VOLATILITY AND SPILL OVER EFFECTS IN INDIAN COMMODITY MARKETS: A CASE OF PEPPER

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Abstract:

Modeling of volatility has been felt one of the major academic contributions in Indian commodity futures market. We have selected black pepper as a commodity for estimating volatility and its spillover incorporating a series of models. We have employed models with their specifications, namely, GARCH (2, 2), EGARCH (2,2), EGARCH (3,3), CGARCH (1,1), MGARCH (Diagonal VECH and BEKK) for both the spot and futures return-series of the commodity. Study reveals that bidirectional spillover is captured under GARCH (2, 2) model whereas unidirectional spillover is found under EGARCH (2, 2) model and results obtained through EGARCH (3,3) are not impressive. News impact curve depicts the steeper movement on the logarithmic conditional variance of futures and spot-return series due to 'positive shocks' and rather than to 'negative shock'. Conditional correlation is also found dynamic and the correlation between spot and futures returns of pepper changes temporally.

Keywords: volatility, spillover, asymmetric effect, news impact

1. Introduction

Modeling volatility of asset-prices has remained one of the highly pursued areas for more than two decades. In due course of time, it has been felt that adequate research works conducted in the realm of volatility and its spillover effects have great implications on market microstructure. Market microstructure embodies a technology driven systematised contract designs which include margin call regime, open interest, settlement patterns, price step/tick size, contract size, determination of (bid-ask) spread. Besides this, other objectives of Modeling volatility is to provide good forecasts of it which can then be used for a variety of purposes including portfolio allocation, evaluation of portfolio, option pricing, performance measurement, financing decisions, estimation of cost of capital, etc (Karmakar, 2005).

A meaningful interpretation of volatility is that a measure of how far the current prices of an asset deviates from its average past prices. At a more fundamental level, volatility indicates the strength or conviction behind a price move. Instinctively, we can posit that the measurement issues of volatility can also be useful to understand the markets integration, their co-movement and spillover effects. Better estimation of volatility can be obtained by modeling time varying conditional variances also, at the methodological level, time varying variance has implications for the efficiency of the parameters describing the dynamics of the underlying process (Krishnan, 2009).

Though volatility is not directly observable, it has some stylized facts are commonly seen in, say asset returns. Few relevant questions are raised and can be answered by proper Modeling of volatility in pepper futures and its underlying spot markets and subsequently, congruence of methodology will lead to parsimonious form of the models for understanding. We can further answer few pertinent questions. Does the volatility of one market lead other markets? Does a shock in one market increase the volatility in another market? Do the sign and the size of such shocks matter? Do correlations between assets change over time?

To consummate the study Pepper as a commodity selected in the present study has its own significance in the Indian futures market vis-à-vis ready cash/spot market. In 2008, pepper markets witnessed high price volatility due to downward pressure observed as demand from the US and European countries were slumped dramatically. There was a downward pressure observed as demand from US and European countries were slumped dramatically. Prices have been suppressed because of low buying. Between 2000 and 2005, world pepper production increased dramatically from 259,270 tonnes to 314,270 tonnes. The increase in global production was mostly due to the emergence of Vietnam as dominant one in production which also largely influenced the world pepper prices. Suddenly, the reduced production of pepper and growing demand of global players have induced the spot and futures prices of pepper to more than Rs.22, 000 per quintal (November 17, 2010) from around Rs.14, 000 in 2009. In India Black pepper ranks fourth among the spices after Chilli, Cumin and Turmeric in terms of its export value. In 2009-10 it has been estimated that total value of export from India was Rs. 3139.30 million (Spice Board of India, 2010).

India has had rather a long and chequered history of futures trading in pepper, extending over more than half a century. Considering the importance, in 1957 first futures trading was started by Indian Pepper and Spice Trade Association (IPSTA) at Kochi. In August 2001, IPSTA offered international pepper futures contract through its international commodity exchange division but the response was too low in exercising the contracts among the clients. The failure of the international contract affected the domestic pepper contract and prices as well. Meanwhile, the national exchanges like Multi Commodity Exchange (MCX), National Commodity and Derivatives Exchange (NCDEX), and National Multi Commodity Exchange (NMCE) came into being and introduced pepper futures contract. Still, the pepper futures market has not attained its past splendor. Today there is no pepper futures contract being offered by any overseas' exchanges. Of late, it has been reported that Singapore Mercantile Exchange has secured approval from the concerned authority to float pepper futures contract through the exchange in a few months. Though being so important spice and no international exchange in pepper, there is no comprehensive study conducted in the realm of volatility and its spillover with special emphasis on pepper. Hence, the study, as a precursor to the future outlook of pepper futures market, can be considered as an academic contribution to the field of modeling volatility and pattern of futures-spot market co-movement to help different market participants understand the underpinnings of pepper markets as a commodity.

We divided the whole paper into four sections. First section presents an extant literature review with respect to empirical evidence of volatility and its spillover effect. Second section describes methodology and models. Third section enumerates the results followed by discussions. Last section concludes.

2. Literature review

Considerable amount of research works have been conducted in the field of volatility and its spillover. The empirical works published in many academic journals contain a mix results with specific to measurement issues of volatility for which econometric techniques were developed in early eighties. Till date, a significant number of research papers have been published in the field of capital and derivative markets with special emphasis on volatility and measurement of its asymmetric effect. Few research works conducted in commodity futures market have not shown the same results with equal magnitude as appeared in financial markets. Significant contributions to this field witnessed in between nineties and twenties for modeling conditional volatility by estimating time varying volatility in the form of a few parsimonious models which are conditional heteroscedasticity adjusted. Preeminence of Bollerslev (1986), Engle (1982), Bollerslev and Engle and (1986) works had kicked off a remarkable pathbreaking research for modeling volatility.

Recently, Gregory and Michael (1996) explored that how volatility of S&P 500 index futures could affect the S&P 500 index volatility. Their study also considered and looked into the effect of good (forward) and bad (backward) news on the spot market volatility. Volatility was captured by employing EGARCH model and their results showed that bad news caused an increase in volatility than good news and the degree of asymmetry was higher for futures market than that of spot market.

The application of multivariate GARCH models in estimating volatility spillover was introduced by Engle et al (1990). They investigated the intraday volatility spillover between US and Japanese foreign exchange markets. The same model was further adapted by many authors (Ng, 2000; Baele, 2002; Christiansen, 2003; Higgs and Worthington, 2004) and applied on various capital markets. Karolyi (1995) used multivariate GARCH model to find the short-run interdependence of return and volatility of Toronto and New York stock market.

In the context of Asian markets, Bekaert and Harvey (1997) analysed the volatilities of emerging equity markets and found that in the integrated markets global factors influence the volatility whereas local factors affect the segmented markets.

In Indian context, study with respect to international linkages have been conducted sparsely and mostly examined with US and some developed Asian markets, namely, Japan, Korea, etc. Employing cross-spectral analysis, Naik and Rao (1990) examined the correlation among US, Japanese, and Indian stock markets and found that the relationship of the Indian market seems to be poor. They put forward that the poor integration of Indian market with US and Japan is because of heavy controls and restriction on trade and capital flow in Indian market throughout the entire seventies.

Nath and Verma (2003) studied the market indices of India, Singapore and Taiwan. They projected that no correlation exists between these indices. Raju and Karande (2003) studied price discovery and volatility on the NSE futures market by employing Granger causality, cointegration tests to explain the direction of causality. Besides this, they also employed GARCH (1, 1) model to capture the volatility. Findings showed that introduction of futures had an impact on cash market and there was a significant presence of migration of speculator from spot or physical market to futures market that led to increase in prices or deviations of prices from expected prices.

Kaur (2004) studied the return and volatility spillover between India (Sensex and Nifty) and US (Nasdaq and S&P 500) markets by using EGARCH and TGARCH volatility models. She found the mixed evidence of return and volatility spillover between the US and the Indian markets. The significant correlation between US and Indian markets was time specific. Batra (2004) analysed time-varying volatility in Indian stock market on account of process of financial liberalizations from the period, 1979-2003. Author employed EGARCH, augmented GARCH models and Pagian and Sussounav (2003) methodology to examine the volatility and its leverage effect.

Mishra and Mukherjee (2006) studied the return and volatility spillover among Indian stock market with that of 12 other developed and emerging Asian countries over a period from November 1995 to May 2005. They modelled open-to-close as well as close-to-open returns and volatility as GARCH process and put forward that Indian open-to-close returns are more related to foreign market than its close-to-open returns. However, the close-to-open (overnight) volatility of India is more affected by the foreign markets.

Kiran and Mukhopadhyay (2007) compared various GARCH models on intraday data of the period, July, 1999-June, 2001 to estimate the volatility spillover from the Nasdaq to the Nifty and found that there seems to have volatility spillover from the US to Indian market significantly. They also added that the simple ARMA-GARCH model outperforms the MGARCH model.

Nath and Lingareddy (2008) investigated about the role of commodity futures for aggravating inflation of commodities which was much discussed topic during the late 2007. They studied the impact of futures trading on spot prices of some foodgrains and pulses which were suspended from the list of tradable commodities at national level exchanges for some time period. Simple regression model with dummies, correlations, and paired Granger causality (parametric), Integrated GARCH were employed. Their argument was that introduction of futures had not increased cash price volatility significantly except for urad. Hodrick-Prescott filter (1997) was employed to examine nominal and real shocks with respect to trend, seasonality and cycle for gram, urad, and wheat-these three important staple commodities.

3. Methodology

Standard econometrics techniques with respect to volatility have been adapted under methodology section. We have selected models and approaches which would explain the theory comprehensively and consistently. Description of methodology primarily deals with different approaches which are spelt out explicitly to explain the volatility and its spillovers effect. We have chosen the commodity, black pepper which is also described in this section with respect to its economic fundamentals, status of its futures contracts, trade volumes, etc.

First, any standard procedure for modeling volatility starts with Modeling of ARMA model followed by the test of ARCH effect. ARCH effect can be detected by conducting heteroscedasticity test which is popularly known as ARCH-LM test. We also conduct Chow break point test to investigate the stability condition of time series data. If breakpoint is found then volatility modeling is carried out in each subsample.

A volatility model consists of two equations; a conditional mean specification, called the mean equation. Diagnostics checks can be conducted b plotting the autocorrelation (ACF) and the partial autocorrelation (PACF) of the daily return series, the absolute returns, and squared returns. Dependency can also be found by doing these. Another specification is a conditional variance specification, called the conditional variance equation. Begin by checking for the significance of correlations in squared residuals, ε_t^2, obtained after de-meaning the series or after fitting, say, an autoregressive (AR) model. To check this, one may use the Ljung-Box (Q) statistic or, alternatively, one may use the Lagrange multiplier, LM, statistic. The steps included are; (a) run a regression of squared residuals, ε_t^2, on p lags of squared residuals and calculate the R^2 of this regression, (b) calculate $LM = T. R^2$ which is asymptotically distributed as a X^2 random variable with (p) degrees of freedom. LM greater than the table value means, there is conditional heteroscedasticity in ε_t. Here T is the sample size. If LM is significant then one may use the PACF of ε_t^2 to decide on the order of conditional heteroscedastic model, say, ARCH/GARCH.

3.1. GARCH Models

GARCH (p, q) models came out into being as a plausible method to model volatility by avoiding the limitation of a long lag structure. The conditional mean (ARMA) and GARCH (p, q) process-generalized autoregressive heteroscedasticity are given as:

$$r^e_t = c + \sum_{i=1}^{p} \alpha_i r^e_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j} + \varepsilon_t \qquad (1)$$

$$\varepsilon_t | \psi_t \sim N(0, h_t)$$

$$\sigma^2_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j} \qquad (2)$$

$$= \alpha_0 + A(L)\varepsilon^2_t + B(L)h_t$$

where $p \geq 0, q > 0, \alpha_0 > 0, \alpha_i \geq 0, i = 1...q, \beta_j \geq 0, j = 1...p$

For $p = 0$, the process reduces to the ARCH (q) process, and for $p = q = 0$, ε_t is simply white noise. In the ARCH (q) process, the conditional variance is specified as a function of past sample variances only, whereas the GARCH (p, q) process allows lagged conditional variances to enter as well. This corresponds to some sort of 'adaptive learning mechanism'. Stationarity of GARCH (p, q) process can be obtained by re-writing the equation through ARMA model.

3.2. EGARCH Models

D.B. Nelson (1991) proposed the exponential GARCH (EGARCH) model which can capture the 'leverage effect' of the return series. This leverage effect is exponential rather than quadratic and forecasts are guaranteed to be non-negative. The effect can be tested by the hypotheses that $\gamma_k > 0$, and the impact is asymmetric if $\gamma_k \neq 0$. ARCH and GARCH effects are the addition of α_i and β_j $(\alpha_i + \beta_j)$ of EGARCH model which implies the total change, that is, one unit decline of ε_{t-1} will induce a change in the logarithm of the conditional variance by $[-\alpha + \beta]$ and one unit increase of ε_{t-1}, volatility will change by $[\alpha + \beta]$. Let us write the equation of EGARCH model.

$$(\sigma^2{}_t) = \log(h_t) = \omega + \sum \alpha_i \left|\varepsilon_{t-i} / \sigma_{t-i}\right| + \sum \beta_j \log(\sigma^2{}_{t-j}) + \sum \gamma_k \varepsilon_{t-k} / \sigma_{t-k} \quad (3)$$

Alternatively, leverage effect can be checked by running a regression. After estimating GARCH model, the standardized residuals ($v_t = \varepsilon_t / \sigma_t$) are extracted and regressed the squared residuals on its lagged values. After the model set up, estimation should be carried out to confirm the presence of leverage effects in residuals. From standardized residuals,

$$v^2{}_t = \alpha_0 + \alpha_1 v_{t-1} + \alpha_2 v_{t-2} + ... + \alpha_i v_{t-i} \quad (4)$$

If no leverage effects found then squared errors should be uncorrelated with the level of error terms. There will be no leverage effect if parameters coefficients ($a_1 = a_2 = a_i$) are not found significantly different from zero.

3.3. CGARCH Models

Engle and Lee (1993) came out with the component GARCH (CGARCH) model which has two parts, one is transitory and another permanent. The equation [CGARCH (1, 1)] is written below.

$$\sigma^2{}_t = \varpi + \alpha(\varepsilon^2{}_{t-1} - \varpi) + \beta(\sigma^2{}_{t-1} - \varpi) \quad (5)$$

$$\sigma^2{}_t - m_t = \alpha(\varepsilon^2{}_{t-1} - m_{t-1}) + \beta(\sigma^2{}_{t-1} - m_{t-1}) \quad (6)$$

$$m_t = \omega + \rho(m_{t-1} - \omega) + \phi(\varepsilon^2{}_{t-1} - \sigma^2{}_{t-1}) \quad (7)$$

m_t takes the place of ω and is the time varying long run volatility. Equation-6 describes the transitory component, ($\sigma^2{}_t - m_t$) converges to zero with power of ($\alpha + \beta$) and transitory dies with time. Equation -7 describes the long run component m_t, which converges to 'ω' with power of. ρ is typically between 0.99 to 1 so that mt approaches to ρ slowly. If ρ equals to '1' then the long-term volatility process is integrated. Speed of mean reversion of long run volatility is determined by ρ. ($\alpha^2{}_{t-1} - \sigma^2{}_{t-1}$) is having '0' mean and serially uncorrelated. Threshold term is also added to capture asymmetry in transitory component.

$$\sigma^2{}_t - m_t = \alpha(\varepsilon^2{}_{t-1} - m_{t-1}) + \beta(\sigma^2{}_{t-1} - m_{t-1}) + \gamma(\varepsilon^2{}_{t-1} - m_t)d_{t-1} \quad (8)$$

Dummy variable (d_t) indicates negative shocks, $\gamma > 0$ indicates the presence of transitory leverage effects in the conditional variance (adding threshold term).

Long run movement of asset-return volatility is dominated by the current expectation of the permanent trend given ($\alpha+\beta$) < 1. The variables in the transitory equation will have an impact on short-run movements in volatility. The value of 'α' indicates (+)/ (-) 've' significant initial impact of a shock to the transitory component, and 'β' indicates (+)/(-) significant degree of memory in the transitory component. ($\alpha+\beta$) implies the persistence of transitory shocks. Higher value of 'ρ' shows the trend persistence. High/low trend persistence, high/low transitory volatility, high/low mean reversion, which are few characteristics can be captured by CGARCH model.

3.4. Spillover effect: Bivariate GARCH and EGARCH

To measure the spillover effect, we can have different models based on their parsimonious forms. At this, GARCH (2,2) model for two asset-return (pepper spot and futures) series which can be written below.

$$\sigma^2{}_{t\,\text{spot}} = \omega_0 + \alpha_{1,\text{spot}}\varepsilon^2{}_{\text{t-1}} + \alpha_{2,\text{spot}}\varepsilon^2{}_{\text{t-2}} + \beta_{1},_{\text{spot}}\,\sigma^2{}_{\text{t-1}} + \beta_{2},_{\text{spot}}\,\sigma^2{}_{\text{t-2}} + \psi_{\text{futures}}(\text{squaredresiduals}_{\text{futures}}) \quad (9)$$

$$[\text{h}_{\text{t-1}} = \sigma^2{}_{\text{t-1}}]$$

In case of EGARCH (2,2) and EGARCH(3,3) model ensures positive coefficients which are illustrated below.

$$\log(\sigma^2{}_{\text{t,spot}}) = \omega_0 + \beta_{1,\text{spot}}\log(\sigma^2{}_{\text{t}-1}) + \beta_{2,\text{spot}}\log(\sigma^2{}_{\text{t}-2}) + \alpha_{1,\text{spot}}\left|\varepsilon_{\text{t}-1}/\sigma_{\text{t}-1}\right| + \alpha_{2,\text{spot}}\left|\varepsilon_{\text{t}-2}/\sigma_{\text{t}-2}\right| + \gamma_{1,\text{spot}}\varepsilon_{\text{t}-1}/\sigma_{\text{t}-1} + \gamma_{2,\text{spot}}\varepsilon_{\text{t}-2}/\sigma_{\text{t}-2} + \psi_{\text{futures}}(\text{residuals}_{\text{futures}}) \quad (10)$$

$$\log(\sigma^2{}_{\text{t,futures}}) = \omega_0 + \beta_{1,\text{futures}}\log(\sigma^2{}_{\text{t}-1}) + \beta_{2,\text{futures}}\log(\sigma^2{}_{\text{t}-2}) + \beta_{3,\text{futures}}\log(\sigma^2{}_{\text{t}-3}) + \alpha_{1,\text{futures}}\left|\varepsilon_{\text{t}-1}/\sigma_{\text{t}-1}\right| + \alpha_{2,\text{futures}}\left|\varepsilon_{\text{t}-2}/\sigma_{\text{t}-2}\right| + \alpha_{3,\text{futures}}\left|\varepsilon_{\text{t}-3}/\sigma_{\text{t}-3}\right| + \gamma_{1,\text{futures}}\varepsilon_{\text{t}-1}/\sigma_{\text{t}-1} + \gamma_{2,\text{futures}}\varepsilon_{\text{t}-2}/\sigma_{\text{t}-2} + \gamma_{3,\text{futures}}\varepsilon_{\text{t}-3}/\sigma_{\text{t}-3} + \psi_{\text{spot}}(\text{residuals}_{\text{spot}}) \quad (11)$$

Where, α_i is reaction of volatility to change in news, $\beta_i h_{t-i}$ explains consistency because this is a function of volatility, and γ_k explains the relationship of volatility (both positive and negative).

News impact curves

A graphical plot of magnitude of asymmetry of volatility to positive (+) and negative (-) shocks is given by news impact curve, introduced by Pagan and Schwert (1990). The curve indicates the next period of volatility ($\sigma^2_{t,}$) that would occur from various positive and negative values of ε_{t-1} in an estimated model. The curve is drawn by extracting conditional variance estimated in the model with its coefficients, and with the lagged conditional variance set to the unconditional variance. Then, following values of ε_{t-1} are used in the equation to estimate would be corresponding values of $h_{t.}$

3.5. MGARCH Models

Multivariate GARCH (MGARCH) models help to provide some answers, namely, long recognized that returns in various markets or returns of various scripts do not move in isolation of other markets or other financial instruments. It has been shown that they co-move and modeling such temporal dependence of asset returns also is paramount in understanding the volatility pattern. This gave rise to extension of the scalar ARCH/GARCH models and they came to be called MGARCH models. Most obvious application of MGARCH models relate to understanding the relations between volatilities and co-volatilities of several markets.
Based on the explanation of the MGARCH models, we have incorporated two models for estimation volatility of pepper futures-spot markets and its spillover by considering with and without asymmetric effects of the MGARCH models. Models are illustrated below.

(a) Model-I

$$r^e{}_{i,t} = u_i + \varepsilon_{i,t}$$

$$\sigma_{ij,t} = \alpha_{0ij} + \alpha_{1\mathrm{ij}}\,\varepsilon_{\mathrm{i},t-1}\varepsilon_{\mathrm{j,t\text{-}1}} + \beta_{\mathrm{ij}}\sigma_{\mathrm{ij,t\text{-}1}} \tag{12}$$

(b) Model-II (with Asymmetric effect)

$$r^e{}_{i,t} = u_i + \varepsilon_{i,t}$$

$$\sigma_{ij,t} = \alpha_{0ij} + \alpha_{1\mathrm{ij}}\,\varepsilon_{\mathrm{i},t-1}\varepsilon_{\mathrm{j,t\text{-}1}} + \alpha_{2ij}\,I_{\varepsilon i,t-1}\varepsilon_{i,t-1}I_{\varepsilon j,t-1}\varepsilon_{j,t-1} + \beta_{\mathrm{ij}}\sigma_{\mathrm{ij,\,t\text{-}1}}$$
(13)

Where indicator variable $I_{k,t}$ equals 1 if $\varepsilon_{k,t}<0$, otherwise 0, k=i,j. In both the model, i=1 refers to the spot pepper returns and i=2 refers to the futures return.

Asymmetric effect in MGARCH model comprises of variances and covariances (conditional). The coefficient of variable (variance) that captures negative shocks, if it is high then it is followed by high conditional variances. Positive sign of covariance coefficient indicates that next period's conditional covariance between returns is higher where there are two negative shocks rather than two positive shocks. It implies that leverage effects in the covariance between other assets are significant.

3.6. Diagnostic Checking

After estimation of every model, diagnosing checking is done by calculating the standardized residuals:

$$\varepsilon'_t = \varepsilon_t / \sigma_t \tag{14}$$

In every model, further presence of ARCH effects is tested using LM test on the standardized residuals. After estimation of Multivariate GARCH model, LM test is conducted on both $\acute{\varepsilon}^2 t$ and cross product of spot $\acute{\varepsilon}_t$ and futures $\acute{\varepsilon}_t$ to check the adequacy of the variance equation and distributional assumptions are also checked by calculating the skewness, kurtosis, and Q-Q plot of $\acute{\varepsilon}^2_t$ and cross product of spot $\acute{\varepsilon}_t$ and futures $\acute{\varepsilon}_{t.}$

4. Results and discussions

4.1. Test of Breakpoint

The study is based on the daily closing returns of spot and futures prices of pepper at the NMCE. We took the data covering the period from July 4, 2006 to March 26, 2010. The prices of spot and futures are estimated as return by taking the first difference of the log prices i.e. $r_t = \ln(P_t/P_{t-1})$. Both fig-1 and fig-2 display the spot and futures prices respectively. It is also found that a break exists in spot returns of pepper. But no break is found in futures returns. Table-1 shows the presence of chow break point on July3, 2006. In order to arrive at the common data series both of the spot and futures prices, same or matching data points are taken to make it a homogenous time frame for the sample period.

Table 1: Chow Breakpoint Test

F-stat	2.700 (0.044)
Log Likelihood Ratio	8.110 (0.044)
Wald Stat	33.159 (0.000)

Figures in parentheses are p value at 5% level of significance. The null hypothesis is No Break Point at Specified Break Points viz. July 3, 2006. We have used EViews-7.0 as a licensed version under the aegis of IRMA for all computational purposes in this paper

Fig 1: Spot prices of Pepper

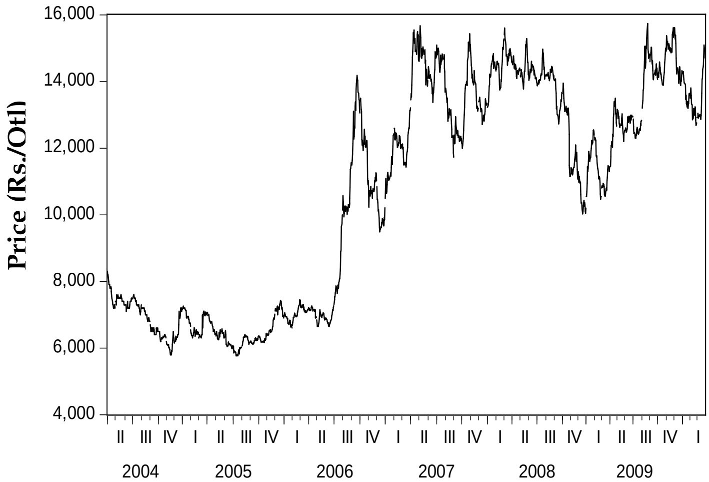
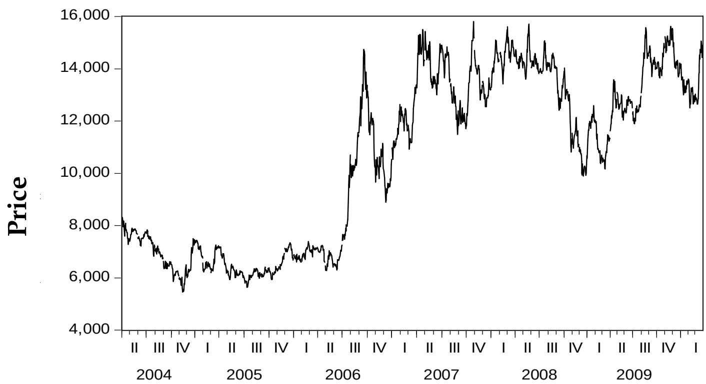


Fig 2: Futures prices of Pepper



4.2. Descriptive Analysis of Spot and Futures Returns of Pepper

Table-2 describes the descriptive statistics of both spot and futures returns. The kurtosis, a measure of peakedness, is high implying fatty tail, not modestly sized deviations. High leptokurtic also signifies non normality of both series. This result is further bolstered by Jarque-Bera (J-B) test for normality which comes very significant and rejects null hypothesis of normality at 5 percent level of significance. Both series are found positively skewed. Augmented Dickey Fuller test with both trend and intercept is also conducted to test the presence of unit root. Unit root is found at price level data and is absent in returns. It means the order of integration is 1 [I (1)].

Table 2: Summary Statistics of Daily Closing Returns on Spot and Futures Pepper Prices

Type	Mean (%)	SD (%)	Skewness	Kurtosis	J-B	ADF
Spot	0.06	1.50	0.17	6.01	425.23 (0.00)	-30.04 (0.01)
Futures	0.06	1.95	0.08	6.65	127.82 (0.00)	-32.76 (0.00)

Figures in parentheses are p-value at 5% level of significance. The null hypothesis of ADF test is Return on Spot (Futures) has Unit Root. The SD is standard deviation. Both mean and SD are expressed in terms of percentage (%).

Fig 3: Return of spot closing prices of Pepper

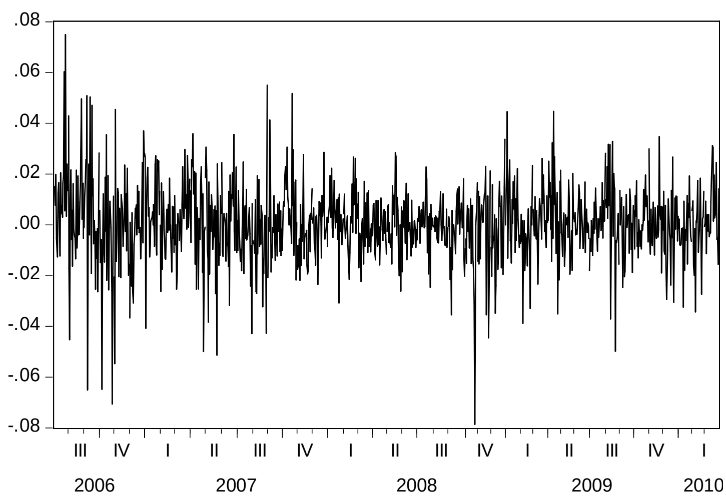
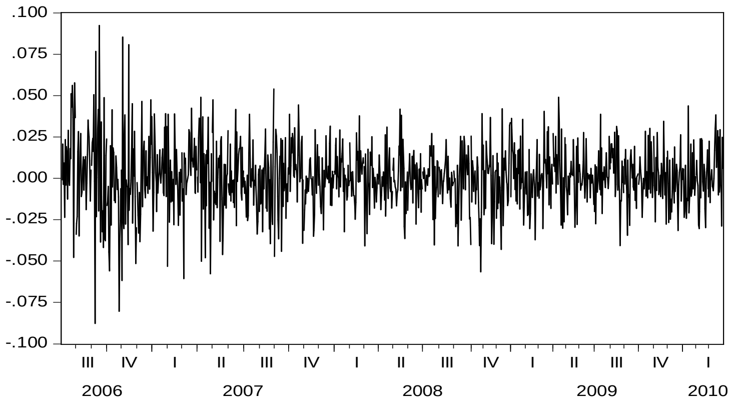


Fig 4: Return of futures closing prices of Pepper



4.3. Estimates of Mean Equations of Spot and Futures Returns

AIC, SC and HQC imply Akaike Information Criterion, Schwarz Criterion and Hannan-Quinn Criterion. The analysis is started with the estimation of ARMA (1, 1) model. This is estimated to identify the mean equation properly. Since, the variance is measured around the mean and hence, any incorrect specification about the mean order would lead to miss-specified variance. It is also conducted to test ARCH effect to ensure that the data is appropriate for GARCH class model. It is evident from table-3 that both the coefficients of AR and MA terms are highly significant. Further, autocorrelation is estimated among the residuals which is found insignificant but autocorrelation is detected among squared level of residuals. Even the ARCH-LM test also strongly rejects the null hypothesis of 'No ARCH Effect' at 5 percent level of significance.

Table 3: Estimates of Mean Equation of Spot and Futures Returns

	Constant	**AR(1)**	**MA(1)**	**AIC**	**SC**	**HQC**	**Q(8)[1]**	**Q^2(8)[2]**	**LM[3]**
Spot Return	0.00 (0.40)	0.82 (0.00)	-0.73 (0.00)	- 5.57	- 5.55	-5.56	5.67 (0.46)	61.13 (0.00)	8.19 (0.00)
Futures Return	0.00 (0.70)	0.98 (0.00)	-0.99 (0.00)	- 5.03	- 5.02	-5.03	7.77 (0.255)	201.11 (0.00)	20.01 (0.00)

[1] represents L-J Box Q Statistics for the residuals from ARMA (1, 1) model.
[2] represents L-J Box Q Statistics for the squared residuals from ARMA (1, 1) model.
[3] represents Lagrange Multiplier Statistics to test for the presence of ARCH effect in the residuals of ARMA (1, 1) model.

4. 4. Estimates of Variance Equations of Spot Returns

Different conditional volatility model are estimated to find out not only the appropriate model but also the effect of different parameters. Four set of models are calculated i.e. GARCH, GARCH-M, EGARCH and CGARCH of spot returns. The order of GARCH and EGARCH is found (2, 2). The order (1, 1) is more parsimonious than order (2, 2) but diagnostic checks of presence of further ARCH effect suggests higher order of all these models. The result presented in table4- shows that all the coefficients of GARCH equation for spot returns indicate positive sign of high persistence of positive conditional variance for long period of time in the said market. In GARCH-in-Mean equation, the coefficient of GARCH term in mean equation is not statistically significant. It is, thus, inferred that there is no feedback from conditional variance to conditional mean. EGARCH (2, 2) model is estimated for identification of asymmetric effect. EGARCH (2, 2) also allows for the leverage effect. γ_2 is highly significant whereas γ_1 is near to significant. Both α (α_1, α_2) and γ (γ_1, γ_2) are positive. So, one unit decline in ε_{t-1} will induce a change in the logarithm of the conditional variance by -0.23 unit (-0.10-0.22+0.33+0.06) whereas one unit increase in ε_{t-1}, conditional volatility rises by 0.43 (0.10+0.22+0.33+0.06) unit. It suggests that 'good news' increases the conditional volatility. Fig-5 of 'news impact curve' of EGARCH (2, 2) model also describes the same. The slope of 'good news' is steeper than the 'bad news'.

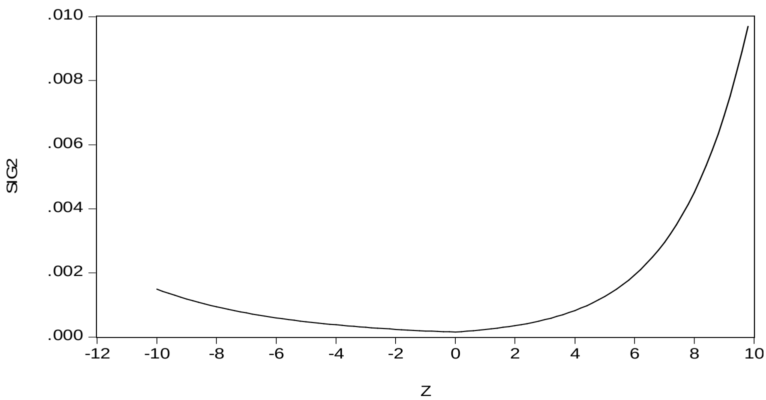
Table 4: Estimates of Mean-Variance Equations of Spot Returns

	Coefficients	GARCH (2, 2)	Mean-GARCH (2, 2)	EGARCH (2, 2)	CGARCH (1, 1)
Mean Equation	**c**	0.00 (0.79)	0.00 (0.64)	0.00 (0.28)	0.00 (0.78)
	AR(1)	0.75(0.00)	0.75 (0.00)	0.74 (0.00)	0.73 (0.00)
	MA(1)	-0.64 (0.00)	-0.64(0.00)	-0.64 (0.00)	-0.63 (0.00)
	GARCH	-	-2.04 (0.70)	-	-
Variance Equation	**c**	0.00 (0.00)	0.00 (0.00)	-0.79 (0.00)	-
	α_1	0.05(0.00)	0.05 (0.00)	0.10 (0.00)	0.14 (0.00)
	α_2	0.11(0.00)	0.11 (0.00)	0.22 (0.00)	-
	β_1	-0.005(0.93)	0.003 (0.95)	0.02 (0.59)	0.64 (0.00)

	β_2	0.76(0.00)	0.76 (0.00)	0.90 (0.00)	-
	γ_1	-	-	0.03(0.06)	-0.035 (0.32)
	γ_2	-	-	0.06 (0.00)	-
	ω	-	-	-	0.00 (0.00)
	ρ	-	-	-	0.99 (0.00)
	φ	-	-	-	0.03 (0.00)
	AIC	-5.65	-5.65	-5.66	-5.65
	SC	-5.62	-5.61	-5.61	-5.61
	HQC	-5.64	-5.63	-5.64	-5.64
	LM (F-stat)[1]	0.79 (0.55)	0.85 (0.51)	0.99 (0.41)	1.59 (0.15)
	LM (TR^2)[2]	3.98 (0.55)	4.26 (0.51)	4.98 (0.41)	7.98 (0.15)

Figures in parentheses are *p*-value at 5% level of significance.
[1, 2] represents Langrange Multiplier Statistics to test the presence of additional ARCH effect in the residuals for all the Mean-variance equations.

Fig 5: News Impact Curve of EGARCH (2, 2) on Volatility of Spot Returns



In order to capture the short-and long-term behaviour of return-volatility, component GARCH (CGARCH) model is also estimated. CGARCH model has both transitory and permanent parts. The value of α (0.14) indicates the positive initial impact of a shock to the transitory component and β (0.64) indicates positive and has significant degree of memory in the transitory component. The summation of α, β (α + β, 0.78) suggests the persistence of transitory shocks. The higher value of ρ (0.99) shows the trend persistence. High trend persistence, high transitory volatility and slow mean-reversion in the long-run are evident in CGARCH model. Checking for presence of ARCH effect through ARCH-LM test in the residuals fails to reject the null-hypothesis of 'no ARCH effect'. It is also indicative that various information criteria select two classes of models, that is, GARCH (2, 2) and EGARCH (2, 2).

4.5. Estimates of Variance Equation of Futures Returns

A set of conditional volatility models are also estimated in futures returns of pepper. Like spot returns, GARCH model of futures returns if found of order (2, 2) but unlike spot EGARCH model it is found of order (3, 3) to pass the diagnostic checks. The result presented in table-5 shows that all the coefficients of GARCH equation for futures returns signify high persistence of positive conditional variance ($\beta_1 + \beta_2$, 0.99)for long period of time in the futures markets. In GARCH-in-Mean equation, the coefficient of GARCH term in mean equation is not statistically significant. It is, thus, inferred that there is no feedback from conditional variance to conditional mean. EGARCH (3, 3) model is estimated for identification of asymmetric effect as well as leverage effect. All the coefficients (γ_1, $\gamma_2$and γ_3) of asymmetric term are statistically insignificant. α_1, α_2 are positive but α_2 is insignificant and α_3 is negative and significant. But it can also be inferred that one unit decline in ε_{t-1} will induce a change in the logarithm of the conditional variance by -0.038 unit (-0.23-0.05+0.22-0.03-0.008+0.06) whereas one unit increase in ε_{t-1}, conditional volatility rises by 0.082 (0.23+0.05-0.22-0.03-0.00+0.06) unit. It advocates that 'good news' increases the conditional volatility. Fig-6 of 'news impact curve' of EGARCH (3, 3) model also describes that the slope of 'good news' is steeper than the slope of 'bad news'.

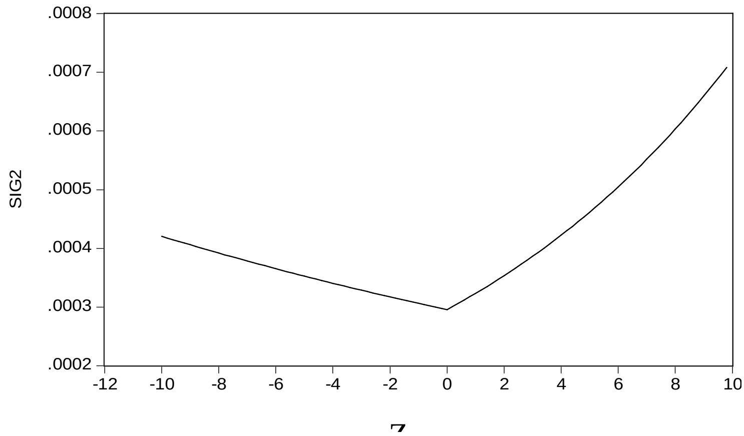
Like spot returns, to capture the short-and long-term behaviour of return-volatility, component GARCH (CGARCH) model is also estimated. CGARCH model has both transitory and permanent parts. The value of α (-0.04) is negative but insignificant and β (-0.83) indicates negative and has significant degree of memory in the transitory component and it is persistent. The value of ρ (0.92) shows the trend persistence which is lower than the ρ of spot returns. High trend persistence, high transitory volatility and slow mean-reversion in the long-run are also evident in CGARCH model of futures returns. Checking for presence of ARCH effect through ARCH-LM test in the residuals fails to reject the null-hypothesis of 'no ARCH effect'.

Table 5: Estimates of Mean-Variance Equations of Futures Returns

	Coefficients	GARCH (2, 2)	Mean-GARCH(2, 2)	EGARCH(3, 3)	CGARCH (1, 1)
Mean Equation	c	0.00 (0.40)	0.00 (0.413)	0.00 (0.138)	0.00 (0.44)
	AR(1)	0.59 (0.036)	0.60 (0.02)	0.70 (0.00)	0.71 (0.01)
	MA(1)	-0.55 (0.06)	-0.55 (0.05)	-0.65 (0.00)	-0.68 (0.02)
	GARCH	-	-1.568 (0.654)	-	-
Variance Equation	c	0.00 (0.25)	0.00 (0.10)	-0.10 (0.07)	-
	α_1	0.13 (0.00)	0.12 (0.00)	0.23 (0.00)	-0.04 (0.13)
	α_2	-0.12 (0.00)	-0.12 (0.00)	0.05 (0.53)	-
	α_3	-	-	-0.228 (0.00)	-
	β_1	1.56 (0.00)	1.56 (0.00)	0.78 (0.01)	-0.83 (0.00)
	β_2	-0.57 (0.00)	-0.57 (0.00)	0.45 (0.32)	-
	β_3	-	-	-0.24 (0.33)	-
	γ_1	-	-	-0.03 (0.43)	0.05 (0.17)
	γ_2	-	-	-0.008 (0.86)	
	γ_3	-	-	0.06 (0.12)	
	ω	-	-	-	0.000 (0.00)
	ρ	-	-	-	0.92 (0.00)
	φ	-	-	-	0.10 (0.00)
	AIC	-5.13	-5.13	-5.12	-5.12
	SC	-5.10	-5.09	-5.06	-5.07
	HQC	-5.12	-5.12	-5.10	-5.10
	LM (F-stat)[1]	0.47 (0.79)	0.46 (0.80)	0.42 (0.83)	0.42 (0.83)
	LM (TR^2)[2]	2.38 (0.79)	2.33 (0.80)	2.10 (0.83)	2.10 (0.83)

Figures in parentheses are *p*-value at 5% level of significance.
[1, 2] represents Langrange Multiplier Statistics to test the presence of additional ARCH effect in the residuals for all the Mean-Variance equations.

Fig 6: News Impact Curve of EGARCH (3, 3) on Volatility of Futures Returns



4.6. Volatility Spillover: Spot and Futures

Table-6 explains volatility spillover from futures to spot and spot to futures. The first panel shows the spillover estimated using residuals extracted after calculating GARCH model for each of the markets and the same is used in variance equation to identify the spillover of shock to other market. In case of GARCH model residuals are taken as squared to ascertain positivity in variance where as in the case of EGARCH only residuals without being squared are used as the underlying assumption EGARCH is that the variance is positive. It is manifested in table-6 that in GARCH model the coefficient ψ is significant in both the markets. It is inferred that there is bi-direction volatility but the spillover effect from spot to futures is much higher than futures to spot. But when same is estimated using EGARCH model the coefficient ψ is significant in case of futures to spot and insignificant in spot to futures. It indicates unidirectional (futures to spot) negative volatility spillover. The estimation of ARCH effect of residuals also authenticates the estimation of the models which describes that there is no after ARCH effect in the respective models.

Table 6: Estimates of Volatility Spillover of Spot and Futures Returns

Coefficients	ARMA (1,1)-GARCH(2,2)		ARMA(1,1)-EGARCH (2,2)	ARMA(1,1)-EGARCH (3,3)
	Futures ↓ Spot	Spot ↓ Futures	Futures ↓ Spot	Spot ↓ Futures
c	0.00 (0.11)	0.00 (0.14)	0.00 (0.07)	0.00 (0.12)
AR(1)	0.82 (0.00)	-0.86 (0.00)	0.75 (0.00)	0.71 (0.00)
MA(1)	-0.76 (0.00)	0.83 (0.00)	-0.66 (0.00)	-0.66 (0.00)

C (x100)	0.00 (0.00)	0.001 (0.00)	-0.89 (0.00)	-0.10 (0.07)
α_1	-0.00 (0.97)	0.047(0.05)	0.12 (0.00)	0.23 (0.00)
α_2	0.03 (0.22)	-0.00 (0.99)	0.22 (0.00)	0.06 (0.50)
α_3	-	-	-	-0.234 (0.00)
β_1	1.12 (0.00)	0.79 (0.00)	0.01 (0.67)	0.78 (0.01)
β_2	-0.40 (0.00)	-0.19 (0.025)	0.91 (0.00)	0.43 (0.33)
β_3	-	-		-0.22 (0.35)
γ_1	-	-	0.055(0.00)	-0.02 (0.57)
γ_2	-	-	0.08 (0.00)	-0.00 (0.92)
γ_3	-	-	-	0.06 (0.14)
ψ	0.12 (0.00)	0.59 (0.00)	-2.97 (0.00)	-0.61 (0.68)
LM (F-stat)[1]	0.27 (0.92)	0.23 (0.94)	1.05 (0.38)	0.44 (0.81)
LM (TR^2)[2]	1.37 (0.92)	1.17 (0.09)	5.30 (0.38)	2.22 (0.81)

Figures in parentheses are *p*-value at 5% level of significance.
[1,2] represents Langrange Multiplier Statistics to test the presence of additional ARCH effect in the residuals for all the Mean-Variance equations.

4.7. Estimates of Multivariate GARCH Model

The estimation of results of MGARCH parameters that explain the dynamics in the variances and covariance are presented in table-7. In both models, the estimated coefficients of covariance term are statistically significant at 5 percent level of significance. So, the constant covariance assumption is rejected. The estimates for the coefficients on product of return shocks ($\varepsilon_i\varepsilon_j$) in model-2 ranges from 0.09 to 0.13 for the variances and 0.04 for the covariance. Positive ARCH coefficients in covariance equation means that two shocks of the same sign influences the conditional covariance between spot and futures returns positively. It is found that the coefficient of lagged variance in the futures return is lower than the lagged variance in the spot return. Subsequently, it is also evident that the constant term of futures return is higher than the spot return in the variance equation. It implies that the volatility of futures return is harder to predict than spot returns. Fig-7, 8, 9 and10 represents the plots of conditional variance, covariance and conditional coefficient over the period of time based on the estimation of model-2. Figures ostensibly indicate that conditional variance and covariance are not constant over time. This is found highly volatile during the end of 2006(lower production due to adverse climatic condition and diseases to pepper vines in major pepper growing centers), end of 2007 and first of 2009 (due to less supply of pepper as the total production fell by 50 percent in Kerala, a major pepper growing state).

To check whether time-variability in covariance is solely due to the variation variance. Conditional correlation is also estimated and plotted overtime. It shows that correlation coefficients vary considerably overtime. It is thus inferred that the variability in covariance is not solely due to time-varying variance.

Conditional variances, covariance and conditional correlation are also plotted based on diagonal BEKK model and presented in fig-11, 12, 13 and 14. It also shows the clustering of variances and covariance overtime. The movement of conditional variances, covariance and conditional coefficient are almost in tandem in the figures under both diagonal VECH and diagonal BEKK model. It is apparent that in fig-12 the variance clustering of futures return is lesser.

Asymmetric Effects in Variances and Covariances

Model-2 in table-7 also captures the asymmetric effects in the variances and covariances (i.e. $I_{\varepsilon i,t}\ \varepsilon_{i,t}$ and $I_{\varepsilon i,t}\ \varepsilon_{i,t}\ I_{\varepsilon j,t}\ \varepsilon_{j,t}$). The asymmetric term is negative and significant (-0.04) in spot return where as it is positive (0.01) but insignificant in futures return. It thus implies that negative return shocks in spot are followed by lower conditional variance. Asymmetry in covariance is found negative (-0.02) and insignificant. But it can be inferred that next period conditional covariance between return is lower when there are two negative shocks rather than two positive shocks. Positive shocks will bring in more conditional variances and covariances.

Table 7: Estimates of Multivariate GARCH Model

	Explanatory Variable	**Model-1**	**Model-2**
Mean Equations	$Const_1$	0.00 (0.52)	0.00 (0.41)
	$Const_2$	0.00 (0.36)	0.00 (0.48)
Covariance Equations	$Const_{11}$ (x100)	0.002 (0.00)	0.001 (0.00)
	$Const_{12}$	0.001 (0.03)	0.001 (0.00)
	$Const_{22}$	0.004 (0.00)	0.006 (0.00)
	$\alpha_{1,1}$	0.09 (0.00)	0.09 (0.00)
	$\alpha_{1,2}$	0.03 (0.00)	0.04 (0.00)
	$\alpha_{2,2}$	0.11 (0.00)	0.13 (0.00)

	$\gamma_{1,1}$	-	-0.05 (0.00)
	$\gamma_{1,2}$	-	-0.02 (0.15)
	$\gamma_{2,2}$	-	0.01 (0.64)
	$\beta_{1,1}$	0.81 (0.00)	0.86 (0.00)
	$\beta_{1,2}$	0.85 (0.00)	0.86 (0.00)
	$\beta_{2,2}$	0.75 (0.00)	0.70 (0.00)

Figures in parentheses are *p*-value at 5% level of significance.

Fig 7: The Estimated Conditional Variance of Spot Returns

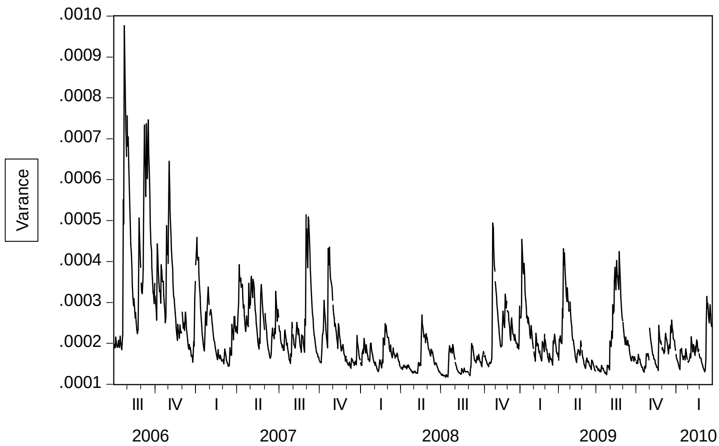


Fig 8: The Estimated Conditional Variance of Futures Returns

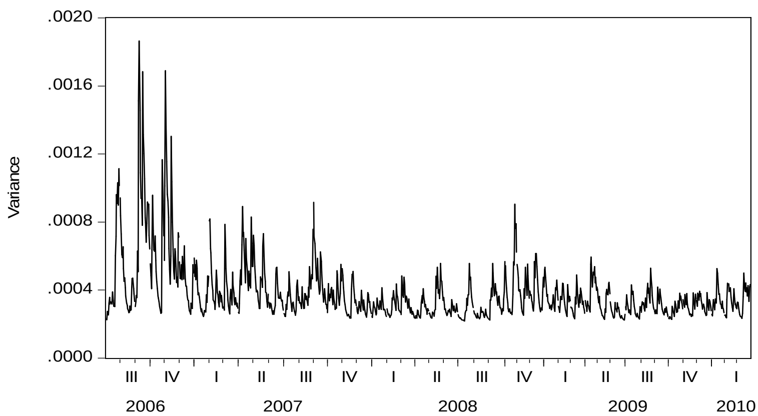


Fig 9: The Estimated Conditional Covariance

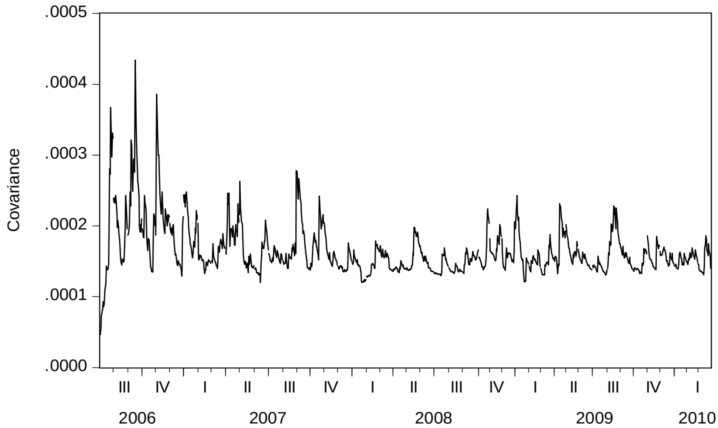


Fig 10: The Estimated Conditional Correlation

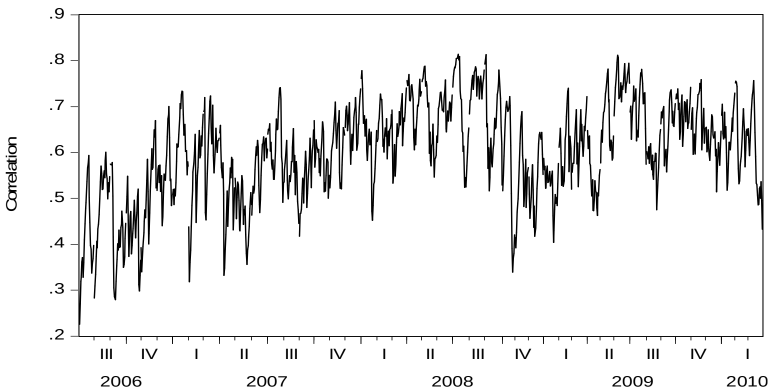


Fig 11: The Estimated Conditional Variance of Spot Returns (Diagonal BEKK)

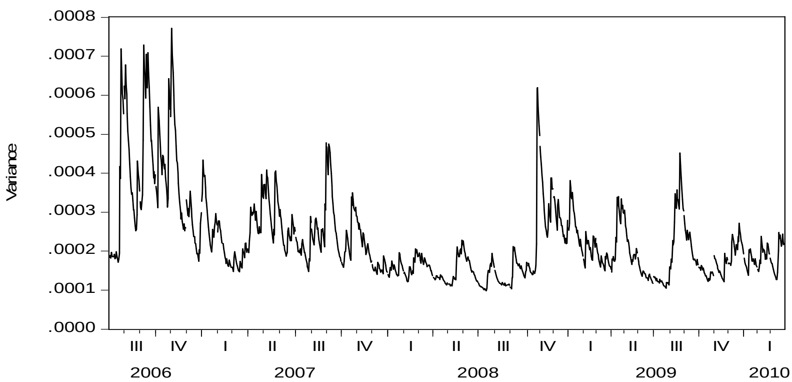


Fig 12: The Estimated Conditional Variance of Futures Returns (Diagonal BEKK)

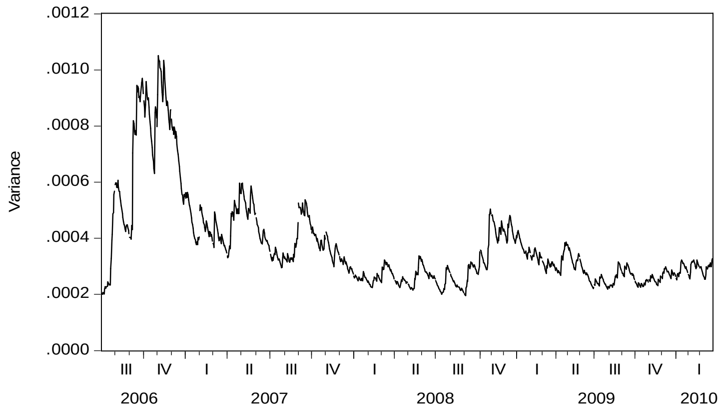


Fig 13: The Estimated Conditional Covariance (Diagonal BEKK)

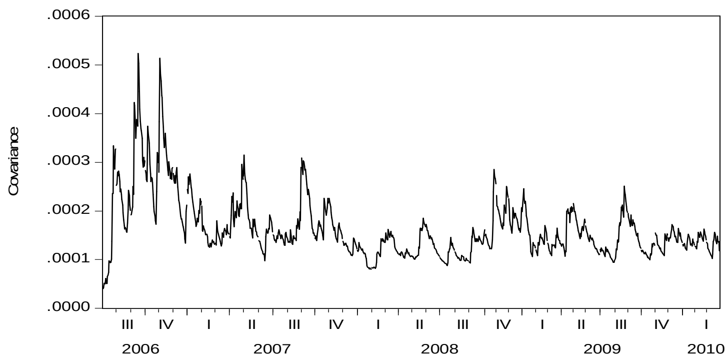
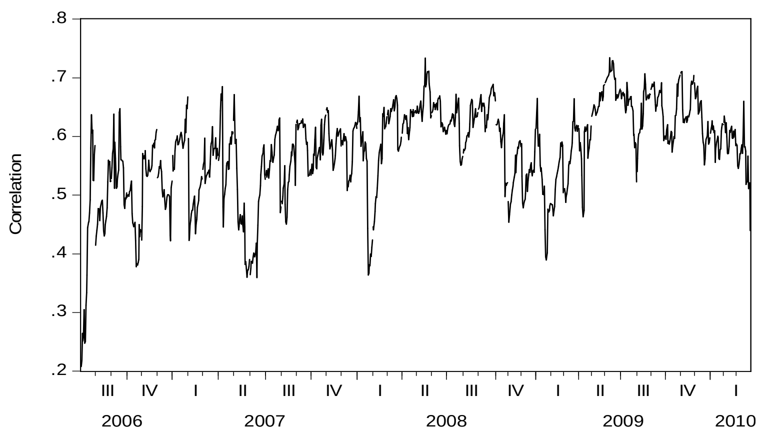


Fig 14: The Estimated Conditional Correlation (Diagonal BEKK)



4.9. Diagnostics Tests for Multivariate GARCH Specifications

A very important and indispensible step in modeling conditional covariance is to test whether the model is a good fit or a parsimonious. It is carried out by taking squared standardized residuals. In table-8, the test statistics of standardized residuals square and cross product of residuals are given to measure the adequacy of asymmetric multivariate GARCH model. The mean, standard deviation, skewness and kurtosis are presented in table-8. The standardized residuals are extracted using square root of conditional correlation and square root conditional covariance. Mean of squared residuals should not statistically differ from 1 (t-statistics is calculated by dividing the mean with standard deviation time √n, where n is the number of observations) and mean of cross product of residuals should not statistically differ from-0. In addition to this, Ljung-Box statistics for serial correlation is conducted both for squared residuals and cross product of residuals which in both cases appear statistically insignificant. Thus, it manifests no temporal dependence.

Table 8: Diagnostic Tests for Covariance Specification

	$\acute{\varepsilon}_1^2$		$\acute{\varepsilon}_2^2$		$\acute{\varepsilon}_1$ **x** $\acute{\varepsilon}_2$	
	√cc	√cv	√cc	√cv	√cc	√cv
Mean	0.97	1.01	1.02	0.98	0.00	-0.01
SD	2.00	2.08	1.70	1.66	0.00	1.05
Skewness	6.80	6.81	4.93	5.10	4.79	0.99
Kurtosis	81.724	81.83	49.24	52.87	39.97	11.49
Ljung-Box Stat.						
Q(4)	2.13 (0.71)	2.30 (0.68)	3.48 (0.48)	2.99 (0.55)	4.32 (0.36)	4.25 (0.37)
Q(8)	2.78 (0.94)	2.97 (0.93)	8.68 (0.37)	8.85 (0.35)	7.28 (0.50)	7.15 (0.52)
Q(12)	5.09 (0.95)	5.49 (0.94)	11.66 (0.47)	12.14 (0.43)	10.11 (0.60)	10.07 (0.61)

√cc and √cv imply standardized residuals using square root of conditional correlation and square root of conditional covariance.

5. Summary and conclusion

The present study does not only throw lights on variance structure of spot and futures markets of pepper but also focuses on inter-linkages in terms of volatility spillover effects between these two markets. Co-movement of spot and futures markets is also analyzed through MGARCH models. Apart from that asymmetric effect is also studied to detect the differential impact of negative and positive shocks or news. It is quite apparent that variances in spot and futures markets behave differently but they are interdependent. Temporal dependence in terms of conditional covariance and conditional correlation is identified. Even the result ostensibly reveals that volatility of one market leads to another market. The spillover effect is found bi-directional under GARCH model where spot gives much higher spill to futures than that of futures to spot. But it remains only unidirectional under EGARCH which is only from futures to spot. The output from EGARCH is not very impressive. As both the markets spill each other so a shock in one market would induce change in volatility in another market.

Asymmetric effect indicates that sign and size of shocks play a vital role. Negative shocks in returns in spot is followed by lower conditional variance as the asymmetric coefficient is negative (-0.05) where it is insignificant in futures (model-2, table-7). Even it is also manifested that asymmetry in covariance is negative but insignificant. But from EGARCH (3, 3) of futures returns asymmetric coefficient is not highly insignificant and it is positive which implies steeper positive logarithmic variance due to positive shocks than negative shocks. Conditional correlation is also found dynamic and is not constant overtime. So, the correlation between spot and futures returns of pepper changes temporally.

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