FINANCIAL CONTAGION AND VOLATILITY SPILLOVER:

AN EXPLORATION INTO INDIAN COMMODITY DERIVATIVE MARKET°

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ABSTRACT

This study measures the extent of financial contagion in the Indian asset markets. In specific it shows the contagion in Indian commodity derivative market vis-à-vis bond, foreign exchange, gold, and stock markets. Subsequently, directional volatility spillover among these asset markets, have been examined. Applying DCC-MGARCH method on daily return of commodity future price index and other asset markets for the period 2006 to 2016, time varying correlation between commodity and other assets are estimated. The degree of financial contagion in commodity derivative market is found to be the largest with stock market and least with the gold market. A generalized VAR based volatility spillover estimation shows that commodity and stock markets are net transmitters of volatility while bond, foreign exchange and gold markets are the net receivers of volatility. Volatility is transmitted to commodity market only from the stock market. Such volatility spillover is found to have time varying nature, showing higher volatility spillover during the Global Financial Crisis and during the period of large rupee depreciation in 2013-14. These results have significant implication for optimal portfolio choice.

Key words: Commodity, DCC-GARCH, Financial contagion, Portfolio, Volatility spillover.

JEL Classification: F36, G11, C58, Q02, G12.

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1. Introduction

This paper investigates into contagion and transmission of volatility shocks in Indian commodity derivative market from other Indian asset markets. Asset return co-movements (or correlation) and transmission of volatility shocks have significant implications for asset pricing and portfolio allocation (Aloui et al. 2011; Jin et al., 2012) as existence of a higher degree of co-movement between asset markets reduces the diversification benefits (Lessard, 1973; Solnik, 1974). Historically, portfolio choice has been dominated by two traditional asset classes, namely stocks and bonds. While searching for non-traditional securities capable of augmenting returns, smoothing volatilities or both, investors have started taking into consideration a “third asset class”, commodity. Commodities actually serve as diversifiers in the process of portfolio choice (Abanomey and Mathur, 2001; Ankrim and Hensel, 1993; Anson, 1999; Becker and Finnerty, 2000; Georgiew, 2001 and Kaplan and Lummer, 1998). More precisely, commodities are believed to have low return correlation with traditional asset classes and hence are useful tools for strategic asset allocation (Jensen et al., 2000; Erb and Harvey, 2006). Global investors use commodities for hedging (Bodie and Rosansky, 1980; Bodie, 1983) especially during financial stress, appraising its nature of positive co-movement with inflation and hence a tendency of backwardation. However, commodities may be considered risky in the presence of financial contagion and volatility spillover from other markets to commodity market. If large numbers of investors hold commodities along with other conventional assets, the set of common state variables driving stochastic factors grows; and adverse shocks in one market may cause liquidation across several markets (Kyle and Xiong, 2001). Integration of commodity market and conventional asset markets may allow systematic shocks to increasingly dominate commodity returns by raising time varying correlation between commodity and other assets (Silvennoinen and Thorp, 2013).

Crises since 1990s have led researchers to examine different channels of financial contagion and volatility transmission; and in the recent past, crisis in the subprime asset backed market created a “near-ideal laboratory” for studying causes and effects of financial contagion (Longstaff, 2010). Though, there is a voluminous literature on financial contagion[1], there is no universally accepted definition of it. By distinguishing it from “interdependence”, Forbes and Rigobon (2002) define contagion as a significant increase in cross market linkages after a shock to one market (or group of markets). The literature on financial contagion literally exploded

[1] See Allen and Gale (2000), Kyle and Xiong (2001), Kodres and Pritsker (2002), Kiyotaki and Moore (2002), Kaminsky et al. (2003), Allen and Gale (2004), Brunnermeier and Pedersen (2005), Brunnermeier et al. (2009) and many others.

since the seminal paper by Forbes and Rigobon (2002) started circulating in the late 1990s (Kenourgios et al., 2011). Prior to Forbes and Rigobon (2002), there were some studies that addressed financial contagion (see for example King and Wadhani. 1990; Longin and Solnik, 1995; Calvo and Reinhart, 1995; Solnik et al., 1996; Ramchand and Susmel, 1998; and Butler and Joaquin, 2002)[2]. However, these studies mainly show "interdependence" and not "financial contagion". Since publication of Forbes and Rigobon (2002), the existence of financial contagion has been studied by many researchers, mainly around the notion of "correlation breakdown" (a statistically significant increase in correlation during the crash period). Financial contagion can be internal (among domestic markets) as well as global (among markets of different countries or regions). In a financially globalised world, any external shock may affect any asset market in an economy and then get transmitted to asset markets in other countries as well. Internal shocks, through inter-linkages spread out to other domestic asset markets. If a crisis hits any market around the globe, foreign investors transmit the negative shock to the same asset market in developing countries and emerging market economics (EMEs). Domestic investors also follow suit by withdrawing funds from other markets anticipating losses. A negative shock thus gets transmitted from a foreign source to any of the domestic asset markets and then to other asset markets in the economy. During the Global Financial Crisis, while asset markets in advanced economies were initially affected, the effect did spread out to other asset markets in emerging market economies through financial contagion. A recent strand of literature studies volatility spillover among different asset markets within an economy (see Yilmaz, 2010; Diebold and Yilmaz, 2012). This study attempts to investigate the nature of financial contagion and volatility spillover, if any, in Indian commodity derivative market vis-à-vis other asset markets during the Global Financial Crisis, Eurozone crisis and phase of large rupee depreciation in 2013-14.

Most of the other studies discuss financial contagion in the equity markets only[3]. A very few of existing empirical studies aim at analyzing the contagion effect between commodity and other asset markets during a financial crisis. The studies on commodities mainly discuss co-movement (or correlation) of commodities along with other assets, mainly stocks (see for example Buyuksahin et al., 2010; Tang and Xiong, 2010; Silvennoinen and Thorp, 2013;

[2] Most of these studies are extensively reviewed in Roy (2016).

[3] See for example King and Wadhani (1990), Lee and Kim (1993), Calvo and Reinhart (1995), Aloui et al. (2011), Syllignakis and Kouretas (2011), Kenourgios et al. (2011), Aloui et al. (2011), Baur (2012), Bekaert et al. (2011), Hwang et al. (2013), and Dungey and Gajurel (2014) etc. These are extensively discussed in Roy (2016).

Lautier and Raynaud, 2011 etc.). Although some very recent studies[4] discuss the evolution of correlations between commodities and financial assets in the aftermath of the Global Financial Crisis, their focus was not on the contagion effect between commodity and other asset markets[5]. Silvennoinen and Thorp (2013) report that all of the oil futures return series switched to a high correlation with US stocks largely in step, during high stock-market volatility, with a sustained increase during the 2008-09 period. Wen et al. (2012), investigating the contagion between oil market and stock market during the Global Financial Crisis, find existence of financial contagion between the oil and US/Chinese stock markets. It is thus reasonable to expect a contagion effect between commodity and other asset markets in emerging market economies including India during the financial crisis.

Even though the literature on financial contagion in commodity market is limited, the literature on volatility spillover taking into account commodities along with other assets or among different commodities is large. With regards to volatility spillover in commodity market, most studies[6] have considered the oil market focusing mainly on three issues: interactions between the crude oil market and other energy markets, equity markets and foreign exchange markets. Among others, the study by Zhang (2008) explores mean spillover, volatility spillover and risk spillover between the U.S dollar exchange rate and crude oil prices. While Mensi et al. (2013) show a significant correlation and volatility transmission across commodity and equity markets. For the Indian commodity market, Ghosh (2011) shows that an increased oil return leads to the depreciation of Indian currency vis-à-vis US dollar.

Prior to the Global Financial Crisis, a commodity price boom, unprecedented in its magnitude and duration, was observed. The real prices of energy and metals more than doubled in five years during 2003-08, while the real price of food commodities increased 75 per cent (Erten and Ocampo, 2012). The commodity boom is a product of rapid income growth, increasing population and resulting increase in demand for food[7], energy and minerals, and other commodities especially in Asian emerging markets including China and India. This

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[4] See, for example, Buyuksahin et al. (2010), Lautier and Raynaud (2011), Silvennoinen and Thorp (2013), Tang and Xiong (2010) etc.

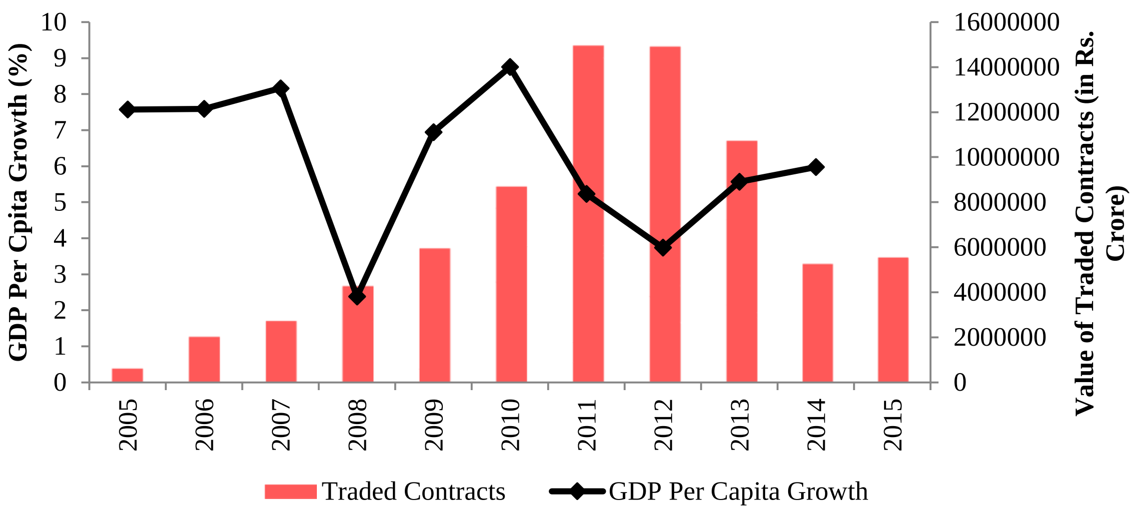
[5] For example, Buyuksahin et al. (2010), Silvennoinen and Thorp (2013) and Tang and Xiong (2010) show how financialization of commodities affects the linear correlations between different commodities or the correlation between commodities and financial assets, while Lautier and Raynaud (2011) focus on integration in energy-derivative markets.

[6] See for example Agren (2006), Arouri et al. (2012), Du et al. (2011), Hassan and Malik (2007), Malik and Hammoudeh (2007), He and Chen (2011), Lien and Yang (2008), Malik and Ewing (2009), Soytas et al. (2009), Sadorsky (2012), Serra (2011), Soytas and Oran (2011) Singh et al. (2010), Syllignakis and Kouretas (2011), Chang et al. (2011), Arouri et al. (2011), Ji and Fan (2012), Awartani and Maghyereh (2013), etc.

[7] Rapid income growth in China and India China was a key factor behind the increase in food commodities after 2007 (see for example Krugman, 2008; Wolf, 2008; and Bourne, 2009).

upsurge in commodity prices ended with the global economic slowdown with easing of commodity demand. In India, on account of high growth and other factors, commodity prices increased at a rapid pace creating investment opportunities. As shown in Figure 1, there is an overall increase in commodity trading in India since 2005. Interestingly, the trend continued even during the Global Financial Crisis. This may be on account of investors opting for commodities to hedge against inflation at the time of financial stress. During different crisis periods, Indian commodity market shows huge volatility. Now, it is important to decipher the origin of the volatility in commodity derivative market; whether the shock hurt the Indian commodity derivative market first and then was transmitted to other Indian asset markets or vice versa.

Figure 1: Economic Growth and Commodity Trading in India



Source: World Bank database (for per capita GDP growth); Multi Commodity Exchange (for traded contracts).

In the literature, different methods have been used to measure financial contagion. The existing empirical literature on financial contagion has several limitations and hence the measure of financial contagion vis-à-vis financial crisis remains a debatable issue. Financial contagion is tested mostly using cross market correlations[8]. When measuring cross market dynamic correlations, the problem of heteroskedasticty may arise due to upsurge of volatility at the time of crisis and hence, the dynamic nature of correlation needs to be analyzed more carefully while studying financial contagion (Forbes and Rigbon, 2002). As argued by Forbes and Rigbon (2002), Bordo and Murshid (2001), and Basu (2002), if there is no significant

[8] The first study to measure contagion using cross market correlations is King and Wadhwani (1990) followed by Lee and Kim (1993) and Calvo and Reinhart (1995).

increase in correlation between asset returns after accounting for heteroskedasticity, then there is "no contagion, only interdependence"[9]. To calculate heteroskedasticty adjusted time varying correlation among assets and hence measure the extent of financial contagion, several studies use Dynamic Conditional Correlation–Multivariate GARCH (DCC-MGARCH) method (see Wang and Thi, 2006; Cappiello et al., 2006; Frank et al., 2008; Wang and Moore, 2012). The DCC-MGARCH method proposed by Engle (2002) has several advantages over other multivariate GARCH models and most importantly, as it accounts for heteroskedasticity by estimating dynamic correlation coefficients of the standardized residuals, the estimated time varying correlation coefficients can be used in estimating financial contagion (Ahmed et. al., 2013).

There are two types of econometric methods of estimating volatility spillover, namely GARCH based and VAR based methods. The seminal paper by Diebold and Yilmaz (2009) developed a VAR based volatility spillover index which was later on modified in Diebold and Yilmaz (2012) Diebold and Yilmaz (2012). Many other studies have used Diebold and Yilmaz methods to estimate volatility spillover (see for example Yilmaz, 2010; Louzis, 2013; Antonakakis and Vergos, 2013; Awartani and Maghyereh; 2013 etc). The Diebold and Yilmaz (2012) method has been used in this study as it has several advantages over other methods that have been applied in the previous studies. First, the measure is simple to compute and it does not depend on the Cholesky factor identification of the VAR model. It is based on aggregating and offsetting invariant forecast error variance decomposition in vector autoregressive models of returns and volatilities: thus the results of variance decomposition do not hinge on the sequence of variables. Second, the measure is tractable, and it allows the measurement of the spillovers in returns or return volatilities across multiples of individual assets, classes of assets and markets over time. Therefore, the measure can be used to study spillovers from one market to multiple markets and vice versa. Third, the dynamics of the measure generated by a rolling-window facilitates the study of both crisis and non-crisis episodes including trends as well as bursts in spillovers. Finally, and more importantly, this method measures the shocks to volatility (or returns) of one market on any market (markets), and net of the aggregated impact in the reverse direction. This distinctive feature provides more information on directional spillovers than merely measuring the significance of a parameter that is estimated under a special variance structure, as in the multivariate GARCH models (Zhou et al., 2012).

[9] This proposition is however challenged by a number of studies including Ang and Chen (2002), Bartman and Wang (2005) etc.

The above review of literature shows some important research gaps. First, studies on financial contagion considering overall commodity market during the period of financial crisis are rare. Further, studies on contagion with regards to Indian commodity derivative market are even more rare. While there are some studies that discuss the nature of the co-movement or correlation or time varying correlation among different commodities or between some specific commodities and equity, there is no study considering contagion in the commodity market. Second, studies discussed above have only considered international financial contagion and not contagion among domestic asset markets. Third, most studies are found to concentrate on intra market volatility spillovers considering only different commodities and few other studies which have consider the inter-market volatility spillovers taking into consideration oil and equity markets. Fourth, it is also important to understand the nature of dynamic and directional spillovers from and to the commodity market. Under these circumstances, it is important to understand the overall nature of volatility spillover from and to the commodity market. Last, but not of least importance, is the methodological issue. These gaps in the literature motivate us to study the nature and extent of financial contagion and volatility spillover in Indian commodity derivative market vis-à-vis other Indian asset markets. This paper is structured as follows. Section 2 provides some stylized facts on daily returns in the Indian commodity derivative market and other asset markets. Section 3 gives a brief on the different econometric methods and data used in this study. An exhaustive analysis of econometric results is presented in section 4. The paper summarizes the major findings in section 5.

2. India's Commodity Derivative Market and Other Asset Markets: Certain Stylized Facts

With wide ranging reforms in commodity trading in India, it is important to understand the time behavior of the commodity market. It is customary to calculate return of an asset as the logarithmic value of the ratio of two consecutive prices. The continuously compounded daily returns are computed using the following logarithmic filter:

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right).$$

Descriptive statistics are calculated on the basis of returns series. Return series are plotted in Figure 2.

Figure 2: Asset Return Series in India

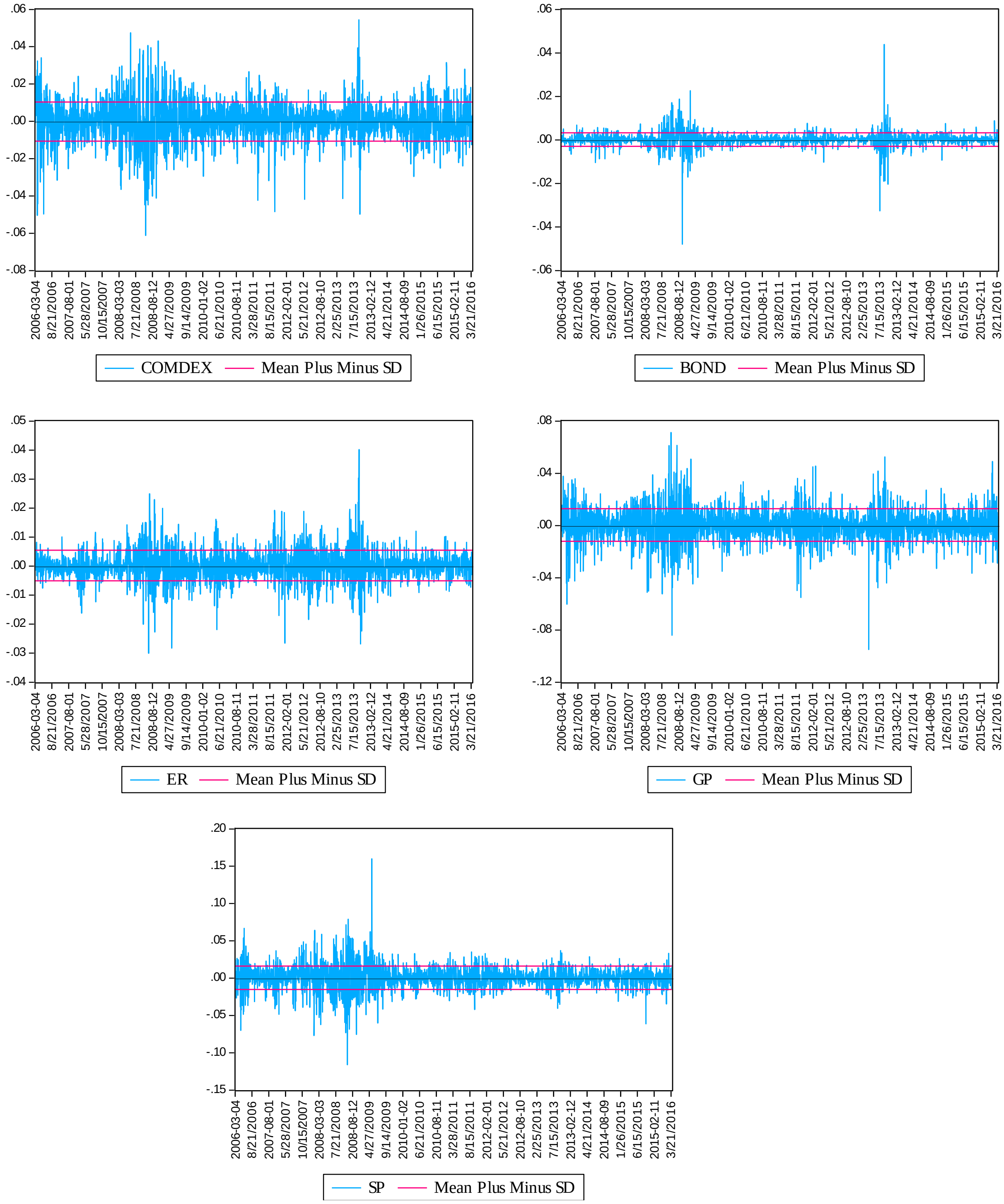


Table 1 shows descriptive statistics of different assets that have been considered, namely commodity future price index (COMDEX), bond price (BOND), exchange rate (ER), gold price (GP), and equity (SP). Investment in equity or stock market, as evident from Table 1, offers highest average daily returns (0.045 per cent) and that in commodity derivative market offers least returns (-0.015 per cent). However, the stock market is most risky, as approximated by a standard deviation of 1.56 per cent followed by gold (1.25 per cent) and commodity (1.05 per cent) markets. This certainly indicates high uncertainty or risk is associated with high potential returns. Further, to arrive at distribution of the asset returns, skewness and kurtosis are calculated. From Table 1 it is observed that foreign exchange and equity returns are positively skewed, while commodity, bond and gold returns show negatively skewed distribution. Thus an asymmetry in the upside and downside potential of price changes is observed. For all asset returns, kurtosis values are much higher than that of a normal distribution, implying that the probability of extreme gains or losses is much larger than predicted by the normal distribution. In order to establish the dynamic nature of correlation between asset returns and presence of financial contagion, time series properties of asset returns and certain diagonistic tests need to be carried out.

Table 1: Descriptive Statistics

	COMDEX	BOND	ER	GP	SP
Mean	-0.000149	0.000223	0.000205	0.000441	0.000456
Maximum	0.054383	0.043870	0.040200	0.071273	0.159900
Minimum	-0.061197	-0.047891	-0.030070	-0.094954	-0.116040
Std. Dev.	0.010500	0.003099	0.005292	0.012463	0.015646
Skewness	-0.313179	-0.846631	0.212833	-0.304208	0.063218
Kurtosis	5.995721	50.94347	7.360316	7.804675	11.01539
Jarque-Bera	1018.235***	250186***	2086.499***	2549.761***	6985.862***
ADF Test	-49.51835***	-44.82219***	-47.3573***	-52.098***	-45.621***
ZA Test	-24.32441*** (Dec 26, 2008)	-45.22736*** (Jan 6, 2009)	-20.9606*** (Nov 21, 2008)	-52.16166*** (Aug 29, 2013)	-45.7969*** (Mar 12, 2009)
Q(5)	11.587***	48.247***	30.801***	4.7844***	34.708***
$Q^2(5)$	438.19***	105.28***	603.9***	200.27***	371.9***
ARCH-LM Test	106.7379***	5.034981***	157.0462***	25.23675***	69.83531***

Note: (a) For ADF test standard t-statistics are reported.
(b) For Zivot Andrews test structural break points are given in parentheses.
(c) Q and Q^2 are Ljung-Box Q statistics for return series and squard return series respectively.
(d) ARCH-LM test shows Engle (1982) test for conditional heteroskedasticity calculated for the first lag only.
(e)*** implies significance at 1 per cent level, ** implies significance at 5 per cent, and * implies significance at 10 per cent level.

Asset prices and exchange rates often exhibit trending behavior or non-stationarity in mean. Econometrically, these series are checked for (non) stationarity using Augmented Dicky Fuller (ADF) unit root test and Zivot-Andrews (ZA) unit root test with structural breaks. Table 1 presents results of two tests for stationarity of daily return series for different assets. The ADF test checks for stationarity in the data series as against the null hypothesis of a presence of unit root. Using intercept and trend it is found that the null hypothesis is rejected at 1 per cent level of significance for each return series, that is, all series used in the empirical analysis are I(0). It is often said that a weakness of the Dicky-Fuller type unit root tests is its potential confusion of structural breaks in the series as evidence of nonstationaity. Econometricians have tried to solve this by devising unit root tests that allow for structural instability in an otherwise deterministic model. One such test is by Zivot and Andrews (1992), that allows for a single structural break in the intercept and the trend of the series, as determined by a grid search over possible break points. Table 1 shows that for each series, null hypothesis of presence of unit root is rejected by the Zivot Andrews test. Except for the return series of gold price, for all other markets the break dates fall in the interlude of financial crisis and that for gold price return series, the date is when rupee value was the lowest against the US dollar[10]. On the whole, the tests show that all return series are I(0).

To check the nature of statistical distribution and presence of ARCH, certain diagnostic tests are done in this sub-section. Skewness and kurtosis coefficients, for each asset return series, shows significant departure from a Gaussian distribution. This fact can be confirmed by the Jarque-Bera test[11] with null hypothesis of normality distributed returns. In all cases, the null hypothesis of normality is rejected. However, it should be remembered that this fact is relevant only for the unconditional distribution of return series. The Ljung-Box Q statistic[12] tests the null hypothesis of no serial correlation or no autocorrelation and is calculated using upto 5 lags for both daily return series and squared return series. A significant Q statistic rejects the null hypothesis of no autocorrelation in returns, while a significant Q statistics for the squared return series rejects the null hypothesis of homoskedastic return series. It is evident from Table 1 that Q statistic to be significant at 10 lags for each return series and thus they are autocorrelated. In other words, no series is a random walk process. On the other hand, the Q statistic of the squared returns is significant for each daily return series indicating strong nonlinear dependence or presence of heteroskedasticity in return series. The ARCH method can be thus used on these daily return series. To confirm this, the ARCH LM test shows significant presence of ARCH effects in all the daily return series. These tests provide the basis of GARCH based approach to estimate dynamic correlations and financial contagion. In Figure 2 also, volatility clustering is observed which points to the existence of ARCH effect.

3. Data and Econometric Methodology

[10] On 28 August 2013, Indian rupee experienced the greatest fall to 68.83 against the US dollar.
[11] Introduced in Jarque and Bera (1987).
[12] See Ljung and Box (1978).

3.1 The Data

The data on five asset markets namely, commodity derivative market, bond market, currency or foreign exchange market, gold market and equity or stock market, used in the study are obtained from various sources. For each market, daily data on actual asset price or asset price index for the time period April 3, 2006 to March 31, 2016 have been used. Commodity future price index data are taken from the database of Multi Commodity Exchange, India. On the other hand, data on bond index, daily rupee/dollar exchange rate, daily gold price and SENSEX are collected from the Clearing Corporation of India (CCIL), the Reserve Bank of India's (RBI) database, the World Gold Council database and the Bombay Stock Exchange (BSE) respectively. The time span chosen for the empirical analysis allows investigating the sensitivity of commodity returns vis-à-vis returns of other financial assets covering major events like the subprime crisis of 2008-09, the Euro zone crisis of 2010-12, and large rupee depreciation of 2013-14.

3.2 Econometric Methodology

The literature on financial contagion suggests that while estimating financial contagion, it is necessary to control for presence of heteroskedasticity. Thus possibly the best way of calculating time varying correlation is to estimate DCC-MGARCH, as the GARCH methods treats heteroskedasticity as variance to be modeled (Engle and Sheppard, 2001). In the financial market, volatility has shown to be autocorrelated and clustered[13] in different time periods. A good method to predict the future volatilities is essential since volatility is not directly observable. Univariate GARCH method introduced by Bollerslev (1986) has been successful in capturing volatility clustering and predicting future volatilities (Hansen and Lunde, 2005). The dynamics of volatility of any financial return series across markets and across groups can be described by univariate GARCH(1,1) method (Engle, 2004). To study common behavior of financial markets, this univariate framework should be extended to a multivariate one. Though, each asset market has its own characteristic often financial volatilities are found to move together more closely over time across assets and financial markets. To study the relations between the volatilities and co-volatilities of several markets MGARCH methods are widely used (Bauwens et. al., 2006). A brief discussion on Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation (DCC) MGARCH methods follows.

3.2.1 DCC-MGARCH Method

[13] That is small changes tend to be followed by small changes, and large changes by large ones.

Following Bauwens et al. (2006), in a stochastic vector process of returns of N assets $\{r_t\}$ of dimension Nx1, the mean equation can be written as

$$\mathbf{r_t} = \boldsymbol{\mu}_\mathbf{t} + \boldsymbol{\eta}_\mathbf{t} \tag{1}$$

where $\boldsymbol{\eta}_\mathbf{t} = \mathbf{H_t^{1/2} z_t}$ and $\mathrm{E}(\boldsymbol{\eta}_\mathbf{t}\boldsymbol{\eta}_\mathbf{t}') = \mathbf{I_N}$. The conditional variance-covariance matrix of $\mathbf{r_t}$ is an NxN matrix denoted by $\mathbf{H_t} = [h_{ijt}]$. The $\mathbf{H_t^{1/2}}$ is an NxN positive definite matrix, may be obtained by the Cholesky factorization of $\mathbf{H_t}$. The conditional covariance matrix can be decomposed into conditional standard deviations and a correlation matrix as follows:

$$\mathbf{H_t} = \mathbf{D_t R_t D_t} \tag{2}$$

where $\mathbf{D_t} = \mathrm{diag}\left(h_{1t}^{\frac{1}{2}}, h_{2t}^{\frac{1}{2}}, \dots \dots, h_{nt}^{\frac{1}{2}}\right)$is the conditional standard deviation and $\mathbf{R_t}$ is the correlation matrix. The DCC-MGARCH method is defined in equation (2) and since $\mathbf{R_t}$ is the conditional correlation matrix of standardized error terms $\boldsymbol{\varepsilon}_\mathbf{t}$,

$$\boldsymbol{\varepsilon}_\mathbf{t} = \mathbf{D_t^{-1}} \boldsymbol{\eta}_\mathbf{t} \sim \mathrm{N}(0, \mathbf{R_t}) \tag{3}$$

Thus, the conditional correlation is the conditional covariance between the standardized disturbances. Before analyzing $\mathbf{R_t}$ further, recall that $\mathbf{H_t}$ has to be positive definite by the definition of the covariance matrix. Since $\mathbf{H_t}$ is a quadratic form based on $\mathbf{R_t}$ it follows from basics in linear algebra that $\mathbf{R_t}$ has to be positive definite to ensure that $\mathbf{H_t}$ is positive definite. Furthermore, by the definition of the conditional correlation matrix all the elements have to equal or less than one. To guarantee that both these requirements are met $\mathbf{R_t}$ is decomposed into

$$\mathbf{R_t} = \mathbf{Q_t^{*-1} Q_t Q_t^{*-1}} \tag{4}$$

where $\mathbf{Q_t}$ is a positive definite matrix defining the structure of the dynamics and $\mathbf{Q_t^{*-1}}$ rescales the elements in $\mathbf{Q_t}$ to ensure $|q_{ij}| \leq 1$. Then $\mathbf{Q_t^*}$ is the diagonal matrix consisting of square root of diagonal elements of $\mathbf{Q_t}$. Thus $\mathbf{Q_t^*} = \mathrm{diag}\left(q_{11t}^{\frac{1}{2}}, q_{22t}^{\frac{1}{2}}, \dots \dots, q_{nnt}^{\frac{1}{2}}\right)$.

Now, $\mathbf{Q_t}$ follows the dynamics in the form of

$$\mathbf{Q_t} = (1 - \theta_1 - \theta_2)\overline{\mathbf{Q}} + \theta_1 \boldsymbol{\varepsilon}_\mathbf{t-1} \boldsymbol{\varepsilon}_\mathbf{t-1}^\mathbf{T} + \theta_2 \mathbf{Q_{t-1}} \tag{5}$$

where $\overline{\mathbf{Q}} = \mathrm{Cov}(\boldsymbol{\varepsilon}_\mathbf{t} \boldsymbol{\varepsilon}_\mathbf{t}^\mathbf{T}) = \mathrm{E}(\boldsymbol{\varepsilon}_\mathbf{t} \boldsymbol{\varepsilon}_\mathbf{t}^\mathbf{T})$ is the unconditional covariance matrix of standardized errors. $\overline{\mathbf{Q}}$ can be estimated as :

$$\overline{\mathrm{Q}} = \frac{1}{\mathrm{T}} \sum_{t=1}^{\mathrm{T}} \varepsilon_t \varepsilon_t^{\mathrm{T}}$$

In equation (5), $\theta_1$and θ_2 are scalars and must satisfy the following conditions:

$$\theta_1 \geq 0, \theta_2 \geq 0 \text{ and } \theta_1 + \theta_2 < 1$$

The log-likelihood to estimative the above model is:

$$\ln(\mathrm{L}(\Phi)) = -\frac{\mathbf{1}}{\mathbf{2}}\sum_{\mathbf{t=1}}^{\mathbf{T}}\left(\mathrm{n}\ln(2\pi) + 2\ln(|\mathbf{D_t}|) + \ln(|\mathbf{R_t}|) + \boldsymbol{\eta}_\mathbf{t}\mathbf{D}_\mathbf{t}^{-1}\mathbf{R}_\mathbf{t}^{-1}\mathbf{D}_\mathbf{t}^{-1}\boldsymbol{\eta}_\mathbf{t}^\mathbf{T}\right) \quad (6)$$

where Φ denotes paramenters of the method. Let the parameters, $\boldsymbol{\Phi}$, be divided in two groups; $(\boldsymbol{\phi}, \boldsymbol{\theta}) = (\boldsymbol{\phi}_\mathbf{1}, \boldsymbol{\phi}_\mathbf{2}, \ldots\ldots, \boldsymbol{\phi}_\mathbf{n}, \boldsymbol{\theta})$, where $\boldsymbol{\phi}_\mathbf{i} = (\alpha_{0i}, \alpha_{1i}, \ldots., \alpha_{qi}, \beta_{1i}, \beta_{2i}, \ldots.., \beta_{pi})$ are the parameters of the univariate GARCH method for the ith asset class and $\boldsymbol{\theta} = (\theta_1, \theta_2)$are the parameters of the correlation structure or DCC parameters. DCC-MGARCH method is designed to allow for two stage estimation as the estimation of correctly specified log-likelihood is difficult. In the first stage from the univariate GARCH methods $\boldsymbol{\phi}_\mathbf{i}$s are estimated for each asset class and then in the second stage parameters θ_1 and$\theta_2$are estimated.

It is noteworthy that most of the financial time series are seen follow non-normal distribution. In the chosen sample, all return series are non-normal in nature (see Table 2). However, Normal distribution has been used for likelihood estimation. When ε_t is seen to follow heavy-tailed and asymmetric distribution, MLE using Student's t or generalized Gaussian distribution is being used (see Bollerslev ,1986; Bollerslev, 1987; Hsieh, 1989 and Nelson, 1991.). However, this technique may produce inconsistent estimator if the distribution of innovation is misspecified. On the contrary, in this case Gaussian Maximum Likelihood Estimation (MLE) or Gaussian Quasi Maximum Likelihood Estimation (QMLE) may produce consistent estimator (see Elie and Jeantheau,1995) and asymptotically normal provided a finite fourth moment of the innovation exists, even if the true distribution is far from Normal (see Hall and Yao, 2003; Berkes et al. 2003).

3.2.2 Financial Contagion: A Regression

From the DCC-MGARCH(1,1) method, pair wise time varying conditional correlations can be obtained, and from the univariate GARCH methods, a series of conditional standard deviation or volatility can be obtained for each asset. Following Chong et al. (2008), Ahmed et al. (2013, 2014) and Syllignakis and Kouretas (2011), conditional correlation is regressed on conditional volatilities

$$\rho_{ijt} = \alpha + \beta_1 h_{it} + \beta_2 h_{jt} + \epsilon_t \quad (7)$$

where ρ_{ijt} is the estimated pair wise conditional correlation coefficient between the commodity returns and the returns from other four assets, such that i=commodity and j=other assets. The h_{it} is the conditional volatility of the commodity returns and h_{jt} is that of other asset returns. A positive β_i (i=1,2) obtained by estimating the above method with least square technique, would suggest that conditional correlation increases at the time of high volatility and hence evidence in favour of financial contagion (see Ahmed et al. 2013, 2014 and Syllignakis and Kouretas, 2011). In case of multiple regressions, $\overline{R}^2$ measures the goodness of fit. Here the same can be interpreted as the degree of financial contagion. Since the degree of financial contagion is not expected to remain constant over time, rolling regression and measuring the degree of financial contagion become important (see Syllignakis and Kouretas, 2011).

3.3.3 Diebold-Yilmaz VAR Based Volatility Spillover Index

The Diebold-Yilmaz (DY) spillover index is used which measure the directional spillovers in a generalized VAR framework that excludes the possible dependence of the results on ordering driven by Cholesky factor orthogonalization.

Let the covariance stationary N-variable VAR(p) process be specified as

$$\mathbf{x_t} = \sum_{i=1}^{p} \emptyset_\mathbf{i} \mathbf{x_{t-1}} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{8}$$

where $\boldsymbol{\varepsilon}$ is a vector that follows iid(0, $\boldsymbol{\Sigma}$) and $\boldsymbol{\Sigma}$ is the variance matrix of the error. Then the above VAR process can be represented as a moving average process as follows:

$$\mathbf{x_t} = \sum_{i=0}^{\infty} \mathbf{A_i} \boldsymbol{\varepsilon}_\mathbf{t-i} \tag{9}$$

where $\mathbf{A_i}$ is the NxN coefficient matrix obeying the recursion process $\mathbf{A_i} = \sum_{\mathbf{k=1}}^{\mathbf{p}} \emptyset_\mathbf{k} \mathbf{A_{i-k}}$, with $\mathbf{A_0}$being an NxN identity matrix and with $\mathbf{A_i} = 0$ for i<0. Variance decomposition allows us to parse the forecast error variances of each variable into parts which are ascribed to various system shocks. When this system of VAR produces contemporaneously correlated innovations, orthogonal innovations for variance decomposition are required. Orthogonality can be achieved by Cholesky factorization. However, in that case variance decomposition becomes highly sensitive to variables ordering. The generalized VAR approach introduced by Koop et al. (1996) and Peseran and Shin (1998), solves this problem.

Now, the H-step-ahead forecast error variance decomposition is as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=o}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=o}^{H-1} \left(e_i' A_h \Sigma e_j\right)} \tag{10}$$

where σ_{jj} is the standard deviation of the error term for the jth equation and e_i is the selection error with value one as the ith element and zero otherwise. It is noteworthy that since the shocks to each variable are not orthogonalised, the sum of the contributions to the variance of forecast error is not necessarily equal to one. In other words, the sum of elements in each row of the variance decomposition matrix is not equal to one, that is $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. Then each element of variance decomposition matrix is normalized by dividing them by respective row sums. Then the new H-step-ahead variance decomposition is

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{11}$$

Then automatically, $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$.

Now, from (11) total spillover index, which measures the contribution of spillovers of volatility shocks across N asset classes to the total forecast error variance can be calculated. The total spillover index denoted by $S^{g}(H)$ is

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)}.100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}.100 \tag{12}$$

The advantage of VAR based volatility spillover index is that it enables us to calculate directional spillover indices. Directional volatility spillovers received by market i from all other markets j is measured as:

$$S_{i.}^{g} = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)}.100 = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}.100 \tag{13}$$

and similarly, directional volatility spillovers transmitted by market i to all other markets j as:

$$S_{.i}^{g} = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)}.100 = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N}.100 \tag{14}$$

After calculating directional volatility spillover from other markets and to other markets, it is certainly possible to calculate net volatility spillover from market i to all other markets as follows:

$$S_{i}^{g} = S_{.i}^{g} - S_{i.}^{g} \tag{15}$$

As the net spillover index provides only summary information that how much each market contributes to volatility in other markets, one may also calculate net pairwise volatility spillovers as follows:

$$S_{ij}^{g} = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)} \right).100 = \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} \right).100 \tag{16}$$

It captures the difference between the gross volatility shocks transmitted from market i to market j and those transmitted from market j to market i. The generalized VAR based approach is superior as any of the volatility indices calculated is not sensitive to the ordering of variables as in the case of Cholesky factorization.

4. Estimation Results and Discussions

4.1 Correlation Analysis

For portfolio choice, analyses of static as well as dynamic correlation are important. Correlation indicates the tendency of the returns of one asset to move in tandem with those of other assets. The movements of one asset can expected to be least affected by the movements of another asset and thus reducing average volatility of the portfolio, if uncorrelated assets are combined.

4.1.1 Static Unconditional Correlation Analysis

The unconditional static correlation matrix, as shown in Table 2, shows that commodity return is relatively highly correlated with gold and stock returns. Commodity return has a negative correlation with bond returns while it has a positive correlation with gold and stock returns. On the contrary, foreign exchange return is found to be uncorrelated with commodity return[14]. An asset is said to be a "hedge" if it is uncorrelated or negatively correlated with another asset or asset portfolio. On the other hand, if an asset is positively but not perfectly correlated with another asset, it is called a "diversifier". Thus from the static unconditional correlation it can be inferred that commodity can be termed a "hedge" against foreign exchange and bond while it is a "diversifier" against gold and equity. Although, gold is also a commodity, it has a correlation of opposite sign with stock returns. This is true for the correlation coefficient with foreign exchange return. This gives evidence in favour of huge heterogenity within the commodity market. However, it is worth mentioning that this correlation analysis is unconditional and static in nature and hence it fails to capture the effects of different unforeseen events. The unconditional static correlation presented here can be interpreted as a long run average. The measured correlation can also be volatile and the shorter the window of observation, the more likely that the realized correlation will differ from the long run average. More importantly, for the analysis of financial contagion dynamic correlation rather than static correlation is more appropriate.

Table 2: Static Unconditional Correlation

	COMDEX	**BOND**	**ER**	**GP**	**SP**
COMDEX	1				
BOND	-0.0403**	1			
ER	-0.0180	-0.0959***	1		
GP	0.3827***	-0.0425**	0.0973***	1	
SP	0.1649***	0.1130***	-0.3069***	-0.0770***	1

Note: *** implies significance at 1 per cent level, ** implies significance at 5 per cent, and * implies significance at 10 per cent level.

[14] Correlation between Commodity index and foreign exchange is very close to zero and insignificant.

4.2 Dynamic Conditional Correlation Analysis

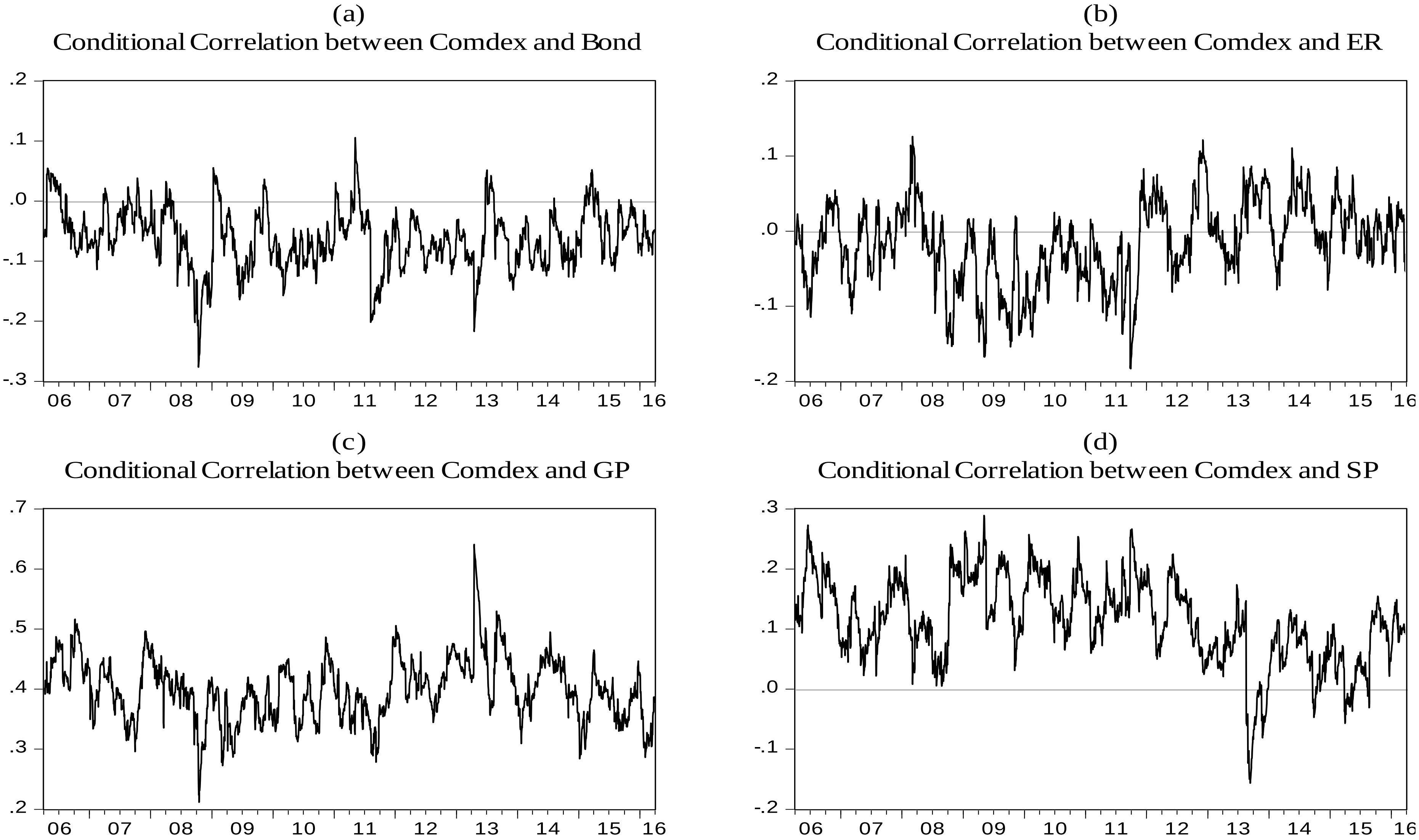
The results of univariate GARCH estimate and correlations, obtained from DCC-MGARCH methods, are reported in Table 3 and Table 4 respectively. Table 3 shows the two coefficients of univariate GARCH methods, namely α and β, are found to be significant for each asset class. Since for every daily return series α and β are positive and (α + β) is found to be less than unity, the stability is assured. The sum of α and β implies the overall persistence of the series. A statistically significant and close to unity value of (α + β) gives evidence in favour of persistence of shocks or persistence of volatility. This can be interpreted as follows: If any shock appears in these asset markets, it takes longer time to die down thus guaranteeing the persistence. The persistence of volatility is checked using Wald test also. For each asset return series, Wald test rejects the null hypothesis, α + β=1. From the Table 3 it can also be seen that two DCC parameters, θ_1 and θ_2 are positive and significant; and (θ_1 + θ_2) is also found to be less than one. Thus, the overall stability condition of DCC-MGARCH method is met. Significance of DCC parameters implies a substantial time-varying co-movement.

Table 3: Univariate GARCH Estimates

	COMDEX	**BOND**	**ER**	**GP**	**SP**
μ	-7.07E-05	0.000221***	3.09E-05	0.000338	0.00074***
	(0.000165)	(3.64E-05)	(6.78E-05)	(0.000215)	(0.000216)
ω	1.74E-06***	7.57E-08***	6.35E-07***	2.34E-06	2.65E-06***
	(6.63E-07)	(2.73E-08)	(1.58E-07)	(2.01E-06)	(9.03E-07)
α	0.076479***	0.098634***	0.161251***	0.060991**	0.092566***
	(0.016487)	(0.023329)	(0.018789)	(0.025622)	(0.01456)
β	0.907993***	0.897656***	0.822151***	0.924422***	0.896941***
	(0.018162)	(0.015294)	(0.018792)	(0.035614)	(0.01456)
α+β	0.984472	0.99629	0.983402	0.985413	0.989507
Wald Test	-56.0126***	-38.638***	-44.6403***	-36.6456***	-62.3226***
θ_1			0.012611***		
			(0.002244)		
θ_2			0.962396***		
			(0.009188)		

Note: (a) Standard errors are mentioned in parentheses.
(b) For Wald test, t Statistics are mentioned.
(c)*** implies significance at 1 per cent level, ** implies significance at 5 per cent, and * implies significance at 10 per cent level

Figure 3: Constant and Dynamic Conditional Correlations



In Table 4, conditional correlations of commodity returns with other assets are reported for DCC-MGARCH method. Average conditional correlations are calculated for each pair of asset returns and then mean tests are done to check whether average conditional correlation differs from zero or not. Engle (2002) suggests that if average correlations are found to be zero from the DCC- MGARCH method then it is meaningful to estimate CCC-MGARCH method rather than DCC-MGARCH method. From Table 4, it can be seen that none of the correlation is found to be significantly equal to zero and thus DCC-MGARCH is the appropriate method here. Figure 3 presents the conditional dynamic correlations. Correlation between bond and commodity returns is found to be negative for most of the time and thus, even in terms of the dynamic correlation commodity is found to be a "hedge" against bond. Prior to the Eurozone crisis, the correlation between commodity and exchange

Table 4: Average Conditional Correlation

	COMDEX	BOND	ER	GP	SP
COMDEX	1				
BOND	-0.062039**	1			
ER	-0.016612*	-0.063**	1		
GP	0.39885***	-0.03882*	0.069019**	1	
SP	0.113488***	0.129379***	-0.3302***	-0.07322***	1

Note: *** implies significance at 1 per cent level, ** implies significance at 5 per cent, and * implies significance at 10 per cent level.

rate is found to be negative for most of the time. Since the Eurozone crisis it shows some ups and downs. It shows some peaks during the Global Financial Crisis and the Eurozone Crisis. The correlation between commodity and gold returns is always positive. Although it does not show any surge during the Global Financial Crisis, a steep rise is seen during the 2013-14 rupee depreciation. Lastly, the correlation between stock price and commodity price is seen to be positive for most of the time. It shows a nosedive during the rupee depreciation of 2013-14. On the other hand, a rise in correlation between the two is also found during the crisis periods.

4.3 Analysis of Financial Contagion

Table 5 shows estimation results on financial contagion, based on Equation 7 using ordinary least squares technique. Coefficients of volatility of commodity in all four cases are found to be negative, implying decreasing conditional correlation between commodity and other assets when volatility increases in the commodity market. When considered along with volatility in commodity market, foreign exchange, gold and stock returns volatilities show significant positive impact on their respective correlations with commodity returns. This indicates that when volatilities increase in these markets, correlation with commodity market also increases. The evidence is thus in favour of existence of financial contagion between commodity market and these asset markets. Here $\overline{R}^2$ measures the degree of financial contagion. Financial contagion of commodity market vis-à-vis other asset markets is found to be maximum with stock and least with gold markets. The degree of financial contagion is found to be 10.67 per cent with stock market followed by 7.42 per cent with exchange rate and 0.86 per cent with gold market. The estimation results presented in Table 5 is from a static analysis of financial contagion. For each pair of returns only one value of degree of financial contagion is obtained. This is somewhat contrary to the dynamic nature and degree of financial contagion in response to many unforeseen events in the economy. To understand the time-varying nature of financial contagion, 200 day rolling regression is estimated and the R^2 values are reported.

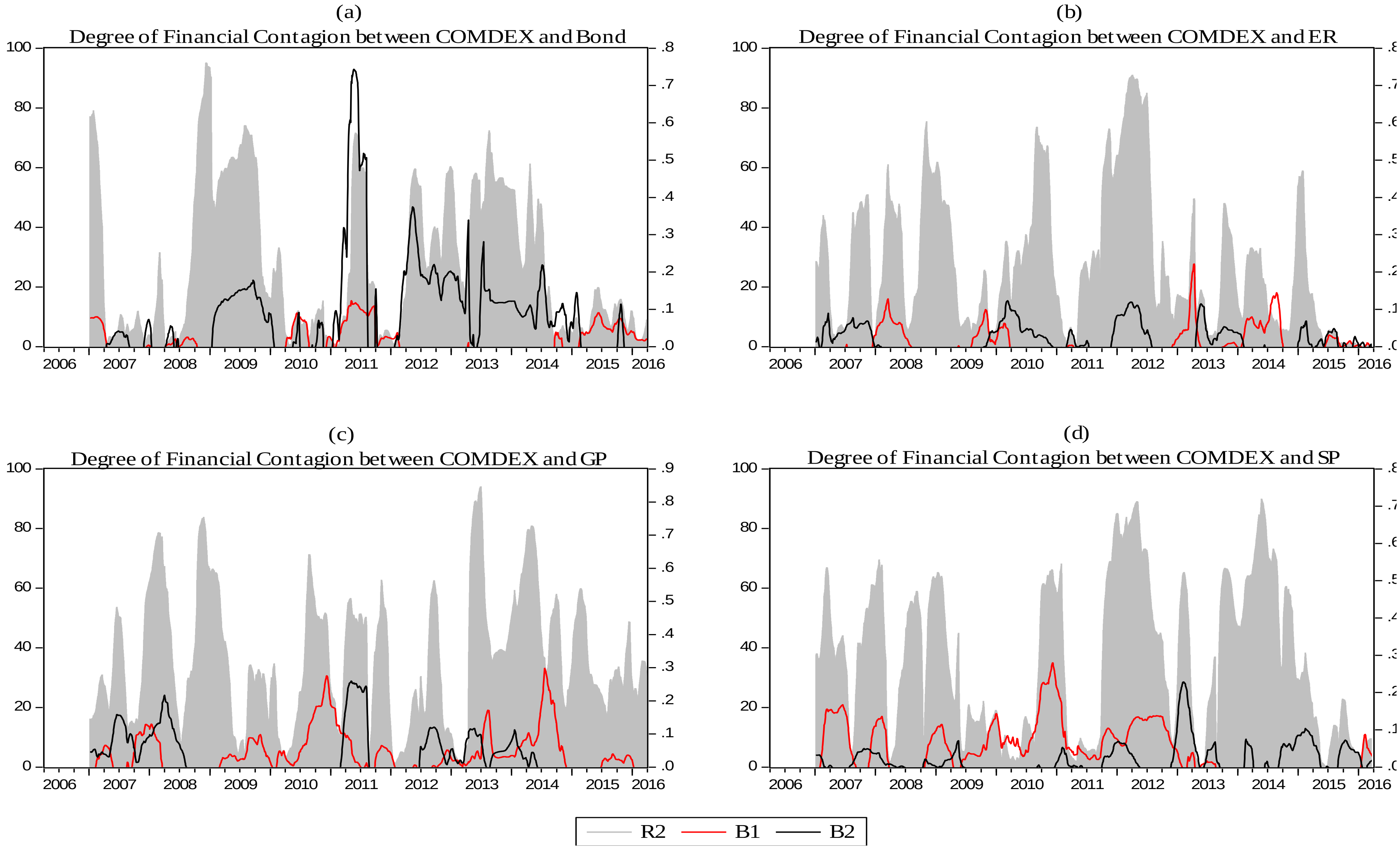
The estimation results presented in Table 5 are from a static analysis of financial contagion. For each pair of returns only one value of degree of financial contagion is obtained. This is somewhat contrary to the dynamic nature and degree of financial contagion in response to many unforeseen events in the economy.

Table 5: Nature and Extent of Financial Contagion

		Constant	β_1	β_2	$\overline{R}^2$
COMDEX	**BOND**	-0.057612***	-0.610325*	0.645656	0.001252
		(0.002996)	(0.337953)	(0.616221)	
	ER	0.023191***	-4.467976***	0.949643**	0.074218
		(0.003357)	(0.317041)	(0.480912)	
	GP	0.405514***	-2.121539***	1.217360***	0.008641
		(0.003385)	(0.448968)	(0.389644)	
	SP	0.081642***	-2.572316***	4.089765***	0.106665
		(0.004015)	(0.553184)	(0.270890)	
Bond	**ER**	-0.080414***	-6.954612***	7.183035***	0.037140
		(0.003352)	(0.898744)	(0.747662)	
	GP	-0.045556***	-2.167203***	1.033027***	0.006230
		(0.0003016)	(0.607433)	(0.289115)	
	SP	0.125793***	8.243789***	-1.240143***	0.039327
		(0.003011)	(0.801209)	(0.215173)	
ER	**GP**	0.037193***	8.461093***	-0.805856**	0.082078
		(0.003875)	(0.580217)	(0.331956)	
	SP	-0.310321***	0.161177	-1.471745***	0.045571
		(0.002488)	(0.431890)	(0.139427)	
GP	**SP**	-0.042086***	-2.648678***	0.020358	0.016845
		(0.004911)	(0.522942)	(0.295069)	

Note: (a) Standard errors are mentioned in parentheses.
(b)*** implies significance at 1per cent level, ** implies significance at 5per cent, and * implies significance at 10per cent level.

Figure 4: Degree of Financial Contagion



To understand the time-varying nature of financial contagion, 200 day rolling regression is estimated and the R^2 values are reported. From panel (a) of Figure 4, it can be seen that degree of contagion between commodity and bond markets increased during the Global Financial Crisis, during the Eurozone crisis and also during the Global Financial Crisis. Interestingly, when no evidence of financial contagion is found from the static analysis, presence and high degree of contagion is found in the dynamic analysis. The highest degree of contagion is seen during the rupee depreciation of 2013-14. If degree of financial contagion between commodity and foreign exchange markets is considered (shown in panel (b) of Figure 4) significant contagion is observed during the Global Financial Crisis and Eurozone crisis. On the other hand, degree of financial contagion between commodity and gold markets are found to be excessive during the Global Financial Crisis, and period of high rupee depreciation(see panel (c) of Figure 4). Lastly, panel (d) of Figure 4 shows degree of contagion between commodity and equity markets. High degree of financial contagion is seen during the Eurozone crisis and during high rupee depreciation. Thus in all four cases, excessive degree of financial contagion is seen during the period of large rupee depreciation.

4.4 Analysis of Volatility Spillover

An analysis of volatility spillover is being presented in this sub-section, which is further divided into two analyses of unconditional volatility spillover and conditional volatility spillover.

4.4.1 Unconditional Patterns: the Full Sample Volatility Spillover Analysis

Table 6 shows the volatility spillovers among different asset markets. The forecast error variance and hence volatility spillover indices are calculated on the basis of VAR of order 1 and generalized variance decomposition of 10 day ahead volatility forecast errors[15]. In the Table 6, j^{th} entry is the estimated contributions to the forecast error variance of market i coming from innovations to market j. The off diagonal column sums (labeled contributions TO others) and row sums (labeled contributions FROM others) are the total volatility spillovers measured from i^{th} market to all other markets and total volatility spillovers measured from all other markets to i^{th} market respectively. Net volatility spillovers are calculated simply by subtracting "FROM spillover" from "TO spillover". It measures total contributions of i^{th} market in the total volatility spillover. Total spillover index is approximately the "grand off-diagonal column sum" (or "grand off-diagonal row sum") relative to the "grand column sum" including

[15] Optimal lag of VAR is selected on the basis of Schwarz Information Criterion (SIC).

diagonals (or row sum including diagonals), expressed as a percentage. Thus an approximate "input-output" decomposition of the total volatility spillover index is shown in the volatility spillover table. The row labeled "TO others" shows the gross directional volatility spillovers to other markets from each of the five asset markets. On the other hand, the last column labeled "FROM others" shows to what extent each asset acquires volatility from other asset markets.

Table 6: Volatility Spillover (unconditional)

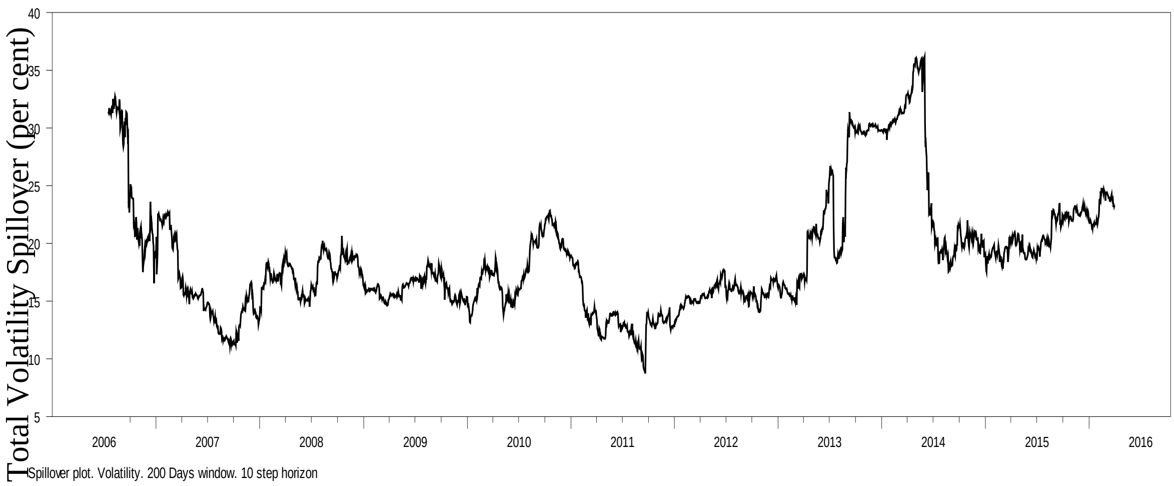
	COMDEX	Bond	ER	GP	SP	FROM Others
COMDEX	84.765	0.151	0.053	12.658	2.373	15.235
Bond	2.358	95.473	0.891	0.190	1.088	4.527
ER	0.060	0.770	85.911	1.369	11.891	14.089
GP	14.874	0.023	0.968	83.480	0.655	16.520
SP	2.233	1.685	7.821	0.704	87.557	12.443
TO Others	19.525	2.629	9.732	14.921	16.007	Total Volatility =62.815 =12.563per cent
Contribution Including Own	104.290	98.102	95.643	98.401	103.564	
Net Volatility Spillover	4.290	-1.898	-4.357	-1.599	3.564	

The total (non-directional) volatility spillover is a distillation of the various directional volatility spillovers into a single index. It measures, on average, across the entire sample, 12.563 per cent of the volatility forecast error variance in all five asset markets comes from spillovers. Commodity market transmits high degree of volatility to other asset markets, which is highest in comparison to the transmission capability of others. At the same time, commodity market receives high volatility from other markets (15.235 per cent) as well. As for the net directional volatility spillover, the largest is of commodity market followed by stock market and gold market. It is clear that bond, foreign exchange and gold markets are net receivers of volatility whereas commodity and stock markets are net transmitters of volatility. If net pairwise spillover is calculated with respect to the commodity market, it is found that the bond, foreign exchange and gold markets receives volatility from the commodity future market, whereas stock market is the only market which transmit volatility to commodity future market.

4.4.2 Conditional and Dynamic Spillover analysis

Since the sample period considered includes some phases of financial market turbulence, it seems unrealistic that any single fixed parameter method would apply over the entire sample. Even though the full sample spillover table and spillover index calculated earlier provides a summary of the "average" volatility spillover behavior of the five markets, it certainly misses out the important secular and cyclical movements in spillovers. To address this issue, volatility spillovers are estimated using 200-day rolling samples, and the extent and nature of the spillover variation over time via the corresponding time series of spillover indices are assessed, which is graphically shown in Figure 5. From the figure above it can be seen that the total volatility spillover shows a downward trend prior to the Global Financial Crisis and since 2011. Following the large rupee depreciation of 2013-14, a sudden leap to near 40 per cent is seen. It can thus be inferred that Indian asset markets are more vulnerable to internal shocks than external shocks.

Figure 5: Total Volatility Spillovers, Five Asset Markets



The analysis of net directional spillover and net pair wise directional spillover vis-à-vis commodity market to understand the dynamic nature of volatility spillover show whether the commodity market is a net transmitter or receiver of volatility. From Figure 6, where the net directional spillovers are presented, it is observed that commodity market for the whole sample period remains a transmitter of volatility. On the contrary, for the whole sample period, bond and foreign exchange markets remain net receivers of volatility. Although, the gold market remains net receiver of volatility for most of the time, it is found to transmit volatility during the Global Financial Crisis and the period of high rupee depreciation. Stock market is found to be transmitter of volatility except for the few small periods. Figure 7 sows net pair wise spillover between commodity derivative market and other asset markets. On an overall basis, commodity market is found to be a transmitter of volatility to bond, foreign exchange and gold markets. Between commodity and bond markets, high volatility is found to be transmitted from the former to the later market at the time of the Global Financial Crisis and during the large rupee depreciation. However, high volatility spillover from the commodity derivative market to the foreign exchange market is found only during 2013-14, the period of plunge in Indian foreign exchange market. The volatility spillover from commodity to gold market shows some ups and downs; but remains positive for most of the time. Although no clear trend in the pattern of volatility spillover between commodity and stock market is found, the degree of volatility transmission is seen to rise during the crisis periods.

Figure 6: Net Directional Volatility Spillover

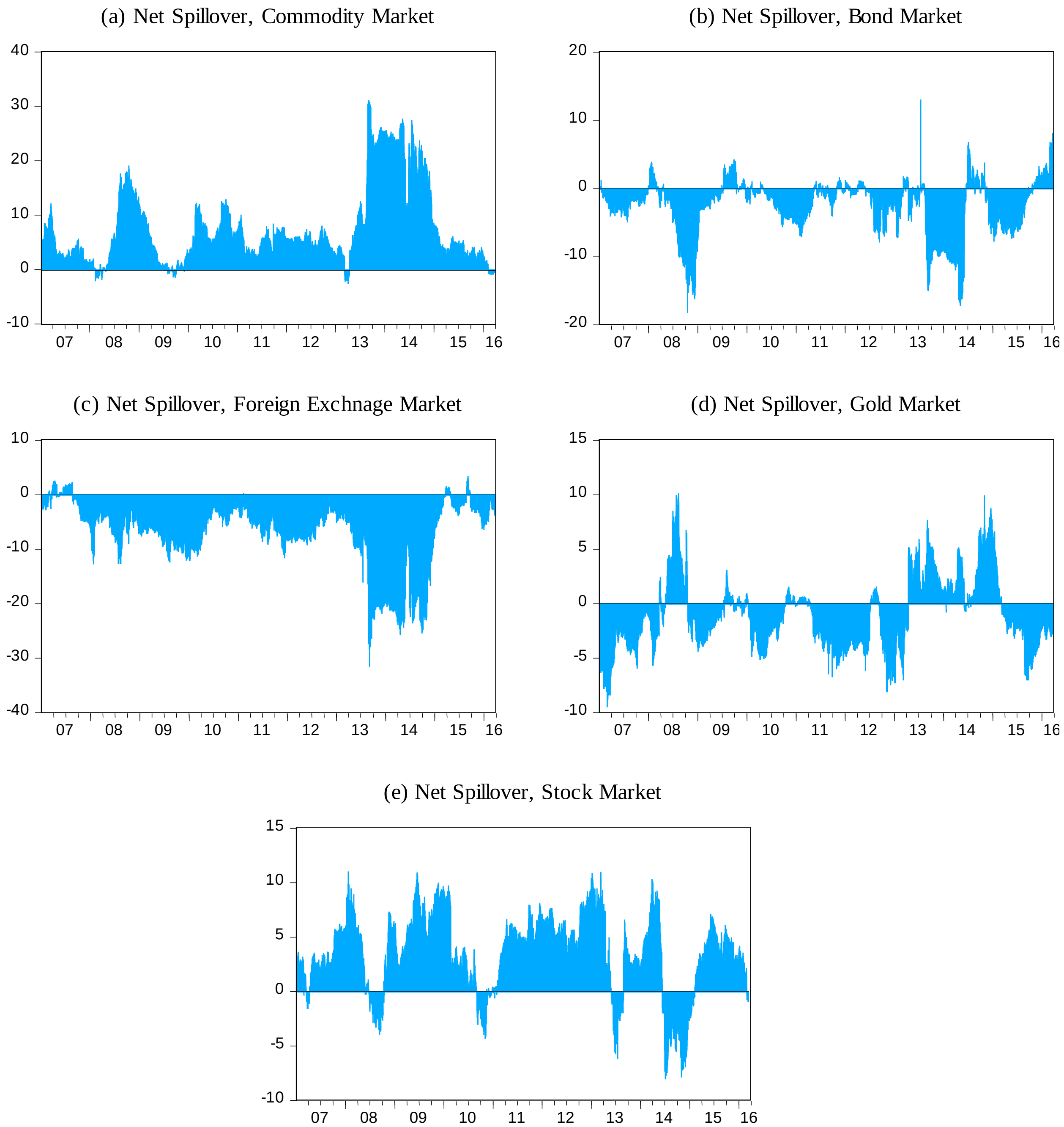
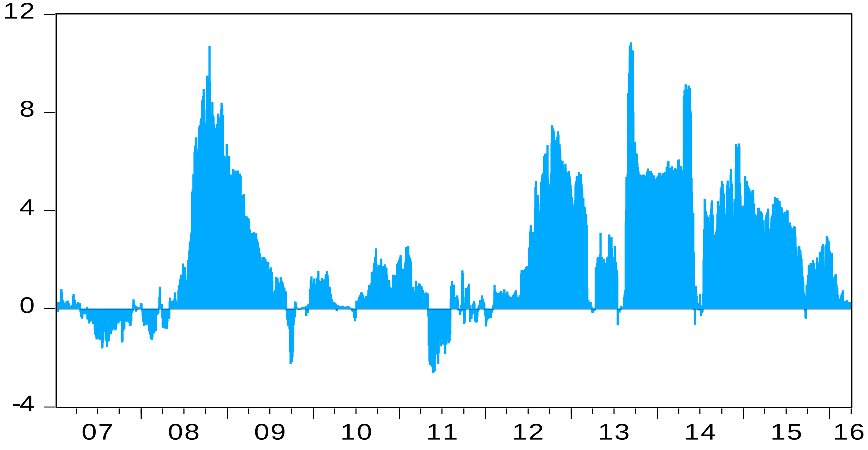
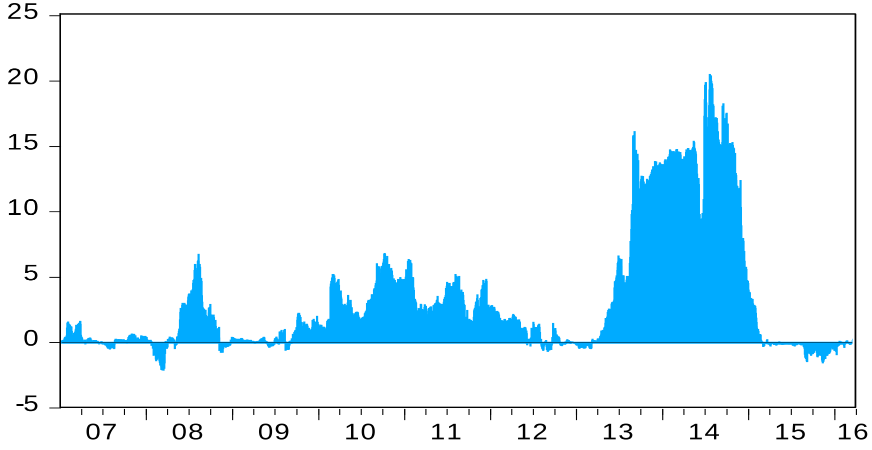


Figure 7: Net Directional Volatility Spillover (Pairwise)

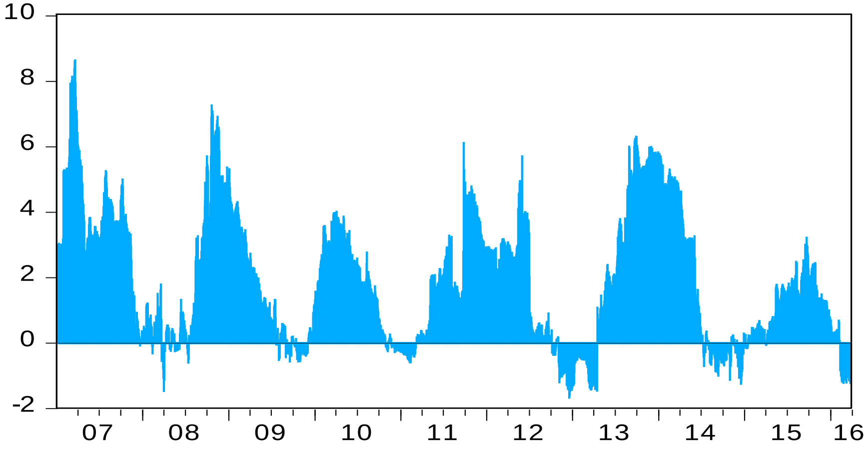
(a) Net Spillover between Commodity and Bond Markets



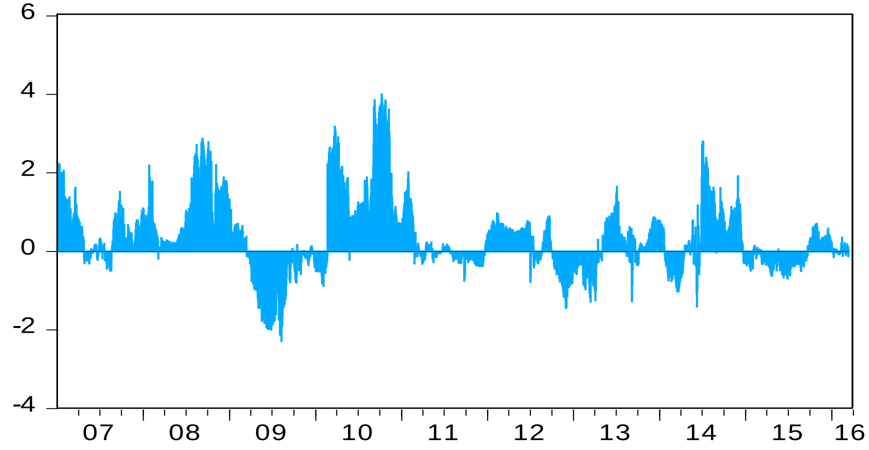
(b) Net Spillover between Commodity and Forex Markets



(c) Net Spillover between Commodity and Gold Markets



(d) Net Spillover between Commodity and Stock Markets



A comparison between degree of financial contagion and extent of volatility spillover is made in Table 7. When degree of financial contagion is found to be highest between commodity derivative market and stock market, directional spillover is found to be maximum between commodity and gold markets. The volatility spillover between stock and commodity markets is also very high. Thus it is observed that between commodity derivative and stock markets there are high degree of financial contagion as well as volatility transmission. Although, volatility transmission is very high between gold and commodity markets, there is very weak evidence of financial contagion between these two markets. Similarly, when very high degree of financial contagion is found between foreign exchange and gold markets, there is no evidence of very high degree of volatility transmission between the two. On the other hand, there is no evidence of financial contagion between foreign exchange and stock market; but the extent of volatility spillover between the two is found to be very high.

Table 7: Financial Contagion and Volatility Spillover: a Comparison

		Degree of Financial Contagion (per cent)	**Volatility Spillover from i to j (per cent)**	**Volatility Spillover from j to i (per cent)**	**Total Volatility Spillover Between i and j (per cent)**
COMDEX	BOND		2.358	0.151	2.509
	ER	7.4218	0.06	0.053	0.113
	GP	0.8641	14.874	12.658	27.532
	SP	10.6665	2.233	2.373	4.606
Bond	ER	3.714	0.77	0.891	1.661
	GP	0.623	0.023	0.19	0.213
	SP	3.9327	1.685	1.088	2.773
ER	GP	8.2078	0.968	1.369	2.337
	SP		7.821	11.891	19.712
GP	SP		0.704	0.655	1.359

Note: (a) Degrees of financial contagion, which is adjusted R^2 expressed as percentages, are taken from Table 5.
(b) Volatility Spillover estimates in row 3 and 4 are taken from Table 6
(c) Total volatility spillover is the sum of digits in column 2 and 3.

5. Conclusions

In the past decade, prior to the Global Financial Crisis, the Indian commodity market witnessed high growth. Evidence point to increasing investments in commodity market in India especially after the deregulation of commodity future trading since 2002-03. The upward trend in commodity prices has been ascribed to increasing demand at the global level; wide fluctuations in commodity prices are observed especially during the Global Financial Crisis. In case of Indian commodity market, fluctuations are found to occur not only during the Global

Financial Crisis, but also during the Eurozone crisis and at the time of high rupee depreciation of 2013-14. Thus for the purpose of portfolio choice, analysis of only long run trend of commodity prices does not suffice. Commodity as an asset bears low correlation with other traditional asset classes in the long run. The static correlation analysis may mislead as it fails to capture different market movements and the nature of changes in the correlation in response of different shocks and financial stress. Under these circumstances, it is necessary to study the behavior of dynamic correlation between commodity and other asset classes.

The correlation between two asset classes may increase over time indicating "interdependence", but the cause for concern is whether there exists financial contagion as the correlation increases during financial stress or financial crisis or at the time of high volatility. On the other hand, in the literature it is often claimed that commodity prices are increasingly influenced by shocks and thus volatility may spillover from other financial markets to the commodity market. Shocks can also lead volatility in commodity market to spillover to other markets. There are many sophisticated methods of estimating financial contagion; dynamic conditional correlation analysis is opted as it is easy to calculate and it generates much other information relevant for the process of optimal portfolio choice. Strong evidence of financial contagion in Indian commodity market vis-à-vis other asset markets such as currency, gold, and equity, is found from the empirical analysis. The extent of financial contagion is maximum between the commodity market and stock market and minimum between the commodity market and the gold market. A rolling regression analysis shows the dynamic nature of the degree of financial contagion, which is found to increase during the crisis period. For the analysis of volatility spillover VAR based spillover analysis introduced by Diebold and Yilmaz (2012) is used. On average, the commodity market receives and at the same time transmits maximum volatility from the gold market, followed by the equity and bond markets. Commodity market is a net transmitter of volatility vis-à-vis bond, foreign exchange and gold markets, and a receiver of volatility from the stock market. Rolling analysis of volatility spillover shows that the commodity market always remained a net transmitter of volatility to other markets. The pair-wise net directional spillover analysis shows that the commodity market transmits volatility to the bond, foreign exchange and gold markets during 2013-14. These results have important implications especially for optimal portfolio choice.

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