Derivatives and Price Risk Management: A Study of Nifty

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Vasantha G
T. Mallikarjunappa
Mangalore University
(naikvasantha@gmail.com)
(tmmallik@yahoo.com)

Executive Summery
Managing the price risk using instruments like futures and options and hedging effectiveness has become an interesting area of study for the investors, policy makers, researchers and academicians. Since the Indian derivatives market is new and the volumes in this market are increasing at an increasing rate, it is important and interesting to analyze the utility of derivatives as a hedging instrument. The study of hedging effectiveness is important because the success of any capital market depends on how effectively risk can be using the available instruments in the derivatives market. In this study we have estimated constant and time varying hedging ratios for stock derivatives market taking in to NSE Nifty spot and its futures contracts. We use intraday data observed at one minute interval of six months from 1 January 2014 to 30 June 2014. We use OLS and VECM models for constant hedge ratios and Generalized Autoregressive Conditional Heteroscedasticity model (GARCH) for time varying hedge ratio. Stationarity tests reveal that the price series are non-stationary and return series are stationary. Among the constant hedge ratio models VECM gives highest hedge ratio (0.8824). The hedge effectiveness of this model is approximately 82%. The D-Vech GARCH model gives highest hedging effectiveness, though the average hedge ratio of this model is lesser than (0.8537) constant hedge ratios. Therefore, our study concludes that time varying hedging models are preferable than the constant hedge ratios.

Price risk management is the primary function of derivatives. Several price risk management techniques have been evolved over the years and their applicability is still debatable. This study deals with constant and dynamic hedging models using intraday day data from spot and derivatives market of National Stock Exchange of India Ltd. (NSE) Nifty index. The OLS, VECM and D-VECH GARCH models are used for estimation of constant and dynamic hedge ratios. We compare the performance of these hedge ratios. This study found that dynamic hedge ratios are preferred as they provide highest hedging effectiveness.

Key Words: Derivatives, NSE-Nifty, Hedge ratio, Price risk management, hedging effectiveness, VECM.

1. Introduction

Managing the financial risk has become an important issue due to the volatile financial and economic environment. Therefore, hedging the risk helps financial market participants to protect their positions against the unexpected price movement in the market. Hedging is harmonizing the positions in the two markets, one in the spot or cash market and the other in the derivatives market. With a variety of products in the financial market, various hedging techniques such as futures, forwards, options etc have been developed in the market. Futures contracts, like any other hedging technique, can be used as an effective instrument to cover the unexpected fluctuations in the prices. Hedging with futures contracts involves purchase (sale) of futures in combination with another commitment, usually with the expectation of favourable change in relative prices of spot and futures market (Castelino, 1992). Since the objective of hedging is to control or reduce the risk of adverse price changes in the market, it is a critical issue to the investor to decide the number of futures contract he should buy (sell) for each unit of short (long) position in the spot market. This is called as the optimal hedge ratio in the derivatives market. To decide the optimal hedge ratio an appropriate model selection is important so that it is possible to obtain a reliable ratio.

The effectiveness of a hedge becomes relevant only in the event of a significant change in the value of the hedged item (Kenourgios, 2008). When the price movements of the hedged item and the hedging derivative instrument nullify or offset each other, then hedge is termed as effective hedge. It is believed that the effectiveness of hedging determines the success of any financial futures contract. Hence, price volatility management through hedging has become an interesting area of research since the previous researches failed to give a generalised solution for the volatility problem.

A number of studies have measured the hedging effectiveness using the simple Ordinary Least Squares (OLS). However, this model is severely criticised by many authors because of its inappropriateness to estimate hedge ratios since it does not consider the problems of serial correlation in the OLS residuals and the heteroskedasticity in cash and futures price series (Herbst, Kare and Marshall, 1993). Another problem faced while estimating the hedge ratio is the nature of co-integration between the spot and future contract prices. As noticed by Ghosh (1993) the presence of co-integration leads to an under-hedged position. This is because of misspecification of the pricing behaviour between these two markets (Ghosh, 1993).

Many empirical works have been done in the international level in the field of estimation of hedge ratio and measuring its effectiveness using different methodologies, asset classes and time frames. However, in Indian case, the number of researches in this field is limited. This is because of nascent stage of Indian derivative market. Some of the prominent Indian studies are of Bhaduri and Durai (2008), Kumar, Singh and Pandey (2008), Gupta and Singh (2009), Rao and Thakur (2010), Srinivan (2011). We find that estimation of hedge ratio and its efficiency is under-researched in Indian context. With this back ground an attempt has been made to compute the hedge ratio and to test the hedging effectiveness using different models.

This paper is organized in six sections. The second section discusses the important studies in this area, section 3 explains data and models used in the study for estimating the hedge ratio and hedging effectiveness, section 4 presents the details of the sample and data used for the study and its characteristic features; empirical results are presented in section 5 and section 6 concludes.

2. Review of Literature

Literature on hedging offers a wide variety of alternative models that can be used to model and quantify the hedge and hedge effectiveness of derivatives products. However, the results on the performance of these models have been mixed. We present a brief review of some important studies under two subsections such as international studies and Indian studies respectively.

2.1 International Studies

Early investigation of hedging includes **Ederington (1979)**. He examines the hedging performance of Government National Mortgage Association (GNMA) and T-Bill of Chicago Board of Trade. He used nearby contracts (3–6 months, 6–9 months and 9–12 months) and a hedging period of 2 and 4 weeks for the study. Using OLS he found that some of the hedge ratios are not different from zero and the hedging effectiveness increases with the length of hedging period. The hedge ratio also increases (closer to unity) with the length of hedging period.

Figlewski (1984) studied the hedging performance and basis risk using US stock data over the period June 1982 to September 1983. He found that the minimum variance hedge ratio (MVHR) give the most effective hedge. The comparison of hedge effectiveness over the time periods, he concluded that one-week hedges perform better than the overnight hedges but no improvement was found when the duration is extended to 4 weeks. His study found that exclusion of dividend does not have any impact over the hedge performance. Similarly, timing of the expiration of the futures has little impact on hedge performance. **Junkus and Lee (1985)** tested the hedging effectiveness of three USA stock index futures; Kansas City Borad of trade, New York Futures Exchange and Chicago Mercantile Exchange; using four futures hedging models such as, a variance-minimizing model introduced by Johnson (1960), the traditional one to one hedge, a utility maximization model developed by Rutledge (1972), and a basis arbitrage model suggested by Working (1953). They found that the MVHR was most effective at reducing the risk of a cash portfolio comprising the index underlying the futures contract. **Lee, Bubnys and Lin (1987)** tested the temporal stability of the minimum variance hedge ratio. They found that the hedge ratio increases as maturity of the futures contract nears.

Cecchetti, Cumby and Figlewski (1988) derived the hedge ratio by maximizing the expected utility. A third-order linear bivariate ARCH model was used to get the conditional variance and covariance matrix. A numerical procedure is used to maximize the objective function with respect to the hedge ratio. It was found that the hedge ratio changes over time and is significantly less than the MV hedge ratio (which also changes over time). Certainty equivalent is used to measure the effectiveness. They concluded that utility-maximizing hedge ratio performs better than the MV hedge ratio.

Myers and Thompson (1989) generalized the estimation of optimal hedge ratios to account for conditioning information that is available at the time a hedging decision is made. The authors argue that the traditional approach of using a simple regression of cash price levels on futures price levels or cash price changes on futures price changes are correct only under a very restrictive set of assumptions. They suggested a regression approach, where the cash price level is regressed against the futures price level plus a set of conditioning variables. The conditioning variables include lags of futures and cash prices and any variables thought to influence prices such as stocks, exports, and storage costs. In an example using corn and soybeans, the authors show that the generalized optimal hedge ratio can vary substantially from the unconditional ratio estimated with price levels; but, they argue that the unconditional hedge ratio estimated with price changes may provide a reasonable estimate of the generalized hedge ratio.

Baillie and Myers (1991) investigated the distribution of cash and futures prices for six different commodities, and applied the results to the problem of estimating the optimal futures hedge ratio. Six different commodities are examined using daily data over two futures contract periods. Bivariate GARCH models of cash and futures prices are estimated. This study found that constant hedge ratios are inappropriate since time varying hedge ratios estimated through the GARCH Model are more appropriate and advanced hedge ratios.

Ghosh (1993, 1995) argued that the minimum variance hedge ratios are biased downwards due to misspecification. Author opines that the standard OLS approach is not well specified in estimating hedge ratios because it ignores lagged values. He suggested that if the spot and futures are co-integrated, an error correction term (ECT) should be used to remove the misspecification in the regression. His studies proved the superiority of error correction model over OLS model for estimating the hedge ratios. **Chou, Denis and Lee (1996)** estimated and compared the hedge ratios of the conventional and the error correction model for Japan’s Nikkei Stock Average (NSA) index and the NSA index futures with different time intervals for the period 1989 to 1993. Examining an out-of-sample performance, they found that the error correction model outperformed the conventional approach, while the opposite position holds when the in- sample portfolio variance was evaluated.

Holmes (1996) examines hedging effectiveness for the FTSE-100 Stock Index futures contract from 1984 to 1992 for intervals of one, two and four weeks. He investigates the appropriate econometric technique to use in estimating minimum variance hedge ratios by undertaking estimations using OLS, an ECM and GARCH. He found that simple OLS outperforms more complex econometric techniques. Additionally, the study examines the impact of hedge duration and time to expiration on estimated hedge ratios and hedge ratio stability over time. It is found that hedge ratios and hedging effectiveness increase with hedge duration, hedge ratios approach unity as expiration approaches and while hedge ratios vary over time they are stationary. **Lypny and Powalla (1998)** examined the hedging effectiveness of the German stock index DAX futures and showed that the application of a dynamic hedging strategy based on a GARCH (1, 1) process is economically and statistically the most effective model.

Kavussanos and Nomikos (1999) studied constant vs. time-varying hedge ratios and hedging efficiency in the Baltic International Financial Futures Exchange (BIFFEX) market. The authors modeled the spot and futures returns as a vector error correction model (VECM) with a GARCH error structure. An augmented GARCH (GARCH-X) model where the error correction term enters in the specification of the conditional covariance matrix is also introduced to link the concept of disequilibrium (as proxied by the magnitude of the error correction term) with that of uncertainty (as reflected in the time varying second moments of spot and futures prices). In- and out-of-sample tests are employed to assess the effectiveness of the futures contract. The tests revealed that GARCH-X model provides greater risk reduction than a simple GARCH and a constant hedge ratio. **Park and Switzer (1995)** examined the risk-minimizing futures hedge ratio for three stock index futures, S&P 500 Index Futures, Major Market (MM) Index Futures and Toronto 35 Index Futures. Using a bivariate co-integration model with a generalized ARCH error structure they estimated optimal hedge ratio as a ratio of the conditional covariance between spot and futures to the conditional variance futures. Both within sample comparisons and out-of-the sample revealed that the dynamic hedging strategy based the bivariate GARCH model improves the hedging performance over the conventional constant hedging strategy.

Malliaris and Urrutia (1991) estimated the minimum variance hedge ratio using regression auto correlated errors model for five currencies such as British pound, German mark, Japanese yen, Swiss franc, Canadian dollar. Using overlapping moving windows, the MV hedge ratio and hedging effectiveness are estimated for both in-sample and out-of-sample cases for the time period from March 1980 to December 1988 (weekly data). In the in-sample case, the 4-week hedging horizon is more effective compared to the 1-week hedging horizon. However, for the out-of-sample case the opposite is found to be true. **Benet (1992)** using weekly data for Australian dollar, Brazilian Cruzeiro, Mexican Peso, South African Rand, Chinese Yuan, Finish Markka, Irish Pound and Japanese Yen studied direct and cross-hedging. For minor currencies, the cross-hedging exhibits a significant decrease in performance from in-sample to out-of-sample. The minimum variance hedge ratios are found to change from one period to the other except for the direct hedging of Japanese Yen. On the out-of-sample case, he reports that the hedging effectiveness is not related to the estimation period length. However, he found that the effectiveness decreases as the hedging period length increases.

Kroner and Sultan (1993) combine the error-correction model with the GARCH model considered by Cecchetti et al. (1988) and Baillie and Myers (1991) in order to estimate the optimum hedge ratio for the five currencies (Co-integration heteroscedastic method). Both within-sample and out-of-sample evidence shows that the hedging strategy proposed in the study is potentially superior to the conventional strategies. **Park and Switzer (1995b)** estimated the risk-minimizing futures hedge ratios for three types of stock index futures: S&P 500 index futures, major market index (MMI) futures and Toronto 35 index futures. Using a bivariate co-integration model with a generalized ARCH error structure, they estimated the optimal hedge ratio. Both within-sample comparisons and out-of-sample comparisons revealed that the dynamic hedging strategy based on the bivariate GARCH estimation improves the hedging performance over the conventional constant hedging strategy.

Lafuente and Novales (2002) studied the optimal hedge ratio under discrepancies between the futures market price and its theoretical valuation according to the cost-of-carry model using data from the Spanish stock index futures market. To estimate the optimal hedge ratio, they employ a bivariate error correction model with GARCH innovations. Ex-ante simulations with actual data reveal that hedge ratios that take into account the estimated, time-varying, correlation between the common and specific disturbances, lead to using a lower number of futures contracts than under a systematic unit ratio, without generally losing hedging effectiveness, while reducing transaction costs and capital requirements. Their empirical results and ex ante simulations indicate that hedge ratios lead into using a lower number of futures contracts than the one under a systematic unit ratio.

Butterworth and Holmes (2001) studied the hedging effectiveness of FTSE-100 and FTSE-mid250 index future contracts for underlying indexes and stocks of 32 investment trust companies. The results of the study showed that the future contracts could reduce risks of underlying index at a rate between 50 to 70%. However, the risk reduction of investment trust company stocks was limited with 20% at most. They also found that the OLS method performs better on the FTSE- mid 250 futures contract when out liers were omitted from the analysis.

Yang (2001) computes the optimal hedge ratios from the OLS regression model, the bivariate vector autoregressive model (BVAR), the error-correction model (ECM) and the multivariate diagonal Vec-GARCH Model for All Ordinary Index and SPI futures on the Australian market. The hedging effectiveness is measured in terms of in-sample and out-of-sample risk-return trade-off at various forecasting horizons. The study found that the GARCH time varying hedge ratios provide the greatest portfolio risk reduction, particularly for longer hedging horizons. **Floros and Vougas (2004)** examined hedging in Greek stock index futures market, focusing on various techniques to estimate constant or time-varying hedge ratios. They used standard OLS regressions, simple and vector error correction models, as well as M-GARCH models and found that Greek stock index futures, M-GARCH models provide best hedging ratios.

2.2 Indian Studies

Since derivatives are introduced in Indian market in 2000s, this market is yet to be studied in depth. A few authors tried to analyze the risk minimizing capacity of derivatives through hedging.

Rao and Thakur (2008) studied of hedging of Nifty price risk through index futures and options using high frequency data for the period from 01.01.2002 to 28.03.2002. They find that estimates of optimal hedge ratio based on competing models, HKM in case of futures (Herbst, Kare and Marshall, 1993) and fBM in case of options are better than those estimated using benchmark models (JSE (Johnson, 1960; Stein, 1961; and Ederington, 1979) for futures and BSM Black-Scholes model for options, respectively). However, the returns on hedged positions using the superior optimal hedge ratios are not significantly different.

Bhaduri and Durai (2008) investigated the optimal hedge ratio and hedging effectiveness of S&P CNX Nifty index futures by employing four models such as OLS, VAR, VECM and multivariate GARCH model. Their results revealed that the time varying M-GARCH performs better in the long run where as OLS is best in the short duration. Similar study was conducted by **Kumar, Singh and Pandey (2008)** by including Nifty index and three commodities. Their results revealed that time varying hedge ratio performs better than the constant hedge ratios. **Kumar and Pandey** (2011) examines hedging effectiveness of four agricultural (Soybean, Corn, Castor seed and Guar seed) and seven non-agricultural (Gold, Silver, Aluminium, Copper, Zinc, Crude oil and Natural gas) futures contracts traded in India. They applied VECM and CCC-MGARCH model to estimate constant hedge ratio and dynamic hedge ratios respectively. Their study concluded that agricultural futures contracts provide higher hedging effectiveness (30-70%) as compared to non-agricultural futures (20%). The results were same for both constant and dynamic hedge ratios. **Gupta and Singh (2009)** estimated the optimal hedge ratio for the Indian derivatives market through the examination of three indices viz. Nifty, Bank Nifty and CNX IT, and 84 most liquid individual stock futures traded on National Stock Exchange of India Ltd. The results suggested that hedge ratio calculated through VAR model and VEC Model performs better and this is due to presence of co-integration between spot and futures markets. **Srinivasan (2011)** found that empirical results for the in-sample hedging performance comparison showed that the conventional OLS regression method generates better than VAR, VEC and GARCH in terms of variance reduction. His study found that VEC Model outperformed the other hedging models for the out-of–sample period in terms of minimizing the risk. **Kumar (2012)** studied the volatility and hedging behaviour of four notional commodity futures indices of Multi Commodity Exchange (MCX) of India using 2175 observations from 6/8/2005 to 8/18/2012. Models like DVECH-GARCH, BEKK- GARCH, CCC-GARCH and DCC-GARCH were used to estimate the time varying hedge ratio. Further, an in-sample performance analysis, in terms of hedged return and variance reduction approaches, of the hedge ratios estimated from the different bivariate GARCH models are also carried out. This study found that all the models are able to reduce the exposure to spot market as perfectly as possible in comparison with the unhedged portfolio and in doing so the advanced extensions of bivariate GARCH models viz DCC-GARCH and CCC-GARCH have a clear edge over DVECH-GARCH and BEKK-GARCH.

The above discussion about literature shows that the results of the evaluating hedging performance of futures markets seemed to be ambiguous. With this back ground, our study emphasizes on determining the optimal hedge ratio and hedging effectiveness for the futures in India by taking NSE Nifty spot and futures.

3. Data, Sample and Methodology

NSE is the prime stock exchange in India with maximum transparency and regulatory framework. NSE recorded an exponential growth in its derivatives segment in a very short time span of a decade. Approximately 92 percent of total trading value of NSE came from the derivative segment in the year 2013-14(NSE fact book-2014 p 03). Currently NSE offers variety of derivatives instruments including stock and index futures and options and currency futures. NSE-Nifty is one of the important indices of NSE which includes fifty prominent stocks of Indian capital market. NSE-Nifty is treated as a major indicator of Indian economy. Therefore, we consider the NSE-Nifty index for this study. We use intraday data of Nifty spot and futures, recorded at one minute interval for the period from 01/01/2014 to 30/01/2014. A time series is constructed using the near month data and hence there are 45840 observations in spot and futures price series individually. Near month data is used as the market is more active in the month of contract expiry than the other months. We use three different methods for estimating the hedge ratio and hedging effectiveness. First two models estimate the constant hedge ratio and the third model estimates the time variant hedge ratio. A brief discussion of these models is given below,

3.1 Ordinary Least Square (OLS) Method

OLS is treated as the simple conventional method for calculating the constant hedge ratio which is given by the following linear regression model,

$$Return_{spot} = Constant\ (\alpha) + \beta Return_{futures} + \varepsilon_t \tag{1}$$

Here the value of β provides the optimal hedge ratio. That is, it is the ratio of covariance between spot and futures returns and variance of spot returns. The coefficient of determination (R^2) of the model indicates the hedging effectiveness. Higher the R^2more efficient will be the hedge ratio and vice versa.

3.2 The Vector Error Correction Model

The OLS method is criticised for not considering the existence of autocorrelation in the residuals (E.g. Myers and Thompson, 1989; Cecchetti, Cumby and Figlewski, 1988 etc.). If two or more sets of series are co-integrated, then there exists a valid error correction representation (Engle and Granger, 1987). This is also confirmed by Ghosh (1993), Lien and Luo (1994); Lien (1996) etc. The error correction framework is shown in the models (2) and (3) below.

$$R_{st} = \alpha_S + \sum_{i=2}^{k} \beta_{Si} R_{st-i} + \sum_{j=2}^{l} \gamma_{Fj} R_{Ft-j} + \lambda_S Z_{t-1} + \varepsilon_{St} \quad (2)$$

$$R_{Ft} = \alpha_F + \sum_{i=2}^{k} \beta_{Fi} R_{Ft-i} + \sum_{j=2}^{l} \gamma_{Sj} R_{St-j} + \lambda_F Z_{t-1} + \varepsilon_{Ft} \quad (3)$$

Where the α, β_S, β_F, γ_S and γ_F are parameters and residuals ε_{St} and ε_{Ft} are independently identically distributed (iid) random vector. $Z_{t-1} = S_{t-1} - \delta F_{t-1}$ is the error correction term with (1- δ) as co - integrating vector. Once the residual series are generated, hedge ratio is calculates as follows,

$$h^* = \frac{\sigma_{sf}}{\sigma_f} \quad (4)$$

Where, h*= $hedge\ ratio$, $\sigma_{sf} = Cov(\varepsilon_{St}, \varepsilon_{Ft})$ and $\sigma_f = Var\ (\varepsilon_{Ft})$.

3.3 The Vech GARCH Model

Bollerslev, Engle and Wooldridge (1988) proposed a Vech GARCH model to estimate the time varying hedge ratios. The main advantage of this model is that it simultaneously models the conditional variance and covariance of two integrated series. In the Vech model, every conditional variance and conditional covariance is a function of all lagged conditional variances and co-variances, as well as lagged squared returns and cross-products of returns. A common specification of the vech model is,

$$Vech\ (H_t) = c + A\ vech\ (\Xi_{t-1}\Xi_{t-1}^{'}) + B\ vech\ (H_{t-1}) \quad (5)$$

$$\Xi_t | \psi_{t-1} \sim N(0, H_t)$$

Where H_t is a 2 X 2 conditional variance- covariance matrix, Ξ_t is a 2X1 error (disturbance) vector, ψ_{t-1} represents the information set at time t-1. C is a 3X1 parameter vector, A and B are 3X3 parameter matrices and vech denotes the column-stacking operator applied to the upper portion of the symmetric matrix. The model requires the estimation of 21 parameters. The above vech model is elaborated with the following sub set of models for better understanding.

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{1t} & h_{11t} \end{bmatrix}, \Xi_t = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}, C = \begin{bmatrix} C_{11} \\ C_{21} \\ C_{31} \end{bmatrix},$$

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

The Vech operator takes the upper triangular portion of a matrix and stacks each element into vector with a single column. For example, in the case of vech (H_t), this becomes

$$\text{Vech}\ (H_t) = \begin{bmatrix} h_{11t} \\ h_{22t} \\ h_{12t} \end{bmatrix}$$

Where h_{iit} represent the conditional variances at time t of the two-asset return series used in the model and $h_{ijt}\ (i \neq j)$ represent the conditional co-variances between the asset returns. In the case of vech ($\Xi_t \Xi_t^{'}$), this can be expressed as

$$vech\ (\Xi_t \Xi_t^{'}) = vech\ \left(\begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \begin{bmatrix} u_{1t} & u_{2t} \end{bmatrix}\right) \quad (6)$$

3.4 $= vech \begin{pmatrix} u_{1t}^2 & u_{1t}u_{2t} \\ u_{1t}u_{2t} & u_{2t}^2 \end{pmatrix}$ (7)

$$= \begin{bmatrix} u_{1t}^2 \\ u_{2t}^2 \\ u_{1t}u_{2t} \end{bmatrix} \quad (8)$$

The vech model in full given by,

$$h_{11t} = c_{11} + a_{11}u_{1t-1}^2 + a_{12}u_{2t-1}^2 + a_{13}u_{1t-1}u_{2t-1} + b_{11}h_{11t-1} + b_{12}h_{22t-1} + b_{13}h_{12t-1} \quad (9)$$

$$h_{22t} = c_{21} + a_{21}u_{1t-1}^2 + a_{22}u_{2t-1}^2 + a_{23}u_{1t-1}u_{2t-1} + b_{21}h_{11t-1} + b_{22}h_{22t-1} + b_{23}h_{12t-1} \quad (10)$$

$$h_{12t} = c_{31} + a_{31}u_{1t-1}^2 + a_{32}u_{2t-1}^2 + a_{33}u_{1t-1}u_{2t-1} + b_{31}h_{11t-1} + b_{32}h_{22t-1} + b_{33}h_{12t-1} \quad (11)$$

Thus, it is clear that the conditional variances and conditional co-variances depend on the lagged value of all of the conditional variances of and conditional co-variances between, all of the asset returns in the series, as well as the lagged squared errors and the error cross-products.

The above mentioned vech model is quite cumbersome task as the model contains 21 parameters to estimate even if at least two assets are included in the sample. If the sample size increased there would be a large number of parameters to estimate which will become infeasible. To overcome this problem a reduced form of vech model is introduced in which the vech model's conditional variance-covariance matrix has been restricted and hence reduced the number of parameters to be estimates is to 9. This model is called as the diagonal vech model and is expressed as follows,

$$h_{11t} = c_{11} + a_{11}u_{1t-1}^2 + b_{11}h_{11t-1} \quad (12)$$

$$h_{22t} = c_{21} + a_{23}u_{1t-1}u_{2t-1} + b_{22}h_{22t-1} \quad (13)$$

$$h_{12t} = c_{31} + a_{32}u_{2t-1}^2 + b_{33}h_{12t-1} \quad (14)$$

3.5 Hedging Effectiveness

For estimating the effectiveness of calculated hedge ratio reductions in the variance in the hedged portfolio is compared with the variance reduction of un-hedged portfolio. This can be shown in the following equation,

$$\frac{Variance\ Unhedged - Variance\ of\ Hedged}{Variance\ of\ Unhedged}$$

Where variance of un-hedged = σ_s^2
Variance of hedged = $\sigma_s^2 + h^2\sigma_f^2 - 2h\sigma_{sf}$

4. Results and Analysis

4.1 Graphical Analysis

The tentative inference about the behaviour and formation of the price series of Nifty spot and futures can be drawn from the graphical analysis. Figure 1 shows the time series plots of Nifty spot and futures prices. We can observe from the time series plot that the study period had seen a steep but steady increase in the price.

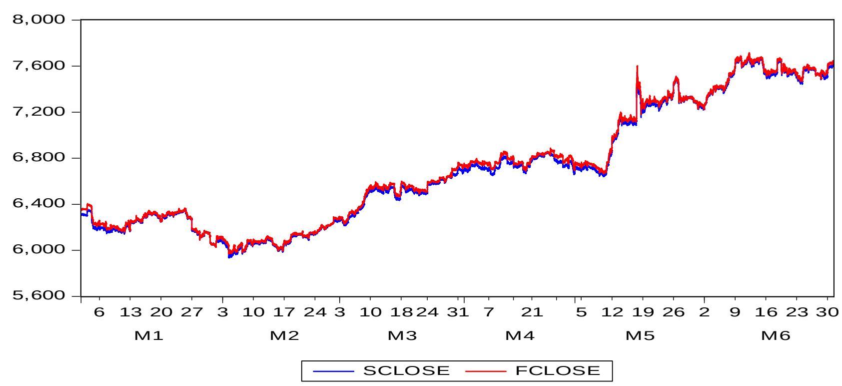

Figure 1 *Time Series Plot of Nifty Spot and Futures Prices*

Time series normally depicts volatility clustering or volatility persistence. Volatility clustering manifests itself as periods of tranquillity interrupted by periods of turbulence. The change between these two extreme regimes is a slow process so that large returns slowly decline until a relatively tranquil state is reached (Modelbrot, 1963). In other words time series indicates phenomena in such a way that lower volatility is followed by further low volatility and higher volatility is followed by higher volatility. In the figure 2 we have presented the volatility clustering in both the return series of Nifty spot and futures.

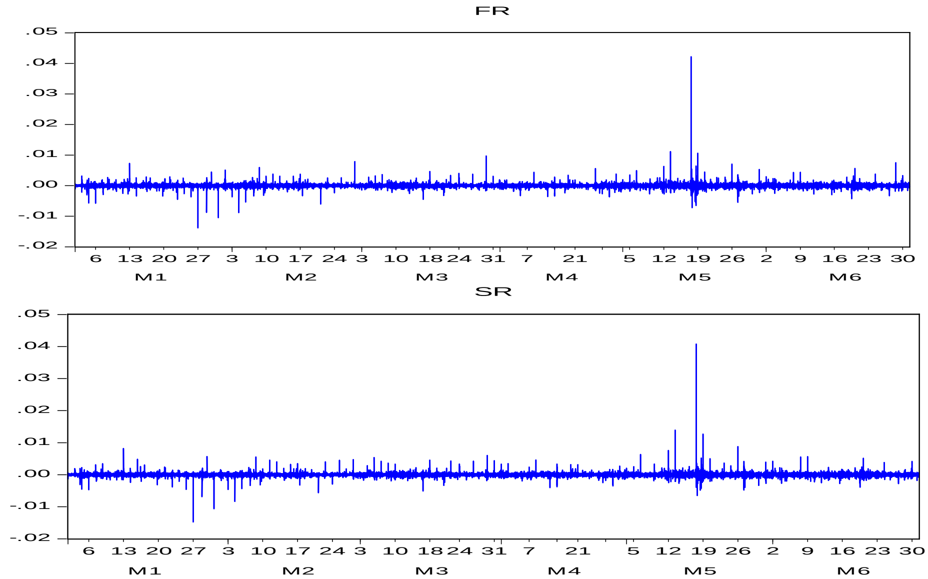

Figure 2 *Spot and Futures Return Series Plots*

4.2 Descriptive Statistics

Statistical properties of the return series are presented in the table 1, where it is clear that the mean retuns of both the market are almost same. The variation, expressed in the standard deviation , in returns is higher in the futures market than the spot market. Clear non-nomality is exhibited in the high positive skewness, kurtosis and Jarque-Bera statistics. Both the return series show excess kurtosis implying that fatter tail than the normal distribution and are skewed to the right.

Table 1 *Descriptive Statistics*

	Futures Returns	Spot Returns
Mean	3.97E-06	4.04E-06
Median	0.00000	6.64E-06
Maximum	0.042143	0.040737
Minimum	-0.013770	-0.014712
Std. Dev.	0000475	0.000461
Skewness	15.20423	15.60912
Kurtosis	1409.513	1419.734
Jarque-Bera	3.78E+09	3.84E+09
Probability	0.000000	0.000000
Observations	45840	45840

4.3 Unit Root Test

Before performing any type of regressions, it is essential to test whether the series contains unit root or not. Presence of unit root implies that the time series under study has a time varying mean or time varying variance or both. The series which contain unit root are called as non –stationary series. If we regress two or more non - stationary series the results would be spurious. In such a case, it becomes necessary to remove the unit root either by differencing the series or by taking log series before further econometric analysis.

The Augmented Dickey-Fuller (1979) and Philips-Perron (1988) are two popularly used stationarity tests in the financial literature. These tests are known for their simplicity and accuracy in estimating the degree of differencing necessary to make the series stationary. The results of these tests indicate in which form the data series should be used for subsequent estimations (Eg. At level, first or second difference form). We present the unit root test results in the table 2. We separately show the test statistics and the probability values for the price series and the return series. The required numbers of lags are selected based on the Schwartz's Bayesian information criterion (SIC). It is very clear from the table that price series are non-stationary and return series are stationary for both spot and futures market. This guides us that we can use the return series than the price series for any further analysis.

Table 2 *Unit Root Test Results*

Variable	ADF Statistics	P value	PP Test statistics	P value
Futures Price	0.1479(55)	0.9693	0.2383	0.9750
Spot Price	0.1394(55)	0.9687	0.2827	0.9775
Futures Returns	-28.6124 (55)	0.0000	-213.9629	0.0001
Spot Returns	-27.6615 (55)	0.0000	-208.9116	0.0001

Note *Figures in Parenthesis Indicates Number of Lags Used*

Empirical Estimation of Hedge Ratio and Hedging Effectiveness

In this section we present the results of alternatives methods used for estimation of hedge ratio and its effectiveness.

4.4 OLS Method

Table 3 *OLS Results*

Symbol	Coefficients	t-statistics	p-value
A	5.67E-07	0.6149 (9.21E-07)	0.5386
B	0.8755	451.8877 (0.001938)	0.0000
R^2	0.8167		

Note *Standard Error is given in the Parenthesis*

Table 3 shows that the hedge ratio calculated from OLS method is 0.8755 and hedging efficiency is represented by R^2 which is 82%. To check the validity of the model used, diagnostics tests of residuals obtained from the above OLS are conducted and the results are presented below.

Table 4 *Diagnostic Test Results*

Diagnostic tests	Test statistics	P. value
Jarque-Bera Null (H_0) : Residuals are normally distributed	5711952	0.000
Breusch Godfrey Serial Correlation LM Test Null (H_0) : No serial correlation between residuals	3996.311	0.000
White Heteroscedasticity Test: Null (H_0): Residuals are homoscedactic	249.3995	0.000

It is very clear from the diagnostic test results of OLS that, in all three tests the null hypothesis are rejected at one percent level of significance. This shows that the model suffers from the problem of serial correlation, heteroscedasticity and non-normality. Since the results are spurious, they cannot be used for further analysis and decision making. Therefore, we estimate the hedge ratio using a bivariate VECM model which is discussed in the next section.

4.5 VEC Model Results

An augmented VAR model with error correction term as one of the independent variables is used to capture the long run as well as the short run relationship simultaneously as simple VAR model ignores the possibility that the two variables have long run relationship or the existence of co-integration. If the two price series are found to be co-integrated, a VAR model should be augmented using an error correction term which accounts for the long run equilibrium between spot and futures price movement (E.g. Gosh (1993), Lien and Luo (1994) and Lien (1996). First, we use Johansen's co-integration test to examine the long-run relationship (co-integration) between spot and futures market. The results are presented in the table 5. Johansen's maximum eigen value and trace statistics indicate that at least one co-integrating vector is present at 0.05 level in the Nifty spot and its derivatives.

Table 5 *Test for Co-integration*

Hypothesis	Eigen value	Trace test	p-value	L max test	p-value

None (r = 0)	0.223466	20481.20	0.0001	11592.36	0.0001
At most 1 (r ≥1)	0.176285	8888.834	0.0000	8888.834	0.0000

Since the co-integration is present between the two markets we use error correction term to the VAR model, so that any disequilibrium will be normalised. A VECM (6, 1) is used for our analysis where 6 denotes the maximum lags which is selected based SIC and 1 denotes the rank order. The VECM results are presented in table 6 and 7 for futures and spot market respectively.

Table 6 *Estimates of VEC Model for Futures Market*

Symbol	Coefficient	Std. Error	t-Statistic	Probability
α_F	0.0000	0.0000	1.8321	0.0669
λ_F	-0.0490	0.0189	-2.5950	0.0095
γ_{F1}	-0.9367	0.0185	-50.5702	0.0000
γ_{F2}	-0.8594	0.0163	-52.8128	0.0000
γ_{F3}	-0.6964	0.0150	-46.3474	0.0000
γ_{F4}	-0.5051	0.0123	-41.0616	0.0000
γ_{F5}	-0.3223	0.0091	-35.4147	0.0000
γ_{F6}	-0.1491	0.0061	-24.5760	0.0000
β_{S1}	0.0859	0.0200	4.2841	0.0000
β_{S2}	0.1331	0.0176	7.5613	0.0000
β_{S3}	0.1018	0.0158	6.4483	0.0000
β_{S4}	0.0557	0.0123	4.5176	0.0000
β_{S5}	0.0052	0.0091	0.5751	0.5652
β_{S6}	-0.0144	0.0063	-2.2848	0.0223

Table 7 *Estimates of VEC Model for Spot Market*

Symbol	Coefficient	Std. Error	t-Statistic	Probability
α_S	0.0000	0.0000	-9.5186	0.0000
λ_F	1.5446	0.0146	106.0773	0.0000
γ_{F1}	-1.1750	0.0144	-81.8680	0.0000
γ_{F2}	-0.9530	0.0122	-78.0917	0.0000
γ_{F3}	-0.7374	0.0109	-67.5437	0.0000
γ_{F4}	-0.5297	0.0090	-58.6663	0.0000
γ_{F5}	-0.3329	0.0061	-54.6581	0.0000
γ_{F6}	-0.1515	0.0036	-42.1682	0.0000
β_{S1}	0.4630	0.0154	30.0682	0.0000
β_{S2}	0.3675	0.0132	27.7426	0.0000
β_{S3}	0.2507	0.0119	21.1496	0.0000
β_{S4}	0.1530	0.0092	16.5581	0.0000
β_{S5}	0.0588	0.0062	9.4226	0.0000
β_{S6}	0.0114	0.0038	3.0247	0.0025

The coefficients of the error correction terms, λ_S and λ_F in VECM (6, 1) are significant at 5% level implying that the long run co-integrating relationship between the spot and futures returns has been appropriately considered in VECM equations. In other words, the error correction co-efficient in futures equation is negative and significant, indicating that the speed of adjustment of spot towards long run equilibrium is significant and the difference between spot and futures prices is positive. The futures market will fall next period to restore the equilibrium. On the other side, the error correction co-efficient in spot equation is positive and significant, indicating rise in futures price towards the equilibrium in the next period. The lags of spot and futures markets are significant in both equations indicating mutual dependency of the two markets. This mutual dependency of the two markets gives important clues to the hedgers about the movement of the market in the immediate future. The residuals of the VECM are used to estimate the hedge ratio and hedging effectiveness which is presented in table 8.

The hedge ratio obtained from VECM model is 0.8824 which is more than that of OLS model. VECM provides 82% (approx) hedging effectiveness which is in line with the OLS model. Therefore, our two constant models gave two different hedge ratios but the effectiveness of these models are equal (82%). Since, both constant hedge ratios provide similar hedging effectiveness a clear conclusion can be drawn about the superiority of the models at this stage. In the next part we provide the results obtained from the GARCH model.

Table 8 *VECM Hedge Ratio Results*

Cov (ε_S, ε_F)	2.27E-07
Var ε_F	2.27E-07
Hedge ratio	0.8824
Variance (Hedged)	3.89E-08
Variance (Unhedged)	2.12E-07
Hedging Effectiveness	0.8166

4.6 GARCH Model

D-Vech GARCH Model is used to estimate the time varying hedge ratio. The resulting time varying hedge ratio is presented in figure 6 and summery statistics are given in the table 9.

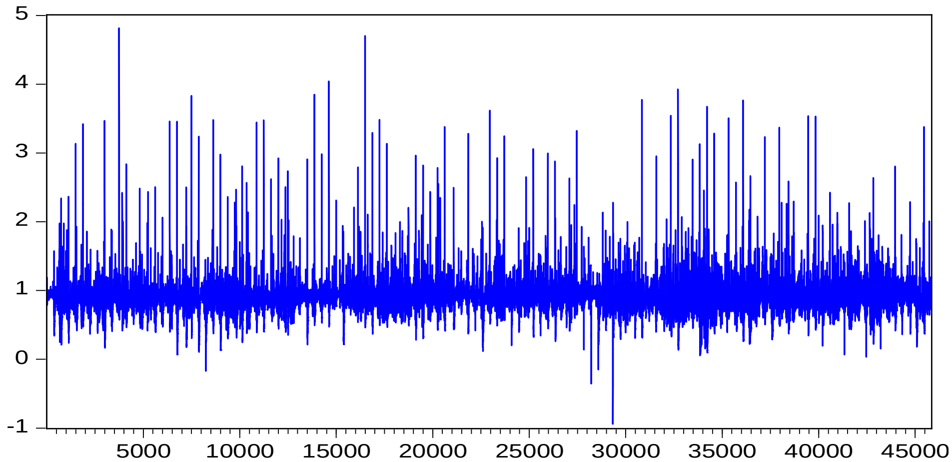

Figure 3 *Dynamic Hedge Ratio*

Table 9 *Descriptive Statistics of Dynamic Hedge Ratio*

	HEDGE RATIO
Mean	0.8537
Median	0.8480
Maximum	4.8148
Minimum	-0.9386
Std. Dev.	0.2227
Skewness	3.0101
Kurtosis	32.3165
Jarque-Bera	1710528
Probability	0.000000

As shown in the Figure 3, the dynamic hedge ratios are less stable and exhibit fluctuations. This suggests that the hedgers of Nifty futures market have to adjust their futures positions more often. As reported in the table 9, the average hedge ratio for the study period is 0.8537 and it ranges from a minimum -0.9386 to a maximum of 4.8148. Also a high Jarque-Bera suggests that the distribution of hedge ratio is not normal. Based on this time varying hedge ratio, we estimate the variances of hedged and unhedged portfolio to calculate the hedge effectiveness. The estimation reports that hedging with the dynamic hedge ratio of Nifty futures is 83% effective.

Finally, a summary of hedging performance obtained by all three models is presented in table 10. Comparison of hedge ratios estimated from the four models reveals all the three models give significant hedging effectiveness. As observed by many studies GARCH family models can perform better in estimation of time varying hedge ratios and hedging effectiveness and we also found that the D-Vech GARCH model provides highest hedging effectiveness.

Table 10 *Comparison of Hedge Ratio and Hedging Effectiveness*

Model	Hedge ratio	Hedging effectiveness
Ordinary least squares	0.8755	81.67%
Vector Error Correction	0.8824	81.67%
D-Vech GARCH	0.8537 (Mean)	83%

5. Conclusions

Managing the price volatility by using instruments like futures and options and hedging effectiveness has become an interesting area of study for the investors, policy makers, researchers and academicians. Since the Indian derivatives market is new and the volumes in this market are increasing at an increasing rate, it is important and interesting to analyze the utility of derivatives as a hedging instrument. The study of hedging effectiveness is important because the success of any capital market depends on how effectively risk can be reduced in using the instruments of derivatives market. In this study, we have estimated the constant and time varying hedging ratios for Indian derivatives market taking into account one of the most active stock derivatives market i.e., NSE Nifty spot and its futures contracts. We use OLS and VECM models for constant hedge ratios and Generalized Autoregressive Conditional Heteroscedasticity model (GARCH) for time varying hedge ratio. Our study found that both time varying and constant hedge ratio models provide somewhat similar hedge ratios. As for as the hedging effectiveness is concerned, GARCH family model out performs the other two models. Further studies can be carried out including more time varying models and the results can be compared between these models.

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