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Investigating the Impact of Hedge Horizon Upon Hedging Effectiveness: Evidence from the National Stock Exchange of India

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ABSTRACT

This study investigated the impact of hedge horizon upon hedging effectiveness in Indian equity futures market by comparing hedging performance of near, next and far month futures contracts of the NIFTY50 index and its 17 composite stocks. Hedging effectiveness was measured using two approaches, namely, Variance Reduction approach and Risk-Return approach. The study found that near month futures contracts are most effective when hedge effectiveness is measured using the variance reduction approach, whereas, far month futures contracts are found to be most effective using the risk-return approach. These results imply that for highly risk-averse investors (concerned with only minimization of risk), near month futures contracts enable effective hedging, whereas for less risk-averse investors (concerned with risk as well as return), far month futures contracts offer superior hedge effectiveness. The study also found that coefficient of correlation between spot and futures returns is a significant factor affecting variance reduction of returns and bears a direct relationship with it.

Keywords: *Hedge horizon, Hedging effectiveness, Futures market, Equity market, Optimal hedge ratio, Heteroskedasticity.*

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INTRODUCTION

Since the last decade, financial derivatives contracts have gained huge popularity, given uncertainty infinancial markets, economic conditions as well as high price volatility in equities, commodities and other financial assets. The number of equity futures contracts traded has recorded a growth of 170.4% in 2017 from 2005. According to Silber (1985), one of the prime functions of the futures market is to hedge the price risk of underlying assets from uncertain price variations. A hedging strategy involves simultaneous investments in both cash as well as futures market, however in the opposite direction, such that gain (loss) in one market can be offset by loss (gain) from another. Strong co-movement between spot and futures in the long-run (Gupta and Singh (2007)) as well as participation of arbitrageurs to correct the disequilibrium in the short-run establishes the basis for a successful hedging strategy.

A huge body of literature has examined hedging performance of futures contracts, and debates upon suggesting a superior methodology for estimating optimal hedge ratio. Most of the studies (see, Park and Switzer (1995), Poomimars et al. (2003), Yang and Allen (2004), In and Kim (2006), Sultan and Hasan (2008), Pok et al. (2009), Wang and Hsu (2010), , Pradhan (2011), Tejada and Goodwin (2014), Zhang and Choudhry (2015) and Basher and Sadorsky (2016)) favour time-varying hedging models for estimating optimal hedge ratio, however, in contrast, numerous studies (See, Holmes (1996), Lien et al. (2002), Moosa (2003), Lien (2005), Bhargava and Malhotra (2007), Maharaj et al. (2008), Rao and Thakur (2008), Lee and Chien (2010), Wen et al. (2011), Alexander et al. (2013), Wang et al. (2015) and Benada (2018)) support constant hedging models for estimating optimal hedge ratios.

Besides this, numerous studies Figlewski (1984), Kamara and Siegel (1987), Moosa (2003), Ripple and Moosa (2007), Chang et al. (2013), Kumar and Pandey (2013) and Gupta et. al (2017)) observe that hedging effectiveness changes with the changing time-to-maturity of futures contracts. Ripple and Moosa (2007), Chang et al. (2013) and Kumar and Pandey (2013) found that hedging effectiveness is relatively higher when near month futures contracts (i.e. futures contracts with one month expiry period) are used as a hedging instrument as compared to futures contracts with a more distant expiry date. However, on the contrary, Kamara and Siegel (1987) and Yaganti and Kamaiah (2012) found superior hedging effectiveness using futures contracts with a distant maturity period (expiry period of more than one month). Kamara and Siegal (1987) investigated hedging effectiveness for soft wheat and hard wheatovera two-week hedge period and four-week hedge period and observed relatively higher variance reduction during a four-week hedge horizon as compared to a shorter hedge horizon for both types of wheat, whereas Yaganti and Kamaiah (2012) investigated hedging effectiveness of nine commodity futures traded in India and observed that for seven commodity futures, variance reduction was higher using a distant futures contracts (having expiry period of more than one month) as compared to a futures contracts expiring within one month.

Further, Milonas (1986) explains that as the futures contract reaches expiry, the futures market tends to respond more strongly to arrival of new information in themarket, which is followed by cash market, thereby leading to increased co-movement between spot-futures prices, hence, increased hedging effectiveness. Moreover, futures contracts near expiration observes a higher liquidity than futures with longer maturities, therefore higher hedging effectiveness is observed because poor liquidity in the market leads to poor hedging effectiveness and vice-versa as observed by Park and Switzer (1995) and Kumar and Pandey (2013).

Besides this, a strand of literature Hou and Li (2013) and Bonga and Umoetok (2016) has found contradicting evidence regarding superiority of constant and time-varying hedge ratio models over long and short hedge horizons. For instance, Hou and Li (2013) found that the constant hedging model generates higher hedging effectiveness over a short hedge horizon, whereas over a long hedge horizon, time-varying model (BGARCH) outperforms. On the contrary, Bonga and Umoetok (2016) found that a short hedge horizon favors aOLS hedge ratio (i.e. constant hedge ratio) whereas a long hedge horizon favours MGARCH (i.e. time-varying hedge ratio).

Furthermore, Chen et al. (2014) found that superiority of different constant and time-varying hedge ratio models over different hedge horizons is also affected by the measure used for estimating hedging effectiveness. Using the variance reduction approach, hedging effectiveness is found to be superior with the OLS hedge ratio over a short hedge horizon and with a

TARCH hedge ratio over a long hedge horizon, whereas using a risk-return approach, the BGARCH hedge ratio performs superior over a short hedge horizon and a OLS hedge ratio performs superior over a long hedge horizon.

Apart from discussion on literature on hedging effectiveness, the Indian equity futures market is one of the leading derivatives markets in the world and ranks among the top ten derivatives markets of the world since year 2011 (See Appendix A). Numerous studies have examined the hedging effectiveness of futures contracts in both equity as well as commodity markets however, to the best of our knowledge, most of the studies examining hedging effectiveness in India have restricted their scope to examine hedging effectiveness of near month futures contracts only, whereas the Indian equity futures market offers futures contracts with three different expiry periods i.e. one month expiry (near month futures contracts), two month expiry (next month futures contracts) and three month expiry (far month futures contracts) which began to trade from June 12, 2000 for indices and from July, 2001 for individual stocks. To the best of our knowledge, Yaganti and Kamaiah (2012), Kumar and Pandey (2013) and Gupta et al. (2017) attempted to address this issue in the commodity futures market, however, none of the studies have examined hedging performance of the next and far month futures contracts in equity futures market in India, despite their respectable trading volume.

Secondly, most of the studies measure hedging effectiveness on the basis of minimization of returns only, whereas few studies suggest better measures of hedging effectiveness that comprises of both risk as well as return on hedged portfolio. To the best of the researchers knowledge, in India, only Ghosh et al. (2013) and Kaur and Gupta (2018b) addressed this issue in the futures market. Hence, in order to plug the literature gap, this study aimed to investigate hedging effectiveness of the equity futures contracts over the long-term and short-term hedge horizon by examining hedging effectiveness of futures contracts with all three expiry periods offered in Indian equity futures market i.e. near month futures, next month futures and far month futures contracts using two different approaches to estimate hedging effectiveness.

DATABASE AND RESEARCH METHODOLOGY

The sample size of the study comprised of spot and futures contracts of the NIFTY50 index as well as 17 individual stocks comprising a part of the NIFTY50 index which have been selected on the basis of their consistent trading history and sufficient liquidity. The sample period comprises of the period from the inception of the futures contracts on the NIFTY50 index (i.e. June 12, 2000) and its 17 composite stocks (See Appendix B) till March 31, 2017.

Research Methods for Estimating Optimal Hedge Ratios

The study employed eightstatistical methods (proposed by the literature) for estimating optimal hedge ratio namely, Naive hedge ratio, Ordinary Least Square (OLS), Autoregressive Moving Average Ordinary Least Square (ARMA-OLS), Vector Autoregressive (VAR), Vector Error Correction Model (VECM), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) and Threshold Autoregressive Conditional Heteroscedasticity (TARCH), which are discussed below:

Model 1: Naive Hedge Ratio

The traditional theory of hedging assumes that futures and cash prices exhibit perfect correlation and hence, difference between cash and futures prices (known as 'basis') remain constant during the hedge duration implying absence of basis risk. Therefore, in order to hedge efficiently, equal investment is required in both spot and futures market. Hence, optimal hedge ratio suggested by this model is one. This is perhaps the simplest of all the models as it is free of any estimation procedure.

Model 2: Ordinary Least Squares (OLS)

As per the assumptions of the cost-of-carry model, futures prices is an unbiased predictor of cash market prices, therefore, Ederington (1979) suggested that the optimal hedge ratio can be estimated by regressing cash market returns upon futures returns. Equation (1) represents the simple regression procedure suggested by Ederington (1979) in which the slope coefficient of regression equation (β) represents the minimum variance hedge ratio, which is the ratio of covariance of spot and futures returns and variance of futures returns.

$$R_{s,t} = \alpha 0 + \beta_1 R_{f,t} + \mu_t \qquad \text{.......................................(1)}$$

In the above equation (1), Rs and Rf represents the returns from the spot market and futures market respectively, βis the optimal hedge ratio, α is the intercept term and μ is the error term of the regression equation.

Model 3: Autoregressive Moving AverageOrdinary Least Squares (ARMA-OLS)

A common feature of the financial time-series is that these are significantly autocorrelated i.e. the present return depends upon its past values, and therefore, significantly predictable, implying that spot and futures returns are not random. Hence, if the spot and futures return exhibit serial correlation, then OHR estimated in equation (1) may be biased on account of ignorance of autocorrelation in spot market returns. Therefore, equation (1) has been improved by incorporating the autoregressive terms $(\sum_{i=1}^{p} \alpha_i R_{s^{\prime},t-i})$ of cash market returns and the resultant equation (2) is presented below:

$$R_{s,t-i} = \alpha 0 + (\sum_{i=1}^{p} \alpha_i R_{s^{\prime},t-i}) + \beta_1 R_{f,t} + \mu_t \qquad \text{..................................(2)}$$

In the given equation (2), $R_{s^{\prime},t-i}$ represents the autoregressive terms of cash returns, whose order is determined by SIC criteria. Lower the value of SIC, better is the model fit. Rf is the futures market return, α is the intercept term and μ is the error term of the regression equation.

Model 4: Vector Autoregressive (VAR) Model

The literature observes that both spot and futures market exhibit lead-lag relationship in the short-run i.e. information gets discounted in futures (cash) market first which is followed by the cash (futures) market. In the Indian equity futures market, significant lead-lag relationship is evident in terms of bidirectional feedback relationship between the spot and the futures market (see Mukherjee and Mishra (2006) and Bose (2007)) i.e. futures market leads the cash market, which is also true the other way round. Hence, considering the short-run dynamics, VAR simultaneously regresses the lagged returns of both the variables as presented in equation (3 and 4) below:

$$R_{s,t-i} = \sum_{i=1}^{M} \alpha_i R_{s,t-i} + \sum_{i=1}^{N} \beta_j R_{f,t-j} + \mu_{st} \qquad \text{.................................(3)}$$

$$R_{f,t} = \sum_{k=1}^{O} \alpha_k R_{s,t-k} + \sum_{l=1}^{P} \beta_l R_{s,t-1} + \mu_{ft} \qquad \text{.................................(4)}$$

The optimal hedge ratio on the basis of the VAR will be measured as the ratio of covariance of errors from equations (3) and (4) and variance of errors from equation (4) i.e. $\sigma_{s,f}/\sigma^2_f$, where $\sigma_{s,f}$=cov(μ_{ft},μ_{st}) and σ^2_f = var(μ_{ft}).

Model 5: Vector Error Correction Model (VECM)

It is a welldocumented fact that both the spot and futures market observe long-run equilibrium relationship in the presence of cost of carry regime and efficient arbitrage mechanism. The VAR model, takes into account the short-run lead-lag relationship but ignores the long-run equilibrium relationship between both the markets. According to the co-integration theory (proposed by Engle and Granger (1987)), if two time-series are non-stationary but the difference between them (i.e. basis) is stationary, then the series is stationary which can be factored by incorporatingthe error correction term (which represents long-run relationship). Therefore, the error correction term must be considered along with lagged returns in order to get statistically robust optimal hedge ratio. Hence, the VAR model (equation (3 and 4)) was transformed to the VECM by incorporating the error correction term as depicted below in equation (5) and (6):

$$R_{f,t} = \alpha_{0f} + \sum_{i=1}^{p} \alpha_{if} (F_{t-i} - S_{t-i}) + \sum_{j=1}^{q} \beta_f R_{f,t-j} + \sum_{k=1}^{m} \beta_f R_{s,t-k} + \mu_{ft} \qquad \text{............(5)}$$

$$R_{f,t} = \alpha_{0s} + \sum_{i=1}^{p} \alpha_{is} (F_{t-i} - S_{t-i}) + \sum_{l=1}^{n} \beta_s R_{s,t-1} + \sum_{h=1}^{o} \beta_s R_{f,t-h} + \mu_{ft} \qquad \text{............(6)}$$

The optimal hedge ratio from VECM will be estimated in a similar way as in the VAR model above i.e. $\sigma_{s,f}/\sigma^2_f$, where $\sigma_{s,f}$ = cov(μ_{ft}, μ_{st}) and σ^2_f = var (μ_{ft}).

Model 6: Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

The estimation procedures discussed above (Equation (1) through Equation (6)) assumes that the variance of error term remains constant over time. However, it is unlikely in the context of the financial time-series that the variance of errors will be constant over time (Brooks, 2008, p. 386) because arrival of new information in the market changes the variance-covariance structure between spot and futures prices. Moreover, another common feature of financial time-series is 'volatility clustering' or 'volatility pooling', which implies that the level of volatility in the current period tends to be positively correlated with its level during the immediately preceding periods. Therefore, in order to address the issue of heteroskedasticity in error terms, Engle (1982) proposed the ARCH model which was further generalized by Bollerslev (1986) in which conditional variance was regressed upon its own past values in addition to past values of squared error term. The GARCH (p,q) specification is presented below:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-i} + \sum_{j=1}^{P} \beta_j h_{t-j} + v_t \qquad \text{.................................(7)}$$

The above equation represents the variance equation of GARCH model where h_t represents conditional volatility, ω represents constant term, $\alpha i \varepsilon^2_{t-i}$ is the ARCH term expressing news about volatility from previous period (measured as lag of squared residual from mean equation) and $\beta j h^2_{t-j}$ represents GARCH term, which is the forecasted volatility from previous period, measured as lag of past values of conditional volatility. If the value of $\alpha_i + \beta_j$ is greater than unity, it implies that shock fades away in a short span of time, whereas αi+βj greater than or equal to unity implies that volatility persist for a longer period of time.

Model 7: Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH)

The EGARCH model, proposed by Nelson (1991), estimates the logarithmic conditional volatility which implies that the leverage effect is exponential and is expressed as follows:

$$\log \sigma^2_\tau = \varpi + \beta \log(\sigma^2_{t-1}) + \gamma\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| \qquad \text{................................ (8)}$$

In the above equation, σ^2_t represents the conditional variance, ϖ, α, β and γ represents the constant parameters. If γ is negative and different from zero, then, it implies that negative shocks generate higher volatility than positive shocks

Model 8: Threshold Autoregressive Conditional Heteroscedasticity (TARCH)

Numerous studies (like, Karpoff (1987) and Veronesi (1999), etc.) found that the reaction of investors vary with the type of information received in the market which generate different levels of volatility. For instance, Veronesi (1999) finds that investors tend to overreact to bad news in good times and under-react to good news in bad times. Hence, it becomes important to segregate the impact of good and bad news to estimate the optimal hedge ratio which is statistically more robust. Therefore, the GARCH (p, q) model was modified to TARCH (p, q) by incorporating the dummy variable in variance equation (7) and the resultant equation (9) is as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{P} \alpha_k \varepsilon^2_{t-1} \xi_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-i} + \upsilon_t \quad \text{..........................(9)}$$

In the above equation, $\varepsilon^2_{t-1} \xi_{t-i}$ represents the dummy variable having value one if the news is negative and zero for non-negative news.

Approaches for Estimating Hedging Effectiveness

After estimating the optimal hedge ratio(s) through the above mentioned statistical procedures, its effectiveness tested by using two different approaches which are based upon different objectives of investors to hedge: Variance Reduction approach (Ederington (1979)) and Risk-Return approach (Howard and D'Antonio (1984)) as discussed below. The hedge ratio that gives the highest hedging effectiveness in each of the two methods would be proposed as efficient hedge ratio.

Approach 1: Variance Reduction Framework

The method suggested by Ederington (1979) measures hedging effectiveness as a proportionate decline in portfolio variance and optimal hedge ratio that declines the portfolio variance to the maximum extent is considered as an efficient hedge ratio. Ederington's hedging effectiveness is calculated as follows:

$$\text{Hedging effectiveness} = \frac{\text{Var (U)} - \text{Var (H)}}{\text{Var (U)}} \qquad \text{.......................(10)}$$

In the above equation,

$$\text{Var (U)} = \sigma_s^2$$

$$\text{Var (H)} = \sigma s^2 + h^{*2}\sigma f^2 - 2h^*_{\sigma s,f}$$

Approach 2: Risk-Return Framework

Ederington's measure of hedging effectiveness suffers from a limitation that it ignores the return component on hedged portfolio. Therefore, in order to address the above issue, Howard and D'Antonio (1984), suggested a measure of hedging effectiveness (λ) which incorporated the return component and computed hedging effectiveness by comparing the risk-adjusted excess return from hedged portfolio with the risk-adjusted excess return from unhedged portfolio. In other words, effectiveness of hedge is measured as ratio of slope of risk-return relative from hedged portfolio and risk-return relative from unhedged portfolio as presented in the following equation:

$$\text{Hedging Effectiveness} \quad \theta \Big/ \frac{\overline{r_s} - i}{\sigma_s} \qquad \text{........................... (10)}$$

Where,

$$\theta = \frac{\overline{R}_p - i}{\sigma_p}$$

$\overline{R}_p$ = expected return from hedged portfolio

σ_p = standard deviation of returns from hedged portfolio

i = risk-free rate of return

$\overline{r}_s$ = expected return from unhedged portfolio

σ_s = standard deviation of returns from unhedged portfolio

RESULTS AND DISCUSSION

The results of descriptive statistics[1] of daily mean returns of the cash and futures markets for all 18 futures contracts indicated that average daily returns are approximately zero which implies that returns are equally distributed among both buyers and sellers. The standard deviation of the returns in the futures market (near, next and far month contracts) was found to be relatively larger than spot market returns for most of the stocks (71.4% near month futures, 93.7% next month futures and 88.9% far month futures contracts).Further, skewness and kurtosis were found to be statistically significant at 1% significance level for all the sixty three futures contracts under examination, which strongly suggests the rejection of the null hypothesis that returns in both the markets are normally distributed. In order to statistically test the null hypothesis, the Jarque-Bera test was applied which also confirms the rejection of the null hypothesis, thus, implying asymmetry in both the cash and future market returns. In a nutshell, summary statistics of the cash and futures market returns reveal that returns from the cash market and futures market are not normally distributed which implies that returns are asymmetric in nature.

Further, since estimation of the optimal hedge ratio using different econometrical procedures involves the statistical process of regressing cash returns upon futures return, therefore, it becomes necessary to check if the series is a stationary series or non-stationary one. In order to diagnose the presence of unit-roots in the return series, ADF unit root test was applied and the results revealed that the cash and futures prices are non-stationary at that level, however, the natural logarithm of first difference of the prices was found to be stationary[2]for cash and futures returns of all 18 futures contracts understudy.

Furthermore, Table 1 reports optimal hedge ratios estimated through eight econometric procedures (namely, Naive hedge ratio, OLS, ARMA-OLS, VAR, VECM, GARCH, EGARCH and TARCH), of which the first five belong to the class of constant hedging models, whereas remaining three i.e. GARCH, EGARCH and TARCH are classified as time-varying

1 The results of descriptive statistics have not been reported here in order to save space, however can be made available upon demand.

2 The results of unit-root test have not been reported here in order to save space, however, can be made available upon demand.

hedging models. It was observed that the coefficients of all the eight optimal hedge ratios were very close to each other which imply that cost of hedging is almost similar across different optimal hedge ratio models. These results are consistent with the findings of Bonga and Umoetok (2016) who also observed that there is not much significant difference between different optimal hedge ratios.

Table 1: Estimation of Optimal Hedge Ratios

Symbol	Contract	Naive	OLS	ARMA OLS	VAR	VECM	GARCH	EGARCH	TARCH
NIFTY50	**Near**	1	0.935901	0.952828	0.939036	0.9402854	0.956706	0.96703	0.962802
	Next	1	0.938648	0.955448	0.942753	0.9434623	0.961040	0.963618	0.964157
	Far	1	0.911975	0.937925	0.926176	0.9277825	0.952483	0.968199	0.966978
BAJFINANCE	**Near**	1	0.999653	0.999331	0.997583	0.997876	0.999333	0.99963	0.999734
	Next	1	0.994764	0.995613	0.994247	0.995029	0.997758	1.001343	1.000086
	Far	1	0.999301	1.001055	0.997447	1.029871	1.003087	1.002209	1.0015
BPCL	**Near**	1	0.976534	0.984169	0.981165	0.981404	0.998079	0.995229	0.994335
	Next	1	0.646840	0.713492	0.722466	0.732859	0.882944	0.983008	0.863803
	Far	1	0.268455	0.269377	0.29323	0.311017	0.319403	0.29024	0.319214
COALINDIA	**Near**	1	0.988323	0.988792	0.990445	0.993639	0.980013	0.995693	0.992754
	Next	1	1.002362	1.003941	1.002452	1.037575	1.007188	1.016566	1.015847
	Far	1	0.62697	0.649704	0.653083	0.767272	0.701205	0.706725	0.700275
EICHERMOT	**Near**	1	0.999024	1.00043	1.000058	1.002258	0.995955	1.004543	0.994432
	Next	1	0.912454	0.982342	0.965756	0.973083	1.00309	1.001769	1.002197
	Far	1	0.27894	0.268584	0.265371	0.442659	0.263289	0.247524	0.245821
GAIL	**Near**	1	0.969722	0.976742	0.973302	0.97368	0.982184	0.99425	0.988726
	Next	1	0.796305	0.821326	0.846312	0.853329	0.866453	0.892099	0.872833
	Far	1	0.193824	0.21013	0.230182	0.239386	0.281625	0.292609	0.256526

HINDPETRO	**Near**	1	0.97283	0.975617	0.974317	0.974771	1.002327	1.003622	1.002063
	Next	1	0.833333	0.898307	0.876354	0.880967	0.913128	0.986474	0.98903
	Far	1	0.172775	0.189143	0.201158	0.215929	0.148920	0.170629	0.159851
HINDUNILVR	**Near**	1	0.988349	0.991899	0.991726	0.993982	1.000784	0.997474	1.003102
	Next	1	0.919649	0.946085	0.941661	0.943392	0.971098	0.993007	0.992279
	Far	1	0.256934	0.269463	0.291104	0.303103	0.32534	0.338422	0.336892
IBULHSGFIN	**Near**	1	0.992401	0.997959	0.990588	0.989543	1.001441	1.003322	0.994208
	Next	1	0.933633	0.963545	0.954623	0.969896	0.975854	0.974132	0.98855
	Far	1	0.250764	0.23679 L	0.238789	0.331074	0.241799	0.250623	0.249976
INFRATEL	**Near**	1	1.009893	1.009444	1.005303	1.001731	1.009321	1.010606	1.009821
	Next	1	0.818736	0.871724	0.902557	0.9231244	0.949254	0.994088	0.949254
	Far	1	0.437317	0.448785	0.442631	0.504172	0.471648	0.473529	0.479069
IOC	**Near**	1	0.974751	0.980081	0.974019	0.974417	0.972546	0.97671	0.990314
	Next	1	0.661837	0.722666	0.72001	0.727624	0.759895	0.974237	0.752779
	Far	1	0.262179	0.263461	0.284158	0.297068	0.324534	0.333604	0.33161
MARUTI	**Near**	1	0.98279	0.990187	0.987937	0.987805	0.995405	1.001165	0.999582
	Next	1	0.890775	0.94421	0.925656	0.929376	0.993758	0.994426	0.99328
	Far	1	0.290865	0.293815	0.307989	0.320654	0.638992	0.637361	0.638257
NTPC	**Near**	1	0.965666	0.967984	0.967432	0.968773	0.977355	0.99118	0.983779
	Next	1	0.946318	0.946825	0.951809	0.955822	0.979035	0.986031	0.985088
	Far	1	0.522219	0.565058	0.582812	0.600818	0.656277	0.656628	0.656316

RELIANCE	**Near**	1	0.993205	0.995733	0.992889	0.992402	0.995948	0.996571	0.996487
	Next	1	0.99691	0.999072	0.998476	0.99889	1.000921	0.999049	1.000886
	Far	1	0.787821	0.837299	0.842671	0.852559	0.982054	0.975675	0.984034
TATASTEEL	**Near**	1	0.976848	0.983592	0.976946	0.976809	0.987318	0.997117	0.988875
	Next	1	0.973624	0.982036	0.976937	0.978926	0.988219	0.996903	0.992118
	Far	1	0.551006	0.566004	0.583188	0.595008	0.914649	0.919908	0.917658
TCS	**Near**	1	0.997971	1.000231	0.999794	0.998656	1.003007	1.000498	0.998895
	Next	1	0.991928	1.002245	0.997576	0.996869	0.991903	0.968424	1.00803
	Far	1	0.250849	0.252261	0.306862	0.319709	0.792811	0.74476	0.750638
ULTRACEMCO	**Near**	1	0.974227	0.992293	0.985736	0.986549	0.999265	0.995578	1.003512
	Next	1	0.253915	0.254944	0.278335	0.285321	0.957579	0.952805	0.95461
	Far	1	0.062793	0.060174	0.055417	0.065452	0.135943	0.146616	0.143645
ZEEL	**Near**	1	1.002231	0.99996	1.002631	1.002615	1.00567	1.004455	1.00268
	Next	1	0.637344	0.777165	0.745639	0.753033	0.920738	0.884747	0.920302
	Far	1	0.057856	0.057596	0.076513	0.088415	0.063105	0.058065	0.076024

In addition to a discussion on optimal hedge ratios, Table 2 and 3 report the coefficients of hedging effectiveness measured using the variance reduction approach and risk-return approach respectively. It was observed that using the variance reduction approach (Table 2), 17 out of total 18index / stocks favor futures contracts with a one-month expiry period (i.e. near month futures contracts). In other words, a near month futures contracts generates highest hedging effectiveness as compared to the next and far month futures. The exception to these results is COALINDIA for which the next month futures contracts were found to be more effective. Moreover, another important finding from Table 2 is that reduction in variance differed significantly over near, next and far month futures contracts i.e. in case of near month futures contracts, reduction in variance ranges from 0.994 (BAJFINANCE) and 0.897 (COALINDIA), while for next month futures contracts, reduction in variance ranges from 0.986 (BAJFINANCE) and -1.212 (ULTRACEMCO), whereas in case of far month futures contracts, reduction in variance ranges from 0.944 (BAJFINANCE) and -0.965 (ZEEL).

Table 2: Hedging Effectiveness using Variance Reduction Approach

Symbol	Contract	Naive	OLS	ARMA OLS	VAR	VECM	GARCH	EGARCH	TARCH
NIFTY50	**Near**	**0.960829**	**0.965391**	**0.965067**	**0.965379**	**0.965368**	**0.964904**	**0.964307**	**0.964580**
	Next	0.955784	0.959917	0.959601	0.959896	0.959889	0.959359	0.959225	0.959195
	Far	0.910158	0.918764	0.918008	0.918535	0.918481	0.916931	0.915244	0.915394
BAJFINANCE	**Near**	**0.994957**	**0.994959**	**0.994960**	**0.994964**	**0.994964**	**0.994960**	**0.994959**	**0.994959**
	Next	0.986929	0.986980	0.986975	0.986982	0.986978	0.986957	0.986907	0.986928
	Far	0.944030	0.944033	0.944023	0.944038	0.943019	0.944004	0.944013	0.944019
BPCL	**Near**	**0.950350**	**0.950912**	**0.950850**	**0.950888**	**0.950886**	**0.950438**	**0.950554**	**0.950587**
	Next	0.412575	0.588160	0.581880	0.580080	0.577712	0.509644	0.429057	0.521851
	Far	-0.548774	0.085333	0.085331	0.084601	0.083179	0.082249	0.084767	0.082272
COALINDIA	**Near**	0.897737	0.897878	0.897877	0.897871	0.897845	0.897825	0.897819	0.897854
	Next	**0.904645**	**0.904647**	**0.904643**	**0.904647**	**0.903483**	**0.904620**	**0.904447**	**0.904465**
	Far	0.247625	0.384123	0.383597	0.383433	0.364737	0.378665	0.377828	0.378800
EICHERMOT	**Near**	**0.977306**	**0.977310**	**0.977304**	**0.977306**	**0.977289**	**0.977310**	**0.977263**	**0.977303**
	Next	0.861508	0.869807	0.864475	0.866667	0.865770	0.860922	0.861175	0.861093
	Far	-0.453339	0.079369	0.079269	0.079193	0.051792	0.079133	0.078388	0.078277
GAIL	**Near**	**0.956282**	**0.957234**	**0.957179**	**0.957218**	**0.957215**	**0.957068**	**0.956606**	**0.956855**
	Next	0.690391	0.738729	0.737999	0.735816	0.734941	0.732996	0.728038	0.731906
	Far	-0.677239	0.041516	0.041220	0.040050	0.039215	0.032981	0.030713	0.037161

HINDPETRO	**Near**	**0.965566**	**0.966334**	**0.966325**	**0.966331**	**0.966330**	**0.966012**	**0.965350**	**0.965455**
	Next	0.766494	0.798536	0.793646	0.796385	0.795901	0.791170	0.771477	0.770741
	Far	-0.755427	0.034434	0.034123	0.033501	0.032280	0.034086	0.033737	0.034275
HINDUNILVR	**Near**	**0.941086**	**0.941223**	**0.941209**	**0.941210**	**0.941190**	**0.941068**	**0.941138**	**0.941006**
	Next	0.843311	0.998384	0.948797	0.957193	0.953912	0.900585	0.857323	0.858776
	Far	-0.673048	0.091325	0.091105	0.089703	0.088366	0.084835	0.082119	0.082461
IBULHSGFIN	**Near**	**0.976603**	**0.976686**	**0.976636**	**0.976689**	**0.976688**	**0.976574**	**0.976530**	**0.976677**
	Next	0.907096	0.911945	0.910904	0.911411	0.910441	0.909930	0.910085	0.908592
	Far	-0.666579	0.083654	0.083409	0.083476	0.074951	0.083557	0.083654	0.083654
INFRATEL	**Near**	**0.981906**	**0.981949**	**0.981951**	**0.981953**	**0.981927**	**0.981952**	**0.981945**	**0.981949**
	Next	0.688707	0.725319	0.722011	0.717274	0.712965	0.706162	0.691029	0.706162
	Far	-0.098567	0.146804	0.146682	0.146773	0.143233	0.145832	0.145726	0.145383
IOC	**Near**	**0.967474**	**0.968139**	**0.968107**	**0.968139**	**0.968139**	**0.968139**	**0.968134**	**0.967926**
	Next	0.448040	0.606710	0.601549	0.601988	0.600676	0.593331	0.471283	0.595198
	Far	-0.554008	0.079989	0.079987	0.079422	0.078565	0.075450	0.074036	0.074363
MARUTI	**Near**	**0.960262**	**0.960566**	**0.960507**	**0.960537**	**0.960538**	**0.960401**	**0.960220**	**0.960276**
	Next	0.828416	0.841131	0.838073	0.839821	0.839529	0.829825	0.829678	0.829929
	Far	-0.553068	0.111757	0.111745	0.111365	0.110577	-0.048506	-0.047008	-0.04783
NTPC	**Near**	**0.955690**	**0.956922**	**0.956915**	**0.956918**	**0.956910**	**0.956774**	**0.956237**	**0.956574**
	Next	0.920625	0.923633	0.923633	0.923599	0.923534	0.922508	0.921980	0.922057
	Far	0.052808	0.326364	0.324149	0.321943	0.318934	0.304788	0.304675	0.304776

RELIANCE	**Near**	**0.986125**	**0.986175**	**0.986167**	**0.986175**	**0.986174**	**0.986166**	**0.986162**	**0.986162**
	Next	0.982751	0.982762	0.982756	0.982759	0.982757	0.982744	0.982756	0.982744
	Far	0.571272	0.616069	0.613618	0.613059	0.611881	0.578523	0.580946	0.577754
TATASTEEL	**Near**	**0.976682**	**0.977243**	**0.977193**	**0.977243**	**0.977243**	**0.977126**	**0.976812**	**0.977089**
	Next	0.965988	0.966711	0.966635	0.966699	0.966680	0.966487	0.966146	0.966353
	Far	0.126723	0.378021	0.377735	0.376719	0.375593	0.213157	0.208356	0.210419
TCS	**Near**	**0.983029**	**0.983034**	**0.983028**	**0.983030**	**0.983033**	**0.983006**	**0.983026**	**0.983033**
	Next	0.954625	0.954693	0.954583	0.954659	0.954666	0.954693	0.954171	0.954432
	Far	-0.486727	0.061405	0.061402	0.058332	0.056764	-0.225488	-0.176877	-0.18258
ULTRACEMCO	**Near**	**0.920405**	**0.921070**	**0.920739**	**0.920932**	**0.920913**	**0.920442**	**0.920611**	**0.920215**
	Next	-1.212221	0.158608	0.158605	0.157128	0.156165	-1.060786	-1.044299	-1.05052
	Far	-1.168795	0.005266	0.005257	0.005194	0.005256	-0.001891	-0.004131	-0.00348
ZEEL	**Near**	**0.980096**	**0.980099**	**0.980096**	**0.980099**	**0.980099**	**0.980085**	**0.980093**	**0.980099**
	Next	0.391614	0.579704	0.551685	0.562878	0.560508	0.464803	0.492113	0.465156
	Far	-0.965637	0.003652	0.003652	0.003271	0.002631	0.003622	0.003652	0.003291

* Figures in bold represent highest hedging effectiveness compared over near, next and far month futures contracts

On the other hand, using the risk-return approach (Table 3), though mixed results have been obtained in respect of different optimal hedge ratio models, on the whole, more than sixty five percent of index / stocks favor far month futures contracts for hedging. In particular, far month futures contracts are supported by seventeen (94.4%) stocks / index using naïve hedge ratio, fourteen (77.8%) stock / index using VECM hedge ratios, thirteen (72.2%) stock / index each using ARMA-OLS, VAR, GARCH and TARCH hedge ratio and twelve (66.7%) stock / index each using OLS and EGARCH hedge ratio. In other words, the results of hedging effectiveness from the risk-return approach indicate that return per unit of risk from the hedged portfolio can be maximized by using a far month futures contracts for hedging.

Table 3: Hedging Effectiveness using Risk-Return Approach

Symbol	Contract	Naive	OLS	ARMA OLS	VAR	VECM	GARCH	EGARCH	TARCH
NIFTY50	**Near**	1.24515	1.237351	1.239464	1.237745	1.237902	1.239943	1.241208	1.240692
	Next	1.241114	1.233795	1.235847	1.234300	1.234387	1.236522	1.236832	1.236896
	Far	**1.245653**	**1.235071**	**1.238298**	**1.236849**	**1.237048**	**1.240069**	**1.241948**	**1.241803**
BAJFINANCE	**Near**	**1.289828**	**1.289778**	**1.289732**	**1.289478**	**1.289521**	**1.289732**	**1.289775**	**1.289790**
	Next	1.256646	1.255992	1.256099	1.255928	1.256026	1.256367	1.256813	1.256657
	Far	1.009472	1.009482	1.009457	1.009507	1.009057	1.009429	1.009441	1.009451
BPCL	**Near**	1.165847	1.163970	1.164586	1.164344	1.164364	1.165695	1.165469	1.165398
	Next	1.273494	1.233446	1.243191	1.244407	1.245789	1.262985	**1.272098**	1.261049
	Far	**1.473917**	**1.251265**	**1.251908**	**1.268059**	**1.279518**	**1.284752**	1.266084	**1.284635**
COALINDIA	**Near**	0.634640	0.636905	0.636814	0.636492	0.635871	0.638533	0.635472	0.636043
	Next	0.644067	0.643622	0.643325	0.643605	0.637106	0.642716	0.640968	0.641101
	Far	**0.692390**	**0.783644**	**0.777268**	**0.776330**	**0.746073**	**0.763242**	**0.761772**	**0.763490**
EICHERMOT	**Near**	1.082755	1.082716	1.082773	1.082758	1.082846	1.082593	1.082937	1.082531
	Next	1.084265	1.081222	1.083680	1.083117	1.083367	1.084366	1.084323	1.084337
	Far	**1.333067**	**1.190396**	**1.185262**	**1.183642**	**1.255315**	**1.182585**	**1.174403**	**1.173500**
GAIL	**Near**	1.221080	1.217786	1.218559	1.218181	1.218223	1.219154	1.220462	1.219866
	Next	1.275265	**1.248808**	**1.252365**	**1.255793**	1.256735	1.258471	1.261774	1.259304
	Far	**1.583892**	1.220185	1.235709	1.254167	**1.262408**	**1.298399**	**1.307274**	**1.277373**

HINDPETRO	**Near**	1.150948	1.148960	1.149167	1.149071	1.149104	1.151116	1.151209	1.151097
	Next	1.186189	1.173201	1.178638	1.176859	1.177237	**1.179807**	**1.185245**	**1.185425**
	Far	**1.464993**	**1.173217**	**1.186892**	**1.196637**	**1.208280**	1.152448	1.171389	1.162089
HINDUNILVR	**Near**	1.312447	**1.310642**	1.311194	1.311167	1.311517	1.312568	1.312058	1.312924
	Next	1.322068	1.309388	**1.313686**	1.312975	1.313254	1.317637	1.321009	1.320898
	Far	**1.593340**	1.294831	1.305593	**1.323476**	**1.333016**	**1.350008**	**1.359599**	**1.358493**
IBULHSGFIN	**Near**	1.069399	1.069145	1.069331	1.069084	1.069049	1.069447	1.069509	1.069205
	Next	1.066213	1.064352	1.065210	1.064958	1.065388	1.065554	1.065506	1.065903
	Far	**1.272405**	**1.163353**	**1.156857**	**1.157803**	**1.195671**	**1.159217**	**1.163289**	**1.162994**
INFRATEL	**Near**	0.739497	0.738192	0.738251	0.738796	0.739268	0.738267	0.738099	0.738202
	Next	0.925919	0.936769	0.933456	0.963877	0.959015	0.928821	0.926252	0.928821
	Far	**1.153834**	**1.124306**	**1.125937**	**1.125070**	**1.132973**	**1.129007**	**1.129249**	**1.129952**
IOC	**Near**	1.430917	1.425498	1.426654	1.425339	1.425425	1.425018	1.425923	1.428854
	Next	1.721565	**1.600387**	**1.626992**	**1.625884**	**1.629050**	**1.642059**	**1.714271**	**1.639246**
	Far	**1.884841**	1.403477	1.405067	1.430229	1.445455	1.476672	1.486636	1.484460
MARUTI	**Near**	1.088539	1.087812	1.088126	1.088031	1.088025	1.088346	1.088587	1.088521
	Next	1.095297	1.091086	1.093226	1.092501	1.092648	1.095073	1.095097	1.095056
	Far	**1.267815**	**1.176397**	**1.177538**	**1.182874**	**1.187439**	**1.253976**	**1.253811**	**1.253902**
NTPC	**Near**	1.386965	1.380345	1.380799	1.380691	1.380954	1.382625	1.385287	1.383867
	Next	1.397259	1.386654	1.386757	1.387767	1.388576	1.393189	1.394557	1.394373
	Far	**1.558308**	**1.413672**	**1.432304**	**1.439594**	**1.446745**	**1.467327**	**1.467450**	**1.467340**

RELIANCE	**Near**	1.178516	1.177914	1.178139	1.177886	1.177843	1.178158	1.178213	1.178206
	Next	1.174761	1.174494	1.174681	1.174629	1.174665	1.174841	1.174679	1.174838
	Far	**1.262145**	**1.237996**	**1.244359**	**1.245020**	**1.246223**	**1.260391**	**1.259756**	**1.260587**
TATASTEEL	**Near**	1.137254	1.135690	1.136150	1.135697	1.135688	1.136402	1.137062	1.136508
	Next	1.139806	1.138004	1.138584	1.138233	1.138370	1.139007	1.139597	1.139272
	Far	**1.273279**	**1.223135**	**1.225852**	**1.228842**	**1.230825**	**1.267426**	**1.267822**	**1.267653**
TCS	**Near**	1.227475	1.227245	1.227501	1.227451	1.227323	1.227814	1.227531	1.227350
	Next	1.230810	1.229895	1.231063	1.230536	1.230456	1.229892	1.227188	1.231712
	Far	**1.495493**	**1.233378**	**1.234405**	**1.271905**	**1.280119**	**1.462337**	**1.451803**	**1.453160**
ULTRACEMCO	**Near**	1.206986	1.204400	1.206220	1.205563	1.205645	1.206913	1.206547	1.207333
	Next	1.363994	**1.236460**	**1.237047**	**1.249774**	**1.253356**	**1.363636**	**1.363579**	**1.363601**
	Far	**1.612720**	1.086687	1.083204	1.076848	1.090210	1.178875	1.191474	1.187989
ZEEL	**Near**	1.242359	1.242627	1.242354	1.242675	1.242673	1.243040	1.242894	1.242681
	Next	1.420061	**1.349825**	**1.382061**	**1.375469**	**1.377048**	**1.408061**	**1.402102**	**1.407991**
	Far	**1.729265**	1.086312	1.085936	1.113062	1.129831	1.093894	1.086615	1.112368

* Figures in bold represent highest hedging effectiveness compared over near, next and far month futures contracts.

An important observation from the results of Table 2 and 3 is that both the approaches of hedging effectiveness favor futures contracts with a different time-to-maturity i.e. variance reduction approach favor near month futures contracts, whereas risk-return approach favors far month futures contracts. Both the approaches differ on the basis of the objective function of the investor i.e. variance reduction approach assumes that the investor aims to reduce maximum variance on hedged portfolio (Ederington (1979), whereas the risk-return approach assumes that the investor aims to maximize return per unit of risk from the hedged portfolio (Howard and D'Antonio (1984). Thus, these results have important implications for investors because for highly risk-averse investors (concerned with only minimization of risk), near month futures contracts is an appropriate choice for hedging, whereas for low risk averse investors (concerned with both risk and return) futures contracts with distant maturity period seems to be an appropriate choice for hedging. These results also indicate that risk-aversion of the investor is a significant factor affecting hedging effectiveness which supports the findings of Yang and Lai (2009) and Chen et al. (2014).

CONCLUSION

This study attempted to investigate the impact of hedge horizon upon hedging effectiveness of futures contracts in the Indian Equity Futures Market for which the sample comprised of benchmark index of the NSE i.e. Nifty50 as well as its 17 composite stocks on which futures trading is permitted (See Appendix B), selected on the basis of consistent trading history and liquidity. The sample period was from the date of inception of the respective index / stock futures contracts till March 31, 2017. Optimal hedge ratios were estimated using eight statistical methods (namely, Naïve, OLS, ARMA-OLS, VAR, VECM, GARCH, EGARCH and TARCH),and it was found that the coefficients of all the eight optimal hedge ratios were very close to each other implying that the cost of hedging is more or less similar across different models.

Further, hedging effectiveness was measured by two different approaches, namely, variance reduction approach (that focuses solely on minimization of portfolio risk) and the risk-return approach (that considers both risk as well as return). It was found that using the variance reduction approach, the NIFTY50 as well all its composite stocks understudy (except COALINDIA) favors near month futures contracts, whereas using the risk-return approach, more than sixty-five percent of the index / stocks favor the far month futures contracts.

Overall, the results indicate that hedging effectiveness is affected by the maturity of the futures contracts as well as the approach used to measure effectiveness of the hedge as a variance reduction approach supports a near month futures contracts, whereas the risk-return approach favors a far month futures contracts for hedging. These findings indicate that risk aversion of investors significantly affects hedging effectiveness because for highly risk-averse investors, hedging spot exposure with near month futures contracts is an appropriate choice, whereas for low risk averse investors, futures contracts with a distant maturity period seems to be an appropriate choice for hedging the spot position as it leads to highest hedging effectiveness as compared to near and next month futures contracts. Thus, these findings may provide important input to investors as well as fund managers for creating an efficient hedging strategy.

REFERENCES

Alexander, C., Prokopczuk, M., &Sumawong, A. (2013). The (de) merits of Minimum-Variance Hedging: Application to the Crack Spread. *Energy Economics*, *36*, 698-707.

Basher, S. A., &Sadorsky, P. (2016). Hedging Emerging Market Stock Prices with Oil, Gold, VIX, and Bonds: A Comparison between DCC, ADCC and GO-GARCH. *Energy Economics*, *54*, 235-247.

Benada, L. (2018). Comparison of the Impact of Econometric Models on Hedging Performance by Crude Oil and Natural Gas. *Acta Universitatis Agriculturae et SilviculturaeMendelianaeBrunensis*, *66*(2), 423-429.

Bhaduri, S. N., &SethuDurai, S. R. (2008). Optimal Hedge Ratio and Hedging Effectiveness of Stock Index Futures: Evidence From India. *Macroeconomics and Finance in Emerging Market Economies*, *1*(1), 121-134.

Bhargava, V., & Malhotra, D. K. (2007). Determining the Optimal Hedge Ratio: Evidence from Cotton and Soybean Markets. *The Journal of Business and Economic Studies*, *13*(1), 38.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-327.

Bonga-Bonga, L., &Umoetok, E. (2016). The Effectiveness of Index Futures Hedging In Emerging Markets during the Crisis Period of 2008-2010: Evidence from South Africa. *Applied Economics, 48*(42), 3999-4018.

Bose, S. (2007). Contribution of Indian Index Futures to Price Formation in the Stock Market. *Money and Finance, 3*(1), 39-56.

Brooks, C. (2008). Introductory Econometrics for Finance.*Cambrige University* Press.

Chang, C. L., González-Serrano, L., & Jimenez-Martin, J. A. (2013). Currency Hedging Strategies using Dynamic Multivariate GARCH. *Mathematics and Computers in Simulation*, *94*, 164-182.

Chen, D. H., Bin, L., & Tseng, C. Y. (2014). Hedging Effectiveness of applying Constant and Time-Varying Hedge Ratios: Evidence from Taiwan Stock Index Spot and Futures. *Journal of Risk & Control*, *1*(1), 31-49.

Das, J. K., & Chakraborty, G. (2015). The Hedging Performance of Commodity Futures in India: An Empirical Study on Some Agricultural Commodities. *International Journal of Information, Business and Management*, *7*(3), 162.

Ederington, L. H. (1979). The Hedging Performance of the New Futures Markets. *The Journal of Finance*, *34*(1), 157-170.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance Of United Kingdom Inflation. *Econometrica: Journal of the Econometric Society*, 987-1007.

Figlewski, S. (1984). Hedging Performance and Basis Risk in Stock Index Futures. *The Journal of Finance*, *39*(3), 657-669.

Ghosh, N., Dey, D., Moulvi, N. A., Jain, N., Sinha, N., &Rachuri, S. (2013). Hedging Efficiency - Measures and Empirical Study on MCX. *Financial Vision, 1*(5), 10-14

Gupta, K., & Singh, B. (2007). Investigating the Pricing Efficiency of Indian Equity Futures Market. *Management and Labour Studies*, *32*(4), 486-512.

Gupta, K., & Singh, B. (2009). Estimating the Optimal Hedge Ratio in the Indian Equity Futures market. *The IUP Journal of Financial Risk Management*, *6*(3), 38-98.

Gupta, S., Choudhary, H., & Agarwal, D. R. (2017). Hedging Efficiency of Indian Commodity Futures: An Empirical Analysis. *Paradigm*, *21*(1), 1-20.

Haq, I. U., & Chandrasekhara Rao, K. (2013). Optimal Hedge Ratio and Hedging Effectiveness of Indian Agricultural Commodities. *IUP Journal of Financial Risk Management*, *10*(2), 30-38.

Holmes, P. (1996). Stock Index Futures Hedging: Hedge Ratio estimation, Duration effects, Expiration effects and Hedge Ratio stability. *Journal of Business Finance & Accounting*, *23*(1), 63-77.

Howard, C. T., &D'Antonio, L. J. (1984). A Risk-Return Measure of Hedging Effectiveness. *Journal of Financial and Quantitative Analysis*, *19*(1), 101-112.

In, F. and Kim, S. (2006). The Hedge Ratio and the Empirical Relationship between the Stock and Futures Markets: A New Approach Using Wavelet Analysis. *The Journal of Business, 79*(2), pp. 799-820.

Karpoff, J. M. (1987). The Relation between Price Changes and Trading Volume: A Survey. *Journal of Financial and quantitative Analysis*, *22*(1), 109-126.

Kamara, A., & Siegel, A. F. (1987). Optimal Hedging in Futures Markets with Multiple Delivery Specifications. *The Journal of Finance*, *42*(4), 1007-1021.

Kaur, M., and Gupta, K. (2018b). Estimation of Hedging Effectiveness Using Variance Reduction and Risk-Return Approaches: Evidence from National Stock Exchange of India.*International Journal of Business Analytics and Intelligence*. *6*(1), 35-46.

Kumar, B., & Pandey, A. (2013). Market Efficiency in Indian Commodity Futures Markets. *Journal of Indian Business Research*, *5*(2), 101-121.

Lee, H. C., &Chien, C. Y. (2010). Hedging performance and stock market liquidity: evidence from the Taiwan futures market. *Asia-Pacific Journal of Financial Studies*, *39*(3), 396-415.

Lien, D. (2005). The use and abuse of the hedging effectiveness measure. *International Review of Financial Analysis*, *14*(2), 277-282.

Lien, D., Tse, Y. K., &Tsui, A. K. (2002). Evaluating the hedging performance of the constant-correlation GARCH model. *Applied Financial Economics*, *12*(11), 791-798.

Maharaj, E. A., Moosa, I., Dark, J., &Silvapulle, P. (2008). Wavelet estimation of asymmetric hedge ratios: does econometric sophistication boost hedging effectiveness?. *International Journal of Business & Economics*, *7*(3), 213-230.

Malhotra, M. (2015). Evaluating the Hedging Performance of Oil and Oilseeds Futures in India. *Paradigm*, *19*(2), 184-196.

Moosa, I. (2003). *International Financial Operations: Arbitrage, Hedging, Speculation, Financing and Investment*. Springer.

Mukherjee, K. N. and Mishra, R. K. (2006). Lead-Lag Relationship Between Equities and Stock Index Futures Market and It's Variation Around Information Release: Empirical Evidence from India, NSE Research Paper, NSE India.

Naliniprava, T. (2011). Hedge Ratio and Hedging Efficiency: Evidence from Indian Derivative Market. *Volume III Issue 1 (5)*, 62.

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica: Journal of the Econometric Society*, 347-370.

Park, T. H., and Switzer, L. N. (1995). Time-Varying Distributions and the Optimal Hedge Ratios for Stock Index Futures. *Applied Financial Economics, 5*, 131-137.

Poomimars, P., Cadle, J., & Theobald, M. (2003). Futures Hedging Using Dynamic Models of The Variance/Covariance Structure. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *23*(3), 241-260.

Pok, W. C., Poshakwale, S. S., & Ford, J. L. (2009). Stock Index Futures Hedging in the Emerging Malaysian Market. *Global Finance Journal*, *20*(3), 273-288.

Pradhan, K. (2011). The Hedging Effectiveness of Stock Index Futures: Evidence for the S&P CNX Nifty Index Traded in India. *South East European Journal of Economics and Business*, *6*(1), 111-123.

Rao, S. N., & Thakur, S. K. (2008). Optimal Hedge Ratio and Hedge Efficiency: An Empirical Investigation of Hedging in Indian Derivatives Market. *Society of Actuaries, Monograph Publication*, 1-27.

Ripple, R. D., &Moosa, I. A. (2007). Hedging Effectiveness and Futures Contract Maturity: The Case of NYMEX Crude Oil Futures. *Applied Financial Economics*, *17*(9), 683-689.

Silber, W. L. (1985). *The economic role of financial futures*. Salomon Brothers Center for the Study of Financial Institutes, Graduate School of Business Administration, Washington, US.

Stoll, H. R., & Whaley, R. E. (1990). The Dynamics of Stock Index and Stock Index Futures Returns. *Journal of Financial and Quantitative analysis*, *25*(4), 441-468.

Sultan, J., & Hasan, M. S. (2008). The Effectiveness of Dynamic Hedging: Evidence from Selected European Stock Index Futures. *The European Journal of Finance*, *14*(6), 469-488.

Tejeda, H. A., & Goodwin, B. K. (2014). Dynamic Multiproduct Optimal Hedging in the Soybean Complex-Do Time-Varying Correlations Provide Hedging Improvements?. *Applied Economics*, *46*(27), 3312-3322.

Veronesi, P. (1999). Stock Market Overreactions to Bad News in Good Times: A Rational Expectations Equilibrium Model. *The Review of Financial Studies*, *12*(5), 975-1007.

Wang, J., & Hsu, H. (2010). Hedge Ratio Stability and Hedging Effectiveness of Time-Varying Hedge Ratios in Volatile Index Futures Markets: Evidence from the Asian Financial Crisis. *Asia-Pacific Journal of Financial Studies*, *39*(5), 659-686.

Wang, Yudong, Chongfeng Wu, and Li Yang (2015). Hedging with Futures: Does Anything Beat the Naïve Hedging Strategy?.*Management Science, 61*(12), 2870-2889.

Woking, H. (1953). Futures Trading and Hedging. *American Economic Review, 43*, 314-343.

Yaganti, H. C., &Kamaiah, B. (2012). Hedging Efficiency of Commodity Futures Markets in India. *IUP Journal of Financial Risk Management*, *9*(2).

Yang, W. and Allen, D. E. (2004). Multivariate GARCH Hedge Ratios and Hedging Effectiveness in Australian Futures Markets. *Accounting and Finance, 45*, pp. 301-321.

Yang, M. J., & Lai, Y. C. (2009). An Out-of-Sample Comparative Analysis of Hedging Performance of Stock Index Futures: Dynamic versus Static Hedging. *Applied Financial Economics*, *19*(13), 1059-1072.

Zhang, Y., & Choudhry, T. (2015). Forecasting the Daily Dynamic Hedge Ratios by GARCH Models: Evidence From the Agricultural Futures Markets. *The European Journal of Finance*, *21*(4), 376-399.

APPENDIX A: WORLD RANKING OF NSE IN FUTURES MARKET

Year	Rank of NSE	
	Stock Futures	*Index Futures*
2011	**5**	**4**
2012	**4**	**4**
2013	**3**	5
2014	2	6
2015	2	7
2016	2	6
2017	2	8

Source: Data compiled from various 'IOMA Derivatives Markets Survey' reports accessed on official website of World Federation of Exchanges (www.world-exchanges.org)

APPENDIX B: SAMPLE SIZE AND SAMPLE PERIOD OF THE STUDY

S. No.	Symbol	Period of study	No. of Observations
1	NIFTY50	June 12, 2000 – March 31, 2017	12564
2	BAJFINANCE	May 29, 2015 – March 31, 2017	1185
3	BPCL	November 9, 2001 - March 31, 2017	11307
4	COALINDIA	August 5, 2011 - March 31, 2017	4014
5	EICHERMOT	September 10, 2014 - March 31, 2017	1704
6	GAIL	September 26, 2003 - March 31, 2017	9897
7	HINDPETRO	November 9, 2001 - March 31, 2017	11307
8	HINDUNILVR	November 9, 2001 - March 31, 2017	11307
9	IBULHSGFIN	November 28, 2014 - March 31, 2017	1554
10	INFRATEL	September 28, 2015 - March 31, 2017	933
11	IOC	September 26, 2003 - March 31, 2017	9897
12	MARUTI	July 09, 2003 - March 31, 2017	10065
13	NTPC	November 5, 2004 - March 31, 2017	9048
14	RELIANCE	November 9, 2001 - March 31, 2017	11307
15	TATASTEEL	November 9, 2001 - March 31, 2017	11307
16	TCS	August 25, 2004 - March 31, 2017	9201
17	ULTRACEMCO	December 29, 2006 - March 31, 2017	7434
18	ZEEL	September 15, 2006 - March 31, 2017	7645