Commodity Price Volatility and Time varying Hedge Ratios: Evidence from the Notional Commodity Futures Indices of India.

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Abstract

This paper examines the price volatility and hedging behavior of four notional commodity futures indices which represents the relevant sectors like Agriculture (AGRI), Energy (ENER), Metal (META) and an aggregate of agricultural, energy and metal commodities (COMDX), retrieved from the commodity future exchange market, Multi Commodity Exchange (MCX), of India. After adjusting for dates and missing observations, due to holidays, a total of 2175 daily closing prices over the period of 6/8/2005 to 8/18/2012 have been employed to measure volatility and hedge ratio. A GARCH (1, 1) model is employed to measure the spot return volatility of respective indices. DVECH-GARCH, BEKK- GARCH, CCC-GARCH and DCC-GARCH are used to estimate the time varying hedge ratio. Further, an in-sample performance analysis, in terms of hedged return and variance reduction approaches, of the hedge ratios estimated from the different bivariate GARCH models are also carried out. The empirical evidence confirms that all the models are able to reduce the exposure to spot market as perfectly as possible in comparison with the unhedged portfolio and in doing so the advanced extensions of bivariate GARCH models viz DCC-GARCH and CCC-GARCH, have a clear edge over its old counterparts.

Keywords: Commodity Indices**,** Volatility, Hedging Ratio**,** DVECH-GARCH, BEKK-GARCH, CCC-GARCH and DCC-GARCH

JEL Classification:

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Introduction

During 1990s, the economic liberalization in many countries led to increasing withdrawal of the government's intervention from the agricultural commodity sector, which made the agricultural prices dependent on the domestic and international market forces (UNCTAD, 1997; 1998). Commodity-using industries around the world have been hit by soaring costs and volatile trading conditions. Years of underinvestment in production capacity have led to shortfalls in the face of soaring demand from emerging markets in Asia, causing prices to surge by 200 per cent (in the case of corn), 400 per cent (oil) to as much as 500 per cent (copper) since 2001(Haque K: 2008).

Ever since the enactment of liberalization measures in developing countries the commodity price volatility has been received great attention from academicians, policy makers, farmers etc. Shively (1996) established that the year in which economic reforms were adopted in Ghana saw both higher and more variable maize prices than either before or after the adoption of liberalization policies. Chavas and Kim (2006) documented that market liberalization has been associated with a large increase in price volatility (e.g., in the mid 1990's). Their analysis also suggests that the price support program has been effective in reducing price volatility. Istiqomah et al (2005) study on the volatility and integration of rice markets in Java, Indonesia showed that the volatility of both producer and retail prices are higher in the post-liberalization period. Apergis and Rezitis (2003) investigation of volatility spillover effect between agricultural input, output and retail food prices in Greece revealed that both agricultural input and retail food price exert significant positive spillover effect on the volatility of agricultural product prices. A study by Swaray (2006) on the volatility of primary commodity price in Sub-Saharan Africa identified that volatility is greater when commodity prices are moving downward than upward.

Sekhar (2004) brought evidence to show the fact that international agricultural prices are uniformly more variable than the domestic prices. Further he established that the intra-year variability is higher in domestic markets while the inter-year variability is higher in the international markets. Ghosh and Chakravarty (2009) examined the effect of trade liberalization on agricultural product price Volatility in India. This study revealed that price volatility estimated as the predictable variance is increased after trade liberalization only in respect of two out of the six crops considered. Those crops were commercial ones as groundnut and cotton, are traded in the global market. Grandhi and Crawford (2007) analysis on price volatility in the cotton yarn industry proved that while exhibiting a fair degree of volatility in the early 1990s, Indian cotton prices have been stabilized in recent years, and have steadily increased despite the expansion in cotton cultivation due in part to increased demand from the export and domestic fabric markets. Patnaik (2002) and Ghosh (2005) also support the view that trade liberalization has effectively imported the volatility of international prices formed in highly imperfect and monopolized market environments into Indian agriculture.

Some Studies Related with Hedging Using Commodity Futures Contract

Baille and Myers (1991) tried to extend the earlier studies on optimal hedge ratio analysis by employing a Bivariate GARCH model. Their main purpose was to estimate an optimal commodity futures hedge. Their study’s conclusion was that the GARCH model is the best specification in order to estimate optimal hedge ratio.   Lien et.al (2002) made an attempt to evaluate the hedging performance of constant-correlation GARCH (CCGARCH) model by using ten different futures markets covering currency futures, commodity futures and stock index futures. They found out that in each market the OLS hedge ratio provides smaller hedged portfolio variance than the GARCH hedge ratios. Bystrom (2003) studies the hedging performance of electricity futures on the Nordic power exchange. In this study the traditional naive hedge and the OLS hedge are compared out-of-sample to more elaborate moving average and GARCH hedges, and the empirical results indicate some gains from hedging with futures despite the lack of straight-forward arbitrage possibilities in the electricity market. Furthermore, he found a slightly better performance of the simple OLS hedge compared to the conditional hedges.

Empirical works related with hedge ratio and performance analysis are extensively utilizing the stock futures contract than commodity futures contract. In this category we have the studies like Kroner and Sultan (1993), Ghosh (1993), Park and Switzer (1995), Cechetti et al(1988), Lypny and Powalla (1998), , Yang (2001), Pattarin and Feretti (2004), Baduri and

Durai (2007) and Lagesh and Puja (2009). These studies are mainly concentrated on the issues like the characteristics of the optimal hedge ratio estimated from a cointegrated spot and futures market and a heteroscedastic series and the effectiveness of hedge ratios obtained through different econometric models.

Bose (2008) analyses the information flow, market integration and correlation between commodity future indices and equity indices and hedge effectiveness of commodity futures indices in India. She utilizes the notional indices constructed by MCX India to empirically analyze the above issues. Her analysis indicates that the notional commodity indices behave like the equity indices in terms of efficiency and flow of information and confirm that both contemporaneous futures and spot prices contribute to price discovery and the futures market can provide information for current spot prices and thus help to reduce volatility in the spot prices of the relevant commodities and provide for effective hedging of price risk.

However the present study focuses on the following issues:

- It makes use of the notional indices constructed by MCX India for empirical analysis. Though these indices are provided to the market participants only for information, however, since they are constructed from real time prices of exchange traded commodities/futures, each index is an indication of the price movements in the spot/futures market as a whole (or the relevant sub-sector) (Bose (2008)).
- We include the time varying feature of the series in estimating volatility and hedge ratio.
- We analyze the effectiveness of hedge ratio estimated from different model through hedged return and minimum variance approach.

Objectives

The specific objectives of the present study are,

1. To measure the price volatility of different commodities in the spot market.
2. To analyze the hedge ratio using different econometric models

3. To estimate the effectiveness of hedge ratio estimated in minimizing exposure to the spot market

Data and methodology

Data

The present study investigate price volatility and hedging behavior of the four notional commodity spot and future indices which represents the relevant sectors like Agriculture (AGRI), Energy (ENER), Metal (META) and an aggregate of agricultural, energy and metal commodities (COMDX), retrieved from the commodity future exchange MCX India. Thus the present study has made use of the variables like logarithmic return of spot and future agricultural index (LRAS & LRAF), energy index (LRES & LREF), metal index (LRMS & LRMF) and aggregate commodity index (LRCS & LRCF)[2]. After adjusting for dates and missing observations, due to holidays, a total of 2175 daily closing prices over the period of 6/8/2005 to 8/18/2012 have been employed for the estimation purpose.

Methodology

I. Modeling Volatility

The simplest model for volatility is the historical estimate. Historical volatility simply involves calculating the variance (or standard deviation) of price in the usual way over some historical period. However this model can't account for time varying variance and volatility clustering or persistence characteristics of the price series.

The heteroscedastic nature of the price series has been recognized by Engle (1982) who introduced the Autoregressive Conditional Heteroscedasticity (ARCH) model, later on Bollerslev, (1986) provided a Generalized Autoregressive Conditional Hetroscedasticity (GARCH) model. The present study employs a GARCH (p, q) model to measure the spot return volatility of respective indices.

The GARCH (1, 1) model can be specified as

[2]For more details on index aggregation please see http://www.mcxindia.com/sitepages/abtcomdex.htm

$$Y_t = \mu_0 + \mu_t Y_{t-1} + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots (1)$$

Where $\varepsilon_t / \Omega_{t-1}$ ~ iid $N(0, \sigma_t^2)$,

Ω_{t-1} indicates the past information set

$$\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1} \quad \ldots\ldots\ldots\ldots\ldots (2)$$

Where equation (1) and (2) are return and variance equations respectively.

II. Methods of Hedge Ratio Analysis

Having understood the fact that the joint distribution of spot and future series are time varying and so the risk minimizing hedge ratios, the Optimal Hedge Ratio (h*) is estimated as follows

$$h*_t \frac{Cov(S_t F_t)}{Var(F_t)} \qquad (3)$$

Where $h*_t$ stands for Optimal Hedge Ratio at time period t, S_t and F_t are logarithmic return of spot and future series at t.

The present study employs Bivariate GARCH models like DVECH-GARCH, BEKK- GARCH, CCC-GARCH and DCC-GARCH to estimate the time varying hedge ratio. These models are well recognized as the model to capture the time varying nature of returns series, volatility spillover between markets or assets and conditional covariance between spot and futures market.

With considering the VECM model as mean equation Brooks et.al (2002) have employed a VECM (k) GARCH model to estimate time varying nature of the second moment. By assuming $\varepsilon_t / \Omega_{t-1} \sim N(0, H_t)$ and by defining h_t as vech (H_t), which denotes the vector-half operator that arrange the lower triangular elements of N×N matrix into [N (N+1)/2] vector, the bivariate VECM GARCH can be written as;

$$vech(H_t) = \begin{bmatrix} h_{ss,t} \\ h_{sf,t} \\ h_{ff,t} \end{bmatrix} = C_0 + A_1 vech(\varepsilon_{t-1}\varepsilon_{t-1}') + B_1 vech(H_{t-1}) \quad (4)$$

this can be explained as:

$$H_t = \begin{bmatrix} h_{ss} \\ h_{sf} \\ h_{ff} \end{bmatrix} = \begin{bmatrix} C_{ss} \\ C_{sf} \\ C_{ff} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{s,t-1} \\ \varepsilon_{s,t-1}\varepsilon_{f,t-1} \\ \varepsilon^2_{f,t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} h_{ss,t-1} \\ h_{sf,t-1} \\ h_{ff,t-1} \end{bmatrix} \quad (5)$$

Where $h_{ss,t}$ and $h_{ff,t}$ represent the conditional variance of the errors $\varepsilon_{s,t}$, $\varepsilon_{f,t}$ from the mean equations, while $h_{sf,t}$ represents the conditional covariance between spot and futures prices.

1. Diagonal Vech-GARCH Model (DVECH-GARCH)

However the above model sufferer from a large number of parameter, (21 parameters) which may make the calculation very difficult. To overcome this problem Bollerslev, Engle and Wooldridge have introduced a diagonal vector GARCH (DVEC-GARCH) model in 1988. This model assumes that the off diagonal elements are zero. The DVEC-GARCH can be sited as:

$$H_t = \begin{bmatrix} h_{ss} \\ h_{sf} \\ h_{ff} \end{bmatrix} = \begin{bmatrix} C_{ss} \\ C_{sf} \\ C_{ff} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon^2_{s,t-1} \\ \varepsilon_{s,t-1}\varepsilon_{f,t-1} \\ \varepsilon^2_{f,t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \begin{bmatrix} h_{ss,t-1} \\ h_{sf,t-1} \\ h_{ff,t-1} \end{bmatrix} \quad (6)$$

In the above vector representation only three parameters appear in each A1 and B1 matrix. Here the variance and covariance equations depend on its own past squared residuals and cross product of residuals.

From the above matrix equation the diagonal representation of the conditional variances elements $h_{ss,t}$ and $h_{ff,t}$ and the covariance $h_{sf,t}$ can be reorganized as;

$$\begin{aligned} h_{ss,t} &= c_{ss} + a_1 \varepsilon_{s,t-1}^2 + b_1 h_{ss,t-1} \\ h_{sf,t} &= c_{sf} + a_2 \varepsilon_{s,t-1}\varepsilon_{f,t-1} + b_2 h_{sf,t-1} \\ h_{ff,t} &= c_{ff} + a_3 \varepsilon_{f,t-1}^2 + b_3 h_{ff,t-1} \end{aligned} \quad (7)$$

2. BEKK GARCH Model

In order to check the positive definite constraint, the present study also employes BEKK-GARCH model, proposed by Bollerslev et al(1995). The mean equation of the model can be written as:

$$R_t = \alpha + u_t \quad (8)$$

$$u_t / \Omega_{t-1} \sim N(0, H_t)$$

Where, $R_t = [R_{1t}, R_{2t}]$ indicates the return vector for cash and futures series. $\alpha = [\alpha_{1t}, \alpha_{2t}]$ indicates the vector of the constant term and u_t shows the residual vector as $u_t = [u_{1t}, u_{2t}]$. Ω_{t-1} shows the information set and H_t is the covariance matrix.

On the basis of above information the conditional variance equation can be stated as follows:

$$H_t = C_0' C_0 + A_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' A_{11} + B_{11}' H_{t-1} B_{11} \quad (9)$$

Which can be explained as:

$$H_t = C_0' C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad (10)$$

Where C_0 is a lower triangular matrix and A_{11} and B_{11} are 2×2 matrices. The positive definiteness of the covariance matrix is ensured owing to the quadratic nature of the term on the right hand side of the equation.

3. Constant Conditional Correlation GARCH Model (CCC-GARCH)

Assuming the time invariant correlation $C = \rho_{SF}$, the structure of CCC-GARCH model will be

$$H_t = D_t C D_t \qquad (11)$$

where D_t is a diagonal matrix of individual GARCH volatilities (standard deviations). Thus the time varying covariance in H_t can be written as

$$h_{ij,t} = \rho_{ij} \sigma_{i,t} \sigma_{j,t} \qquad (12)$$

4. Dynamic Conditional Correlation GARCH(DCC-GARCH)

Engel (2002) extended the CCC-GARCH model to a Dynamic Conditional Correlation GARCH (DCC-GARCH) model, which is argued to have the flexibility of univariate GARCH models and to provide at the same time parsimonious correlation specifications without the computational difficulties of multivariate GARCH models, due to a two-step approach.

The residuals of Equation (8) are assumed to be conditionally normal and the conditional covariance is specified using dynamic conditional correlation (DCC) analysis:

:
$$\varepsilon_{i,t} / I_{t-1} \sim N(0, H_t) \ , \ H_t = \begin{bmatrix} \sigma^2_{i,t} & \sigma^2_{ij,t} \\ \sigma^2_{ji,t} & \sigma^2_{j,t} \end{bmatrix}$$

for *i*= cash and *j*= futures

$$H_t = D_t \, R_t \, D_t \ \text{........................}(13)$$

where I_{t-1} is the information set at time period *t-1*, *Ht* is the 2×2 conditional variance-covariance matrix at time t, R_t is the 2×2 time varying correlation matrix at time t, and *Dt* is a 2×2 diagonal matrix of time varying standard deviations obtained from univariate GARCH (1,1) specifications:

$$h_{ii,t} = \omega_i + \alpha_{i,1} \ \varepsilon^2_{i,t-1} + \beta_{i,1} h_{ii,t-1} \qquad (14)$$

for *i* = cash and *j* = futures

The conditional covariance terms are then assumed to follow the DCC (1,1) specification:

$$h_{ij,t} = \rho_{ij,t}\sqrt{h_{ii,t}}\sqrt{h_{jj,t}}$$

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} \quad and$$

$$q_{ij,t} = \bar{\rho}_{ij}(1-a-b) + aq_{ij,t-1} + b\eta_{i,t-1}\eta_{j,t-1} \qquad (15)$$

for *i*= Cash and *j*= futures

where $q_{ij,t}$ is the conditional covariance between the standardized residuals ($\eta_{i,t-1} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$) from Equation (8); $\bar{\rho}_{ij}$ is the unconditional correlation between model residuals ($\varepsilon_{i,t}$). The average of $q_{ij,t}$ will be $\bar{\rho}_{ij}$ and the average variance will be 1. The $q_{ij,t}$ expression will be mean-reverting when a+b<1. The specification reduces the number of parameters to be estimated and makes the estimation and time-varying correlation more tractable.

As per Engle and Sheppard (2001) and Engle (2002), the DCC model can be estimated by using a two – stage approach to maximizing the log - likelihood function. Let θ denote the parameters in D_t and Φ the parameters in R_t , then the log likelihood function is given below:

$$I_t(\Theta, \Phi)$$

$$= [-\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t|^2 + \varepsilon_t^{'} D^{-2}\varepsilon_t)] + [-\frac{1}{2}\sum_{t=1}^{T}(\log(2\pi) + \log|R_t| + \mu_t^{'} R_t^{-1}\mu_t - \mu_t^{'}\mu_t)] \text{....(16)}$$

The first part of the likelihood function in equation (16) is volatility, which is the sum of individual GARCH likelihoods. The log – likelihood function can be maximised in the first stage over the parameter in D_t. Given the estimated parameters in the first stage, the correlation component of the likelihood function in the second stage (the second part of the equation (16) can be maximised to estimate correlation coefficients. Quasi-maximum likelihood estimation (QMLE) of Bollerslev and Wooldridge (1992) is adopted in parameter estimation, which allows inference in the presence of departure from conditional normality.

III. Performance Analysis

The in-sample performance of naïve (i.e. h*=1) and time varying hedge ratios estimated through four bivariate GARCH models are estimated through the hedged portfolio return and variance reduction approaches (Ediringtion, 1979). The mean return of the unhedged and hedged portfolio can be written as:

$$r_u = S_t - S_{t-1} \quad (17)$$

and

$$r_h = (S_t - S_{t-1}) - h^*(F_t - F_{t-1}) \quad (18)$$

Where r_u and r_h are the mean return on the unhedged and hedged portfolios respectively. S_t and F_t are the logged spot and futures prices at time period 't' and h^* is the optimal hedge ratio.

The variance of unhedged and hedged portfolios can be calculated as:

$$Var(U) = \sigma_S^2 \quad (20)$$

and

$$Var(H) = \sigma_S^2 + h^{*2}\sigma_F^2 - 2h^*\sigma_{S,F} \quad (21)$$

Where $Var(U)$ and $Var(H)$ indicates the variance of hedged and unhedged portfolios. σ_S^2 and σ_F^2 are the standard deviations of spot and futures prices respectively and σ_{SF} shows the covariance of spot and futures series. Edirington (1979) suggest that the hedging performance of optimal hedge ratios obtained from different econometric methods can be find out through a percentage variance reduction approach. The variance reduction is to be estimated as:

$$= \frac{Var(U) - Var(H)}{Var(U)}$$

As per these two methods, the effective hedge ratio is one which provides the highest portfolio return and the lowest variance.

Empirical Discussion

Table 1 depicts the descriptive statistics on spot and futures return of Agriculture (LRAS&LRAF), Energy (LRES&LREF), Metal (LRMS&LRMF), and Comdex (LRCS&LRCF), indices. Negative skewness, except for agri spot return, high kurtosis and a significant Jarque-Bera statistics are clear evidence for asymmetry in distribution, thick tail and non-normality respectively. These evidences support the statement that the given series are asserting the common characteristics of financial time series. Therefore a hedge ratio estimated from the model which assume that the variance remain constant over time, may become an over hedged one.

Table 2 displays the result of spot market volatility analysis of four commodity indices. The significant coefficients of ARCH and GARCH terms give evidence for the existence of volatility in the respective series. The values of $(\alpha + \beta)$ are close to one for all indices. This observation confirms that shocks to conditional variance are highly persistent.

Keeping above outcome in mind we went for estimating a time varying optimal hedge ratio, which is expected to minimize the spot market risk as perfectly as possible, by introducing four extensions of bivariate GARCH models: Diagonal Vech GARCH(1,1), Diagonal BEKK-GARCH(1,1), Constant Conditional Correlation GARCH(1,1) and Dynamic Conditional Correlation(DCC-GARCH(1,1)). Table 3, 4, 5 and 6 portray the result from DVECH-GARCH, DBEKK-GARCH, CCC-GARCH and DCC-GARCH (1, 1) respectively. Most of the coefficients have the expected sign and report highly significant.

Figure 1 plots time varying optimal hedge ratios estimated from different bivariated GARCH models: DVECH-GARCH, DBEKK-GARCH, CCC-GARCH and DCC-GARCH (1, 1), for four commodity notional indices. The first four figures i.e. AGRI DVECHH, AGRIBEKKH, AGRICCH and AGRIDCCH are dynamic hedge ratios for the Agricultural indices estimated from DVECH-GARCH, DBEKK-GARCH, CCC-GARCH and DCC-GARCH models respectively. Table 7 present sample mean of the time varying hedge ratios estimated through DVECH-GARCH, DBEKK-GARCH, CCC-GARCH and DCC-GARCH models. On the agricultural indices, on average, the hedge ratio estimated using the advanced extension of bivariate GARCH model i.e DCC-GARCH provides an optimal one, i.e. 0.4168 to the traders. Therefore by holding, on average, 0.4168 units of agricultural futures indices a trader can hedge or minimize the spot risk as low as possible.

The figures named ENERGYDVECHH, ENERGYBEKKH, ENERGYCCH and ENERGYDCCH are the Energy hedge ratios estimated from DVECH-GARCH, DBEKK-GARCH, CCC-GARCH and DCC-GARCH models respectively. Among these hedge ratios the one estimated through CCC-GARCH marks the optimal (0.4901). In the same way third and fourth column of table 7 report, on average, the time varying hedge ratios for Metal and Comdex indices, respectively. Among these hedge ratios the one estimated with DCC-GARCH for Metal index (0.239255) and CCC-GARCH for Comdex index (0.394589) are found optimal.

In-sample Performance analysis based on hedged return and variance reduction approaches is listed in Table 8. The unhedged return marks a high return in in-sample period for all indices but with a high variance. The hedged returns are different from the un-hedged returns. Among the hedged returns CCC-GARCH offers a comparatively large return for the traders in AGRI and DCC-GARCH produces a large return for the traders in ENER. Further, those who followed the DBEKK-GARCH hedge ratios in trading META received a comparative higher return. Finally, DCC-GARCH provided a higher return for the traders in COMDX indices. The bottom part of the table 8 exhibits performance of hedge ratios, in terms of variance reduction approach, estimated through different bivariate GARCH models. Among the three bivariate GARCH models DCC-GARCH reports a higher variance reduction in AGRI (60.255%) and META (54.338%) markets. CCC-GARCH provides higher variance reduction in ENER (70.407%) and COMDX (46.343%) markets. The DVECH-GARCH model stands second best in variance reduction in both ENER and COMDX markets. In COMDX index, which is an aggregate of agricultural, energy and metal commodities, DVECH-GARCH presents a maximum variance reduction (77.1%). It is DBEKK-GARCH and CCC-GARCH which stand second in variance reduction in AGRI and META markets respectively.

Concluding Remarks

This study looks into the price volatility and hedging behavior of four notional commodity spot and futures indices which represents the relevant sectors like Agriculture (AGRI), Energy (ENER), Metal (META) and an aggregate of agricultural, energy and metal commodities (COMDX), retrieved from the commodity future exchange market, Multi Commodity Exchange (MCX), of India. After adjusting for dates and missing observations, due to holidays, a total of 2175 daily closing prices over the period of 6/8/2005 to 8/18/2012 have been employed to measure volatility and hedge ratio. A GARCH (1, 1) model is employed to measure the spot return volatility of respective indices. DVECH-GARCH, DBEKK- GARC, CCC-GARCH and DCC-GARCH are used to estimate the time varying hedge ratio. Further we went for an in-sample performance analysis of the hedge ratios estimated from bivariate GARCH models by employing hedged return and variance reduction approaches.

To be concluded, the over analysis reports that the advanced extensions of bivariate GARCH models viz DCC-GARCH and CCC-GARCH, have a clear edge over its old counterparts in producing optimal hedge ratio to the traders. The above evidence suggests that one must incorporate correlation in bivariate GARCH models while estimating hedge ratios. The performance analysis further establishes the superiority of the advanced bivariate GARCH models over its counterparts. It is the hedge ratios estimated using DCC-GARCH and CCC-GARCH models which outperform its counterparts in both attaining a good hedged return and maximum variance reduction in all four markets. Finally, one can observe that the optimal hedge ratios obtained from the different econometric models are able to reduce the exposure to spot market as perfectly as possible.

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Table 1.Descriptive Statistics on Spot and Future Return of the Agricultural,Energy,Metal and COMDEX Indices.

	LRAF	LRAS	LREF	LRES	LRMF	LRMS	LRCF	LRCS
Mean	0.0004	0.0005	0.0003	0.0003	0.0005	0.0006	0.0004	0.0004
Maximum	0.0676	0.0550	0.1131	0.1498	0.1356	0.0684	0.0491	0.0779
Minimum	-0.0759	-0.0523	-0.0873	-0.1859	-0.1377	-0.1355	-0.0612	-0.0638
Std. Dev.	0.0081	0.0060	0.0166	0.0207	0.0131	0.0119	0.0105	0.0114
Skewness	-0.1649	0.3022	-0.0663	-0.2378	-1.2916	-1.0450	-0.4681	-0.2661
Kurtosis	18.3671	12.1862	6.2983	11.2253	23.9908	16.9112	6.5033	7.7678
Jarque-Bera	21400.7800	7677.0540	987.0437	6148.9290	40516.8000	17925.5600	1191.1010	2084.7700
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 2. Spot Return Volatility of Agricultural, Energy, Metal and Aggregate Indices from GARCH (1, 1) Model

	LRAS	LRES	LRMS	LRCS
μ	0.000408* (3.61998)	0.000596*** (1.708505)	0.000741* (3.757749)	0.000548* (2.736896)
c	0.000001* (6.715504)	0.000004* (4.141257)	0.000001* (3.846462)	0.000001* (3.521425)
α	0.067418* (10.06832)	0.045751* (8.361325)	0.054775* (15.22852)	0.048453* (9.287281)
β	0.919809* (120.6547)	0.94203* (130.21)	0.942004* (244.337)	0.942494* (147.268)

Note: The parenthesis shows the z statistics and the asterisk *, ** and *** reveals significant at 1%, 5% and 10% levels.

Table 3. Estimates of the Diagonal Vech-GARCH (1, 1) Model.

	LRAS	LRES	LRMS	LRCS

M(1,1)	0.000001* (7.214284)	0.000004* (5.195952)	0.000012* (11.7856)	0.000002* (6.431236)
M(1,2)	0.000000* (5.143683)	0.000002* (3.332299)	0.000000* (1.720547)	0.000001* (2.938361)
M(2,2)	0.000001* (6.779412)	0.000006* (4.848309)	0.000001* (4.27096)	0.000002* (4.507259)
A1(1,1)	0.108731* (18.34271)	0.035267* (8.020233)	0.106524* (16.1269)	0.057883* (10.65147)
A1(1,2)	0.036736* (10.37108)	0.018019* (4.467396)	0.00987* (2.72297)	0.020033* (4.889784)
A1(2,2)	0.054517* (10.13408)	0.045651* (8.353016)	0.054925* (15.24859)	0.048375* (9.5365)
B1(1,1)	0.887147* (191.0838)	0.949995* (150.1194)	0.818906* (65.72631)	0.918347* (113.0807)
B1(1,2)	0.94761* (252.3435)	0.96499* (122.473)	0.981998* (143.2061)	0.963244* (115.3684)
B1(2,2)	0.929592* (129.2272)	0.937668* (125.367)	0.940349* (232.9746)	0.936922* (137.9378)

Note: The parenthesis shows the z statistics and the asterisk *, ** and *** reveals significant at 1%, 5% and 10% levels.

Table 4. Estimates of the Diagonal-BEKK GARCH (1, 1) Model.

	LRAS	**LRES**	**LRMS**	**LRCS**
M(1,1)	0.000001* (5.855598)	0.000002* (5.218673)	0.000013* (13.1083)	0.000001* (6.642648)
M(1,2)	0.000000* (7.025609)	0.000002* (5.286208)	0.000001* (4.50856)	0.000001* (4.457086)
M(2,2)	0.000001* (6.3923)	0.000006* (5.340323)	0.000001* (4.467866)	0.000001* (4.352885)
A1(1,1)	0.31227* (38.26163)	0.162337* (19.2588)	0.340659* (39.54906)	0.205557* (22.63805)
A1(2,2)	0.220525* (22.59249)	0.204205* (17.52269)	0.219522* (32.37153)	0.204018* (20.99911)
B1(1,1)	0.951407* (489.5638)	0.982409* (531.9033)	0.898017* (139.2219)	0.971929* (377.7604)
B1(2,2)	0.969028* (315.0887)	0.970664* (286.8317)	0.973649* (567.5774)	0.973629* (361.9051)

Note: The parenthesis shows the z statistics and the asterisk *, ** and *** reveals significant at 1%, 5% and 10% levels.

Table 5. Estimates of the CCC GARCH(1,1) Model.

	LRAS	LRES	LRMS	LRCS
M(1)	0.000001* (4.756011)	0.000002* (4.65765)	0.000012* (11.79603)	0.000001* (6.369367)
A1(1)	0.110257* (17.87373)	0.027965* (7.745619)	0.107555* (16.08575)	0.042732* (10.38853)
B1(1)	0.894773* (192.7604)	0.962998* (195.8071)	0.819659* (64.86996)	0.943715* (171.4398)
M(2)	0.000001* (6.754902)	0.000005* (4.377435)	0.000001* (4.183564)	0.000001* (4.141118)
A1(2)	0.067808* (10.86184)	0.046992* (8.512789)	0.057019* (14.90605)	0.051152* (9.500869)
B1(2)	0.922013* (132.3436)	0.940528* (130.5362)	0.938797* (224.6861)	0.93754* (139.5633)
R(1,2)	0.40127* (23.9648)	0.410018* (26.2319)	0.225992* (11.11055)	0.364178* (23.50277)

Note: The parenthesis shows the z statistics and the asterisk *, ** and *** reveals significant at 1%, 5% and 10% levels.

Table 6. Estimates of the DCC GARCH (1,1) Model

	LRAS	LRAF	LRES	LREF	LRMS	LRMF	LRCS	LRCF
μ	0.000408* (3.831486)	0.000468* (3.717705)	0.167903* (5.534659)	-0.078102 (-0.508052)	0.000744* (4.069237)	0.000643* (3.146204)	-0.014028 (-0.385632)	0.065715* (2.718886)
ω	0.000001* (2.885155)	0.000001* (4.060394)	1.291172* (15.88622)	0.013022 (0.165114)	0.000001* (2.808238)	0.000011** (1.858185)	0.051868* (4.37022)	0.11299 (1.443767)
α	0.067418* (5.791222)	0.113317* (5.814023)	1.737569* (27.43024)	0.129713*** (1.78633)	0.055225* (3.669626)	0.106337* (2.225407)	0.107061* (3.847447)	0.029332 (0.859276)
β	0.919809* (93.23643)	0.889189* (64.8084)	0.231226* (17.44252)	0.920016* (179.7331)	0.941741* (70.57069)	0.822727* (19.44748)	0.89174* (58.84695)	0.89863* (29.20534)
Δ_{dcc1}	0.022566* (5.094714)		0.004994* (12.07283)		-0.00107* (-5.793736)		0.047571* (5.01653)	
Δ_{dcc2}	0.97045* (160.1906)		0.996993* (2987.598)		0.967938* (11937.16)		0.754878* (8.005567)	

Note: The parenthesis shows the z statistics and the asterisk *, ** and *** reveals significant at 1%, 5% and 10% levels.

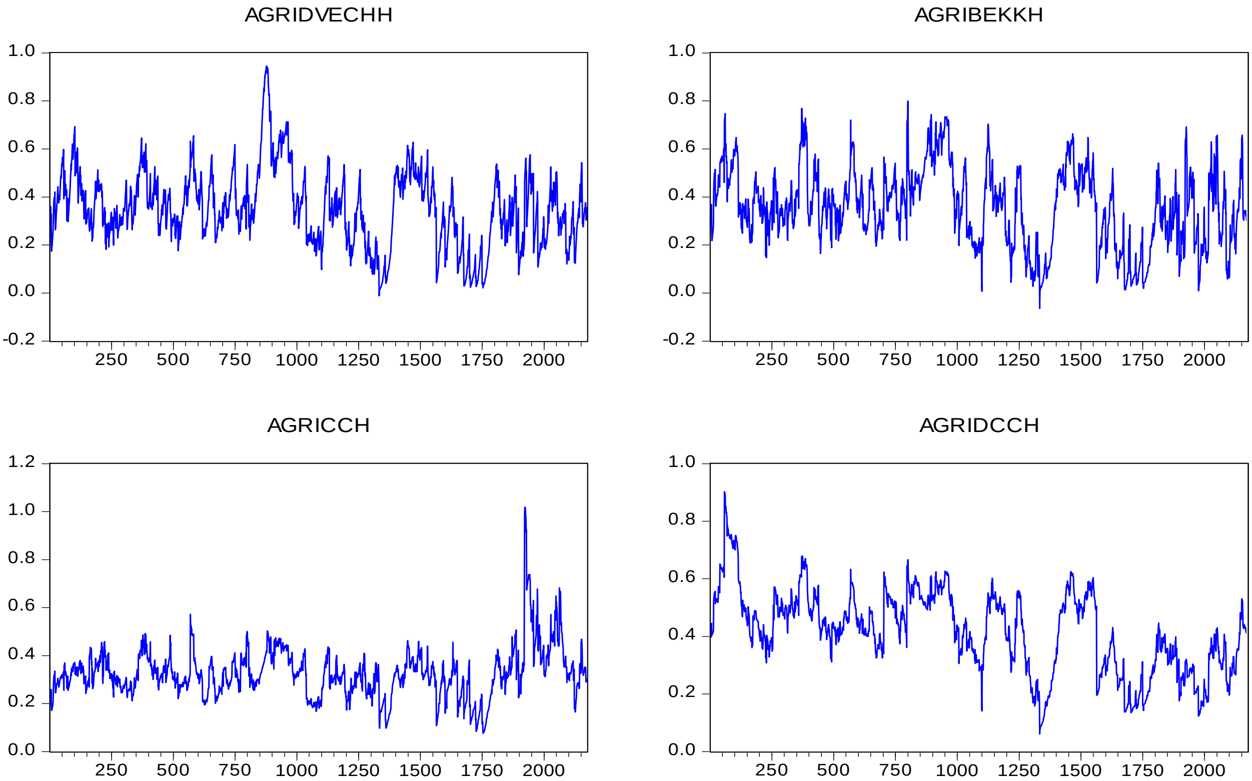
Table 7. Estimates of Optimal Hedge Ratio (h^*)

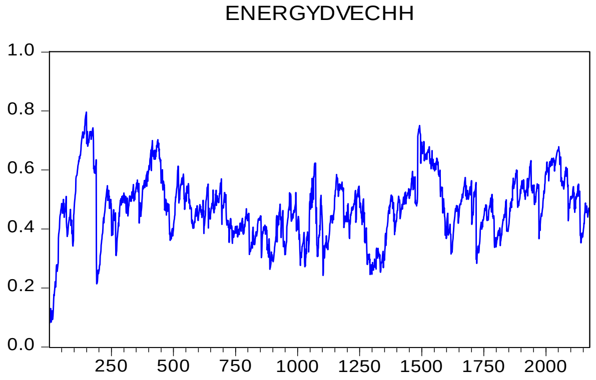
Method	AGRI	ENER	META	COMDX
DVECH-GARCH	0.350354	0.472592	0.204878	0.393184
DBEKK-GARCH	0.357448	0.468792	0.194596	0.382027
CCC-GARCH	0.325245	0.490104	0.206651	0.394589
DCC-GARCH	0.416676	0.380774	0.239255	0.2706

Table 8. In-sample Performance analysis of hedge ratios (h^*)

Hedged Return Approach				
Model	**AGRI**	**ENER**	**META**	**COMDX**
Un hedged	0.000538	0.000281	0.000625	0.000427
DVEC-GARCH	0.000392	0.000148	0.000513	0.000266
DBEKK-GARCH	0.000389	0.000149	0.000519	0.000271
CCC-GARCH	0.000402	0.000143	0.000512	0.000265
DCC-GARCH	0.000364	0.000174	0.000495	0.000316
Variance				
Un hedged	0.09266	0.04580	0.04195	0.11923
DVEC-GARCH	0.043924	0.014365	0.023784	0.064140
DBEKK-GARCH	0.043133	0.014544	0.024495	0.065454
CCC-GARCH	0.046787	0.013554	0.023664	0.063975
DCC-GARCH	0.036829	0.019032	0.019154	0.079380
Variance Reduction Approach (%)				
DVEC-GARCH	52.59799268	68.63550721	43.29954459	46.20488423
DBEKK-GARCH	53.45195904	68.24388694	41.60555044	45.10235953
CCC-GARCH	49.50810802	70.40668259	43.58653512	46.34286133
DCC-GARCH	60.25482041	58.4458799	54.33829344	33.42279415

Figure 1. Time Varying Hedge Ratios Estimated from DVECH-GARCH, DBEKK- GARCH, CCC-GARCH and DCC-GARCH on AGRI, ENER, META and CONDX Markets.

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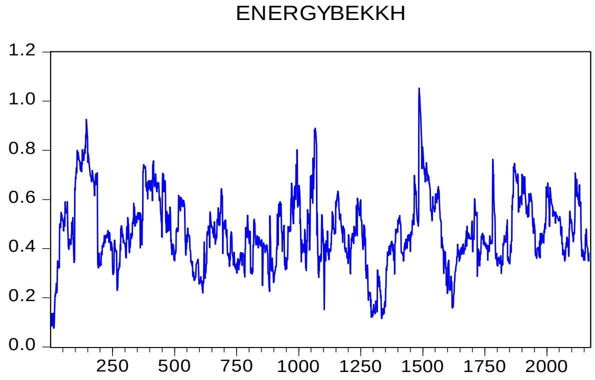
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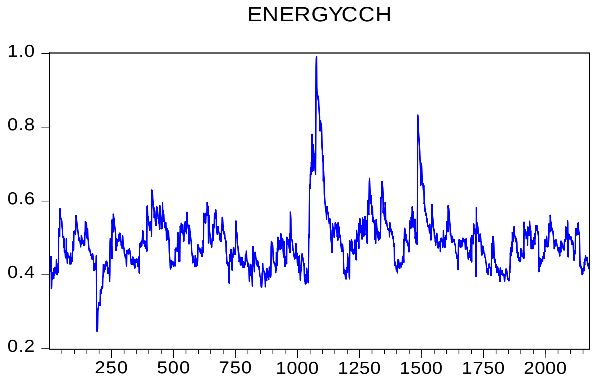
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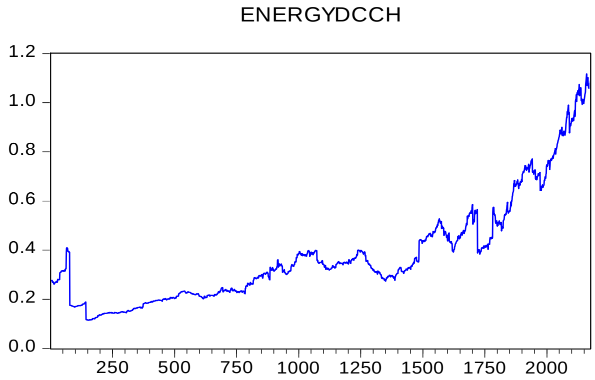
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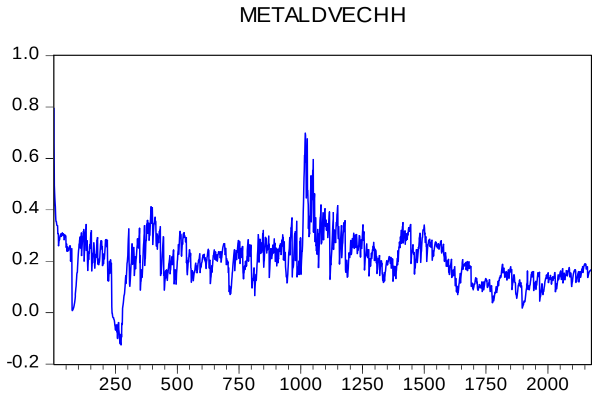
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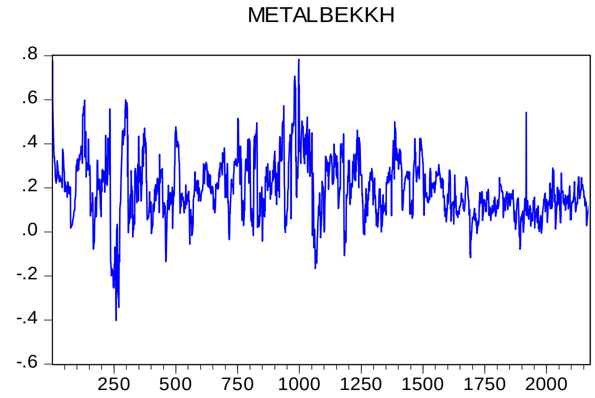
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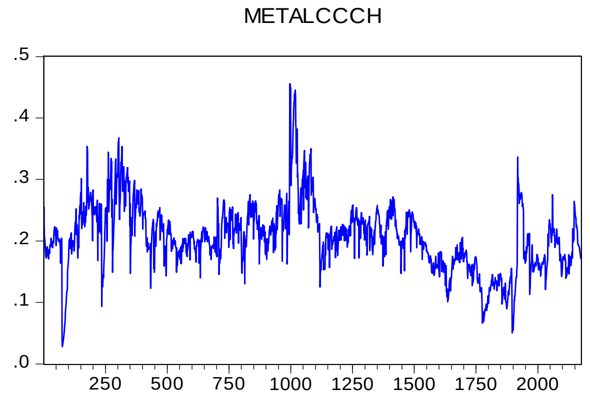
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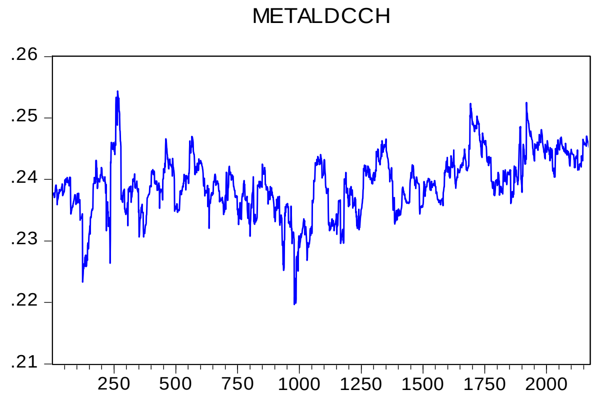
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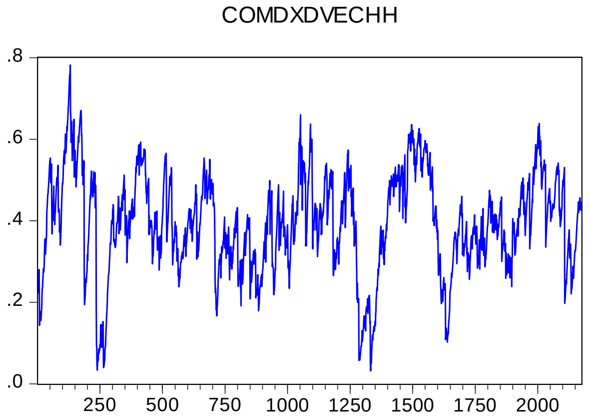
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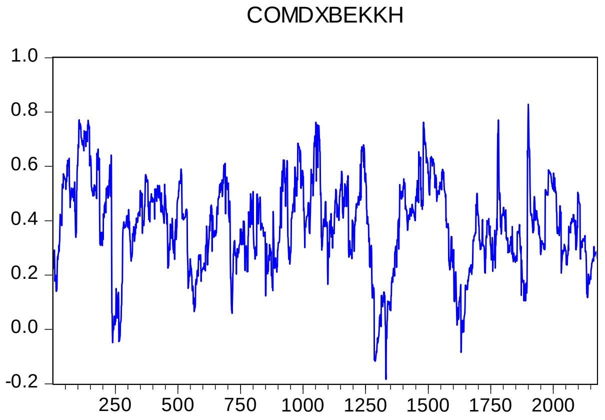
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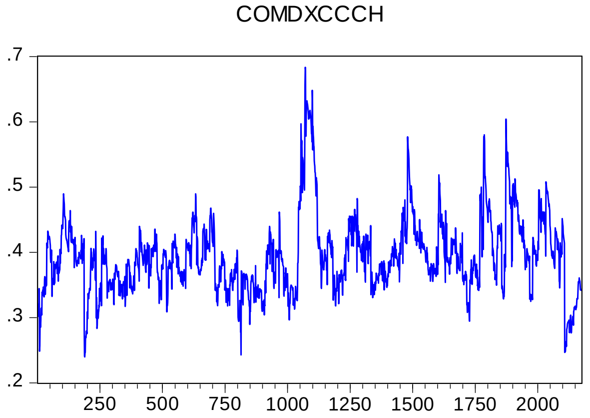
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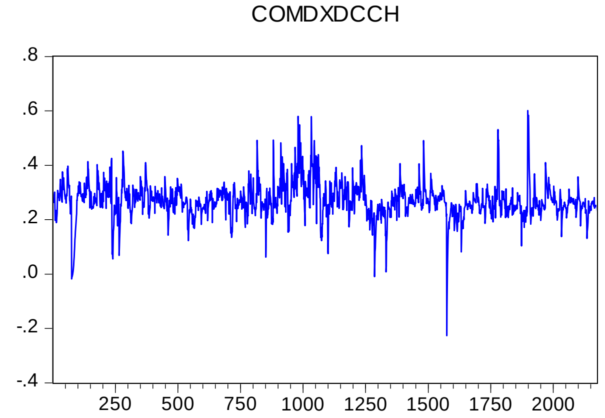
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