# Hedging Effectiveness of Stock Index Futures Contracts in the Indian Derivative Markets

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**Abstract**

This paper studies hedging effectiveness in Indian stock index futures market. The main focus is on various procedures to estimate time-varying and static optimal hedge ratios. For the S&P CNX Nifty futures contract 5 different econometric models that are employed. The data set used is from 2001-2008. Traditional OLS regressions, modified OLS viz. LTS , error correction model (ECM), vector error correction model (VECM) and multivariate generalized autoregressive heteroscedastic (M-GARCH) models are used to estimate hedge ratios, not only for mirror index underlying the futures contract but also for mutual funds. It is the first exhaustive study of its kind on the Indian stock index futures market and reveals that mutual funds tend to be a good proxy for market portfolios. Simple OLS seems to provide the best hedging effectiveness in terms of risk reduction for the Indian futures market. However, the use of more complex models like VECM cannot be sublimed as they provide more or less same hedging effectiveness.

**Keywords:** Hedge ratios, OLS, VECM, M-GARCH, Nifty futures.

**JEL Classification:** C01, C22, C51, C53

## 1. Introduction

Futures contract play a very important role in the field of finance and investments today. They expand an investor's opportunity set through the opening of negative correlation not normally found in cash markets. This introduction of futures contracts allowed investors to avoid market risk, which would have not been possible by using cash assets only. Such a technique used by investors to eliminate market risk can be termed as hedging.

The main incentive behind hedging is to reduce/eliminate the variability of profits and firm value that arises from market fluctuations or volatility. In general hedge is the action taken by a buyer or seller to insulate his assets against a change in prices. It is a technique of minimizing uncertain value movements of financial portfolios by mixing a portfolio of risky assets with a position in a financial instrument, which is extremely negatively correlated with the portfolio. Hence, the upward (downward) movement in the value of the portfolio will be off-set by the downward (upward) movement in the value of the hedging instrument i.e. the futures contracts. Futures and options were introduced in the Indian stock market in June 2001, the trading turnover in the introductory year ended with £294.7 million and as reported in 2006-2007 it had crossed £601.1 billion[1]. This spectacular growth in the Indian future and options market calls for a sophisticated study of the hedging effectiveness of the futures contract. In this paper we will analyze the hedging

[1] Conversion rate from Indian Rupees to Pounds is 1 £=80 INR. The turnover figures are downloaded from www.nseindia.com.

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effectiveness of the CNX Nifty 50 futures contracts. Since the contract relates to an index involving the 50 highest market capitalization firms it is questionable whether it is appropriate for hedging risk associated with portfolios of minor companies.

In our analysis we have used a wide range of cash portfolios which not only mirror index future contracts but are infact a range of mutual funds[2]. By analyzing hedging effectiveness for these mutual funds portfolio we will analyze the hedging effectiveness for actually well diversified portfolios unlike portfolios constructed by researchers particularly for analysis. They should be a good proxy for actual market portfolios. Our study we will measure the hedging effectiveness using the approach indicated by Butterworth & Holmes, 2001. It is the ratio of the difference in the standard deviations of the unhedged and hedged portfolio to unhedged portfolio.

The first study of hedging effectiveness of stock index futures was by Figlewski, 1984 and extensive work followed till date. The literature has concentrated on 3 hedging strategies one-to-one hedge (naive hedge), beta hedge and minimum variance hedge (Jhonson, 1960). In order, to use any of these 3 strategies the foremost step is to analyze the optimal hedge ratios ($h$). In the naive hedge strategy the investors holds an opposite position of equal magnitude but in opposite position. Thus, the hedge ratio in this case is $h = -1$. It is assumed that if the price movements are exact in both the markets and if this happens then price risk is eliminated. The beta hedge strategy is similar but it recognizes the cross hedge problem i.e. the cash portfolio is not exactly the same as the underlying futures contract. In beta hedge h is calculated as negative of the beta of the spot position.

However, when it comes to hedging in reality, the price changes in the cash and futures market do not move together. This is due to the basis. Basis risk arises as the spot price and future price do not converge on the expiration date. This difference is defined as basis. Many reason can be supported for the existence of basis, one of the main being, all principles of efficient market hypothesis do not hold true another technical reason could be different expiration date of the futures contract and selling date of the spot asset. Thus the beta hedge or naive hedge would not be able to minimize risk, the minimum variance hedge ratio (henceforth, MVHR) takes into consideration this imperfect correlation and estimates a hedge ratio which minimizes risk, it is estimated as $\frac{\text{Cov}(R_s, R_f)}{\text{Var } R_f}$. Similarly, $h$ with a negative sign indicates opposite position as compared to spot position.

Various techniques are introduced in the literature to calculate hedge ratios. Early study for estimation of hedge ratios used basic OLS regressions. Figlweski, 1984 showed that basic OLS could be used on historical data to estimate ex post hedge ratios. Jhonson, 1960 and Stein, 1961 explained that high $R^2$ say 0.90 of the OLS regression indicates an effective hedge. However this is not valid in all the cases. We will use OLS and modified OLS termed as LTS which is described in detail later in the paper to estimate hedge ratios. Finally, more recently many researchers use other more advance and complex econometric models to estimate these hedge ratios. They estimate two types of hedge ratios static and dynamic hedge ratios. Dynamic hedge ratios adjust themselves on the basis of the change in risk and information over time.

The spot and future returns have a cointegrating relationship which is ignored by traditional regressions. Kroner and Sultan, 1993 suggest ECM and VECM which take care of this cointegrating relationship which generate better hedge ratios. But the hedge ratios obtained from these error correction models are static, another model proposed by Bollerslev et al, 1988 known as the GARCH model generates hedge ratios who take into consideration that the joint distribution of spot and future returns change over time (Cecchetti et al, 1988) generating dynamic hedge ratios. We even use these recent models to estimate hedge ratios and compare their risk reductions.

The rest of the paper unfolds in the following way. Section 2 gives the literature review followed by data description in Section3 and the methodology used in our analysis in Section 4. Section 5 discusses our empirical results and findings and Section 6 concludes the paper.

## 2. Literature Review

It is apparent that many researchers have proposed different models to be effective for different markets and different data sets. Many researchers have propagated that the estimation of time-varying optimal hedge ratios or dynamic hedge ratios for stock index futures based on basic GARCH and different extensions and innovations

[2] A mutual fund is a close ended fund which generates capital by issuing shares and uses that capital to form a well diversified portfolios, they are managed full time by professional portfolio managers. In context to India an ITC is similar to a mutual fund

of GARCH are significant in order to execute a good hedge. Few of the main researchers who support GARCH and its extensions are Myers & Thomson, 1989; Baillie and Myers, 1991; Myers, 1991; Kroner and Sultan, 1993; Park and Switzer, 1995; Sim and Zurbruegg, 2001; and Choudhry, 2003.

However, it is very well recognized that financial historical data of stock and future prices posses the property of cointegration in such scenarios the inclusion of error correction terms is indispensable which is in line with the findings of Ghosh, 1993; Lien, 1993; Kroner and Sultan, 1993; Lien and Luo, 1994 and Bhaduri & Durai, 2008. Moreover, more complex alternatives to the econometric problems of the traditional GARCH model have been offered in recent literature by Bera et al 1997; Moschini and Myers, 2001; Yang, 2001; and Brooks, 2002.

Though these more complex techniques of estimating hedge ratios have been very useful and exhibit the potential of better hedging effectiveness there are some drawback which cannot be neglected. First of all, these methods tend to be extremely complex for estimation and thus can even lead to high transaction costs Lien, 2002. Whereas, the simple techniques like basic OLS or LTS can some time lead to better performance of the hedge and prove to be more satisfactory, this argument is also supported by Myers,1991; Holmes, 1995; and Butterworth & Holmes, 2001.

Hence, conclusively it can be stated that different hedges and different models to estimate these hedge ratios differ from market to market and data sets. Further there is not enough evidence available in the literature in order to suggest the establishment of a unique model. The paper highlights the following research issues: (i) Hedging effectiveness of Nifty index on corresponding Nifty futures contract. (Beta hedge), (ii) Hedging effectiveness of Nifty Futures contract for different cash portfolios or market portfolios (Mutual funds are taken as proxy for market portfolios), (iii) estimation of optimal hedge ratios, (iv) the best model to estimate optimal hedge ratio for the Indian derivatives market among OLS, LTS, ECM, VECM and GARCH and (iv) does the problem of cross hedging exist in India.

## 3. Data and Basic Statistics

Hedging performance for CNX Nifty 50 futures contract of the National Stock Exchange of India has been analyzed in this study for a period ranging from 2001-2008 (where, 2001 is the year of introduction of Nifty futures contracts). A period of 6 years is chosen which is in line with the past literature. The S&P CNX Nifty 50 index consists of the top 50 companies in the Indian securities market which comprise of 60% of the total exchange's capitalization. The weight for each constituent is on the basis of market capitalization. All weekly closing prices of the Nifty futures contracts are downloaded from www.nseindia.com, which is the official webpage for the Indian National Stock Exchange.

Similarly, the weekly closing net asset values (henceforth, NAVs)[3] of 10 mutual funds have been downloaded from www.amfiindia.com for a period ranging from 2001-2008. The details are provided in the Table 1. It is an official government owned association which is mainly responsible for rating different mutual funds across the country. 11 cash portfolios are maintained of which 10 are for mutual funds and 1 portfolio exactly replicates the Nifty futures contract, it is basically the underlying index of the futures contract. Selecting mutual funds as a proxy for cash portfolios is also supported by Butterworth and Holmes, 2001. They support this methodology because investment trust companies (mutual funds), represent returns of well diversified and professionally managed portfolios by portfolio managers. They can be also considered to be the market portfolios as most investors would try to replicate these mutual fund's portfolios. Hence estimating hedging effectiveness of these portfolios may provide new insights into the abilities for hedging real portfolios.

Description for different mutual funds is given below and they are selected in a way that they provide a range of portfolios which diverge significantly in their composition[4].

1. Taurus Discovery Fund is mainly oriented towards mid-cap stocks.
2. Taurus Star Share Fund's main investment strategy is investing in small, large and mid cap stocks.
3. Taurus Index Fund significantly invests in the constituents of the Index. Minimum 80% in index shares.

[3] Net asset value is simply a measure of value of one share of a mutual fund. NAV is the price at which mutual funds are traded.

[4] All information for mutual funds is taken from Associations of Mutual funds India's webpage.

4. LIC Nifty Index Fund invests only in the constituents of the index.
5. SBI MGLF 94 invests in stocks of all Indian sectors, bonds and partly/fully convertible debentures.
6. Reliance Short Term Mutual fund invests with short term durations in stocks and fixed income securities.
7. Sahara Income fund has at least 70% of its assets in Indian companies whose policy is to accentuate income growth.
8. BOB ELSS 96 is an equity linked saving scheme. It has all its assets in Indian companies with stocks chosen to emphasize capital growth.
9. GIC is a general fund with 80% investment in Indian companies.
10. SBI MTP 94 invests 90% of its fund in property equities.

**Table 1. List of Cash Portfolios**

| MUTUAL FUND | ACRONYM |
|---|---|
| 1. Bank of Baroda Equity Linked Saving Scheme 96 | BOB ELSS |
| 2. General Insurance Company Mutual Fund | GIC |
| 3. Life Insurance Company Nifty Fund | LIC NIFTY |
| 4. State Bank Of India Mutual Fund MTP 94 | CP MTP 94 |
| 5. Reliance Short Term Mutual Fund | REL ST MF |
| 6. Sahara Income Fund | SAHARA INCOME FUND |
| 7. State Bank Of India MGLF 94 | SBI MGLF 94 |
| 8. Taurus Discovery Mutual Fund | TAURUS DISCOVERY FUND |
| 9. Taurus Index Mutual Fund | TAURUS INDEX FUND |
| 10. Taurus Star Share Mutual Fund | TAURUS STAR SHARE |
| 11. S&P CNX Nifty 50 Index | NIFTY |

Funds are selected on the basis of two criteria: (i) availability of a wide range of data set, and (2) to avoid the problem of thin trading only mutual funds with a starting capital of minimum £12.5 million are selected.

The returns for cash and future portfolios are calculated by taking the first logged difference of their weekly closing prices[5].

$$R_t = \left(\frac{P_t}{P_{t-1}}\right) \quad (3.1)$$

Where, $R_t$ weekly return of cash or future portfolio at time $P_t$ & = price at time $t$.

The summary statistics as shown in Table 1indicates that the lowest standard deviation is for the Nifty index this can be supported by the argument that the index consists of the top 50 best performing companies in the country. Its standard deviation is also lower than most of the mutual funds as it can be reasonably stated that the index is well diversified. The mean return through the entire time period for all portfolios is positive. 7 out of 10 mutual funds display mean return more than the index indicating good performance by mutual funds in India. Skewness is generally negative indicating longer tails towards the left. Excess kurtosis are comparatively large and always positive indicate fatter tails.

Thus the skewness and kurtosis suggest that the data is not normally distributed this is also confirmed by performing normality test. The results for which are shown in Table 2. Few reasons for non normality in the data can be due to economic factors. In the year 2001 the stock market crashed due to the flight 9/11 terrorist attacks in the USA and exposure of stock price ragging a few of the big Indian banks. While in 2008 all time high inflation in the country also led to a crash of the index.

In order to evade the pitfall of spurious correlation in the OLS regression for the estimation of MVHR it is desirable that the series is stationary. Few other diagnostic tests have been carried out to confirm the stationarity of the data. Unit root test such as Augmented Dickey Fuller (henceforth, ADF) test confirm that unit root does not exist in the data-set and thus the stationarity of the data is confirmed by the $t$-values of ADF which are significantly different from zero. The results are shown in following Table 3. The values indicate that all the variables are stationary and thus can be used to carry out OLS and GARCH regressions.

[5] In case of mutual fund the NAVs are taken as closing prices.

**Table 2. Summary Statistics**

| *STATISTICS* | *BOBELSS 96* | *GIC* | *LIC* | *CP MTP 94* | *NIFTY* | *REL ST* | *SAHARA* | *SBI* | *TAURUS DISC* | *TAURUS INDX* | *TAURUS STAR* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.0038 | 0.0030 | 0.0046 | 0.0016 | 0.0036 | 0.0053 | 0.0051 | 0.0023 | 0.0037 | 0.0055 | 0.0037 |
| Standard Error | 0.0018 | 0.0026 | 0.0023 | 0.0026 | 0.0018 | 0.0021 | 0.0017 | 0.0021 | 0.0018 | 0.0021 | 0.0018 |
| Median | 0.0077 | 0.0071 | 0.0104 | 0.0041 | 0.0071 | 0.0105 | 0.0104 | 0.0046 | 0.0071 | 0.0109 | 0.0071 |
| Standard Deviation | 0.0311 | 0.0441 | 0.0347 | 0.0324 | 0.0307 | 0.0349 | 0.0304 | 0.0313 | 0.0308 | 0.0339 | 0.0308 |
| Sample Variance | 0.0009 | 0.0019 | 0.0012 | 0.00105 | 0.0009 | 0.0012 | 0.0009 | 0.00098 | 0.00095 | 0.0011 | 0.0009 |
| Kurtosis | 2.2475 | 68.909 | 1.3533 | 1.0873 | 2.2508 | 1.1592 | 1.7283 | 1.6923 | 2.2023 | 1.2340 | 2.2023 |
| Skewness | –0.7898 | –6.0392 | –0.5875 | –0.6756 | –0.7542 | –0.4445 | –0.6846 | –0.7085 | –0.7503 | –0.6281 | –0.7503 |
| Range | 0.2307 | 0.6241 | 0.2307 | 0.1954 | 0.2307 | 0.2345 | 0.2224 | 0.2034 | 0.2307 | 0.2307 | 0.2307 |
| Minimum | –0.1271 | –0.520 | –0.1271 | –0.1165 | –0.1271 | –0.1271 | –0.1271 | –0.1271 | –0.1271 | –0.1271 | –0.1271 |
| Maximum | 0.103613 | 0.10361 | 0.10361 | 0.078865 | 0.10361 | 0.10741 | 0.0953 | 0.0762 | 0.1036 | 0.1036 | 0.10361 |
| Sum | 1.09214 | 0.8664 | 0.8694 | 0.24290 | 1.05269 | 1.37784 | 1.4826 | 0.4925 | 1.0885 | 1.4423 | 1.0885 |
| Count | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 |

**Table 3. Results of Normality Tests**

| *CASH PORTFOLIOS* | *N TEST* |
|---|---|
| BOBELSS 96 | 279.34 [0.0000]** |
| CP MTP94 | 25.155 [0.0000]** |
| SAHARA | 4826.8 [0.0000]** |
| SBI | 42.690 [0.0000]** |
| TAURUS DISC | 14.801 [0.0006]** |
| TAURUS INDX | 107.66 [0.0000]** |
| TAURUS STAR | 16.527 [0.0003]** |
| REL | 59.891 [0.0000]** |
| GIC | 4063.4 [0.0000]** |
| LIC | 25.671 [0.0000]** |
| NIFTY | 21.167 [0.0000]** |

**indicates rejection of null hypothesis at 5% significance level

HO (Null Hypothesis): Errors are normally distributed.

## 4. Methodology

The literature review suggests that different models are best estimators of optimal hedge ratios in different markets. Hence, we will employ 5 different models to calculate the optimal hedge ratios. Analysis is carried out for only weekly duration because firstly the data is more stable than for daily data. According to Laws and Thompson, 2005, "various studies also suggest that weekly hedges are more effective then daily". Three type of hedging strategies are analyzed one to one hedge, minimum variance hedge ratio (MVHR) and in case of Nifty index beta hedge is analyzed.

### 4.1 OLS Based Model

Figlewski, 1984 proved that MVHR can be estimated by regressing cash returns on future returns by running a simple OLS regression. In view of the equation for MVHR which is equal to the negative of the slope of the regression coefficient '*b*' in the equation. It is a common technique among fund managers to calculate optimal hedge ratios using simple OLS. Usually they will use data from past 100 trading days to calculate optimal hedge ratios. Hence, by using the OLS technique used by Butterworth and Holmes, 2001 we run the following regression

$$RS_t = a + bRF_t + \in_t \quad \in \sim i.\ i.\ d(0, \sigma^2) \qquad (4.1)$$

Where, $RS_t$ is the return on cash portfolio at time $t$; $RF_t$ is the return on future portfolio at time $t$; $t$ is an error term and '*a*' and '*b*' are regression parameters out of which *b* is the MVHR, '*h*' .

Although the MVHR estimated by OLS has many desirable properties it is characterized by an objectionable property of being sensitive to outliers. In order to take into account this pitfall and also to take into consideration that future prices are often associated with high kurtosis and to minimize the impact of outliers we use a technique indicated by Knez and Ready, 1997 known as the Least Trimmed Squares (henceforth, LTS) approach. To calculate LTS hedge ratio the residual series derived by running regression equation (4.1) are saved. Then both the spot and future return are ranked in accordance to the absolute size of the corresponding residual term. Hence the first return in spot and future series will be the one with lowest absolute residual term and the final will be one with the highest absolute residual term. We further trim away the 10% of the observations which are related to the largest absolute residual term from the spot and futures return series use a trimming coefficient as used by Butterworth & Holmes, 2001 and Knez and Ready, 1997 of 10%. Then by employing OLS to the remaining 90% of the observations we estimate the optimal hedge ratio which is unaffected by extreme observations or kurtosis. For OLS and LTS regression of the underlying Nifty index on the corresponding Nifty futures contract is performed, to estimate the beta hedge ratio. To estimate MVHR regressions are run on the similar equations for cash portfolios.

**Table 4. Durbin Watson Test Results**

| *MF* | *DW* | *CORRELATION* |
|---|---|---|
| TAURUS INDX | 1.84 | No |
| BOB ELSS96 | 1.99 | No |
| GIC | 1.99 | No |
| TAURUS STAR | 2.02 | No |
| TAURUS DISC | 2.00 | No |
| LIC | 2.00 | No |
| SAHARA | 1.89 | No |
| SBI MGLF | 2.33 | No |
| REL ST | 1.45 | Positive |
| CP MTP 94 | 2.33 | No |
| NIFTY INDEX | 2.69 | No |

However there are some limitations to the simple OLS technique hence we do some diagnostic testing to check if our OLS is BLUE (Best Linear Unbiased Estimator). Autocorrelation and heteroscedasticity may affect the OLS based regressions therefore we carry out certain diagnostic tests. The Durbin-Watson (hence forth, DW) test is carried out to check the presence of autocorrelation (Table 4 shows the result). The null hypothesis states that no autocorrelation is present. But the DW tests results may be inappropriate in a few cases. For instance the DW test would fail if the errors are not normally distributed or if the dependent variable is present in the regression in a lagged form in the independent variables. In order to overcome these drawbacks we will check the results for the Lagrange-Multiplier test (henceforth, LM) with the same hypothesis as DW test. To test for normal distribution of the error terms we will run the normality test (Shown in table 5). Eventually to check if there is volatility clustering we will also perform ARCH test (Engle, 1982).

**Table 5. Langrange Multiplier Test Results**

| *CASH PORTFOLIOS* | *R2*N* | *AUTO CORRELATION* |
|---|---|---|
| TAURUS INDX | 158.8854 | Yes |
| BOB ELSS96 | 137.2104 | Yes |
| GIC | 312.1896 | Yes |
| TAURUS STAR | 224.1353 | Yes |
| TAURUS DISC | 199.5071 | Yes |
| LIC | 183.7147 | Yes |
| SAHARA | 1.05276 | Yes |
| SBI MGLF 94 | 85.41562 | Yes |
| REL ST | 16.62543 | Yes |
| CP MTP 94 | 106.6764 | Yes |
| NIFTY INDEX | 360.2595 | Yes |

HO (Null Hypothesis): Autocorrelation is not present

The above diagnostic tests reveal that the conventional approach can lead to inefficient estimates of the optimal hedge ratios. Several violations of the assumptions can lead to misspecification problems. Thus further estimation of optimal hedge ratios is necessary to calculate the best estimates.

## 4.2 Error Correction Model (ECM)

Following the findings of Chou et al, 1996 and Lien, 1996 presence of cointegration between spot and future prices leads to a downward biasness of the hedge ratios estimated by the traditional approaches like OLS, due to the exclusion of the error correction term (ECT). The study by Engle and Granger, 1987 provide theory that if two or more series are cointegrated then they can be estimated using an ECM. The foremost advantage of ECM is that it incorporates a long and short run memory into the data. In our case the spot and future prices are cointegrated and hence the hedge ratios can be calculated using an ECM. In order to check if cointegration exists between spot and futures return series we will employ the Engle-Granger test for cointegration. Furthermore, Chou et al, 1996 developed an ECM based on the theory provided by Engle and Granger, 1987 to calculate hedge ratios. We will use an ECM as proposed by Christos Floros and Dimitrios V. Vougas, 2004. The assumption under this model holds that series are cointegrated.

The ECM is of the form

$$\Delta S_t = c + a\varepsilon_{t-1} + b\Delta F_t + \sum_{i=1}^{n} \theta \Delta F_{t-i} + \sum_{j=1}^{k} \phi \Delta S_{t-j} + u_t \quad (4.2)$$

Where

$$\Delta S_t = S_t - S_{t-1} \quad (4.3)$$

$$\Delta F_t = F_t - F_{t-1} \quad (4.4)$$

$$\varepsilon_{t-1} = S_{t-1} - (a + bF_{t-1}) \quad (4.5)$$

$b$ = optimal hedge ratio

$\theta = \phi$ = regression parameters

In order to determine n and k in the above equation we plot the autocorrelation function (henceforth, ACF) and partial autocorrelation function (henceforth, PACF) graph. The lag values for which the histograms ACF and PACF are significant are taken as the values of n and k.

Thus by applying the above model alternate estimates of hedge ratios are estimated and then compared with the other models. By using the above model the last period's equilibrium errors are taken into account.

## 4.3 Vector Error Correction Model (VECM)

Since the problem of cointegration can lead to spurious results and the past literature by authors like Kroner and Sultan, 1991; Ghosh, 1993; Liean and Luo, 1994; and Lien, 1996 indicate that if the spot and futures prices are cointegrated and excluding the ECT in VAR model which is used to calculate the optimal hedge ratios may lead to misspecification problems and downwardly biased hedge ratio. Therefore in order to avoid these problems we will use the VECM proposed by Ghosh, 1993 and Lien, 1996.

The equation for the VECM

$$\Delta S_t = \sum_{i=1}^{n} \beta \Delta S_{t-i} + \sum_{j=1}^{k} \delta \Delta F_{t-j} - a_s Z_{t-1} + \varepsilon_{S,t} \quad (4.6)$$

$$\Delta F_t = \sum_{i=1}^{n} \gamma \Delta S_{t-i} + \sum_{j=1}^{k} \phi \Delta F_{t-j} - a_f Z_{t-1} + \varepsilon_{F,t} \quad (4.7)$$

Where,

$\varepsilon_{s,t}$ and $\varepsilon_{F,\tau}$ are white noise error terms,
$\beta$, $\delta$, $\phi$ and $\gamma$ are regression parameters,
$Z_{t-1}$ is the error correction term (ECT)

Similar to the ECM, the n and k values are determined in VECM. The hedge ratio is estimated as $\rho_{sf}\left(\frac{\sigma_s}{\sigma_f}\right)$ where $\rho_{sf}$ is the correlation coefficient between the residuals or error terms $\varepsilon_{S,t}$ and $\varepsilon_{F,t}$ whereas, $\sigma_s$ and $\sigma_f$ are the standard deviations of the error terms of the above mentioned two series. Basically, the unconditional variances of the spot and future prices i.e. $\sigma_{ss}$ and $\sigma_{ff}$ and the covariance for the two series are obtained from the residual variance-covariance matrix of the above mentioned two VECM equations. Thus the hedge ratio is calculated by dividing the covariance and the unconditional variance of future prices. Thus hedge ratio is: $h = \frac{\sigma_{sf}}{\sigma_{ff}}$ .

## 4.4 Multivariate GARCH Model

Previous models employed in this study including OLS and VECM implicitly assume that the risk in spot and futures position is constant over time. Hence this leads to the estimation of a static hedge ratio. However, as we know heteroscedasticity has been detected in most of the financial time series data furthermore the risk is also not constant over time and varies with availability of new information in the market. This leads to the invalidation of the traditional models thus their constant hedge ratios are not effective in minimizing risk.

Thus, if ARCH effect is detected in the data, dynamic hedge ratios must be estimated in order to maximize risk reduction. In order to calculate such dynamic hedge ratios, ARCH model provided by Engle, 1982 and further characterized by Bollerslev, 1986 is used largely in the past literature. In the light of these ARCH and GARCH models conditional variance covariance matrix can be estimated by lagged error terms and its own lagged values. Therefore, these models generate better hedge ratios by capturing volatility clustering in the spot and future positions. GARCH models are usually preferred over

ARCH models in financially modelling and forecasting since it avoids overfitting problem and its parsimonious approach.

In this paper the final model employed for estimating dynamic hedge ratios is a multivariate GARCH model as used by Floros et al, 2004 which is a restricted version of BEKK by Engle and Kroner, 1995. “The Bivariate cointegration model, with GARCH error structure, (BGARCH), incorporate time-varying hedge conditional coefficient between spot and future price and generate time varying hedge ratios.” Floros et al, 2004. The original BEKK parameterization contained 21 parameters to be estimated where as Bollerslev, 1990 proposed another way to simplify the estimation of Ht (the variance covariance matrix based on the information set). He offered the ‘constant correlation specification’ by assuming that the conditional correlation among is not time-varying. Under this framework Ht is defined as

$$\begin{bmatrix} h^2_{ss,t} & h^2_{sf,t} \\ h^2_{fs,t} & h^2_{ff,t} \end{bmatrix} = \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{f,t} \end{bmatrix} \begin{bmatrix} 1 & \sigma_{St} \\ \sigma_{St} & 1 \end{bmatrix} \begin{bmatrix} h_{S,t} & 0 \\ 0 & h_{F,t} \end{bmatrix} \quad (4.8)$$

Positive definiteness is certain if . Its estimation is simple as it contains only 7 parameters to be estimated instead of 21.

The bivariate cointegration GARCH (1, 1) expressions and distributions of spot and futures are given by:

$$\Delta S_t = \alpha_0 + \alpha_1(S_{t-1} - \gamma F_{t-1}) + \varepsilon_{st} \quad (4.9)$$

$$\Delta F_t = \beta_0 + \beta_1(S_{t-1} - \gamma F_{t-1}) + \varepsilon_{ft} \quad (4.10)$$

$$\varepsilon = \begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} |\psi_{t-1} \sim N(0, H_t) \quad (4.11)$$

$$h^2_{ft} = c_s + a_s \varepsilon_{s,t-1} + b_s h^2_{s,t-1} \quad (4.12)$$

$$h^2_{ft} = c_f + a_f \varepsilon^2_{f,t-1} + b_f\, h^2_{f,t-1} \quad (4.13)$$

Where,

$|\psi_{t-1}$ is the information at time $t-1$

$(S_{t-1} - \gamma F_{t-1})$ is the error term obtained from expression $S_t = \delta + \gamma F_t + et$

Akakies’ information criteria (henceforth, AIC) is used to select the best model among the models with up to six lags. Therefore the model with the lowest AIC value is selected as it is the best fit to the data. Finally, the dynamic (time-varying hedge ratio) estimated by the BGARCH model is expressed as:

$$\frac{h_{sf,t}}{h_{ff,t}} = \left( \frac{\text{Cov}(\varepsilon_{st}, \varepsilon_{ft})}{\text{Var}(\varepsilon_{ft})} \right) \quad (4.14)$$

## 4.5 Hedging Effectiveness

Once different hedge ratios have been estimated using the above models a comparison study is done between the different hedged and unhedged portfolios. Main consideration is given to the extent of risk reduction, which is calculated for comparing mean. The standard deviation values are also analyzed. Following the methodology of Butterworth and Holmes, 2001 the degree of risk reduction will be calculated using the following expression:

$$\text{Degree of risk reduction} = \frac{\sigma_u - \sigma_h}{\sigma_u} \times 100 \quad (4.15)$$

Where,

$\sigma_u$ = standard deviation of the unhedged portfolio (cash portfolio)

$\phi_h$ = standard deviation of the hedged portfolio.

The value of the hedged portfolio is given by the following equation as give in Jhon C. Hull, 2007.

$$\text{Value of hedged portfolio} = S_t - [(-h) \times F_t] \quad (4.16)$$

Where,

$S_t$ = Spot price of cash portfolio at time t
$h$ = optimal hedge ratio
$F_t$ = Price of futures contract at time t.

Finally, once the best model is selected which gives the maximum risk reduction; it is required to check if the model works efficiently for forecasting. Thus, forecasting is done for the best selected models to confirm the hedging effectiveness of those models. In order to forecast hedge ratios we use 3/4$^{th}$ of the data to forecast for the next 1/4$^{th}$ of the observations. The forecasted returns are used to estimate new hedge ratios, the forecasted hedge ratios, for evaluating the hedging effectiveness. Junkus and Lee, 1985; Butterworth and Holmes, 2001 study also suggest that exante hedging effectiveness is very crucial to investors in real market scenarios. Since ex-post hedge ratios are estimated by regressing historical data series it implicitly assumes that investors have perfect foresight and can predict the market movements aptly, contradicting the real time scenario. Portfolio managers have to calculate optimal ex-ante hedge ratios and use it to execute ex-post hedging. Thus ex-ante hedging effectiveness is evaluated for all models and ex-post for the most efficient model.

# 5. Empirical Findings

## 5.1 Estimates from OLS Based Models

The first optimal hedge ratios are estimated by running equation 2. The coefficients of the independent variables are the corresponding hedge ratios and are provided in Table 6. Along with the optimal hedge ratios (h) estimated using OLS regression the table also includes the corresponding $R^2$ value. $R^2$ statistic measures the goodness of fit of a model; it measures as to how well the regression estimates are close to the real data points. The regression is said to be better when the $R^2$ is close to unity. It seems from the table that the $R^2$ value for the cash portfolio which exactly replicates the Nifty futures contract i.e. the Nifty Index has the highest $R^2$ value of 0.971508. This can be easily explained since Nifty Index should be entirely reflected by Nifty futures contract, and their performances are expected to perfectly match each other. However, except for 2 cash portfolios rest all have a reasonably low $R^2$ statistic which is in consistence with Laws and Thompson, 2005, where they found $R^2$ to be very low in the UK markets. This can be explained as the two markets differ from each other and the Nifty futures contract consists of only 50 stocks which is easier for mutual funds to track. Unlike UK indices which consist of 100 and 250 stocks. Thus, it can be concluded that the cross hedge problem is not that stern in the Indian stock markets.

**Table 6.** **$R^2$ and Hedge Ratio Estimates of OLS**

| CASH PORTFOLIOS | OLS R^2 | OLS H |
|---|---|---|
| BOB ELSS 96 | 0.478085 | 0.940594 |
| GIC | 0.802544 | 1.08759 |
| LIC | 0.85848 | 0.85064 |
| CP MTP 94 | 0.735699 | 0.904215 |
| NIFTY INDEX | 0.971508 | 0.976313 |
| REL ST | 0.06469 | 0.007235 |
| SAHARA | 0.003407 | 0.011907 |
| SBI MGLF | 0.410652 | 0.847401 |
| TAURUS DISC | 0.543616 | 0.986879 |
| TAURUS STAR | 0.610723 | 0.960008 |
| TAURUS INDX | 0.613457 | 0.903935 |

The estimated hedge ratios for all 11 cash portfolios are less than unity or close to unity. Apparently the optimal hedge ratio for the Nifty index which exactly replicates the futures contract is also very close to 1 (i.e. 0.976313).

The mean returns and the standard deviation of portfolios hedged using OLS estimated optimal hedge ratios are provided in Table 7. The mean returns of OLS based hedged portfolios are lower than unhedged portfolios but the standard deviations are also lower. This is consistent with the normal phenomenon of risk return trade-off; of lower the risk lower the returns. The results are also in line with findings of Butterworth & Holmes, 2000 who propose that in order to gain risk reduction a minor amount of mean returns needs to be lost.

**Table 7.** **Standard Deviation and Mean Return of OLS**

| CASH PORTFOLIOS | STANDARD DEVIATION | MEAN RETURN |
|---|---|---|
| BOB ELSS | 0.031162694 | 0.003791364 |
| GIC | 0.04217365 | 0.003288711 |
| LIC | 0.030187 | 0.004053148 |
| MTP 94 | 0.032399928 | 0.001676596 |
| REL ST | 0.0181 | 0.003661419 |
| SAHARA | 0.006242816 | 0.003190975 |
| SBI MGLF 94 | 0.031355632 | 0.002375019 |
| TAURUS DISC | 0.032575275 | 0.003210113 |
| TAURUS INDEX | 0.033958341 | 0.005554504 |
| TAURUS STAR | 0.032571758 | 0.003224563 |
| NIFTY INDEX | 0.031997062 | 0.003185962 |

## 5.2 Estimates from LTS

To avoid the impact of extreme outliers LTS approach is also used to estimate the MVHR i.e. optimal hedge ratios. The LTS estimated hedge ratios are lower than the one estimated using OLS this indicates that fund managers need to hedge less future contracts then the one estimated using OLS. This reduces the cost of hedging. The LTS estimates are lower in 7 instances out of 11 which are provided in Table 8 for comparison. As suggested by Butterworth & Holmes, 2001 if the MVHR calculated using LTS are significantly different from the one estimated using OLS then it would strongly indicate that MVHR is being motivated by a small number of extreme observations. Thus raising the problem of biasness of the MVHR by outliers which would have a great implications when ex ante hedge ratios are estimated using historical data.

**Table 8. Comparison between OLS and LTS Estimates of $R^2$**

| CASH PORTFOLIOS | OLS $R^2$ | OLS H | LTS H | LTS $R^2$ |
|---|---|---|---|---|
| BOB ELSS 96 | 0.478085 | 0.940594 | 0.913291 | 0.86554 |
| GIC | 0.802544 | 1.08759 | 0.913291 | 0.86554 |
| LIC | 0.85848 | 0.85064 | 0.876225 | 0.967471 |
| CP MTP 94 | 0.735699 | 0.904215 | 0.910247 | 0.836674 |
| NIFTY INDEX | 0.971508 | 0.976313 | 0.970646 | 0.987361 |
| REL ST | 0.06469 | 0.007235 | 0.004413 | 0.072341 |
| SAHARA | 0.003407 | 0.011907 | 0.006994 | 0.021782 |
| SBI MGLF | 0.410652 | 0.847401 | 0.908034 | 0.77126 |
| TAURUS DISC | 0.543616 | 0.986879 | 0.965943 | 0.678973 |
| TAURUS STAR | 0.610723 | 0.960008 | 0.934297 | 0.701756 |
| TAURUS INDX | 0.613457 | 0.903935 | 0.936299 | 0.986942 |

Further when compared the R2 value between LTS and OLS which is given in table 8 it can be seen that R2 value for LTS is much higher than that of OLS. This indicates that LTS regressions are better estimators than OLS. However the risk reduction between the two with other models will be compared later in detail. Again standard deviation and mean of the returns estimated using LTS are reported in table 9.

**Table 9. Standard Deviation and Mean Returns of LTS**

| CASH PORTFOLIOS | STANDARD DEVIATION | MEAN RETURNS |
|---|---|---|
| BOB ELSS | 0.031162178 | 0.003790949 |
| GIC | 0.00329021 | 0.042178393 |
| LIC | 0.031863286 | 0.002798037 |
| MTP 94 | 0.294746484 | 0.032400257 |
| REL ST | 0.017804978 | 0.00441332 |
| SAHARA | 0.002758559 | 0.006251 |
| SBI MGLF 94 | 0.002374546 | 0.03135834 |
| TAURUS DISC | 0.032575276 | 0.003210029 |
| TAURUS INDEX | 0.005554992 | 0.033959163 |
| TAURUS STAR | 0.032480961 | 0.003070158 |
| NIFTY INDEX | 0.03199755 | 0.003185962 |

## 5.3 Estimates from ECM

As tested before the price series can be defined as I(1) process. The existence of cointegration between spot and future prices will lead to biasness in the estimation of optimal hedge ratios if the error correction term is neglected Chou et al., 1996 and Lien, 1996. Before running the ECM on the return series it is necessary to confirm that the spot and future portfolio are cointegrated. Engle-Granger test is performed and the results are provided in table 10. The t-adf value is reported with the lowest AIC value. The significant t-adf values indicate that all the 11 return series of the spot portfolios are cointegrated with the return series of the future's portfolio. Hence it is confirmed that cointegration exists between spot and futures position which indicates a long run association between the two series. Further more changes in spot prices may not be just related to the changes in future position prices but also with the lagged residual terms and lagged price changes. This relationship between the two series invalidates the other models and hence an ECM is used in order to estimate the optimal hedge ratios.

**Table 10. Results from Engle-Granger Test**

| CASH PORTFOLIOS | LAGS | T-ADF | AIC |
|---|---|---|---|
| BOB ELSS | 0 | –16.80** | –6.961 |
| GIC | 0 | –19.59** | –7.58 |
| LIC | 0 | –13.90** | –8.827 |
| MTP 94 | 0 | –13.15** | –7.861 |
| REL ST | 2 | –7.245** | –14.12 |
| SAHARA | 0 | –16.42** | –10.08 |
| SBI MGLF 94 | 0 | –16.33** | –6.954 |
| TAURUS DISC | 0 | 18.40** | –7.063 |
| TAURUS INDEX | 0 | –15.93** | –7.405 |
| TAURUS STAR | 10 | –6.235** | –7.434 |
| NIFTY INDEX | 4 | –8.030** | –10.94 |

**indicates rejection of null hypothesis at 5% significance level

HO : Cointegration is not present

In the present scenario the spot and future positions are cointegrated hence an ECM is used as explained in equation (3). The table 11 reports the series of hedge ratios estimated using the ECM with their significant *t*-values. For convenience the optimal hedge ratios are highlighted. The coefficients of change in future returns are the optimal hedge ratios. All the hedge ratios in the hedge ratio equation are significantly different from zero at 5% significance level.

**Table 11. Hedge Ratios Estimated using the ECM and Other Coefficients**

| *CASH PORTFOLIOS* | | | |
|---|---|---|---|
| | | Coefficient | *t*–value |
| BOB ELSS | Constant | –2.77E–05 | –0.0151 |
| | Error | –1.02177 | –12 |
| | Ft | 0.936162 | 18.4 |
| | sum ft | 0.518519 | 0.197 |
| | st sum | 3.99928 | 0.488 |
| | | Coefficient | t–value |
| GIC | Constant | –2.26E–05 | –0.0277 |
| | ERROR TERMS | 0.990012 | 27.5 |
| | Deltaft | 1.08086 | 67 |
| | SUM ST | 58.3296 | 19.7 |
| | SUM FT | 42.5142 | 16.5 |
| | | Coefficient | t–value |
| LIC | Constant | –1.53E–05 | –0.0179 |
| | error term | –1.00649 | –14.3 |
| | delta ft | 0.847193 | 46.7 |
| | sum ft | 0.274701 | 1.92 |
| | sum st | 0.151496 | 1.09 |
| | | Coefficient | t–value |
| MTP 94 | Constant | 0.00022473 | 0.205 |
| | error term | 0.884445 | 13.6 |
| | Deltaft | 0.899043 | 28.9 |
| | sum st | 0.502159 | 9.97 |
| | Sumft | 0.818036 | 6.64 |
| | | Coefficient | t–value |
| REL ST | Constant | –7.52E–07 | –0.0169 |
| | Deltaft | 0.00594552 | 6.12 |
| | Sumst | –2.05108 | –13.4 |
| | Sumft | –0.431696 | –1.7 |
| | error term | 0.80971 | 17.3 |
| | | Coefficient | r t–value |
| SAHARA | Constant | 1.17E–11 | 0.0466 |
| | error term | 1.58E–07 | 2.91 |
| | Deltaft | 0.0142855 | 0.77 |
| | Sumft | 0.703206 | 0.77 |
| | Sumst | 33.0849 | 2.55E+07 |
| | | Coefficient | *t*–value |
| SBI MGLF 94 | Constant | –0.0001623 | –0.0736 |
| | Deltaft | 0.791458 | 12.6 |
| | Sumst | –0.27789 | –0.663 |
| | Sumft | –0.290966 | –0.717 |
| | error term | –1.21478 | –11.2 |
| | | Coefficient | t–value |
| TAURUS DISC | Constant | –1.74E–05 | –0.0159 |
| | Deltaft | 0.993574 | 34.3 |
| | Sumst | –79.8471 | –18.9 |
| | Sumft | 11.2863 | 13 |
| | error term | 0.99678 | 26.7 |
| | | Coefficient | t–value |
| TAURUS INDEX | Constant | –1.74E–05 | –0.0159 |
| | Deltaft | 0.993574 | 34.3 |
| | Sumst | –79.8471 | –18.9 |
| | Sumft | 11.2863 | 13 |
| | error term | 0.99678 | 26.7 |
| | | Coefficient | t–value |
| TAURUS STAR | Constant | –7.76E–06 | 6.77E+01 |
| | error term | 1 | 3.69E+16 |
| | delta ft | 0.86732 | 6.72E+16 |
| | sum ft | –5.39E–17 | –4.59 |
| | sum st | –3.10E–17 | –3.21 |
| | | Coefficient | t–value |
| NIFTY INDEX | Constant | –3.20E–11 | –0.7 |
| | error term | 1.05E–08 | 0.866 |
| | delta ft | 0.0208897 | 0.407 |
| | sum ft | –0.0610102 | –0.407 |
| | sum st | –2.86235 | –1.45E+00 |

When the ECM estimated hedge ratios are compared with those estimated using the conventional approach of OLS it seems that 7 out of 11 ratios are lower as compared to OLS. This is in line with the findings of Chou et al., 1996 and Lien, 1996 who provide evidence of ECM hedge ratios are downward biased as compared to OLS. Thus it can be concluded that OLS technique overestimates the optimal hedge ratios which needs the investors to buy more future contracts in order to hedge their positions Ghosh and Clayton, 1996. Also this implies that Indian investors would need less future contracts to hedge their positions and the Indian fund managers could incur major losses by using conventional techniques. The hedge standard deviation of the returns of hedged portfolios using ECM hedge ratios and the mean returns are displayed in table 12.

**Table 12. Standard Deviation and Mean Returns of ECM**

| CASH PORTFOLIOS | STANDARD DEVIATION | MEAN RETURNS |
|---|---|---|
| BOB ELSS | 0.030937308 | 1.004280435 |
| GIC | 0.003288754 | 0.042173785 |
| LIC | 0.003790889 | 0.030210483 |
| MTP 94 | 0.001676596 | 0.032399925 |
| REL ST | 0.0034756 | 0.017886009 |
| SAHARA | 0.0035401 | 0.006198664 |
| SBI MGLF 94 | 0.002375518 | 0.03135278 |
| TAURUS DISC | 0.003210126 | 0.032575275 |
| TAURUS INDEX | 0.005554584 | 0.033958476 |
| TAURUS STAR | 0.003225787 | 0.032571429 |
| NIFTY INDEX | 0.009985408 | 0.003184542 |

## 5.4 Estimates from VECM

Furthermore Ghosh, 1993 suggest that if cointegration exists between spot and future prices the non-inclusion of the ECT in the VAR model used to estimate the optimal hedge ratios will lead to misspecification difficulty and downward biasness of the optimal hedge ratios. Thus in this section we use a VECM to estimate the hedge ratios. Thus, by using equation (4.7) and (4.8) unconditional variances of spot and future prices and covariance of the two series are obtained from the variance-covariance matrix of the error terms. The number of lags is taken by considering at the ACF and PACF graphs. The ratio between the covariance of two series and the variance of the futures is the optimal hedge ratio. The estimated hedge ratios are given in Table 13 with their mean returns, standard deviations, and variance covariance of the residual terms are provided. When the hedge ratios are compared to the estimates from other models they are lower than the estimates of OLS, LTS and ECM. (See table 19). This is not in consistence with the results obtained by Floros et al 2004 and Ghosh, 1993. The performance of these hedge ratios will also be compared in detail later.

**Table 13. Descriptive Statistics of the Residual Terms of VECM**

| CASH PORTFOLIOS | SD | MEAN | VARIANCE | COVARIANCE | H RATIO |
|---|---|---|---|---|---|
| BOB ELSS | 0.030937 | 1.00428 | 0.0012982 | 0.001211079 | 0.932876741 |
| GIC | 0.003289 | 0.042174 | 0.0025597 | 0.002759534 | 1.078077553 |
| LIC | 0.03021 | 0.003791 | 0.002243 | 0.00189621 | 0.845381267 |
| MTP 94 | 0.0324 | 0.001677 | 0.0012531 | 0.001118688 | 0.89275551 |
| NIFTY INDEX | 0.031998 | 0.003043 | 0.0005885 | 0.000573456 | 0.974339 |
| REL ST | 0.017852 | 0.003472 | 0.0021108 | 1.25002E-05 | 0.005922108 |
| SAHARA | 0.006205 | 0.003439 | 0.0013355 | 2.27739E-05 | 0.017053283 |
| SBI MGLF | 0.031353 | 0.002376 | 0.0012377 | 0.000974812 | 0.787616203 |
| TAURUS DISC | 0.032575 | 0.00321 | 0.0014234 | 0.001410406 | 0.990859547 |
| TAURUS STAR | 0.033958 | 0.005555 | 0.0012589 | 0.001088871 | 0.905576171 |
| TAURUS INDX | 0.032571 | 0.003226 | 0.001426 | 0.001574737 | 0.864950527 |

## 5.5 Estimates from Multivariate GARCH Model

The final approach used in this paper to estimate the time-varying hedge ratios is by employing a multivariate GARCH (M-GARCH model). A constrained version of the bivariate BEKK proposed by Engle and Kroner, 1995 is used. The main motive for using GARCH models by numerous academics is the heteroscedastic nature of financial time series data and varying risk over time. Time varying hedge ratios are estimated using bivariate cointegration model explained by equation (4.10) and (4.11). In order to take care of cointegration the mean equations is modelled with a bivariate ECM, in addition time-varying variance and covariances are also considered by modelling with a bivariate GARCH(1,1) model as proposed in Engle and Kroner, 1995 and for our data set the correlations between the spot and future returns is also time varying. As a result a dynamic model estimated with time-varying variances and covariances will be more efficient.

Before employing the BGARCH (1, 1) models at different lags it is essential to test if ARCH effect is present in the data. Hence, we run an ARCH test. The F-test values and the presence or absence of ARCH effect are provided in table 14. The test indicates that ARCH effect is present in 6 out of 12 series.

**Table 14.** **Results from ARCH Test**

| *CASH PORTFOLIOS* | *F-VALUE[T-PROB]* | *ARCH EFFECT* |
|---|---|---|
| BOB ELSS | 2.092181 [0.9999]* | √ |
| GIC | 2.0058993 [1.0000]* | √ |
| LIC | 1.2435 [0.2666] | X |
| MTP 94 | 2.4244 [0.0123]* | √ |
| NIFTY INDEX | 1.3852 [0.1856] | X |
| REL ST | 1.4722 [0.1513] | X |
| SAHARA | 0.0049063 [1.0000] | X |
| SBI MGLF | 0.17152 [0.9979] | X |
| TAURUS DISC | 2.2246 [0.0163]* | √ |
| TAURUS STAR | 2.73395 [0.6924]* | √ |
| TAURUS INDX | 0.051796 [1.0000] | X |
| NIFTY FUTURES | 2.5993 [0.1054]* | X |

The hedge ratios are calculated using equation (4.15). Table 15 reported in the appendix displays the results from BGARCH (1, 1) model with lowest AIC value among models up to 6 lags. Although past literature have used BGARCH (1,1) with a single lag for $\Delta S$ and $\Delta F$ it is found that for the data from Indian market generates lowest AIC values for models more than lag 1. Along with the lowest AIC values table 15 also includes hedge ratios series for different portfolios[6] from BGARCH (1, 1) model. Table 16 provides an example of the selection criterion for the best GARCH model.

[6] Hedge ratios could not be generated for 2 portfolios viz. Sahara Mutual Fund and Reliance Short term Mutual Fund due to the presence of non positive covariance matrix.

**Table 15.** **Lowest AIC, and Hedge Ratio Estimates of BGARCH (1, 1)**

| *CASH PORTFOLIOS* | *LOWEST AIC STOCK RETURN* | *LOWEST AIC FUTURE RETURN* | *LAGS* | *H RATIO* |
|---|---|---|---|---|
| BOB ELSS | –4.22824 | –4.1057 | 1 | 0.937 |
| GIC | –3.360622 | –3.528543 | 4 | 1.084 |
| LIC | –4.180614 | –3.857081 | 1 | 0.846 |
| MTP 94 | –4.2470213 | –4.034417 | 1 | 0.892 |
| NIFTY INDEX | –4.10878 | –4.051209 | 1 | 0.973 |
| SBI MGLF | 4.4404975 | –4.109335 | 3 | 0.843 |
| TAURUS DISC | –4.064744 | –4.03832 | 1 | 0.984 |
| TAURUS STAR | –4.126319 | –4.044692 | 1 | *0.957* |
| TAURUS INDX | -4.1232556 | –3.912259 | 4 | 0.900 |

**Table 16.** **Example for GARCH Selection Criterion for MTP 94**

| *LAGS* | *AIC STOCK RETURN* | *AIC FUTURE RETURN* |
|---|---|---|
| 1 | –4.24702133 | –4.034417 |
| 2 | –4.2355963 | –4.0229921 |
| 3 | –4.2166177 | –4.0040135 |
| 4 | –4.2022402 | –3.989798 |
| 5 | –4.2088609 | –3.99625671 |
| 6 | –4.1807012 | –3.968097 |

**Table 17.** **Standard Deviations and Mean Returns of BGARCH (1, 1)**

| *CASH PORTFOLIOS* | *STANDARD DEVIATION* | *MEAN RETURN* |
|---|---|---|
| BOB ELSS | 0.03118297 | 0.003705126 |
| GIC | 0.042173707 | 0.003288729 |
| LIC | 0.030198765 | 0.004053102 |
| MTP 94 | 0.03239974 | 0.001676605 |
| SBI MGLF 94 | 0.031355434 | 0.002375053 |
| TAURUS DISC | 0.032575275 | 0.003210094 |
| TAURUS INDEX | 0.033958248 | 0.005554448 |
| TAURUS STAR | 0.032571749 | 0.003224593 |
| NIFTY INDEX | 0.032175804 | 0.003185964 |

Finally, table 17 provides standard deviation and mean returns from the hedged portfolio using BGARCH (1, 1) hedge ratios. Remarkably hedge ratios estimated from GARCH model are lower than the one estimated from other models (Table 18). Thus, it can be concluded that GARCH models underestimate the hedge ratios as compared to other models and they may not be very effective in risk reduction.

**Table 18. Optimal Hedge Ratio Series from All 5 Models**

| *CASH PORTFOLIOS* | *VECM H* | *ECM H* | *OLS H* | *LTS H* | *BGARCH (1,1) H* |
|---|---|---|---|---|---|
| BOB ELSS | 0.932877 | 0.936162 | 0.940594 | 0.913291 | 0.937305 |
| GIC | 1.078078 | 1.080860 | 1.087590 | 0.913291 | 1.084761 |
| LIC | 0.845381 | 0.847193 | 0.850640 | 0.876225 | 0.846647 |
| MTP 94 | 0.892756 | 0.899043 | 0.904215 | 0.910247 | 0.892911 |
| NIFTY INDEX | 0.974339 | 0.020890 | 0.976313 | 0.970646 | 0.973032 |
| REL ST | 0.005922 | 0.005946 | 0.007235 | 0.004413 | 0.000000 |
| SAHARA | 0.017053 | 0.020148 | 0.011907 | 0.006994 | 0.000000 |
| SBI MGLF | 0.787616 | 0.791458 | 0.847401 | 0.908034 | 0.843267 |
| TAURUS DISC | 0.990860 | 0.993574 | 0.986879 | 0.965943 | 0.984160 |
| TAURUS STAR | 0.905576 | 0.909100 | 0.960008 | 0.934297 | 0.957385 |
| TAURUS INDX | 0.864951 | 0.867320 | 0.903935 | 0.936299 | 0.900390 |

## 5.6 Hedging Effectiveness

Thus far, five techniques have been employed in our study to estimate optimal hedge ratios. In this section of the paper, hedging effectiveness of the hedge ratios is analyzed over an ex post horizon. For this analysis of the hedge ratio series an unhedged portfolio and a corresponding hedged portfolio are formed. Where the hedged portfolio consists of one spot portfolio (or is only made of cash position) and the hedged portfolio consists of a combination of spot portfolio and futures contracts. The estimated hedge ratio by different models, determines the optimal number of future contracts to be held to hedge the portfolio. The value of such hedged portfolio is estimated using equation (4.17) and the returns are calculated by taking the first dlogged difference of the value.

The standard deviations of returns of hedged and unhedged portfolios are obtained and the risk reduction is calculated using equation (4.16). The risk reductions obtained for different portfolios using the 5 models is provided in table 19. Further table 19 reports the series of hedge ratios obtained from the 5 models viz. OLS, LTS, ECM, VECM and BGARCH (1,1). It can be seen that the hedge ratios from the VECM model are not greater than the other models which should have been the case when compared with the past literature for eg. Ghosh, 1993. In our study the cointegration relationship between the spot and futures position is not ignored hence the hedge ratios are not downward biased for VECM.

On analyzing table 19 carefully and plotting the values as clustered columns in order to compare the risk reduction across different portfolios using hedge ratios estimated using different values it is can be clearly noted that the highest risk reduction takes place in case of the Nifty index portfolio. The Nifty futures contract provides an average risk reduction of 68.82% for Nifty Index portfolio which reflects exactly the same stocks underlying the futures contract. When compared the risk reduction for other cash portfolios comprising of the mutual funds they are much lower, with the lowest being 2.05% and highest 26.50%.

Thus, it can be easily concluded that the reason for such huge difference in the risk reduction between Nifty Index portfolio and other mutual funds is the weak covariance between mutual funds and futures contract.

**Table 19. Risk Reduction Series**

| *CASH PORTFOLIOS* | *OLS* | *LTS* | *VECM* | *ECM* | *1TO1* | *BGARCH(1,1)* |
|---|---|---|---|---|---|---|
| BOB ELSS | 26.534 | 25.974 | 26.505 | 26.504 | 25.970 | 25.925 |
| GIC | 17.587 | 17.578 | 17.587 | 17.587 | 17.583 | 17.587 |
| LIC NIFTY | 5.260 | 5.260 | 5.187 | 5.187 | 5.187 | 5.223 |
| CP MTP 94 | 4.203 | 4.202 | 4.203 | 4.203 | 4.660 | 4.203 |
| REL ST MF | 10.486 | 10.966 | 10.731 | 10.561 | 10.385 | 0 |
| SAHARA INCOME FUND | 2.517 | 2.328 | 3.045 | 3.145 | 3.146 | 0 |
| SBI MGLF 94 | 24.479 | 24.472 | 24.486 | 23.327 | 24.451 | 24.479 |
| TAURUS DISCOVERY FUND | 25.252 | 25.252 | 25.252 | 25.252 | 25.461 | 25.252 |
| TAURUS INDEX FUND | 13.415 | 13.413 | 13.415 | 13.414 | 13.674 | 13.415 |
| TAURUS STAR SHARE | 18.604 | 18.831 | 18.605 | 18.605 | 18.831 | 18.605 |
| NIFTY | 69.947 | 0.0197 | 0.0195 | 68.799 | 65.790 | 68.563 |

Apparently, risk reduction across different mutual funds is also remarkably different. This is usually the case in reality because different mutual funds have different investment styles. For example CP MTP 94 which has risk reduction as low as only 4%, the main reason is because it invests 80% of the funds in property equities. The Nifty futures contract which is used to hedge has hardly 8 companies out of 50, whose core business is realty. Hence, a weak covariance is noticed among the cash and futures position. On the contrary, the highest risk reduction among the mutual funds is obtained for BOB ELSS 96 which is 26%. The main reason is because BOB ELSS 96 invests all its funds in the Indian companies. Although the cross hedge problem prevails in the Indian derivatives market, since the mutual funds achieve low risk reductions on an average. These results are in line with Butterworth and Holmes, 2000 who also achieve a risk reduction of 10-15%. Nevertheless, the Nifty Index portfolio which achieves a risk reduction of around 68% instead of a full 100%, which indicates the movements in basis, exists among Nifty Index and Nifty Futures contract.

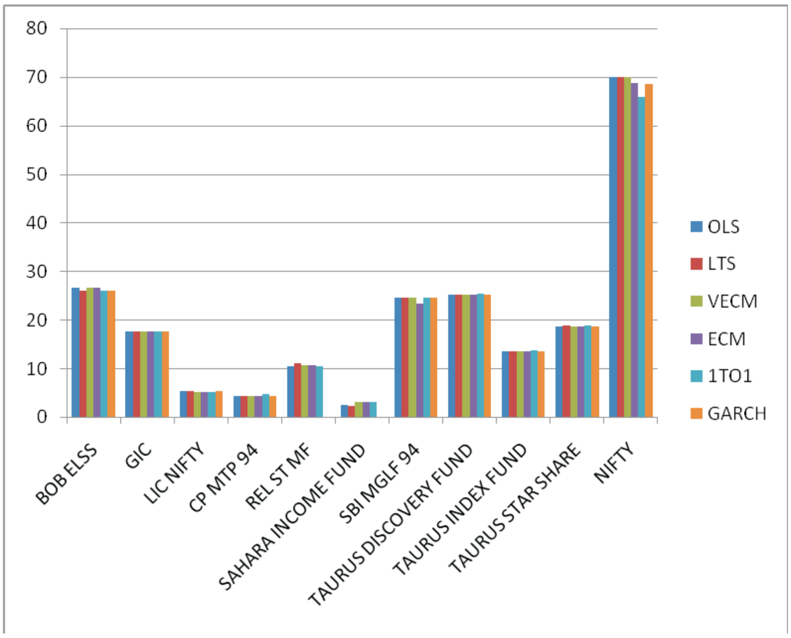



**Figure 1 Risk Reduction among Different Models**

Risk reductions from naive hedge strategy of holding a single futures contract is also provided in table 20 for convenience. Surprisingly the naive hedge also provides similar risk reduction among different portfolios. The main reason is the estimated hedge ratios are close to 1 in most of the cases. But using the naive hedge strategy will cause the investors a high amount of money due to unnecessary purchase of more number of futures contract and gaining comparatively low risk reduction.

Finally, for selecting the best model for the Indian derivatives market we use a simple logical method. Firstly, we compare each portfolio's risk reduction to the same portfolio's risk reduction but for the hedge ratio estimated from a different model. One example is provided in table 20 below. For instance we compare how many times risk reduction is greater by OLS as compared to LTS, ECM, VECM AND BGARCH (1, 1) for all the portfolios. As an example, if OLS scores over the other models for six or more than six times then it can be stated to be the best model, as 11 portfolios are considered in the study. In this way the model which beats the other model maximum time is the best model. This technique is employed since there is a very minute difference in risk reduction among different models. According to the above technique OLS seems to be the best model for the Indian markets and investors are strongly recommended to use this model as it is also clear from the figure 1 above that OLS provides the highest risk reduction as compared to other models.

**Table 20. Risk Reduction Comparison**

| *COMPARISON* | *OLS>LTS* | *OLS>VECM* | *OLS>ECM* | *OLS>1TO1* | *OLS>GARCH* |
|---|---|---|---|---|---|
| CASH PORTFOLIS | | | | | |
| BOB ELSS | OLS>LTS | OLS>VECM | OLS>ECM | OLS>1TO1 | OLS>GARCH |
| GIC | OLS>LTS | OLS>VECM | OLS>ECM | OLS>1TO1 | OLS>GARCH |
| LIC NIFTY | OLS<LTS | OLS>VECM | OLS>ECM | OLS>1TO1 | OLS>GARCH |
| CP MTP 94 | OLS>LTS | OLS<VECM | OLS<ECM | OLS<1TO1 | OLS<GARCH |
| REL ST MF | OLS<LTS | OLS<VECM | OLS<ECM | OLS>1TO1 | OLS>GARCH |
| SAHARA INCOME FUND | OLS>LTS | OLS<VECM | OLS<ECM | OLS<1TO1 | OLS>GARCH |
| SBI MGLF 94 | OLS>LTS | OLS<VECM | OLS>ECM | OLS>1TO1 | OLS<GARCH |
| TAURUS DISCOVERY FUND | OLS>LTS | OLS<VECM | OLS<ECM | OLS<1TO1 | OLS>GARCH |
| TAURUS INDEX FUND | OLS>LTS | OLS>VECM | OLS>ECM | OLS<1TO1 | OLS<GARCH |
| TAURUS STAR SHARE | OLS<LTS | OLS<VECM | OLS<ECM | OLS<1TO1 | OLS<GARCH |
| NIFTY | OLS>LTS | OLS>VECM | OLS>ECM | OLS>1TO1 | OLS>GARCH |
| TOTAL | 8 | 5 | 6 | 6 | 7 |

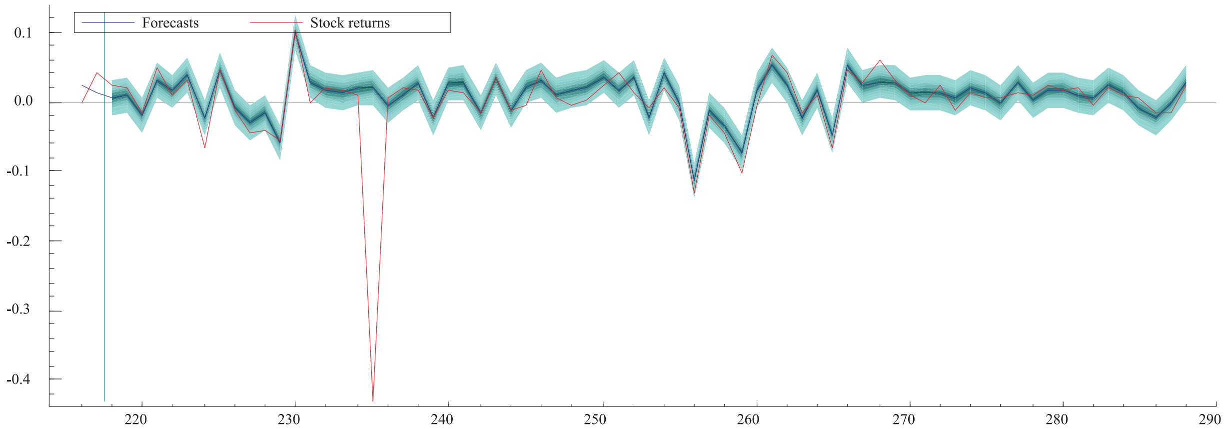
OLS risk reductions are not very high as compared to VECM. But VECM can be preferred over OLS due to the simplicity of the model. These findings are also in consistence with Butterworth & Holmes, 2001.

## 6. Conclusion

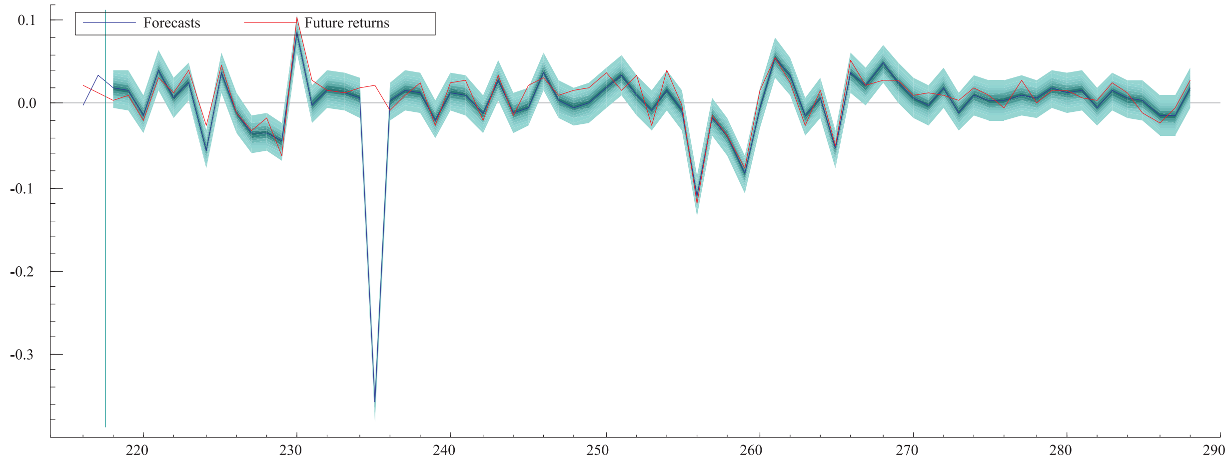
This paper investigates the hedging effectiveness of the Nifty Futures contract and focuses on determining the appropriate model among OLS, LTS, GARCH, ECM and VECM for estimating optimal hedge ratios for the Indian futures market. The time period taken under consideration ranges from 2001-2008.

Finally in order to confirm that our selected two models viz. OLS and VECM are the best estimators of hedge ratios we use them to forecast hedge ratios since investors need to anticipate the fluctuations before they actually take place. The forecasted results for BOB ELSS 96 are provided in figure 2. They suggest that OLS estimated hedge ratios provide higher risk reduction as compared to VECM and nonetheless the root mean square error and SD error are also lower in the case of OLS. Hence we can strongly recommend Indian risk managers to use OLS for estimation of hedge ratios.

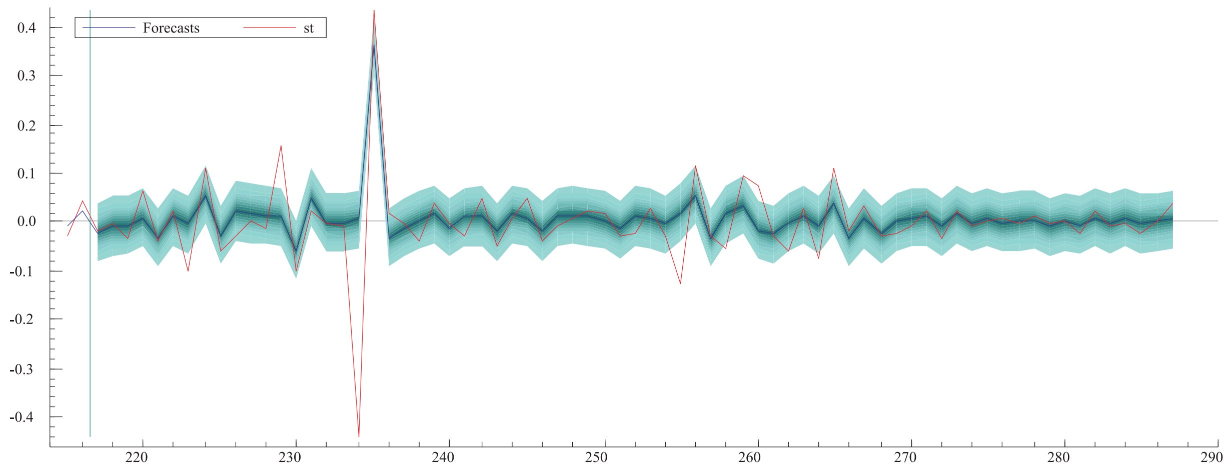
(i) Stock Returns using OLS




(ii) Future Returns using OLS




(iii) Stock Returns using VECM



(iv) Future Returns using VECM

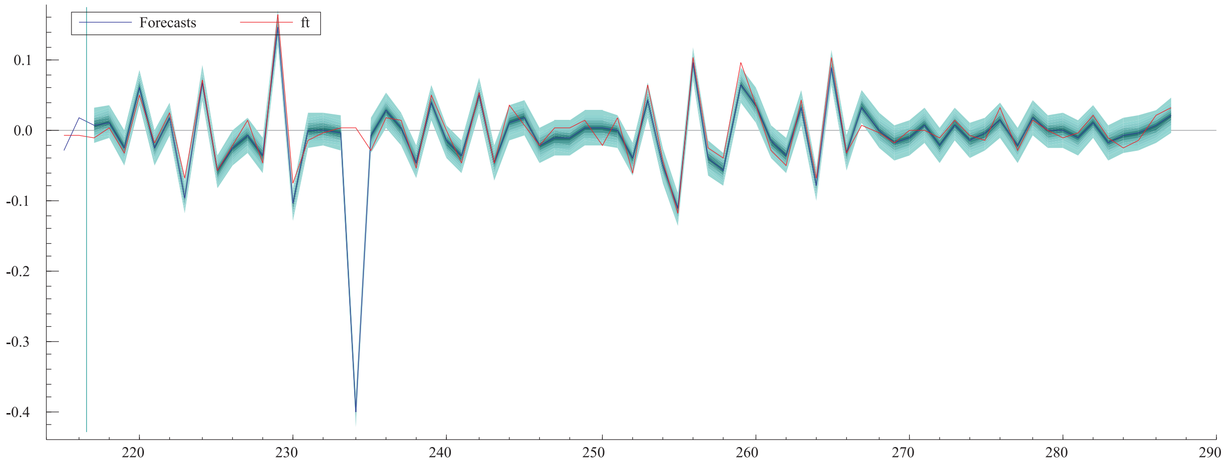



**Figure 2 Forecasted Graphs for BOB ELSS 96**

While, the outliers do not affect significantly to our data set and the hedge ratios estimated from LTS approach are not significantly different then OLS. But when risk reduction is compared OLS outperforms LTS. These findings are also in line with Butterworth & Holmes, 2001.

Overall, all the models provide similar risk reduction when compared to naive hedge strategy and unhedged portfolio. The performance of other models like BGARCH (1, 1) and ECM are surprisingly not efficient when compared to other models. These results are quite unexpected as hetroscedasticity and autocorrelation were found in most of the data sets. Further, the problem of cross hedge does exist in the Indian markets as maximum risk reduction is obtained for Nifty Index portfolio as compared to other mutual funds. Hence the Nifty futures contracts are not certainly effective enough to hedge actual market portfolios.

The results mentioned above may be data specific and several variations which can be used in further research could lead to different results. If investor's degree of risk aversion is taken into consideration it could lead to a different conclusion. Hence, a utility based comparison proposed by other authors like Gagon et al 1998 can definitely expand the set of conclusions. Estimations with different hedge periods (window size) instead of weekly could also propose different results. At last by incorporating transaction costs in the study could throw light on many new advantages and disadvantages. All these questions are left for further research.

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