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DEBASISH MAITRA,

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Do Seasonality, Break And Spillover Effects Explain Commodity Price Volatility? Evidence from Indian Commodity Markets

1. Introduction

Commodity markets play an integral role in the economics of developing and developed countries. Producers, traders and processors (market players) face price or market risk, where adverse movements in prices of commodities result in unforeseen losses to them. Commodity price volatility is a matter of immense concern for any economy. Volatility is given emphasis as it is a proxy for risk. A rise in volatility implies a rise in risk which deters traders and others from markets. Volatility in agro commodity markets cannot be studied alone because the seasonality, cyclical fluctuation related to the calendar year, is a common phenomenon in agricultural commodities. This seasonality or cyclical fluctuation of price behaviour occurs due to many reasons namely, weather conditions, producers' futures expectation of yield, input and output market prices. Producers' sowing decision of the crop is also indirectly influenced by the possibility of making a profit due to price changes in the international markets (Piot-Lepetit and M'Barek, 2011).

The seasonal behaviour is noted in both, equity and commodity market though the fundamentals between these two markets are different. Unlike equities and bonds, commodities have their own production refining processes (Brooks, Prokopczuk and Wu, 2013). It is found that price changes and their deviation in commodity futures are not constant, change over time. This behaviour becomes more conceivable in soft commodities (agro commodities), which are periodically cultivated. Seasonality in commodity markets is largely attributed to an imbalance between supply and demand (Crawn and Lee, 1996). Supply side seasonality occurs due to unfavourable weather, which disrupts the supply of that particular commodity. On the demand side, seasonality is observed because the demand for many industrial commodities is affected by the performance of that industry under the different economic scenario.

The paper contributes in a number of ways. It makes a noble attempt to explore whether seasonality does exist and persist in commodities, whether seasonality explains return and volatility, if the answer is yes, then it could be inferred that existence of seasonality leads to violation of weak form of efficient market hypothesis (Fama, 1970). Under the weak form of efficiency, the market is not random rather prices can be predicted based fundamental factors. Moreover, there are many studies where seasonal effects were studied in futures markets but, such studies are rarely available for the spot markets.

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Besides seasonality, the feature which also makes the volatility of commodity markets a distinct is its persistence. But sometimes high persistence in volatility may be spurious if there are structural shifts in conditional volatility (Diebold, 1986). So, before jumping to any conclusion about volatility persistence, the presence of structural breaks are essential to be identified.

Apart from seasonality and breaks, this paper also analyses volatility spillover effects between spot and futures markets. The issue of volatility spillover effect is important for several reasons: firstly, volatility spillover signifies volatility transmission between spot and futures markets. Futures markets are supposed to alter the information and transmit it to the spot markets as futures markets attract more investors and liquidity. In a way, it may absorb new information more quickly (Cox, 1976). So, the direction of spillover is an important concern for further examination. Secondly, volatility spillover the transfer of shocks or news from one market to another market. Thus, understanding of volatility spillover enables market players to form expectations about risk and return as this affects their decision of hedging. The knowledge of spillover helps policy makers figure out the source of market volatility and its transmission. This study makes a further attempt to explore asymmetric nature of market co-movement which was examined in financial assets but, not in the commodity markets. Moreover, Indian commodity futures markets are of recent origin. As a result of this, the role of futures market being more informationally efficient than spot markets has already been challenged by many researchers. Therefore, this study also makes a contribution to the related literature of nascent or emerging futures markets. Finally, this study would be able to deliver the results regarding the forecasting power of volatility, especially for seasonal commodities, whether the forecasting power of volatility improves by considering the aspects of seasonality, breaks and spillover effects.

In this backdrop, this paper attempts to answer five questions in the context of Indian commodity markets. First, do commodity price volatility show seasonality? Second, does volatility in commodity markets have structural breaks? Third, does volatility in one market of a commodity spills over to the other market of the same commodity? Fourth, is volatility transmission unidirectional or bi-directional and which market dominates if there is bidirectional volatility spillover? Fifth, do the seasonal effects, breaks and spillover effects explain volatility?

The paper is organised into four sections. Section II presents a brief literature review. Section III narrates the methodology adopted. Section IV reports the results and finally section V concludes.

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2. A Brief Literature Review

The literature on commodity markets is found to have to two broad categories, one which talks about price discovery and market efficiency, and the other states about risk management, volatility, spillover effects and various factors affecting volatility.

2.1.Price Discovery and Market Efficiency

The role of futures markets in providing an efficient price discovery mechanism remained an area of extensive research since long. The issue of lead-lag relationship between spot and futures markets was widely examined. Garbade and Silber (1983) investigated the price discovery of futures prices and suggested that the role of futures markets might be affected by liquidity and market size. Previous studies which have tested market efficiency include Tomek and Gray (1970), Kofi (1973), Leuthhod and Hartman (1979), and Martin and Garcia (1981). Koontz et al. (1990) examined the spatial price discovery mechanism in the livestock market and found a strong relation between cash and futures prices.

Mckenzi and Holt (2002) studied market efficiency in agricultural futures markets and suggested that live cattle, corn, and soybean meal futures markets are efficient and unbiased in the long-run. Kuiper et al. (2002) revealed that the spot prices adjust fully to its new equilibrium level if the price discovery function of the future market works well.Chen and Lin (2004), and Cologni and Manera (2008) investigated market efficiency using co-integration analysis. Wang and Ke (2005) examined the efficiency of agricultural commodity futures markets in China. They concluded that soybean futures markets are more efficient whereas wheat futures market in China is inefficient. Government regulation in wheat market may account for the inefficiency.

However, it is seen that the characteristics of emerging markets are very different from that of developed markets. Bakaert and Harvey (1997), and Antonion and Ergel (1997) opined that emerging markets are featured with low liquidity, thin trading volume, higher sample average returns, low correlation with developed market returns, higher volatility, and small size sample availability. This is common to find emerging markets with higher price variability and poor information processing capability (Tomek, 1980).With respect to emerging market, many empirical investigations on price discovery and market efficiency of Indian commodity futures markets have been conducted by Sahi and Raizada, 2006; Lokare, 2007, Kumar et al. 2008, Sahoo and Kumar, 2009; Ali and Gupta, 2011. Most of the studies focused on price discovery and risk management.

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Iyer and Pillai (2010) found that futures markets are delivering the role of price discovery in five out of six commodities by employing regime switching models. The futures market is found inefficient for chick pea, nickel, and rubber. Maitra and Dey (2011) examined the volatility spillover in pepper and found bi-directional volatility spillover between futures and spot markets. Sehgal et al. (2012) confirmed the price discovery by futures markets for agro-commodities except Turmeric. Soni (2013) suggested that guar seed futures market is inefficient and biased in both short and long run, which might be caused by over speculation or market manipulation. Soni (2013) provided an argument on the nature of Indian commodity futures markets. He confirmed that non-linearity exists in metal and energy markets, contradicting unpredictable criterion of weak-form efficient market hypothesis, and conditional heteroscedasticity is the main reason behind non-linearity in metal indices. Soni (2014) examined the efficiency of agro commodity futures markets. He concluded that long-term relationship exists between futures and spot prices of chick pea, wheat, soybean, and maize, however, the markets are inefficient and biased. Consistent non-linear causality is not found between spot and futures prices of ago commodities. All studies highlight the common issue of inefficiency in Indian commodity futures markets, especially in agro commodity futures markets, although futures markets of a few agro commodities are delivering the role of price discovery. However, these studies on agro commodities did not address the issue of seasonality which is a relevant issue in agro commodities.

2.2.*Seasonality and Volatility*

The first seasonality effects were observed by Wachtel (1942). The study was conducted on stock markets where he pointed out the existence of seasonality of Dow-Jones Industrial Average (DJIA) from 1927 to 1942 and there were bullish tendencies from December to January. Murphy (1987) stated that neither expected return nor the contribution of agricultural futures to the risk of diversified investment portfolios varies seasonally. On the contrary, Choi and Longstaff (1985) favoured the argument that agricultural futures prices contain seasonal volatility, as agricultural commodity prices are subject to production-consumption cycle and show seasonal patterning in prices. Anderson (1985) also reported that in a variety of American markets the dispersion of futures prices is not constant. This pattern is stronger for annually-harvested and storable goods.

Fama and French (1987, 1988) pointed out that seasonality in production (supply) and demand can cause seasonality in inventories. Consequently, seasonality in inventory as the theory of storage suggests brings in seasonality in marginal convenience yield and in the

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basis (the difference between future and spot prices). Before the time of harvest, spot prices become higher than future prices as inventory declines and therefore, marginal convenience yield also goes high. Hence, the theory of storage and marginal convenience yield together explain the seasonal nature of spot and futures prices. Gorton and Rouwenhorst (2005) put forward that commodities differ from financial assets in terms of seasonal nature in the price level and volatilities. They also mentioned that futures price takes into account the foreseeable fluctuation when they are formed and unlikely to be influenced by spot price seasonality. Brooks *et al.* (2013) investigated whether forecast power of commodity futures can be attributed to the extent to which they exhibit seasonality, and found strong evidence of seasonality in the basis, which supports the theory of storage. Richter and Sorensen (2013) acknowledge that soybean futures contracts exhibit seasonality patterns in both spot prices level and volatility.

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Back, Prokopczuk and Rudolf (2013) observed that seasonality in volatility is an important aspect to consider when valuing contracts. They stated that return volatility of commodity futures shows the a strong seasonal pattern as the degree of price uncertainty changes through the year. This seasonal pattern is most apparent in agricultural markets as the supply of commodities depends on the harvesting cycle. It is noted that just before the harvest, the price uncertainty becomes higher than post-harvest because by this time market participants already come to know about crop yields, causing a seasonal pattern in volatility. Kumar and Sing (2008) also found that seasonality has a significant effect on soybean futures return volatility, but not on returns. However, there is a dearth of literature on seasonality and volatility in Indian commodity futures markets.

2.3.*Structural Breaks, Volatility and Spillover Effects*

Moreover, volatility modelling with seasonality can be misleading sometimes if structural shifts are not tested or taken into consideration. Empirically the change points have been detected by incorporating Bai and Perron (1998, 2003) methodology and then dummy variables are introduced into the variance equation of the GARCH model to account for the sudden changes in variance.

Sometimes persistence in volatility can be because of the shocks from other markets. For instance, Chatrath and Song (1998) investigated the intraday behaviour of spot and futures markets following the release of information and also investigated the role of such information in volatility spillover between two markets. They supported that one market leading to greater volatility in the other is due to the arrival of information and therefore, the

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leading role is played by the futures markets. Many scholars (Karolyi, 1995; Ng, 2000; Baele, 2002; Worthington and Higgs, 2004 and Christiansen, 2007) have used multivariate GARCH model to find out the spillover effects and market co-movements.

The availability of literature on volatility spillover in commodity markets is very thin and of very recent origin. Asymmetry transmission of volatility was examined in financial assets by many researchers (Aspergis and Rezitis, 2001; Reyes, 2001) but has not been scrutinized in commodity especially agro-commodity markets. Apergis and Rezitis (2003) studied agricultural price volatility spillover effects in Greece and found that both agricultural input and retail food prices exert positive spillover effects on the volatility of agricultural output prices. Beckmann and Czudaj (2014) investigated the issue of volatility spillover across agricultural futures markets and concluded with evidence in favour of short-run volatility transmission process in agricultural futures markets.

In the Indian context, studies on spillover effects have mostly been conducted with respect to international linkages and mostly restricted to financial markets.

In India, Karande (2006) investigated the spot price volatility during pre-futures, futures early period and futures late period in castor seed and put forward that opening of futures market has a beneficial effect on spot market volatility during futures early period. However, the efficiency of Indian commodity futures markets is sometimes questioned. It was commented by Kumar and Sunil (2004) that the futures markets are not able to incorporate the full information and confirmed the inefficiency of futures markets.

Nath and Ligareddy (2008) conducted a study on the impact of futures trading on the spot price volatility. They found that volatility in Urad prices was higher during futures trading that in the period prior to futures trading or after the ban on futures contracts. However, this is not true for chick pea.

Srinivasan (2012) found bi-directional volatility spillover persists and volatility spillover from spot to the futures markets is dominant in case of all MCX markets. Mahalik *et al.* (2014) found that there is a presence of bi-directional volatility spillover between futures and spot markets in energy and agri index whereas unidirectional spillover exists in the commodity index, from futures to spot. However, the magnitude of spillover from futures to spot is more than otherwise with an exception in agri index. Sehgal et al. (2014) state that in the short-run, there is strong volatility spillover from spot to futures, but in the long-run, it is exactly opposite. Volatility bases informal spillover is low in agri futures markets.

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Kumar and Shollapur (2015) studied price discovery and volatility spillover in agri commodity futures markets in India and found long-term equilibrium relationship between spot and futures and volatility spillover.

3. Data & Methodology

3.1.Data and Sample

The study has been conducted in Indian commodity markets. The Indian markets are having a few unique characteristics which are not commonly found in other developed countries. The commodity markets are highly regulated in which banks and institutions are excluded from trading. Therefore, even while there has been a rapid growth in the risk appetite of traders in India, the commodity markets have been kept away from foreign institutional investment. Therefore, Indian commodity futures markets are at least partly segmented (Baharam *et al,* 2014). Indian commodity futures markets have witnessed policy upheavals concerning suspension of trading. In fact, Indian commodity markets face one of the most restrictive environments, from dealing with barriers for movement of goods to regulations that discourage storage. Not surprisingly, backwardation is very common in Indian commodity prices (e.g., see Naik and Jain,1999, and Thomas, 2003).
Four commodities- pepper, cumin and soy oil in food commodity category and guar seed in non-food commodity category- are selected for the present study. The data are collected from the National Commodity and Derivatives Exchange (NCDEX) being the leading commodity exchange in agricultural commodities and the National Multi Commodity Exchange (NMCE). The NCDEX has its own index, Dhaanya, which constitutes 10 liquid agro commodities with the highest weightage given to wheat (27.63 percent), oil seeds, grain/pulses, spices and others with the weightings of 23.88 percent, 40.41 percent, 15.43 percent and 20.25 percent, respectively. Trading times for commodities within NCDEX is 10 am to 5:00 pm Monday – Friday, and between 10 am to 2 pm on Saturday.

The study has only focused on agro commodities because the price discovery and risk management functions of agro commodity futures markets are highly debated in India.

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Moreover, agro commodity futures markets in India are also subject to high regulations. The commodities have been chosen in this study in such a way that they do not have Minimum Support Price (MSP) which is a government determined pricing mechanism for agro commodities in India. The prices of these commodities are not directly government regulated. Thus, their price can fluctuate as market forces decide. The volatility of returns cannot be studied well if the prices are controlled. These four commodities were selected based on their economic and trading importance which are decided by their weights on the whole index and trading volume (liquidity). Cumin is considered to be one of the highest exported spices contributed up to ten percent of the value of total spice export. India is the largest exporter, producer and consumer of cumin. Cumin is sown in October-November and harvested from February to May. So, markets get flooded with Cumin from March. The cumin markets are influenced by many fundamental factors

Like, weather, production (supply), export and domestic demand, international price and carry over stock. Cumin price falls lowest to Rs. 8462/qtl during March 2008 due to a bumper crop and touches the highest peak of Rs. 16531/qtl during November 2009 due to the reason of low production. Cumin prices show seasonality in line with the demand from domestic as well as export markets. The price generally starts rising up from Dec-Feb when demand begins to arrive and these are the months when the total estimation of crop arrival is predicted. Thereafter prices again soar up during July-August by grabbing the export opportunities. This period is followed by moderation during October-November when the new crop season starts.

Pepper prices have a high degree of seasonality owing to different factors like level of production in India and in the world, export by other competing country like Vietnam, carry over stock, weather and government regulations on exports and imports. Pepper takes 6-8 months to ripe after flowering. Harvesting is carried out during December-January in plains and during January- March in hills. Price usually starts rising from June till September owing to many festivals during this season.

It is a fact that pepper and cumin are the highest and second highest traded and liquid spices commodities with INR 79518.79 trillion and INR 55982.69 trillion volume of trade in 2011-12, respectively (Forward Markets Commission, March 2012 Report). In NCDEX (National Commodity and Derivatives Exchange) platform, Dhanya the commodity futures index gives a weight of 17.42 to the spice group (chilli, cumin, pepper and Turmeric), in which pepper and cumin have 3.11 and 4.33 weightages, respectively. Systematic risk of pepper is 0.68 and

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cumin is 1.51 (NCDEX Institute of Commodities Market and Research Report, November 2011).

Refined soy oil is the highest traded agro commodity. The value of futures trading of soy oil is INR 538383.46 trillion implying 35.44 percent of total value of major food items and 24.51 percent of total value agro commodities (Market Review of April 2012, Forward Markets Commission Monthly). High volatility due to international price movement is the characteristics of soy oil. Soy oil price is a complex function of soybean production, consumption of soy oil, the profitability for extractors, prices of competitor oil like palm oil, weather factors, carryover stocks and government support for soybean (Minimum Support Price). The volume of trade declines during May-September when the crop is in the field and during October onwards volume starts rising and reaches its peak in March when demand from all over the world soars up.

Soybean is sown in June-July and harvested in September-October. During last two decades edible oil consumption increased by 4.3 percent of compounded growth rate (Vision 2030, Directorate of Oilseeds Research, ICAR). Import of soy oil occupies 50 percent of total oil consumption. The highest market share of vegetable oil is occupied by palm oil (46 percent) followed by refined soy oil (15-18 percent). Soy oil extraction largely depends on soybean production. India has to import major share of its soy oil every year. In 2008-09, soy oil price in India was very high which even called upon banning of futures trading of soy oil from May to December 2008. In India, Mumbai represents imported soy oil market while Indore is the market for domestic soy oil.

Guar seed trading is the highest in the category of the non-food commodity in 2011-12. During 2011-12, the volume and value of trading of guar seed stood at 73.31 mill tonnes with a total value of INR 338216.190 trillion (Forward Markets Commission, March 2012 Report). Guar seed also enjoys the status of being the second highest traded agro commodity after refined soy oil. Guar is sown in July-August after the first rainfall and harvested in October-November. The crop needs two spells of rainfall. The main product of guar seed is guar gum which is extracted at the rate of 28-29 percent. From 2004-05 and onwards guar seed production has been increasing till 2008-09. In 2009-10, the production has dipped drastically to 350 thousand tonnes only. It happened due to unfavourable monsoon which caused lower production and because of which farmers also shifted to other crops.

In 2010-11 the export of guar gum touched all time high of 403 thousand tonnes which earned India a total revenue of Rs.2816 crores 146 percent higher than 2009-10. High demand of Indian guar gum is received from the United States and China.

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The data of cumin, pepper and guar seed ranges from March 2005 to December 2011 (total number of observations of 1917), from August 2004 to December 2011 (total number of observations of 2170) and from July 2004 to December 2011 (total number of observations of 2240), respectively. The sample period of soy oil is taken from December 2008 to December 2011. The price data of soy oil is of 10 MT contracts, and the data availability is from August 2007. Soy oil price data of August 2007 is not taken because of illiquidity. Price data of all commodities are taken from the contracts which are floated at a regular interval in the exchange, and the duration of each contract of a commodity is similar which helped to avoid inconsistency.

The futures price data are taken from near month contracts which capture better information on trading activity. Thus, price series of each commodity is prepared with near month futures contracts' data. This enables to create time series with roll over mechanism as well.

3.2. Methodology

3.2.1. Data Characteristics

The study is based on the daily closing returns of spot and futures prices of the commodity. Spot prices data are taken from the spot markets which are considered as reference markets by the exchanges for floating futures contracts. Hence, the spot markets for cumin, pepper, soy oil, and guar seed are Unjha (in the state of Gujarat), Kochi (in the state of Kerala), Indore (in the state of Madhya Pradesh), and Jodhpur (in the state of Rajasthan). Spot prices are available at three different points of time in a day. The price of the latest time i.e.closing spot price is taken to maintain consistency with the futures closing prices. The returns of spot and futures prices are estimated by taking the first difference of the log prices i.e. r_t = ln(Pt/Pt-1).

3.2.2. Measuring Structural Changes

Volatility is subject to structural change, thus, normal Generalised Autoregressive Conditional Heteroscedastictity (GARCH) model does not suffice. Augmented GARCH family models are applied. In order to do this, first volatility shifts are to be identified using

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Cumulative Sum of Square Test (CUSUM) test. The iterated cumulative sum of squares algorithm, developed by Inclan and Tiao (1994), is used to detect discrete changes in variance in the series.

Let $C_k = \sum_{i=1}^{k} r^2{}_t$ be the cumulative sum of squares of a series of uncorrelated standardised residuals of variance, r_t, with mean 0 and variance , $\sigma^2{}_t$ = 1, 2, 3, . . ., T. Let the mean centered cumulative sum of squares be defined as:

$$D_k = [C_k / C_T] - [k / T], k = 1..., T \text{ with } \mathrm{D}_0 = \mathrm{D}_t = 0 \qquad (1)$$

For a series with homogeneous variance over the sample period, the D_k statistic oscillates around zero. In contrast, when there is a sudden change in variance, the D_k value will drift away from zero. Inclan and Tiao (1994) calculated the critical values under the null hypothesis of constant variance from the asymptotic distribution of D_k. When the maximum absolute value of D_k is greater than the critical value, the null hypothesis of no changes is rejected. Let k* be the value of k at which $\max_k |D_k|$ is attained. If the maximum of $\sqrt{T/2} \times |D_k|$ is larger than the critical value of ±1.358 at the 5% level (90%, 95% and 99% percentile (two-tailed) critical values of this distribution are 1.22, 1.36 and 1.63, respectively.) then k* is considered as an estimate of the change point. The factor $\sqrt{T/2}$ is required to standardize the distribution.

The statistical test is compared with the asymptotic and finite sample critical values. The critical values proposed by Sanso, Argo and Carrion (2002) is used to find the critical values as it is found to be the robust method.

The estimation for 5% quantile (α=0.05),

$$q_T^{\alpha=0.5} = 1.359167 - 0.737020 \quad T^{-0.5} - 0.06915556 \quad T^{-1}$$
$$where \;, T \text{ is sample size, assuming a normally distribute d } iid \text{ series} \qquad (2)$$

If the series s assumed to be *iid,* but not normally distributed, the estimated response-surface for 5% quartile is;

$$q_T^{\alpha=0.5} = 1.363934 - 0.942936 \quad T^{-0.5} - 0.500405 \quad T^{-1} \qquad (3)$$

However, change point analysis can also be done by 'changepoint' (an R package). Killick and Eckley (2014) designed an R package which can identify multiple changes within a given time series or sequence.

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After estimation of breaks or shifts, augmented GARCH (EGARCH) model is applied

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2{}_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{\rho=1}^{n} d_\rho b_\rho \quad (4)$$

d_ρ is the dummy variable taking the value of one for the period after the occurrence of a sudden change of variance and zero elsewhere.

The GARCH (p, q) process-generalized autoregressive heteroscedasticity along with seasonality and structural breaks is as follows;

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2{}_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{k=1}^{11} d_k m_k + \sum_{\rho=1}^{n} d_\rho b_\rho$$

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

Where, $p\geq 0$, $q>0$, $\alpha_0>0$, $\alpha_i\geq 0$, $i=1....q$, $\beta_i\geq 0$, $j=1....p$, and d_k denotes the dummy coefficients of monthly dummy and d_p implies dummy coefficients of breaks.

The present paper also follows EGARCH model (Nelson, 1991) with seasonality and structural breaks with the full specification;

$$(\sigma^2{}_t) = \log(h_t) = \omega + \sum \alpha_i \left|\varepsilon_{t-i}/\sigma_{t-i}\right| + \sum \beta_j \log(\sigma^2{}_{t-j}) + \sum \gamma_k \varepsilon_{t-k}/\sigma_{t-k} + \sum_{k=1}^{11} d_k m_k + \sum_{\rho=1}^{n} d_\rho b_\rho \quad (5)$$

It has been observed that returns are negatively related with volatility. It indicates more volatility in response to 'bad news' than 'good news'. In this case, a symmetrical GARCH would not be sufficient to capture the volatility. EGARCH is the model which captures the asymmetric effect. In the above mentioned EGARCH equation, the asymmetric coefficient is γ. It is also termed as leverage effect when the effect of bad news on volatility is more than the good news.

3.2.3. Measuring Spillover Effects and Volatility Co-movements

To measure the spillover effect, different models based on their parsimonious forms have been employed. GARCH model for two markets series can be written as;

$$\sigma^2{}_{t\ \text{futures}} = \omega_0 + \alpha_{1,\mathrm{a}} \varepsilon^2{}_{\text{t-1}} + \beta_{1,\mathrm{a}} \sigma^2{}_{\text{t-1}} + \psi_{\mathrm{b}} (\text{squared residuals}_{\text{spot}}) \quad (6)$$

$$\sigma^2{}_{t\ \text{spot}} = \omega_0 + \alpha_{1,\mathrm{b}} \varepsilon^2{}_{\text{t-1}} + \beta_{1,\mathrm{b}} \sigma^2{}_{\text{t-1}} + \psi_a (\text{squared residuals}_{\text{futures}}) \quad (7)$$

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

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In case of EGARCH model ensures positive coefficients which are illustrated below.

$$\log(\sigma^2{}_{\text{t,futures}}) = \omega_0 + \beta_{1,a}\log(\sigma^2{}_{t-1}) + \alpha_{1,a}\left|\varepsilon_{t-1}/\sigma_{t-1}\right| + \gamma_{1,a}\varepsilon_{t-1}/\sigma_{t-1} + \psi_b(\text{residuals}_{\text{spot}}) \tag{8}$$

$$\log(\sigma^2{}_{\text{t,spot}}) = \omega_0 + \beta_{1,b}\log(\sigma^2{}_{t-1}) + \alpha_{1b}\left|\varepsilon_{t-1}/\sigma_{t-1}\right| + \gamma_{1,b}\varepsilon_{t-1}/\sigma_{t-1} + \psi_a(\text{residuals}_{\text{futures}}) \tag{9}$$

Where, α_i is the 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 asymmetry and 'leverage effect'. Ψ indicates the spillover effect from one market to another market.

3.2.4. Bivariate GARCH Model

Bivariate GARCH models provide some answers to the long recognized idea 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 modelling 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 called multivariate GARCH models. Most obvious application of bivariate GARCH models relates to understanding the relations between volatilities and co-volatilities of several markets.

3.2.4.1.The Diagonal VECH Model

Diagonal VECH model generates 21 parameters when the volatility of two asset returns is examined. Due to a high number of parameter generation the VECH model becomes inapplicable when number of asset is more. Hence, the VECH model's conditional variance-covariance matrix has been restricted to the form developed by Bollerslev, Engle, and Wooldridge (1988), in which A and B are assumed to be diagonal. This reduces the number of parameters to be estimated to 9 (as A and B each have 3 elements) and the model, known as a diagonal VECH (Brooks, 2008), is now illustrated by,

$$r_{jt} = c_{jt} + \alpha \sum_j \omega_{jt-1} \begin{pmatrix} h_{1jt} \\ h_{2jt} \\ h_{3jt} \end{pmatrix} + \begin{pmatrix} u_{it} \\ u_{2t} \\ u_{3t} \end{pmatrix} \tag{10}$$

Where, r_t is an asset-return series, u_t is exactly similar (predictable component) with ε_t and h_t is conditional variance which equals to expected ε_t. This can be expressed by the given equation,

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$$h_{ij,t} = w_{ij} + \alpha_{ij} u_{i,t-1} u_{j,t-1} + \beta_{ij} h_{ij,t-1} \; for \text{ i, j} = 1,2,... \quad (11)$$

Where w_{ij}, α_{ij} and β_{ij} are parameters. A disadvantage of the VECH model is that there is no guarantee of a positive semi-definite covariance matrix.

In order to estimate bivariate GARCH model with asymmetric effect, the final bivariate model which was estimated is as follows;

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

$$\sigma_{ij,t} = \alpha_{0ij} + \alpha_{1\text{ij}} \varepsilon_{\text{i},t-1} \varepsilon_{\text{j,t-1}} + \alpha_{2ij} I_{\varepsilon i,t-1} \varepsilon_{i,t-1} I_{\varepsilon j,t-1} \varepsilon_{j,t-1} + \beta_{\text{ij}} \sigma_{\text{ij,t-1}} \quad (12)$$

Where, $\alpha_{0\ ij}$ is the constant and $\alpha_{1\ ij}$ and β_{ij} are the coefficients of ARCH term and GARCH term of one asset when i=j as well as the co-movement term when i≠j. The indicator variable $I_{k,t}$ equals 1 if $\varepsilon_{k,t}<0$, otherwise 0, k=i,j. In both the model, i=1,2,3.. refers to returns in different markets.

The asymmetric effect in MGARCH model comprises of variances and covariances (conditional). A 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 effect is present when the covariance between two markets is positive and significant.

4. Results and Discussion

This section discusses the effects of seasonality, structural shifts and spillover effects on the selected food and non-food category commodities. Then best-fit GARCH model is estimated by including seasonal dummy. Afterwards, the presence of volatility shift or structural break is identified which leads to augmentation of the GARCH model. In order to figure out asymmetry in the volatility, EGARCH model is employed, respectively. To find out volatility spillover effects between futures and spot markets and volatility co-movement between these two markets, GARCH with squared residuals as well as EGARCH with residuals of the other market, and MGARCH are modelled.

4.1.Descriptive Analysis of Spot and Futures Returns

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Table-1 presents the descriptive statistics of both futures and spot returns. The mean return is almost same for both the markets. The observed standard deviation of the futures market is higher than the spot markets since futures market is more exposed to the information and provides price adjustment support to the spot market. Skewness of daily return indicates asymmetry as it is different from zero. Returns are mostly positively skewed and having longer tails to the right except in the case of soy oil. Excess kurtosis indicates that the return is leptokurtic, fat-tailed and sharply peaked. The return data of futures market of cumin is not serially correlated which indicates that ARIMA (Auto Regressive Integrated Moving Average) model is not necessary to achieve white noise while in rests autocorrelation is present. However, squared returns of both futures and spot markets are highly autocorrelated signifying the presence of volatility clustering. The returns series are also tested for the presence of unit root and all are found stationary.

[Table-1 here]

4.2.Identification of Volatility Shift or Volatility Structural Breaks

Table 2 discusses the results of appropriate variance equation of futures returns, modeling is started with best-fit GARCH equation till the residuals are found white noise and the squared residuals are free from autocorrelation or further ARCH effect. Then seasonal dummies are included to capture the seasonal effects. It is conducted prior to the test of structural breaks. When monthly seasonal dummies are included, a joint significance test of all seasonal dummies is tested by likelihood ratio (LR) test [-2(Log Likelihood$_{\text{restricted}}$[1] $_{\text{(no seasonal dummy)}}$ – Log Likelihood $_{\text{unrestricted (with seasonal dummy)}}$)]. The test follows a χ^2 distribution with 11 degrees of freedom (11 is the number of monthly dummies). The results are found significant in every commodity at 95% level of confidence. This suggests that the joint effects of all seasonal dummies are significantly different from zero confirms that there is a presence of seasonal effects.

The standardized residuals are extracted and examined for the presence of volatility shifts or breaks by testing the significance of D_k statistics. The number of significant volatility shifts[2] is found 3 in cumin futures, 2 in soy oil futures and spot and 3 in Guar seed spot.

[Table-2 here]

[1] [2]Detailed results of GARCH model (restricted) without seasonality and breaks are not reported. This can be obtained from the author on request.

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4.3. *Estimates of Conditional Variance Equations of Futures and Spot Returns*

To find out the effects of seasonality and breaks on conditional volatility GARCH and EGARCH models with seasonality and structural breaks are estimated. The order of GARCH is found (1,1) in the futures of cumin, soy oil and guar seed whereas it is (2,1) in pepper futures. The spot return volatility is mostly of order (2,1) except pepper where it is (2,2). However, the order of EGARCH is mostly found (1,1) in both futures and spot return with the exception in returns of cumin spot and pepper futures where it is (2,1). It is found that all the breaks are significant. All seasonal dummies are jointly significant. This is obtained by Log Likelihood Ratio (LR) test which follows χ^2 distribution with number of restriction as the degree of freedom. In most of the commodities (cumin, soy oil and pepper) the effects of seasonality is more in spot return than futures returns. This finding is consistent with Gorton and Rouwenhorst (2005) to the extent that futures market seasonality consider seasonality well in advance and embed the same in the prices. The value of α is positive and significant. This implies that volatility sensitive to large shock and both negative and positive large shocks increase volatility.

Seasonality and breaks significantly explain or reduce the volatility. The significance is tested by LR test. The inclusion of seasonal dummies and breaks reduces conditional volatility ($\alpha+\beta$) from 0.818 to 0.411. However, in soy oil spot returns a minimal reduction of volatility is found from 0.948 to 0.805 and from 0.978 to 0.93, respectively[3]. Pepper futures and spot return volatility also do not show any reduction of volatility. So, persistence in volatility is statistically l explained by seasonality and structural breaks, but they do not reduce volatility by a greater extent (table-3 & 4).

4.4. *The Effect of Asymmetry*

Asymmetry effect is captured by EGARCH equation and presented in table-4. The asymmetry term γ is found positive (except in cumin futures) and significant, suggesting that there are different responses to the arrival of good news and bad news. Asymmetry is volatility is commonly understood as volatility reacts asymmetrically to negatives news as given by negative γ. However, in agro commodity, volatility reacts asymmetrically to the positive news as this is evident by positive γ. So, one unit decline in ε_{t-1} will induce a change in the logarithm of the conditional variance by ($-\alpha+\gamma$) unit whereas one unit increase in $\varepsilon_{t-1,}$

[3] The results without seasonal and break dummies can be obtained from the author. In the interest of brevity, the entire results are not shown.

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conditional volatility rises by the (α+γ) unit. The steepness of the impact of 'good news' on volatility is higher than the steepness of the impact of 'bad news' on volatility. This implies that when return goes up volatility increases with a higher rate than the rate at which volatility falls when return declines. It is apparent in table-5 that when standardised innovation or shock is positive 1 in the market, the γ causes a decrease in volatility by 5.4% and 4.4% in cumin and pepper futures, respectively. In all other cases, γ (standardised innovation or shock is positive 1 in the market) has caused an increase in volatility, highest of which is found in soy oil futures (11%).

[Table-3,4 & 5 here]

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4.5. Volatility Spillover: Futures and Spot

Table-5 and 6 explain volatility spillover from futures to spot and spot to futures by both GARCH and EGARCH models. In the case of GARCH model residuals are taken as squared to ascertain positivity in variance whereas 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-5 and 6 that all the spillover terms (ψ) in both GARCH and EGARCH model are significant in both the markets except in EGARCH equation of spillover from futures to spot returns of guar seed. It is also evident that information criteria and log-likelihood of GARCH models in both markets outperform EGARCH in explaining spillover effects. So, considering GARCH it is inferred that there is bidirectional volatility, both from futures to spot and from spot to futures. However, the spillover effect from spot to futures is more than the otherwise. It is also noteworthy that after inclusion of spillover effect in GARCH model, lagged conditional variance (β) becomes insignificant and persistence (α+β) is significantly reduced. This gives the evidence that much of persistence is explained by the shocks from the other markets. The result of higher spot spillover is because of the producers in Indian agro commodity markets mainly consist of small and marginal and they do not directly participate in the futures platform. Results also show that cumin, pepper, and guar seed futures markets are yet away from its role of providing informational incentives to the farmers. The findings of guar seed are in line with the argument of Soni (2013). It is also evident that only in soy oil the futures spillover effect is much more than spot spillover effect. This can be due to the fact that the futures soy oil market is better participated than other

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futures markets. This has rendered soy oil futures markets informationally more efficient than spot markets. The important feature of the study is that the role of spot market is very much distinguishable, implying that spot markets play at least the similar role, if not better, in information spillover process. This finding is in agreement with Sehgal et al., (2014).

[Table-6 & 7 here]

4.6. Bivariate GARCH Spillover and Asymmetry: Futures and Spot

The results of bivariate GARCH parameters that explain the dynamics of variances and covariance are presented in Table-7. Bivariate GARCH model with asymmetry shows that covariance term of ARCH effect [$\alpha_{1,2(-1)}$] and GARCH effect ($\beta_{1,2}$) are positive and significant for all the commodities, with the highest value of ARCH covariance in cumin (0.175) and GARCH covariance in pepper (0.936). Positive significant coefficients in covariance equation mean that two shocks of the same sign influence the conditional covariance between spot and futures returns positively. Last panel (γ coefficients) in Table-7 captures the asymmetric effects in the variances and covariances (i.e. $I\varepsilon_{i,t}\ \varepsilon_{i,t}$ and $I_{\varepsilon i,t}\ \varepsilon_{i,t}\ I\varepsilon_{j,t}\ \varepsilon_{j,t}$). Asymmetry in covariance or market co-movement [$\gamma_{1,2\,(-1)}$] is found insignificant except in guar seed. If the asymmetric terms are significant and the sum of two terms [$\alpha_{1,\,2(-1)}$ + $\gamma_{1,\,2(-1)}$] were positive then, it could be inferred that next period conditional covariance between return is higher when there are two negative shocks rather than two positive shocks.

[Table-8 here]

5. Conclusion and Implications

The results reveal interesting insights to understand the volatility and its dynamics in Indian commodity markets. Cumin, soy oil, pepper in the category of food commodities and guar seed in the category of non-food commodity were analysed for seasonality, breaks and volatility spillover effects. The study has intended to investigate whether seasonality and breaks have effects on volatility. The paper has also examined volatility transmission between spot and futures markets, and asymmetric nature of market co-movements.

The effect of seasonality on volatility is found significant in all the commodities. Seasonality explains spot market volatility more than the futures markets. The seasonality effect is observed before harvesting of the crop when inventory goes low and spot prices become

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higher. The seasonal nature of volatility also challenges the efficient market assumption. Cumin, soy oil and guar seed are found to have structural breaks in futures, both futures and spot, and spot market, respectively. Statistically, seasonality and breaks, in all the commodities statistically, could reduce the persistence of volatility, but not to a greater extent, except in cumin futures market where persistence is reduced to a higher extent.

In addition to this, when spillover effect between futures and spot markets are examined, it is viewed that in all commodities bidirectional spillover is present with a stronger effect of spot market on futures markets. It is quite appealing that in some cases (cumin and soy oil) the spillover effect from spot market to the futures market has rendered the long run persistence (β) of futures market insignificant. The higher spillover from the spot markets challenges the efficiency of the Indian commodity futures market, which is at its nascent stage of development. This finding is consistent with Sehgal et al.(2014).

The market co-movements of ARCH (short run) and GARCH terms (long run) are positive and significant. Hence, there are volatility co-movements between spot and futures markets. However, the co-movement is not asymmetric in nature. This suggests that there is no differential response to the good or bad news. Finally, this study is able to conclude that spillover effects, seasonality and breaks together improve the forecasting power of volatility. Nevertheless, spillover effects play the highest role in explaining volatility while seasonality and breaks have negligible power to reduce volatility.

The present study has implications for both the- traders and policy makers. The understanding of seasonality would help traders and producers to know the nature and movement of volatility well in advance and accordingly, they can plan their sowing and storing decisions as Murphy (1987) outlined that during the time of high (low) production of agricultural commodity holding a long position of agricultural futures contracts is subjected to suffer from low (high) return due to the negative correlation between prices and speculators' return with a contribution to the risk of the entire portfolio. The effect of seasonality also helps investors to understand when volatility becomes high or low. This study also guides the hedgers that Indian commodity futures markets may not provide a good hedging mechanism as it is still away from playing an efficient role of transmitting the information to spot markets.

One important finding emerged is that higher spillover effect from spot to futures markets is only found in soy oil. This suggests that futures markets, though, is not efficient in raw agro commodities, however, is playing its role for processed commodity- refined soy oil. Another important feature of this study is noteworthy that comovement of spot and futures markets in

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guar seed has an asymmetric effect, whereas the same is not found in food agro commodities. Guar seed being a non-food agro item behaves differently from other food agro commodities. This difference is also captured in EGARCH model with spillover effects, where it is ostensible that spillover from futures to spot market is not significant, yet is significant in GARCH model with spillover effect. This could lead to future scope of research where the role of futures markets can be studied for raw vis-à-vis processed agro commodity, and food and vis-à-vis non-food agro commodities.

In terms of policy implications, a reasonable conclusion is that when there is high volatility found in futures markets, the first task for policy makers is to identify the source of volatility instead of banning that particular commodity trading in the futures markets. The banning would not serve the purpose, which was also put forward by Nath and Lingareddy (2008). Higher volatility spillover from spot to futures markets than otherwise does not only indicate that spot markets are causing volatility in the futures markets but it also reflects inefficiency of futures markets in terms of informational flow to the spot markets. The study warrants the need for Indian agro commodity futures market reforms so that it can deliver the role of better price discovery and risk management.

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Fig 1Futures Close Price of Cumin

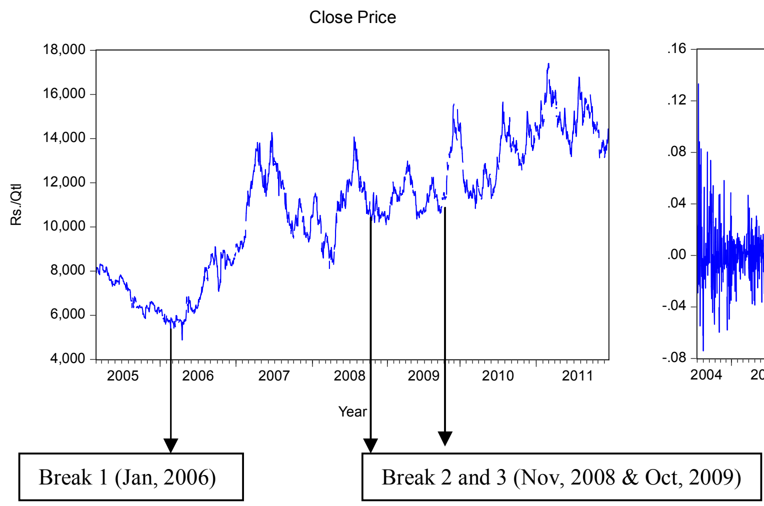

Fig 2. Futures Close Return of Cumin

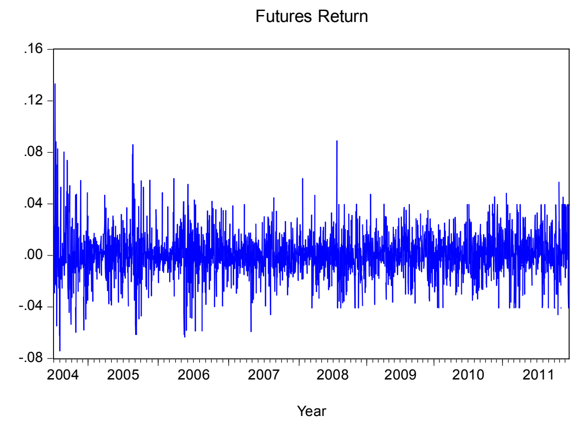

Fig 3. Spot Price of Cumin

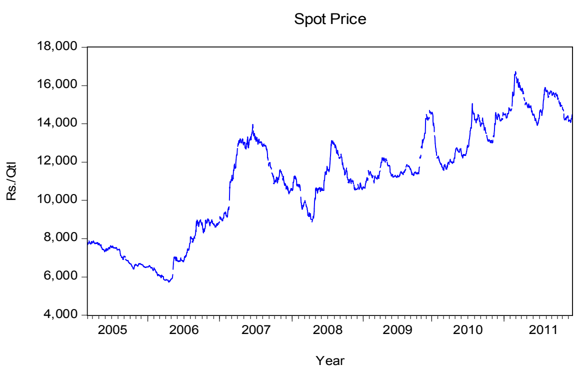

Fig 4. Spot Return of Cumin

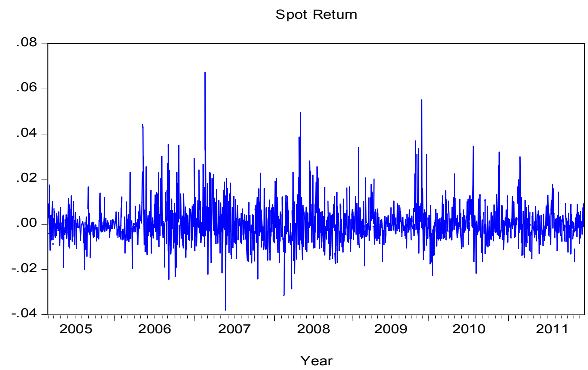

Fig 5.Close Futures Price of Soya Oil

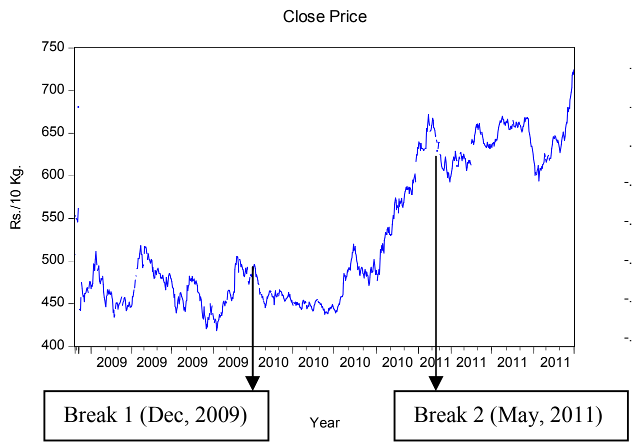

Fig 6. Futures Return of Soya Oil

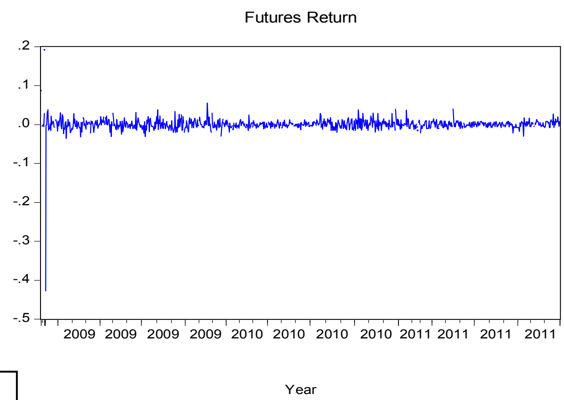

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Fig 7. Spot Price of Soya Oil

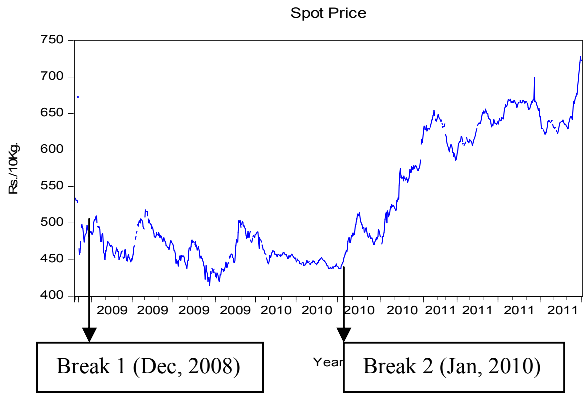

Fig 8. Spot Return of Soya Oil

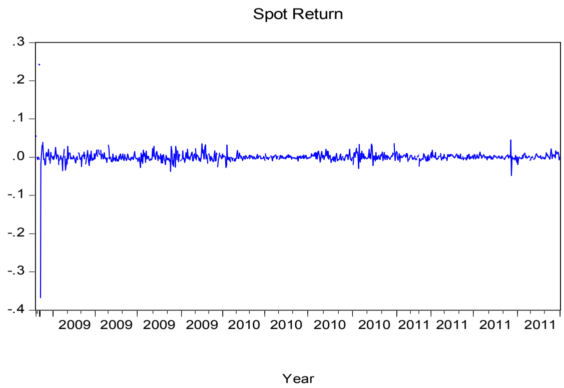

Fig 9. Close Futures Price of Pepper

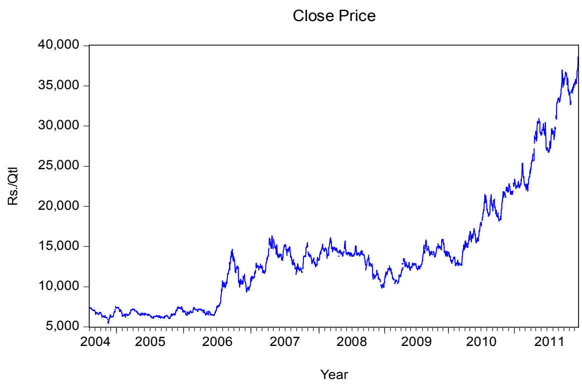

Fig 10. Futures Return of Pepper

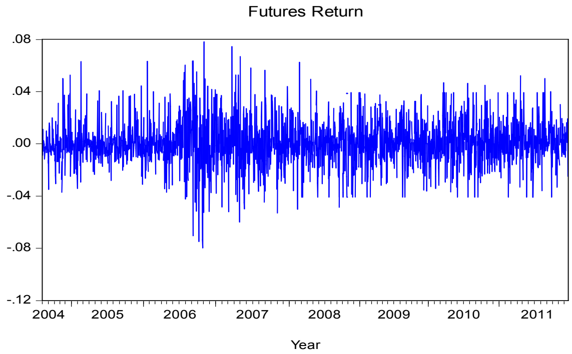

Fig 11. Spot Price of Pepper

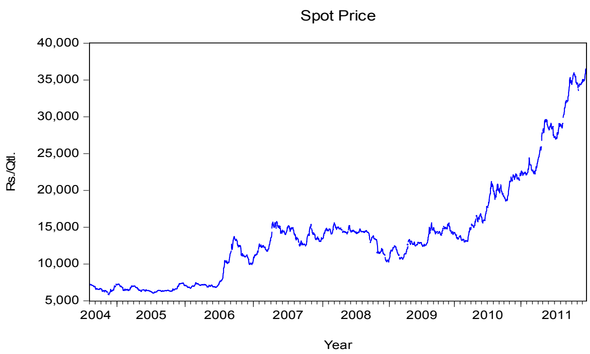

Fig 12. Spot Return of Pepper

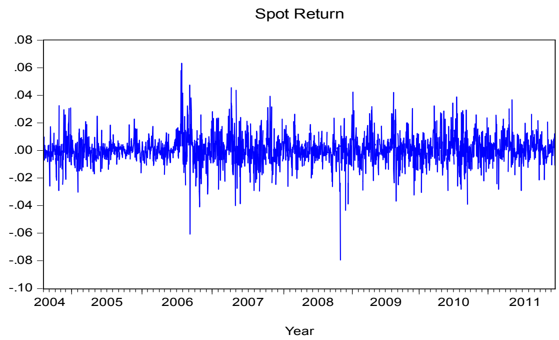

Fig 13. Close Futures Price of Guar seed

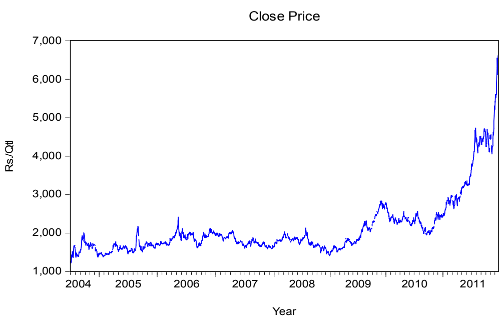

Fig 14. Futures Return of Guar seed

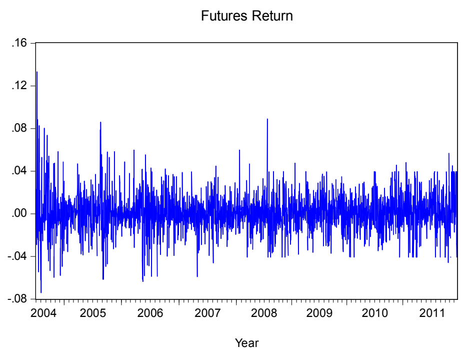

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Fig 15. Spot Price of Guar seed

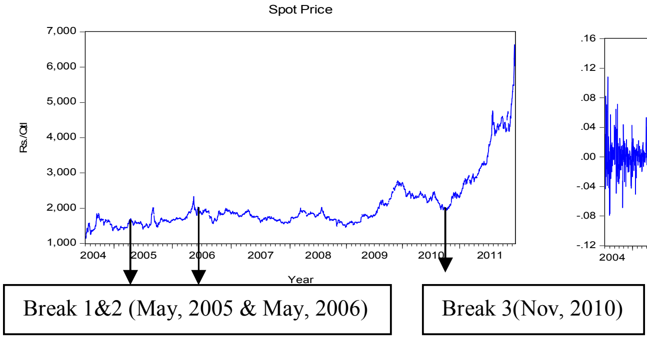

Fig 16. Spot Return of Guar seed

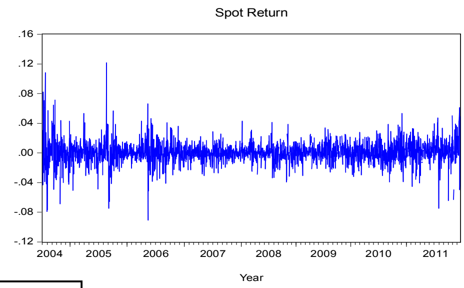

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Table 1. Descriptive Statistics

Indicators	Cumin		Soy Oil		Pepper		Guarseed	
	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
Mean (%)	0.03	0.03	0.039	0.039	0.075	0.074	0.075	0.077
Std. Dev (%)	1.89	0.84	1.888	1.736	1.763	1.072	1.853	1.534
Skewness	0.975	1.225	-11.562	-7.598	0.128	0.105	0.335	0.206
Kurtosis	9.690	9.269	304.609	268.113	4.599	7.489	6.113	9.305
J-B Stat	3882.90 (0.000)	3622.329 (0.000)	3435.183 (0.000)	2647278 (0.000)	237.353 (0.000)	1816.515 (0.000)	945.096 (0.000)	3721.272 (0.000)
LB Q(4)	6.50 (0.165)	127.93 (0.000)	48.442 (0.000)	76.011 (0.000)	16.005 (0.003)	158.43 (0.000)	12.158 (0.016)	28.566 (0.000)
LB Q(8)	9.4108 (0.309)	158.36 (0.000)	62.999 (0.000)	89.004 (0.000)	23.829 (0.002)	191 (0.000)	20.355 (0.009)	44.044 (0.000)
$LBQ^2(4)$	20.170 (0.000)	136.16 (0.000)	32.524 (0.000)	118.43 (0.000)	148.64 (0.000)	163.78 (0.000)	149.51 (0.000)	174.01 (0.000)
LB $Q^2(8)$	21.758 (0.000)	151.80 (0.000)	33.801 (0.000)	118.68 (0.000)	217.67 (0.000)	195.93 (0.000)	218.72 (0.000)	270.86 (0.000)
ADF (Constant and Trend)	-42.637*	-20.289*	-26.021*	-26.805*	-44.181*	-27.282*	-44.225*	-42.471*

*(**) indicates level significance at 5% (10%) level.
Critical Values ADF (Constant and Trend) at 5 %(10%) level are -2.862 (-2.567)

Table 2. Structural Shifts

Cumin (D_k Stat at peak)		Soy Oil (D_k Stat at peak)		Pepper (D_k Stat at peak)		Guarseed (D_k Stat at peak)	
Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
1.711*,2.477*,0.873,1.506*,0.416,0.461	1.108	2.204*,1.118,1.710*,0.596	1.946*,1.509*,0.436,1.266	0.806	0.736	1.082	1.495*,1.760*,2.081*,1.026,0.882,1.021

(*) indicates significance at 5% level. The critical value is 1.340 (approx.).

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Table 3. Estimates of GARCH model with seasonality and structural break[1]

	Coefficient	Cumin		Soy Oil		Pepper		Guar seed	
		Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
Variance	`	$7.05\times10^{-7*}$ (0.000)	$-2.07\times10^{-7*}$ (0.032)	$1.70\times10^{-5*}$ (0.000)	$3.72\times10^{-4*}$ (0.000)	$3.77\times10^{-6**}$ (0.091)	-1.71×10^{-7} (0.355)	3.29×10^{-6} (0.261)	$2.41\times10^{-5*}$ (0.000)
	α_1	0.183^{*} (0.000)	0.184^{*} (0.000)	-0.028^{*}(0.000)	0.149^{*}(0.000)	0.145^{*}(0.000)	0.152^{*}(0.000)	0.038^{*}(0.000)	0.031^{**} (0.059)
	α_2		-0.120^{*} (0.000)		-0.117^{*} (0.000)	-0.125^{*} (0.000)	-0.142^{*}(0.000)		0.069^{*} (0.000)
	β_1	0.228^{*} (0.012)	0.929^{*} (0.000)	0.938^{*} (0.000)	0.773^{*} (0.000)	0.972^{*} (0.000)	1.627^{*} (0.000)	0.931^{*} (0.000)	0.830^{*} (0.000)
	β_2						-0.638^{*} (0.000)		
	JAN	1.97×10^{-6} (0.925)	$1.52\times10^{-6*}$ (0.000)	-3.42×10^{-6} (0.209)	-1.47×10^{-6} (0.688)	-2.09×10^{-6} (0.580)	2.70×10^{-7} (0.427)	$7.3\times10^{-6*}$ (0.046)	1.68×10^{-6} (0.605)
	FEB	-1.24×10^{-5} (0.633)	$3.27\times10^{-6*}$ (0.000)	$-6.69\times10^{-6*}$ (0.002)	$-8.63\times10^{-6*}$ (0.000)	-3.49×10^{-7} (0.896)	4.31×10^{-7} (0.112)	-1.05×10^{-6} (0.701)	-2.67×10^{-7} (0.924)
	MARCH	2.50×10^{-5} (0.304)	-4.87×10^{-8} (0.943)	$-8.71\times10^{-6*}$ (0.000)	$-6.99\times10^{-6*}$ (0.010)	$-5.03\times10^{-6**}$ (0.093)	-1.43×10^{-7} (0.547)	$8.4\times10^{-6*}$ (0.007)	-2.77×10^{-6} (0.313)
	APRIL	2.11×10^{-5} (0.382)	$1.05\times10^{-6*}$ (0.007)	$-5.75\times10^{-6*}$ (0.016)	$-8.21\times10^{-6*}$ (0.000)	$6.14\times10^{-6**}$ (0.072)	$9.92\times10^{-7*}$ (0.002)	$8.57\times10^{-6*}$ (0.018)	$8.96\times10^{-6*}$ (0.018)
	MAY	-4.32×10^{-6} (0.814)	6.27×10^{-7} (0.148)	$-4.39\times10^{-6*}$ (0.016)	$-1.14\times10^{-6*}$ (0.000)	$-7.48\times10^{-6*}$ (0.009)	$-4.98\times10^{-7*}$ (0.003)	-1.84×10^{-6} (0.569)	-3.31×10^{-6} (0.220)
	JUNE	$-3.11\times10^{-5*}$ (0.048)	4.94×10^{-7} (0.187)	$-4.77\times10^{-6*}$ (0.003)	$-1.07\times10^{-6*}$ (0.000)	-3.93×10^{-6} (0.137)	$4.74\times10^{-7*}$ (0.029)	$6.7\times10^{-6**}$ (0.056)	4.59×10^{-6} (0.126)
	JULY	1.67×10^{-5} (0.433)	$7.64\times10^{-7**}$ (0.068)	$-3.76\times10^{-6*}$(0.029)	$-5.7\times10^{-6*}$ (0.027)	2.91×10^{-6} (0.293)	$4.94\times10^{-7*}$ (0.025)	$1.57\times10^{-5*}$ (0.000)	$1.38\times10^{-6*}$ (0.020)
	AUG	$9.79\times10^{-5*}$ (0.004)	$1.11\times10^{-6*}$ (0.009)	$-4.77\times10^{-6*}$ (0.005)	$-5.51\times10^{-6*}$ (0.020)	-9.10×10^{-8} (0.969)	2.80×10^{-7} (0.185)	$1.09\times10^{-5**}$ (0.075)	$1.81\times10^{-5*}$ (0.000)
	SEP	3.68×10^{-6} (0.830)	9.58×10^{-8} (0.772)	$1.43\times10^{-6*}$ (0.578)	$1.03\times10^{-5*}$ (0.002)	-4.04×10^{-6}(0.136)	-1.92×10^{-7}(0.351)	1.64×10^{-6}(0.654)	5.8×10^{-7}(0.867)
	OCT	$1.9\times10^{-4*}$	$2.87\times10^{-6*}$	$7.34\times10^{-}$	$5.16\times10^{-}$	$2.62\times10^{-}$	$9.86\times10^{-}$	$7.88\times10^{-}$	$8.15\times10^{-}$

[1] In the interest of brevity, only the results of variance or volatility component are given. However, the estimates of mean equation are available with authors.

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		(0.000)	(0.000)	^{7}(0.757)	^{7}(0.863)	^{6}(0.332)	^{7*}(0.000)	^{6*}(0.038)	^{6*}(0.028)
	NOV	-2.74 x10^{-5} (0.164)	-3.87 x10^{-7} (0.394)	-3.22 x10^{-6} (0.201)	1.31 x10^{-6} (0.963)	-4.97 x10^{-6} (0.213)	2.41x10^{-8} (0.941)	8.97 x10^{-6**} (0.079)	3.24 x10^{-6} (0.289)
	D_1	1.89x10^{-4*} (0.000)		-5.19 x10^{-6*} (0.000)	-3.45x10^{-4*} (0.000)				-1.5 x10^{-6*} (0.000)
	D_2	-1.56x10^{-4*} (0.000)		-5.59 x10^{-6*} (0.000)	-1.34 x10^{-5*} (0.000)				-2.71 x10^{-6**} (0.075)
	D_3	8.54 x10^{-5*} (0.000)							1.67 x10^{-5*} (0.000)
	AIC	-5.212	-6.960	-6.377	-6.743	-5.327	-6.444	-5.274	-5.760
	SC	-5.128	-6.874	-6.217	-6.578	-5.246	-6.362	-5.202	-5.681
	HQC	-5.181	-6.929	-6.316	-6.680	-5.297	-6.414	-5.245	-5.731
	Log Likelihood	5030.152	6701.883	2899.813	3065.617	5805.519	7016.371	5924.406	6473.959
	Q(6)	9.466 (0.149)	1.967 (0.923)	3.217 (0.781)	1.1749 (0.978)	2.133(0.830)	9.349(0.155)	6.719(0.348)	6.673(0.352)
	Q^2 (6)	3.561 (0.736)	4.400 (0.162)	2.775 (0.836)	5.960(0.428)	5.758(0.451)	4.231(0.645)	4.632(0.592)	3.049(0.803)
	ARCH-LM(F-stat)	0.104(0.900)	1.818 (0.162)	0.585(0.557)	1.387(0.250)	0.184(0.832)	1.729(0.177)	0.902(0.342)	0.558(0.572)
	ARCH-LM (TR^2)	0.209 (0.900)	3.3653 (0.162)	1.172(0.556)	2.776(0.2490	0.368(0.832)	3.458(0.177)	0.903(0.342)	1.117(0.572)

*(**) indicates statistically significant at 5% (10%) level of significance. Data in parentheses show *p*-value.

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Table 4. Estimates of EGARCH model with seasonality and structural break[2]

	Coefficient	Cumin		Soy Oil		Pepper		Guar seed	
		Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
Variance	c	-4.371* (0.000)	-0.342* (0.000)	-9.256 (0.000)	-0.448* (0.000)	-0.220* (0.000)	-0.391* (0.000)	-0.219* (0.000)	-0.421* (0.000)
	α_1	0.314* (0.000)	0.187* (0.000)	0.408(0.000)	0.188*(0.000)	0.281*(0.000)	0.166*(0.000)	0.065*(0.000)	0.139*(0.000)
	α_2		-0.072** (0.067)			-0.216*(0.000)			
	β_1	0.542* (0.000)	0.977* (0.000)	-0.078(0.595)	0.793*(0.000)	0.978*(0.000)	0.972*(0.000)	0.981*(0.000)	0.961*(0.000)
	γ_1	-0.109* (0.000)	0.173* (0.000)	0.211* (0.000)	0.082* (0.008)	-0.090* (0.002)	0.053* (0.000)	0.033* (0.000)	0.049* (0.000)
	γ_2		-0.075* (0.015)			0.109* (0.000)			
	JAN	0.007 (0.928)	0.069* (0.000)	-0.034(0.870)	0.039(0.494)	-0.009(0.584)	-0.008(0.653)	0.014(0.363)	-0.013(0.541)
	FEB	0.012 (0.885)	0.079* (0.000)	-0.327 (0.198)	-0.147* (0.022)	9.83x10^{-4} (0.934)	0.025 (0.109)	-0.007 (0.526)	-0.019 (0.290)
	MARCH	0.053 (0.524)	0.030* (0.042)	0.183**(0.082)	-0.101(0.136)	-0.01(0.240)	-0.021(0.162)	0.034*(0.007)	-0.001(0.930)
	APRIL	0.085 (0.314)	0.038* (0.007)	-0.531**(0.052)	-0.107*(0.045)	0.029*(0.032)	0.036*(0.003)	0.012(0.343)	0.008(0.653)
	MAY	0.093 (0.238)	0.029** (0.067)	-0.219 (0.295)	-0.263* (0.001)	-0.029* (0.031)	-0.016 (0.273)	-0.005 (0.737)	-0.020 (0.252)
	JUNE	-0.195* (0.014)	0.026** (0.082)	-0.995* (0.000)	-0.263* (0.001)	-0.020 (0.128)	-0.012 (0.408)	0.021 (0.111)	0.022 (0.184)
	JULY	0.091 (0.215)	0.025** (0.090)	-0.484** (0.061)	-0.054 (0.349)	0.013 (0.293)	0.039* (0.005)	0.032* (0.009)	0.0371* (0.033)
	AUG	0.206* (0.019)	0.052* (0.000)	-0.299(0.196)	-0.133*(0.006)	0.012(0.308)	0.033*(0.031)	0.021**(0.084)	0.029**(0.086)
	SEP	-0.005 (0.941)	0.019 (0.253)	-0.017 (0.946)	0.183* (0.000)	-0.018 (0.205)	-0.027 (0.121)	4.7x10^{-4} (0.972)	0.005 (0.748)
	OCT	0.397* (0.000)	0.069* (0.000)	0.473*(0.024)	-0.012(0.847)	0.018(0.155)	0.075*(0.000)	0.023*(0.060)	0.023(0.156)
	NOV	-0.047 (0.559)	0.035* (0.006)	0.143 (0.502)	0.009 (0.843)	-0.010 (0.513)	08.58x10^{-4} (0.957)	0.019 (0.229)	-0.006 (0.757)

[2] In the interest of brevity, only the results of variance or volatility component are given. However, the estimates of mean equation are available with authors.

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	D_1	0.547* (0.000)		-0.949* (0.000)	-1.490* (0.000)				-0.015(0.125)
	D_2	-0.376* (0.000)		-0.795* (0.000)	-0.242* (0.000)				-0.023* (0.001)
	D_3	0.242* (0.000)							0.032* (0.000)
	AIC	-5.220	-6.976	-6.288	-6.780	-5.327	-6.446	-5.265	-5.758
	SC	-5.133	-6.883	-6.123	-6.615	-5.241	-6.368	-5.191	-5.678
	HQC	-5.188	-6.942	-6.225	-6.717	-5.296	-6.417	-5.238	-5.729
	Log Likelihood	5038.556	6718.680	2860.736	3082.194	5808.014	7017.959	5915.520	6471.117
	Q(6)	10.895 (0.09)	1.656 (0.647)	2.812(0.832)	0.991(0.986)	13.157(0.041)	7.206(0.302)	4.069 (0.667)	6.944(0.225)
	Q^2 (6)	2.898 (0.822)	3.157 (0.789)	5.936(0.430)	4.338(0.631)	2.898(0.821)	8.882(0.180)	6.791(0.341)	5.345(0.500)
	ARCH-LM(F-stat)	0.069(0.933)	0.270 (0.603)	2.057(0.128)	0.994(0.370)	0.017 (0.982)	2.114(0.121)	1.211(0.271)	1.718(0.180)
	ARCH-LM (TR^2)	0.138 (0.933)	0.271 (0.602)	4.109(0.128)	1.990(0.369)	0.035(0.982)	4.226 (0.121)	1.211(0.271)	3.436(0.179)

*(**) indicates statistically significant at 5% (10%) level of significance. Data in parentheses show *p*-value.

Table 5. Impact of Asymmetry on Volatility

Impact of Asymmetry	Cumin		Soy Oil		Pepper		Guar seed	
	Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
$e^{\gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}}$	0.896	1.188	1.235	1.0534	0.914	1.054	1.033	1.050
$\sqrt{e^{\gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}}}$	0.946	1.089	1.111	1.026	0.956	1.026	1.016	1.025
Impact on volatility (as a % of increase of decrease)	-5.4	8.9	11.1	2.6	-4.4	2.6	1.6	2.5

Impact of asymmetry on volatility is estimated when standardised shock is 1. Then, the impact of asymmetry on volatility is a factor $\sqrt{e^{\gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}}}$ (Sharma, 2012).

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Table 6. Estimates of Spillover Effects by GARCH [3]

	Coefficient	Cumin		Soy Oil		Pepper		Guar seed	
		Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
Variance	c	$5.74\times10^{-5*}$ (0.000)	0.797^{*} (0.003)	$2.1\times10^{-4*}$ (0.004)	-1.87×10^{-4} (0.820)	$1.15\times10^{-4*}$ (0.000)	$4.71\times10^{-6*}$ (0.053)	$9.92\times10^{-5*}$ (0.000)	$3.49\times10^{-6*}$ (0.003)
	α_1	0.202^{*} (0.000)	0.114^{*} (0.000)	-0.004 (0.766)	0.071^{*} (0.002)	0.122^{*} (0.000)	0.008 (0.382)	-0.006 (0.524)	0.014 (0.274)
	α_2		0.074^{*} (0.010)		0.035 (0.198)	0.005 (0.823)	0.041^{*} (0.001)		0.029^{*} (0.041)
	β_1	-0.007 (0.796)	0.405^{*} (0.000)	0.056 (0.809)	0.256^{*} (0.000)	0.075^{*} (0.045)	0.588^{*} (0.000)	0.076^{*} (0.000)	0.254^{*} (0.000)
	β_2						-0.151^{*}(0.000)		
	JAN	-2.03×10^{-5} (0.249)	-2.62×10^{-6} (0.172)	$-5.70\times10^{-5**}$ (0.074)	-1.25×10^{-6} (0.898)	1.26×10^{-5} (0.572)	-3.15×10^{-6} (0.275)	-1.67×10^{-5} (0.345)	3.94×10^{-6} (0.547)
	FEB	$-5.83\times10^{-5*}$ (0.026)	$7.17\times10^{-6*}$ (0.030)	$-7.69\times10^{-5*}$ (0.031)	$-1.37\times10^{-5*}$ (0.073)	6.68×10^{-6} (0.776)	4.91×10^{-6} (0.192)	$-3\times10^{-5**}$ (0.077)	1.68×10^{-6} (0.807)
	MARCH	3.31×10^{-5} (0.224)	3.36×10^{-6} (0.248)	$-1.05\times10^{-4*}$ (0.005)	-1.17×10^{-5} (0.128)	1.37×10^{-5} (0.512)	-7.43×10^{-8} (0.981)	-2.56×10^{-5} (0.129)	-3.99×10^{-6} (0.533)
	APRIL	-3.51×10^{-6} (0.870)	2.50×10^{-7} (0.918)	$-9.87\times10^{-5*}$ (0.009)	$-1.32\times10^{-5**}$ (0.069)	1.43×10^{-5} (0.534)	-7.76×10^{-7} (0.785)	-1.64×10^{-5} (0.432)	$-1.14\times10^{-5*}$ (0.062)
	MAY	1.37×10^{-5} (0.468)	5.97×10^{-9} (0.997)	$-6.46\times10^{-5*}$ (0.041)	$-1.34\times10^{-5**}$ (0.065)	5.09×10^{-6} (0.833)	2.58×10^{-7} (0.938)	$-4.51\times10^{-5*}$ (0.014)	-3.02×10^{-6} (0.621)
	JUNE	$-2.72\times10^{-5**}$ (0.088)	2.14×10^{-6} (0.316)	$-7.41\times10^{-5*}$ (0.021)	-1.15×10^{-5} (0.102)	-1.34×10^{-5} (0.469)	-1.09×10^{-6} (0.687)	-1.88×10^{-5} (0.308)	-6.32×10^{-6} (0.354)
	JULY	2.3×10^{-5} (0.256)	-9.55×10^{-7} (0.669)	$-7.43\times10^{-5*}$ (0.022)	-6.79×10^{-6} (0.385)	-2.45×10^{-5} (0.277)	-2.44×10^{-6} (0.373)	-9.02×10^{-6} (0.692)	3.44×10^{-6} (0.706)
	AUG	$1.39\times10^{-4*}$ (0.000)	$-4.80\times10^{-6*}$ (0.002)	$-7.10\times10^{-5*}$ (0.029)	-1.22×10^{-5} (0.103)	-2.26×10^{-5} (0.236)	-7.02×10^{-7} (0.803)	$3.88\times10^{-5**}$ (0.072)	1.16×10^{-5} (0.255)
	SEP	-1.59×10^{-5} (0.359)	$-3.39\times10^{-6**}$ (0.067)	$-5.33\times10^{-5**}$ (0.063)	$5.05\times10^{-6*}$ (0.000)	-9.16×10^{-6} (0.237)	2.62×10^{-6} (0.368)	2.44×10^{-5} (0.215)	-6.92×10^{-6} (0.322)
	OCT	1.84×10^{-5}	-1.49×10^{-6}	-7.47×10^{-5}	-9.08×10^{-6}	7.19×10^{-6}	2.70×10^{-6}	1.52×10^{-5}	1.63×10^{-6}

[3] In the interest of brevity, only the results of variance or volatility component are given. However, the estimates of mean equation are available with authors.

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		(0.432)	(0.521)	(0.801)	(0.321)	(0.746)	(0.397)	(0.431)	(0.828)
	NOV	-8.27 x10^{-5} (0.692)	9.51 x10^{-7} (0.707)	-6.27 x10^{-5*} (0.043)	-1.46 x10^{-5**} (0.053)	3.22 x10^{-5} (0.198)	-4.73 x10^{-6} (0.074)	2.64 x10^{-5} (0.177)	3.89 x10^{-6} (0.643)
	D_1	1.64 x10^{-5*} (0.000)		-6.95 x10^{-5*} (0.001)	2.31 x10^{-4} (0.778)				-1.33 x10^{-5} (0.215)
	D_2	-9.93 x10^{-5*} (0.000)		-4.73 x10^{-5*} (0.001)	-2.89 x10^{-5*} (0.000)				-1.15 x10^{-5*} (0.001)
	D_3	3.41 x10^{-5**} (0.056)							1.46 x10^{-5*} (0.015)
	ψ	2.009* (0.000)	0.074* (0.000)	0.072* (0.000)	0.302* (0.000)	1.458* (0.000)	0.178* (0.000)	1.055* (0.000)	0.417* (0.000)
	AIC	-5.131	-7.087	-6.438	-6.916	-5.416	-6.719	-5.539	-6.112
	SC	-5.227	-6.999	-6.273	-6.746	-5.332	-6.635	-5.465	-6.029
	HQC	-5.282	-7.054	-6.375	-6.851	-5.385	-6.688	-5.512	-6.082
	Log Likelihood	5123.887	6823.683	2928.317	3144.637	5902.714	7315.992	6221.632	6864.937
	Q(6)	8.373 (0.212)	3.641 (0.725)	3.051 (0.802)	1.859 (0.932)	11.352 (0.078)	8.998 (0.174)	5.305 (0.505)	8.538 (0.201)
	Q^2 (6)	5.443 (0.488)	5.016 (0.542)	3.772 (0.707)	7.950 (0.242)	3.274 (0.774)	20.934* (0.002)	6.333 (0.387)	6.978 (0.323)
	ARCH-LM(F-stat)	0.141 (0.868)	0.219 (0.803)	1.430 (0.239)	1.817 (0.163)	0.758 (0.468)	0.158 (0.853)	2.155 (0.116)	0.899 (0.407)
	ARCH-LM (TR^2)	0.283 (0.867)	0.440 (0.802)	2.861 (0.239)	3.631 (0.162)	1.518 (0.468)	0.317 (0.853)	4.308 (0.116)	1.800 (0.406)

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Table 7. Estimates of Spillover Effects by EGARCH[4]

	Coefficient	Cumin		Soy Oil		Pepper		Guar seed	
		Futures	Spot	Futures	Spot	Futures	Spot	Futures	Spot
Variance	c	-3.492* (0.000)	-0.429* (0.000)	-7.853* (0.000)	-0.282 (0.241)	-0.149* (0.000)	-0.376* (0.000)	-0.223* (0.000)	-0.421* (0.000)
	α_1	0.278* (0.000)	0.251* (0.000)	0.449* (0.000)	0.186* (0.000)	0.259* (0.000)	0.163* (0.000)	0.065* (0.000)	0.138* (0.000)
	α_2		-0.101*(0.013)			-0.204*(0.000)			
	β_1	0.642* (0.000)	0.971* (0.000)	0.075 (0.619)	0.799* (0.000)	0.986* (0.000)	0.973* (0.000)	0.980* (0.000)	0.961* (0.000)
	γ_1	-0.206* (0.000)	0.031 (0.338)	0.233* (0.000)	0.071* (0.029)	-0.173* (0.000)	0.044* (0.003)	0.002 (0.862)	0.047 *(0.000)
	γ_2		-0.038(0.206)			0.107*(0.000)			
	JAN	0.108 (0.101)	0.056* (0.003)	-0.220 (0.281)	0.037 (0.509)	-0.010 (0.551)	-0.008 (0.655)	0.015 (0.338)	-0.013 (0.535)
	FEB	0.058 (0.429)	0.089* (0.000)	-0.492* (0.043)	-0.139 (0.031)	0.011 (0.431)	0.025 (0.101)	-0.006 (0.569)	-0.019 (0.285)
	MARCH	0.133** (0.058)	0.023 (0.157)	-0.622* (0.023)	-0.098 (0.146)	-0.014 (0.376)	-0.021 (0.171)	0.035* (0.006)	-0.001* (0.916)
	APRIL	0.142* (0.041)	0.031* (0.045)	-0.591* (0.023)	-0.107* (0.039)	0.029** (0.054)	0.035* (0.034)	0.019 (0.135)	0.008 (0.657)
	MAY	0.148* (0.036)	0.032* (0.037)	-0.352** (0.085)	-0.257* (0.001)	-0.018 (0.197)	-0.017 (0.241)	-0.002 (0.843)	-0.020 (0.235)
	JUNE	-0.067 (0.299)	0.013 (0.426)	-0.973* (0.000)	-0.256* (0.001)	-0.002 (0.849)	-0.012 (0.415)	0.021 (0.123)	0.022 (0.183)
	JULY	0.137* (0.038)	0.016 (0.327)	-0.581* (0.021)	-0.053 (0.349)	0.020 (0.162)	0.039* (0.005)	0.036* (0.004)	0.035* (0.041)
	AUG	0.204* (0.008)	0.048* (0.004)	-0.445* (0.046)	-0.133* (0.006)	0.017 (0.225)	0.031* (0.039)	0.019 (0.114)	0.029 (0.102)
	SEP	0.093 (0.141)	0.019 (0.268)	-0.188 (0.437)	0.180* (0.004)	-0.014 (0.353)	-0.027 (0.110)	0.001 (0.910)	0.005 (0.749)

[4] In the interest of brevity, only the results of variance or volatility component are given. However, the estimates of mean equation are available with authors.

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	OCT	0.286* (0.000)	0.069* (0.000)	0.238 (0.241)	-0.016 (0.781)	0.022* (0.100)	0.074* (0.000)	0.024 (0.043)	0.022 (0.154)
	NOV	0.069 (0.285)	0.025 (0.123)	-0.015 (0.938)	0.007 (0.876)	-0.003 (0.874)	0.001 (0.929)	0.019 (0.238)	-0.006 (0.751)
	D_1	0.399* (0.000)		-0.755* (0.000)	-1.599* (0.000)				-0.014 (0.141)
	D_2	-0.257* (0.000)		-0.779* (0.000)	-0.234* (0.000)				-0.023* (0.001)
	D_3	0.159* (0.001)							0.0321* (0.000)
	ψ	25.851* (0.000)	6.499* (0.000)	2.531* (0.000)	1.473 (0.483)	9.676* (0.000)	0.531 (0.465)	2.213* (0.013)	0.093 (0.858)
	AIC	-5.255	-6.994	-6.302	-6.778	-5.336	-6.445	-5.267	-5.757
	SC	-5.165	-6.898	-6.131	-6.607	-5.247	-6.364	-5.190	-5.676
	HQC	-5.222	-6.958	-6.237	-6.713	-5.303	-6.415	-5.239	-5.727
	Log Likelihood	5067.933	6736.793	2868.204	3082.335	5818.611	7018.012	5918.306	6469.215
	Q(6)	10.254 (0.114)	4.590 (0.597)	2.360 (0.884)	1.0118 (0.985)	15.689 (0.016)	7.2181 (0.301)	7.431 (0.283)	8.096 (0.231)
	Q^2 (6)	5.058 (0.409)	4.619 (0.593)	12.120** (0.06)	4.3203 (0.633)	6.788 (0.341)	9.0712 (0.170)	6.463 (0.373)	5.403 (0.493)
	ARCH-LM(F-stat)	0.246 (0.781)	0.556 (0.573)	12.120* (0.004)	1.924 (0.166)	0.038 (0.962)	2.276 (0.103)	1.984 (0.138)	1.735 (0.176)
	ARCH-LM (TR^2)	0.493 (0.781)	1.113 (0.573)	11.218** (0.004)	1.925 (0.165)	0.077 (0.962)	4.549 (0.103)	3.967 (0.137)	3.471 (0.176)

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Table 8. Bivariate GARCH for Volatility Spillover

Parameters	Commodity			
	Cumin	Soy oil	Pepper	Guar Seed
$const_1$	$6.54\text{x}10^{-5}(0.706)$	$-2\text{x}10^{-4}(0.547)$	$1.31\text{x}10^{-5}(0.971)$	$7.02\text{x}10^{-4**}(0.056)$
$const_2$	$1.92\ \text{x}10^{-5}(0.204)$	$-4.01\text{x}10^{-4*}(0.079)$	$3.12\text{x}10^{-4}(0.131)$	$5.76\text{x}10^{-4*}(0.041)$
$const_{1,1}$	$6.54\ \text{x}10^{-5*}(0.000)$	$4.67\ \text{x}10^{-4*}(0.000)$	$2.27\ \text{x}10^{-6*}(0.000)$	$8.56\text{x}10^{-6*}(0.000)$
$const_{1,2}$	$1.92\text{x}10^{-5*}(0.000)$	$3.27\ \text{x}10^{-4*}(0.000)$	$3.76\ \text{x}10^{-6*}(0.000)$	$8.5\ \text{x}10^{-6*}(0.000)$
$conts_{2,2}$	$5.65\text{x}10^{-6*}(0.000)$	$2.29\ \text{x}10^{-4*}(0.000)$	$6.21\ \text{x}10^{-6*}(0.000)$	$8.44\ \text{x}10^{-6*}(0.000)$
$\alpha_{1,1(-1)}$	$0.166^{*}(0.000)$	$0.043^{*}(0.000)$	$0.018^{*}(0.000)$	$0.030^{*}(0.000)$
$\alpha_{1,2(-1)}$	$0.175^{*}(0.000)$	$0.059^{*}(0.000)$	$0.032^{*}(0.000)$	$0.039^{*}(0.000)$
$\alpha_{2,2(-1)}$	$0.013^{*}(0.000)$	$0.184^{*}(0.000)$	$0.128^{*}(0.000)$	$0.087^{*}(0.000)$
$\alpha_{1,1(-2)}$	-	-	0.794(0.110)	-
$\alpha_{1,2(-2)}$	-	-	-0.087(0.850)	-
$\alpha_{2,2(-2)}$	-	-	$-0.741^{*}(0.000)$	-
$\beta_{1,1}$	$0.689^{*}(0.000)$	$0.925^{*}(0.000)$	$0.976^{*}(0.000)$	$0.947^{*}(0.000)$
$\beta_{1,2}$	$0.675^{*}(0.000)$	$0.881^{*}(0.000)$	$0.936^{*}(0.000)$	$0.915^{*}(0.000)$
$\beta_{2,2}$	$0.787^{*}(0.000)$	$0.848^{*}(0.000)$	$0.843^{*}(0.000)$	$0.897^{*}(0.000)$
$\gamma_{1,1(-1)}$	$0.176^{*}(0.000)$	$-0.043^{*}(0.000)$	$0.218^{*}(0.000)$	$-0.015^{*}(0.026)$
$\gamma_{1,2(-1)}$	0.013(0.626)	-0.004 (0.851)	$-8.37\ \text{x}10^{-4}(0.977)$	$-0.023^{*}(0.002)$
$\gamma_{2,2(-1)}$	$-0.079^{*}(0.000)$	-0.042 (0.166)	0.015(0.514)	$-0.057^{*}(0.000)$
$\gamma_{1,1(-2)}$	-	-	$-1.017^{*}(0.042)$	-
$\gamma_{1,2(-2)}$	-	-	0.070(0.878)	-
$\gamma_{2,2(-2)}$	-	-	$0.671^{*}(0.001)$	-

*(**) indicates statistically significant at 5% (10%) level of significance. Data in parentheses show *p*-value.

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