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Hedging Effectiveness of Constant and Time Varying Hedge Ratio in Indian Stock and Commodity Futures Markets

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Abstract

This paper examines hedging effectiveness of futures contract on a financial asset and commodities in Indian markets. In an emerging market context like India, the growth of capital and commodity futures market would depend on effectiveness of derivatives in managing risk. For managing risk, understanding optimal hedge ratio is critical for devising effective hedging strategy. We estimate dynamic and constant hedge ratio for S&P CNX Nifty index futures, Gold futures and Soybean futures. Various models (OLS, VAR, and VECM) are used to estimate constant hedge ratio. To estimate dynamic hedge ratios, we use VAR-MGARCH. We compare in-sample and out-of-sample performance of these models in reducing portfolio risk. It is found that in most of the cases, VAR-MGARCH model estimates of time varying hedge ratio provide highest variance reduction as compared to hedges based on constant hedge ratio. Our results are consistent with findings of Myers (1991), Baillie and Myers (1991), Park and Switzer (1995a,b), Lypny and Powella (1998), Kavussanos and Nomikos (2000), Yang (2001), and Floros and Vougas (2006).

***Keywords**:* Hedging Effectiveness, Hedge ratio, Bivariate GARCH, S&P CNX Nifty index and futures, Commodity futures

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1. INTRODUCTION

Rising price volatility has led to a number of specialized financial instruments that allow participants to hedge against unexpected price movement. Like any other derivative, futures contracts can be used as an insurance against unfavorable price fluctuations. In Indian context, S&P CNX Nifty index futures and commodity futures are comparatively new and were introduced in the year 2000 and 2003 respectively. In last 4-5 years, the Indian stocks as well as commodity markets have grown considerably[4]. Bose (2007) found that Indian stock markets are more volatile as compared to developed markets. Indian commodity futures markets are going through many ups and downs and many a times allegations of speculative activity have been made in the popular press. Despite controversies, there is a need for systematic investigation of stock and commodity derivatives markets to asses their effectiveness in transferring the risk. This research investigates the hedging effectiveness provided by the futures market. Hedging effectiveness of futures markets is one of the important determinants of success of futures contracts (Silber, 1985; Pennings & Meulenberg, 1997).

Price risk management, using hedging tools like futures and options and their effectiveness, is an active area of research. Hedging decisions based on futures contracts have to deal with finding optimal hedge ratio and hedging effectiveness. Role of hedging using multiple risky assets and using futures market for minimizing the risk of spot market fluctuation has been extensively researched. Several distinct approaches have been developed to estimate the optimal hedge ratio. Techniques like OLS, VAR, and VECM estimate constant hedge ratio and bivariate GARCH models estimates dynamic hedge ratios which factor in conditional distribution of spot and futures returns. However, there has been extensive debate on which model generates the best hedging performance (Baillie & Myers, 1991; Ghosh, 1993; Park & Switzer, 1995; Kavussanos & Nomikos, 2000; Lien et al., 2002; Moosa; 2003, Floros & Vougas, 2006). Superior performance of bivariate GARCH models was supported by Baillie and Myers (1991), Park and Switzer, (1995), Kavussanos and Nomikos, (2000), Floros and Vougas (2006) etc. Ghosh (1993), however, found better performance of VECM among constant hedge models and Lien et al. (2002) and Moosa (2003) found that the basic OLS approach clearly dominates other alternatives.

[4] http://indiabudget.nic.in/es2007-08/chapt2008/chap53.pdf

Traditionally, hedging is envisaged using a hedge ratio of '-1', i.e., taking a position in futures contract which is equal in magnitude and opposite in sign to the position in spot market. If the movement of changes in spot prices and futures prices is exactly the same, then such a strategy eliminates the price risk. Such a perfect correlation between spot and futures prices is rarely observed in markets and hence a need was felt for a better strategy. Johnson (1960) proposed 'minimum variance hedge ratio (MVHR)', which factored in less than perfect relationship between spot and futures prices.. Risk was defined as the variance of returns on a two-asset hedged position.

The Minimum-Variance Hedge Ratio (Benninga, *et al.,* 1983, 1984) has been suggested as slope coefficient of the OLS regression in which changes in spot prices is regressed on changes in futures price. The optimal hedge ratio for any unbiased futures market can be given by ratio of covariance of (cash Prices, futures Prices) and variance of (futures Prices). In other words, MVHR is the regression coefficient of the regression model (changes in spot prices over changes in futures prices) which gives maximum possible variance reduction or hedging effectiveness.

Many researchers have defined hedging effectiveness as the extent of reduction in variances as a risk minimization problem (Johnson, 1960; Ederington, 1979). However, Rolfo (1980) and Anderson and Danthine (1981) calculated optimal hedge ratio by maximizing traders' expected utility, which is determined by both expected return and variance of portfolio. Because of the relationship (trade-off) between risk and return, they argued that optimal ratio must be estimated in mean-variance framework rather than for minimizing only risk.

Using OLS regression for estimating the hedge ratio and assessing hedging effectiveness based on its R-square, has been criticized mainly on two grounds (Baillie & Myers, 1991; Park & Switzer, 1995). First, the hedge ration estimated using OLS regression is based on assumption of unconditional distribution of spot and futures prices; whereas, the use of conditional distributions is more appropriate because hedging decision made by any hedger is based on all the information available at that time. Second, OLS model is based on assumption that the relationship between spot and future prices is time invariant but empirically it has been found that the joint distribution of spot and futures prices are time variant (Mandelbrot, 1963; Fama, 1965).

Recent advancements in the time series modeling techniques have tried to remove the deficiencies of the OLS estimation. Multivariate GARCH (Bollerslev *et al*, 1988) has been used to calculate time varying hedge ratio. Many recent works on the hedging effectiveness estimate time varying hedge ratios (Baillie & Myers, 1991; Park & Switzer, 1995; Holmes, 1995; Lypny & Powella, 1998; Kavussanos & Nomikos, 2000; Choudhry, 2004; Floros & Vougas, 2006; Bhaduri & Durai, 2008). Park and Switzer applied MGARCH approach to calculate hedge effectiveness of three types of stock index futures: S&P 500, MMI futures and Toronto 35 index futures and found that Bivariate GARCH estimation improves the hedging performance. Lypny and Powella (1998) used VEC-MGARCH (1,1) model to examine the hedging effectiveness of German stock Index DAX futures and found that dynamic model was superior than constant hedge model. However, some recent studies such as those of Lien *et al*. (2002) and Moosa (2003) have found that the basic OLS approach clearly dominates. Thus, empirical findings across markets seem to suggest that the best model for hedging may be country and market specific.

There are very few empirical investigations of the stock futures markets and hedge ratios in emerging market context (Choudhry, 2004; Floros & Vougas, 2006; Bhaduri & Durai, 2008) and especially in context of Indian commodity futures. Choudhary (2004) investigated the hedging effectiveness of Australian, Hong Kong, and Japanese stock futures markets. Both constant hedge models and time varying models were used to estimate and compare the hedge ratio and hedging effectiveness. He found that time-varying GARCH hedge ratio outperformed the constant hedge ratios in most of the cases, inside-the-sample as well as outside-the-sample. Floros and Vougas (2006) studied the hedging effectiveness in Greek Stock index futures market for the period of 1999-2001 and found that time varying hedge ratio estimated by GARCH model provides highest variance reduction as compared to the other methods. Bhaduri and Durai (2008) found similar results while analyzing the effectiveness of hedge ratio through mean return and variance reduction between hedge and unhedged position for various horizon periods of NSE Stock Index Futures. However, the simple OLS-based strategy also performed well at shorter time horizons. Roy and Kumar (2007) studied hedging effectiveness of wheat futures in India using least square method and found that hedging effectiveness provided by futures markets was low (15%).

Since the hedging effectiveness has been found to be contingent on model used to estimate hedge ratio and whether it is kept constant or allowed to vary over the hedging horizon, it is interesting to investigate the same in Indian context. While there has been some work in this direction for the Stock Index Futures, Indian Commodity Futures have not been extensively researched empirically on the choice of model for estimating hedge ratio and resultant hedge effectiveness. Presumably, this research would help in understanding effectiveness of commodity futures contracts once the relationship between spot and futures prices is modeled and factored in estimating hedge ratio. It may also help concerned exchanges and the government to devise better risk management tools or supports towards commodity-specific public policy objectives. At the time of writing this paper, reports suggest that the Indian government is planning on aggregation model to encourage participation of farmers on the commodity exchanges. Finally, this study may help hedgers in devising better hedging strategies.

This study investigates optimal hedge ratio and hedge effectiveness of select futures contracts from Indian markets. Three different futures contracts have been empirically investigated in this study. One of these is a Stock index futures on S&P CNX Nifty, which is a value-weighted index consisting of 50 large capitalization stocks maintained by National Stock Exchange. The other two futures contracts are- Gold futures and Soybean futures. All futures contracts traded in the market at any point in time have been considered. Daily closing price data on S&P CNX Nifty index and its futures contracts[5] (all three) available at any given time, and similarly three Gold futures[6] and three Soybean futures[7] contracts trading contemporaneously are included. Since hedge effectiveness of NIFTY futures was investigated by Bhaduri and Durai (2008) for the period 4 September 2000 to 4 August 2005, we have used data for the period of 1st Jan 2004 to 8th May 2008 of NIFTY futures to supplement their work.

This paper is organized as follows: several model specifications used for estimating the hedge effectiveness and hedge ratio are presented in Section 2. In Section 3, description

[5] S&P CNX Nifty futures contracts have a maximum of 3-month trading cycle - the near month (one), the next month (two) and the far month (three). A new contract is introduced on the trading day following the expiry of the near month contract (http://www.nseindia.com)

[6] Gold futures contracts are started from 22nd July 2005 on NCDEX and there are only three contemporary futures contacts of different maturity (http://www.ncdex.com).

[7] Soybean futures are stared prior to 4th October 2004on NCDEX; however, because of less trading volume, futures prices before 4th October 2004, were behaving erratically, we considered the data from abovementioned date. We are able to construct three contemporary series of futures prices for the total period.

of the data used for the study and its characteristics is given. Results are presented in Section 4 and the final section concludes the findings of the study.

2. HEDGE RATIO AND HEDGING EFFECTIVENESS

In this study, four models, conventional OLS, VAR, VEC and VAR-MGARCH are employed to estimate optimal hedge ratio. The OLS, VAR and VECM models estimate constant hedge ratio whereas time varying optimal hedge ratios are calculated using bivariate GARCH model (Bollerslev *et al.,* 1988). In this section, first we discuss the hedge ratio and hedging effectiveness and then all four models are presented.

In portfolio theory, hedging with futures can be considered as a portfolio selection problem in which futures can be used as one of the assets in the portfolio to minimize the overall risk or to maximize utility function. Hedging with futures contracts involves purchase/sale of futures in combination with another commitment, usually with the expectation of favorable change in relative prices of spot and futures market (Castelino, 1992). The basic idea of hedging through futures market is to compensate loss/ profit in futures market by profit/loss in spot markets.

The optimal hedge ratio is defined as the ratio of the size of position taken in the futures market to the size of the cash position which minimizes the total risk of portfolio. The return on an unhedged and a hedged portfolio can be written as:

$$\begin{aligned} R_U &= S_{t+1} - S_t \\ R_H &= \left(S_{t+1} - S_t\right) - H\left(F_{t+1} - F_t\right) \end{aligned} \qquad [1]$$

Variances of an unhedged and a hedged portfolio are:

$$\begin{aligned} Var(U) &= \sigma_S^2 \\ Var(H) &= \sigma_S^2 + H^2\sigma_F^2 - 2H\sigma_{S,F} \end{aligned} \qquad [2]$$

where, S_t and F_t are natural logarithm of spot and futures prices, H is the hedge ratio, R_H and R_U are return from unhedged and hedged portfolio, σ_S and σ_F are standard deviation of the spot and futures return and $\sigma_{S,F}$ is the covariance.

Hedging effectiveness is defined as the ratio of the variance of the unhedged position minus variance of hedge position over the variance of unhedged position.

$$Hedging\ Effectiveness(E) = \frac{\left(Var(U) - Var(H)\right)}{Var(U)} \qquad [3]$$

2.1 MODELS FOR CALCULATING HEDGING EFFECTIVENESS AND HEDGE RATIO

Several models have been used to estimate hedge ratio and hedging effectiveness such as conventional OLS model, Vector Autoregressive regression (VAR) model, Vector Error Correction model (VECM), Vector Autoregressive Model with Bivariate Generalized Autoregressive Conditional Heteroscedasticity model (VAR-MGARCH). Hedge performance estimated by OLS, VAR, and VECM is based on assumption that the joint distribution of spot and futures prices is time invariant and does not take into account the conditional covariance structure of spot and futures price, whereas VAR-MGARCH model estimates time varying hedge ratio and time varying conditional covariance structure of spot and futures price.

2.1.1 MODEL 1: OLS METHOD

In this method changes in spot price is regressed on the changes in futures price. The Minimum-Variance Hedge Ratio has been suggested as slope coefficient of the OLS regression. It is the ratio of covariance of (spot prices, futures prices) and variance of (futures prices). The R-square of this model indicates the hedging effectiveness. The OLS equation is given as:

$$R_{St} = \alpha + HR_{Ft} + \varepsilon_t \qquad [4]$$

Where, R_{St} and R_{Ft} are spot and futures return, H is the optimal hedge ratio and ε_t is the error term in the OLS equation. Many empirical studies use the OLS method to estimate optimal hedge ratio, however this method does not take account of conditioning information (Myers & Thompson, 1989) and ignores the time varying nature of hedge ratios (Cecchetti, Cumby, & Figlewski, 1988). It also does not consider the futures returns as endogenous variable and ignores the covariance between error of spot and futures returns. The advantage of this model is the ease of implementation.

2.1.2 MODEL 2: THE BIVARIATE VAR MODEL

The bivariate VAR Model is preferred over the simple OLS estimation because it eliminates problems of autocorrelation between errors and treat futures prices as endogenous variable. The VAR model is represented as

$$R_{St} = \alpha_S + \sum_{i=1}^{k} \beta_{Si} R_{St-i} + \sum_{j=1}^{l} \gamma_{Fj} R_{Ft-j} + \varepsilon_{St}$$
$$R_{Ft} = \alpha_F + \sum_{i=1}^{k} \beta_{Fi} R_{Ft-i} + \sum_{j=1}^{l} \gamma_{Sj} R_{St-j} + \varepsilon_{Ft} \qquad [5]$$

The error terms in the equations, ε_{St}, and ε_{Ft} are independently identically distributed (IID) random vector. The minimum variance hedge ratio are calculated as

$$H = \frac{\sigma_{sf}}{\sigma_f}$$
$$\text{where ,}$$
$$Var(\varepsilon_{St}) = \sigma_s \qquad [6]$$
$$Var(\varepsilon_{Ft}) = \sigma_f$$
$$Cov(\varepsilon_{St}, \varepsilon_{St}) = \sigma_{sf}$$

The VAR model does not consider the conditional distribution of spot and futures prices and calculates constant hedge ratio. It does not consider the possibility of long term integration between spot and futures returns.

2.1.3 MODEL 3: THE ERROR CORRECTION MODEL

VAR model does not consider the possibility that the endogenous variables could be co-integrated in the long term. If two prices are co-integrated in long run then Vector Error Correction model is more appropriate which accounts for long-run co-integration between spot and futures prices (Lien & Luo, 1994; Lien, 1996). If the futures and spot series are co-integrated of the order one, then the Vector error correction model of the series is given as:

$$R_{St} = \alpha_S + \beta_S S_{t-1} + \gamma_F F_{t-1} + \sum_{i=2}^{k} \beta_{Si} R_{St-i} + \sum_{j=2}^{l} \gamma_{Fj} R_{Ft-j} + \varepsilon_{St}$$
$$R_{Ft} = \alpha_F + \beta_F F_{t-1} + \gamma_S S_{t-1} + \sum_{i=21}^{k} \beta_{Fi} R_{Ft-i} + \sum_{j=2}^{l} \gamma_{Sj} R_{St-j} + \varepsilon_{Ft} \qquad [7]$$

where, S_t and F_t are natural logarithm of spot and futures prices. The assumptions about the error terms are same as for VAR model. The minimum variance hedge ratio and hedging effectiveness are estimated by following similar approach as in case of VAR model.

2.1.4 MODEL 4: THE VAR-MGARCH MODEL

Generally, time series data of return possesses time varying heteroscedastic volatility structure or ARCH-effect (Bollerslev *et al*, 1992). Due to ARCH effect in the returns of spot and futures prices and their time varying joint distribution, the estimation of hedge ratio and hedging effectiveness may turn out to be inappropriate. Cecchetti, Cumby, and Figlewski (1988) used ARCH model to represent time variation in the conditional covariance matrix of Treasury bond returns and bond futures to estimate time-varying optimal hedge ratios and found substantial variation in optimal hedge ratio. The VAR-MGARCH model considers the ARCH effect of the time series and calculate time varying hedge ratio. A bivariate GARCH (1,1) model is given by:

$$
\begin{aligned}
R_{St} &= \alpha_S + \sum_{i=1}^{k} \beta_{Si} R_{St-i} + \sum_{j=1}^{l} \gamma_{Fj} R_{Ft-j} + \varepsilon_{St} \\
R_{Ft} &= \alpha_F + \sum_{i=1}^{k} \beta_{Fi} R_{Ft-i} + \sum_{j=1}^{l} \gamma_{Sj} R_{St-j} + \varepsilon_{Ft} \\
\begin{bmatrix} h_{ss} \\ h_{sf} \\ h_{ff} \end{bmatrix} &= \begin{bmatrix} C_{ss} \\ C_{sf} \\ C_{ff} \end{bmatrix}_t + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_s^2 \\ \varepsilon_s \varepsilon_f \\ \varepsilon_f^2 \end{bmatrix}_{t-1} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \alpha_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} h_{ss} \\ h_{sf} \\ h_{ff} \end{bmatrix}_{t-1}
\end{aligned} \qquad [8]
$$

where, h_{ss} and h_{ff} are the conditional variance of the errors ε_{st} and ε_{ft} and h_{sf} is the covariance.

Bollerslev *et al*. (1988) proposed a restricted version of the above model in which the only diagonal elements of **α** and **β** matrix are considered and the correlations between conditional variances are assumed to be constant. The diagonal representation of the conditional variances elements h_{ss} and h_{ff} and the covariance element h_{sf} is presented as (Bollerslev *et al.,* 1988):

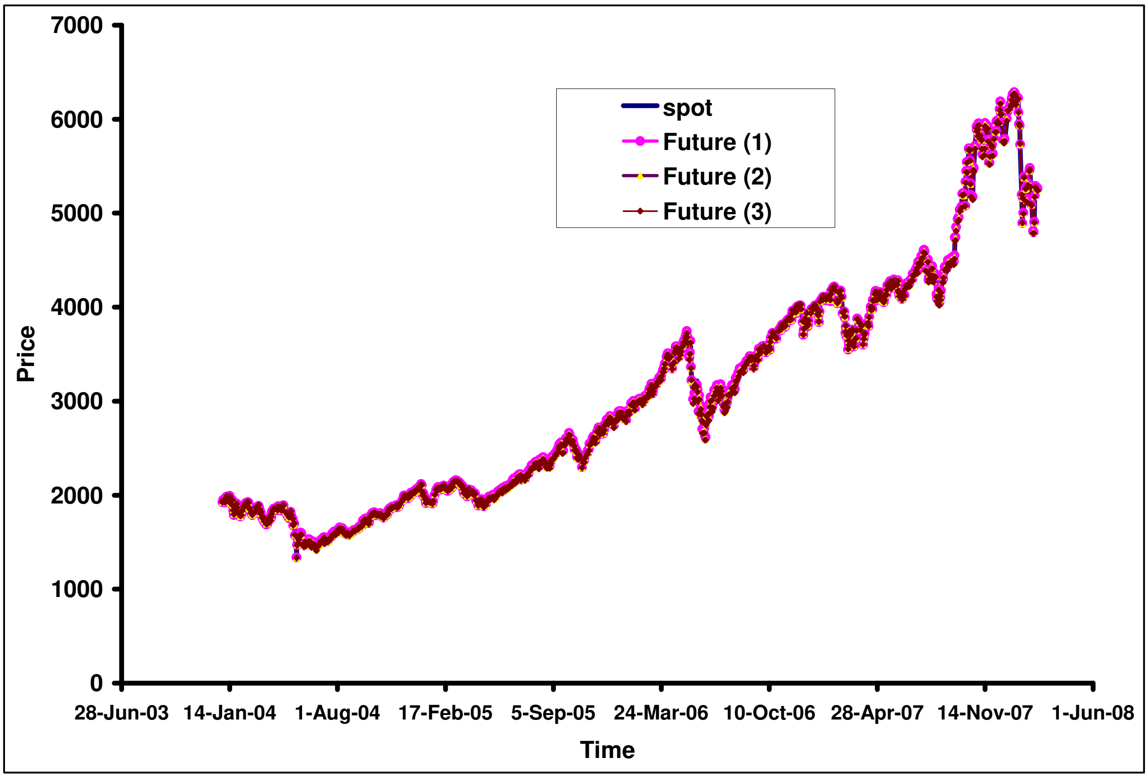
$$
\begin{aligned}
h_{ss,t} &= C_{ss} + \alpha_{ss}\varepsilon_{s,t-1}^2 + \beta_{ss} h_{ss,t-1} \\
h_{sf,t} &= C_{sf} + \alpha_{sf}\varepsilon_{s,t-1}\varepsilon_{f,t-1} + \beta_{sf} h_{sf,t-1} \\
h_{ff,t} &= C_{ff} + \alpha_{ff}\varepsilon_{f,t-1}^2 + \beta_{ff} h_{ff,t-1}
\end{aligned} \qquad [9]
$$

Time varying hedge ratio is calculated as follows:

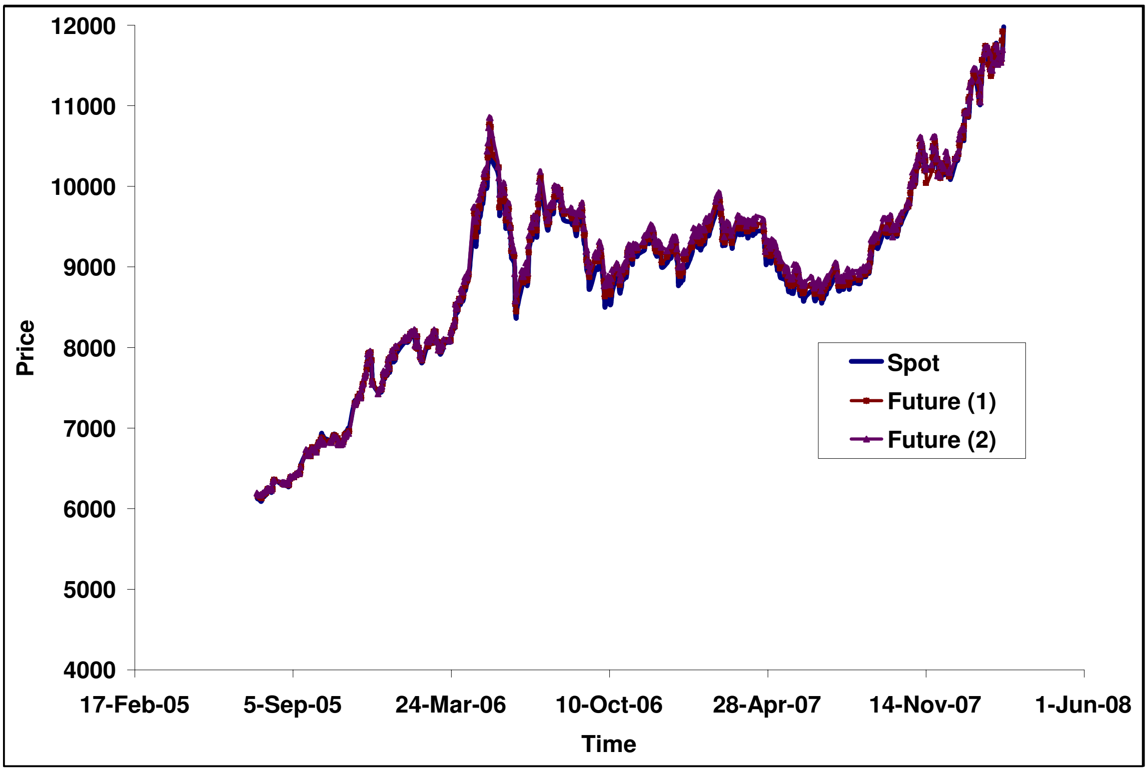
$$H_t = \frac{h_{sft}}{h_{fft}} \qquad [10]$$

3. CHARACTERISTICS OF FUTURES PRICES

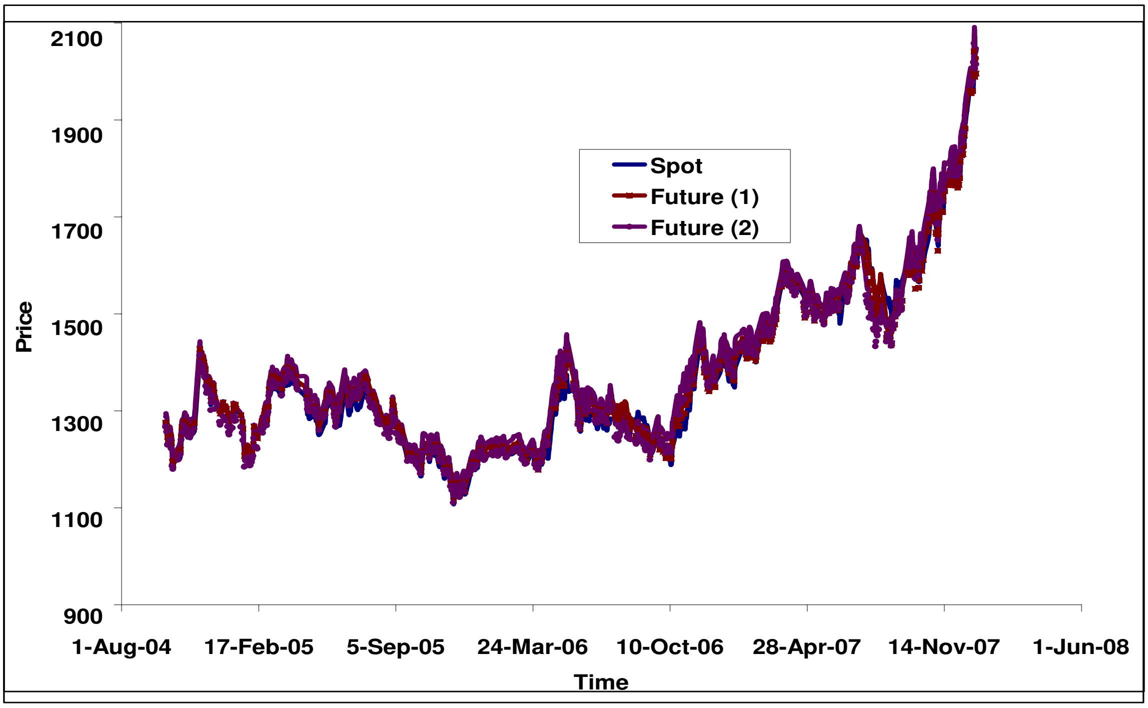
Daily closing price data on S&P CNX Nifty index and its futures contracts, published by NSE India, for the period from 1st January 2004 to 8th May 2008 has been analyzed in this study. All three futures contracts trading at a given point of time are analyzed and compared. Data for the period of 21st February 2008 to 8th May 2008 has been used for out-of-the-sample analysis. Similarly, two Gold futures for the period from 22nd July 2005 to 8th May 2008 and two Soybean futures from 4th October 2004 to 8th May 2008 are also considered. For Gold and Soybean, data for the period of 21st February 2008 to 8th May 2008 and 1st January 2008 to 8th may 2008 has been are used for out-of-the-sample analysis respectively. These commodities are traded on National Commodity Exchange, India. Spot prices obtained from the commodity exchanges are not reliable as there is no spot trading and they are collected from some regional markets. These prices might not be a true representation of spot prices because of market imperfection, difference in quality and policy restriction on the movement of commodities. Hence, following Fama and French (1987), Bailey and Chan (1993), Bessembinder *et al.* (1995), Mazaheri (1999) and Frank and Garcia (2008), the nearby futures prices Gold and Soybean are used as a proxy for the spot price and the subsequent futures price as the futures price. Time series of spot and futures prices of these assets are given in Figure 1.



a) Nifty



b) Gold



c) Soybean

Figure 1: Spot and futures prices of a) Nifty b) Gold and c) Soybean

3.1: TEST OF UNIT ROOT AND COINTEGRATION

Stationarity of the prices and their first difference are tested using ADF and KPSS test statistics. KPSS is often suggested as a confirmatory test of stationarity. The null hypothesis for ADF test is that the series contains unit root whereas stationarity of the series is used as the null hypothesis for KPSS test. The summary statistics are shown in Table 1.

Table 1: Unit root tests on prices and returns

Asset	Price series	ADF (t stat)	KPSS (LM stat)	Return series	ADF (t stat)	KPSS (LM stat)
Nifty	Spot	-3.1287	0.518785**	Spot	-30.512**	0.053376
	Future1[8]	-3.0217	0.512487**	Future1	-32.2084**	0.061826
	Future2	-3.0141	0.510871**	Future2	-32.31197**	0.054473
	Future3	-3.0036	0.512137**	Future3	-32.27063**	0.051550
Gold	Spot	-1.4494	0.349708**	Spot	-24.59546**	0.156087
	Future1	-1.4692	0.364389**	Future1	-23.59079**	0.128691
	Future2	-1.7648	0.374682**	Future2	-22.9685**	0.123841
Soybean	Spot	-0.2678	0.745553**	Spot	-27.48925**	0.047505
	Future1	-0.1900	0.692446**	Future1	-28.09060**	0.031771
	Future2	-1.2823	0.240624**	Future2	-27.99354**	0.035745

*(**) denotes rejection of the hypothesis at the 5%(1%) level

[8] The near month futures are named as Future 1, next to near month futures as Future 2 and Future 3 subsequently. So for Nifty futures there are three futures series (Future 1, Future 2 and Future 3) and for Gold and Soybean, there are two futures series only.

Both ADF and KPSS test statistics confirm that all prices have unit root (non-stationary) and return series are stationary. They have one degree of integration (I(1)- process). The co-integration between spot and futures prices is tested by Johansen's (1991) maximum likelihood method. The results of co-integration are presented in Table 2. It can be observed that spot and futures prices have one co-integrating vector and they are co-integrated in the long run.

Table 2: Johansen co-integration tests of spot and futures prices

		Spot-Future 1		Spot-Future 2		Spot-Future 3	
	Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Eigenvalue	Trace Statistic	Eigenvalue	Trace Statistic
Nifty	None	0.04048**	43.028**	0.01973**	22.3309**	0.014**	16.737**
	At most 1	0.00236	2.325366	0.002744	2.706341	0.0029	2.8595
Gold	None	0.02739**	20.726**	0.02351**	18.62156	--	--
	At most 1	0.0046	2.950516	0.005287	3.392959	--	--
Soybean	None	0.02551**	23.823**	0.01589**	13.6849**	--	--
	At most 1	0.00408	3.255157	0.00117	0.931647	--	--

*(**) denotes rejection of the hypothesis at the 5%(1%) level

4. HEDGE RATIO AND EFFECTIVENSS: EMPIRICAL PERFORMANCE OF MODELS

Hedge ratio and hedging effectiveness of Index futures (Nifty) and commodity futures (Soybean and Gold) is estimated through four models (OLS, VAR, VECM and bivariate GARCH) described earlier. We also estimated the time varying hedge ratio for Nifty and Gold futures by VAR-MGARCH approach[9]. In-sample and out-of-sample estimates of hedge ratio and hedging effectiveness calculated from these models are compared.

4.1 IN-SAMPLE RESULTS

4.1.1 OLS ESTIMATES

OLS regression (equation [4]) has been used to calculate the hedge ratio and hedging effectiveness. The slope of the regression equation gives the hedge ratio and R^2, the hedging effectiveness.

[9] For Soybeans futures, we did not get the optimized solution. As addressed by Bera and Higgins (1993), one disadvantage of Diagonal GARCH models is that the covariance matrix is not always positive definite and therefore the numerical optimization of likelihood function may fail.

Table 3: OLS regression model estimates

	Nifty			Gold		Soybean	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**	**Future 1**	**Future 2**
α	-0.00708	-0.00172	0.00209	0.01025	0.01986	-0.02749*	-0.03430*
β	0.91181*	0.90519*	0.90836*	0.92387*	0.73613*	0.93092*	0.90329*
R^2	0.9696	0.9641	0.9483	0.8076	0.4749	0.9264	0.8856

**(*) denotes significance of estimates at 5%(10%) level

For all futures contracts, the hedge ratio is higher than 0.90 except for Gold far month maturity contract (Future 2). Hedge ratio estimated from OLS method provides approximately 90% variance reduction except for Gold far month maturity contract (Future 2), which indicates that the hedge provided by these contracts in Indian markets is effective. Hedging effectiveness was highest for Nifty futures. Near month Gold futures provides 81% of hedging effectiveness as compared to 47% for distant futures. Hedging effectiveness decreases as we move from near-month futures to distant futures (except Nifty futures where this decrease is not very high).

4.1.2 VAR ESTIMATES

To calculate the hedge ratio and hedging effectiveness, system of equations (equation [5]) is solved and errors are estimated. We used errors from the equation [5] to calculate hedge ratio and hedging effectiveness (equation [6]) of futures contracts. The estimates of the parameters of the spot and futures equations are given in Table 3 and the optimal hedge ratio and hedge effectiveness is presented in Table 4.

Table 3: Estimates of VAR model

a) Spot prices

	Nifty			Gold		Soybean	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**	**Future 1**	**Future 2**
α	0.09214	0.08637	0.08509	0.06614	0.06546	0.00085	-0.00353
β_{S1}	0.14468	0.2071	0.12434	0.09816	0.11122**	-0.19642	-0.13519
β_{S2}	-0.12895	-0.16246	-0.30353*	0.36298**	0.12681	0.03143	-0.07937
β_{S3}	0.10678	-0.03455	-0.03626	0.09341	-0.00594*	0.04543	0.00736
β_{S4}	0.50512**	0.19228	0.19243	0.10787	0.14862*	-0.00664	-0.00246
β_{S5}	-0.32561*	-0.31132*	-0.20545	0.10335	-0.05476	0.15701	0.15894
γ_{F1}	-0.10171	-0.16171	-0.08523	-0.08508	-0.12387**	0.22555*	0.16481
γ_{F2}	0.04836	0.07645	0.21881	-0.31548**	-0.02595	-0.02557	0.08449
γ_{F3}	-0.15247	-0.01885	-0.01435**	-0.06837	0.01545*	-0.04081	0.00479
γ_{F4}	-0.42778*	-0.12553	-0.13059	-0.01858	-0.10056	0.04695	0.04648
γ_{F5}	0.27177	0.2698*	0.17751	-0.13055	0.10731	-0.1385	-0.1397
R^2	0.0246	0.0201	0.0213	0.0285	0.0319	0.0084	0.0094

**(*) denotes significance of estimates at 5%(10%) level

b) Futures prices

	Nifty			Gold		Soybean	
	Future 1	Future 2	Future 3	Future 1	Future 2	Future 1	Future 2
α	0.12091	0.10755	0.09914	0.05415	0.05605	0.02916	0.03014
β_{F1}	-0.4732**	-0.5627	-0.492**	-0.53844	-0.4942**	0.22818*	0.18973*
β_{F2}	-0.0285	-0.05761	0.06083	-0.40597	-0.3183**	0.00498	0.11157
β_{F3}	-0.19424	-0.05445	-0.09935	-0.22715	-0.1462**	-0.00003	0.03671
β_{F4}	-0.4963**	-0.20183	-0.2154	-0.0619	-0.13343	0.02607	0.03589
β_{F5}	0.33615*	0.34771	0.2572**	-0.17291	0.04439*	-0.13979	-0.08613
γ_{S1}	0.4955**	0.58919	0.51681**	0.6106	0.63558**	-0.23662*	-0.20014
γ_{S2}	-0.06068	-0.04133	-0.14814	0.45884	0.39217**	-0.00376	-0.11967
γ_{S3}	0.14156	-0.00243	0.03812	0.24972	0.17249**	-0.00964	-0.04245
γ_{S4}	0.57068**	0.27239	0.27647	0.16595	0.19705**	0.01516	0.00659
γ_{S5}	-0.4091**	-0.40625	-0.3009**	0.12147	0.01591	0.1641	0.11441
R^2	0.0301	0.0296	0.0332	0.084	0.2229	0.0073	0.0089

**(*) denotes significance of estimates at 5%(10%) level

Table 4: Estimation of hedge ratio and hedging effectiveness

	Nifty			Gold		Soybean	
	Future 1	Future 2	Future 3	Future 1	Future 2	Future 1	Future 2
Covariance(ε_F, ε_S)	1.955675	1.964752	1.927051	0.626340	0.446827	0.572247	0.562553
Variance (ε_F)	2.136124	2.155891	2.105059	0.643147	0.505961	0.616320	0.622840
Hedge Ratio	0.915525	0.911341	0.915438	0.973868	0.883125	0.928490	0.903207
Variance (ε_S)	1.840382	1.848928	1.846569	0.720482	0.717998	0.574066	0.573491
Variance(H)	0.049913	0.058369	0.082473	0.110509	0.323394	0.042741	0.065389
Variance(U)	1.840382	1.848928	1.846569	0.720482	0.717998	0.574066	0.573491
Hedging Effectiveness, E	0.972879	0.968431	0.955337	0.846618	0.549590	0.925547	0.885981

Hedge ratio calculated from VAR model are higher and perform better than OLS estimates in reducing variance. Hedge ratio estimated through VAR model increased from 0.71 (OLS estimate) to 0.88 in case of Gold Futures 2. For the same futures, hedging effectiveness also increase from 47%, in case of OLS, to 55%. Improvement is also observed for other futures contracts.

4.1.3 VECM estimates

Using the same approach as in case of VAR model, errors are estimated and hedging effectiveness and hedge ratio are calculated for VECM model. Results of the equation [7] are presented in Table 5. Table 6 illustrates the estimates of hedge ratio and hedging effectiveness of futures contracts.

Table 5: Estimates of VECM model

a) Spot prices

	Nifty			Gold		Soybean	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**	**Future 1**	**Future 2**
α	-0.00001	-0.00149	-0.00224	-0.00532	-0.00202	-0.02532	-0.0408**
β_S	0.05004	0.08557	0.09408	0.20126	0.10592	-0.09951	-0.07257
β_{S2}	0.46701**	0.55394**	0.42326**	-0.3692**	-0.05038	0.28075**	-0.1840**
β_{S3}	0.05165	0.08965	-0.02764	-0.01643	0.05927	-0.19247*	-0.14661*
β_{S4}	0.05019**	0.18872	0.32751*	-0.06997	-0.02164	-0.04046	-0.03318
β_{S5}	0.54985	0.68071**	0.64861**	0.01489	0.17944**	-0.2038**	-0.08434
γ_F	-0.04993	-0.08532	-0.09376	-0.20043	-0.10544	0.10293	0.07811
γ_{F2}	-0.36327*	-0.4412**	-0.32379*	0.40538**	0.05899	0.28704**	0.1867**
γ_{F3}	-0.12872	-0.16659	-0.04819	0.04557	-0.01813	0.15622	0.10214
γ_{F4}	-0.07455	-0.20544	-0.33422	0.03953	-0.00939	0.05576	0.04407
γ_{F5}	-0.4718**	-0.5920**	-0.5729**	-0.02166	-0.2352**	0.24222**	0.1148
R^2	0.0243	0.0318	0.0358	0.0258	0.0307	0.0384	0.0385

**(*) denotes significance of estimates at 5%(10%) level

b) Futures prices

	Nifty			Gold		Soybean	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**	**Future 1**	**Future 2**
α	-0.003	-0.00339	-0.00415	-0.00749	-0.00367	-0.00949	-0.0205
β_F	-0.2064**	-0.1512**	-0.14817	-0.2663	-0.15307	0.04014	0.03983
β_{F2}	-0.6994	-0.90632	-0.8538**	-0.27776*	-0.4906**	0.28336**	0.18402**
β_{F3}	-0.26479	-0.36496	-0.32946*	-0.25836	-0.3937**	0.15243	0.0755
β_{F4}	-0.16024	-0.2986**	-0.5275**	-0.2692*	-0.2634**	0.01391	0.03344
β_{F5}	-0.6037**	-0.76175	-0.7618**	-0.1454	"-0.259**	0.16678	0.07962
γ_S	0.20687	0.15161	0.14868	0.26741	0.15376	-0.03881	-0.03701
γ_{S2}	0.79099**	1.01436**	0.95749**	0.3334**	0.55949**	-0.2917**	-0.1886**
γ_{S3}	0.19292	0.29177	0.26873**	0.30404*	0.43944**	-0.18824	-0.12756
γ_{S4}	0.1372	0.28757	0.52992**	0.24972	0.261**	-0.00141	-0.03412
γ_{S5}	0.69213**	0.86826**	0.855**	0.14775	0.26046**	-0.1378**	-0.06379
R^2	0.034	0.0475	0.0604	0.0551	0.1828	0.0201	0.0181

**(*) denotes significance of estimates at 5%(10%) level

Although VECM model does not consider the conditional covariance structure of spot and futures price, it is supposed to be best specified model for the estimations of constant hedge ratio and hedging effectiveness because it factors in any long term co-integration between spot and futures prices. It has been found that in-sample performance of VECM model provides better variance reduction that VAR and OLS model. OLS seems to be least efficient. Our results are consistent with the findings of Ghosh (1993).

Table 6: Estimation of hedge ratio and hedging effectiveness

	Nifty			Gold		Soybean	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**	**Future 1**	**Future 2**
Covariance(ε_F, ε_S)	0.00029897	0.00029729	0.00029241	0.00010045	0.00007981	0.00011045	0.00010678
Variance (ε_F)	0.00032731	0.00032633	0.00032054	0.00010070	0.00008141	0.00012089	0.00012563
Hedge Ratio	0.91341151	0.91101612	0.91224194	0.99757688	0.98027566	0.91357658	0.85001364
Variance (ε_S)	0.00027996	0.00027782	0.00027665	0.00011035	0.00010979	0.00011397	0.00011395
Variance(H)	0.00000688	0.00000698	0.00000991	0.00001013	0.00003155	0.00001307	0.00002318
Variance(U)	0.00027996	0.00027782	0.00027665	0.00011035	0.00010979	0.00011397	0.00011395
Hedging Effectiveness, E	0.97542167	0.97487147	0.96418452	0.90816098	0.71260213	0.88532617	0.79655091

4.1.4 VAR-MGARCH MODEL

VAR-MGARCH model is used to modify the estimation of hedge ratio for time varying volatility and to incorporate non-linearity in the mean equation. Errors of the VAR and VECM models are analyzed for presence of "ARCH effect" and it was found that the errors have time varying volatility. Errors obtained from the VAR and VECM model are shown in Appendix 1[10]. VAR models with bivariate Diagonal GARCH (1,1) are used and results are presented in Table 7.

Table 7: GARCH estimates of the VAR-MGARCH (1,1) model

	Nifty			Gold	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**
C_{ss}	1.88922**	1.89082**	1.74192**	0.67245**	0.68831**
C_{sf}	2.01818**	2.00367**	1.85564**	0.58417**	0.43065**
C_{ff}	2.19812**	2.17527**	2.20075**	0.53565**	0.47647**
α_{11}	0.0014**	0.14607**	-0.43134**	0.69091**	0.32432**
α_{22}	-0.00147**	0.15032**	-0.42755**	0.55232**	0.26384**
α_{33}	0.00312**	0.16131**	-0.39683**	0.45838**	0.32959**
β_{11}	-0.00523**	0.02881**	-0.05434**	0.00961**	-0.01095**
β_{22}	0.01247**	0.00045**	-0.02726**	0.05161**	0.01465**
β_{33}	-0.00589**	-0.03453**	-0.05503**	0.10733**	-0.06218**

**(*) denotes significance of estimates at 5%(10%) level

[10] Results of ARCH text on residuals, obtained from VAR and VECM, can be obtained from authors on request.

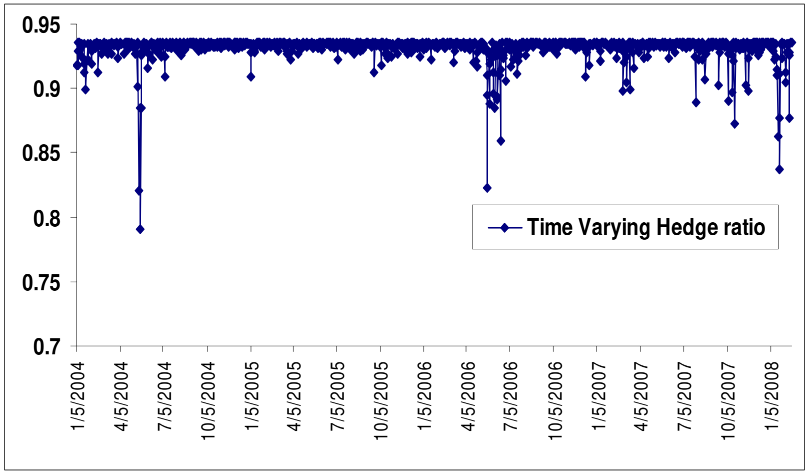
Time varying hedge ratio for Nifty and Gold futures has been estimated using error structure and GARCH (1,1) parameters obtained from equation [8]. Time varying hedge ratio estimated from constant conditional correlation and time varying covariance structure of spot and futures prices are shown in Figure 2. Statistical properties of Hedge ratio obtained from M-GARCH model for Nifty and Gold futures are given in table 8.

Table 8: Statistical properties of dynamic hedge ratio fromVAR-MGARCH model

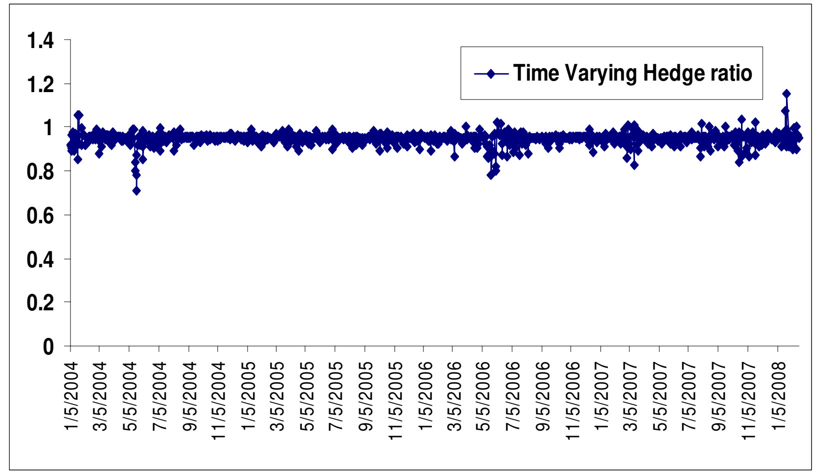
	Hedge Ratio	Min	Max	Mean	SD
Nifty	Future 1	0.79112	0.935219	0.931028	0.011024
	Future 2	0.710722	1.153131	0.9476	0.027281
	Future 3	-9.039	9.616319	0.842709	0.655289
Gold	Future 1	-0.56527	1.884075	1.028782	0.141592
	Future 2	-0.46332	3.213549	0.951656	0.201246

The mean hedge ratio estimated from the time-varying conditional variance and covariance between spot and futures returns are higher than other methods (except Nifty Futures 3). The average optimal hedge ratio for Nifty Futures 1, Futures 2 and Futures 3 are 0.9310, 0.9476 and 0.8427 respectively. For Gold Futures 1 and Futures 2, this ratio is 1.0288 and 0.9516 respectively. It is found that as we move to distant futures the variation in hedge ratio increases (0.011024 to 0.655289 in case of Nifty and 0.141592 to 0.201246 in case of Gold).

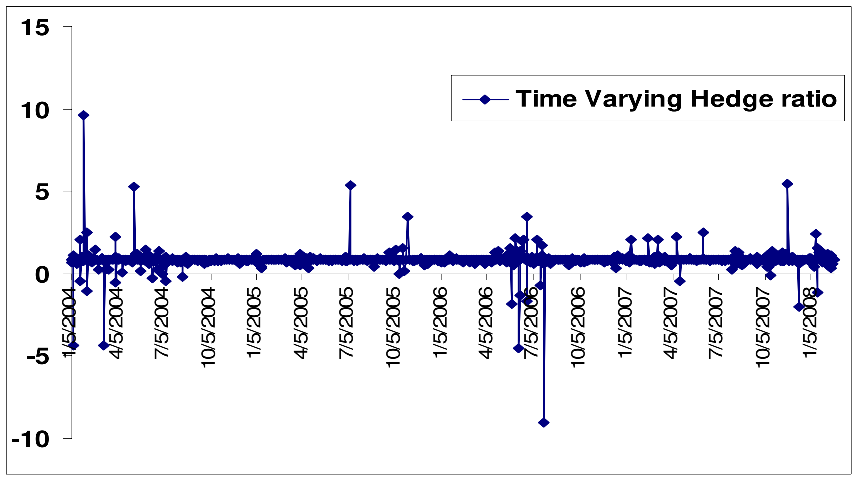
Since the dynamics hedge ratio are less stable and having pronounced fluctuations, the hedger has to adjust their futures positions more often. The negative hedge ratio reflects the fact that spot and futures prices may move in opposite direction (negative covariance) in short run (Tong, 1996). It requires the hedger to go long in futures market to hedge the long spot position.



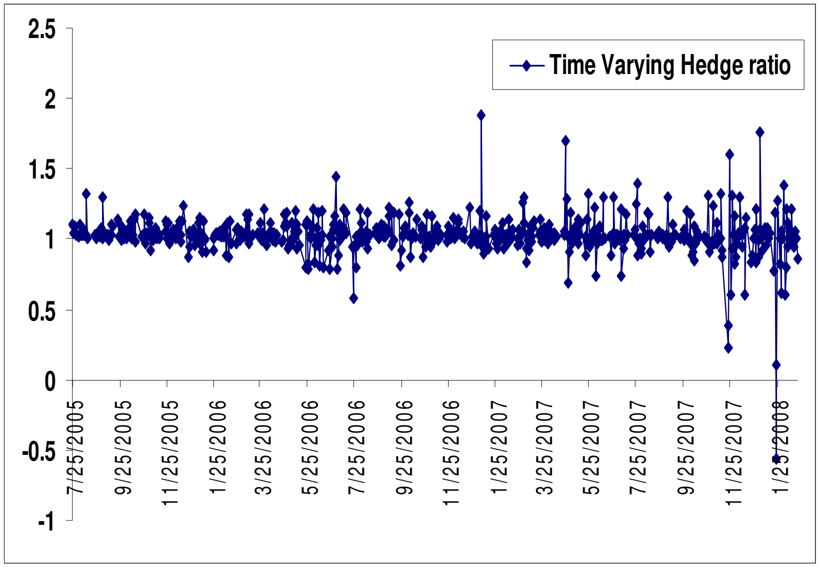
a) Nifty Future 1



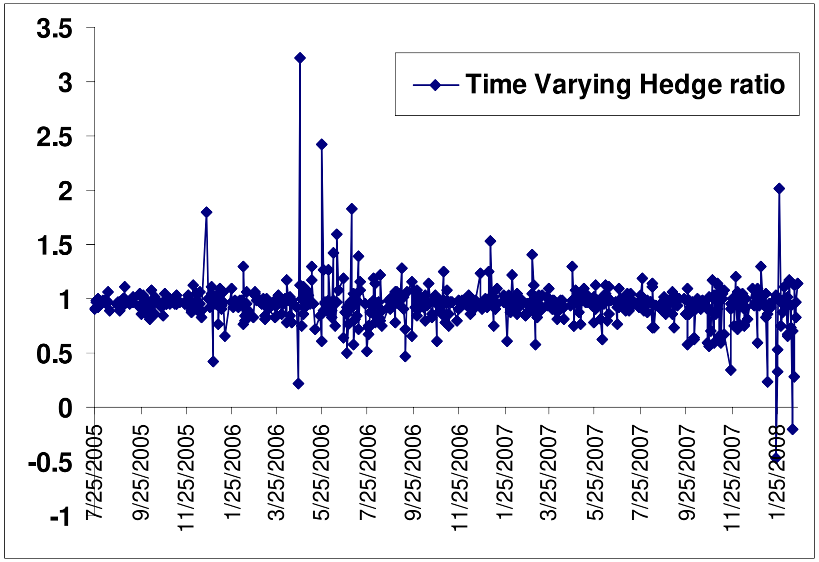
b) Nifty Future 2



c) Nifty Future 3



d) **Gold Future 1**



e) Gold Future 2

Figure 2: Estimates of time varying hedge ratio from VAR-MGARCH model.

Constant hedge ratio obtained from OLS, VAR, VECM and average of time varying hedge ratio obtained from VAR-MGARCH model is compared in Table 9 & 10. Our results show that hedge ratio calculated from VAR-MGARCH (1,1) are higher and provide greater variance reduction than other models. Similar results were reported in the previous studies of Myers (1991), Baillie and Myers (1991) and Park and Switzer (1995a,b) in the US financial and commodity markets. In case of constant hedge ratio estimation, VECM performs better than OLS and VAR models. Similar results were found by Ghosh (1993).

Table 9: In-sample comparison of optimal hedge ratio estimates by different models

	Nifty			Gold		Soybean	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**	**Future 1**	**Future 2**
OLS	0.91181	0.90519	0.908360	0.92387	0.73613	0.93092	0.90329
VAR	0.91552	0.91134	0.915438	0.97387	0.88312	0.92849	0.903207
VECM	0.913411	0.91102	0.912242	0.99758	0.980275	0.913576	0.850013
VAR-MGARCH	0.93103	0.9476	0.84271	1.02878	0.95165	--	--

Table 10: In-sample comparison of optimal hedging effectiveness estimates by different models

	Nifty			Gold		Soybean	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**	**Future 1**	**Future 2**
OLS	0.9696	0.9641	0.9483	0.8076	0.4749	0.9264	0.8856
VAR	0.972879	0.968431	0.955337	0.846618	0.54959	0.925547	0.88598
VECM	0.9754217	0.9748715	0.964184	0.908161	0.712602	0.8853262	0.79655
VAR-MGARCH	1.009626	0.977068	0.911171	0.892781	0.597047		

4.2 OUT-OF-THE-SAMPLE RESULTS

Brook and Chong (2001) suggested that out-of-the-sample evaluation of models is more appropriate because traders are more concerned with future performance. This is particularly true for comparing performance of a model using dynamic hedge ratio. Hence, data for the period of 21st February 2008 to 8th May 2008 has been used for out of sample analysis for nifty futures. Similarly, for Gold and Soybean, data for the period of 21st February 2008 to 8th May 2008 and 1st January 2008 to 8th May 2008 has been used for out-of-sample analysis respectively. For OLS, VAR and VECM models, the estimated hedge ratios from the estimation period are used for testing their out-of the-sample performance. For bivariate GARCH, we estimate one-period-ahead estimates of conditional variance and covariance of spot and futures prices from parameters estimated from estimation period. Out of sample estimates of hedge ratio and their statistical properties for VAR-MGARCH (1,1) are presented in Table 11. Figure 3 illustrates the comparison of out-of-sample estimates of hedge ratio from GARCH model and in-sample estimates of OLS, VAR and VEC model.

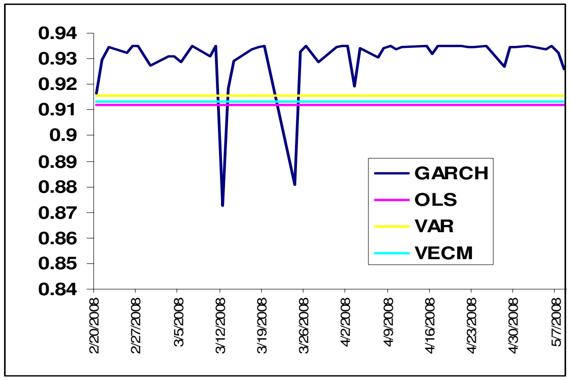
Table 11 Out of sample estimates of hedge ratio and their statistical properties

	Hedge Raio	Min	Max	Mean	SD
Nifty	Future 1	0.872641	0.935207	0.929749	0.012059
	Future 2	-0.20942	1.392218	0.730338	0.321048
	Future 3	-6.21891	2.526035	0.524149	1.452091
Gold	Future 1	0.211217	1.953885	0.989963	0.241402
	Future 2	1.099314	16.79628	3.456777	2.652792

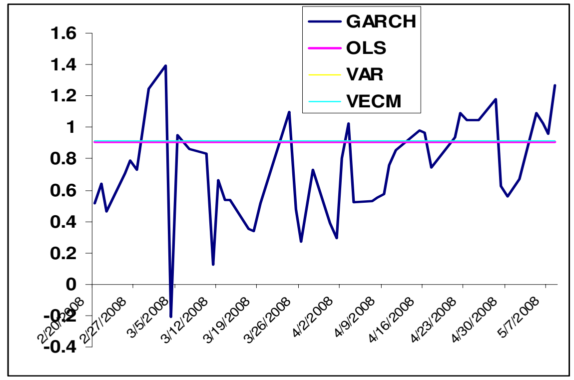
Out-of-sample estimates of dynamic hedge ratio in Nifty and Gold futures have higher variability than in-sample estimates. As observed in in-sample results, variation in the dynamic hedge ratio of distant month futures is more than in near month futures. Out-of sample performance of hedging effectiveness calculated from OLS, VAR, and VECM model are estimated and given in Table 12 to 14.

Table 12: OLS model

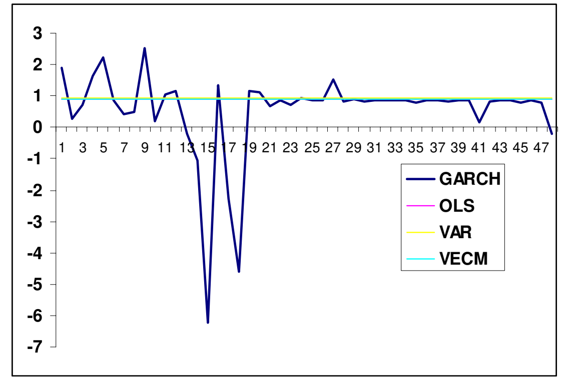
	Nifty			Gold		Soybean	
	Future 1	Future 2	Future 3	Future 1	Future 2	Future 1	Future 2
Covariance(ε_F, ε_S)	2.497725	2.810920	1.855876	0.645968	0.417951	2.127770144	2.100567881
Variance (ε_F)	2.728433	5.152587	4.004857	0.978732	3.410071	2.307298235	2.300496681
Hedge Ratio, H	0.911810	0.905190	0.908360	0.92387	0.73613	0.93092	0.90329
Variance (ε_S)	2.452104	2.452104	2.452104	1.08058933	1.08058933	2.094264	2.094264
Variance (Hedged)	0.165615	1.585141	2.384976	0.726082	3.107916	0.132059	0.248292
Variance (Unhedged)	2.452104	2.452104	2.452104	1.08058933	1.08058933	2.094264	2.094264
Hedging Effectiveness, E	0.932460	0.353559	0.027376	0.328069	-1.876130	0.936942	0.881442



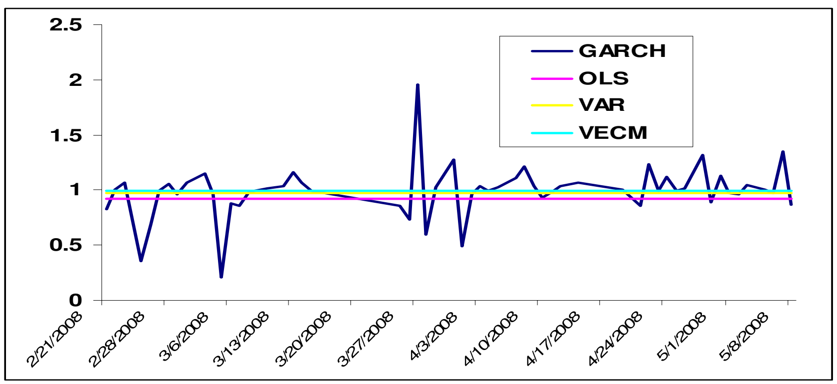
a) Nifty Future 1



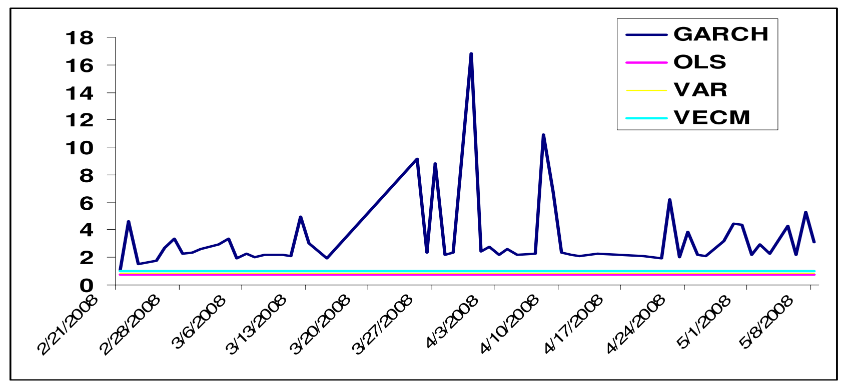
b) Nifty Future 2



c) Nifty Future 3



d) Gold Future 1



e) Gold Future 2

Figure 3: Out-of-sample comparison of hedge ratio

Table 13: VAR model

	Nifty			Gold		Soybean	
	Future 1	Future 2	Future 3	Future 1	Future 2	Future 1	Future 2
Covariance(ε_F, ε_S)	2.695598	2.459859	2.223129	0.621495702	0.767535287	2.101569844	2.088639265
Variance (ε_F)	2.868049	3.841825	4.037208	0.647550447	3.492637982	2.292162006	2.297210329
Hedge Ratio, H	0.915525	0.911341	0.915438	0.973868	0.883125	0.92849	0.903207
Variance (ε_S)	2.692616	2.460410	2.923080	1.086411499	1.241911142	2.060467463	2.08568957
Variance (Hedged)	0.160799	1.167668	2.236094	0.490051	2.610194	0.133953	0.186767
Variance (Unhedged)	2.692616	2.460410	2.923080	1.086411499	1.241911142	2.060467463	2.08568957
Hedging Effectiveness, E	0.940281	0.525417	0.235021	0.548927	-1.101756	0.934989	0.910453

Table 14: VECM Model

	Nifty			Gold		Soybean	
	Future 1	Future 2	Future 3	Future 1	Future 2	Future 1	Future 2
Covariance (ε_F, ε_S)	0.0002501	0.0007967	0.0004581	6.63211E-05	-3.89E-06	0.0002335	0.0002289
Variance (ε_F)	0.000278	0.0013100	0.0008337	9.34037E-05	0.000346896	0.0002415	0.0002106
Hedge Ratio, H	0.913411	0.911016	0.9122419	0.99757688	0.98027566	0.913576	0.850013
Variance (ε_S)	0.00024	0.000590	0.000426	0.000113105	0.000111004	0.0003519	0.0002116
Variance (Hedged)	0.000020	0.000225	0.000284	0.000074	0.000452	0.000127	-0.000025
Variance (Unhedged)	0.000245	0.000590	0.000426	0.000113105	0.000111004	0.0003519	0.0002116
Hedging Effectiveness, E	0.917644	0.617806	0.333268	0.348076	-3.071775	0.639576	1.119445

Out-of- the sample, among constant hedge models, OLS and VAR models perform better than VECM for near month futures. However, for distant month futures VECM perform better than OLS and VAR[11] models. We also compare the out-of- the sample hedging effectiveness of constant hedge ratio models and dynamic hedge ratio models, bivariate GARCH. These comparisons are presented in Table 15.

[11] In case of Gold futures 2, we find negative hedge effectiveness estimated from all constant hedge models. This may be because of higher futures return variance.

Table 15: Out-of-sample comparison of optimal hedging effectiveness of different models

	Nifty			Gold		Soybean	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**	**Future 1**	**Future 2**
OLS	0.93246	0.353559	0.027376	0.32807	-1.87613	0.936942	0.88144
VAR	0.94028	0.525417	0.235021	0.54893	-1.10175	0.934989	0.91045
VECM	0.91764	0.617806	0.333268	0.34808	-3.07177	0.639576	1.11945
VAR-MGARCH	1.00710	0.752793	1.312628	0.787436	2.69272		

Across all futures contracts, dynamic hedge ratio model, bivariate GARCH, performs better than constant hedge ratio models in variance reduction. Similar results were found in studies of Myers (1991), Baillie and Myers (1991) Park and Switzer (1995) Kavussanos and Nomikos (2000), Yang (2001), and Floros and Vougas (2006). However, hedging strategy suggested by VAR-MGARCH model may requires frequent shift in hedging positions and would result in associated transaction costs.

5. CONCLUSIONS

In an emerging market like India, where stock and commodity markets are growing at a fast rate and derivatives have been introduced recently, it is important to evaluate the hedging effectiveness of derivatives. In the present paper, we report hedge ratios of Nifty, Gold and Soybean futures from four alternative modeling frameworks, an OLS-based model, a VAR model, a VECM model and a multivariate GARCH model. We compare the hedging effectiveness of the contacts using these models, *ex post* (in-sample) and *ex ante* (out-of-sample).

Our results show that futures and spots prices are found to be co-integrated in the long run. Among constant hedge ratio models, in most of the cases, VECM performs better than OLS and VAR models, which is consistent with previous findings of Ghosh (1993b). Time varying hedge ratio derived from VAR-MGARCH model provides highest variance reduction as compared to the other methods in both in-sample as well as out-of sample period for all contracts. This result is consistent with the results of Myers (1991), Baillie and Myers (1991), Park and Switzer (1995a,b), Lypny and Powella (1998), Kavussanos and Nomikos (2000), Yang (2001), and Floros and Vougas (2006). VAR-MGARCH hedge ratio, however, varies dramatically over time and calls for frequent changes in hedging positions. Transaction cost in implementing dynamic hedging using VAR-MGARCH may nullify some of the gains provided by it. Both stock market and commodity derivatives markets in India provide a reasonably high level of hedging effectiveness (90%) and it can be said that derivatives markets in Indian context provide useful risk management tool for hedging and for portfolio diversification.

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APPENDIX

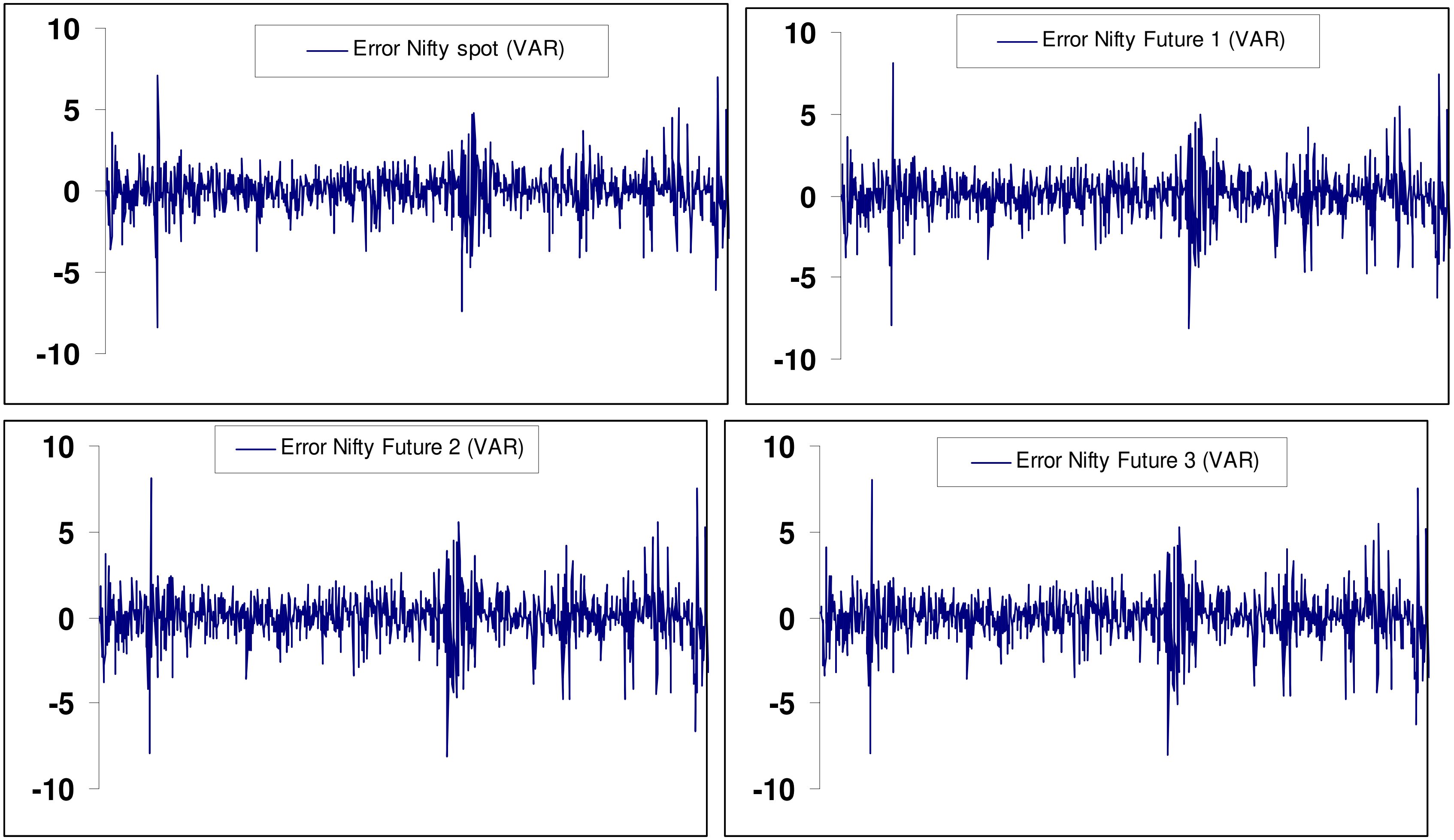

Figure 1: Residual series from spot and futures equation in VAR model for nifty

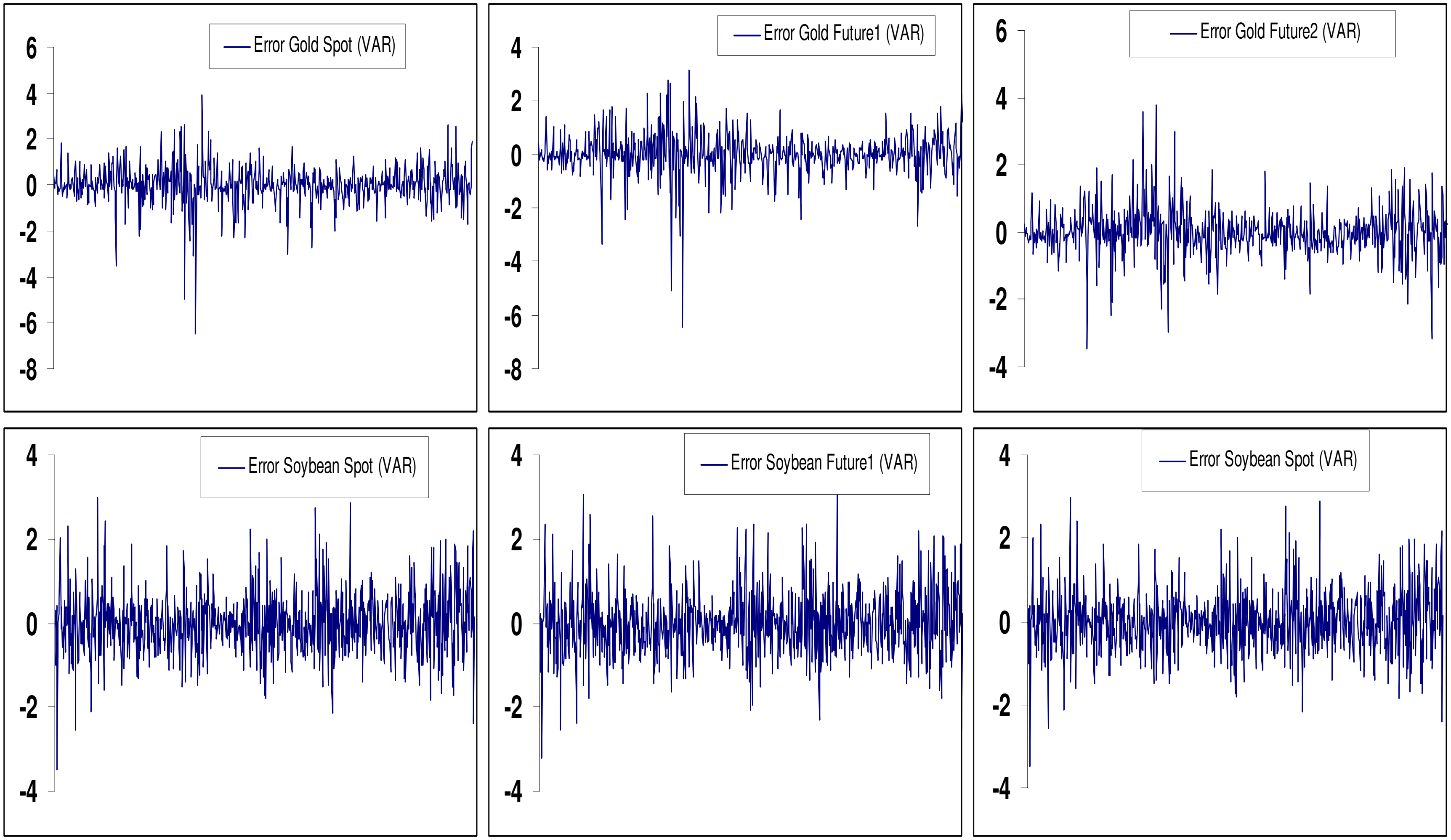

Figure 2: Residual series from spot and futures equation in VAR model for Gold and Soybean

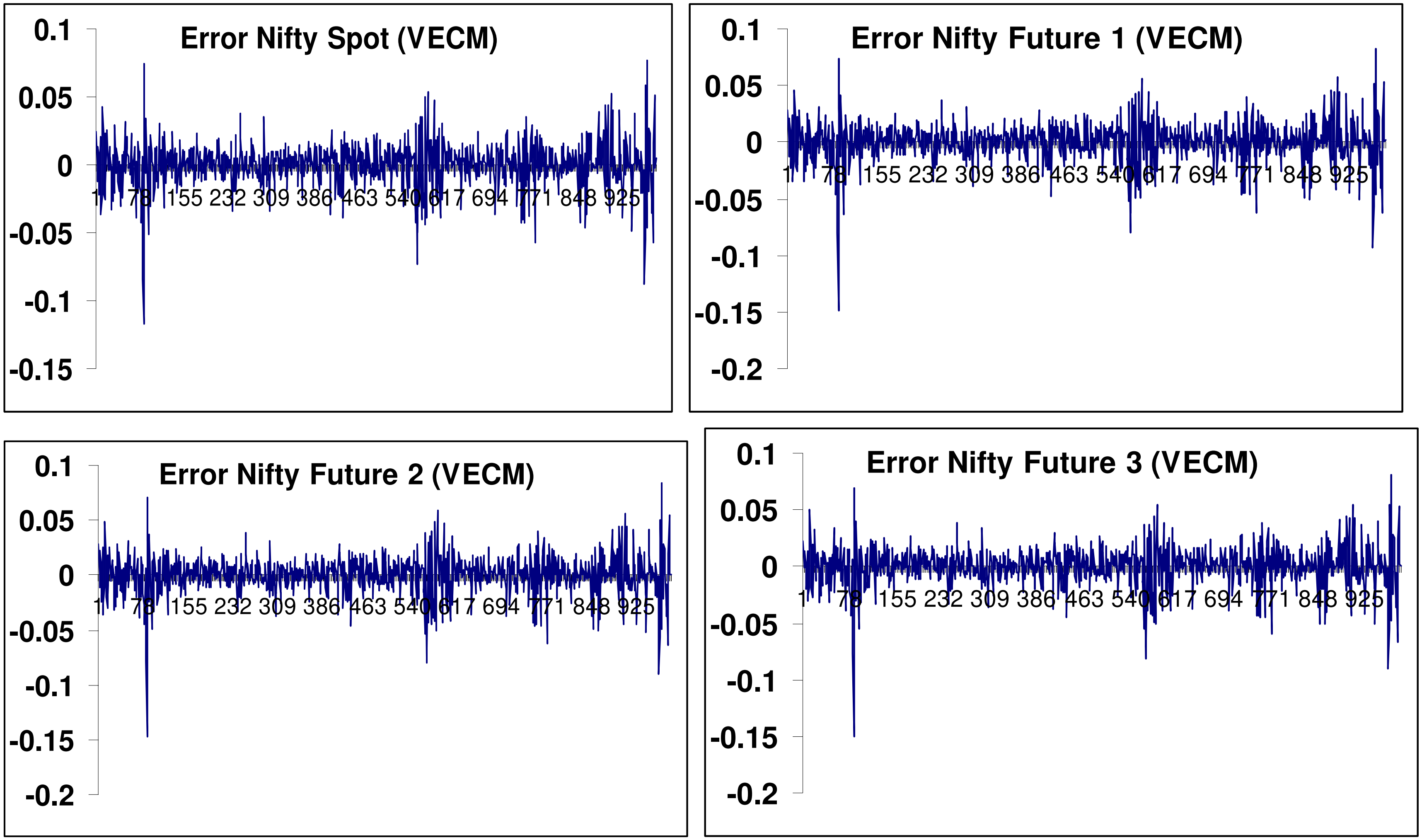

Figure 3: Residual series from spot and futures equation in VECM for Nifty

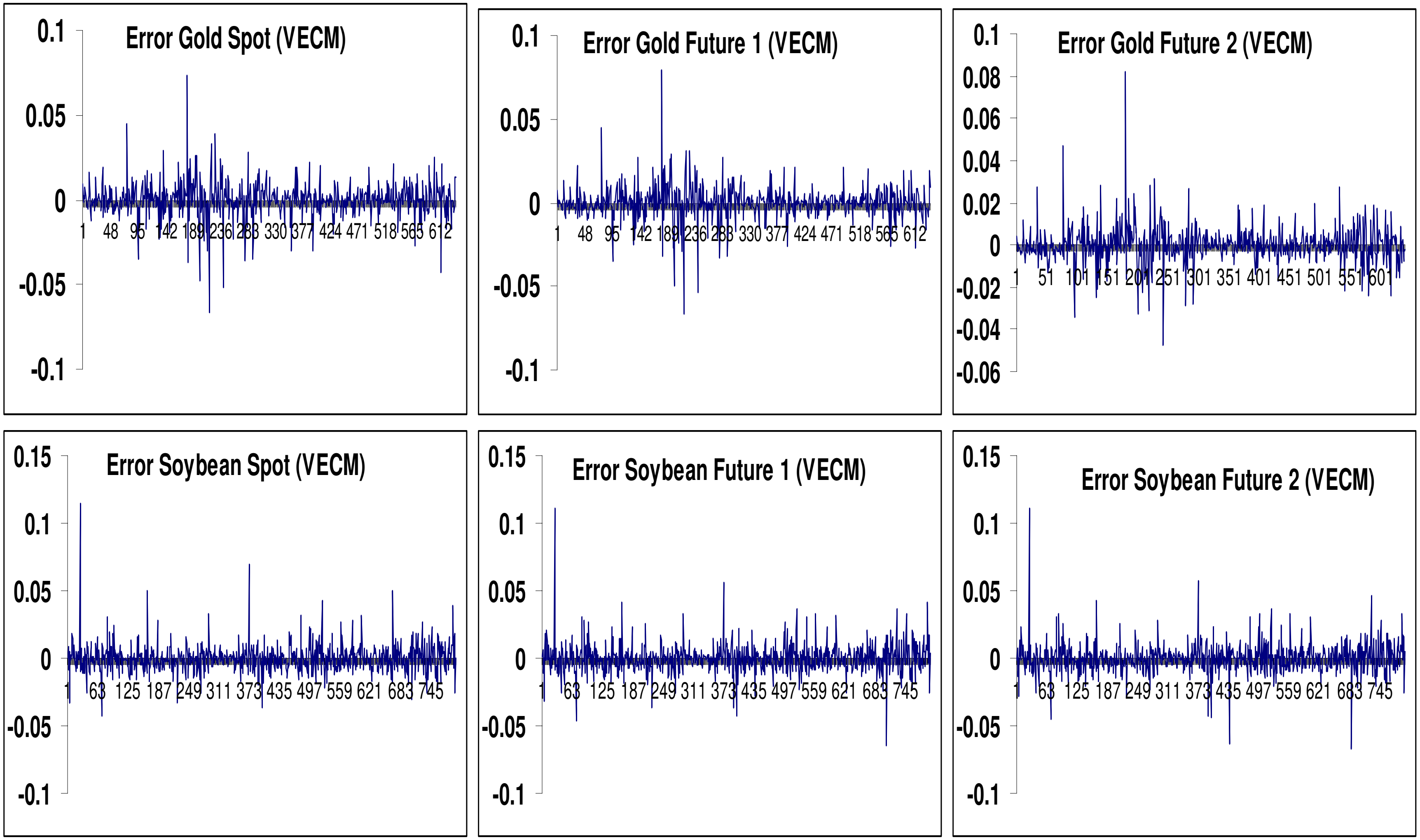

Figure 4: Residual series from spot and futures equation in VECM for Gold and Soybean