**International Research Journal of Management and Commerce**
ISSN: (2348-9766)
**Impact Factor-** 5.564, Volume 5, Issue 3, March 2018
**Website-** www.aarf.asia, **Email** : editor@aarf.asia , editoraarf@gmail.com

# HEDGING EFFECTIVENESS OF CONSTANT AND TIME-VARYING HEDGE RATIO IN INDIAN COMMODITY FUTURES MARKET: A STUDY OF CORIANDER TRADED IN THE NATIONAL COMMODITY AND DERIVATIVES EXCHANGE

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## ABSTRACT

*In an emerging market like India, the growth of commodity futures market would depend on effectiveness of derivatives in managing risk. The optimal hedging strategies help the investors to reduce the uncertainty from the amount of capital without significantly reducing the expected return, moreover perceiving optimal hedge ratio is essential for compassing effective hedging strategy for managing risk. This paper investigates the optimal hedge ratio and hedging effectiveness in Indian commodity futures market. Constant and time-varying competing econometric models such as OLS regression model, VECM and diagonal VECH-GARCH model are employed to estimate optimal hedge ratios for Coriander traded in NCDEX for the period from January 2009 to December 2017. Data from January 2017 to December 2017 were used for out-sample period. The hedging effectiveness of the optimal hedge ratios is examined by variance reduction between hedged and un-hedged positions for 1-day, 5-day, 10-day horizons for both in-sample and in-sample periods. From the results, authors concluded that the time-varying Diagonal VECH-GARCH hedge ratio performs better than the other models in minimizing the risk for Coriander traded in NCDEX India for the period of the study. These* *findings imply that in selecting the most suitable hedge ratio, degree of risk aversion of investors plays a significant role. This indicates that risk aversion being the major goal of an investor, and the time-varying Diagonal VECH-GARCH is the most optimal hedging strategy and performs best in deducting the conditional variance of the hedged portfolio.*

**Keywords:** Diagonal VECH-GARCH, Hedging effectiveness, OLS regression model, Optimal hedge ratio, VECM.

## 1. Introduction

During recent decades, many methods have been developed to determine optimal hedging ratios and hedging strategies. Constant and time-varying are the two broad categories of hedging strategies Static point of view considers that hedging ratio is constant over the sample because it tries to manage the unconditional variance. Econometric models and regressions are used to find optimal constant hedge ratios. The OLS regression, the bivariate VAR and the Vector Error Correction models are the most common econometric and regression models used to calculate constant hedge ratio. The time-varying point of view considers that joint distribution of spot and futures prices is revolving during the time. The conditional variance and covariance of spot and futures prices are incorporated in the time-varying models to detect optimal hedge ratio. The multivariate GARCH model has been widely used in the literature to calculate time-varying hedge ratios (Engle & Kroner, 1995).

Among many studies, there is a consensus that proposes time-varying GARCH hedge ratios as the preferable hedging strategies over the constant hedge ratio models for risk reduction. However, such preference depends upon the contract and market specifications and may differ among the markets. Based on these strategies to compute how effective the hedge procedure is, hedging effectiveness is expanded.

The main objective of this paper is to compute and compare the optimal hedge ratios and hedging effectiveness of different hedging strategies: OLS regression model, VECM and diagonal VECH multivariate GARCH model.

There are various national and international studies related to estimate optimal hedge ratio and hedging effectiveness. Hedging effectiveness of futures markets is one of the important determinants of success of futures contracts (Pennings & Meulenberg, 1997). According to Heifner (1972), the hedging effectiveness is appraised as the proportional reduction in profit variance obtained through hedging. Ederington (1979), described hedging effectiveness as the reduction in risk of returns between un-hedged and hedged positions. Howard and D'Antonio (1984) proposed modern portfolio theory as superseded to mean variance approach to define hedge ratio and hedging effectiveness. Their study is one of the fundamental theoretical efforts to define hedging ratios and hedging effectiveness of futures contracts by taking into consideration the risk-return trade off.

There are different models to estimate the constant and time-varying optimal hedge ratios such as OLS regression, bivariate VAR, VECM, and GARCH models. However, there has been vast discussion on which model makes the best hedging performance (Ghosh, 1993; Lien et al., 2002; Moosa, 2003; Awang et al., 2014). Ghosh (1993) found better performance of VECM model amongst constant hedging models. Lien et al. (2002) and Moosa (2003) detected that the OLS regression model clearly performs better than other constant hedging models. Better execution of GARCH models was supported by Park and Switzer, (1995), Kavussanos and Nomikos, (2000), Floros and Vougas (2006) etc. Hedge ratios acquired by simple regressions have been reviewed by Cecchetti, Cumby and Figlewski (1988).

Holmes, 1995; Lypny and Powella, 1998; Choudhry, 2004;; Bhaduri and Durai, 2008; Kenourgios, et al.2008; Chang, et al.(2013); Zuppiroli and Revoredo-Giha, 2016 are the recent studies on the hedging effectiveness estimated by time varying hedge ratios. Lypny and Powella (1998) used VEC-MGARCH (1,1) model to estimate the hedging effectiveness of German stock Index futures. Authors detected that time-varying model was better than constant hedge ratio estimation model. However, some recent studies such as study of Awang et al., (2014) found that the OLS model could serve as a better hedging model than other constant and time-varying models in a direct hedge using stock index futures.

Choudhry, 2004; Bhaduri & Durai, 2008; kenourgois, et al. 2008; are the recent studies on optimal hedge ratio and hedging effectiveness in stock markets. Choudhary (2004) studied the hedging effectiveness of Australian, Hong Kong, and Japanese stock futures markets. Author applied both constant hedge models and time-varying models to estimate the hedge ratio and hedging effectiveness. He detected that time-varying GARCH hedge ratio performed better than the constant hedge ratios in most of the cases for both the in-sample as well as the out-sample periods. Bhaduri and Durai (2008) detected similar results to analyze effectiveness of hedge ratio through mean return and variance reduction between hedge and un-hedged position for different horizons NSE Stock Index Futures. kenourgois, et al. (2008) estimated optimal hedge ratios and examined the hedging effectiveness the S&P 500 index using both constant and time-varying alternative models. Authors concluded that the Error Correction Model better than other models applied in terms of risk reduction.

There are very few empirical studies in estimating hedge ratio and hedging effectiveness in Indian commodity futures markets (Kumar, et al. 2008; Ul Haq 2015). Kumar, et al. (2008) estimated optimal hedge ratio and hedging effectiveness in Indian commodity futures market. Authors concluded that in most of the cases, VARMGARCH model is the best model in variance reduction, and among constant hedging strategies, VECM performs better than OLS and VAR models. Ul Haq (2015) estimated the optimal hedge ratios and hedging effectiveness of agricultural futures. Author applied OLS, ECM and WAVELET Approach models for the study. The results indicated that the hedge ratio estimated from wavelet approach is higher than hedge ratio estimated from OLS and ECM models.

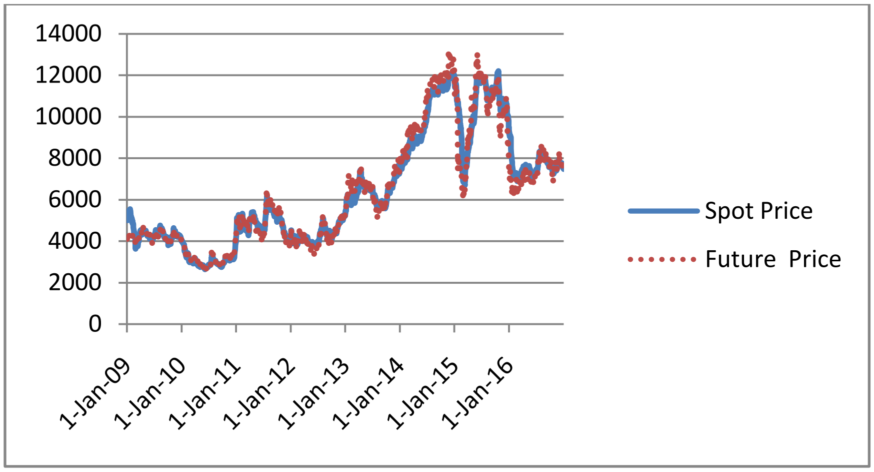
This study attempts to investigate optimal hedge ratio and hedge effectiveness of Coriander traded in NCDEX India. The rest of this paper is arranged as follows: The description of the data that used in the study is given in section 2. The econometric methodology to detect optimal hedge ratios and suggestion of an appropriate strategy for testing the hedging effectiveness are presented in section 3. The empirical results are presented in section 4. And the conclusions of the study are expressed in last section.

## 2. Data

The daily closing spot and futures prices of Coriander traded in NCDEX India for the period from 1$^{st}$ of January 2009 to 31$^{st}$ of December 2017 has been used for this study. Analyze of this study is taken for both in-sample and out-sample periods. The data for the period of 1$^{st}$ of January 2009 to 31$^{st}$ of December 2016 has been applied for in-sample period, and the data for the period of 1$^{st}$ of January 2017 to 31$^{st}$ of December 2017 has been applied for out-sample period. Authors use three competing constant and time-varying hedging strategies: OLS, VECM and Diagonal VECH-GARCH models and test the hedging effectiveness of mentioned models for both in-sample and out-sample periods for different time horizons: 1-Day, 5-Day and 10-Day.

Time series of spot and futures prices movements of Coriander traded in NCDEX India for the period from 1st of January 2009 to 31st of December 2016 is given in Figure 1.

**Figure 1:** Spot and futures prices movement for Coriander from 2009 to 2016




Source: Survey Data

## 3. The Econometric Methodology to Detect Optimal Hedge Ratios

Different models have been applied to estimate hedge ratio and hedging effectiveness such as OLS regression model, Vector Error Correction model (VECM) and Diagonal VECH-GARCH model. The OLS and VECM models have been used to estimate constant hedge ratio Diagonal VECH-GARCH model has been used to estimate time-varying hedge ratio.

### 3.1. Constant Hedging Models

#### 3.1.1. The Ordinary least Square regression Model (OLS)

The first model is the OLS regression of spot returns on futures returns that estimates minimum variance hedge ratio which is offered by Ederington (1979). It can be estimated as follows:

$$r_{st} = \alpha + \beta_t r_{ft} + \varepsilon_t \qquad (1)$$

Where the $r_{st}$ and $r_{ft}$ as returns of spot and futures are calculated as the first difference of logarithmic spot and futures prices for time t. The value of $\beta_t$ is estimated as the OHR at time t.

### 3.1.2. The Vector Error Correction Model (VECM)

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. If the spot and futures prices are co-integrated of the order one, then the Vector error correction model of the series is given as:

$$r_{st} = \alpha_s + \sum_{i=1}^{m} \beta_{si} r_{st-i} + \sum_{i=1}^{n} \delta_{si} r_{ft-i} + \gamma_s Z_{t-1} + \varepsilon_{st} \quad (2)$$

$$r_{ft} = \alpha_f + \sum_{i=1}^{m} \beta_{fi} r_{st-1} + \sum_{i=1}^{n} \delta_{fi} r_{ft-1} + \gamma_f Z_{t-1} + \varepsilon_{ft} \quad (3)$$

Where the $s_t$ and $f_t$ are natural logarithm of spot and futures prices. $\alpha_s$ and $\alpha_f$ are intercepts. $Z_{t-1} = S_{t-1} - \delta F_{t-1}$ is the error correction term with $(1 - \delta)$ as co-integration vector. $\gamma_s$ and $\gamma_f$ are the adjustment parameters. After estimating the equations, the residuals are generated for calculate the hedge ratio. Let var($\varepsilon_{st}$)=$\sigma_s$, var($\varepsilon_{ft}$)=$\sigma_f$ and cov($\varepsilon_{st}$,$\varepsilon_{ft}$)= $\sigma_{sf}$, then the minimum $h^*$=$\sigma_{st}/\sigma_f$.

### 3.2. Time-Varying Diagonal VECH-GARCH Model

The conditional covariance matrix of asset returns varies over the time following the GARCH model, it assumes that mean and covariance of the returns updates subsequent to the information released by the previous returns .A number of multivariate GARCH model have been developed in the literature out of which the most popular models are VECH-GARCH, BEKK-GARCH, Diagonal VECH-GARCH and Diagonal BEKK-GARCH. To examine the dynamic hedging strategies, authors used Diagonal VECH-GARCH models. They applied Diagonal VECH-GARCH model developed by Bollerslev et al. (1988). Using variance and covariance of residuals of eq. (2) and (3) this model is expressed as follows:

$$\begin{matrix}\varepsilon_{st} \\ \varepsilon_{ft}\end{matrix} \Big| \Psi_{t-1} \sim N(0, H_t) \quad (4)$$

$$H_{st} = \mu_s + \sum_{i=1}^{m} \alpha_{s,i}\, \varepsilon_{st-i}^2 + \sum_{j=1}^{n} \beta_{s,j} H_{st-j}^2 \quad (5)$$

$$H_{ft} = \mu_f + \sum_{i=1}^{m} \alpha_{f,i}\, \varepsilon_{ft-i}^2 + \sum_{j=1}^{n} \beta_{f,j} H_{ft-j}^2 \quad (6)$$

$$H_{sft} = \mu_{sf} + \sum_{i=1}^{m} \alpha_{sf,i} \varepsilon_{st-i} \varepsilon_{ft-i} + \sum_{j=1}^{n} \beta_{sf,j} H^2_{sft-j} \quad (7)$$

Where $\Psi_{t-1}$ is information set at time t-1, $\varepsilon_{st}$ and $\varepsilon_{ft}$ are the residuals, $H_{st}$, $H_{ft}$ and $H_{sft}$ are variance of spot returns, variance of futures returns and covariance between spot and futures returns, respectively. $\mu = (\mu_s, \mu_f, \mu_{sf})$ is a 3x1 vector. $\alpha_i = (\alpha_{s,i}, \alpha_{f,i}, \alpha_{sf,i})$ and $\beta_j = (\beta_{s,j}, \beta_{f,j}, \beta_{sf,j})$ are 3x1 vectors. Number of coefficients in the model is equal to 3+3m+3n. $\alpha_i$ and $\beta_j$ matrices are diagonal restricted. This implies that conditional variance of spot and futures returns are only affected by their own past values and squared recent innovations. The conditional covariance between spot and futures returns follows the same structures. Since the model is diagonal restricted, authors use only the upper triangular of variance and covariance matrices and only nine parameters are estimated in these matrices. This parsimoniousness in number of coefficients is viewed as an advantageous over standard VECH model. The Maximum Likelihood estimation method is used to estimate GARCH coefficients at different hedging horizons. After estimating the model optimal hedge ratio is estimated using $H_{ft}$ and $H_{sft}$ series as follows:

$$h^* = H_{sft} / H_{ft} \quad (8)$$

### 3.3. Hedging Effectiveness

The hedging performances of alternative strategies have been examined using hedging effectiveness obtained from each of them. One of the most extensively used hedging effectiveness models has been suggested by Ederington (1979). This measurement is accessed by the variance reduction of hedged portfolio compared with un-hedged portfolio. This hedging effectiveness ratio can be expressed as follows:

$$HE = 1 - \left[\frac{Var_{hedged}}{Var_{un\,hedged}}\right] \quad (9)$$

The returns and variances of hedged and un-hedged portfolios can also be calculated as follows:

$$R_{uhedged} = S_{t+1} - S_t \quad (10)$$

$$R_{hedged} = (S_{t+1} - S_t) - h^*(f_{t+1} - f_t) \quad (11)$$

where $R_{uhedged}$ and $R_{hedged}$ are returns of unhedged and hedged portfolios, respectively. $S_t$ and $f_t$ are logged prices of spot and futures at time t and $h^*$ denotes their hedging ratio. The un-hedged spot return series and futures return series are calculated as the first difference logarithmic price series.

$$Var_{uhedged} = \sigma_s^2 \quad (12)$$

$$Var_{hedged} = \sigma_s^2 + h^{*2}\sigma_f^2 - 2h^*\sigma_{sf} \quad (13)$$

Where $Var_{uhedged}$ and $Var_{hedged}$ are variances of un-hedged and hedged portfolios, and $\sigma_s^2, \sigma_f^2$ and $\sigma_{sf}$ are the variance of spot and futures prices and covariance between them, respectively.

## 4. Empirical Results

### 4.1. Unit Root Test

Augmented Dickey Fuller Test (ADF) and Phillips Perron Test (PP) test are used to check whether the data series are stationary at level and first difference. The null hypothesis for ADF test and PP test is the existence of unit root for the level data of spot and futures prices of Coriander traded in NCDEX India for the period from 1st of January 2009 to 31st of December 2016. The results of ADF and PP test are presented in Table 1 and 2 respectively.

**Table 1:** Augmented Dickey-Fuller Test Statistics (ADF) results

| market | Augmented Dickey-Fuller Test Statistics (ADF) | | | | |
|---|---|---|---|---|---|
| | Critical value at 0.05 level | Level | | 1st Difference | |
| | | t-Statistic | Prob.* | t-Statistic | Prob.* |
| Spot | -2.8627 | -0.9586 | 0.7696 | -37.9065 | 0.0000 |
| Futures | | -1.3899 | 0.5887 | -42.5660 | 0.0000 |

Source: Survey Data

*MacKinnon (1996) one-sided p-values.

**Table 2:** Phillips-Perron Test Statistics (PP) results

| market | Phillips-Perron Test Statistics (PP) | | | | |
|---|---|---|---|---|---|
| | Critical value at 0.05 level | Level | | 1st Difference | |
| | | t-Statistic | Prob.* | t-Statistic | Prob.* |
| Spot | -2.8627 | -1.1374 | 0.7030 | -39.2286 | 0.0000 |
| Futures | | -1.4551 | 0.5564 | -42.7261 | 0.0000 |

Source: Survey Data

*MacKinnon (1996) one-sided p-values.

Results of table 1show the non-rejection of the null hypothesis of the ADF test for Coriander price series indicating that all the price series under study are non stationary at level series, but it is clear that the null hypothesis of no unit roots for time series are rejected at their first differences since the ADF test P-values are less than 0.05 at 5% level of significances according to table 1. Results of table 2 show the non-rejection of the null hypothesis of the PP test for Coriander price series indicating that all the price series under study are non stationary at level series, but it is clear that the null hypothesis of no unit roots for time series are rejected at their first differences since the PP test P-values are less than 0.05 at 5% level of significances according to table 2.

### 4.2. Johansen Co-integration Test

After testing that data series are stationary or non-stationary, the authors applied Johansen Co-integration Test to test the co-integration between the stationary variables to determine the existence of a long-run relationship between the spot and futures prices of Coriander traded in NCDEX for the period from 1st of January 2009 to 31st of December 2016. The result of Johansen Co-integration Test for spot and futures price of Coriander is represented in Table 3.

**Table 3:** Johansen co-integration test results

| Hypothesis | Trace Test | | | Maximum Eigenvalue Test | | |
|---|---|---|---|---|---|---|
| | Trace Statistics | 5% Critical Value | P-Value** | Max-Eigen Statistics | 5% Critical Value | P-Value** |
| None* | 72.66798 | 20.26184 | 0.0000 | 70.17053 | 15.89210 | 0.0000 |
| At most 1 | 2.497450 | 9.164546 | 0.6780 | 2.497450 | 9.164546 | 0.6780 |

Source: Survey Data

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

The results of table 3 show that there is evidence of co-integrating vector(s) according to the Trace statistic for Coriander. That is between Coriander spot price and futures price. The co-integration results demonstrate that the null hypothesis of no co-integration equation (none) between the spot price and futures price of Coriander can be rejected using the 5% critical value. This implies that the Coriander spot and futures prices are co-integrated with one co-integrating vector. The existence of co-integration between the spot and futures prices corroborates the first an important necessary condition for long-run market relationship. Based on the Johansen Co-integration Test, authors conclude that there is a long-run relationship between spot and futures prices of Coriander traded in NCDEX India for the period from 2009 to 2016.

### 4.3 Optimal Hedging strategies Estimation

In this section, authors estimate the optimal hedge ratio and hedging effectiveness of Coriander futures via OLS and VECM, and Diagonal VECH-GARCH model which described earlier for both in-sample and out-sample periods, and then compare them.

At first, authors calculated the optimal hedge ratio and hedging effectiveness from OLS regression. According to equation 1, the slope of the regression equation and $R^2$ is the optimal hedge ratio and the hedging effectiveness, respectively. The optimal hedge ratio for Coriander is around 0.3811 for 1-day horizon. Table 4 presented the results from the OLS regression model.

**Table 4:** OLS Regression Model Estimates

| Coefficients | 1-Day | 5-Day | 10-Day |
|---|---|---|---|
| α | 0.00005 | 0.0001 | 0.0002 |
| β | 0.3811* | 0.5811* | 0.6824* |
| R2 | 0.3058 | 0.5821 | 0.7241 |
| F-Statistics | 911.3433 | 572.5341 | 535.2969 |

Source: Survey Data

*denotes 5% level of significance.

To calculate the optimal hedge ratio from VECM, authors estimated equations (2) and (3) with eight lags and the results are presented in Table 5(panel A and B). For VECM, The optimal hedge ratio is derived as $h^{*}=\sigma_{sf}/\sigma_{f}$, where $\sigma_{sf}$ and $\sigma_{f}$ are the covariance between spot and futures residuals and the variance of futures residuals, respectively.

**Table 5:** Vector Error Correction Model Estimates

Panel A: Estimates of Equation (2)

| Variables | Coefficients | | |
|---|---|---|---|
| | 1-Day | 5-Day | 10-Day |
| $\alpha_s$ | 5.24E-06 | 9.38E-05 | 0.000339 |
| $\beta_{s1}$ | -0.211608** | -0.702224** | -0.463054** |
| $\beta_{s2}$ | -0.164147** | -0.525313** | -0.080787 |
| $\beta_{s3}$ | -0.08238** | -0.331221** | _ |
| $\beta_{s4}$ | -0.037404* | -0.083518 | _ |
| $\beta_{s5}$ | _ | -0.066529 | _ |
| $\beta_{s6}$ | _ | 0.026493 | _ |
| $\delta_{f1}$ | -0.334139** | 0.079005 | -0.092555 |
| $\delta_{f2}$ | -0.254185** | -0.010179 | -0.133931 |
| $\delta_{f3}$ | -0.232427** | -0.051278 | _ |
| $\delta_{f4}$ | -0.129262** | -0.192931 | _ |
| $\delta_{f5}$ | _ | -0.163584 | _ |
| $\delta_{f6}$ | _ | -0.175345** | _ |
| $\gamma_s$ | 0.430868** | 0.91611** | 0.927911** |
| $R^2$ | 0.366343 | 0.410014 | 0.34628 |
| Durbin-Watson-Statistics | 2.040661 | 2.039094 | 2.109216 |

Panel B: Estimates of Equation (3)

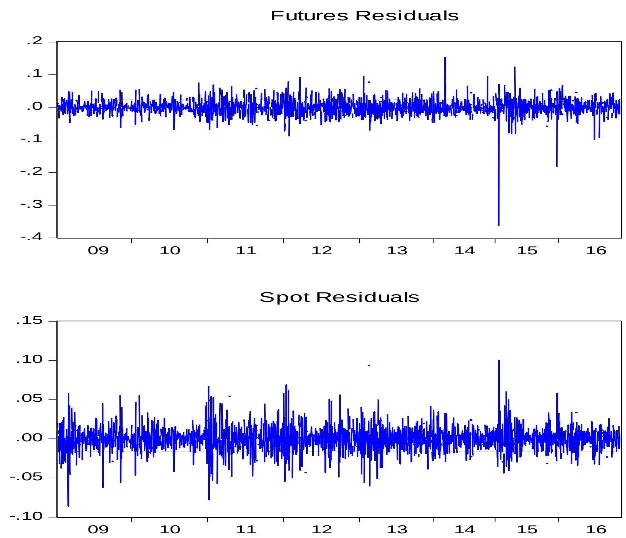
| Variables | Coefficients | | |
|---|---|---|---|
| | 1-Day | 5-Day | 10-Day |
| $\alpha_f$ | 3.97E-06 | 1.25E-05 | -8.06E-05 |
| $\beta_{s1}$ | -0.117652* | -0.438361* | -0.433037* |
| $\beta_{s2}$ | -0.127798** | -0.329463 | -0.139944 |
| $\beta_{s3}$ | -0.078054* | -0.14932 | _ |
| $\beta_{s4}$ | -0.043553** | -0.002604 | _ |
| $\beta_{s5}$ | _ | -0.01564 | _ |
| $\beta_{s6}$ | _ | -0.030093 | _ |
| $\delta_{f1}$ | -0.698061** | -0.225743 | -0.232622 |
| $\delta_{f2}$ | -0.496288** | -0.319356 | -0.129759 |
| $\delta_{f3}$ | -0.400998** | -0.247648 | _ |
| $\delta_{f4}$ | -0.18626** | -0.3164* | _ |
| $\delta_{f5}$ | _ | -0.294894* | _ |
| $\delta_{f6}$ | _ | -0.200992* | _ |
| $\gamma_f$ | -0.838892** | -0.476235 | -0.174548 |
| $R^2$ | 0.420314 | 0.402769 | 0.294405 |
| Durbin-Watson-Statistics | 2.030154 | 2.022489 | 2.077021 |

Source: Survey Data

*and ** denote 10% and 5% level of significance, respectively.

The features of residuals are tested to examine the efficiency of VECM. Figure 2 plots the actual values of the residuals for spot and futures equations of Coriander from VECM, respectively. It obviously shows the presence of ARCH effects.

**Figure 2:** Residual series from spot and futures equation in VECM for Coriander




The residual plots indicate the presence of ARCH effects, which support the assumption of dynamic variance over time. Therefore, different time-varying GARCH models may give the better results. Thus, authors estimate Diagonal VECH-GARCH model. The estimated coefficients of the Diagonal VECH-GARCH model from equation 4 and 5 are presented in table 6. The condition of stationary covariance ($\boldsymbol{\alpha_{ii}^2} + \boldsymbol{b_{ii}^2} < \mathbf{1}$) are satisfied in Diagonal VECH-GARCH models.

**Table 6:** Diagonal VECH-GARCH model Estimates

| Variables | Coefficients | | |
|---|---|---|---|
| | 1-Day | 5-Day | 10-Day |
| $\mu_s$ | 0.000004** | 0.0006** | 0.0024** |
| $\mu_{sf}$ | 0.000002** | 0.0004** | 0.0016** |
| $\mu_f$ | 0.000005** | 0.0005** | 0.0013** |
| $\alpha_s$ | 0.0622** | 0.1565** | 0.3467** |
| $\alpha_{sf}$ | 0.0518** | 0.1670** | 0.3160** |
| $\alpha_f$ | 0.0843** | 0.2512** | 0.3099** |
| $\beta_s$ | 0.9390** | 0.6726** | 0.3566** |
| $\beta_{sf}$ | 0.9406** | 0.6181** | 0.3927** |
| $\beta_f$ | 0.8990** | 0.4395** | 0.3868** |
| $\alpha_s^2 + \beta_s^2$ | 0.8856 | 0.4769 | 0.2473 |
| $\alpha_f^2 + \beta_f^2$ | 0.8152 | 0.2562 | 0.2456 |

Source: Survey Data

*and ** denote 10% and 5% level of significance, respectively.

Figure 3illustrates the time-varying hedge ratio obtained from Diagonal VECH-GARCH model. The average value of the time-varying hedge ratio series is 0.3995.

**Figure 3:** Time-varying hedge ratio obtained from Diagonal VECH-GARCH model for Coriander

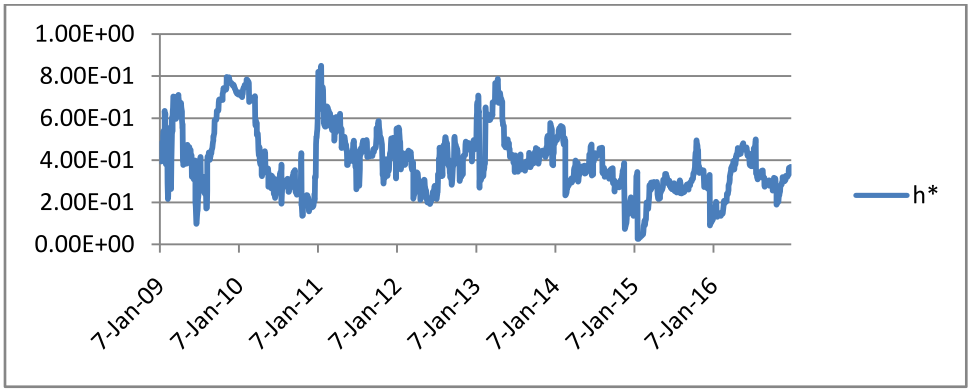



Table 7 and 8 exhibit the optimal hedging ratios and hedging effectiveness (% Variance Reduction) obtained by alternative constant and time-varying hedging strategies for in-sample and out-sample periods, respectively. The results show that the hedge ratio obtained by VECM is higher than hedge ratio obtained by OLS and Diagonal VECH-GARCH model in 1-day horizon, but in longer horizons, the hedge ratio obtained by Diagonal VECH-GARCH model is higher than the hedge ratio obtained by VECM and OLS models.

The estimation of the most effective hedge ratios according to variance reduction (hedging effectiveness) reveals that the Diagonal VECH-GARCH strategy with time-varying hedge ratio perform better than OLS and VECM strategies in all horizons in the in-sample period, and 5-day horizon in the out-sample period. But the VECM strategy performs better than OLS and Diagonal VECH-GARCH strategies for 1-day and 10-day horizon in the out- sample period. By and large, Diagonal VECH-GARCH time-varying strategy is the most optimal hedging strategy.

**Table 7:** In-sample Optimal Hedge Ratios and Hedging Effectiveness

| Method | 1-Day | | 5-Day | | 10-Day | |
|---|---|---|---|---|---|---|
| | h* | HE | h* | HE | h* | HE |
| Naïve | 1 | -0.5012 | 1 | 0.2749 | 1 | 0.5570 |
| OLS | 0.3811 | 0.3055 | 0.5812 | 0.5793 | 0.6824 | 0.7170 |
| VECM | 0.4073 | 0.3651 | 0.5819 | 0.6386 | 0.6630 | 0.7928 |
| D-VECH | 0.3995 | 0.2818 | 0.6230 | 0.6650 | 0.6974 | 0.7853 |
| D-VECH | Time Varying | 0.3668 | Time Varying | 0.7117 | Time Varying | 0.8360 |

Source: Survey Data

**Table 8:** Out-sample Optimal Hedge Ratios and Hedging Effectiveness

| Method | 1-Day | | 5-Day | | 10-Day | |
|---|---|---|---|---|---|---|
| | h* | HE | h* | HE | h* | HE |
| Naïve | 1 | -0.3712 | 1 | 0.0950 | 1 | 0.4762 |
| OLS | 0.3811 | 0.4089 | 0.5812 | 0.5911 | 0.6824 | 0.6943 |
| VECM | 0.4073 | 0.5208 | 0.5819 | 0.6813 | 0.6630 | 0.7160 |
| D-VECH | 0.3995 | 0.4240 | 0.6230 | 0.7870 | 0.6974 | 0.1993 |
| D-VECH | Time Varying | 0.4282 | Time Varying | 0.7948 | Time Varying | 0.2188 |

Source: Survey Data

## 5. Conclusion

In an emerging market like India, the growth of commodity futures market would depend on effectiveness of derivatives in managing risk. The optimal number of futures contracts to buy or sell for each unit of underlying asset is provided by Optimal hedging ratios. Hedging strategies be categorized in two broad categories namely constant and time -varying. The constant viewpoint presumes that hedge ratio is stable over the time. However, time-varying viewpoint presumes that hedge ratios are changing over the time. This paper tries to find the optimal hedging strategies among competing constant OLS regression and VECM, and also time-varying Diagonal VECH-GARCH models. Daily closing spot and futures prices of Coriander traded in NCDEX India have taken for the period from 1st of January 2009 to 31st of December 2016 for developing the optimal hedge ratios and for the period from 1st of January 2017 to 31st of December 2017 for out-sample data. The empirical results for both in-sample and out-sample hedging strategies demonstrate that the time-varying Diagonal VECH-GARCH hedge ratio performs better than other models in minimizing the risk for Coriander traded in NCDEX India for the period of the study. These findings imply that in selecting the most suitable hedge ratio, degree of risk aversion of investors plays a significant role. This indicates that risk aversion being the major goal of an investor, and the time-varying Diagonal VECH-GARCH is the most optimal hedging strategy and performs best in deducting the conditional variance of the hedged portfolio.

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