Australian Journal of Business and Management Research
New South Wales Research Centre Australia *(NSWRCA)*

Vol.05 No.09 | 2018 ISSN: 1839 - 0846

VOLATILITY SPILLOVER BETWEEN SPOT AND FUTURES MARKET OF HIGHLY TRADED COMMODITIES IN INDIA: The DCC-GARCH Approach

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ABSTRACT

This study intends to examine the volatility spillover effects and measure the time-varying correlations between futures and spot prices of thirteen highly traded commodities traded on Multi Commodity Exchange (MCX) of India. The research uses Exponential GARCH proposed by Nelson (1991) to explore the direction and magnitude of spillover effects between futures and spot commodity market and employs Dynamic Conditional Correlation (DCC) GARCH proposed by Engle (2002) to demonstrate the time varying conditional correlation between heteroscedastic coefficients of the futures and spot markets. Empirical results show that significant and asymmetric bi-directional volatility spillover effects exist in case of most of the selected commodities, even though, the magnitude of volatility spillover is found larger in the direction from futures market to spot market. The dynamic correlation between the conditional variance of the spot and future markets is found to be significant in case of all the commodities except Silver and Copper. It proves that significant volatility spillover effect is present between spot and futures markets of selected commodities. Understanding of volatility transmission and interrelationship between spot and futures commodity market will help investors make right investment decisions, portfolio optimization and financial risk management. Policy makers and regulators can use this knowledge in planning and implementing appropriate regulatory framework. Much of the earlier research focuses on inter market volatility spillover taking into consideration two or more different financial markets. This study focuses on intra market volatility spillover by studying the interactions of spot-futures prices of commodities. Also, considering the time-varying nature of conditional correlations, this study employs EGARCH and multivariate GARCH (DCC) to capture the volatility spillover effects instead of univariate GARCH or standard linear VAR models.

Keywords - *DCC-GARCH, EGARCH, Volatility Spillovers, Commodity Market*
JEL Code*:* C32; C58; G13; Q02

I. INTRODUCTION

Commodity markets have attracted great attention in India since the past decade due to its spectacular growth in terms of network, volume and technological up gradation. Even though, commodity futures trading began in the country in the year 1875 with the setting up of the Bombay Cotton Trade Association Ltd., these markets have witnessed a turbulent history and a strict regime of rules and regulations. In 1966, futures trading was totally banned in India. After 1980, futures trading was allowed in select commodities which ended up lifting of bans on futures trading for all commodities in 2003. The economic reforms of 1990s led to the revival of these markets and significant and apt government policies paved a way for their magnificent growth in the country. Again in 2003, a number of steps were taken by the government which provided a real boost to the commodity futures market in India.

Over the recent years, the issue of volatility spillover between futures and spot prices of commodities has been focused by several researchers. Analyzing the spillover effects between futures and spot commodity markets is worthy of examination as it helps the stakeholders to know about the flow of information across the markets and thus, they can avoid underlying financial risk. 'Volatility' refers to variations in asset prices and represents uncertainty and risk in the market. Information flow from one market to the other steers the volatility process of an asset's (Anderson, 1996). In a highly volatile market, the conditional variance varies between extremely high and low values. Volatility is a key information source which is useful in probing the process through which volatility of a particular market influences the volatility of some other market (Chan et al. 1991). Cross-market hedging and change in the usually available information in the market lead to volatility spillovers impacting the participants' expectations across markets (Engle et al. 1990). The knowledge of volatility spillover between assets or markets is vital as it makes clear that a big shock elevates the volatility in its own market as well as in other markets (Hong, 2001).

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Vol.05 No.09 | 2018 ISSN: 1839 - 0846

Modeling the volatility spillovers between futures and spot commodity market is an important and timely topic to explore. So far, there are abundance of studies that have addressed the issue of volatility spillover across different markets. But, most of the studies are related to developed countries focusing mainly on volatility spillover across two or more same or different financial markets or assets (Manera et. al. (2012); Sehgal et. al. (2014); Aftab et. al. (2015); Chen & Wu (2016) and Bala & Takimoto (2017)). There are only a handful of studies examining the volatility spillover between futures-spot commodity market especially in India. Most of the earlier studies examining volatility spillover in futures-spot commodity market have used the methods like GARCH, EGARCH, BEKK. But, the literature examining futures-spot volatility spillover in commodity market using DCC-GARCH method in India is very limited. Considering the time-varying and dynamic properties of volatility spillover effect in the commodity futures and spot markets, this study tests the time-varying volatility relationship between futures and spot commodity markets by employing high dimensional dynamic conditional correlation model. Further, the study uses exponential GARCH (EGARCH) model to quantify the direction and magnitude of volatility spillover across the underlying markets. The study uses secondary data relating to daily closing spot and futures prices of thirteen highly traded commodities traded on Multi Commodity Exchange of India Ltd. These commodities are selected because of their frequent trading on the MCX platform. The commodities selected for study are bullion commodities namely, Gold and Silver; metal commodities, namely, Aluminium, Copper, Lead, Nickel and Zinc; energy commodities namely, Crude Oil and Natural Gas and agricultural commodities namely, Cardamom, Cotton, Crude Palm Oil and Mentha Oil. The collection of data is done from the official website of MCX and Bloomberg database. MCX is the most leading commodity exchange in India offering electronic trading across various commodity segments *viz.* bullion, metals, energy and agri commodities. MCX captures over 90% market share in terms of the trading value of the commodity futures contracts traded in financial year 2017.

The paper is structured as follows: Section 2 presents the literature review concerning the topic of the study. Section 3 outlines the description of empirical models used in the study, section 4 explains the objectives and methodology. Data analysis, results and interpretations are included in section 5. Section 6 contains conclusions and discussions.

II. REVIEW OF LITERATURE

The need to have accurate estimation of volatility spillover and correlation in portfolio designing and optimization, pricing of derivatives, risk management and hedging strategies calls for modelling and forecasting volatility and correlations in financial econometrics (Sadorsky, 2012). A good number of research studies on volatility spillover between two or more asset classes have applied GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and its family models like BEKK (Baba, Engle, Kraft, and Kroner) and DCC (Dynamic Conditional Correlation). When there are more than two variables in a model, BEKK model can behave with poor likelihood function making optimization difficult or impossible sometimes. Dynamic Conditional Correlation (DCC) model addresses such issues and works well critically for large data sets. The bivariate DCC model is nonlinear and fine estimation of a range of time-varying correlation processes can be obtained with it (Engle, 2002). The seminal work of Engle (1982) and Bollerslev (1986) led to the applications of GARCH and its family of models for modeling volatility in commodity spot and futures prices as well. Many studies have used DCC-GARCH methodology for modelling volatility spillover across different markets. Studies such as Xiao & Dhesi (2010); Al-Zeaud (2014); Mohammadi & Tan (2015); Bala & Takimoto (2017); Panda & Nanda (2017) have applied DCC-GARCH for testing volatility spillover across different stock markets. Xiao & Dhesi (2010) tested the co-movements between two major stock markets namely, European and United States by covering their indices CAC, DAX, FTSE100 and S&P500. The results of BEKK model proved that there existed asymmetric volatility spillover effects widely between these markets. UK is the main transmitter of volatility and US is the main exporter of volatility within Europe. The results of DCC GARCH model showed that there are conditional as well as time-varying correlations having a mean-reverting process among them. Al-Zeaud (2014) tested the spillover between the stock markets of US and Europe by using DCC form of EGARCH model. The author put forth that there is spillover effect from London to the stock markets of New York, Paris and Frankfurt. Unidirectional volatility spillover effects are reported from Frankfurt to Paris and also from Paris to London. The bad news impact on volatility is more and is transmitted more robustly in comparison to volatility declines. Mohammadi & Tan (2015) studied the returns spillovers and conditional volatility in four equity markets of the United States, Hong Kong and mainland China (two stock exchanges) by using GARCH and DCC model. The study provided the evidence of unidirectional return spillovers and ARCH and GARCH effects originating from United States to the other countries. There is highest correlation between the Chinese markets under study in comparison to the other markets studied. Also, the DCC model results showed that correlation between China and other markets risen after the financial crisis of 2007. Bala & Takimoto (2017) examined volatility spillovers of stock returns in the markets of developing and developed countries by applying variants of MGARCH models and found that in case of developed markets correlation is more implying more interaction than in case of emerging markets. Also, volatility spillovers of the stock market itself are greater in comparison to the cross-volatility spillovers especially for emerging markets. Also, the emerging markets are less efficient than the developed markets as the impact of any shock in the markets of these countries takes greater time to dissipate. The authors suggested DCC-with-skewed-t density model for capturing the volatility dynamics if fat tails and skewness is present in the data. Panda & Nanda (2017) in their study aimed to study the short-term and long-term relationship and the conditional correlation existing between the stock markets of South American and Central American by using VECM, variance decomposition and GARCH-DCC. The authors identified that there existed long-run equilibrium and strong linkages among national stock markets. The results confirm that market integration is increasing and conditional correlations in stocks are asymmetric. Also, the correlation is higher towards the last part of the sample period than the starting part of it.

Many researchers have used DCC-GARCH methodology for investigating dynamic spillover across diverse financial markets such as stock market vs. commodity markets, stock market vs. currency or exchange markets. Ghorbel et. al. (2012) applied BEKK-GARCH model, the CCC-GARCH model and the DCC-GARCH model to find out the dynamic relationship of crude oil and stock index returns. They reported that strong spillovers of volatility along with the significant conditional correlations is exiting from crude oil to the stock markets of each of the oil-importing as well as oil-exporting countries. Demiralay & Ulusoy (2014) investigated the links between commodity markets represented by Dow Jones commodity indices and stock market represented by S&P 500 index using asymmetric dynamic conditional correlation (ADCC) model. Emphasizing on diversification benefits of commodity markets and the financialization process, the study proved the existence of very high volatile correlations that augmented greatly after the financial crises of 2007 and 2008. As the conditional correlations and variances are positively connected, the diversification benefits are very less. Also, external shocks impact the correlations differently. Lagesh et. al. (2014) estimated the linkages between the indices of Indian commodity market with conventional asset class indices applying the DCC–GARCH model under both pre-crisis period and crisis period to examine the portfolio diversification possibilities. The results of the study indicated low dynamic conditional correlations between the returns of the indices of commodity market and asset class symptomatic of the possibility of portfolio diversification and thereby pointing to the conclusion that for tactical asset allocation commodity futures can be successfully used. As traditional asset markets becomes more risky, there are more diversification benefits of commodity futures. Lu et. al. (2014) in their study on gold and stocks tested the time-varying volatility spillover effects between the markets by using VAR-DCC-BVGARCH model. The authors have found that there are considerable bidirectional return as well as spillover effects across the assets under study with spillover from gold to stock to be quite strong. Dynamic conditional correlations between the assets also vary noticeably taking positive or negative values eventually. Aftab et. al. (2015) explored the dynamics between currency and Chinese stock markets focusing on the exchange rate liberalization by applying DCC-GARCH method and suggested a negative relation of stock prices with exchange rate which even becomes more during the period of financial crisis. The weak relationships between both the markets point to the fact that there is gradual movements of Chinese markets towards globalization and market integration. Also, the impact of market forces on the interrelationships between the markets is weak. Aimer (2016) studied the volatility spillovers and conditional correlations of shocks in oil prices with the stock indices of Middle East countries covering oil importing as well as oil exporting countries. The study used multivariate GARCH models - BEKK-GARCH and DCC-GARCH model. The results showed significant bidirectional volatility spillover impacts and dependence of oil returns and these stock markets. The dynamic conditional correlation of crude oil with index returns change considerably eventually but, no variation is reported in oil exporter or oil importer countries. The 2008 crisis impact is found more on correlation coefficients than the impact of any other events. Wei (2016) in his study on US dollar exchange rate and CRB commodity markets (energy and non-energy) testes the volatility surprise effects by using five MGARCH models (BEKK, CCC, DCC and others). The author explained that there exist significant own persistence effects and cross-market spillover persistence effect in short-term as well as in the long-term among US dollar exchange rate and commodity markets in all the GARCH models signifying that the dollar exchange rate and commodity market are inter-related with each other. Roy & Roy (2017) measured the financial contagion along with directional volatility spillover in commodity derivative market in India with foreign exchange, bond, gold, and also stock markets by using DCC-MGARCH method. The authors found evidence of presence of financial contagion in commodity market of India with other asset markets under study with the fact that there is maximum contagion between the commodity and stock market and minimum contagion between the commodity and gold market. But, the nature of financial contagion is dynamic and time-varying as it is more in period of Global Financial Crisis. Commodity and stock markets are recognized to be the volatility senders whereas foreign exchange, bond, and gold markets are volatility acquirers.

Australian Journal of Business and Management Research
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Vol.05 No.09 | 2018 ISSN: 1839 - 0846

Few studies are existing on volatility spillover in commodity markets examining the spillover effects of one commodity's prices on the other(s) using DCC-GARCH model. Manera et. al. (2012) studied financial speculation in energy and agricultural commodities futures markets by applying DCC GARCH models and using Working's T index as the proxy of financial speculation. The authors concluded that the significance of financial speculation is low in modelling commodities returns suggesting that excess speculation leads to fall in returns. Examining the role of macroeconomic factors in driving commodities returns, they put forth that only S&P 500 index and the exchange rate are significant in affecting the returns. Further, spillovers are also existing between commodities and the conditional correlations between agricultural and energy commodities became high around 2008. Chang et. al. (2015) analyzed the theory and practice of examining the volatility spillovers between energy and agricultural markets by using multivariate BEKK and DCC models. They recommended for the appropriate and sound statistical techniques for testing such volatility and co-volatility spillovers. Chen & Wu (2016) in their study on commodity markets have tested the co-movements and volatility spillover applying two methods. Firstly, they used dynamic conditional correlation model (DCC) for finding time-varying dependence structure of twenty commodities in the Goldman Sachs Commodity Index (GSCI). Secondly, they applied Diebold and Yilmaz (2014) model to find out the direction and magnitude of volatility spillover for the purpose of assessing the network connectedness of commodity markets. The authors found that both DCC and VAR models provide uniform results. They put forth that even though the correlations and volatility spillover of commodity markets have risen during the financial distress period of 2007 to 2009, but after this period these were at pre-crisis level.

Also, a number of other applications of DCC-GARCH model include studies such as Chevallier (2012); Sehgal et. al. (2014); Carsamer (2016) and de Oliveira et. al. (2018). Chevallier (2012) applied BEKK, CCC and DCC-MGARCH models to test the correlations dynamic between gas, oil and CO_2 variables. The study found that own-volatility, persistent volatility effects and cross-volatility spillovers are present in almost all the markets under study and there are significant time varying correlations across all the markets. Sehgal et. al. (2014) also applied GARCH-BEKK model, CCC and DCC models to study the price discovery as well as the volatility spillover in spot-futures prices concerning four currencies and confirmed the presence of long-run equilibrium relationship in the markets under study. Highlighting the supremacy of futures market over spot market in currency market of India, they proved that futures price take a lead over the spot price in the short-run and the volatility spillover is from futures to spot in the short-run but spot to futures in the long-run. They found that in terms of volatility spillover, Multi-Commodity Stock Exchange (MCX-SX) dominates over National Stock Exchange (NSE). Carsamer (2016) modeled the exchange rate volatility transmission in Africa to explore its sources using augmented DCC model. The study found that outside shocks impact the African markets more than the regional shocks. Macroeconomic factors such as trade balance, interest rate and GDP impact volatility transmission and co-movements. In a recent study, de Oliveira et. al. (2018) evaluated the spillover effects and transmission of volatility to and from the Brazil stock market during the most volatile period of 2014-2016. The authors applied MGARCH-BEKK along with DCC and t-Copulas models and observed that main source of volatility to Brazil are US monetary policy and rebalancing of portfolios. And, Brazil also induces volatility to commodity markets and US bonds market playing the role of an intermediary of these markets.

The review of existing literature indicate few noteworthy research gaps. Firstly, most of the studies are found to concentrate on volatility spillover between two or more same or different financial markets such as between different stock markets, different commodities, currencies or between commodity and stock markets, stock and currency markets and many more combinations. Studies focusing on volatility spillover effects between futures and spot commodity market of a commodity has received less attention. Secondly, considering the dynamic and time-varying nature of conditional correlations between futures and spot markets, this study employs more recent methods like EGARCH and multivariate GARCH (DCC) to capture the volatility spillover effects in comparison to the univariate GARCH and standard linear VAR models as used in many earlier studies. These literature gaps provide motivation to explore the nature, direction and magnitude of volatility spillover between spot and futures commodity market.

III. EMPIRICAL MODELLING

The paper follows two empirical models to analyze the futures-spot volatility spillover in commodity market. Firstly, it applies Exponential GARCH proposed by Nelson (1991) to explore the direction and magnitude of spillover effects between futures and spot market. Secondly, it uses Dynamic Conditional Correlation (DCC) GARCH proposed by Engle (2002) between futures and spot prices of selected highly traded commodities.

Exponential Generalized Autoregressive Conditional Heteroskedasticity Model (EGARCH)

The popular non-linear model to deal with the heteroskedasticity of the data is the autoregressive conditional heteroscedastic (ARCH) model, proposed by Engle (1982). Its generalization was undertaken by Bollerslev (1986) in the form of Generalized ARCH (GARCH) model for parsimonious representation of ARCH. GARCH model takes the conditional variance as a linear function of own lags. However, the GARCH model is ineffective for modeling and forecasting a series having symmetric as well as asymmetric patterns and concerns with merely the shock's magnitude leaving its positive or negative impacts. Later, Nelson (1991) extended the GARCH model in the form of Exponential GARCH (EGARCH), which captures the asymmetric impacts of shocks or innovations on the conditional variance of future observations along with the shock's magnitude and its positive or negative impact. The conditional variance equation specification is (see Brooks, 2014) is:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] \quad (1)$$

where, $\boldsymbol{\sigma_t^2}$ is the conditional variance because it is the next period's variance forecast ascertained using its previous information. ω, β, γ, α are the model's parameters that need to be estimated. α stands for 'GARCH' effect which shows the model's symmetric effect; β quantifies the persistence of conditional volatility in the market and the parameter γ quantifies the leverage effect or asymmetry in the model, thus of great significance. If β is comparatively big, it implies that volatility takes an extended time to fade away subsequent to a market shock (see Alexander, 2009). The value of γ = 0 denotes symmetric model, γ < 0 denotes that impact of positive shocks/news is lower in comparison to the negative/bad news and γ > 0 is implicative of positive innovations causing greater volatility in comparison to the negative ones. Negative and significant indicates the presence of leverage effect in the model. Key advantages of estimating this model are that firstly, since $\mathbf{ln}(\boldsymbol{\sigma_t^2})$ is modeled, , $\boldsymbol{\sigma_t^2}$ will be positive in spite of the negative parameters, thus, eliminating the requirement of imposing non-negativity restrictions on the model parameters. Secondly, it is free from the constraints concerning the parameters used in the formula (Nelson and Cao, 1992).

Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity Model (DCC-GARCH)

As serial dependence is observed in futures and spot prices of the commodities, it dictates the use of some volatility associated model. Therefore, this paper applies Engle's Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) Model to investigate the relationship between futures and spot commodity market. In finding the direct linkages of two or more markets, it is an effective technique. Other important advantages of this approach include integrating heteroskedasticity by standardized residual coefficient ascertainment (Chiang *et al.*, 2007), adjustment of correlation based on dynamic or time-varying volatility without volatility bias (Celik, 2012; Cho and Parhizgari, 2008; Forbes and Rigobon, 2002) and modeling of the variance and covariance directly without rigidity. In enquiring into the time-varying relationships, DCC is more useful and significant in comparison to the subjective-based structural breaks (Moore and Wang, 2014). The estimation of DCC-GARCH procedure has two steps. Firstly, conditional variance is estimated with univariate GARCH for all the price series, and secondly, parameters of the dynamic time-varying conditional correlation matrix are estimated on the basis of the standardized residuals obtained from the first step. This specification incorporates conditions which result in the positive covariance matrix always and stationary covariance. Multivariate DCC-GARCH equation can be specified as: $X_t = \mu_t + H_t^{1/2}\varepsilon_t$, where X_t is a vector of historic observations, H_t is a multivariate conditional variance, μ_t is a vector of conditional returns and ε_t is a vector of standardized returns. The GARCH element in DCC-GARCH model can be explained by the variance-covariance matrix as: $H_t = D_t R_t D_t$, where $D_t = diag\{\sqrt{h_{it}}\}$ is a 2 × 2 diagonal matrix of conditional or time-varying standard deviation from the univariate GARCH models, and $R_t = \rho_{ijt}$ for i, j=1 and 2 is a conditional correlation matrix, which is dynamic. This model is a generalization of Constant Conditional Correlation (CCC) GARCH model of Bollerslev (1990). D_t component follows the univariate GARCH(p,q) models expressed as:

$$\boldsymbol{h_{it} = \alpha_i + \sum_{q=1}^{Q_i} \gamma_{iq}\, \varepsilon_{i,t-q}^2 + \sum_{p=1}^{P_i} \delta_{ip}\, h_{i,t-p}} \quad (2)$$

As the parameters of the matrix D_t is always positive, the matrix itself is positive. Also, R_t elements are less than or equal to one denoting correlations. To insure that R_t is positive, this matrix is broken down into two different matrices. Accordingly, the second step of DCC-GARCH structure includes DCC(m,n) structure specification which is written as:

$$\boldsymbol{R_t = Q_t^{*-1} Q_1 Q_t^{*-1}} \quad (3)$$

where,

$$Q_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\bar{Q} + \sum_{m=1}^{M} a_m(\varepsilon_{t-m}\varepsilon_{t-m}^T) + \sum_{n=1}^{N} b_n Q_{t-n}$$

$Q_1 = q_{ijt}$ is a conditional variance-covariance matrix using the standardized residuals,
$\bar{Q} =$ unconditional covariance matrix of the standardized errors ε_t estimated using equation (2).
Q_t^{*-1} = diagonal matrix consisting of the square root of the diagonal elements of Q_t.
This study focuses on R_t which is $\rho_{ijt} = q_{ij,t}/\sqrt{q_{ii,t}}\, q_{jj,t}$ and attempts to highlight the conditional correlation between spot and futures prices of the select commodities.
Before applying the EGARCH model, the presence of ARCH effects are also tested. It is done by applying the least squares (LS) method firstly to find out the regression residuals. And then the ARCH LM test is applied on the residuals to examine the existence of time varying volatility clustering.

IV. OBJECTIVES AND METHODOLOGY

The objective of this paper is to investigate the volatility spillover effects and test time-varying (dynamic) correlations between the futures and spot markets of selected commodities namely, Gold, Silver, Aluminium, Copper, Lead, Nickel, Zinc, Crude Oil, Natural Gas, Cardamom, Cotton, Crude Palm Oil and Mentha Oil in India. The hypothesis tested in the study is mentioned below:

Hypothesis: "There exists significant volatility spillover between the futures and spot market of selected commodities in India."

***Data description*:** The study is based on secondary data related to the futures and spot prices of thirteen highly traded commodities traded on MCX India. In particular, there are two bullion commodities namely, Gold and Silver; five metal commodities namely, Aluminium, Copper, Lead, Nickel and Zinc; two energy commodities namely, Crude Oil and Natural Gas and four agricultural commodities namely, Cardamom, Cotton, Crude Palm Oil and Mentha Oil. The data consists of daily closing futures and spot prices of these commodities. The data has been collected from trustworthy sources such as official website of MCX India Ltd. and Bloomberg database. The data period ranges from January, 2007 to December, 2017 for all commodities except for Cotton where data period ranges from October, 2011 to December, 2017 and Crude Palm Oil where data period ranges from June, 2008 to December, 2017 due to availability of data for this period only.

Empirical methods: The volatility spillover between the markets is analyzed by using EGARCH model and DCC-GARCH model. The descriptive statistics of the futures and spot prices of the commodities is also mentioned. Since most of the asset prices in finance is found to have the unit root, the ADF test and Phillip and Perron (PP) test are used on the spot and future prices of the selected commodities. Using intercept and trend, it is found that all price series are non stationary at levels and are integrated to the order one i.e. I(1). The prices of commodities in spot and future markets are transformed into returns as logarithmic value of the ratio of two consecutive prices using the formula:
$\mathbf{R_t = \ln(\frac{P_t}{P_{t-1}})}$**.** The analysis is done using MS Excel, Eviews and R software.

V. DATA ANALYSIS

This section deals with data analysis and detailed discussion of the empirical results.

Descriptive Statistics

The time series analysis aims to identify and analyze the past data so that it can be used for forecasting future values. To begin with the preliminary investigation, it is imperative to use simple descriptive statistics. Descriptive statistics help to understand the nature and type of data collected by summarizing the large amounts of data in a sensible and understandable manner. It also helps to choose appropriate econometric model. It involves calculating central tendency measures, dispersion measures, kurtosis and skewness characteristics of variables. The descriptive statistics in numerical form is presented in table 1:

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Table 1

Descriptive Statistics of Commodities

Price Series	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob
GOLD(F)	21967.86	25686	34439	8597	7536.241	-0.398	1.636	307.417	0
GOLD(S)	21965.61	25710	32943	8513	7548.755	-0.398	1.633	308.290	0
SILVER(F)	37253.17	37864	71554	15999	13729.48	0.164	1.893	164.227	0
SILVER(S)	36988.27	37455	73288	16075	13562.4	0.146	1.884	163.932	0
ALUMINI(F)	106.685	108.05	142.25	62.6	13.063	-0.967	4.481	747.660	0
ALUMINI(S)	106.044	107.3	146.6	62.55	13.134	-0.939	4.455	710.437	0
LEAD(F)	111.491	113.35	166.85	42.05	21.227	-0.659	3.701	268.624	0
LEAD(S)	111.073	112.9	169.45	41.5	21.434	-0.638	3.693	253.913	0
COPPER(F)	356.796	360.3	509.95	141.35	70.258	-0.702	3.165	252.134	0
COPPER(S)	354.734	358.85	497.55	135.65	70.047	-0.735	3.234	279.907	0
NICKEL(F)	942.146	916.75	2240	455	296.583	1.654	7.447	3867.804	0
NICKEL(S)	938.304	909.9	2259.9	439.9	301.009	1.730	7.787	4393.602	0
ZINC(F)	110.467	105.75	197.05	51	27.298	0.629	3.846	261.675	0
ZINC(S)	109.849	105.1	199.75	49.45	27.516	0.623	3.842	257.336	0
NATGAS(F)	225.332	203.7	587.3	100.2	76.611	1.648	6.834	3224.452	0
NATGAS(S)	224.724	203.100	587.900	99.000	76.529	1.648	6.831	3220.784	0
CRUDEOIL(F)	4053.842	3729	7507	1641	1180.474	0.422	2.269	157.211	0
CRUDEOIL(S)	4047.076	3720	7527	1656	1179.841	0.414	2.274	153.216	0
CARDAMOM(F)	882.112	815.4	2038.2	367	291.119	0.918	3.594	458.138	0
CARDAMOM(S)	865.004	805.125	1770	373.5	287.825	0.801	3.224	321.852	0
COTTON(F)	18077.96	17830	23650	13990	1988.754	0.339	2.022	90.448	0
COTTON(S)	18140.28	17880	23720	14420	2154.703	0.453	2.170	96.564	0
CRUPALMOIL(F)	462.145	475.9	628.7	232.3	86.957	-0.479	2.352	140.245	0
CRUPALMOIL(S)	462.3069	475.9	622.3	48	88.063	-0.491	2.449	133.236	0
MENTHAOIL(F)	867.509	850.2	2570.3	416.2	335.638	1.312	6.108	2033.712	0
MENTHAOIL(S)	955.982	958.75	2769.3	477.1	375.955	1.124	5.286	1264.781	0

Results of descriptive statistics of all the 13 highly traded commodities are reported in table 1. The mean, median, maximum and minimum values of futures and spot price series of all the commodities are almost similar. High standard deviation value indicates that the data is highly dispersed. Skewness values indicate that the data for both futures and spot prices for all the commodities is far from zero (symmetric distribution). The data is skewed either positively or negatively. The kurtosis values of commodities indicate that the distribution is leptokurtic and far from normal distribution. The probability of Jerque-Bera test statistic is very small indicating the rejection of null hypothesis of normality of data. Thus, the results confirm asymmetric, highly volatile and non-normal distribution of the futures and spot price series of all the commodities under study.

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ISSN: 1839 - 0846

Results of EGARCH Model

The EGARCH model is used in the study in order to examine the influence of the lagged square error term of other market of the respective commodity. The lagged squared error term is estimated with the help of mean equation applied on the other market of the commodity. This squared error term is included in the EGARCH model as an exogenous regressors. The spillover effect is studied in the direction of spot to future as well as future to spot with the help of EGARCH models as mentioned below in equation 4 and equation 5:

$$\ln(\sigma_{st}^2) = \omega + \beta\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| + \lambda\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\ \ln(\sigma_{t-1}^2) + \rho\ (\varepsilon^2 f_{t-1}) \qquad (4)$$

$$\ln(\sigma_{ft}^2) = \omega + \beta\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| + \lambda\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\ \ln(\sigma_{t-1}^2) + \rho\ (\varepsilon^2 s_{t-1}) \qquad (5)$$

where **ω** represents the intercept term of the EGARCH equation. It represents the long term average volatility in the asset returns. The second coefficient of the equation $\boldsymbol{\beta}$ represents the effect of the magnitude of the previous shock coming in the market, **λ** represents asymmetric effect of volatility, $\boldsymbol{\alpha}$ indicates the coefficient of GARCH term and coefficient of the fifth term $\boldsymbol{\rho}$ shows the significance of volatility spillover between futures and spot market in the study. The results of EGARCH model in case of the selected commodities is shown in table 2 and table 3.

Table 2
Volatility Spillover from Futures to Spot

Commodities	Gold	Silver	Aluminium	Copper	Lead	Nickel	Zinc
Ω	1.897 (0.114) [0.000]**	3.94 (0.123) [0.000]**	0.002 (0.014) [0.909]	2.172 (0.034) [0.000]**	-0.031 (0.009) [0.000]**	-0.008 (0.009) [0.399]	-0.064 (0.008) [0.000]**
β	0.214 (0.018) [0.000]**	0.265 (0.021) [0.000]**	0.018 (0.016) [0.259]	0.076 (0.017) [0.000]**	0.132 (0.009) [0.000]**	0.061 (0.005) [0.000]**	0.142 (0.008) [0.000]**
Λ	0.019 (0.013) [0.148]	0.022 (0.015) [0.144]	0.090 (0.013) [0.000]**	0.058 (0.012) [0.000]**	0.019 (0.008) [0.021]**	0.039 (0.003) [0.000]**	0.008 (0.007) [0.290]
α	0.794 (0.012) [0.000]**	0.656 (0.010) [0.000]**	0.806 (0.018) [0.000]**	0.072 (0.012) [0.000]**	0.917 (0.009) [0.000]**	0.993 (0.002) [0.000]**	0.951 (0.007) [0.000]**
ρ	0.000 (0.000) [0.000]**	0.000 (0.000) [0.000]**	0.055 (0.005) [0.000]**	0.023 (0.001) [0.000]**	0.012 (0.001) [0.000]**	0.000 (0.000) [0.000]**	0.006 (0.001) [0.000]**
Commodities	**Natural Gas**	**Crude Oil**	**Cardamom**	**Cotton**	**Crude Palm Oil**	**Mentha Oil**	
Ω	1.611 (0.051) [0.000]**	6.129 (0.122) [0.000]**	-0.050 (0.004) [0.000]**	0.160 (0.029) [0.000]**	0.157 (0.032) [0.000]**	0.045 (0.007) [0.000]**	
β	0.210 (0.018) [0.000]**	0.019 (0.027) [0.483]	0.168 (0.005) [0.000]**	0.180 (0.013) [0.000]**	0.180 (0.015) [0.000]**	0.223 (0.012) [0.000]**	
Λ	0.101 (0.016) [0.000]**	-0.018 (0.019) [0.348]	0.019 (0.003) [0.000]**	0.049 (0.006) [0.000]**	-0.034 (0.007) [0.000]**	0.089 (0.006) [0.000]**	
α	0.381 (0.016) [0.000]**	0.204 (0.014) [0.000]**	0.985 (0.001) [0.000]**	0.969 (0.003) [0.000]**	0.891 (0.012) [0.000]**	0.952 (0.003) [0.000]**	
ρ	0.009 (0.000) [0.000]**	0.000 (0.000) [0.000]**	0.000 (0.000) [0.000]**	0.000 (0.000) [0.004]**	0.001 (0.000) [0.000]**	0.000 (0.000) [0.000]**	

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The results indicate value of the coefficients, standard error and the probability value of all the regression coefficients in the EGARCH model for all the commodities selected in the study. The result indicates the there exists significant volatility spillover in the direction of future market to spot market since the probability of the last term is found to be below five percent significance level for all the selected commodities. In other words, if the sudden/unexpected shock or news comes in the future markets for the selected commodities, this will also influence the volatility in the spot prices of the commodity on the next day. In the paper the EGARCH model is also applied on the variance equation of the future series of the commodity. Here, the lagged (lag one) square of the residuals of the mean equation of the spot markets are included as the exogenous regressors. The results of the volatility spillover analysis in the direction of spot to future is also reported in table 3.

Table 3
Volatility Spillover from Spot to Futures

	Gold	Silver	Aluminium	Copper	Lead	Nickel	Zinc
ω	0.006 (0.018) [0.747]	00.032 (0.021) [0.122]	-0.040 (0.008) [0.000]**	0.069 (0.025) [0.006]**	-0.043 (0.007) [0.000]**	-0.026 (0.0128) [0.045]	-0.049 (0.005) [0.000]**
β	0.130 (0.007) [0.000]**	0.152 (0.007) [0.000]**	0.063 (0.012) [0.000]**	0.110 (0.011) [0.000]**	0.073 (0.009) [0.000]**	0.083 (0.008) [0.000]**	0.071 (0.007) [0.000]**
λ	0.041 (0.005) [0.000]**	0.049 (0.005) [0.000]**	0.030 (0.006) [0.000]**	-0.020 (0.006) [0.001]**	0.029 90.004) [0.000]**	0.034 (0.004) [0.000]**	0.027 (0.004) [0.000]**
α	0.991 (0.001) [0.000]**	0.989 (0.002) [0.000]**	0.952 (0.009) [0.000]**	0.949 (0.009) [0.000]**	0.985 (0.002) [0.000]**	0.993 (0.002) [0.000]**	0.991 (0.002) [0.000]**
ρ	0.000 (0.000) [0.012]**	0.000 (0.000) [0.4532]	0.007 (0.002) [0.000]**	0.000 (0.000) [0.004]**	0.001 (0.000) [0.000]**	0.000 (0.000) [0.039]**	0.001 (0.000) [0.000]**

	Natural Gas	Crude Oil	Cardamom	Cotton	Crude Palm Oil	Mentha Oil
ω	-0.008 (0.012) [0.531]	16.901 (0.053) [0.000]**	0.040 (0.007) [0.000]**	2.247 (0.222) [0.000]**	-0.035 (0.009) [0.000]**	5.755 (0.162) [0.000]**
β	0.087 (0.011) [0.000]**	0.020 (0.006) [0.000]**	0.115 (0.005) [0.000]**	0.437 (0.021) [0.000]**	0.103 (0.009) [0.000]**	0.879 (0.028) [0.000]**
λ	0.031 (0.006) [0.000]**	-0.012 (0.002) [0.000]**	-0.024 (0.004) [0.000]**	-0.097 (0.016) [0.000]**	-0.003 (0.003) [0.374]	-0.025 (0.024) [0.295]
α	0.981 (0.003) [0.000]**	-0.982 (0.004) [0.000]**	0.982 (0.001) [0.000]**	0.760 (0.021) [0.000]**	0.987 (0.003) [0.000]**	0.075 (0.024) [0.002]**
ρ	0.000 (0.000) [0.000]**	0.000 (0.000) [0.082]	0.000 (0.000) [0.000]**	0.000 (0.000) [0.196]	0.000 (0.000) [0.189]	0.000 (0.000) [0.000]**

The result of the volatility spillover in the direction of spot markets to future markets indicates that the volatility spillover in the direction of spot market to future market is significant only in case of few commodities namely Gold, aluminium, Copper, Lead, Nickel, Zinc, Natural Gas, Cardamom and Mentha Oil. The probability value of the fifth and last term is found to be less than five percent significance level in case of these commodities. In such commodities it can be concluded that any unexpected shock or news affecting the spot markets on any day will also influence the volatility in the future prices of that commodity on the next day. However, the volatility spillover in the direction from spot to future for few commodities namely Silver, Crude Oil, Cotton and Crude Palm Oil is not found significant. The magnitude of the spillover effect is also examined with the help of z-statistic of the fifth term included in the EGARCH equation. These z-statistic of all the commodities estimated in EGARCH model is shown in figure 1:

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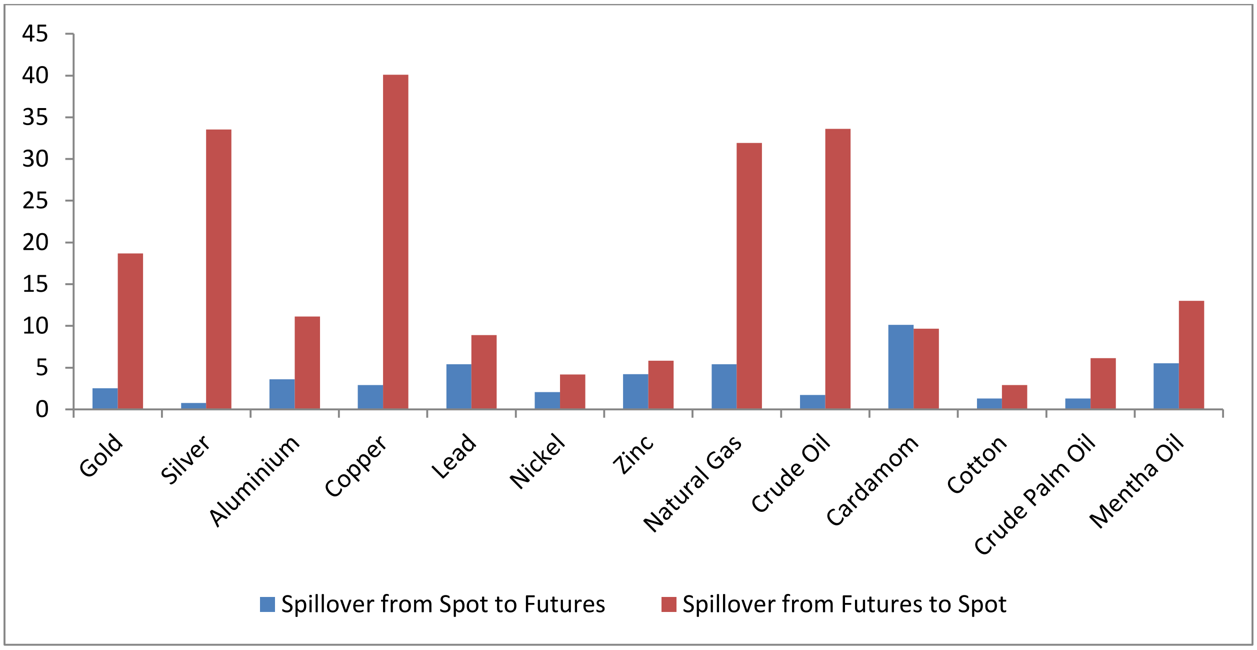

Figure 1
Magnitude of Spillover from Spot to Futures and from Futures to Spot

The figure 1 indicates that the magnitude of volatility spillover from futures market to spot market is greater in comparison to the magnitude of volatility spillover from spot to futures market in all the selected commodities. The reason of higher volatility spillover in the direction of future markets to spot markets can be attributed to the presence of larger number of market participants specially speculators, high volume of trading, the leverage benefits, several structural advantages of future markets, low transaction costs, high liquidity and automated platform in the future market. If any new information comes in the markets the market participants reacts to the information and take the suitable position in the future market of commodity. This is in order to take the advantage of the information to make supernormal profits. Due to this the future prices may move away from the spot prices which provides arbitrage opportunities to the market participants. Hence the spot prices also fluctuates as a results of several reasons namely arbitrage positions, change in price of the commodity in the spot market by merchants and traders etc. The volatility spillover is also examined with the help of multivariate GARCH model i.e. DCC-GARCH. The DCC-GARCH helps in identifying the dynamic interaction between the futures and spot markets of the commodities. DCC-GARCH model estimates the time varying correlation between the conditional variance of the both the markets of different commodities. The time varying conditional correlation also helps in achieving the purpose of studying the volatility spillover between the markets in multivariate context. The results of DCC-GARCH model is discussed in next section.

Results of DCC-GARCH Model

The DCC-GARCH is a multivariate GARCH model where the conditional variance of both futures and spot prices of the commodities are estimated. The results of DCC-GARCH model is shown in table 4 where the coefficients of GARCH(1,1) are reported. The $\boldsymbol{\Omega}$ indicates the intercept term of the GARCH(1,1) model, the $\boldsymbol{\alpha 1}$ indicates the coefficient of the ARCH term in the model, $\boldsymbol{\beta 1}$ is the coefficient of the GARCH term of the model, the joint DCCα indicates the volatility spillover as a results of unexpected shocks as captured by errors of the mean equation whereas DCCβ indicates volatility spillover between the conditional variance of the spot and future markets estimated with the help of GARCH model. The results of DCC-GARCH model in case of all the commodities are reported in table 4:

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Table 4: Results of DCC-GARCH

	Gold	Silver	Aluminium	Copper	Lead	Nickel	Zinc
Ω (fut_r)	0.000 (0.000) [0.964]	0.000 (0.000) [0.786]	0.000 (0.000) [0.000]**	0.000 (0.000) [0.425]	0.000 (0.000) [0.006]**	0.000 (0.000) [0.855]	0.000 (0.000) [0.062]
α1 (fut_r)	0.053 (0.285) [0.853]	0.110 (0.062) [0.076]	0.030 (0.002) [0.000]**	0.055 (0.025) [0.027]**	0.036 (0.003) [0.000]**	0.046 (0.067) [0.490]	0.034 (0.002) [0.000]**
β1 (fut_r)	0.938 (0.289) [0.001]**	0.832 (0.325) [0.010]**	0.961 (0.001) [0.000]**	0.932 (0.030) [0.000]**	0.960 (0.002) [0.000]**	0.948 (0.076) [0.000]**	0.964 (0.001) [0.000]**
Ω (spot_r)	0.000 (0.000) [0.677]	0.000 (0.000) [0.000]**	0.000 (0.000) [0.463]	0.000 (0.000) [0.179]	0.000 (0.000) [0.855]	0.000 (0.000) [0.003]**	0.000 (0.000) [0.871]
α1 (spot_r)	0.067 (0.050) [0.183]	0.072 (0.010) [0.000]**	0.0376 (0.020) [0.061]	0.056 (0.012) [0.000]**	0.047 (0.063) [0.453]	0.033 (0.002) [0.000]**	0.060 (0.103) [0.566]
β1 (spot_r)	0.919 (0.054) [0.000]**	0.903 (0.012) [0.000]**	0.951 (0.024) [0.000]**	0.930 (0.014) [0.000]**	0.948 (0.068) [0.000]**	0.964 (0.001) [0.000]**	0.935 (0.114) [0.000]**
DCCα (joint)	0.0418 (0.014) [0.002]**	0.028 (0.011) [0.010]**	0.045 (0.014) [0.001]**	0.008 (0.010) [0.430]	0.013 (0.007) [0.061]	0.047 (0.018) [0.007]**	0.034 (0.013) [0.011]**
DCCβ (joint)	0.557 (0.159) [0.000]**	0.082 (0.299) [0.784]	0.602 (0.181) [0.001]**	0.580 (0.532) [0.276]	0.952 (0.033) [0.000]**	0.289 (0.101) [0.004]**	0.771 (0.107) [0.000]**

	Natural Gas	Crude Oil	Cardamom	Cotton	Crude Palm Oil	Mentha Oil
Ω (fut_r)	0.000 (0.000) [0.040]**	0.000 (0.0000 [0.911]	0.000 (0.000) [0.000]**	0.000 (0.000) [0.189]	0.000 (0.000) [0.815]	0.000 (0.000) [0.015]**
α1 (fut_r)	0.044 (0.005) [0.000]**	0.057 (0.147) [0.698]	0.006 (0.001) [0.000]**	0.242 (0.116) [0.037]**	0.047 (0.057) [0.409]	0.009 (0.001) [0.000]**
β1 (fut_r)	0.945 (0.005) [0.000]**	0.937 (0.159) [0.000]**	0.987 (0.001) [0.000]**	0.526 (0.268) [0.049]**	0.945 (0.059) [0.000]**	0.990 (0.000) [0.000]**
Ω (spot_r)	0.000 (0.000) [0.409]	0.000 (0.000) [0.421]	0.000 (0.000) [0.549]	0.000 (0.000) [0.319]	0.000 (0.000) [0.000]**	0.000 (0.000) [0.010]**
α1 (spot_r)	0.064 (0.025) [0.010]**	0.052 (0.021) [0.015]**	0.086 (0.033) [0.009]**	0.111 (0.032) [0.001]**	0.123 (0.013) [0.000]**	0.157 (0.016) [0.000]**
β1 (spot_r)	0.918 (0.016) [0.000]**	0.942 (0.024) [0.000]**	0.913 (0.031) [0.000]**	0.867 (0.032) [0.000]	0.834 (0.0165) [0.000]**	0.810 (0.059) [0.000]**
DCCα (joint)	0.000 (0.003) [0.808]	0.000 (0.000) [0.999]	0.006 (0.004) [0.098]	0.006 (0.006) [0.302]	0.007 (0.002) [0.000]**	0.007 (0.005) [0.136]
DCCβ (joint)	0.974 (0.025) [0.000]**	0.921 (0.174) [0.000]**	0.984 (0.007) [0.000]**	0.972 (0.019) [0.000]**	0.993 (0.002) [0.000]**	0.983 (0.009) [0.000]**

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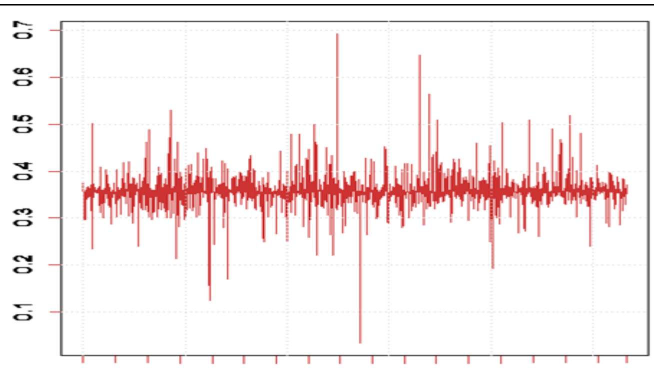
The results reported the two category of spillovers between the futures and spot prices of the selected commodities namely DCCα and DCCβ. Here, DCCα shows the volatility spillover due to sudden shocks as captured by errors of the mean equation and DCCβ represents the volatility spillover between the conditional variance of two markets i.e. spot and futures estimated using GARCH model. Hence, the results report two aspects of dynamic correlation i.e. between the errors of the mean equation and between their conditional variance. In case of dynamic correlation as indicated by DCCα the probability value is found to be significant in case of the spot and futures market of commodities namely Gold, Silver, Aluminium, Nickel, Zinc and Crude Palm Oil. However the p value is not found significant in case of Copper, Lead, Natural Gas, Crude Oil, Cardamom, Cotton and Mentha Oil. Hence in case of Gold, Silver, Aluminium, Nickel, Zinc and Crude Palm Oil, the significant volatility spillover as a result of unexpected shock in the market is concluded. This is due to the fact that Gold, Silver, Aluminium, Nickel, Zinc and Crude Palm Oil have sound spot markets where market participates are very active for different trading purposes such as speculation and arbitrage profits. However, in case of commodities such as Copper, Lead, Natural Gas, Crude Oil, Cardamom, Cotton and Mentha Oil, the spot and futures markets are not affected as a result of unexpected market news and information. The DCCβ indicates the dynamic correlation between the conditional variance of the spot and future markets of selected commodities. The probability value is found to be significant in case of the spot and futures market of commodities namely Gold, Aluminium, Lead, Nickel, Zinc, Natural Gas, Crude Oil, Cardamom, Cotton, Crude Palm Oil and Mentha Oil. However, the p value is not found significant in case of Silver and Copper. This can be concluded from the results that almost every commodity has significant spillover effect between the spot and future markets. The GARCH term in the univariate GARCH model indicates the presence of volatility persistence in the series. The summation of the coefficients of ARCH ($\boldsymbol{\alpha 1}$) and GARCH terms ($\boldsymbol{\beta 1}$) is approaching to 1 indicating the presence of high persistence (decaying at a lower rate) in conditional variances. The significant dynamic correlation between the conditional variance of the spot and future markets of most of the selected commodities indicates that both the markets maintain the comovement equilibrium. In other words, the volatility in one market also leads to disturbance in other markets. In fact, as indicated by the EGARCH results in previous section the future markets of all the commodities are found to be more exogenous and any disturbance in future market influence the disturbance in the other markets.

Graphic representation of DCC-GARCH

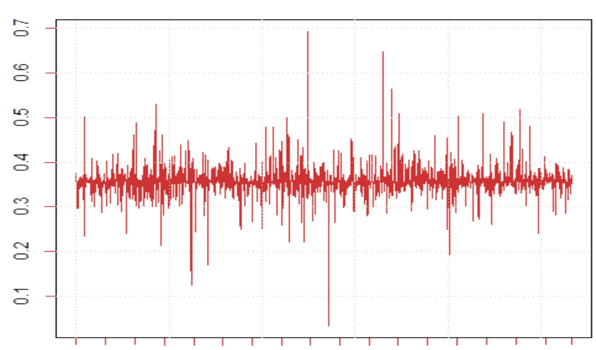
The dynamic conditional correlations implied in the DCC-GARCH model are plotted in graph1. These figures provide visual support to the conditional correlation obtained from the DCC-GARCH model.

Graph 1

Time-Varying Conditional Correlation Between Spot and Futures Returns



Gold



Silver

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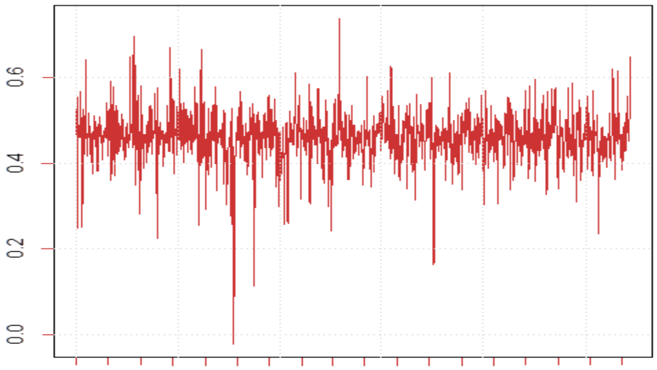
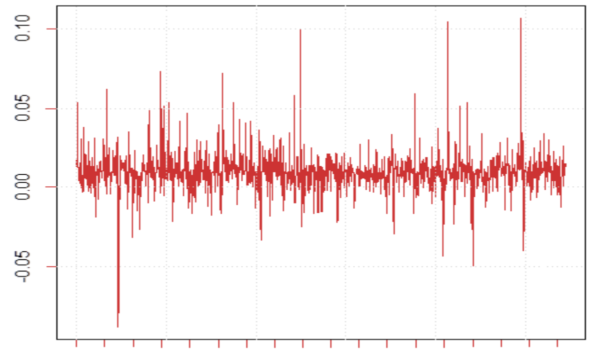
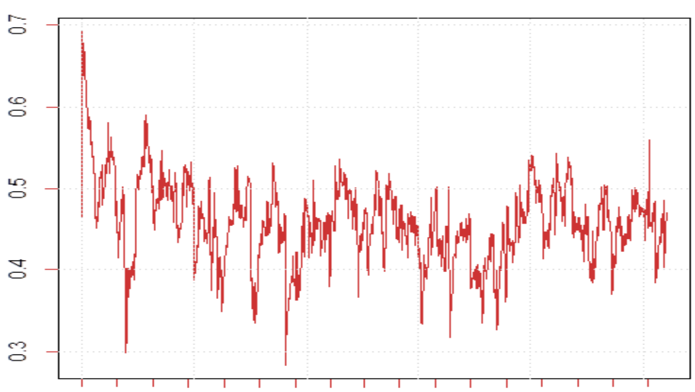


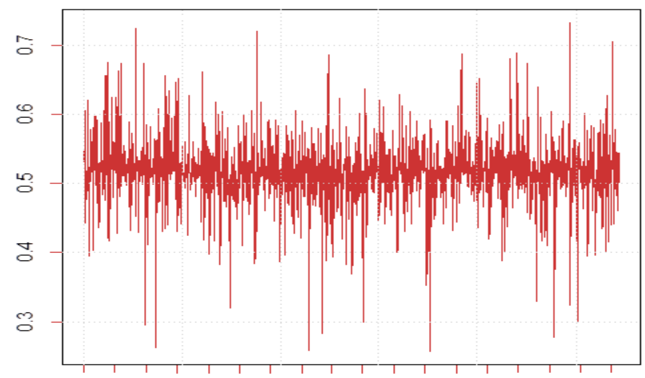
Aluminium



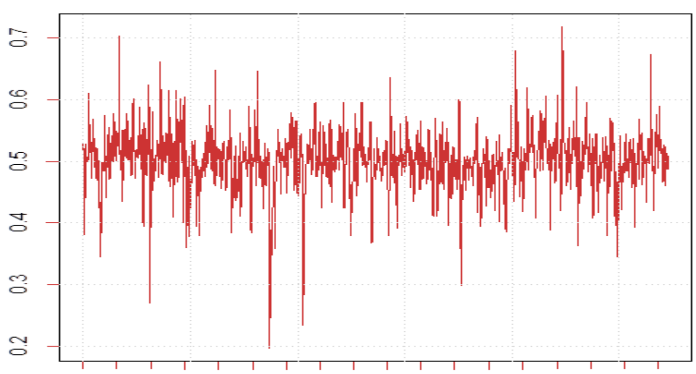
Copper



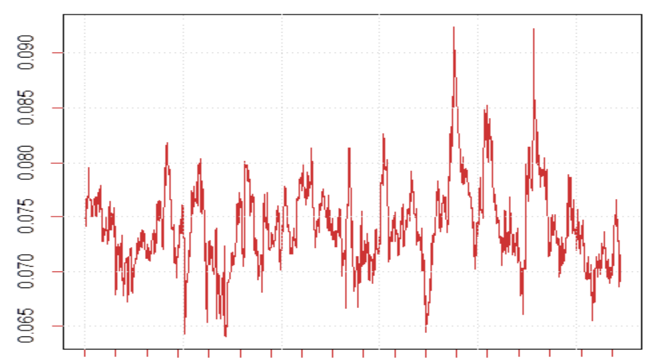
Lead



Nickel



Zinc



Natural Gas

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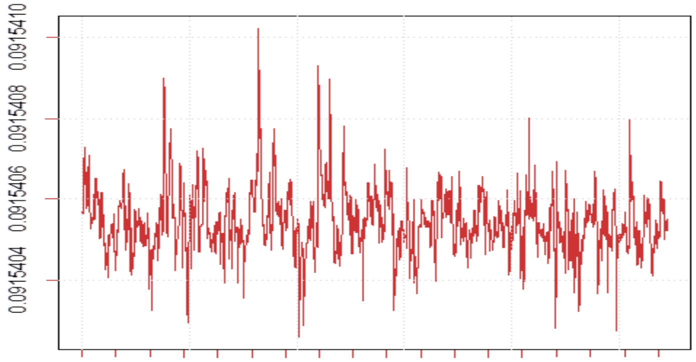
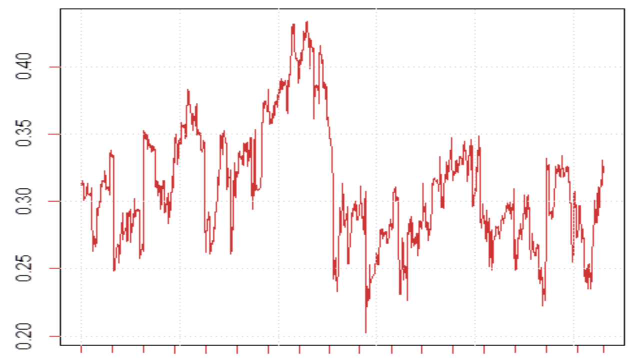
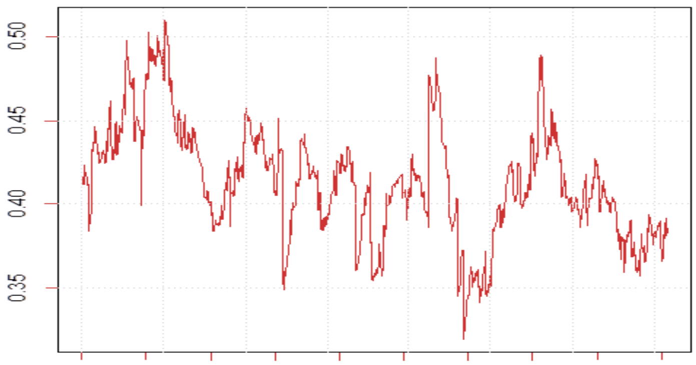


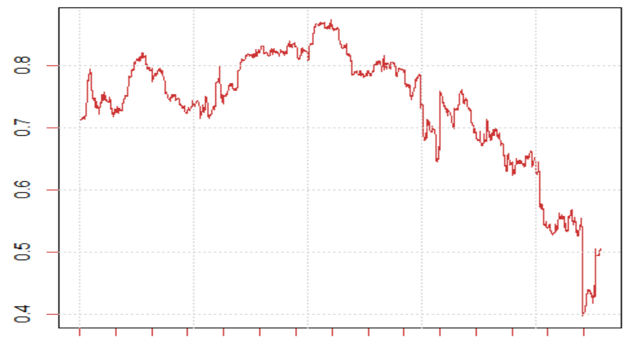
Crude Oil



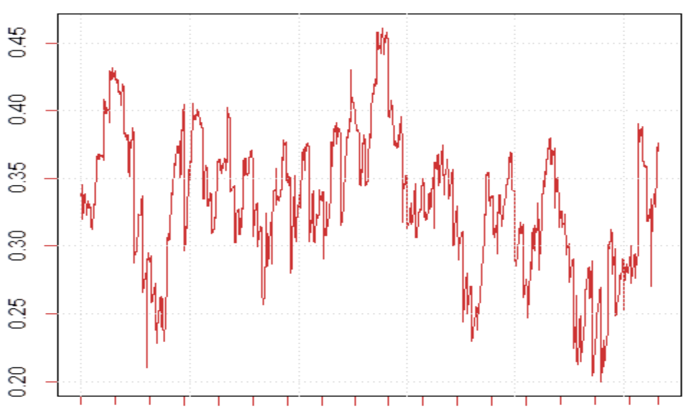
Cardamom



Cotton



Crude Palm Oil



Mentha Oil

The graphs indicate that in case of commodities, Lead, Natural Gas, Crude Oil, Cardamom, Cotton, Crude Palm Oil and Mentha Oil high fluctuations in the dynamic correlation between spot and futures markets are observed. However, range-bound correlation is found in other commodities namely, Gold, Silver, Aluminium, Copper, Nickel and Zinc.

VI. CONCLUSIONS AND DISCUSSIONS

It is now widely accepted that volatilities have co-movements over time across spot and futures commodity markets. Understanding the temporal relations of the returns of the two markets raises the question: Is the volatility in one market leading to the volatility in the other market? Such issue can be studied by using multivariate empirical model rather than working with separate univariate models. This study applies EGARCH and multivariate model i.e. DCC-

GARCH for examining the volatility spillover effects between futures and spot commodity markets of selected highly traded commodities in India. It is found in the study that significant and asymmetric bi-directional volatility spillover effects are exhibited in case of most of the commodities. However, the magnitude of volatility spillover is concluded higher in case of futures market to spot market. This is due to the efficiency of futures market in comparison to the spot market in terms of automation, high volume of trading, low transactional costs, leverage benefits and other structural advantages. Further, DCC-GARCH model illustrates the time varying conditional correlation between heteroscedastic coefficients of the spot and futures markets. The dynamic correlation between the conditional variance of the spot and future markets is found to be significant in case of all the commodities except Silver and Copper. It proves that significant volatility spillover effect is present between futures and spot markets of selected commodities. As indicated by graphs, correlation is fluctuating highly in case of commodities, Lead, Natural Gas, Crude Oil, Cardamom, Cotton, Crude Palm Oil and Mentha Oil as against the range-bound fluctuation in other commodities, Gold, Silver, Aluminium, Copper, Nickel and Zinc. The study has important implications for different stakeholders connected with the commodity market. Generally also, the knowledge of volatility in any market is important for market participants. It opens doors for commodity producers, traders and farmers in better decision making, hedging and risk management. Understanding of volatility transmission and interrelationship between spot and futures commodity market will help investors make right investment decisions, diversification, portfolio optimization and hence, they can lessen the financial risk involved. Financial practitioners, policy makers and regulators can use this knowledge of volatility spillover in planning and implementing appropriate regulatory framework.

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