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Evaluation of Hedging Effectiveness for CNX Bank and Nifty Index Futures

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Abstract

The hedging effectiveness for bank futures and CNX nifty are evaluated in this study. The study is based on 9569 observations of the daily data for these index futures. For evaluation OLS, co-integrated OLS, GARCH (1, 1) and constant correlation GARCH (1, 1) hedging methods are estimated and compared. Result shows that constant correlation GARCH (1, 1) is an efficient hedging method that maximizes investors' utility function considering transaction costs. Therefore, investors can rely on this constant correlation GARCH (1, 1) hedging method.

Key words: Hedging effectiveness, Constant correlation GARCH (1, 1) hedging method, Bank futures, CNX nifty.

JEL Classification: G10, G12, G21

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1. Introduction

Market participants make the market with market-making information, which are often asymmetrical in nature. For example in the context of foreign exchange-rate exposure trading, information like firm size and use of interest-based or commodity-based derivatives may determine the probable use of currency derivatives for speculation in their (firms') optimal hedging strategies (Geczy et al. 1997). Therefore, hedging is ultimately considered as to minimize risks in trading. With this light of observation and using the constant correlation generalized ARCH (1, 1) hedging model, this study attempts to evaluate the utility of hedging models in minimizing the risk and maximizing returns of CNX bank and nifty Index futures[1] investors.

The India Index Service and Product Limited manage CNX bank Index. It captures the capital market performance and provides investors and market intermediaries with a benchmark of the Indian banking sector. This Index has twelve scrips from banking sector, which is traded in the National Stock Exchange of India Limited (NSE). 'The total traded value for the last six months of CNX bank Index stocks is approximately 96.46% of the traded value of the banking sector. It represents about 87.29% of the total market capitalization of the banking sector as on March 31, 2009. The total traded value for the last six months of all the CNX bank Index constitutes is approximately 15.26% of the traded value of all stocks at the NSE. CNX bank Index constitutes represent about 7.74% of the total market capitalization as on March 31, 2009 (www.nseindia.com). The market has witnessed a steady growth in investor preference in banking scrips. Consequently, these scrips have often exhibited high level of volatility too.

[1] These indices are out of the joint venture between the Credit Rating and Information Services of India Limited (CRISIL) and the National Stock Exchange of India Limited (NSE) and hence CNX bank and nifty index.

In this context, this study intends to measure and analyze the economic viability of hedging models for both CNX bank and nifty Index futures (hereafter bank futures and CNX nifty respectively). This is because, hedging is a prominent method used by market participants to minimize risk. Empirical results suggest that constant correlation GARCH (1, 1) hedge provides an improved hedging method where investors maximize their utility functions considering transaction costs.

The reminder of the paper is organized as follows. The next section presents methodology. Each of the successive sections presents data, empirical findings, and discussions. The last section presents conclusion.

2. Methodology

This study follows the bivariate GARCH (1, 1) model (Bollerslev 1986, 1987, 1988; Park and Switzer 1995; Prasanna and Supriya 2007). Hedging models are constructed using a two-period investment decision based on utility maximization model. Using spot price (S_t) and futures price (F_t) for both these indices, hedging models are estimated and analyzed. Futures price is calculated by using the cost of carry model where the Mumbai inter-bank call rate is considered the proxy for the financing rate. That is futures price[2] = closing price + [closing price × (call rate – dividend yield)] × (T-t/365). Where, 'T' is total number of trading days for the futures contract (i.e. 91/92 days consisting of three months) and 't' is the actual trading days for the contract (i.e. five days in a week so in total 60 days). The dividend yield is included in the calculation of futures price. This is based on the assumption that the financial market and derivatives market are linked and thereby have a bearing on the bank futures and CNX nifty spot prices. Moreover, the relationship between call interest rate and investment decision in the financial market is fairly interdependent. Consequently, these have a significant impact on investment in bank futures and CNX nifty contracts by individuals, banks, and financial

[2] See Edwards and Ma (1992, p.231 and 232)

institutions. It is observed that both the interest that is paid in the call market against the loan for investment and the dividend on securities are not zero over this study period.

In this study, contracts for both the bank futures and CNX nifty are considered with the call rate as financing rate. It is further assumed that the particular call rate is same throughout the contract period of three months for all those who have invested on a particular trading day. The call rate is subject to change, in response to the demand and supply pressure in the call money market. The investor makes investment decisions based on the call-financing rate of the day. Past and future call rates are immaterial to the investor on account of urgency in requirement of financial resources for purpose of investment. It is likely that these investors are ready to invest in derivatives market for a particular settlement date without much heed to prospective call rates. This is because, it is observed in the market that even considering other financing rate e.g. the Treasury bill rate, futures contract has been trading irrespective of its maturing period of three months depending upon the market conditions. Therefore, to observe the actual market position until the last month of the contract, this study has considered expiry wise contracts than contracts of near month futures. Again, these various financing rates are non-stochastic in nature in the market as far as the investors' investment perspective is concerned. Therefore, the point is that any of financing rates in the financial market supports for the equal importance of money sources at the face of its opportunity cost. Here, there is no issue on what the contract period is. At least this holds good at the investors' psychology as far as investment in derivatives market is concerned (Prasanna, 2011). Therefore, the call rate is considered as the financing rate for the period of three months where the cost of carry period is 'T - t' = 91 - 60 = 31 days.

Now, the dynamic returns for both indices i.e. '$S_{t-2} - \gamma F_{t-2}$' are calculated considering the importance of basis[3] in the market. Here, dividends are subtracted from

[3] This is because in the context of expiry contracts (far month contracts) basis (spot price as premium or discount to futures price) should be with zero value. That is the magnitudes (in units) of spot and futures positions should promote futures-gain (loss) position by offsetting loss (gain) in the value of spot position.

the spot prices (S_t) to represent the accurate cost of carry model of future prices. Hence, this study has considered this dynamic return as the independent variable in the model specification[4] where the relevance of it in the context of evaluation of hedging effectiveness against futures contracts sustains. In this case, the GARCH (1, 1) model specifies mean equations as,

$$\begin{aligned} S_t &= \alpha_0 + \alpha_1\left(S_{t-2} - \gamma F_{t-2}\right) + \varepsilon_{st} \\ F_t &= \beta_0 + \beta_1\left(S_{t-2} - \gamma F_{t-2}\right) + \varepsilon_{ft} \end{aligned} \qquad \begin{bmatrix} \varepsilon_{st} \\ \varepsilon_{ft} \end{bmatrix} | \psi_{t-1} \sim N(0, H_t) \tag{1}$$

Both '$S_t = S_t - S_{t-1}$' and '$F_t = F_t - F_{t-1}$' returns depend on the dynamic returns i.e. $\left(S_{t-1} - \gamma F_{t-1}\right)$, which shows the dynamic changes in spot and futures prices. Here, $\left(\varepsilon_{st}, \varepsilon_{ft}\right) \sim N(0, H_t)$ and 'ψ_{t-1}' represents the information set. This study has considered the time-varying variances and covariances, where second moment is parameterized with bivariate constant correlation GARCH (1, 1) model (hereafter CCGARCH (1, 1)). The following model (Equation 3) has parameterized conditional variances of two variables as ARMA models in squared residuals. Here, the assumption is that there is the constant correlation between these two. Therefore the variance vector is,

$$H_t = \begin{bmatrix} h_{ss,t} & h_{sf,t} \\ h_{fs,t} & h_{ff,t} \end{bmatrix} = \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{f,t} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} h_{s,t} & 0 \\ 0 & h_{f,t} \end{bmatrix} \tag{2}$$

So that the price risk elimination is also expected in this type of contracts. However, one question arises here. Do they (contracts) work in the expected manner? Answer to this question is discussed in the successive explanations.

[4] It is estimated and observed that error terms from the regressions of 'S_{t-1}' on 'F_{t-1}'for both indices are stationary where the estimated coefficients of their one lag terms as independent variables for the dependent first differenced error terms are negative at 0.01 level ((Augmented) Dickey - Fuller test). It is also estimated that 'S_{t-1}' and 'F_{t-1}' are cointegrated as the one lag error terms (from the initial regressions of 'S_{t-1}' on 'F_{t-1}') in the Error Correction Models are negative at 0.01 level.

with the conditional variance and covariance equations as,

$$h_{s,t}^2 = c_s + a_s \varepsilon_{s,t-1}^2 + b_s h_{s,t-1}^2$$
$$h_{f,t}^2 = c_f + a_f \varepsilon_{f,t-1}^2 + b_f h_{f,t-1}^2 \quad (3)$$

Equation (2) shows the structure of time varying bivariate conditional variance vector with constant correlation. Equations (3), represents the bivariate GARCH (1, 1) conditional variance-covariance model. With the existence of long-run co-integration relationship between spot and futures returns (dynamic returns), the hedge ratios are calculated with the variance estimates from Equation (2) as,

$$\hat{b}_t^* = \frac{\hat{h}_{sf,t}}{\hat{h}_{ff,t}} \quad (5)$$

The one period forecasted optimal hedge ratio '$\hat{b}_t^*$' is calculated for the last half of observations using estimated hedge ratio from the first half of observations. In addition, the OLS hedge ratio is defined with the restriction '$\alpha_1 = \beta_1 = a_s = b_s = a_f = b_f = 0$'. The OLS hedge ratio that accounts for the long-run co-integration between spot and futures returns (dynamic returns) are defined with the restriction '$a_s = b_s = a_f = b_f = 0$'. After estimating optimal hedge ratios, the variances of the returns to the constructed portfolios i.e. $\sigma^2\left(S_t - \hat{b}_t^* F_t\right)$ are calculated and evaluated over the second half of the total sample, where '$\hat{b}_t^*$' is the forecasted optimal hedge ratio based on the first half of the total sample.

The hedging models are constructed using a two-period investment decision based on maximization of consumption utility in future period. This study has modeled that 'S_t' and 'F_t' are the spot and futures returns, where assumption is that only hedging instrument is available to the investor. In this case, hedge portfolio consisting spot and futures is constructed. Here, 'S_{t+1}' and 'F_{t+1}'are the changes in spot and futures returns between

time '*t*' and '*t+1*' and 'b_t' represents futures at time '*t*'. The payoff at '*t*+1' is $x_{t+1} = S_{t+1} - b_t F_{t+1}$. This implies that the investor is purchasing one unit of the spot and going short in 'b_t' units of futures at time '*t*'. Here, optimal hedge ratio '$\hat{b}_t^*$' maximizes the investors' consumption utility and minimizes risk of portfolios. The assumption is that futures prices are martingale i.e. the expected value of futures price at '*t*' is equal to the expected value at '*t+1*'. In successive analysis, the first and second half of data are considered at time periods of '*t*' and '*t+1*' respectively.

Finally, this study has evaluated the performance of each type of hedge methods and compared it by using the mean-variance expected spot-futures portfolio utility function. Here, investors appear to have maximized their utility thus establishing the economic sense of the CCGARCH (1, 1) hedging model for both the bank futures and CNX nifty.

3. Data, Empirical findings, and Discussions

The present study has used the contract expiry wise daily data for bank futures and CNX nifty contracts from June 13, 2005 to December 21, 2010 consisting 1367 daily observations with the total of 9569 observations. Daily spot price data for both bank futures and CNX nifty are collected from the NSE website. Daily futures price data for both these indices are calculated with the cost of carry model discussed earlier. The call rate data are collected from the RBI website. The dividend yields for both the index futures are collected from the NSE website. The public sector bank dividend yields data are included in this study as the proxy yields for the bank futures for study period until November 16, 2007. Thereafter, bank futures dividend yields data available in NSE website are used. Dynamic returns are calculated for both the index futures.

This study has considered the econometric model specification, where all of the variables like spot, futures, and dynamic returns are modeled without any logarithmic

transformation. The reasons are explained here. With logarithmic transformation of spot and futures returns, it is observed that autocorrelation problem exists in the initial regression estimation where spot and future returns are independent and dependent variables respectively. It is observed that without logarithmic transformation of returns, error terms (ε_{st} and ε_{ft}) in Equation (1) are stationary where the estimated coefficients of their one lag terms as independent variables for the dependent first differenced error terms are negative at 0.01 level ((Augmented) Dickey - Fuller test).

In addition, the long-run relationship between spot and dynamic returns is also established with the Engle-Granger-2-step procedure in the following manner. Equation (6) and (7) represent equilibrium correction or error correction models for both indices respectively. With $S_{bt} = S_{bt} - S_{bt-1}$, $S_{nt} = S_{nt} - S_{nt-1}$, $D_{bt} = S_{bt-2} - \gamma F_{bt-2}$, $D_{nt} = S_{nt-2} - \gamma F_{nt-2}$, $\Delta S_{bt} = (S_{bt} - S_{bt-1})_{bt} - (S_{bt} - S_{bt-1})_{bt-1}$, $\Delta S_{nt} = (S_{nt} - S_{nt-1})_{nt} - (S_{nt} - S_{nt-1})_{nt-1}$, $\Delta D_{bt} = D_{bt} - D_{bt-1}$, $\Delta D_{nt} = D_{nt} - D_{nt-1}$ the bank futures equilibrium correction model is,

$$\begin{aligned} S_{bt} &= \lambda_{b0} + \lambda_{b1} D_{bt} + u_{bt} \\ \Delta S_{bt} &= \zeta_{b0} + \delta_{b1} \hat{u}_{bt-1} + \zeta_{b2} \Delta D_{bt} + \upsilon_{bt} \end{aligned} \tag{6}$$

and the CNX nifty equilibrium correction model is;

$$\begin{aligned} S_{nt} &= \lambda_{n0} + \lambda_{n1} D_{nt} + u_{nt} \\ \Delta S_{nt} &= \zeta_{n0} + \delta_{n1} \hat{u}_{nt-1} + \zeta_{n2} \Delta D_{nt} + \upsilon_{nt} \end{aligned} \tag{7}$$

Here, equilibrium correction terms like '$\delta_{b1}\hat{u}_{bt-1}$' and '$\delta_{n1}\hat{u}_{nt-1}$' are included as independent variables, where the co-integrating vectors are $\left(1 - \hat{\lambda}_{b0} - \hat{\lambda}_{b1}\right)$ and $\left(1 - \hat{\lambda}_{n0} - \hat{\lambda}_{n1}\right)$. From Table (1), it is observed that estimated constant and slope coefficients

in co-integrating regressions are positive respectively. With the unrestricted $\Delta\hat{u}_{bt} = c_0 + c_1 t + c_2\hat{u}_{bt-1} + c_3\Delta\hat{u}_{bt-1} + e_{bt}$ & $\Delta\hat{u}_{nt} = c_0 + c_1 t + c_2\hat{u}_{nt-1} + c_3\Delta\hat{u}_{nt-1} + e_{nt}$ and restricted $\Delta\hat{u}_{bt} = c_0 + c_3\Delta\hat{u}_{bt-1} + e_{bt}$ & $\Delta\hat{u}_{nt} = c_0 + c_3\Delta\hat{u}_{nt-1} + e_{nt}$ residual regressions, it is estimated that the computed 'F' ratio statistic values are 500.89 and 541.89 respectively. These values are greater than the (A)DF critical value 8.34 at 1% level with the restriction of c_0, $c_1 = 0$, and $c_2 = 0$ where $c_2 = \rho - 1$ and $\rho = 1$ (Dickey and Fuller, 1981, Table VI, p.1063). Therefore, this study rejects the residual random walk hypothesis at 1% level. In addition, DF tests on estimated residuals (with constant and trend) show that absolute estimated values |-24.84| and |-25.55| are greater than the critical value |-3.98| at 1% level (Table 1). Therefore, from each of Equation (6) and (7) the null of a unit root is rejected. Therefore, alternative hypothesis i.e. stationary '$\hat{u}_{bt}$' and '$\hat{u}_{nt}$' are accepted. From these results, it is concluded that 'S_{bt}' & 'D_{bt}' and 'S_{nt}' & 'D_{nt}' are co-integrated respectively. Whether the individual variables are stationary is also already tested with I(0) process (Footnote 4).

Table 1: Co-integrating Regressions

Estimators	**Bank Futures** $S_{bt} = \lambda_{b0} + \lambda_{b1}D_{bt} + u_{bt}$	**CNX Nifty** $S_{nt} = \lambda_{n0} + \lambda_{n1}D_{nt} + u_{nt}$
	Estimates	Estimates
$\hat{\lambda}_{b0}$ & $\hat{\lambda}_{n0}$	9.6076	5.5584
$\hat{\lambda}_{b1}$ & $\hat{\lambda}_{n1}$	0.1788	0.1946
'F' ratio test statistic	500.8896*	541.8910*
DF test statistic on residuals	-24.8351*	-25.5451*

* Significant at 0.01 level. 'S_{bt} & S_{nt}' = Spot prices, and 'D_{bt} & D_{nt}' = Dynamic returns.

In second step estimation (Table 2), estimators like '$\hat{\delta}_{b1}$' and '$\hat{\delta}_{n1}$' are significantly negative and different from zero by -0.9426 and -0.9938 respectively. This implies that if

the difference between spot and dynamic returns is positive in one period, the spot returns will decrease during the next period to restore the equilibrium. Similarly, if the difference between spot and dynamic returns is negative in one period, the spot returns will increase during the next period to restore the equilibrium. The estimators like '$\hat{\zeta}_{b2}$'and '$\hat{\zeta}_{n2}$' suggest that the dynamic returns affect spot returns positively in case of both bank futures and CNX nifty futures respectively. This long-run equilibrium will be maintained with efficient call money market, which is related with liquidity adjustment mechanism of the Reserve Bank of India (RBI). It is also examined that dynamic returns granger cause spot and futures returns for both indices. In addition, it is estimated that the cointegrating durbin-watson '*d*' statistics for both regressions are greater than 0.5 at higher significance level. Thus, the long-run relationship between spot and dynamic returns for both the indices are confirmed.

Table 2: Estimated Error Correction Models

Estimators	**Bank Futures**		**CNX Nifty**	
	$\Delta S_{bt} = \zeta_{b0} + \delta_{b1}\hat{u}_{bt-1} + \zeta_{b2}\Delta D_{bt} + \upsilon_{bt}$		$\Delta S_{nt} = \zeta_{n0} + \delta_{n1}\hat{u}_{nt-1} + \zeta_{n2}\Delta D_{nt} + \upsilon_{nt}$	
	Estimates	*p*-values	Estimates	*p*-values
$\hat{\zeta}_{b0}$ & $\hat{\zeta}_{n0}$	-0.0374	0.9933	-0.0044	0.9984
$\hat{\delta}_{b1}$ & $\hat{\delta}_{n1}$	-0.9426*	0.0000	-0.9938*	0.0000
$\hat{\zeta}_{b2}$ & $\hat{\zeta}_{n2}$	0.0844	0.8721	0.2702	0.4705

* Significant at 0.01 level.

In this section, the hedging effectiveness with each of models is compared. The full hedging effectiveness (FHE) is defined as 1 minus the ratio whose numerator is the variance of changes in the difference of spot (S_t) and futures price (dynamic return) and whose denominator is the variance of changes of the spot price (Houthakker and Williamson 1996). Here the calculated FHE for both indices are -0.0052 and -0.0051. This

shows that hedging is negative and approaching to zero. Using FHE and respective partial hedging effectiveness (PHE) i.e. -63.14 and -37.01 for both indices, hedge ratios are calculated with the formula PHE = $HR^2/(2HR\text{-}FHE)$. As a result, respective hedge ratios for both indices are -0.005 and -0.005. Other roots for both indices are -126.275 and -37.008 respectively[5]. It can be observed that these hedge ratios are negative and approaching zero. Therefore, this observation concludes that the Indian futures markets have been experiencing inefficient hedging at the face of illiquidity situation.

Applying maximum likelihood estimation OLS, OLS co-integration, GARCH (1, 1), and CCGARCH (1, 1) models' parameters are estimated. The hedging effectiveness is measured through the dynamic hedging performance of the above models for the out-of-sample periods. Here the first 683 daily observations are used to estimate parameters for all hedging models. Using these estimated parameters and last observation (i.e. 683rd observation), the one step forecast hedge ratio is estimated which is the one-period forecast of covariance divided by one-period forecast of variance. After estimating the optimal hedge ratio '$\hat{b}_t^*$' of each hedge method, the variances of the returns to the constructed portfolios $\sigma^2{}_{(S_t - \hat{b}_t^* F_t)}$ are calculated for the half of the total sample. Therefore, the portfolios implied by the hedge ratios are compared for each hedge methods.

It is observed that except CCGARCH (1, 1) hedge ratios, other hedge ratios do not show for the perfect hedging. These other hedge-ratio values are obtained from one-step forecast values those depend on each of 683rd estimated variances and covariances. These other hedge ratios imply that hedging is imperfect by worsening the hedger's position. Therefore, subtract from (add to) the loss (gain) is not realized where optimal hedge ratios

[5] Roots for both indices are calculated from the algebraic quadratic equation '$aHR^2 + bHR + c = 0$', where a = 1, b = -2PHE, and c = PHE.FHE.

for respective hedging models are imperfect with the existence of basis risk[6] which does not help to minimize (maximize) the expected loss (gain). In this context, it is already observed that hedging in near month futures contract is more effective for some of specific futures contract (Ederington, 1979). However, in this study the query on 'what about the case of far month futures contract investments' is focused having equal importance of money sources at the face of its opportunity cost. It is observed that rational and perfect hedging is implied with CCGARCH (1, 1) hedge model where CCGARCH (1, 1) hedge ratios are 1.02 and 1.01 for both indices. It seems these CCGARCH (1, 1) hedge ratios show for perfect hedging comparing the particular GARCH (1, 1) and other hedge ratios. This is because lower hedge ratio figures may not be desirable with the existence of zero-sum game trading with speculation or arbitration in the market. So these lower figures may represent as unprofitable speculation or futile arbitration ratio as the part of optimal hedging activity (Table 3). Therefore, technically and theoretically it seems CCGARCH (1, 1) hedge ratios[7] are more efficient than the GARCH (1, 1) hedge ratios.

Table 3: Optimal Hedge Ratios with Hedging Models*

Hedging Models	Bank Futures	CNX Nifty
OLS	0.9963	0.9888
Co-integrated OLS	0.9928	0.9881
GARCH (1, 1)	0.9880	0.9880
Constant correlation GARCH (1, 1)	1.0187	1.0057

* Hedge ratios are estimated from the ratio of one-period forecast of covariance to one-period forecast of variance.

[6] It is observed that the average rates of changes of basis [spot – futures (dynamic returns) in unit terms] are higher at 13% and 14% for both indices over the sample period.

[7] Here if we consider the original 'S_t' and 'F_t' (not dynamic returns), the FHE for both indices are 1.00. Therefore, comparing this we can say here that CCGARCH (1, 1) hedge method is efficient than other hedging methods.

Table 4: Variance Reduction*

% Variance reduction of CCGARCH (1, 1) hedge over	Bank Futures	CNX Nifty
OLS hedge	-1897	-22
Co-integrated OLS hedge	-1084	-13
GARCH (1, 1)	-372	-11
Constant correlation GARCH (1, 1) hedge		

* The estimation period is from June 13, 2005 to March 07, 2008. Total sample considers the period from June 13, 2005, to December 21, 2010. Percentage variance reductions of CCGARCH (1, 1) hedge over other hedge models are calculated as $[(\sigma^2_{OTHERS} - \sigma^2_{CCGARCH}) / \sigma^2_{OTHERS}] \times 100$ using the second half of the total sample. This is because, it is proved that CCGARCH (1, 1) hedge ratios are efficient.

The variance reductions of portfolio returns are calculated as $[(\sigma^2_{OTHERS} - \sigma^2_{CCGARCH}) / \sigma^2_{OTHERS}] \times 100$ using the second half of total sample (March 10, 2008 to December 21, 2010). Here the portfolio returns have used hedge ratios ($\hat{b}^*_t$), which are estimated from the first half of the sample (June 13, 2005 to March 07, 2008). It is observed that all hedging models reduce the variance of spot portfolio significantly in this second half of the sample. The variance reduction is greater for CNX nifty. Table (4) shows the percentage variance reductions of CCGARCH (1, 1) hedge over other hedge positions. This implies that there is improvement of hedging effectiveness through CCGARCH (1, 1) over other hedge models in both cases.

Now, the hedging methods are compared using mean-variance expected consumption utility functions. It can be assumed that the mean-variance expected consumption utility of spot-futures hedge portfolio function with given information is

$u'(c_t)x_t = \xi E\left[u'(c_{t+1})(x_{t+1}) \mid I_t\right]$ (Grossman and Shiller, 1981). Assume that investor relies on this mean-variance expected utility function where the expected product of two variables is the product of their mean and covariances. If returns are with high negative covariances having the marginal rate of substitution between present and future utility consumption (trading with portfolios), then these portfolios are risky in nature. Therefore, the utility function with perfect foresight can be represented as $EU(x_t) = E(x_t) - \lambda.Var(x_t)$ where 'x_t' is returns from the spot-futures hedge portfolio and *'λ'* is the risk aversion parameter (Park and Switzer, 1995). Here, *'λ = 4'* and $E(x_t) = 0$. Now, this mean-variance expected perfect consumption utility from hedging is $-y - 4 \times Var(x_t)$. Here, $Var\ (x_t)$ is the one-period forecasted variance based on the first half of the sample. '$-y$' is the negative return due to the transaction cost and this is considered as impact cost (%) for both indices.

The monthly nifty (individual scrip) impact-cost data are available in NSE website and the average percentage rate of change of bank nifty settlement price is considered as the proxy for its impact cost. This is because in the absence of data, it is assumed that the cost of trading only deviates contract's settlement price. For portfolio returns comparisons, this study has considered the total impact cost of five scrips like HDFC bank, ICICI bank, OBC/AXIS bank[8], PNB, and SBIN of CNX nifty[9]. For bank futures, all 12 scrips are considered for the impact cost calculation[10]. Here, the mean-variance hedging usually considers the market lots for both indices. This is because, lot size and hence the number of market lots determines the contract size. In turn, this contract size determines the tick value (tick size × contract size) through which the futures hedge

[8] It is observed in the data set that AXIS bank scrip appears with the CNX bank nifty index in the year of 2009 and Oriental Bank of Commerce scrip does not appear with the CNX bank nifty index from the year of 2009.

[9]Impact cost (for CNX nifty) = [(Actual Buy Price – Ideal Price)/Ideal Price] × 100. Impact costs for considered bank scrips are collected at their respective sample months. Then, the total of each of these impact costs are taken into consideration for the entire sample period i.e. from June 13, 2005 to December 20, 2010.

[10] Impact cost (for Bank futures) = $[\{(\text{Settlement Price})_t - (\text{Settlement Price})_{t-1}\}/(\text{Settlement Price})_{t-1}] \times 100$.

position is determined. Therefore, considering number of market lots, investor usually takes short positions of bank futures and CNX nifty to cover losses or gain with required number of futures contracts.

The consumption utility functions for both first and second half of the time-periods with all hedging models are compared. In the dynamic hedging model, investors, market participants and other market players prefer the consumption utility function only if the potential utility gains from the first half compensates the losses, which are due to the transaction costs. Therefore, the consumption utility functions for the last half of the sample i.e. from March 10, 2008 to December 20, 2010 are calculated and compared with the consumption utility functions of the sample i.e. from June 13, 2005 to March 07, 2008 for four hedging models. It is observed that increased utility is with CCGARCH (1, 1) than other hedging methods like GARCH (1, 1) particularly in the case of CNX nifty (Table 5). This is also explained in Table 4. Here, the mean-variance expected utility maximizing investor should prefer the CCGARCH (1, 1) hedge method than other conventional methods. Therefore, it can be justified that the CCGARCH (1, 1) model provides an efficient hedging method.

Table 5: Mean-variance Expected Utility Comparisons*

Hedge methods	Bank Futures	CNX Nifty
OLS hedge	-4.43 (12)	-0.53 (5)
Co-integrated OLS hedge	-4.42 (12)	-0.53 (5)
GARCH (1, 1)	-4.55 (12)	-0.55 (5)
Constant correlation GARCH (1, 1) hedge	-7.66 (12)	-0.49 (5)

* One-step forecast variances from the first half of sample are used for both indices. Parentheses (.) indicate the number of scrips, which are considered for the calculation of impact cost (%) for respective indices.

4. Conclusion

From this study, it is concluded that there is a long-run relationship between the spot and dynamic and hence futures returns. Optimal hedge ratios were calculated using all four hedging models. It is observed that the CCGARCH (1, 1) is an efficient hedging method. Considering the mean-variance consumption utility function for all hedging methods, it is also observed that CCGARCH (1, 1) is an efficient hedging method. Together this indicates that the CCGARCH (1, 1) hedge provides an improved hedging method even considering the transaction costs.

This study finds that the estimated variance coefficient matrices for CCGARCH (1, 1) are with the specification $a(2,2)+b(2,2)\approx\begin{bmatrix}1, & 1\\ 1, & 1\end{bmatrix}$. In addition, stationary variance holds as the conditional variance forecast has converged upon the long-term average value of the variance. Thus suggesting a better model fit.

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