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Estimation of Hedging Effectiveness Using Variance Reduction and Risk-Return Approaches: Evidence from National Stock Exchange of India

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Abstract

Present study estimates the hedging effectiveness by applying variance-reduction framework and risk-return framework using near month contracts of three benchmark indices (NIFTY50, NIFTYIT, and BANKNIFTY) traded at National Stock Exchange of India (NSE) for the sample period from June 2000 to March 31, 2017 by using nine optimal hedge ratio models. Out of these nine models, six are constant hedging models and three are time-varying hedging models. The study finds that using variance-reduction framework, highest hedging effectiveness is achieved using Ordinary Least Square model; whereas, 1:1 naïve hedge ratio gives lowest hedging effectiveness. On the other hand, when hedging effectiveness is estimated in a risk-return framework, naïve hedge ratio gives highest hedging effectiveness; whereas, OLS gives the least estimate. Secondly, the coefficients of both optimal hedge ratio as well as hedging effectiveness have increased during post-crisis period implying an increase in the cost of hedging. These findings suggests that conventional hedging models are more efficient than highly complicated time-varying hedging models for estimating optimal hedge ratio, these findings are consistent with the findings of Lien (2005), Bhaduri and Durai (2007), Bhargava (2007), Mandal (2011), Wang et al. (2015).

Keywords: Hedging Effectiveness, Optimal Hedge Ratio, Equity Futures Market, Generalized Auto-regressive Conditional Heteroscedasticity (GARCH), Constant Hedge Ratio, Time-Varying Hedge Ratio

JEL: C13, C22, C32, D81, D82, G12, G14, N25, and O16

Introduction

The globalization of financial markets as well as political and economic disturbances around the world have increased the exposure to financial risk. Therefore, as a need to hedge the financial risk, derivative contracts have been introduced which includes futures contracts, options contracts, swaps, swaptions, and so on. Literature observes that although futures market plays a significant role in hedging price risk, price discovery and increasing cash market efficiency, yet hedging is considered the primary function of futures market.

The co-movement and long-term equilibrium relationship between spot and futures market enables hedger to offset price fluctuations in underlying asset prices by taking opposite position in both spot and futures market. However, numerous studies[1] document the fact that such a relationship gets disturbed in the shortrun due to the presence of market frictions such as: noise trading, infrequent trading of component stocks of underlying index, difference in the trading cost in both the markets, violation of assumptions of cost of carry model, etc. Such disturbances lead to basis risk, which mandates a hedger to estimate the required number of futures contracts to achieve superior hedging effectiveness (according to specific objective function to be optimized).

While designing an efficient hedge strategy, the objective of investors to hedge is of prime consideration. There are three different views on hedging based upon investor's objective to hedge. The traditional theory assumes

[1] Castelino (1992); Figlewski (1984); Stoll and Whaley (1990)

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investor as a pure-risk avoider, whereas Working (1953) views hedger as a pure risk-taker speculating on the spread between futures and cash prices. The third theory adopts a hybrid approach and claims that a hedger neither purely avoids risk nor does he increases his risk to highest levels. Instead, a hedger prefers a portfolio that optimizes his level of risk and return. This theory, known as Portfolio Hedging Theory, became the most widely accepted framework for designing hedge strategy.

The literature on estimation of optimal hedge ratio initiated with the proposal of Minimum-Variance Hedge Ratio (MVHR) framework suggested by Ederington (1979), Johnson (1960), and Stein (1961). Johnson (1960) and Stein (1961) prepared a theoretical background for estimating MVHR, known as Portfolio theory, based upon which, Ederington (1979) suggested that MVHR could be estimated as the ratio of covariance of spot-futures returns and variance of futures returns. In this view, Ederington (1979) suggested single regression equation (Ordinary Least Square (OLS)) that regresses cash returns upon futures return for estimating optimal hedge ratio. Ederington's OLS is the most simplest of all the models, and thus highly appreciated by a large body of literature (Bhargava & Malhotra (2007); Bonga & Umoetek (2016); Deaves (1994); Lien (2005); Lien et al. (2002); Lee & Chien (2010); Malliaris & Urrutia (1991); Mandal (2011); Moon et al. (2009)).

Further, despite huge popularity of Ederington's model, voluminous literature[2] observes that Ederington's OLS hedge ratio does not account for heteroscedasticity, i.e., it ignores the fact that financial time-series exhibits time-varying volatility; therefore, OLS technique results in biased estimate of optimal hedge ratio. In order to overcome these limitations, ARCH model proposed by Engle (1982) and generalized by Bollerslev (1986) has been extensively used in literature to improve the effectiveness of hedge. For instance, Choudhary (2004) compared the hedging performance of Ederington's OLS and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model and concluded that hedging performance is improved by using time-varying GARCH relative to OLS technique. As such, voluminous literature (Bekkerman, 2011; Giha & Zuppiroli, 2014; Kroner & Sultan, 1993; Myers, 1991; Park & Switzer, 1995; Srinivasan, 2011; Yang & Allen, 2004), and found improved hedging effectiveness using time-varying hedging models.

As discussed previously, numerous studies claim superior performance of the time-varying hedge ratios. Alternatively, a strand of literature favours the use of constant hedging models. For instance, Lee and Chien (2010) analysed hedging performance of TAIFEX index futures contracts by comparing standard OLS model with GARCH and found that OLS provided superior hedging effectiveness over GARCH model. Similarly, Awang et al, (2014), Bonga and Umoetek (2016) and Mandal (2011)compared OLS technique with other time-varying models and concluded that OLS performed better than time-varying hedging models.

Furthermore, Ederington (1979) suggested a measure of hedging effectiveness, which is measured as proportionate reduction in standard deviation of returns from hedged portfolio. The hedge ratio that gives highest hedging effectiveness is popularly known as MVHR. Ederington's measure of hedging effectiveness has been widely appreciated in the literature (Bhargava and Malhotra (2007), Bhaduri and Durai (2007); Chen et al. (2002); Floros and Vougas (2004, 2006); Gupta and Singh (2009); Holmes (1995); Hou and Li (2013); Lypny and Powella (1998); Men and Men (2008); Park and Switzer (1995); Pradhan (2011); Yang and Allen (2005)) mainly due to its simplicity to compute and understand.

Furthermore, despite huge popularity of Ederington's measure of hedging effectiveness, a strand of literature criticizes it on the ground that it focuses solely on variance reduction and ignores any changes in portfolio returns. In other words, hedging is viewed as comprising of minimization of risk only; whereas, on the contrary, Brailsford et al. (2001) and Penning and Meulenberg (1997) suggest that hedging should comprise of both risk reduction as well as return maximization. Therefore, in order to overcome this limitation, few models have been proposed in the literature (see, Chang and Shanker (1987); Hsin et al. (1994); Howard and D'Antonio (1984); Lindahl (1991), etc.), which take into consideration changes in expected return on hedged as well as unhedged portfolio

[2] Basher and Sadorsky (2016); Bekkerman (2011); Choudhary (2003); Choudary (2004); Floros and Vougas (2004); Floros and Vougas (2006); Lee and Yoder (2007); Lypny and Powalla (1998); Moschini and Myers (2002); Park and Switzer (1995); Srinivasan (2011); Yang and Allen (2005).

in addition to risk minimization. For, instance, Howard and D'Antonio (1984) suggested a risk-return measure of hedging effectiveness based upon Sharpe's measure, which is further elaborated in Equation (11).

Apart from the previously discussed issues on optimal hedge ratio and hedging effectiveness, it is observed that futures trading is not only popular in developed markets of the world, but is also equally popular in emerging markets like India, which is evident from the fact that Indian equity futures market consistently rank amongst the top five markets of the world for the last decade. However, in India, to the best of our knowledge, only few attempts have been made to examine the hedging effectiveness[3] and these studies have primarily focused on examining a superior methodology for determining optimal hedge ratio in variance-reduction framework. To the best of our knowledge, none of these studies has attempted to examine hedging effectiveness in a risk-return framework. Therefore, present study is an attempt to examine the hedging effectiveness in a risk-return framework as suggested by Howard and D'Antonio (1984), in addition to estimating hedging effectiveness based upon measure proposed by Ederington (1979) and optimal hedge ratios using nine econometric models. In addition, an attempt has been made to study the impact of financial crisis on optimal hedge ratio and hedging effectiveness.

[3] Bhaduri and Durai, 2007; Rao and Thakur, 2008; Gupta and Singh, 2009, Pradhan, 2011, Haq and Rao, 2013, Kumar and Pandey, 2013, Malhotra, 2015

Database and Research Methodology

In India, L.C. Gupta committee recommended the introduction of equity derivative market, which initiated with the launch of equity futures contracts at NSE and BSE from June 2000. Since inception of derivative market, equity futures market has shown a phenomenal growth[4] both in terms of volume of contracts and number of products, which include stock and index futures and options contracts, interest rate futures contracts, currency futures and options, etc. As far as the present study is concerned, only equity futures contracts have been considered and the sample size of the study comprises of near month futures contracts of NIFTY, NIFTYIT, and BANKNIFTY. These indices have been selected based on their uninterrupted trading history and high liquidity and the data has been collected from official website of the National Stock Exchange of India (NSE), i.e., www.nseindia.com. The period of the study is from inception date of respective indices until March 31, 2017 as presented in Table 1 below:

[4] During 2015–16, the total number of index futures traded on NSE is 140,538,674 and stock futures is 234,243,967, source; www.nseindia.com

Table 1: Sample Size and Sample Period of Study

Symbol	*Period of study*	*Number of Observations*		*Total*
		Pre-Crisis	*Post-Crisis*	
NIFTY50	June 12, 2000 – March 31, 2017	1898	2290	4188
NIFTYIT	August 29, 2003 – March 31, 2017	1092	2290	3382
BANKNIFTY	June 13, 2005 – March 31, 2017	638	2290	2928

Unit-root Test

The first step to analyze the time-series data is to investigate if the series under study is stationary or non-stationary. This is because estimation of optimal hedge ratio involves regression analysis where cash market returns are regressed upon futures market returns. Hence, to avoid the spurious statistical results, stationarity of series is a pre-requisite. Augmented Dickey Fuller (ADF) test has been used to investigate the presence of unit-roots. It has been observed that the both spot and futures prices are non-stationery at levels. Therefore, the price series have been transformed into return series by taking the natural log of first difference of prices, which is found to be stationery[5]. Thus, cash and futures returns have been used for estimating optimal hedge ratio.

[5] The estimated results are not reported in the paper, butcan be provided on demand.

Estimation of Optimal Hedge Ratio

In the present study, optimal hedge ratio has been estimated using nine econometrical procedures andan efficient hedge ratio would be the one that provides the highest reduction in the portfolio variance. The models are explained as follows:

Model 1: Naive one-to-one Model

Naïve hedge ratio is a model free estimation procedure, whichassumes that futures and cash market observes perfect correlation. Therefore, optimal hedge ratio suggested by this model is one, which implies equal investment in both futures and spot market.

Model 2: Ordinary Least Square (OLS)

The second is OLS Method also known as single-equation method in which cash market returns are regressed upon futures returns to estimate optimal hedge ratio as given in Equation (1). Suggested by Ederington (1979), this method is the most widely used for estimating OHR as discussed in Section 2 and is specified as follows:

$$R_{s,t} = \alpha_0 + \beta_1 R_{f,t} + \mu_t \quad (1)$$

In the given regression Equation (1), $R_{s,t}$ represent returns from cash market, $R_{f,t}$ represent returns from futures market, α_0 is the intercept term, β_1 is the optimal hedge ratio and μ_t is the error term.

Model 3: Autoregressive Moving Average OLS

The standard OLS model mentioned in Equation (1) does not take into account serial correlation of stock returns, i.e., the present stock prices are dependent upon its past values;therefore, the estimated coefficient of optimal hedge ratio may be biased. In other words, stock prices are not random and any information set continues to affect stock prices for some time. Autocorrelation in stock returns has become stylized in the financial literature Therefore, autoregressive terms are incorporated in Equation (1) and the modified estimation procedure is presented in Equation (2) as follows:

$$R_{s,t} = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{s,t-i} + \beta_1 R_{f,t} + \mu_t \quad (2)$$

The autoregressive terms in Equation (2) is represented by $\left(\sum_{i=1}^{p} \alpha_i R_{s,t-i}\right)$. The order of the autoregressive terms is determined according to Schwartz Information Criteria.

Model 4: Modified OLS

It is observed that futures prices are an unbiased predictor of cash prices and basis, as an error correction term, corrects the deviation between current spot price and its equilibrium price. Therefore, Equation (2) has been further improved by Gupta and Singh (2009) by including first lag of both futures return and basis as presented in Equation (3), where $R_{f,t-1}$ represents lagged futures return and $(R_{f,t-1} - R_{s,t-1})$ represents lagged basis.

$$\begin{aligned} R_{s,t} &= \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{s,t-i} + \beta_1 R_{f,t} + \beta_2 R_{f,t-1} \\ &\quad + \beta_3 (R_{f,t-1} - R_{s,t-1}) + \varepsilon_t \end{aligned} \quad (3)$$

Model 5: Vector Autoregression (VAR)

VAR overcomes the limitation of OLS regression equation (Equation 1) by modelling the serial correlation of residual series, which OLS fails to capture. VAR model can be specified as under:

$$R_{s,t} = \sum_{i=1}^{M} \alpha_i R_{s,t-i} + \sum_{j=1}^{N} \beta_j R_{f,t-j} + \mu_{st} \quad (4)$$

$$R_{f,t} = \sum_{k=1}^{O} \alpha_k R_{s,t-k} + \sum_{l=1}^{P} \beta_1 R_{s,t-1} + \mu_{ft} \quad (5)$$

After running the given regression equations, optimal hedge ratio can be estimated as ratio of covariance of $\mu_{s,t}$ and variance of μ_{ft}. However, this model fails to capture the long-run cointegration between spot and futures prices.

Model 6: Vector Error Correction (VEC) Model

Ghosh (1993) and Lien (2004) argue that when spot-future prices are cointegrated in the longrun, the OLS equation gives an underestimated value of the optimal hedge ratio. Therefore, VAR model with an error correction term (known as VECM) is used to account for long-run co-integrating relationship in addition to capturing short-run lead-lag relationship. The VECM model can be specified as below:

$$R_{f,t} = \alpha_{0f} + \sum_{i=1}^{p} \alpha_{if}(F_{t-i} - S_{t-i}) + \sum_{j=1}^{q} \beta_f R_{f,t-j} + \sum_{k=1}^{m} \beta_f R_{s,t-k} + \mu_{ft} \tag{6}$$

$$R_{s,t} = \alpha_{0s} + \sum_{i=1}^{p} \alpha_{is}(F_{t-i} - S_{t-i}) + \sum_{l=1}^{n} \beta_s R_{s,t-l} + \sum_{h=1}^{o} \beta_s R_{f,t-h} + \mu_{st} \tag{7}$$

The optimal hedge ratio using VECM can be estimated as ratio of covariance of ($\mu_{s,t}$) and variance of (μ_{ft}), as computed in case of VAR model above.

Model 7: Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

The estimation procedures discussed earlier (Equations (1) though (7)) assume that volatility of asset returns remain constant; however, literature[6] argues that covariance and variance of returns are timevarying. Therefore, in order to capture the time-varying volatility of stock returns, GARCH model, proposed by Bollerslev (1986), has been used to estimate optimal hedge ratio. GARCH models the time-varying volatility by using a variance equation (Equation (8)) along with the mean equation as given in Equation (2). The variance equation is as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \upsilon_t \tag{8}$$

In Equation (8), h_t is the conditional volatility, α_i is the coefficient of autoregressive term and β_j is the coefficient of GARCH term.

Model 8: Exponential GARCH (EGARCH)

Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model, proposed by Nelson (1991), captures such asymmetric relationship between conditional volatility and conditional mean. The specification of EGARCH model is as follows:

$$h_t = \gamma_1 + \gamma_2 \left|\frac{\mu^2_{t-1}}{h_{t-1}}\right| + \gamma_3 \frac{\mu^2_{t-1}}{h_{t-1}} + \gamma_4 h_{t-1} \tag{9}$$

Model 9: Threshold ARCH (TARCH)

Numerous studies (like, Karpoff (1987), Veronesi (1999), etc.) find 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. Therefore, in order to capture the asymmetric investor's reactions, TARCH model is used, whose variance equation is represented as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \alpha_k \varepsilon_{t-1}^2 \xi_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j} + \upsilon_t \tag{10}$$

In Equation (10), $\varepsilon_{t-1}^2 \xi_{t-i}$ represents the dummy variable having value one if the news is negative and zero for non-negative news.

Estimation of Hedging Effectiveness

The previous statistical procedure suggests the optimal hedge ratio(s); however, the effectiveness of these estimated optimal hedge ratio(s) shall have to be computed based upon two criteria: first, variance-reduction criterion suggested by Ederington (1979) and second, risk-return criterion suggested by Howard and D'Antonio (1984). The hedge ratio that gives the highest hedging effectiveness in each of the two methods would be proposed as efficient hedge ratio.

Framework 1: Variance-Reduction Framework

After estimating the optimal hedge ratio(s) using the given econometric procedures, their effectiveness has been tested by using a measure suggested by Ederington (1979). The method suggested by Ederington measures hedging effectiveness as 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. The Ederington's hedging effectiveness is based upon Sharpe's measure and is calculated as follows:

$$\text{Hedge effectiveness} = \frac{\text{Var(U)} - \text{Var(H)}}{\text{Var(U)}} \tag{11}$$

In Equation (11), variance of unhedged portfolio is the same as variance of cash returns, whereas the variance of hedged portfolio is measured as $\sigma_s^2 + h^{*2}\sigma_f^2 - 2h^*\sigma_{s,f.}$

Framework 2: Risk-Return Framework

As already mentioned in Section I, the variance reduction measure of hedging effectiveness gained huge popularity

[6] Engle(1982), Bollerslev (1986), Lypny and Powalla (1998) and Floros and Vougas (2004)

in the academic literature. However, this method does not take into account the return on hedged and unhedged portfolio(s). Therefore, Howard and D'Antonio (1984) suggested a measure of hedging effectiveness (λ) that incorporates the return component.Equation (12) specifies the estimation of hedging effectiveness which is measured as ratio of slope of risk-return relative from hedged portfolio and risk-return relative from unhedged portfolio.

$$HE = \theta \Big/ \frac{\bar{r}_s - i}{\sigma_s} \qquad (12)$$

Where, $\theta = \dfrac{\bar{R}_p - i}{\sigma_p}$

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

σ_p = standard deviation of returns from hedged portfolio

i = risk-free rate of return

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

σ_s = standard deviation of returns from unhedged portfolio

Results and Analysis

The descriptive statistics of cash and futures returns for all the indices under study is reported in Table 2. All the stocks show excess kurtosis and their coefficient of skewness is negative implying that the return series are leptokurtic in nature. These statistics indicate that the returns are not normal which is further supported by Jarque-Bera test that rejects the null hypothesis that cash and futures returns are normal.

Table 2: Descriptive Statistics of Returns

Contract	variables	Count	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
NIFTY50	Futures Return	4187	0.000425	0.015731	-0.493672	12.83305	16029.05(0.00)
	Cash Return	4187	0.000427	0.015061	-0.296783	11.83627	12872.65(0.00)
	Basis	4188	25.02533	43.84938	1.049673	3.455654	757.6089(0.00)
NIFTYIT	Futures Return	3381	-9.20E-05	0.045839	-43.78679	2257.988	6.65E+08(0.00)
	Cash Return	3381	-9.13E-05	0.045663	-43.98293	2271.964	6.73E+08(0.00)
	Basis	3382	8.270341	41.38112	-0.231291	59.98556	424078.3 (0.00)
BANKNIFTY	Futures Return	2927	0.000559	0.020685	0.038455	7.632446	2396.083(0.00)
	Cash Return	2927	0.000556	0.020167	0.075152	7.537706	2300.967(0.00)
	Basis	2728	17.07549	38.06139	0.636343	4.800262	542.7752(0.00)

Further, optimal hedge ratio(s) have been estimated using nine econometrical procedures: Naive, Ederington's Model, ARMA (p,q), Modified OLS, VAR, VECM, GARCH (p,q), EGARCH (p,q), and TARCH (p,q) and the results are reported in Table 3. Two important observations can be seen. Firstly, in case of all these indices, Ederington's OLS gives the lowest coefficient of hedge ratio. Secondly, coefficient of optimal hedge ratio(s) estimated through constant hedge ratio models is relatively smaller than the hedge ratio estimated through time varying models, i.e., GARCH, EGARCH, and TARCH. These findings imply that the constant hedge ratio models offer economical hedging as compared to time-varying models because lower coefficient of hedge ratio means lower investment in the futures contracts.[7] Furthermore, these results remain consistent during pre-crisis as well as post-crisis period (Table 4), which implies that the state of market does not affect the hedging model to be used to estimate hedging effectiveness. However, a slight increase in the coefficients of hedge ratio for NIFTY and BANKNIFTY during post-crisis period has been observed; whereas in case of NIFTYIT, coefficients of only time-varying hedge ratios have been increased.

[7] Lower hedge ratio implies lower investment in futures contracts.

Table 3: Estimation of Optimal Hedge Ratio

Contract	Naïve	OLS	ARMA OLS	Modified OLS	VAR	VECM	GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)
NIFTY50	1	0.936	0.953	0.941	0.939	0.940	0.955	0.967	0.962
NIFTYIT	1	0.993	0.998	0.996	0.996	0.996	0.998	0.997	1.002
BANKNIFTY	1	0.967	0.979	0.970	0.968	0.968	0.981	0.987	0.984

Furthermore, Table 5 reports the hedging effectiveness in the form of variance reduction, proposed by Ederington (1979), after taking hedging position with the estimated optimal hedge ratio(s). It is observed that constant hedging models (OLS, Modified OLS, VAR , and VECM) give highest hedging effectiveness[8]. On the other hand, traditional 1:1 naïve gives poorest hedging effectiveness. Moreover, there is very insignificant difference between the coefficients of hedging effectiveness estimated from different hedge ratio models understudy. These findings are consistent with the findings of Lien et al. (2002), Lien (2005) and Maharaj et al. (2008) who find no significant improvement in hedging effectiveness using sophisticated econometric methods. Moreover, the impact of financial crisis of 2008 on hedging effectiveness has been studied and results have been reported in Table 6 and it is interesting to note that OLS model dominates over other hedging models in obtaining highest hedging effectiveness, while remaining unaffected by the impact of financial crisis 2008. Another observable fact is that hedging effectiveness increases after the global financial crisis, for all indices understudy, except NIFTYIT.

[8] These findings are consistent with the findings of Lien et al (2002), Moosa (2003), Lien (2005), Maharaj et al. (2008), Bhargava and Malhotra (2008), Rao and Thakur (2008)).

Table 4: Optimal Hedge Ratio Over Pre- and Post-Crisis Period

Contract	*Period*	*Naïve*	*OLS*	*ARMA OLS*	*Modified OLS*	*VAR*	*VECM*	*GARCH (1,1)*	*EGARCH (1,1)*	*TARCH (1,1)*
NIFTY50	Pre-crisis	1	0.919	0.941	0.921	0.923	0.925	0.936	0.931	0.935
	Post-crisis	1	0.950	0.964	0.958	0.949	0.950	0.967	0.976	0.976
NIFTYIT	Pre-crisis	1	0.995	0.999	0.998	0.997	0.998	0.999	0.997	0.996
	Post-crisis	1	0.982	0.988	0.983	0.993	0.994	1.004	1.007	1.005
BANKNIFTY	Pre-crisis	1	0.953	0.976	0.959	0.957	0.962	0.982	0.985	0.982
	Post-crisis	1	0.970	0.979	0.969	0.971	0.971	0.982	0.988	0.984

Table 5: Hedging Effectiveness in Variance-Reduction Framework

Contract	*Naïve*	*OLS*	*ARMA OLS*	*Modified OLS*	*VAR*	*VECM*	*GARCH (1,1)*	*EGARCH (1,1)*	*TARCH (1,1)*
NIFTY50	96.083	96.539	96.507	96.536	96.538	96.537	96.490	96.431	96.458
NIFTYIT	99.359	99.365	99.362	99.364	99.364	99.364	99.362	99.361	99.357
BANKNIFTY	97.969	98.088	98.069	98.088	98.088	98.088	98.066	98.044	98.054

Table 6: Hedging Effectiveness in Variance-Reduction Framework Over Pre- and Post-Crisis Period

Contract	*Period*	*Naïve*	*OLS*	*ARMA OLS*	*Modified OLS*	*VAR*	*VECM*	*GARCH (1,1)*	*EGARCH (1,1)*	*TARCH (1,1)*
NIFTY50	Pre-crisis	93.805	94.547	94.489	94.547	94.545	94.543	94.512	94.531	94.519
	Post-crisis	97.894	98.168	98.147	98.160	98.168	98.168	98.136	98.091	98.091
NIFTYIT (previously CNXIT)	Pre-crisis	99.553	99.556	99.555	99.555	99.556	99.555	99.555	99.556	99.557
	Post-crisis	96.437	96.473	96.468	96.472	96.459	96.457	96.422	96.408	96.415
BANKNIFTY	Pre-crisis	95.930	96.182	96.115	96.179	96.178	96.171	96.084	96.064	96.085
	Post-crisis	98.418	98.512	98.502	98.512	98.512	98.512	98.498	98.479	98.492

Furthermore, Table 7 reports the hedging effectiveness estimated using risk-return criteria proposed by Howard and D'Antonio (1984) that incorporates both risk and return components on hedged portfolio. It is observed that naïve hedge ratio gives highest hedging effectiveness for NIFTY, NIFTYIT, and BANKNIFTY; whereas, Ederington's OLS hedge ratio gives lowest hedging effectiveness. Furthermore, the impact of financial crisis on hedging effectiveness has been examined and results have been reported in Table 8. It is observed that Naïve hedge ratio gives highest hedging effectiveness (except NIFTYIT post-crisis); whereas, Ederington's OLS gives lowest hedging effectiveness. Moreover, it is found that there has been an increase in hedging effectiveness during post crisis (except NIFTYIT post-crisis).

Table 7: Hedging Effectiveness in Risk-Return Framework

Contract	*Naïve*	*OLS*	*ARMA OLS*	*Modified OLS*	*VAR*	*VECM*	*GARCH (1,1)*	*EGARCH (1,1)*	*TARCH (1,1)*
NIFTY50	1.2452	1.2374	1.2395	1.2379	1.2377	1.2379	1.2399	1.2412	1.2407
NIFTYIT	1.3245	1.3234	1.3241	1.3238	1.3239	1.3238	1.3242	1.3239	1.3247
BANKNIFTY	1.16203	1.1594	1.1604	1.1594	1.1594	1.1595	1.1605	1.1609	1.1608

Table 8: Hedging Effectiveness in Risk-Return Framework over Pre- and Post-Crisis Period

Contract	*Period*	*Naïve*	*OLS*	*ARMA OLS*	*Modified OLS*	*VAR*	*VECM*	*GARCH (1,1)*	*EGARCH (1,1)*	*TARCH (1,1)*
NIFTY50	Pre-crisis	1.1053	1.1013	1.1024	1.1014	1.1015	1.1016	1.1022	1.1019	1.1021
	Post-crisis	1.2810	1.2741	1.2760	1.2753	1.2740	1.2742	1.2765	1.2778	1.2778
NIFTYIT	Pre-crisis	1.2899	1.2891	1.2897	1.2896	1.2894	1.2896	1.2897	1.2894	1.2893
	Post-crisis	1.3857	1.3822	1.3834	1.3825	1.3843	1.3845	1.3864	1.3869	1.3867
,BANKNIFTY	Pre-crisis	1.0570	1.0557	1.0563	1.0559	1.0558	1.0559	1.0565	1.0566	1.0565
	Post-crisis	1.1983	1.1954	1.1963	1.1953	1.1954	1.1955	1.1965	1.1971	1.1967

Further, it is observed that NIFTYIT has been an exception to the previous findings related to optimal hedge ratio and hedging effectiveness. Such exception may be due to severe impact of global financial crisis on Indian IT industry and investor sentiment. This is quite evident from the correlation between spot and futures prices as well as trading of IT stocks, both of which declined after the global financial crisis (see Tables 9 and 10).

Table 9: Descriptive Statistics of Volume of Futures Contract

Symbol	*Period*	*Count*	*Mean*	*Minimum*	*Maximum*	*Std. Dev.*
NIFTY50	Pre	1898	135556.2	19	1338598	183077.1
	Post	2290	415608.1	14371	1343511	207469.5
NIFTYIT	Pre	1092	471.1612	0	3683	480.5841
	Post	2290	315.1019	1	3395	289.932
BANKNIFTY	Pre	638	2011.188	27	10453	1.409485
	Post	2290	73973.49	557	343417	46689.565

Table 10: Correlation Coefficient between Cash and Futures Returns

Symbol	*Period*	*Count*	*Correlation Coefficient*
NIFTY50	Pre-Crisis	1897	0.973
	Post-Crisis	2290	0.991
NIFTYIT	Pre-Crisis	1091	0.999
	Post-Crisis	2290	0.983
BANKNIFTY	Pre-Crisis	637	0.982
	Post-Crisis	2290	0.994

Conclusion

Indian equity futures market has recorded voluminous growth since its inception in year 2000 and to the best of our knowledge, there have been only a few attempts to study it (see, Bhaduri and Durai, 2007; Gupta and Singh, 2009; Haq and Rao, 2013; Malhotra, 2015; Pradhan, 2011; Rao and Thakur, 2008) all of which have restricted their scope to examine the hedging effectiveness in a traditional risk minimization framework that ignores the changes in return on hedged portfolio. Therefore, present study is an attempt to examine hedging effectiveness by two methods: variance reduction criteria proposed by Ederington (1979) and risk-return criteria proposed by Howard and D' Antonio (1984) by using three benchmark indices of NSE (NIFTY, NIFTYIT, and BANKNIFTY) from their respective date of inception till March 31, 2016. Also, an attempt has been made to study the impact of financial crisis of 2008 by segregating the return series into pre-crisis period (inception date–December 31, 2007) and post-crisis period (January 1, 2008–March 16, 2016).

In the present study, optimal hedge ratio has been estimated using constant hedging models (Ederington's OLS model, Modified OLS, VAR, VECM, and ARMA (p,q))and time-varying hedging models (GARCH, EGARCH, and TARCH). It is observed that coefficient of optimal hedge ratio estimated through constant hedging models is comparatively smaller than the hedge ratios estimated through time-varying models. Secondly, after segregating the data series into pre- and post-crisis period, it is observed that hedge ratios during the post-crisis period are relatively higher than pre-crisis period, which implies that the cost of hedging has been increased after the financial crisis.

Furthermore, it is found that in a variance-reduction framework, Ederington's OLS hedge ratio gives highest hedging effectiveness (except for NIFTYIT where VECM gives highest hedging effectiveness); whereas, Naïve hedge ratio gives the lowest hedging effectiveness. These findings are consistent with the findings of Collins (2000), Lien et al. (2002), Moosa (2003), Lien (2005), Bhargava and Malhotra (2007), Rao and Thakur (2008) and remain consistent when the data series is segregated into pre- and post-crisis period. However, when hedging effectiveness is computed in a risk-return framework, Naïve hedge ratio gives highest hedging effectiveness (except for CNXIT post-crisis), whereas OLS gives lowest hedging effectiveness. Once again, the results obtained remains consistent when series is segregated into pre and post crisis period.

From the given findings few important implications can be drawn. Firstly, constant hedging models give highest hedging effectiveness whether estimated based on variance-reduction criteria or risk-return criteria proposed by Howard and D'Antonio (1984). These findings are consistent with the findings of Maharaj et al. (2008) and Wang et al. (2015) who question if sophisticated econometrical procedures can really help in achieving highest hedging effectiveness. However, on the contrary, these findings are inconsistent with numerous studies[9], which suggest that time-varying hedging models dominate constant hedging models. The reason for such anomaly may be attributed to the fact that hedging model to be used may be country specific (Hou and Li, 2013). Secondly, since both the measures of hedging effectiveness suggest different optimal hedging models, selection of right hedging model becomes vital for investor, which depends upon his objective to hedge. Thirdly, there has been increase in estimates of both optimal hedge ratio and hedging effectiveness (except CNXIT) during post-crisis period, which implies an increase in the cost of hedging. The reason for increase in both these estimates can be due to increase in correlation coefficient computed over the post-crisis period.

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