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Estimating hedging effectiveness using variance reduction and risk-return approaches: evidence from National Stock Exchange of India

Keywords: optimal hedge ratio, hedging effectiveness, GARCH, OLS, equity futures market.

J E L Classification: C1, C5, G11, G17.

Abstract: The present study examines hedging effectiveness of futures contracts in India by using variance reduction approach and risk-return approach by applying eight econometric models. It is observed that OLS hedge ratio generates highest hedging effectiveness using variance reduction approach, whereas Naïve hedge ratio generates highest hedging effectiveness using risk-return approach. Overall, it is observed that time-invariant hedging model generates superior hedging effectiveness as compared to time-variant hedging model.

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Introduction

Futures contracts have been widely used by investors for managing the price risk involved in underlying assets, commonly known as hedging. As the spot and futures market observes co-movement and long term equilibrium relationship (Tse & Chan 2010), this allows the hedger to offset price fluctuations by taking opposite position in both the spot and futures market. However, in reality, the presence of lead-lag relationship during short-run gives rise to basis risk (Floros & Vougas 2006). Due to basis risk, the number of futures contracts required to hedge a given spot position departs from unity and therefore requires an optimal hedge ratio to be estimated in order to achieve superior hedging effectiveness.

An analysis of hedging literature suggests three different hedging theories i.e. conventional hedging theory, working's hedging theory (Woking, 1953) and portfolio hedging theory. Portfolio Theory Approach, proposed by Johnson (1960) and Stein (1961), extended and quantified by Ederington (1979) is by far the most widely used approach. An important contribution of the portfolio approach is the concept of the Minimum-Variance Hedge Ratio (MVHR), i.e., the hedge ratio that minimizes the risk of the hedged position.

The minimum-variance hedge ratio / OLS hedge ratio has been popularly used due to its simplicity to compute and understand. However, it suffers from two limitations. Firstly, it ignores the time-varying nature of financial time series and secondly, it computes constant hedge ratio. Therefore, in order to address this issue, various econometric models like GARCH, EGARCH, BGARCH, etc, have been proposed in literature which helps in estimating time-varying hedge ratios. Henceforth, voluminous literature (Park & Switzer, 1995; Lypny & Powalla, 1998; Yang & Allen, 2004; Floros & Vougas, 2006; Bhaduri & Durai, 2008; Lee & Yoder, 2007; Yang & Lai, 2009 and Hou & Li, 2013) has appreciated time-varying hedge ratios over constant hedge ratios.

Numerous studies claim superior performance of time-varying hedge ratios over constant hedge ratios. However, despite a significant advancement in econometrics, a strand of literature observes that constant hedge ratios still dominate time-varying hedge ratios and therefore, argues that econometric sophistication does not help to improve hedging effectiveness (Maharaj, Moosa, Dark & Silvapulle, 2008; Gupta & Singh, 2009; Wang et al., 2015). Especially, the superiority of Ederington's OLS hedge ratio over time-varying hedge ratio is prominent in the literature (Lien, Tse & Tsui, 2002; Lien, 2005; Maharaj et al., 2008; Awang, Azizan, Ibrahim & Said, 2014).

Furthermore, Ederington (1979) suggests a measure of hedging effectiveness, based upon portfolio theory approach to hedging proposed by Johnson (1960) and Stein (1961). According to this approach, hedging effectiveness is measured as proportionate reduction in standard deviation of returns from hedged portfolio. Ederington's measure of hedging effectiveness has been widely appreciated in the literature (see Park & Switzer, 1995; Holmes, 1995; Floros & Vougas, 2006; Bhargava & Malhotra, 2007; Pradhan, 2011; Hou & Li, 2013) 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, Corrigan and Heaney (2001) suggests 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, Howard & D'Antonio, 1984; Lindahl, 1991, etc.). These models take into consideration changes in expected return on hedged portfolio in addition to risk minimization. For, instance, Howard and D'Antonio (1984) suggested a risk-return measure of hedging effectiveness which is further elaborated.

Apart from the above 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 equally popular in emerging markets like India. It is quite evident from the fact that Indian equity futures market consistently ranks amongst the top five markets of the world for the last decade. However, to the best of our knowledge, in Indian context only few attempts have been made to examine hedging effectiveness (Bhaduri & Durai, 2008; Gupta & Singh, 2009; Pradhan, 2011; Haq & Rao, 2013; Ghosh, Dey, Moulvi, Jain, Sinha & Rachuri, 2013; Malhotra, 2015; Kaur & Gupta, 2018 and Kumar & Bose, 2019). These studies have primarily focused on examining a superior methodology for determining optimal hedge ratio, using variance reduction framework as a measure for examining hedging effectiveness. To the best of researcher's knowledge, only Ghosh et al. (2013) attempted to examine hedging effectiveness in a risk-return framework in commodity futures market. Therefore, in order to plug the literature gap, present study is an attempt to examine the hedging effectiveness in a risk-return framework, in addition to estimating optimal hedge ratios and hedging effectiveness based upon measure proposed by Ederington (1979). Also, an attempt has been made to study the impact of financial crisis on optimal hedge ratio and hedging effectiveness.

The research methodology and the course of the research process

As far as present study is concerned, the sample size of the study comprises of three benchmark indices of NSE i.e. NIFTY, NIFTYIT and BANKNIFTY which has been selected on the basis of their consistent trading history and high liquidity. The data has been collected for near month for all three indices comprising sample size of study 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 till March 31, 2016 as presented below:

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, 2016	1898	2042	3940
NIFTYIT	August 29, 2003 – March 31, 2016	1092	2042	3134
BANKNIFTY	June 13, 2005 – March 31, 2016	638	2042	2680

Source: compiled by author on the basis of data downloaded from official website of NSE.

Unit-root Test

The estimation of hedge ratio is a statistical process, therefore, the very first step in any econometric investigation of a time series is to examine whether the time series under examination contains unit roots. Hence, stationarity of three indices understudy has been tested by using the Augmented Dickey Fuller (ADF) test and it is observed that the prices (both futures prices and cash prices) are non-stationery, whereas, natural log of first difference of prices (i.e. $\ln(p_t / p_{t-1})$) is stationery[1]. Thus, returns of futures contracts and cash market are considered for estimating hedge ratio.

Estimation of Optimal Hedge Ratio

As both cash and futures markets are linked through arbitrage process (Stoll & Whaley, 1987). Therefore, appreciating the stationary and stable long-run relationship between two markets, eight econometrical procedures have been undertaken. These procedures address various economic as well as statistical issues involved in estimating an optimal hedge ratio. The hedge ratio which reduces the portfolio variance to minimum level would be considered as an efficient hedge ratio.

Naïve Hedge Ratio

Traditionally, cash and futures market was presumed to be perfectly correlated and therefore, equal number of futures contracts was required to obtain a perfect hedge. Hence, it suggests an optimal hedge ratio of one. Since, this methodology ignored basis risk, which is considered vital to the estimation of optimal hedge ratio, therefore, this theory failed to mark its presence in the literature.

Ederington's OLS Hedge Ratio

Ederington (1979) suggested minimum variance hedge ratio, which presumes strong and stable long run relationship between two markets. Equation (1) explains the procedure suggested by Ederington (1979), which works efficiently when futures market returns are unbiased predictor of cash market returns. In equation (1), $R_{s,t}$ is cash market returns, $R_{f,t}$ is futures market returns, α_o is intercept term and ε_t is error term as detailed below:

$$R_{s,t} = \alpha_0 + \beta_1 R_{f,t} + \varepsilon_{t.} \tag{1}$$

[1] The estimated results are not reported in the paper, but, can be provided on demand.

ARMA-OLS Hedge Ratio

Equation (1) though may be economically justifiable but the estimated value of β_1 won't be reliable, if series under investigation are autocorrelated. Hence, equation (1) has been modified to equation (2) (to include autoregressive terms of cash market returns), In equation (2), $R_{s,t}$ is cash market returns, $R_{f,t}$ is(are) futures market returns, $R_{s,t-i}$ is autoregressive term(s) whose order varies between i to p determined as per Schwartz Information Criteria (SIC), α_o is intercept term and ε_t is error term.

$$R_{s,t} = \alpha_0 + \sum_{i=1}^{p} \alpha_i R_{s,t-i} + \beta_1 R_{f,t} + \varepsilon_t \tag{2}$$

GARCH Hedge Ratio

In equation (1 and 2), if the variance of error term is constant, the hedge ratio estimated through Ordinary Least Square (OLS) method will be valid, however, vast amount of academic literature[2] has evidenced that stock returns are heteroscedastic in nature. Therefore, Autoregressive Conditional Heteroscedasticity model (ARCH) ((Engle (1982)) generalized by Bollerslev (1986) called GARCH (p,q) in which conditional variance depends not only upon the squared residuals of the mean equation but also on its own past values. The GARCH (p, q) model is given by equation (3)

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \upsilon_t \tag{3}$$

Where, h_t is the conditional volatility, α_i is the coefficient of ARCH term with order i to p and βj is the coefficient of GARCH term with order j to q. The conditional volatility as defined in equation (3) is determined by three effects namely the intercept term (ω), the ARCH term ($\alpha_i \varepsilon^2_{t-i}$) and the forecasted volatility from the previous period called GARCH component ($\beta_j h_{t-j}$).

[2] Engle (1982), Bollerslev (1986), Park and Switzer (1995), Floros and Vougas (2004).

EGARCH Hedge Ratio

Exponential GARCH (EGARCH) model (Nelson (1991)) is based upon the logarithmic expression of conditional volatility in cash and futures market returns. Therefore, if the stock returns are asymmetric and the interaction between old and new information observes leverage effect, EGARCH model (i.e. equation (4)) may help to estimate an improved hedge ratio as compared to that estimated through GARCH process in equation (3)

$$h_t = \gamma_1 + \gamma_2 \left| \frac{\varepsilon^2_{t-1}}{h_{t-1}} \right| + \gamma_3 \frac{\varepsilon^2_{t-1}}{h_{t-1}} + \gamma_4 h_{t-1} \tag{4}$$

TARCH Hedge Ratio

Equation (4) reports the leverage relationship between old and new information. But in the speculative markets, besides the leverage effect, it has been observed that traders react heterogeneously to positive and negative news. Therefore, it would be more appropriate to segregate the impact of both positive and negative news. This can be done by specifying the variance equation in TARCH (Threshold Autoregressive Conditional Heteroscedasticity) framework (equation (5), where, equation (4) is modified to include $\varepsilon^2_{t-i}\xi_{t-i}$, which is a dummy for negative news having value 1 if there is negative news and 0 otherwise.

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{p} \alpha_k \varepsilon^2_{t-1} \xi_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j} + \upsilon_t \tag{5}$$

where,

(a) $\xi_{t-i} = 1$, if $\varepsilon_{t-i} < 0$

(b) $\xi_{t-i} = 0$, if $\varepsilon_{t-i} > 0$

VAR and VECM Hedge Ratio

As volatility spillover is bidirectional and continuous in both the markets, therefore, regressing only the cash market returns on lagged returns of both futures and cash market, may be biased. Therefore, either Vector Autoregression Model (VAR) (when both markets observe causal relationship) or Vector Error Correction Methodology (VECM) (when both markets are cointegrated) may estimate robust hedge ratio. VAR model simultaneously regress the lagged returns of both variables, whereas, VECM in addition to lagged returns also considers the error correction term (if both series are cointegrated). Hence both methodologies estimate the optimal hedge ratio by considering theoretical relationship between two markets (i.e. lead-lag in short-run and cointegration in long-run), which confirms the volatility spillover between two markets through arbitrage process. Equations (6) and (7) specify the estimation process of VAR methodology and equations (8) and (9) stimulate the estimation procedure of VECM. The hedge ratio on the basis of VAR and VECM will be computed as $\sigma_{s,f} / \sigma^2 f$ where $\sigma_{s,f} = \mathrm{cov}(\varepsilon_{ft}, \varepsilon_{st})$ and $\sigma^2 f = \mathrm{var}(\varepsilon_{ft})$.

$$R_{s,t} = \sum_{i=1}^{M} \alpha_i R_{s,t-i} + \sum_{j=1}^{N} \beta_j R_{f,t-j} + \varepsilon_{st} \tag{6}$$

$$R_{f,t} = \sum_{k=1}^{O} \alpha_k R_{s,t-k} + \sum_{l=1}^{P} \beta_1 R_{s,t-1} + \varepsilon_{ft} \tag{7}$$

$$R_{f,t} = \alpha_{0f} + \sum_{i=1}^{p} \alpha_{if} (F_{t-i} - S_{t-i}) + \sum_{j=1}^{q} \beta_f R_{f,t-j} + \sum_{k=1}^{m} \beta_f R_{s,t-k} + \varepsilon_{ft} \tag{8}$$

$$R_{s,t} = \alpha_{0s} + \sum_{i=1}^{p} \alpha_{is} (F_{t-i} - S_{t-i}) + \sum_{l=1}^{n} \beta_s R_{s,t-l} + \sum_{h=1}^{o} \beta_s R_{f,t-h} + \varepsilon_{st} \tag{9}$$

Therefore, in the present study, optimal hedge ratio is estimated through Naïve, OLS, ARMA-OLS, GARCH, EGARCH, TARCH, VAR and VECM procedures, which may be constant or time-varying, depending upon the property of the series understudy.

ESTIMATION OF HEDGING EFFECTIVENESS

After estimating the optimal hedge ratio through above mentioned statistical procedures, the hedging effectiveness of all hedge ratios shall be computed on the basis of two approaches i.e variance reduction approach (Ederington, 1979) and risk-return approach (Howard & 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.

VARIANCE-REDUCTION FRAMEWORK

As proposed by Ederington (1979), hedging effectiveness will be measured as percentage decline in portfolio variance as shown in equation (10), where Var (U) and Var (H) represents variance of un-hedged and hedged portfolios respectively. σ_s and σ_f are standard deviation of the cash and futures returns respectively, $\sigma_{s,f}$ represents the covariability of the cash and futures returns and h* is the optimal hedge ratio.

$$\text{Hedge effectiveness} = \frac{\text{Var (U) - Var (H)}}{\text{Var (U)}} \tag{10}$$

$$\text{Var (U)} = \sigma_s^{\,2} \tag{11}$$

$$\text{Var (H)} = \sigma_s^{\,2} + h^{*2}\sigma_f^{\,2} - 2h^{*}\sigma_{s,f} \tag{12}$$

RISK-RETURN FRAMEWORK

The variance reduction approach suffers from a limitation that it ignores the return component on hedged portfolio. Therefore, in order to address this issue, Howard and D'Antonio (1984), suggested a measure of hedging effectiveness (λ) incorporating the return component, which is measured as ratio of slope of risk-return relative from hedged portfolio and risk-return relative from unhedged portfolio.

$$\text{HE} = \theta \Big/ \frac{\overline{r_s} - i}{\sigma_s} \tag{13}$$

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

Where,
$\overline{R}_p$ = 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 Analysis

Table 2 discusses the time-series properties of the series understudy and provides that returns of both futures and cash markets are significantly negatively skewed and their coefficient of kurtosis is significantly different from three which implies that futures and cash market returns do not conform to normal distribution. The null hypothesis that futures and cash market returns follow normal distribution is further tested through Jarque-Bera test which is statistically significant, and rejects the null hypothesis for all index futures and cash market returns.

Table 2. Descriptive Statistics for NIFTY, NIFTYIT and BANKNIFTY

Contract	Variable	Period	Count	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
NIFTY50	Futures Return	Pre	1897	0.000762	0.015545	-1.005812	12.427	7344.651
		Post	2041	0.000114	0.015902	-0.047154	13.246	10751.74
		Total	3939	0.000425	0.015731	-0.493672	12.833	16029.05
	Cash Return	Pre	1897	0.000764	0.014686	-0.779820	8.7388	2795.453
		Post	2041	0.000113	0.015401	0.098257	14.242	8928.543
		Total	3939	0.000427	0.015061	-0.296783	11.836	12872.65
	Basis	Pre	1898	-3.021286	10.72971	-1.162111	7.1572	1793.986
		Post	2042	51.09412	46.82309	0.121282	2.6293	16.6923
		Total	3940	25.02533	43.84938	1.049673	3.4556	757.6089
NIFTYIT	Futures Return	Pre	1091	-0.001046	0.073914	-29.97677	958.69	41683009
		Post	2041	0.000424	0.017493	-0.207287	7.9567	2104.046
		Total	3133	-9.20E-05	0.045839	-43.78679	2257.9	6.65E+08
	Cash Return	Pre	1091	-0.001045	0.073612	-30.13482	965.58	42285710
		Post	2041	0.000425	0.017467	-0.161584	8.5813	2658.066
		Total	3133	-9.13E-05	0.045663	-43.98293	2271.9	6.73E+08
	Basis	Pre	1092	6.301374	62.32855	-0.114054	33.204	41513.72
		Post	2042	9.323286	23.42619	0.010648	7.0464	1393.181
		Total	3134	8.270341	41.38112	-0.231291	59.985	424078.3
BANKNI-FTY	Futures Return	Pre	637	0.001590	0.019675	-0.338606	4.5637	77.07465
		Post	2041	0.000234	0.020989	0.141173	8.3753	2464.022
		Total	2679	0.000559	0.020685	0.038455	7.6324	2396.083
	Cash Return	Pre	637	0.001564	0.019084	-0.254725	4.4809	65.10121
		Post	2041	0.000239	0.020492	0.164530	8.2504	2353.569
		Total	2679	0.000556	0.020167	0.075152	7.5377	2300.967
	Basis	Pre	638	6.641144	23.44068	0.155635	6.0061	242.8022
		Post	2042	20.33558	41.05308	0.500584	4.2283	213.6537
		Total	2680	17.07549	38.06139	0.636343	4.8002	542.7752

S o u r c e : calculated by author using secondary data downloaded from official website of NSE.

Furthermore, table 3 reports the optimal hedge ratio(s) estimated through Naive, OLS, ARMA OLS (p,q), VAR, VECM, GARCH (p,q), EGARCH (p,q) and TARCH (p,q) for near month contracts of all the three indices understudy. It is observed that in all these indices OLS model gives lowest coefficient of hedge ratio. Secondly, hedge ratio estimated through OLS, ARMA, VAR and VECM are constant hedge ratios and their hedging coefficients are relatively smaller than the hedge ratios estimated through time varying models i.e. GARCH, EGARCH and TARCH. From the above observation, one conclusion can be drawn that the cost of hedging through constant hedge ratio are lower than time varying hedge ratios. Furthermore, the coefficients of hedge ratio estimated through VAR and VECM are very close to hedge ratios estimated through Ederington's OLS model which implies that it incorporates the property of cost of carry model.

Table 3. Estimation of Optimal Hedge Ratio

Contract	Naïve	OLS	ARMA OLS	VAR	VECM*	GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)
NIFTY50	1	0.940	0.956	0.943	0.944	0.962	0.964	0.962
NIFTYIT	1	0.993	0.998	0.996	0.996	1.00152	1.00157	1.00156
BANKNIFTY	1	0.966	0.979	0.967	0.968	0.982	0.986	0.984

* VECM estimation results available on demand.

Source: calculated by author using secondary data downloaded from official website of NSE.

Furthermore, table 4 reports the optimal hedge ratio(s) estimated through all eight models over pre and post financial crisis period. It is observed there has been a slight increase in the coefficient of hedge ratios for NIFTY50 and BANKNIFTY during post crisis period, irrespective of model used for estimating optimal hedge ratio. However, the results are different for NIFTYIT, where coefficient of hedge ratio(s) increased only for time-varying hedging models (i.e. GARCH, EGARCH and TARCH). It implies that the cost of hedging using NIFTYIT is increased during post crisis period, if time-varying models are used for estimating optimal hedge ratio.

Table 4. Estimation of Correlation Coefficient and Optimal Hedge Ratio over Pre and Post Crisis Period

Contract	Period	Correlation Coefficient	Naïve	OLS	ARMA OLS	VAR	VECM	GARCH	EGARCH	TARCH
NIFTY50	Pre-crisis	0.9728	1	0.919	0.941	0.923	0.925	0.936	0.931	0.935
	Post-crisis	0.9906	1	0.959	0.966	0.959	0.960	0.977	0.978	0.981
NIFTYIT	Pre-crisis	0.9986	1	0.995	0.999	0.997	0.998	0.999	0.997	0.996
	Post-crisis	0.9827	1	0.981	0.988	0.992	0.993	1.006	1.007	1.005
BANKNIFTY	Pre-crisis	0.9822	1	0.953	0.976	0.957	0.962	0.982	0.985	0.982
	Post-crisis	0.9934	1	0.970	0.980	0.970	0.970	0.982	0.986	0.985

Source: calculated by author using secondary data downloaded from official website of NSE.

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 ratios. An important observation is that Ederington's OLS model gives highest hedging effectiveness, whereas, naive hedging model gives lowest hedging effectiveness among all the models. Moreover, there is no significant difference between the hedge effectiveness estimated through all models understudy (except Naïve). These findings are consistent with the findings of Lien (2005) and Wang (2015) which suggest that knowledge of sophisticated econometric procedures does not help to construct a better portfolio and improve hedging effectiveness.

Table 5. Hedging Effectiveness (Ederington, 1979) [In percent]

Contract	Naïve	OLS	ARMA OLS	VAR	VECM	GARCH	EGARCH	TARCH
NIFTY50	96.06	96.45	96.42	96.45	96.45	96.40	96.39	96.40
NIFTYIT	99.37	99.37	99.37	99.37	99.37	99.365	99.366	99.366
BANKNIFTY	98.03	98.15	98.13	98.15	98.15	98.13	98.11	98.12

Source: calculated by author using secondary data downloaded from official website of NSE.

Moreover, the impact of financial crisis of 2008 on hedging effectiveness has been studied (table 6). It is interesting to note that OLS model still dominates over other hedging models in obtaining highest hedging effectiveness, while remaining unaffected by the impact of financial crisis 2008. Another important observation is that there has been an increase in hedging effectiveness after the crisis of 2008, for all indices understudy (except NIFTYIT post-crisis). Overall an interesting observation from the above findings is that it suggests the use of traditional OLS model, proposed by Ederington, 1979, for estimating optimal hedge ratio which is much simple to compute and understand rather than using complicated econometric models which are considered to be an improvement over the OLS model.

Table 6. Hedging Effectiveness over Pre and Post Crisis Period (Ederington, 1979) [In percent]

Contract	Period	Naïve	OLS	ARMA OLS	VAR	VECM	GARCH	EGARCH	TARCH
NIFTY50	Pre-crisis	93.805	94.547	94.489	94.545	94.543	94.512	94.531	94.519
	Post-crisis	97.873	98.052	98.047	98.052	98.052	98.016	98.016	98.001
NIFTYIT	Pre-crisis	99.553	99.556	99.555	99.556	99.555	99.555	99.556	99.557
	Post-crisis	96.439	96.476	96.471	96.462	96.460	96.414	96.406	96.417
BANKNIFTY	Pre-crisis	95.930	96.182	96.115	96.178	96.171	96.084	96.064	96.085
	Post-crisis	98.508	98.606	98.595	98.606	98.606	98.588	98.576	98.582

Source: calculated by author using secondary data downloaded from official website of NSE.

Furthermore, table 7 reports the hedging effectiveness estimated using risk-return criteria that incorporate both risk and return components on hedged portfolio. It is observed that Naïve hedge ratio gives highest hedging effectiveness for all three indices, whereas, OLS hedge ratio gives lowest hedging effectiveness. Furthermore, the impact of financial crisis on hedging effectiveness has been examined (table 8) and it is observed that Naïve hedge ratio gives highest hedging effectiveness (except NIFTYIT post-crisis), whereas 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).

Further, this paper uses two different approaches for estimating hedging effectiveness i.e. variance reduction approach and risk-return approach, both of which are based upon different objective functions of the investor. The variance reduction approach assumes that main objective of investor is risk aversion whereas, risk-return approach assumes that main objective of investor is to maximize return per unit of risk. An interesting observation from the results of hedging effectiveness using the two different approaches is that variance reduction approach favours OLS hedge ratio, whereas risk-return approach favours Naïve hedge ratio, both of which are constant hedge ratios. Therefore, on the whole, these findings suggest superiority of constant hedge ratios over dynamic hedge ratios. Moreover, investors with different objective functions need to use different hedge ratio models in order to maximize their respective objective function.

Table 7. Hedging Effectiveness (Howard & D'Antonio, 1984) [In percent]

Contract	Naïve	OLS	ARMA OLS	VAR	VECM	GARCH	EGARCH	TARCH
NIFTY50	1.2538	1.2462	1.2483	1.2470	1.2467	1.2490	1.2493	1. 2490
NIFTYIT	1.2780	1.2771	1.2778	1.2775	1.2775	1.2782	1.2782	1.2782
BANKNIFTY	1.1763	1.1733	1.1744	1.1734	1.1734	1.1735	1.1747	1.1751

Source: calculated by author using secondary data downloaded from official website of NSE.

Table 8. Hedging Effectiveness over Pre and Post Crisis Period (Howard and D'Antonio, 1984) [In percent]

Contract	Period	Naïve	OLS	ARMA OLS	VAR	VECM	GARCH	EGARCH	TARCH
NIFTY50	Pre-crisis	1.1053	1.1013	1.1024	1.1014	1.1015	1.1016	1.1022	1.1019
	Post-crisis	5.3292	5.2412	5.2552	5.2393	5.2421	5.2802	5.2807	5.2881
NIFTYIT	Pre-crisis	1.2899	1.2891	1.2897	1.2894	1.2896	1.2897	1.2894	1.2893
	Post-crisis	1.2833	1.2807	1.2816	1.2823	1.2824	1.2841	1.2843	1.2840
BANKNIFTY	Pre-crisis	1.0570	1.0557	1.0563	1.0558	1.0559	1.0565	1.0566	1.0565
	Post-crisis	1.4237	1.4173	1.4194	1.4172	1.4174	1.4199	1.4208	1.4204

Source: calculated by author using secondary data downloaded from official website of NSE.

From these results, an important finding is that the result of optimal hedge ratio and hedging effectiveness for NIFTYIT has been consistently an exception to the results of other two indices. The reason for such an exception might be due to the fact that global financial crisis of 2008 adversely affected the business of Indian IT industry and sentiments of investors which is evident from two facts. First, the correlation coefficient of spot and futures price series for NIFTYIT declined during post-crisis period (see table 4). Second, the average traded volume for NIFTYIT contracts show a declining trend after 2007 (see table 9) which might be due to negative sentiment among investors towards IT stocks. The negative sentiment of the investors and thus, lower trading volume of IT stocks is justified as there has been substantial decline in the annual growth rates of the Indian IT sector since year 2007-08 (See appendix A).

Table 9. Descriptive Statistics of Futures Contracts Volume

Symbol	Period	Count	Mean	Minimum	Maximum	Std. Dev.
NIFTY50	Pre-Crisis	1898	135556.2	19	1338598	183077.1
	Post-Crisis	2042	415608.1	14371	1343511	207469.5
NIFTYIT	Pre-Crisis	1092	471.1612	0	3683	480.5841
	Post-Crisis	2042	315.1019	1	3395	289.932
BANKNIFTY	Pre-Crisis	638	2011.188	27	10453	1.409485
	Post-Crisis	2042	73973.49	557	343417	46689.565

Source: calculated by author using secondary data downloaded from official website of NSE.

Conclusion

Present study is an attempt to examine hedging effectiveness of three benchmark indices of NSE (NIFTY, NIFTYIT and BANKNIFTY) from their respective date of inception till March 31, 2016 by two methods: variance reduction approach (Ederington, 1979) and risk-return approach (Howard & D' Antonio, 1984). Additionally, 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).

Optimal hedge ratios have been estimated by employing eight different methodologies: Naïve, Ederington's Model, VAR, VECM, ARMA (p,q), GARCH(p,q), EGARCH(p,q) and TGARCH(p,q) for aggregate as well as for pre and post crisis period. The present study finds that hedge ratios estimated through constant hedging models [OLS, VAR, VECM and ARMA (p,q)] are relatively smaller than the hedge ratios estimated through time varying models (GARCH, EGARCH and TGARCH). These results imply that cost of hedging through constant hedge ratio models is relatively lower than time-varying hedge ratio 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 for all optimal hedge ratio models, which implies that the cost of hedging has been increased after the financial crisis.

Furthermore, hedging effectiveness has been estimated using two approaches i.e. variance-reduction framework and risk-return framework (table 5 and 7 respectively). It is found that 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 Moosa (2003), Lien (2005) and Kaur and Gupta (2018). These findings remain consistent even after the data series is segregated into pre and post-crisis period. However, on the contrary, Naïve hedge ratio gives highest hedging effectiveness using risk-return approach (except for NIFTYIT post crisis), whereas OLS gives lowest hedging effectiveness. Once again, the results obtained do not change when series is segregated into pre and post crisis period.

From the above findings few important implications can be drawn. Firstly, constant hedging models give highest hedging effectiveness whether examined on the basis variance-reduction approach or risk-return approach. These findings are consistent with the findings of Wang, Chongfeng and Li (2015) and Kaur and Gupta (2018) who argue whether econometric sophistication really helps to improve hedging effectiveness. However, on the contrary, these findings are inconsistent with numerous studies (Park & Switzer, 1995; Lypny & Powalla, 1998; Floros & Vougas, 2004; Floros & Vougas, 2006; Lee & Yoder, 2007; Bhaduri & Durai, 2008; Hou & Li, 2013 and Kumar & Bose, 2019) 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 & Li, 2013). Secondly, since both the measures of hedging effectiveness suggest different optimal hedging models, therefore, 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 NIFTYIT) 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 between spot and futures returns over post-crisis period as observed by Majid and Kassim (2009) and Joshi (2012) that post financial crisis, market integration improved.

This paper has few implications for investors. Firstly, it suggests that in order to hedge, investors can simply choose the optimal hedge ratio suggested by constant hedging models (especially OLS) instead of time-varying hedging models which are more time-consuming and of complex nature. It is because OLS gives the highest hedging effectiveness while giving lowest optimal hedge ratio which implies lower investment in futures contracts. On the contrary, other models suggest comparatively higher optimal hedge ratio and a lower hedging effectiveness. Secondly, this study suggests hedge ratio suggested by OLS for pure hedgers who are mainly concerned with minimization of variance, while the investors whose are also concerned with enhancing their return by hedging might choose Naive hedge ratio. Overall, the study favours constant hedging models instead of time-varying hedging models which is in line with the findings of Lien, Tse and Tsui (2002), Lien (2005), Bhargava and Malhotra (2007), Maharaj et al. (2008), Awang et al. (2014), Wang, Chongfeng and Li (2015) and Kaur and Gupta (2018).

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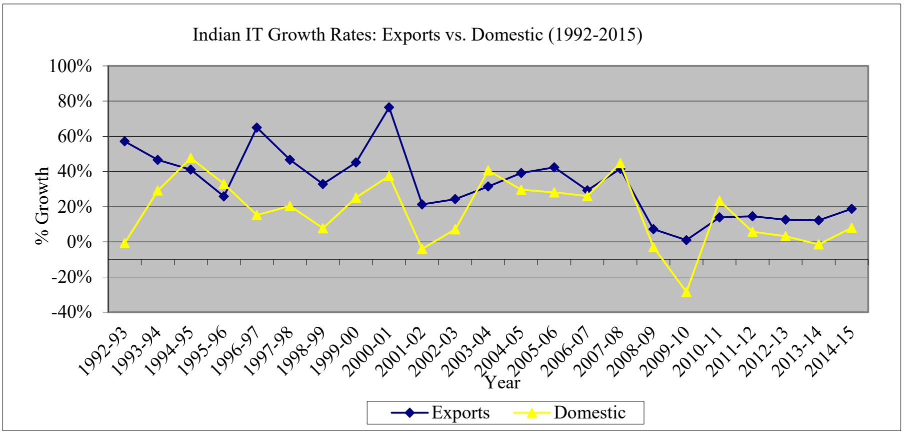
Appendix A. Growth Rate of Indian IT Sector



Source: Heeks (2015).