduction and ^{L} Lowest variance reduction				