HEDGING EFFECTIVENESS AND OPTIMAL HEDGE RATIO IN INDIAN STOCK AND COMMODITY DERIVATIVES MARKETS: A VAR-MGARCH APPROACH

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This paper examines the effectiveness of risk management provided by the Indian capital and commodity derivatives markets in terms of hedging effectiveness and hedge ratio. In a developing market context (India), the future growth of capital and commodity futures market is highly dependent upon their effectiveness in risk management. Understanding optimal hedge ratio is effective in devising effective hedging strategy to minimize portfolio risk.

Dynamic and constant hedge ratio is estimated for S&P CNX Nifty index futures, Gold futures and Soybean futures. Various techniques (OLS, VAR model, VECM, and VAR-MGARCH) are used to calculate constant and dynamic hedge ratio. It was found that VAR-MGARCH model estimates of time varying hedge ratio provides highest variance reduction as compared to the other methods which is consistent with findings of Lypny and Powella (1998) and Park and Switzer (1995).

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1. INTRODUCTION

Risk management and price discovery are the two main functions of futures market. Futures market serves a risk -shifting function, and can be used to lock-in prices instead of relying on uncertain price developments. One of the determinants of success of futures contract is its hedging effectiveness (Pennings and Meulenberg, 1997). Price risk management using hedging tools like futures and options is an active area of research. Role of hedging while using multiple risky assets, using futures market for minimizing the risk of spot market fluctuation is well addressed in literature. 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 in futures market 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 one market by profit/loss in other market.

In empirical financial research, finding out an optimal hedge ratio and hedging effectiveness provided by futures contract is well documented and researched. The hedge ratio is defined as the ratio of the size of position taken in the futures market to the size of the position in spot. There is long debate in the literature about the optimal hedge ratio. Traditionally the estimation is done using hedge ratio of '-1'i.e. taking a position in futures which is equal in magnitude and opposite in sign to spot market. If the movement of changes in spot prices and futures prices is same, then such a strategy eliminates the price risk. Such a perfect correlation between spot and future prices is rarely observed in market and hence there was a need felt for a better strategy. Johnson (1960) came up with a strategy called 'minimum variance hedge ratio (MVHR)'. The main objective of minimizing the risk was kept intact but the concept of utility maximization (mean) was also brought. Risk was defined as the variance of return on a two-asset hedged position.

The Minimum-Variance Hedge Ratio (Benninga, *et al.,* 1984) has been suggested as slope coefficient of the OLS regression, for changes in spot prices 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). The R-square of this model indicates the hedging effectiveness.

Many authors defined hedging effectiveness as the reduction in variance and considered utility function as 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 advocate that optimal ratio must be estimated in mean-variance frame work.

Risk minimizing hedge ratio is optimal when the future market is unbiased i.e. the expected return from the futures contracts are zero (Benninga, Eldor and Zilcha, 1984). In case of biased futures market minimum-variance hedge ratio is adjusted according to expected futures and cash prices, and the resulting basis level.

The regression method of calculating the hedge ratio and hedging effectiveness is criticized on mainly two grounds. First, it is based on unconditional second moments, but the covariance and variance should be conditional because hedging decision made by any trader is based on all the information available at that time. Second, the estimation based on regression is time invariant but the joint distribution of spot and future prices are time variant.

Recent advancement in the time series modeling techniques tries to remove the deficiencies of the OLS estimation. A multivariate GARCH (Bollerslev et al, 1988) is being used to calculate time varying hedge ratio. Many recent works on the hedge effectiveness calculate time varying hedge ratios (Park and Switzer, 1995, Holmes, 1995 etc.). 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 future and found that Bivariate GARCH estimation improves the hedging performance. Lypny and Powella (1998) used VEC-MHARCH (1,1) model to examine the hedging effectiveness of German stock Index DAX futures and found that dynamic model is superior than constant hedge model.

The present study investigates optimal hedge ratio and hedge effectiveness of Indian derivatives markets. Stock index futures, gold futures contract and soy bean futures contracts have been taken for analysis. All futures contracts traded in the market are considered. Daily closing price data on S&P CNX Nifty index and its futures contracts (all three), a value-weighted stock index of National Stock Exchange, Mumbai, derived from prices of 50 large capitalization stocks, published by NSE India (www.nseindia.com), for the period from 1st January 2004 to 20th February 2008 are considered. Three gold contracts for the period from 22nd July 2005 to 20th February 2008 and three soy bean contracts from 4th October 2004 to 31st December 2007 are also included. These commodities are traded on National Commodity Exchange, India (www.ncdex.com).

The stock index futures and the commodity market in India are comparatively new and are in development phase. Also, in recent years the Indian equity as well as commodity market has been showing tremendous growth potential. The growths in these markets are also inducing volatility which requires a systematic investigation of hedge effectiveness provided by these markets. It will help in designing better hedging strategy and diversified portfolio. This paper is organized as follows: several model specifications used for calculating the hedge effectiveness and hedge ratio is presented in Section 2. In Section 3, description of the data used for the study is given. Section 4 discusses the results and the final section concludes the findings of the study.

2. METHODOLOGY

In this study, four models including, conventional OLS method, VAR model, VEC model and VAR-GARCH are employed to estimate optimal hedge ratio. Time varying optimal hedge ratio is calculated using bivariate GARCH model (Bollerslev *et al.,* 1988). Hedge ratio and hedging effectiveness is also discussed in this section.

2.1 HEDGE RATIO AND HEDGING EFFECTIVENESS

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.

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

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

2.2 MODELS FOR CALCULATING HEDGE EFFECTIVENESS AND HEDGE RATIO

Several models are used to estimate hedge ratio and hedging effectiveness such as conventional OLS method, Vector Autoregressive regression (VAR), Vector Error Correction model (VECM), Vector Autoregressive Regression Model with Bivariate Generalized Autoregressive Regressive Conditional Heteroscedasticity Model (VAR-BGARCH). Hedge performance estimated by OLS, VAR model, VECM are time invariant and do not consider the conditional covariance structure of spot and futures price, whereas VAR-BGARCH model estimates time varying hedge ratio and assumes constant conditional correlation and time varying conditional covariance structure of spot and futures price.

2.2.1 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.

2.2.2 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 presented 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

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

2.2.3 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 and Luo (1994), Lien, 1996). The futures and spot series are co-integrated of the order one, so Vector error correction model of the series is given as

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

The assumptions about the error terms are same as for VAR model. The minimum variance hedge ratio and hedging effectiveness are calculated by the same approach as discussed in VAR model approach.

2.2.4 MODEL 4: THE VAR-BGARCH MODEL

Generally, time series data possesses time varying heteroscedastic volatility structure (ARCH-effect). Because of ARCH effect in the return 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-BGARCH model considers the ARCH effect of the time series and calculate time varying hedge ratio. A bivariate GARCH (1,1) model is given by

$$R_{St} = \alpha_S + \sum_{i=1}^{k} \beta_{Si} R_{St-i} + \sum_{j=1}^{l} \gamma_{Fj} R_{Ft-j} + \varepsilon_{St}$$

$$R_{Ft} = \alpha_F + \sum_{i=1}^{k} \beta_{Fi} R_{Ft-i} + \sum_{j=1}^{l} \gamma_{Sj} R_{St-j} + \varepsilon_{Ft}$$

$$\begin{bmatrix} h_{ss} \\ h_{sf} \\ h_{ff} \end{bmatrix} = \begin{bmatrix} C_{ss} \\ C_{sf} \\ C_{ff} \end{bmatrix}_t + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_s^2 \\ \varepsilon_s \varepsilon_f \\ \varepsilon_f^2 \end{bmatrix}_{t-1} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \alpha_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix} \begin{bmatrix} h_{ss} \\ h_{sf} \\ h_{ff} \end{bmatrix}_{t-1} \qquad \textbf{[8]}$$

where,

h_{ss} and h_{ff} are the conditional variance of the errors $(\varepsilon_{st}, \varepsilon_{ft})$ from the mean equation.

Bollerslev, Engle and Wooldridge (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)

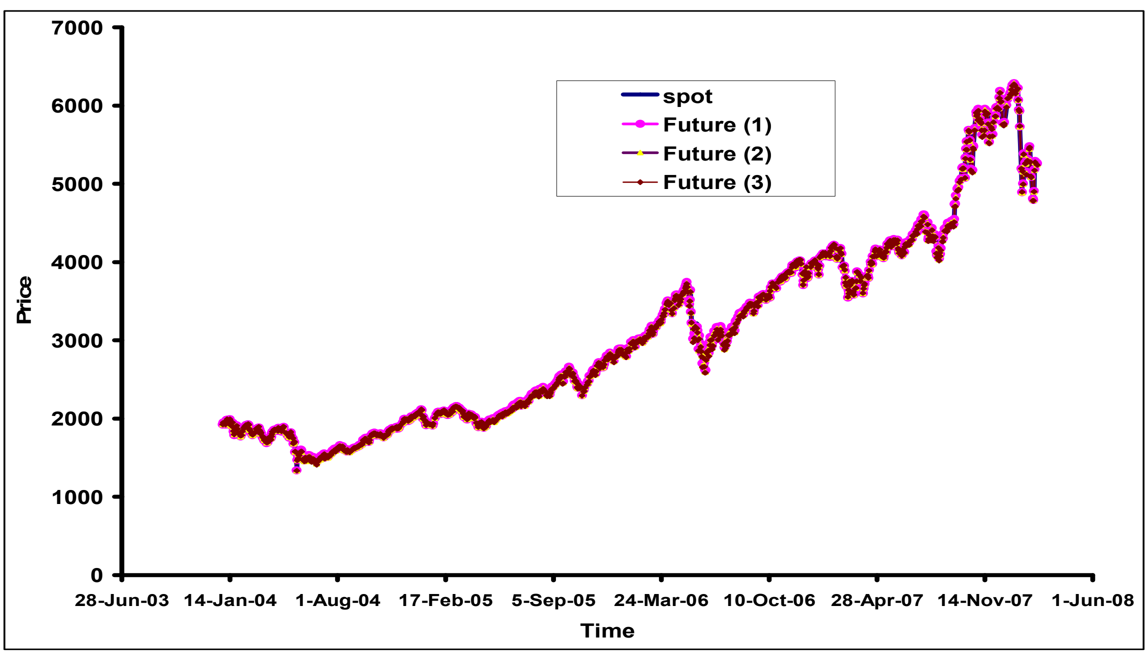
$$\begin{aligned} h_{ss,t} &= C_{ss} + \alpha_{ss} \varepsilon_{s,t-1}^2 + \beta_{ss} h_{ss,t-1} \\ h_{sf,t} &= C_{sf} + \alpha_{sf} \varepsilon_{s,t-1} \varepsilon_{f,t-1} + \beta_{sf} h_{sf,t-1} \\ h_{ff,t} &= C_{ff} + \alpha_{ff} \varepsilon_{f,t-1}^2 + \beta_{ff} h_{ff,t-1} \end{aligned} \qquad [9]$$

Time varying hedge ratio is calculated as follows

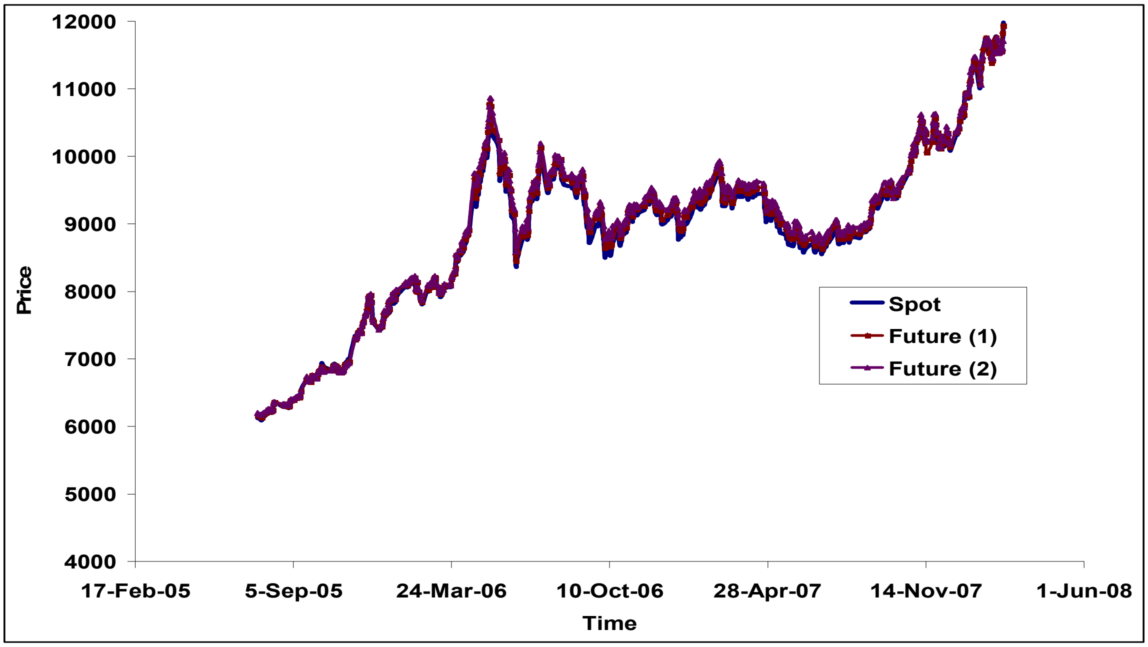
$$H_t = \frac{h_{sft}}{h_{fft}} \qquad [9]$$

3. DATA USED AND ITS PROPERTIES

Daily closing price data on S&P CNX Nifty index and its futures contracts, published by NSE India (www.nseindia.com), for the period from 1st January 2004 to 20th February 2008 are considered. S&P CNX Nifty futures contracts have a maximum of 3-month trading cycle - the near month, the next month and the far month. All three months futures contracts are analyzed and compared. Similarly, three gold contracts for the period from 22nd July 2005 to 20th February 2008 and three soy bean contracts from 4th October 2004 to 31st December 2007 are also considered. These commodities are traded on National Commodity Exchange, India (www.ncdex.com) and daily data is published. For commodities futures, gold and soy bean the near month futures prices are used as spot prices. Spot and futures prices of these assets are given in Figure 1.



a)



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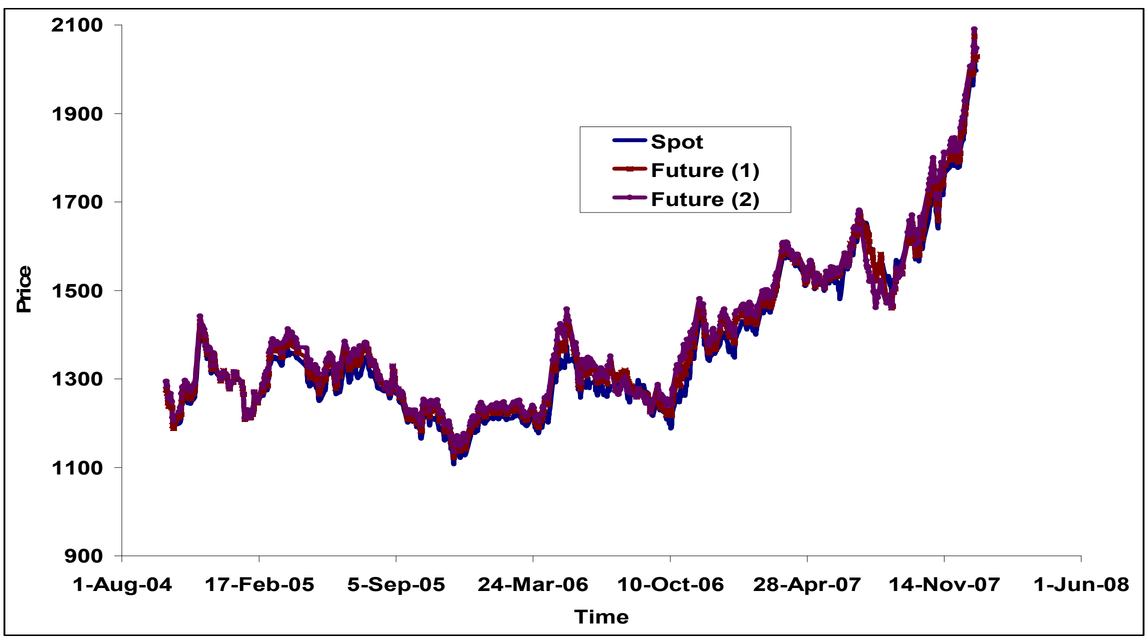


c)

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

3.1: TEST OF UNIT ROOT AND C0-INTEGRATION

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 no unit root is used as null hypothesis for KPSS test. The summary statistics are shown in Table 1.

Table 1: Unit root tests on prices and returns

Asset	Level 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	-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
Soy	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

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 prices and futures prices are tested by Johansen's (1991) maximum likelihood method. The results of co-integration are presented in Table 2. It has been 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 **	0.040481	43.02874	0.019726	22.3309	0.01399	16.73723
	At most 1	0.002358	2.325366	0.002744	2.706341	0.002899	2.859566
Gold	None **	0.027392	20.7262	0.023514	18.62156	--	--
	At most 1	0.0046	2.950516	0.005287	3.392959	--	--
Soy	None **	0.025509	23.82355	0.015894	13.68486	--	--
	At most 1	0.004081	3.255157	0.00117	0.931647	--	--

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

4. RESULTS AND DISCUSSIONS

Hedge ratio and hedging effectiveness of Index futures (Nifty) and commodity futures (Soybean and Gold) are calculated through four models described in section 2. We also estimated the time varying hedge ratio for nifty and gold futures by VAR-BGARCH approach. Results are presented in this section.

4.1 OLS ESTIMATES

OLS regression (equation [4]) is 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.

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*
R2	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 gold far month (Future 2) maturity contract. Hedging effectiveness was highest for Nifty futures. Near month gold futures provides 81% of hedge effectiveness as compared to 47% by distant future. Hedging effectiveness decreases as we move from near future to distant future (except Nifty future where decrease is not high).

4.2 VAR ESTIMATES

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

Table 3: Estimates of VAR model

a) Spot prices

	Nifty			Gold		Soybean	
	Future 1	Future 2	Future 3	Future 1	Future 2	Future 3	Future 1
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 3	Future 1
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

The optimal hedge ratio and hedge effectiveness are presented in Table 4.

Table 4: Estimation of hedge ratio and hedging effectiveness

	Nifty			Gold		Soybean	
	Future 1	Future 2	Future 3	Future 1	Future 2	Future 3	Future 1
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	2.840382	3.840382	4.840382	5.840382	6.840382	7.840382
Hedging Effectiveness, E	0.972879	0.979450	0.978525	0.977169	0.944628	0.993752	0.991660

Hedge ratio calculated from VAR model performs better than OLS estimates in variance reduction. Hedge ratio estimated through VAR model is increased from 0.71 (OLS estimate) to 0.88 for the Gold Future 2. For the same future hedging effectiveness also increase from 47%, in case of OLS, to 94%. Improvement is also observed for other futures contracts.

4.3 VECM estimates

We also estimated the hedging performance of the futures contracts by VECM model. Using the same approach used in VAR model, errors are estimated and hedging effectiveness and hedge ratio are calculated. Results of the equation [7] are presented in Table 5 and Table 6 shows the hedge ratio and hedging effectiveness of futures contracts.

Although VECM does not consider the conditional covariance structure of spot and futures price, it is supposed to be best specified model in estimations of constant hedge ratio and hedging effectiveness. It has been found that the hedge ratio calculated by VECM provides better variance reduction that VAR and OLS model. OLS seems to be least efficient. Our results are consistent with the findings of Ghosh (1993b).

Table 5: Estimates of VECM model

a) Spot prices

	Nifty			Gold		Soybean	
	Future 1	Future 2	Future 3	Future 1	Future 2	Future 3	Future 1
α	0.09244	0.0424	0.01956	0.00525	0.00314	0.04273	0.04806
β_S	3.81625	2.88434	1.99853	0.78265	-0.25208	1.07639**	0.61468
β_{S2}	-3.9249**	-2.9941**	-2.3379**	-1.4396**	-0.4986**	-1.9025**	-1.4255**
β_{S3}	-3.0978**	-2.3452**	-1.998**	-0.8052**	-0.2674	-1.4918**	-1.1882**
β_{S4}	-1.9773**	-1.5123**	-1.3011**	-0.4987**	-0.1977	-1.0357**	-0.8473**
β_{S5}	-0.4938**	-0.4803**	-0.4166**	-0.2021*	0.0311	-0.6302**	-0.5171**
γ_F	-4.1288	-3.00596	-2.0844	-0.83017	0.26567	-1.318**	-1.1691**
γ_{F2}	3.43486**	2.3553**	1.6576**	0.6407*	-0.3663*	1.31618**	1.09275**
γ_{F3}	2.68033**	1.8098**	1.4308**	0.21831	-0.3314*	1.04281**	0.93178**
γ_{F4}	1.67139**	1.1174**	0.8885**	0.09976	-0.2358**	0.72415**	0.6719**
γ_{F5}	0.41376	0.3391	0.2567**	0.06127	-0.2541**	0.48883**	0.44607**
R^2	0.4333**	0.4066	0.4005	0.4214	0.4308	0.4197	0.4491

**(*) 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	0.12119	0.06419	0.03509	0.0048	0.01452	0.06535	0.06302
β_F	-5.42292	-4.53237	-3.68863	-2.57828	-1.78568	-2.07819	-1.55982
β_{F2}	3.38888**	2.48757**	1.86266**	0.95525**	0.30701**	1.10985**	0.59585**
β_{F3}	2.60016**	1.8167**	1.48801**	0.46261**	0.02923**	0.90065**	0.55099**
β_{F4}	1.59496**	1.09815**	0.87255**	0.1948*	-0.0636**	0.66047**	0.41903**
β_{F5}	0.31296**	0.25272**	0.16726**	0.11676**	-0.1422**	0.44258**	0.28138**
γ_S	5.01231	4.34901	3.53664	2.43071	1.69437	1.69722	0.8201
γ_{S2}	-3.8098**	-3.0862**	-2.4956**	-1.6217**	-0.96674*	-1.6138**	-0.8135**
γ_{S3}	-2.9652**	-2.3275**	-2.0153**	-0.94283*	-0.50503	-1.2897**	-0.7314**
γ_{S4}	-1.86386*	-1.4747**	-1.260**	-0.52044	-0.28213	-0.9444**	-0.5613**
γ_{S5}	-0.36677	-0.37434	-0.30714	-0.20151	-0.03167	-0.5731**	-0.3427**
R^2	0.4806	0.4606	0.4545	0.4504	0.5308	0.4516	0.4831

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

Table 6: Estimation of hedge ratio and hedging effectiveness

	Nifty			Gold		Soybean	
	Future 1	Future 2	Future 3	Future 1	Future 2	Future 3	Future 1
Covariance(ε_F, ε_S)	2.1783178	2.2844704	2.2682194	0.7170272	0.5147403	0.6405542	0.5922696
Variance (ε_F)	2.3471495	2.4714572	2.4388817	0.7174252	0.5512855	0.6754320	0.6418017
Hedge Ratio	0.9280695	0.9243415	0.9300244	0.9994453	0.9337090	0.9483622	0.9228233
Variance (ε_S)	2.0757602	2.1735131	2.1959541	0.8335559	0.8200764	0.6531985	0.6201781
Variance(H)	0.0541299	0.0618824	0.0864548	0.1169265	0.3394588	0.0457211	0.0736178
Variance(U)	1.8403819	2.8403819	3.8403819	4.8403819	5.8403819	6.8403819	7.8403819
Hedging Effectiveness, E	0.9705877	0.9782134	0.9774880	0.9758435	0.9418773	0.9933160	0.9906104

4.4 VAR-BGARCH MODEL

VAR-BGARCH model is used to correct the estimation of hedge performance for time varying volatility and to incorporate non-linearity in the mean equation. Errors of the VAR and VECM models are analyzed for 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[1]. VAR models with Bivariate Diagonal GARCH (1,1) are used and results are presented in Table 7.

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

	Nifty			Gold	
	Future 1	Future 2	Future 3	Future 1	Future 2
C_{ss}	1.88922**	1.89082**	0.672451**	0.688306**	0.68831**
C_{sf}	2.01818**	2.00367**	0.584168**	0.430647**	0.43065**
C_{ff}	2.19812**	2.17527**	0.575654**	0.47647**	0.47647**
α_{11}	0.0014**	0.14607**	0.690908**	0.32432**	0.32432**
α_{22}	-0.00147**	0.15032**	0.552324**	0.263836**	0.26384**
α_{33}	0.00312**	0.16131**	0.458376**	0.329593**	0.32959**
β_{11}	-0.00523**	0.02881**	0.009606**	-0.010951	-0.01095**
β_{22}	0.01247**	0.00045**	0.05161**	0.014652	0.01465**
β_{33}	-0.00589**	-0.03453**	0.10732**	-0.062182**	-0.06218**

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

[1] 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 are calculated 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 future prices are shown in Figure 2.

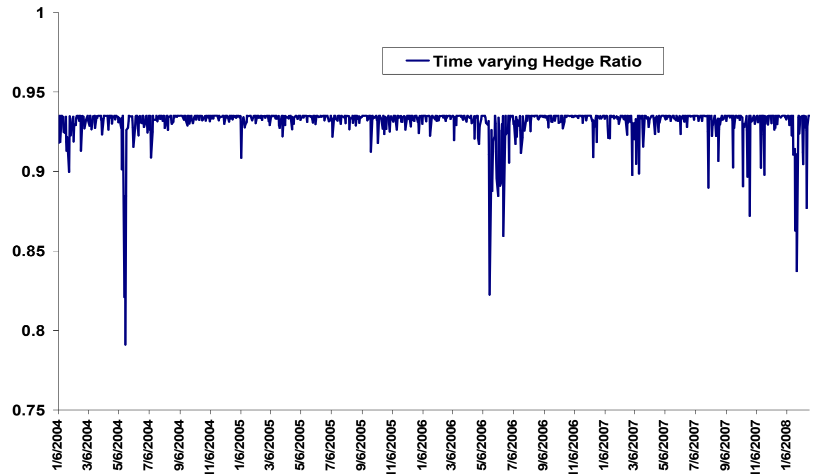
4.5: COMPARISON OF OPTIMAL HEDGE RATIO

Constant hedge ratio obtained from OLS, VAR, VECM and mean of time varying hedge ratio obtained from VAR-BGARCH model is compared (Table 8). Our results show that hedge ratio calculated from VAR-BGARCH (1,1) model provides greater variance reduction than other models. Similar type of results were found in the previous studies of Myers (1991), Baillie and Myers (1991) and Park and Switzer (1995a,b) on the US financial and commodity markets.

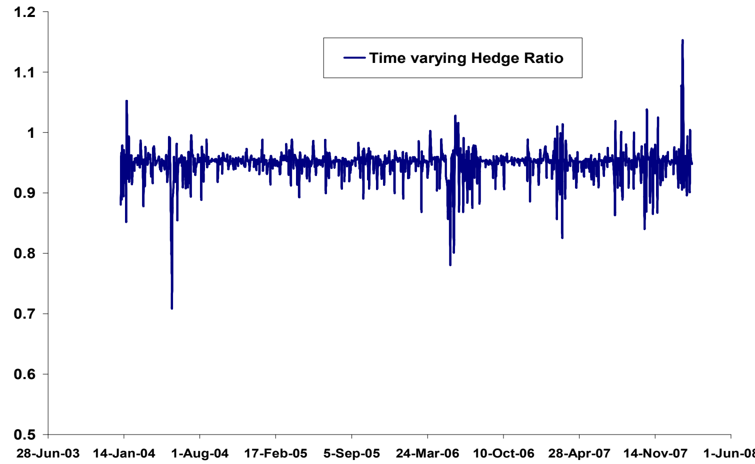
Table 8: Comparison of optimal hedge ratio by different methods

	Nifty			Gold		Soybean	
	Future 1	**Future 2**	**Future 3**	**Future 1**	**Future 2**	**Future 3**	**Future 1**
OLS	0.91181	0.90519	0.90836	0.92387	0.73613	0.93092	0.90329
VAR	0.915525	0.911341	0.915438	0.973868	0.883125	0.928490	0.903207
VECM	0.928069	0.924341	0.930024	0.999445	0.933709	0.948362	0.922823
VAR-GARCH	0.931028	0.947602	0.969694	0.959061	0.951656	--	--

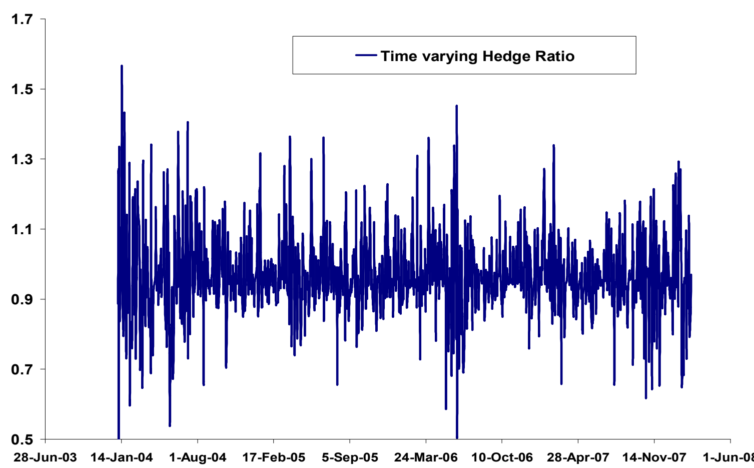
In case of constant hedge ratio estimation, VECM performs better than OLS and VAR models. Similar result was found by Ghosh (1993b). When VAR-GARCH model is used then all near month as well as distant futures provide nearly equal mean variance reduction. All futures contracts, nifty, gold as well as soybean, provide about 95% of variance reduction.



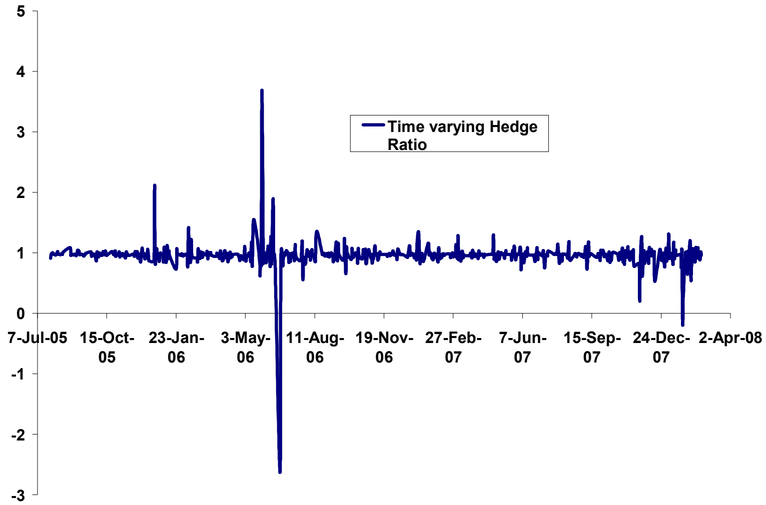
a) Nifty Future 1



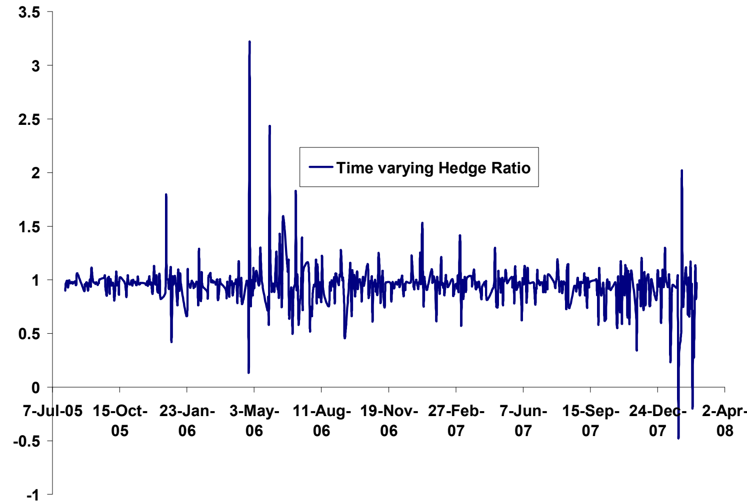
b) Nifty Future 2



c) Nifty Future 3



d) Gold Future 1



e) Gold Future 2

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

5. CONCLUSIONS

Derivatives markets are used as price risk management tool where hedgers take position opposite to spot market. Effectiveness of these markets can be evaluated on the basis of hedge effectiveness provided by them. In developing market like India, where stock and commodity market are growing at a faster rate, it is of prime importance to evaluate their risk management efficiency.

Hedge effectiveness is defined as the reduction in the variance of the portfolio. Understanding of hedging effectiveness and hedge ratio provided by futures contracts are very important for developing an effectiveness hedging strategy. Recent development in the modeling techniques attracts sophisticated tools to measure hedge ratio and hedging effectiveness.

Hedging effectiveness of Indian stock market (Nifty Index Futures) and Indian commodity market (Gold and Soybean futures) are investigated. We estimated both constant and time varying hedge ratio. Constant hedge ratio is calculated through OLS, VAR, and VEC models. Time varying hedge ratio is estimated by VAR-MGARCH which incorporates constant conditional correlation and time varying covariance structure of spot and futures prices.

Results show that unit root is present in all price series and the difference series are stationary. Futures and spots prices are also found to be co-integrated in a long run. In constant hedge ratio estimation, VECM performs better than OLS and VAR models, which coincides 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. This result is consistent with the results of Lypny and Powella (1998), Myers (1991), Baillie and Myers (1991), and Park and Switzer (1995a,b). Both stock market and commodity derivatives market in India provide effective hedge (90%). These markets are providing useful risk management tool for hedging and portfolio diversification.

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APPENDIX

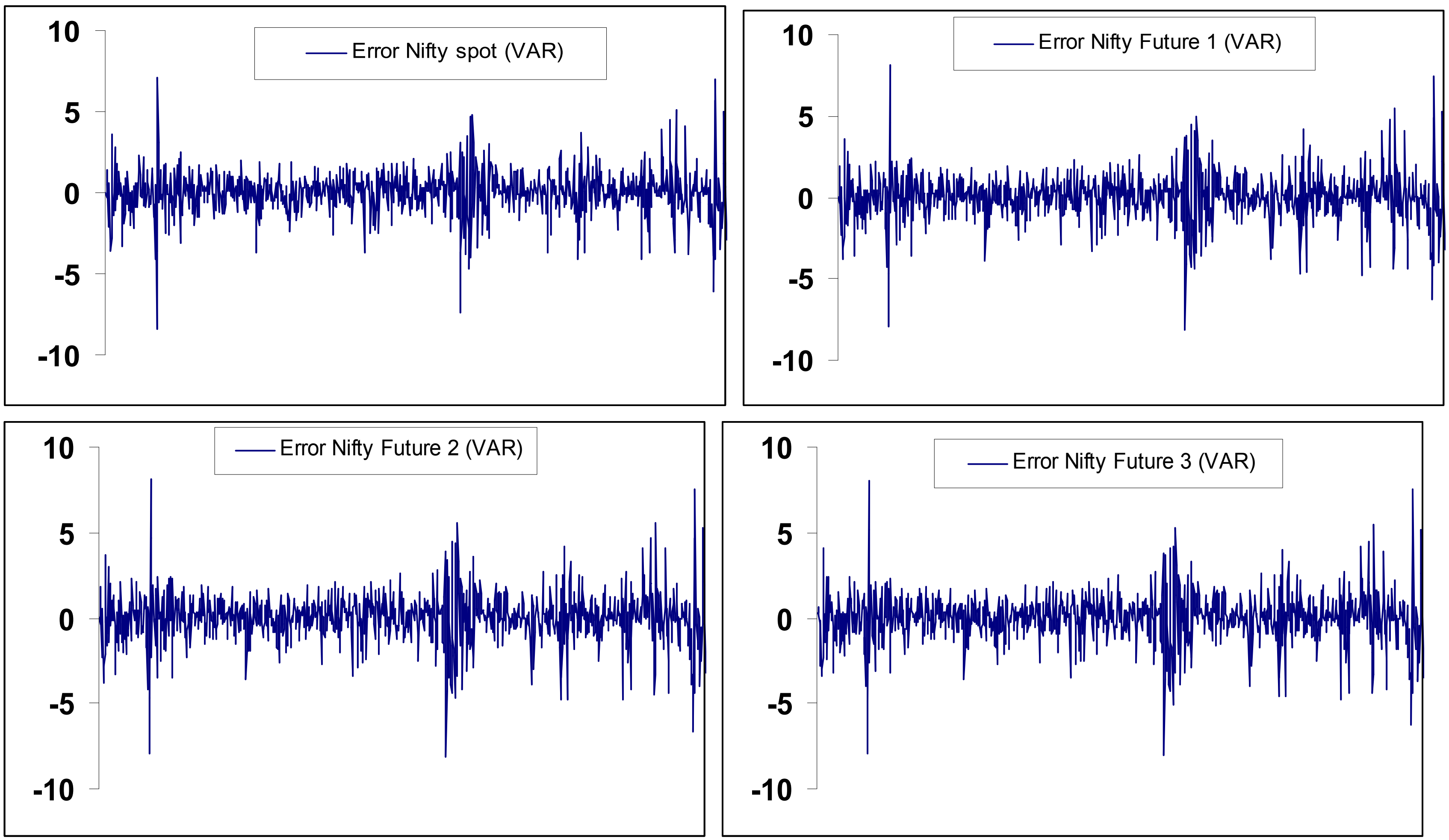

Figure 1: Residual series from spot and future equation in VAR model for nifty

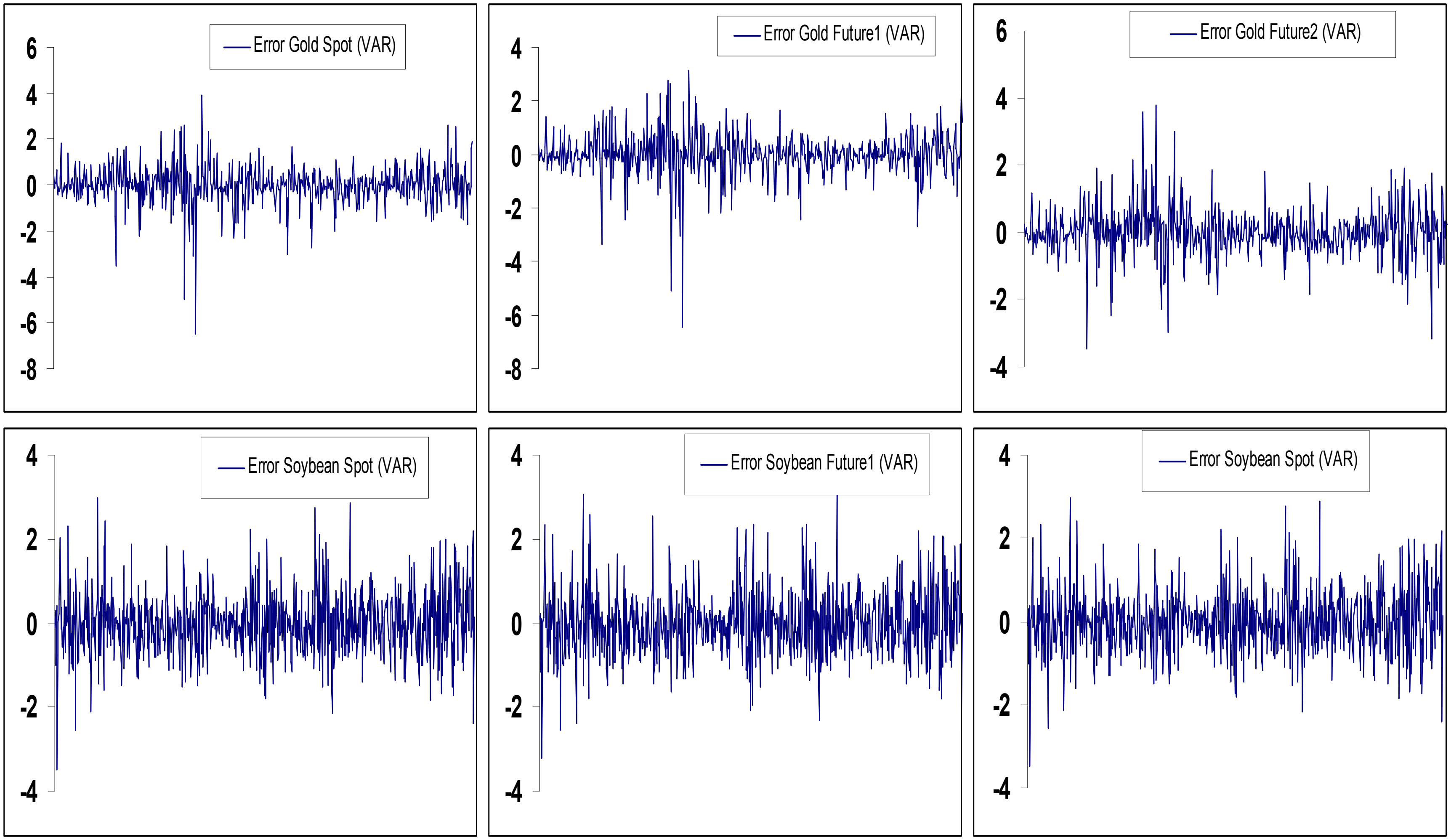

Figure 2: Residual series from spot and future equation in VAR model for gold and Soybean

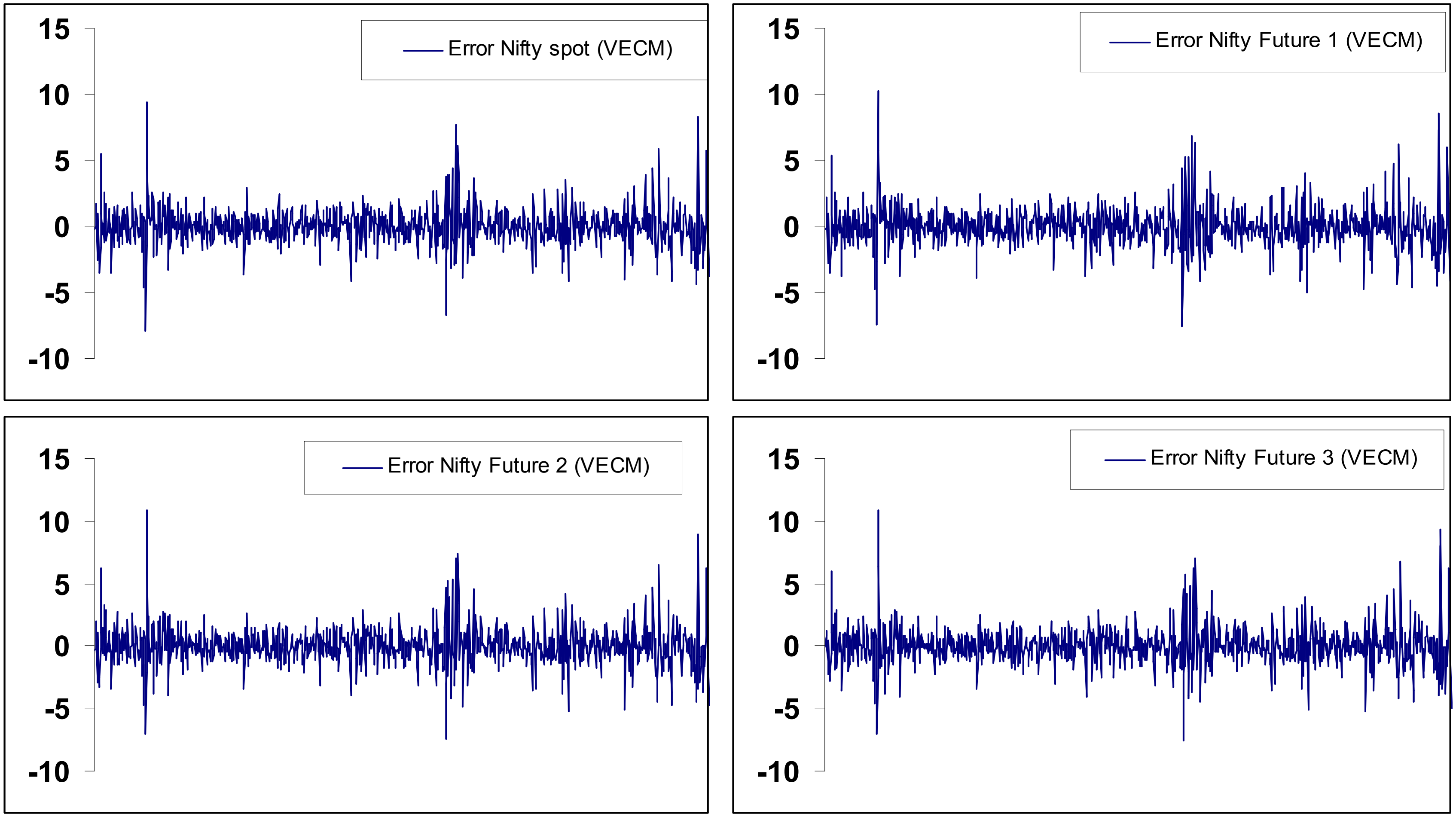

Figure 3: Residual series from spot and future equation in VECM for nifty

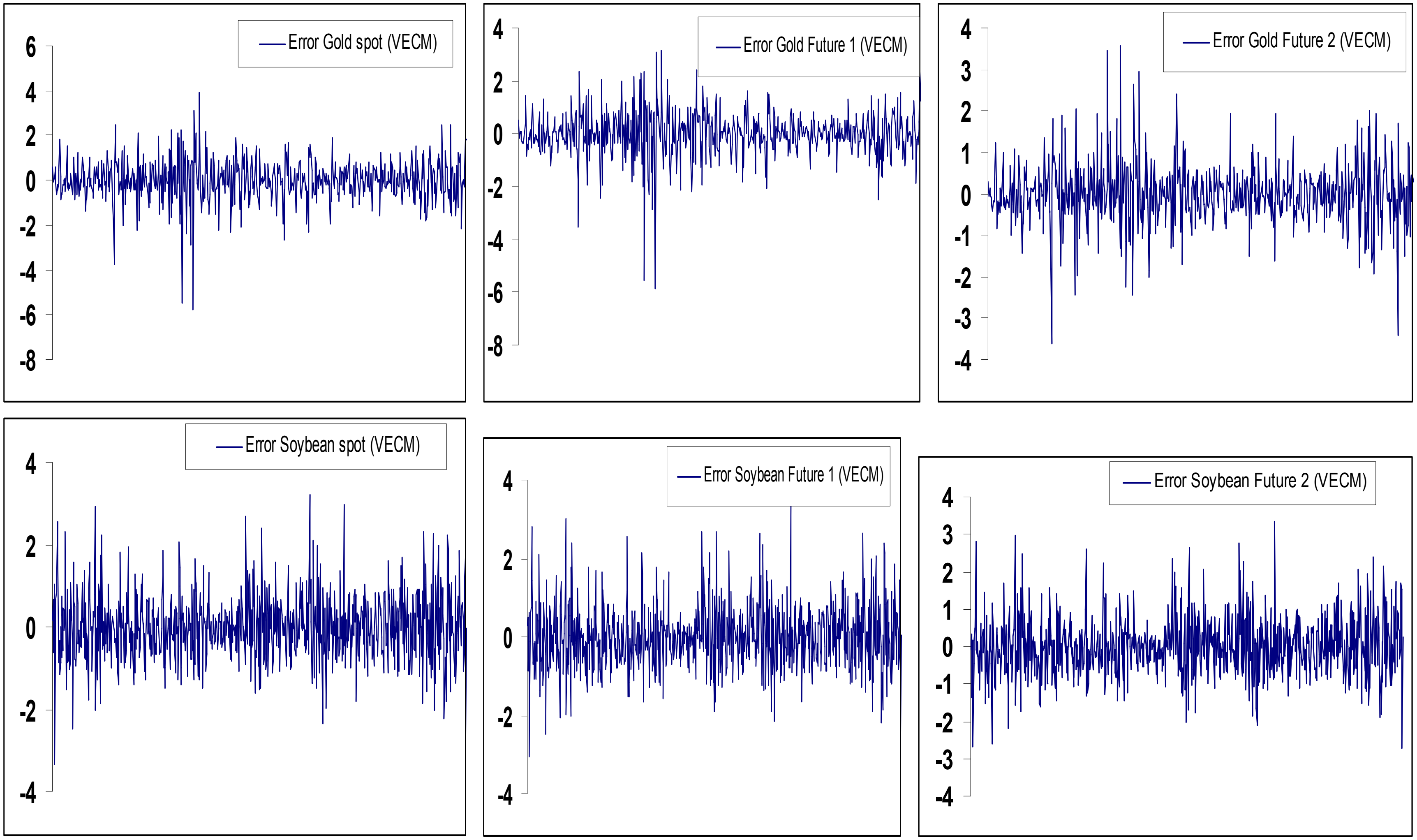

Figure 2: Residual series from spot and future equation in VECM for gold and Soybean