Hedge Ratio Estimates and Hedging Effectiveness: Evidence for Nifty 50 Index Futures

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ABSTRACT

This study investigates the hedge ratio and hedging effectiveness for NIFTY 50 Index on NSE in India. For accomplishing the objective NIFTY 50 Index traded on NSE India is considered for a period from April 2005 to December 2015. The sample used in this study includes daily future close prices and spot closing prices for NIFTY 50 Index on NSE in India (www.nseindia.com). Since most of the trading activity takes place in near month contracts, only near month contracts are studied using econometric tools unit root test, OLS, Co-integration Bi-VAR, Vector Error Correction Method and GARCH(1,1). The analysis reveals OLS model can be used to calculate the risk reduction and help the hedgers to compare and take advantage for a given position from the different future position.

Keywords: Futures closing price, Spot closing price, Co-integration, Bi-VAR, VECM, GARCH

I. INTRODUCTION

The derivative market in India, like its counterparts abroad, is increasingly gaining significance. Since the time derivatives were introduced in the year 2000, their popularity has grown manifold. This can be seen from the fact that the daily turnover in the derivatives segment on the National Stock Exchange currently stands at Rs. crore, much higher than the turnover clocked in the cash markets on the same exchange.

The hedge ratio is defined as the number of Futures contracts required to buy or sell so as to provide the maximum offset of risk. This depends on the:

- ✓ Value of a Futures contract;
- ✓ Value of the portfolio to be Hedged; and
- ✓ Sensitivity of the movement of the portfolio price to that of the Index (Called Beta).

The Hedge Ratio is closely linked to the correlation between the asset (portfolio of shares) to be hedged and underlying (index) from which Future is derived.

The performance of the hedging strategies can be examined by finding the hedging effectiveness of each strategy. In order to compare the performances of each type of hedging strategy unhedged position is constructed on the spot market and the hedged position in particular commodity is constructed with the combination of both the spot and the futures contracts. The hedge ratios estimated from each strategy determines the number of futures contracts to be held for minimization of risk. The hedging effectiveness is calculated by the variance reduction in the hedged position compared to unhedged position for each time horizon. Previous literatures have used different methods to discover the optimal hedge ratio and hedging effectiveness this study therefore examines the extent of consistency of the previous studies. This study analyses four models namely, Ordinary Least Squares (OLS), Vector Autoregressive Model (VAR), Vector Error Correction Model (VECM) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to estimate the optimal hedge ratios and hedging effectiveness.

II. LITERATURE REVIEW

(Awang, Azizan, Ibrahim, & Said, 2014)employs OLS, VECM, EGARCH, and Bivariate GARCH to tests the hedging effectiveness of stock index futures market in Malaysia and Singapore. Higher hedging effectiveness in KLFI futures using OLS, VECM and EGARCH was observed than for STI futures using bivariate GARCH model. Compared to all the static and time varying models OLS model performs effectively.

(Gupta & Singh)suggest that hedge ratios estimated form VAR or VECM are found to be more consistent as both the markets are co-integrated. The suggestion drawn was from Nifty, Bank Nifty and CNXIT indices and 84 liquid stock futures on NSE for a period Jan.2003 to Dec.2006.

(Yang & Lai, 2009)dynamic and static hedging strategies performance was examined for DJIA, S&P500, NASDAQ100, FTSE, CA, DAXC30 and Nikkei225 index futures. The results empirically summarizes that portfolio risk is reduced from almost all the models but in comparison to the models Error Correction is superior for investors with different degrees of risk aversion.

(P.Srinivasan, 2011)employs OLS, BVAR, VECM and DVEC-GARCH models for investigating hedging effectiveness of S&P CNX Nifty index futures. Among all the models VECM outperformed in terms of risk minimization and the multivariate GARCH with ECM captured the time varying hedge ratio.

(Lee, Wang, & Chen, 2009) the optimal hedge ratios and effectiveness for Taiwan, S&P 500, Nikkei 225, Hang Seng, Singapore Straits Times and Korean KOSPI 200 Index futures using four static (OLS Minimum Variance Hedge ratio, Mean-Variance Hedge Ratio, Sharpe Hedge Ratio and MEG hedge Ratio) and one dynamic (bivariate GARCH Minimum Variance Hedge Ratio) was evaluated. The results indicated every model for optimal hedging differs in different markets are hence are not same.

(Moon, Yu, & Hong, 2009)article estimates hedging performance using OLS and multivariate GARCH models for Korea Securities Dealers Automated Quotation (KOSDAQ) STAR (KOSTAR) index futures. It was observed that the dynamic hedging model GARCH outperforms OLS for out-of-sample period but OLS is superior to multivariate GARCH models.

(Holmes, 1995)estimates the hedging effectiveness of FTSE-100 stock index futures contract for a period from 1984-92 using Minimum Variance Hedge Ratio for ex ante determined on the historical information. It proves that though hedge ratios vary overtime, future contracts can be used to reduce risk substantially.

(Ghosh & Clayton, 1996)extended the traditional hedge ratio estimates to co-integration for France (CAC 40), United Kingdom (FTSE 100), Germany (DAX) and Japan (NIKKEI) stock index futures contracts. It is said that hedge ratios obtained from error correction method are better than the traditional methods.

(Olgun & Yetkiner, 2011) determines the optimal hedge strategy for Istanbul Stock Exchange (ISE)-30 stock index futures. Standard regression and bivariate GARCH frameworks were employed and estimated that dynamic hedge strategy outpaces the static hedge strategy.

(Bhaduri & Durai) Analyzed OLS, VAR, VECM and M-GARCH models estimating the single point and time-varying hedge ratios for NSE Stock Index Futures and S&P CNX Nifty Index. Multivariate GARCH model having higher mean and higher average variance reductions proves to be a better model for hedge ratio estimations.

(Pennings & Meulenberg, 1997) describes risk reduction and a new measure of hedging efficiency, this measure take reduced cash price risk, futures trading risk, basis risk and market depth risk. The results indicate that futures exchange can be managed using this proposed hedging efficiency measure.

III. METHODOLOGY

The purpose of this study is to estimate the Optimal Hedge Ratio and Hedging effectiveness of Nifty 50 Index in India. In this study Nifty 50 Index Future Closing Prices and Spot Closing Prices are examined. There are total 2669 observations for Nifty 50 Index data ranging from 1st April 2005 to 31st December 2015.The present study employs OLS regression, Bi-variateVAR model, VECM and GARCH model to determine the optimal hedge ratio and the hedging effectiveness.

Hedge Ratio Estimates

OLS Regression Model

The model is a simple linear regression of change in spot prices on the change in futures prices.

$$\mathrm{r}_{st} = \alpha + \beta_{\mathrm{r}_{ft}} + \varepsilon_t \text{ ....Eq (1)}$$

Where, r_{st} is the spot return, $r_{ft}$is the future return, ε_t is the error from OLS estimation and the slope coefficient β is the optimal hedge ratio.

Bi-VariateVAR

The limitation of the simple OLS model is that the errors may be auto correlated. To overcome this limitation the Bi-variate Vector Autoregressive (VAR)model has been used. The optimal lag length for spot and futures returns m, n are decided by restating for each lag until the autocorrelation in the errors are removed.

$r_{st} = \alpha_s + \sum_{i=1}^{m} \beta_{si} r_{st-i} + \sum_{j=1}^{n} \gamma_{si} r_{ft-i} + \varepsilon_{st}$ ……………. Eq (2)
$r_{ft} = \alpha_f + \sum_{i=1}^{m} \beta_{fi} r_{st-i} + \sum_{j=1}^{n} \gamma_{fi} r_{ft-i} + \varepsilon_{ft}$ …………….Eq (3)

After the system equation was estimated the residual series were generated to calculate the hedge ratio. Where var(ε_{st}) = σ_s,var(ε_{ft}) = $\sigma_f$and cov$(\varepsilon_{st}, \varepsilon_{ft}) = \sigma_{sf}$, then the minimum variance hedge ratio is h* = σ_{sf}/ σ_f.

VECM

If the level series of spot and future are not stationary and are integrated of order one then the following vector error correction model is used to estimate the optimal hedge ratio.

$r_{st} = \alpha_s + \sum_{i=1}^{m} \beta_{si} r_{st-i} + \sum_{j=1}^{n} \gamma_{si} r_{ft-i} + \lambda_s Z_{t-1} + \varepsilon_{st}$ …………….Eq (4)
$r_{ft} = \alpha_f + \sum_{i=1}^{m} \beta_{fi} r_{st-i} + \sum_{j=1}^{n} \gamma_{fi} r_{ft-i} + \lambda_f Z_{t-1} + \varepsilon_{ft}$ …………….Eq (5)

Where, Z_{t-1} = S_{t-1} - δF_{t-1} is the error correction term with (1- δ)as co integrating vector and λ_s, λ_f as speed adjustment parameters. Same process of generating the residual series and then calculating the variance, covariance of the series to estimate the minimum variance hedge ratio as depicted in the bivariate VAR model has been followed.

GARCH

Majority of the empirical studies expressed that time series of the returns always indicate volatility clustering. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) can deal with the heteroskedasticity characteristic of the price series. GARCH (1, 1) model assumes that the conditional heretoskedasticity of the current return on assets is not only related to the residual squares in last periods but also related to the last period conditional heteroskedasticity. The relationship between spot and futures price can be described as follows.

$$r_{st} = \alpha + \beta_{r_{ft}} + \varepsilon_t \text{ …………….Eq (6)}$$
$$\varepsilon_t \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \text{ …………….Eq (7)}$$

Where, ε_t signifies the error term, σ_t^2 is the conditional variance on day t,α_0, α_1 andβ_1 are the GARCH (1, 1) parameters. The regression coefficient β is the optimal hedge ratio.

Hedging Effectiveness

The hedging effectiveness of the portfolio is calculated from the variance reduction of the hedged portfolio compared to that of the un hedged portfolio. The returns of the un -hedged and hedged are expressed as follows.

$R_{unhedged} = S_{t+1} - S_t$
$R_{hedged} = (S_{t+1} - S_t) - h^*(F_{t+1} - F_t)$

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

$Var_{unhedged} = \sigma_S^2$
$Var_{hedged} = \sigma_s^2 + h^{*2}\sigma_f^2 - 2h^* \sigma_{sf}$

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

$$HE = \frac{\text{Varunhedged} - \text{Varhedged}}{\text{Varunhedged}}$$

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

IV. DATA ANALYSIS

Unit Root and Cointegration

The standard Augmented Dickey Fuller (ADF) Test was employed to check the stationarity of the spot and future price data series. This is crucial from hedging viewpoint as a series that is not stationary may provide spurious regression and hence the hedge ratios obtained from such model will be invalid. The unit root test from ADF indicates that the spot and future price series are stationary at first difference and represent that they are integrated at order one I(1).Johansens's Cointegrationtest was performed to examine the long run relationship between the spot and futures price series and is presented in Table 1. The results indicate that the future close price and spot close price are co-integrated in long run. The trace test indicates the existence of two co-integrating equation at 5 % level of significance. Maximum Eigen Value test makes the confirmation of this result. Thus the two variables of the study have a long run equilibrium relationship between them.

Table 1.Johansen's Cointegration Test Results

INDEX	NO.OF CE(S)	EIGENVALUE	TRACE STATISTIC	PROBABILITY
NIFTY50	NONE	0.049519	135.6209	0.0001*
	AT MOST 1	0.000584	1.543138	0.2142

Source: Computed Value

Hedge Ratio

At the very outset the optimal hedge ratio from the simple OLS regression is estimated. Table 2 reports the results from the OLS regression model from Eq(1).

Table 2: Hedge Ratio & Hedging Effectiveness Results from OLS Regression Model

INDEX	OPTIMAL HEDGE RATIO [β]	HEDGING EFFECTIVENESS [R^2]
NIFTY50	0.934675* (0.002650)	0.979072

Source: Computed Value *significant at 5% Levelof Significance

To calculate the optimal hedge ratio from a Bi-Variate VAR model we estimate the equation (2) and (3) with 3 lags and the results are presented in Table 3 for the calculation of residual from the Bi-Variate VAR model equations (2) and (3). Further we use these residual series to estimate the variance and covariance to find the hedge ratio. Where var(ε_{st}) = σ_s, var(ε_{ft}) = σ_f and cov($\varepsilon_{st}, \varepsilon_{ft}$) = σ_{sf} , then the minimum variance hedge ratio is h* = σ_{sf}/σ_f. The hedge ratio from Bi-Variate VAR are reported in Table .4.

Table 3. Estimates from a Bi-Variate VAR Model

Eq.(2)	COEFFICIENT	Eq.(3)	COEFFICIENT
α_s	0.000519 (0.00030)	α_f	0.000511 (0.00032)
β_{s1}	-0.108386 (0.14038)	β_{f1}	0.212001 (0.14903)
β_{s2}	-0.007336 (0.14580)	β_{f2}	0.135469 (0.15478)
β_{s3}	-0.108046 (0.13316)	β_{f3}	-0.016002 (0.14136)
γ_{s1}	0.161923 (0.13222)	γ_{f1}	-0.181522 (0.14037)
γ_{s2}	-0.006769 (0.13911)	γ_{f2}	-0.146290 (0.14769)

γ_{s3}	0.084581 (0.12745)	γ_{f3}	-0.013204 (0.13530)
R^2	0.005311	R^2	0.001871

Source: Computed Value

Table 4: Hedge Ratio Results from Bi-Variate VAR Model

INDEX	$VAR\varepsilon_s$	$VAR\varepsilon_f$	Covariance ($\varepsilon_s\ \varepsilon_f$)	H*
NIFTY50	0.000234	0.000264	0.000246	0.933056

Source: Computed Value

The hedge ratio from Vector Error Correction (VEC) Model are estimated from equation (4) and (5) with 3 lags and the results are presented in Table 5.Where, Z_{t-1} = S_{t-1} - $\delta\ F_{t-1}$ is the error correction term with (1- δ) as cointegrating vector and λ_s, λ_f as speed adjustment parameters. Same process of generating the residual series and then calculating the variance, covariance of the series to estimate the minimum variance hedge ratio from VECM is incorporated. Further we use these residual series from equation (4) and (5) to estimate the variance and covariance to find the hedge ratio. Where var(ε_{st}) = σ_s, var(ε_{ft}) = σ_f and cov($\varepsilon_{st}, \varepsilon_{ft}$) = σ_{sf} , then the minimum variance hedge ratio is h* = σ_{sf}/ σ_f. The hedge ratio from VECM are reported in Table 6.

Table 5: Estimates from Vector Error Correction (VEC) Model

Eq.(4)	COEFFICIENT	Eq.(5)	COEFFICIENT
α_s	-9.55E-07 (0.00033)	α_f	-2.51E-06 (0.00035)
β_{s1}	-1.680082* (0.32958)	β_{f1}	-2.111846* (0.34839)
β_{s2}	-1.217673* (0.24838)	β_{f2}	-1.476758* (0.26256)
β_{s3}	-0.818421* (0.14638)	β_{f3}	-0.931796* (0.15474)
γ_{s1}	0.983667* (0.32636)	γ_{f1}	1.385571* (0.34498)
γ_{s2}	0.745319* (0.24456)	γ_{f2}	0.987439* (0.25852)
γ_{s3}	0.562833* (0.14212)	γ_{f3}	0.664749* (0.15023)
λ_s	0.953636* (0.39744)	λ_f	2.730956* (0.42012)
R^2	0.335211	R^2	0.368235

Source: Computed Value

Table 6: Hedge Ratio Results from Vector Error Correction Model (VECM)

INDEX	$VAR\varepsilon_s$	$VAR\varepsilon_f$	Covariance ($\varepsilon_s\ \varepsilon_f$)	H*
NIFTY50	0.000294	0.000328	0.000308	0.938877

Source: Computed Value

The hedge ratio from Generalized Autoregressive Conditional Heteroskedasticity Autoregressive GARCH (1, 1) Model are estimated from equation (7) and the results are presented in Table7,where, ε_t signifies the error term, σ_t^2 is the conditional variance on day t, α_0, α_1 and α_2 are the GARCH (1, 1) parameters. The regression coefficient β is the optimal hedge ratio.

Table 7: Hedge Ratio Results from GARCH (1,1) Model

INDEX	B	α_0	α_1	β_2	R^2
NIFTY50	0.940245 (0.001688)	1.44E-06 (1.43E-07)	0.239224 (0.019450)	0.522231 (0.039302)	0.976867

Source: Computed Value

Hedging Effectiveness

The effectiveness of hedging (HE) can be measured by the percentage reduction in the variance of a hedged portfolio as compared with the variance of an unhedged portfolio (Ederington, 1979). The Hedging effectiveness from OLS Regression model is presented in Table 2, from Bi-Variate VAR model in Table8, Vector Error Correction Model (VECM) in Table9 and GARCH (1, 1) in Table 10.

Table 8: Hedging Effectiveness Results from Bi-Variate VAR Model

INDEX	VAR_u	VAR_h	HE*
NIFTY50	0.000235	5.598E-06	0.9762038

Source: Computed Value

Table 9. Hedging Effectiveness Results from VECM

INDEX	VAR_u	VAR_h	HE*
NIFTY50	0.000235	5.609E-06	0.9761553

Source: Computed Value

Table 10. Hedging Effectiveness Results from GARCH (1, 1) Model

INDEX	VAR_u	VAR_h	HE*
NIFTY50	0.000235	5.614E-06	0.9761329

Source: Computed Value

The optimal hedge ratios obtained from four different models are reported in Table 11.The results show that the hedge ratios from different models are significant at 5% level which specifies that the stock and index futures can be used to hedge against the underlying spot prices. It also indicates that the hedge ratio obtained from GARCH (1, 1) is the highest for Nifty 50 index. VECM ranks second in obtaining the hedge ratios and the least is Bi-variate VAR model. As directed from the literature that from the different models used in computing the hedge ratios the GARCH models are superior in estimating the hedge ratios. Thus from the present study we can conclude that the GARCH model is superior in estimating the hedge ratios for the hedgers to adjust their future positions to that of the spot price fluctuations.

Table 11.Comparison of Hedge Ratios from Different Models

INDEX	OLS	BI-VARIATE VAR	VECM	GARCH
NIFTY50	0.934675	0.933056	0.938877	0.940245

Source: Computed Value

It is mere not only vital to compute the hedge ratio, it is further require to test whether the hedge ratios obtained from the different models provide the greatest variance reduction and better hedging performance. The hedge ratios obtained from all four models were further used in estimating the hedging effectiveness and discover which model provides the greatest variance reduction. The hedging effectiveness from different models is presented in Table 12. It is being reported that the OLS model out performs all other models in providing the greatest variance reduction on the other hand GARCH(1,1) models provides the lower variance reduction for Nifty 50 index. Thus we can conclude that though the hedge ratio obtained from GARCH(1,1) model is the highest among all the other models the variance reduction from the GARCH(1,1) model is lower and the OLS model provides the maximum reduction in the risk though it is the static model in assessing hedging strategy.

Table 12: Comparison of Hedging Effectiveness from Different Models

INDEX	OLS	BI-VARIATE VAR	VECM	GARCH
NIFTY50	0.979072	0.9762038	0.9761553	0.9761329

Source: Computed Value

CONCLUSIONS

The main objective of this study was to estimate the optimal hedge ratio and hedging effectiveness of index and stock futures in India by applying four different models namely OLS, Bi-Variate VAR, VECM and GARCH (1,1) model. The empirical analysis was conducted for the daily data series from April, 2005 to December 2015. It was observed that the GARCH (1, 1) model is the superior model since the hedge ratio obtained was highest among all the other models but on the contrary it was found to be least in providing the risk reduction. The OLS model which is static in nature provided the highest variance reduction among all other models in the study. Thus we can conclude from the empirical analysis that the OLS model can be used to calculate the risk reduction and help the hedgers to compare and take advantage for a given position from the different future position.

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