FINANCIAL CONTAGION AND VOLATILITY SPILLOVER:
AN EXPLORATION INTO INDIAN COMMODITY DERIVATIVE MARKET

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ABSTRACT

This study is an endeavour to measure the extent of financial contagion in the Indian financial market taking into accounts the effects of gold, stock, foreign exchange and government securities markets on Indian commodity derivative market. Subsequently, we examine directional volatility spillover -- the cause and/or effect of financial contagion -- from other financial markets to commodity market. Considering daily return of commodity spot indices and other asset markets for the period 2005 to 2015 and applying DCC-MGARCH model, we have estimated time varying correlation between commodity spot price and other financial assets. Regression analysis of conditional correlation on conditional volatilities across different markets elucidates the state of contagion in Indian asset markets vis-à-vis commodity market. The contagion is found to be the largest with gold market and least with government securities market. Our analysis of generalized VAR based volatility spillover shows that commodity and foreign exchange markets are volatility transmitter while government security, gold and stock markets are the net receivers of volatility. Volatility is transmitted to commodity market mostly from gold market and stock market. Such volatility spillover is found to have time varying nature, showing higher volatility spillover during global financial crisis and during large rupee depreciation of 2013-14. These results have significant implication for optimal portfolio selection.

Key words: Commodity, financial contagion, portfolio, DCC-GARCH, volatility spillover.

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

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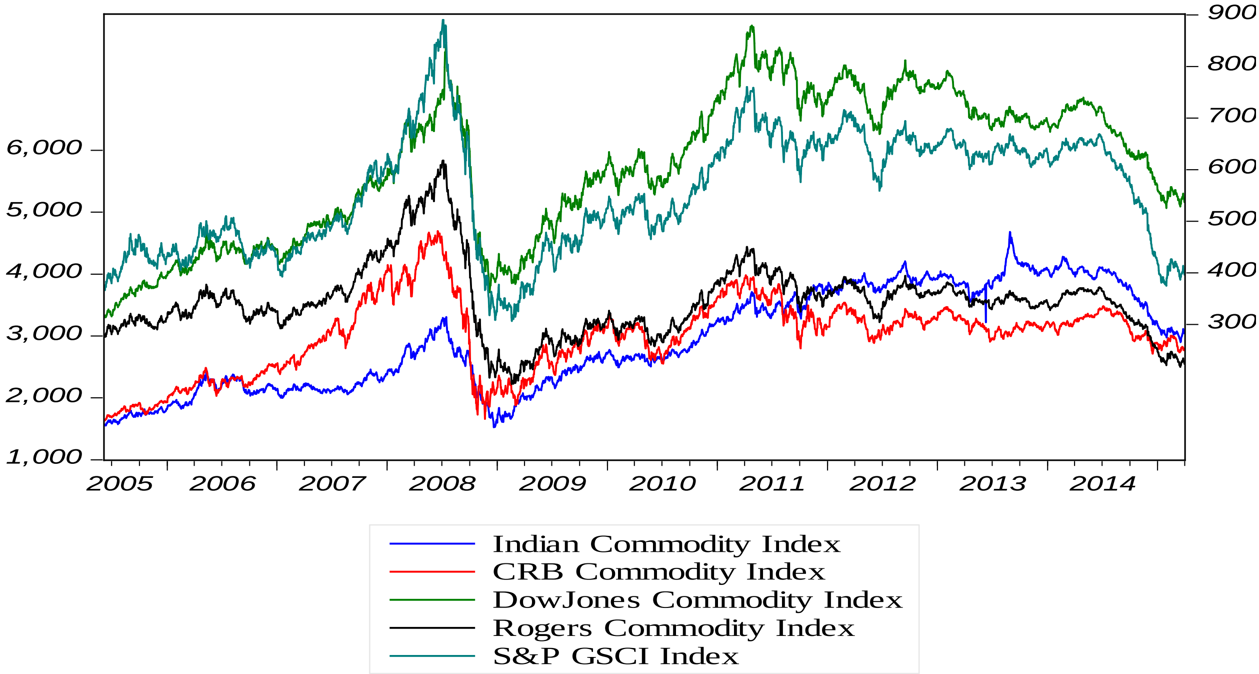
1. INTRODUCTION

Consideration of financial contagion is essential in the process of optimal portfolio selection. Financial contagion can be internal as well as international or external. Though, international financial contagion is more common in the literature, internal or domestic financial contagion is of equal importance especially to the investors and policy makers. From any external shock the most contagious asset market in the economy gets affected and then it gets transmitted to other asset markets as well. Similarly, if any internal shock crops up in any asset market, then due to inter-linkages, it spreads out to other markets. In a financially globalised world, if a crisis hits any market around the globe, foreign investors, being anxious, withdraw their funds mostly from the emerging market economies (EMEs) in search of a "safe haven" and thus transmit the negative shock to that asset market in EMEs. Following the foreign investors, domestic investors also lose their confidence and follow the suit by withdrawing their funds from other markets anticipating high amount of financial loss. Thus a negative shocks gets transmitted from a foreign source to any of the domestic asset market and then to other asset markets of the economy. During the global financial crisis period also, some asset markets were affected and then due to financial contagion, the effects got spread out to other asset markets.

Historically, portfolio construction process has been dominated mainly by two traditional asset classes: stocks and bonds. Of late, investors have become immensely attracted by the impressive returns of a "third asset class", commodities, while rummaging for non-traditional securities capable of augmenting returns, smoothing volatilities or both of a portfolio. Commodities have an interesting set of risk-return and correlation characteristic from a portfolio allocation perspective. Sometimes investors hold commodities as a hedge, especially during periods of stress, appraising its nature of positive co-movement with inflation and hence a tendency of backwardation. However, due to huge heterogeneity, commodities are considered to be risky as the risk-return profile of one commodity may drastically differ from that of another. A further source of risk is the contagion of financial markets and hence, volatility spillover from other markets to commodity market. If large number of investors holds commodities along with other conventional assets, the set of common state variables driving stochastic factors grows; and bad news 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).

However, in the current age of continual financial bubbles, financial economists predict that soon commodity market may experience a bubble of their own. After dominating the asset market in the first half of the first decade in twenty-first century, commodity market underwent a 48% plunge following the global financial crisis. However, it didn't fail to set a soon recovery and rose by 112% from the depth of crisis to the mid of 2011[3]. It is widely believed that the rise of China and India's economies from their extremely depressed twentieth century levels contributed legitimately to the world wide commodities boom. Figure 1 below shows the co-movement of Indian commodity index and four other major commodity indices of the world, namely: Commodity research Bureau (CRB) commodity index, Rogers Commodity Index, Dow Jones commodity index and Standard and Poor (S&P) commodity index.

Figure:1 Indian Commodity Index along with World major Commodity Indices



Note: Dow Jones commodity index and S&P GSCI index are plotted against the secondary axis.

Some economists firmly believe that commodity market bubble was equally responsible for the crisis. In the aftermath of the crisis, Indian economy had been pulled down by capital outflow and by falling exports and commodity prices. Now it's a debatable issue whether originated in the global commodity market, the shock hurt the Indian commodity market first

[3] Calculated on the basis of CRB commodity index.

and then got channelized to other Indian asset markets or Indian commodity market received the shock from any other Indian asset markets. This study attempts to find an answer for this question by examining the extent of financial contagion in a commodity market vis-à-vis other asset markets.

This paper is structured as follows: This introduction is followed by a review of contemporary, analogous and pertinent literature in section 2. Section 3 gives a brief idea of different econometric techniques used in this study. Description of data and an exhaustive econometric analysis is presented in section 4 and lastly summary and conclusions are presented in section 5.

2. LITERATURE REVIEW

A number of crises since 1990s have compelled 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 researchers studying causes and effects of financial contagion arisen at the time of stress (Longstaff, 2010). Though, there is voluminous literature on financial contagion[4] probably, there is no universally accepted definition of it. By distinguishing it from "interdependence", Forbes and Rigobon (2002), in a seminal paper; define contagion as a significant increase in cross market linkages after a shock to one market (or group of markets). Contagion can be identified with the general process of shock transmission across markets in both tranquil and crisis periods. In a more restrictive sense, contagion can be defined as the propagation of shocks between two markets in excess of what should be expected by fundamentals and considering co-movements triggered by the common shocks (Billio and Pelizzon, 2003). Many others define financial contagion as an interlude when there is significant increase in cross market linkages after a shock transpired in one market (see Dornbusch et al., 2000; Kaminsky et al. 2003; Bae et al., 2003 etc.).

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. Some studies focus on financial contagion by providing evidence of significant increase in cross market correlations and/or volatility (see Saches et al., 1996). There is a voluminous literature studying the cross market time-varying correlation especially at the time of stress and when

[4] 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, 2009 and many others.

transmission of shocks in evident[5]. Some other studies have contributed in the same line by connecting two literature of cross market correlation and contagion and also have referred increase in cross market correlation as contagion[6]. Baig and Goldfajn (1999) show that during the Asian crisis cross market correlation increased significantly and hence opines that there exists financial contagion. However, some researchers argue that after accounting for heteroskedasticity if there is no significant increase in correlation between asset returns then there is "no contagion only interdependence" (see Forbes and Rigbon, 2002; Bordo and Murshid, 2001; Basu, 2002 etc.). To decipher, 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). However, this proposition is challenged by a number of studies. Ang and Chen (2002) argue that volatility is not the factor driving market dependence upward in a crisis period while correlations are asymmetric for up-markets and down-markets. Bartman and Wang (2005) also argue that market dependence may not be generally conditional on volatility regimes and bias in a measure may occur only for some particular assumptions about the time series dynamics. Thus several controversies are inextricable with the literature of financial contagion[7].

Very few researchers have studied inter-market financial contagion. Studies measuring financial contagion considering commodity market along with other markets are even rare. However, in the recent past some studies have focused on the volatility and shock transmission between the energy and agricultural commodity markets, using different database and various econometric techniques[8]. Mensi et al. (2013) exerts a VAR-GARCH model to investigate the return links and volatility spillover between commodity and stock markets. They find significant correlation and volatility spillover across commodity and equity markets. In particular, volatility spillover from stock market to oil, gold and beverages markets and surging of volatility during crisis, are found in the study. This study goes in line with Malik and Hammoudeh (2007), Park and Ratti (2008), Arouri et al. (2011), Mohanty et

[5] See Aloui et al., 2011; Cappiello et al., 2006; Kim et al., 2005; Marçal et al., 2011; Phylaktis and Ravazzolo, 2005; Samarakoon, 2011

[6] See Ang and Bekaert, 1999; Chiang et al., 2007; Dooley and Hutchison, 2009; Forbes and Rigobon, 2002; Lessard, 1973; Longin and Solnik, 1995, 2001; Solnik, 1974; Syllignakis and Kouretas, 2011 etc.

[7] For a more detail study of problems associated with correlation approach of financial contagion see Chiang et al. (2007).

[8] See for example, Chen et al., 2010; Creti et al., 2013; Du et al., 2011; Hammoudeh et al., 2012; Ji and Fan, 2012; Mensi et al. 2013; Nazlioglu, 2011; Nazlioglu and Soytas, 2011; Nazlioglu et al., 2013 Serra, 2011 etc

al. (2011) and Silvennoinen and Thorp (2013) though contradict Hammoudeh and Choi's (2006) peroration of no volatility spillover from oil market to stock market.

To overcome the heteroskedasticity problem raised by Forbes and Rigbon (2002), and discussed earlier, many studies have used DCC-MGARCH model to calculate heteroskedasticty adjusted time varying correlation among assets and hence to measure the extent of financial contagion. Boyer et al. (2006) name contagion a phenomenon which can either be investor induced through portfolio rebalancing or fundamental based. The latter can be associated with what has been described by Forbes and Rigobon (2002) as interdependence, while the former case is described in behavioral finance literature as herding. Herding majorly occurs when a pool of investors starts following other investors, and has been defined as the "convergence of behaviors" (see e.g., Hirshleifer and Teoh (2003)). Some recent empirical studies[9] have used the DCC measure to investigate possible herding behavior as well as contagion effects on emerging financial markets during examined crisis periods. Chiang et al. (2007) have used DCC-MGARCH model to study the behavior of financial contagion considering stock market returns of Asian countries and two phases of Asian Crisis. To test for the link between stock and commodity markets volatility Creti et al. (2013) have used DCC-MGARCH model considering 25 different commodities and S&P 500 stock index for the time period 2001 to 2011, and found increase in correlation between commodities and stock especially during financial crisis; and thus, emergence of commodities as a substitute of stocks. Using VAR-BEKK-GARCH and VAR-DCC-GARCH models for the daily spot prices of eight major commodities, Mesnsi et al. (2014) have estimated dynamic volatility spillovers among these markets and also examined impacts of OPEC news announcements on the same. They find significant volatility spillover between energy and cereal markets; and significant impact of OPEC news announcement on oil as well as on oil-cereal relationship.

Though, DCC model is used extensively for exploring correlation dynamics in large systems, the simple dynamic structure may be too restrictive for many applications. For example volatility and correlation may response asymmetrically in the signs of past shocks. Similarly, presence of positive relationship between conditional volatility changes and correlation changes can have serious consequences for hedging effectiveness of portfolios (Anderson et al., 2004). This problem has motivated researchers like Franses and Hafner (2003), Pelletier

[9] See Bekaert and Harvey, 2000; Corsetti et al., 2005; Jeon and Moffett, 2010; Suardi, 2012; Syllignakis and Kouretas, 2011

(2004), and Cappiello, Engle and Shepard (2004) to extend the DCC model to more general dynamic correlation specification. For example, in Indian context, Kumar (2014) uses Vector Autoregressive (VAR) Asymmetric Dynamic Conditional Correlation Bivariate GARCH (VAR-ADCC-BVGARCH) model to investigate the return and volatility transmission between gold market and stock market[10]. The study fails to find any significant evidence of volatility spillover from gold to Indian stock market. However, the nature of time varying correlation, negative at the time of crises and positive for the rest of the period, is captured.

On the other hand, the literature of volatility spillover is relatively inadequate. To measure volatility spillover some studies have used univariate GARCH models (see Engle et al., 1990, Hamao et al., 1990, Susmel and Engle, 1994, and Lin et al., 1994, for example) and some others have used multivariate GARCH models[11]. Emphasizing on the importance of nature of different phases, some studies have used multivariate GARCH models combined with regime switching (Edwards and Susmel, 2001, 2003, and Baele, 2005). Though, multivariate GARCH models and VEC models are used extensively to study volatility spillover, these models suffers from interpretative limitations and most importantly, they fail to quantify spillovers in sufficient details (Barunik et al., 2014). A more sophisticated method based on forecast error variance decomposition from VAR has been introduce by Diebold and Yilmaz (2009) and further improved in Diebold and Yilmaz (2012) by using generalized VAR to eliminate the biases due to Cholesky ordering of variables. This method has got two advantages. Firstly, it allows the clear decomposition of total shocks or volatility among its different contributors. Secondly, by employing rolling window analysis it enables researchers to study different nature of volatility spillover in both crisis and non-crisis period (Prasad et al. 2014).

3. METHODOLOGY

In the financial market, volatility has shown to be autocorrelated and clustered[12] in different time periods. A good model to predict the future volatilities is essential since volatility is not directly observable. Univariate Generalized Autoregressive Conditional Hetroscedasticity (GARCH) model introduced by Bollerslev (1986) has been successful in capturing volatility clustering and predicting future volatilities (Hansen and Lunde, 2005). The dynamics of

[10] For his study, Kumar (2014) uses six Indian industrial sectoral stock indices.
[11] See Soriano and Climent (2006) for a survey.
[12] That is small changes tend to be followed by small changes, and large changes by large ones.

volatility of any financial return series across markets and across groups can be described by univariate GARCH(1,1) model (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 multivariate GARCH (MGARCH) models are widely used (Bauwens et. al., 2006). Here we shall briefly discuss Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation (DCC) models.

3.1 DCC-MGARCH Model

Let us consider a stochastic vector process of returns of N assets $\{r_t\}$ of dimension Nx1 with $E(r_t) = 0$. The information set ψ_{t-1}, as mentioned earlier, is generated by the observed series $\{r_t\}$ up to the time point t-1. The return series is described by the conditional mean vector $\boldsymbol{\mu}_t$ and an iid error process $\boldsymbol{\eta}_t$.

$$\mathbf{r}_t = \boldsymbol{\mu}_t + \boldsymbol{\eta}_t \tag{1}$$

where $\boldsymbol{\eta}_t = \mathbf{H}_t^{1/2}\mathbf{z}_t$ and $E(\boldsymbol{\eta}_t\boldsymbol{\eta}_t') = \mathbf{I}_N$. The conditional variance-covariance matrix of $\mathbf{r}_t$ is an NxN matrix denoted by $\mathbf{H}_t = [h_{ijt}]$. On the other hand, $\mathbf{z}_t$ is an Nx1 random vector with two moments $E(\mathbf{z}_t) = \mathbf{0}$ and $Var(\mathbf{z}_t) = E(\mathbf{z}_t\mathbf{z}_t') = \mathbf{I}_N$. With aforementioned specification and assuming $\mathbf{r}_t$ to be conditionally heteroskedastic, we may write,

$$\mathbf{r}_t = \mathbf{H}_t^{1/2}\mathbf{z}_t \tag{2}$$

given the information set ψ_{t-1}. Therefore, $Var(\mathbf{r}_t|\psi_{t-1}) = \mathbf{H}_t$. When $\mathbf{H}_t$ is the conditional variance matrix of $\mathbf{r}_t$, $\mathbf{H}_t^{1/2}$ is an NxN positive definite matrix, may be obtained by the Cholesky factorization of $\mathbf{H}_t$.

The CCC-MGARCH and DCC-MGARCH models emerge from the idea of modeling conditional variance and correlations instead of straightforward modeling of the conditional covariance matrix. Thus the conditional covariance matrix can be decomposed into conditional standard deviations and a correlation matrix as follows:

$$\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t \tag{3}$$

where $\mathbf{D_t} = \mathrm{diag}(h_{1t}^{\frac{1}{2}}, \dots \dots, h_{nt}^{\frac{1}{2}})$is the conditional standard deviation and $\mathbf{R_t}$ is the correlation matrix. To reduce the number of parameters and thus simplify the estimation, Bollerslev (1990) assumes that conditional correlations are constant and thus conditional covariances are proportional to the product of the corresponding conditional standard deviations. Thus the CCC-MGARCH model is defined as:

$$\mathbf{H_t} = \mathbf{D_t R D_t} = h_{it}^{\frac{1}{2}} h_{jt}^{\frac{1}{2}} \rho_{\mathbf{ijt}} \ ; i \neq j \tag{4}$$

However, the assumption of constant correlation may seem unrealistic in many empirical applications and hence Christodoulakis and Satchell (2002), Engle (2002) and Tse and Tsui (2002) propose a generalization of CCC-MGARCH model by making constant correlation matrix time dependant and hence the DCC-MGARCH model develops.

Then we go back to the equation number (3) and specify the conditional standard deviation and conditional correlation matrices as: $\mathbf{D_t} = \mathrm{diag}\left(h_{1t}^{\frac{1}{2}}, h_{2t}^{\frac{1}{2}}, \dots \dots, h_{nt}^{\frac{1}{2}}\right)$and since $\mathbf{R_t}$is the conditional correlation matrix of standardized error terms $\boldsymbol{\varepsilon_t}$,

$$\boldsymbol{\varepsilon_t} = \mathbf{D_t^{-1}} \boldsymbol{\eta_t} \sim N(0, \mathbf{R_t}) \tag{5}$$

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

$$\mathbf{R_t} = \mathbf{Q_t^{*-1} Q_t Q_t^{*-1}} \tag{6}$$

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

$$\mathbf{Q_t} = (1 - \theta_1 - \theta_2)\overline{\mathbf{Q}} + \theta_1 \boldsymbol{\varepsilon_{t-1}} \boldsymbol{\varepsilon_{t-1}^T} + \theta_2 \mathbf{Q_{t-1}} \tag{7}$$

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

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

In equation (7), θ_1 and θ_2 are scalars and must satisfy the following conditions:

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

For the purpose of estimation let us assume that the standardized errors $\boldsymbol{\varepsilon}_t$, are multivariate Gaussian distributed with the joint distribution function: $f(z_t) = \prod_{t=1}^{T} \frac{1}{(2\pi)^{n/2}} \exp\{-\frac{1}{2}\mathbf{z}_t^T\mathbf{z}_t\}$ where $\mathrm{E}(\mathbf{z}_t) = 0$ and $\mathrm{E}(\mathbf{z}_t\mathbf{z}_t^T) = \mathbf{I}$. We know that $\boldsymbol{\eta}_t = \mathbf{H}_t^{1/2}\mathbf{z}_t$. Then the log-likelihood function becomes:

$$\ln(L(\Phi) = -\frac{1}{2}\sum_{t=1}^{T}\left(n\ln(2\pi) + \ln(|\mathbf{H}_t|) + \boldsymbol{\eta}_t\mathbf{H}_t^{-1}\boldsymbol{\eta}_t^T\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}\left(n\ln(2\pi) + \ln(|\mathbf{D}_t\mathbf{R}_t\mathbf{D}_t|) + \boldsymbol{\eta}_t\mathbf{D}_t^{-1}\mathbf{R}_t^{-1}\mathbf{D}_t^{-1}\boldsymbol{\eta}_t^T\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}\left(n\ln(2\pi) + 2\ln(|\mathbf{D}_t|) + \ln(|\mathbf{R}_t|) + \boldsymbol{\eta}_t\mathbf{D}_t^{-1}\mathbf{R}_t^{-1}\mathbf{D}_t^{-1}\boldsymbol{\eta}_t^T\right) \quad (8)$$

where Φ denotes paramenters of the model. Let the parameters, $\boldsymbol{\Phi}$, be divided un tow groups; $(\boldsymbol{\phi}, \boldsymbol{\theta}) = (\boldsymbol{\phi_1}, \boldsymbol{\phi_2}, \ldots\ldots, \boldsymbol{\phi_n}, \boldsymbol{\theta})$, where $\boldsymbol{\phi_i} = (\alpha_{0i}, \alpha_{1i}, \ldots, \alpha_{qi}, \beta_{1i}, \beta_{2i}, \ldots, \beta_{pi})$ are the parameters of the univariate GARCH model for the ith asset class and $\boldsymbol{\theta} = (\theta_1, \theta_2)$are the parameters of the correlation structure or DCC parameters. DCC-MGARCH model 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 models $\boldsymbol{\phi_i}$s are estimated for each asset class and then in the second stage parameters θ_1 and$\theta_2$are estimated. We have discussed the estimation technique of DCC-MGARCH(1,1) model. The generalized model DCC-MGARCH(p,q) can be estimated in the same manner.

3.2 Financial Contagion

From the DCC-MGARCH (1,1) model we obtain pair wise time varying conditional correlations. And from the univariate GARCH models we get a series of conditional standard deviation or volatility for each asset. Following Chong et al. (2008), Ahmed et al. (2013, 2014) we then regress conditional correlation on conditional volatilities.

$$\rho_{ijt} = \alpha + \beta_1 h_{it} + \beta_2 h_{jt} + \epsilon_t \quad (9)$$

A positive β_i, obtained by estimating the above model with least square technique, would suggest that conditional correlation increases at the time of high volatility and hence evidence in favour of financial contagion. In case of multiple regressions, adjusted R^2 or $\overline{R^2}$measures the goodness of fit. Here we can interpret the same as the degree of financial contagion.

3.3 Diebold Yilmaz (DY) VAR Based Spillover Index

Here we follow DY spillover index measuring the directional spillovers in a generalized VAR framework that excludes the possible dependence of the results on ordering driven by Cholesky factor orthogonalization.

Let us consider a covariance stationary N-variable VAR(p) process as

$$\mathbf{x_t} = \sum_{i=1}^{p} \emptyset_{\mathbf{i}} \mathbf{x_{t-1}} + \boldsymbol{\varepsilon}_{\mathbf{t}} \tag{10}$$

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:

$$\mathbf{x_t} = \sum_{i=0}^{\infty} \mathbf{A_i} \boldsymbol{\varepsilon}_{\mathbf{t-i}} \tag{11}$$

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, we require orthogonal innovations for variance decomposition. Orthogonality can be achieved by Cholesky factorization. But then variance decomposition becomes highly sensitive to variables ordering. The generalized VAR approach introduced by Koop, Peseran and Potter (1996) and Peseran and Shin (1998), hereafter KPSS, solves this problem.

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

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=o}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=o}^{H-1} \left(e_i' A_h \Sigma e_j\right)} \tag{12}$$

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 we normalize each element of variance decomposition matrix by dividing them by respective row sums. Then the new H-step-ahead variance decomposition is

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{13}$$

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 (13) we can calculate total spillover index, which measures the contribution of spillovers of volatility shocks across N asset classes to the total forecast error variance. The total spillover index denoted by $S^g(H)$ is

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

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

$$S_{i.}^{g} = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} . 100 = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} . 100 \tag{15}$$

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

$$S_{i.}^{g} = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} . 100 = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} . 100 \tag{16}$$

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:

$$S_{i}^{g} = S_{.i}^{g} - S_{i.}^{g} \tag{17}$$

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:

$$S_{ij}^{g} = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)} \right) . 100 = \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} \right) . 100 \tag{18}$$

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. EMPIRICAL RESULTS AND DISCUSSION

4.1 Data and Descriptive Statistics

For our analysis, we have considered daily close returns from June 7, 2005 to March 31, 2015. The selection of time period for our analysis is to some extent purposive in the sense that the starting date is selected on the basis of availability of commodity index data. We have used commodity index data from the database of Multi Commodity Exchange, India and they started reporting commodity indices from June 7, 2005. In this analysis, we have also used data of daily rupee/dollar exchange rate collected from Reserve Bank of India's database, daily data of gold price in India collected from World Gold Council database, daily government securities index data constructed by National Stock Exchange, India and SENSEX data of Bombay Stock Exchange (BSE). The period of time we choose for our analysis allows us to investigate the sensitivity of commodity returns vis-à-vis returns of other financial assets to the following major effects: the Subprime crisis of 2007-09, Eurozone crisis of 2010-12, and large rupee depreciation of 2013-14.

It is customary to calculate return of an asset as the logarithmic value of the ratio of two consecutive prices (see Figure 2 in Appendix 1 for the graphical representation). More precisely, the continuously compounded daily returns are computed using the following logarithmic filter:

$$r_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{19}$$

To have a gross idea of basic feature of data we should check the descriptive statistics for each series. Table 1 below shows relevant descriptive statistics for each daily return series. The data suggest that over the sample period, stock market offers highest average daily returns (0.046%) and exchange rate arbitrage offers least reruns (0.012%). However, this stock market is the most risky, as approximated by a standard deviation of 1.27% followed by the gold market (1.07%) and commodity market (0.99%). This certainly gives indication towards the conjecture that high uncertainty or risk is associated with high potential returns. The commodity market offers medium return with a moderate risk; and hence investors can use commodity as a "diversifier" in their portfolios. It is important to look into the skewness coefficients to understand the nature of statistical distribution. Interestingly, commodity, exchange rate and government securities returns are positively skewed, while gold and stock returns show negatively skewed distribution. For all markets, kurtosis values are much higher than that of a normal distribution implying significant departure from normal distribution. This fact can be confirmed by the Jarque-Bera test with null hypothesis of normality distributed returns. In all cases, the null hypothesis of is persuasively rejected. However, we should remember that these facts are relevant only for the unconditional distributions of return series. The Ljung-Box Q statistic test the null hypothesis of no serial correlation or no autocorrelation and is calculated using upto 10 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.

Table:1 Descriptive Statistics

	Commodity Index	Exchange Rate	Gold Price	Government Securities Index	Stock Index
Mean	0.000215	0.000117	0.000453	0.000164	0.000461
Std. Dev.	0.009979	0.004311	0.010664	0.007368	0.012747
Skewness	1.099377	0.104052	-0.27792	0.016001	-0.20365
Kurtosis	41.23012	10.00512	6.92503	13.40685	9.795132
Jarque-Bera	187696.2***	6286.717***	2011.497***	13862.86***	5931.483***
Q(10)	46.964***	35.375***	29.661***	317.47***	97.740***
Q^2(10)	318.33***	1019.1***	467.36***	472.3***	1198.2***
BG-LM Test	20.15117***	13.60745***	15.68209***	215.9399***	62.20436***
ARCH-LM Test	231.2622***	379.0894***	101.0645***	220.3142***	190.2782***

Note: (a) Q and Q^2 are Ljung-Box Q statistics for return series and squard return series respectively.
(b) BG-LM test and ARCH-LM test show Breusch Godfrey serial correlation LM test and Engle (1982) test for conditional heteroskedasticity respectively. Both are calculated for the first lag only.
(c) *** implies significance at 1% level, ** implies significance at 5%, and * implies significance at 10% level

Table 1 reports 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 in the squared returns is significant for each daily return series indicating strong nonlinear dependence or presence of heteroskedastic return series. Thus ARCH type of model can be safely used for these daily return series. We have also done two confirmatory tests. Significant Breusch-Godfrey serial correlation LM test statistics for each daily return series confirms the presence of autocorrelation. Similarly, the Engle (1982) test for conditional heteroskedasticity shows that ARCH effects are significantly present in all the daily return series, which clearly supports our decision to use the GARCH based approach to examine the return and volatility transmissions among the asset markets.

Table 2 below presents different tests for stationarity of daily return series. Here we have performed four tests, namely Augmented Dicky Fuller (ADF) unit root test, Phillips Perron (PP) unit root test, Kwiatkowski Phillips Schmidt Shin (KPSS) stationarity test and Zivot-Andrews unit root test with structural breaks. ADF test and PP test rejects the null hypothesis of presence of unit root and hence each daily return series is found to be stationary. KPSS test is a confirmatory test with a null hypothesis of stationarity. KPSS test accepts the null hypothesis for each daily return series. Zivot and Andrews (1992) propose three models and in all three models for testing unit root test, the null hypothesis is that the series contains a unit root with a drift that excludes any structural break; and the alternative hypothesis is that the series is a trend stationary process with a one-time break occurring at an unknown point of time. Table 2 below shows that for each series, null hypothesis of presence of unit root is rejected for Zivot Andrews test. It is interesting that except for the exchange rate, for all other markets break dates fall in the interlude of financial crisis. For the exchange rate break date is found on the date when rupee was at its pinnacle[13].

Table:2 Unit root Tests

	ADF Test	PP Test	KPSS Test	Zivot Andrews Test
Commodity Index	-39.928***	-51.0514***	0.084293	-40.32372*** (24th Dec, 2008)
Exchange Rate	-51.8388***	-52.1147***	0.050696	-23.79214*** (29th Aug, 2013)
Gold Price	-51.6235***	-51.5531***	0.0392	-51.67665*** (7th Jul, 2007)
Government Securities Index	-29.9934***	-89.1908***	0.031967	-38.42199*** (7th Jan, 2009)
Stock Index	-32.156***	-47.8907***	0.093062	-32.47446*** (21st Nov, 2008)

Note: (a) For ADF and Zivot Andrews tests standard t-statistics are reported.
(b) For PP test adjusted t statistics are reported and significant statics are chosen on the basis of MacKinnon (1996) probability values.
(c)For KPSS test, LM statistics are reported.
(d)For Zivot Andrews test structural break points are given in parentheses.
(e)*** implies significance at 1% level, ** implies significance at 5%, and * implies significance at 10% level.

Table 3 below shows the unconditional correlation matrix. It is seen that commodity index is relatively highly correlated with gold price and stock price. It is captivating to see that commodity returns has a negative correlation with exchange rate and Gsec returns while it has a positive correlation with gold price and stock price. Another interesting fact is that though gold is also a type of commodity, it bears a negative correlation with stock returns. This is true even when the correlation coefficients with exchange rate return are considered. The stock return, on the other hand, is also highly negatively correlated with the exchange rate returns. Gsec returns has a low correlation with all other assets returns, indicating that government securities can be used as a "safe haven" in an asset portfolio. But this correlation

[13] On August 28, 2013 Indian rupee experienced greatest fall and had gone down to 68.825 against the US dollar.

analysis is unconditional and static in nature. Since it is static, it fails to capture effects of different unforeseen events.

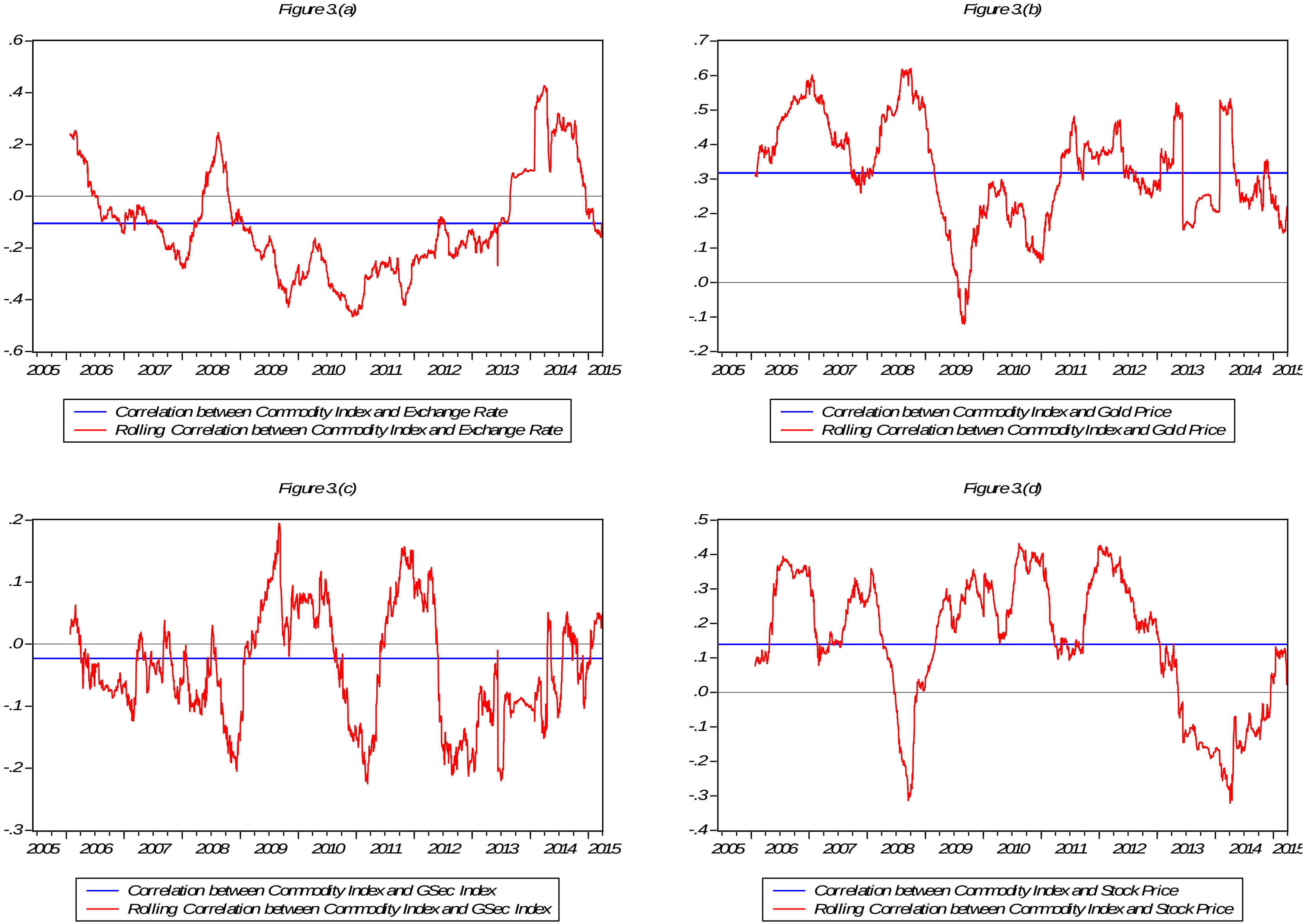
Table: 3 Unconditional Correlation

	Commodity Index	Exchange Rate	Gold Price	Government Securities Index	Stock Index
Commodity Index	1				
Exchange Rate	-0.10532*** (-5.86801)	1			
Gold Price	0.317153*** (18.52923)	0.108191*** (6.029974)	1		
Government Securities Index	-0.02313 (-1.28192)	-0.03205* (-1.77681)	-0.05096*** (-2.82714)	1	
Stock Index	0.139491*** (7.805175)	-0.38872*** (-23.3762)	-0.03176* (-1.76088)	0.0682*** (3.787606)	1

Note: (a) t-statistics are mentioned in parentheses.
(b)*** implies significance at 1% level, ** implies significance at 5%, and * implies significance at 10% level.

To understand the changes in correlation pattern during different crises, we have also calculated 200 day rolling correlation for each asset pairs. Since our main focus is to study the behavior of the commodity market, in figure 3 we have plotted 200 day rolling correlation of different asset returns with the commodity returns. Correlation between exchange rate and commodity returns is found to be negative for most of the time though altered during the financial crisis and large rupee depreciation of 2013-14. Correlation between commodity and gold returns is always positive except for a small period of financial crisis. Correlation between Gsec and commodity returns is always volatile in nature although negative in sign for most of the time. The pattern of correlation between commodity and stock returns is exactly opposite to that between commodity and exchange rate returns. Though it remained positive for most of the time, during financial crisis and rupee depreciation of 2013-14 it became negative. From, the rolling correlation analysis though we have an overall idea of dynamic correlation between two asset returns, this unconditional correlation series should not be used for an analysis of financial contagion or optimal portfolio selection for two reasons. Firstly, rolling correlation analysis is very sensitive to the selection of rolling window. Secondly, it fails to capture the heteroskedastic nature of the return series. Thus for

Figure 3: 200 day Rolling Correlation.



our analysis of financial contagion we have decided to use conditional correlation series obtained from MGARCH analysis.

4.2 Analysis of Dynamic Correlation and Financial Contagion

Table 4 below reports results of CCC-MGARCH and DCC-MGARCH models. The upper part of the table shows univariate GARCH results for each daily return series. The two coefficients of univariate GARCH models, namely α and β, are found to be significant for each asset class. The sum of α and β implies the overall persistence of the series. Since for every daily return series α and β are positive and $(\alpha + \beta)$ is found to be less than one, the stability condition is said to be satisfied. A high and close to one value of $(\alpha + \beta)$ gives evidence in favour of persistence of shocks or persistence of volatility, i.e. if any shock appears in these markets, it takes longer time to die down. From the table it can also be seen that two DCC parameters, θ_1 and θ_2 are positive and significant; and $(\theta_1 + \theta_2)$ is also found to be less than one. Thus, the overall stability condition of DCC-MGARCH model is also satisfied. Significance of DCC parameters implies a substantial time-varying co-movement.

In the lower part of the table conditional correlations of commodity index with other assets are reported for both CCC-MGARCH and DCC-MGARCH models. For DCC-MGARCH model, we have calculated mean conditional correlation of commodity return with other 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 model then it is meaningful to estimate CCC-MGARCH model. None of the correlation is found to be zero and thus DCC-MGARCH is the appropriate model here. It is interesting to note that correlation coefficients obtained from CCC-MARCH and DCC-MGARCH models do not differ significantly in terms of magnitude and sign; and thus give evidence in favour of flawless estimation of both models. Although conditional correlations are higher than unconditional correlations, their sign remain unaltered.

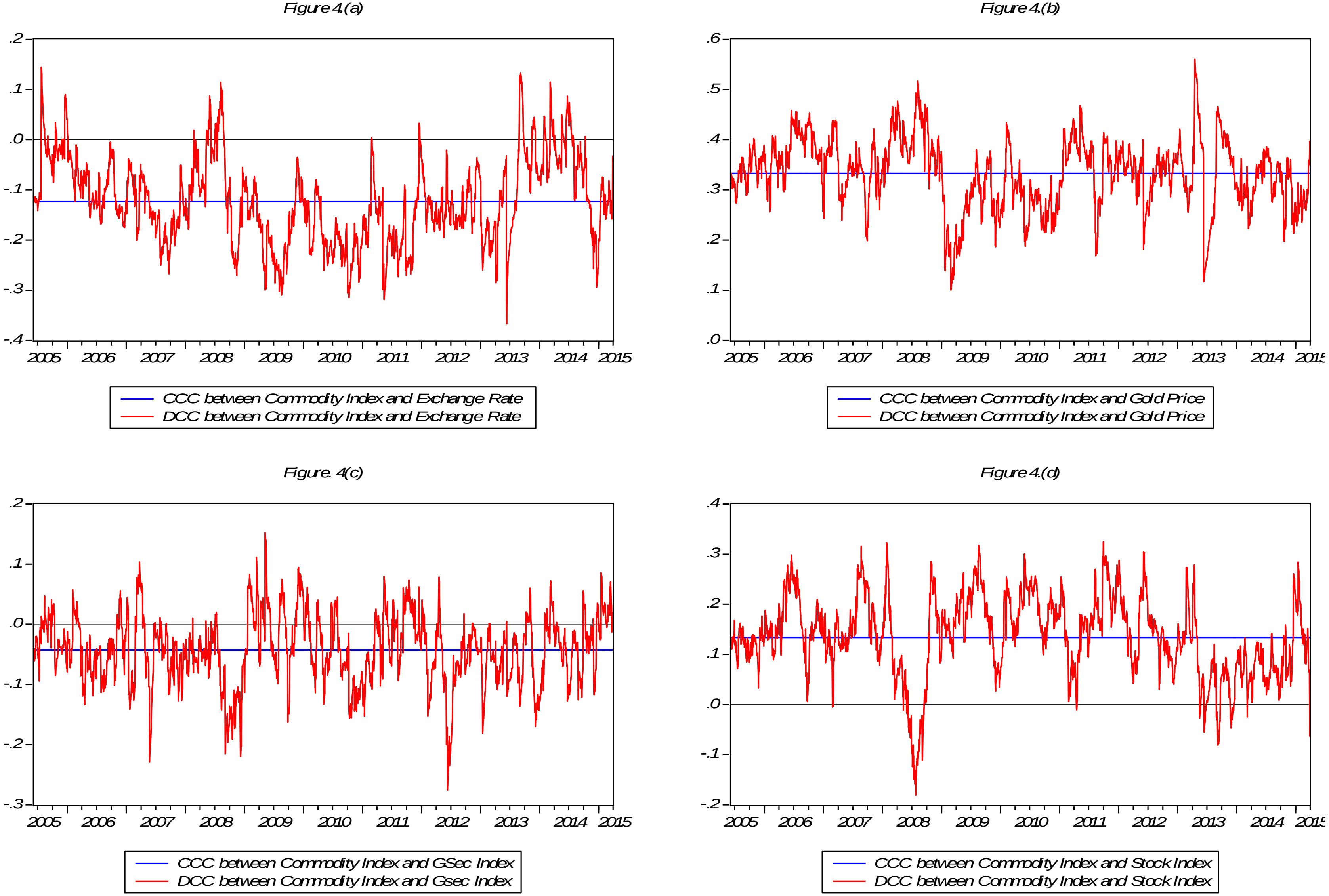
In the literature, contagion is defined as significant increases in cross market correlations during the turmoil period, while any continued increase in cross market correlation at high levels is referred as interdependence. This is mainly because it is assumed that if there is a significant increase in correlation, there is a strengthening of transmission mechanisms between the two markets under consideration (see Collins and Biekpe, 2003; Forbes and Rigobon, 2002). To confirm this, we now analyze the estimated dynamic conditional correlation. Conditional correlations (both constant and dynamic) are shown in figure 3.

Table: 4 CCC-MGARCH and DCC-MGARCH results with average Correlations.

	CCC-MGARCH					DCC-MGARCH				
	Commodity Index	**Exchange Rate**	**Gold Price**	**Government Security Index**	**Stock Index**	**Commodity Index**	**Exchange Rate**	**Gold Price**	**Government Security Index**	**Stock Index**
μ	5.39E-05 (0.412845)	-9.11E-06 (-0.152024)	0.000265* (1.6769)	0.00033*** (4.21986)	0.000845*** (5.550561)	4.03E-05 (0.217836)	1.41E-05 (0.249608)	0.000338** (2.140407)	0.000323*** (3.158759)	0.000815*** (4.595350)
ω	8.57E-07*** (5.885968)	2.45E-07*** (10.05371)	8.87E-07*** (6.65504)	1.20E-06*** (11.61662)	1.94E-06*** (7.697098)	8.19E-07*** (3.620011)	2.21E-07*** (3.141093)	9.16E-07** (2.034635)	1.19E-06*** (3.768450)	1.88E-06*** (3.229232)
α	0.058748*** (22.29055)	0.071123*** (14.54964)	0.041851*** (12.38704)	0.187062*** (22.52277)	0.074442*** (14.21827)	0.060934*** (3.536532)	0.082989*** (6.683661)	0.047413*** (4.397705)	0.187538*** (6.877660)	0.082431*** (6.278558)
β	0.934096*** (282.5845)	0.915872*** (174.6334)	0.950232*** (265.7461)	0.81164*** (147.2014)	0.911657*** (163.3532)	0.932845*** (56.65161)	0.908127*** (73.61097)	0.944886*** (72.46170)	0.811340*** (32.35832)	0.905511*** (64.32363)
α+β	0.992844	0.986995	0.992083	0.998702	0.986099	0.993779	0.991116	0.992299	0.998923	0.987942
θ_1								0.015620*** (6.558015)		
θ_2								0.951165*** (93.95479)		
Corr(Commodity Index, Exchange Rate)			-0.12348*** (-8.04712)					-0.123624*** (-80.49825)		
Corr(Commodity Index, Gold Price)			0.332613*** (24.26903)					0.332567*** (266.6531)		
Corr(Commodity Index, Government Security Index)			-0.04255*** (-2.57834)					-0.042285*** (-40.38605)		
Corr(Commodity Index, Spot Index)			0.133969*** (8.524783)					0.135749*** (92.76282)		

Note: (a) z-statistics are mentioned in parentheses. For correlations of DCC model t-statistics are mentioned in parentheses.
(b)*** implies significance at 1% level, ** implies significance at 5%, and * implies significance at 10% level.

Figure 4: Constant and Dynamic Conditional Correlations



The overall trend of conditional correlations does not differ significantly from that of the unconditional correlation. However, in many cases unconditional correlation fails to capture significant market movements and in some other cases it overestimates correlation and thus overemphasizes significance of some shocks.

For example, if we notice the dynamic correlation between commodity index and exchange rate (in figure 4.(a)), we find similarity with the unconditional (rolling) correlation. However, in unconditional case, as heteroskedasticity is pushed aside, correlation is overestimated especially during financial crisis of 2007-09 and rupee depreciation of 2013-14. The correlation between the two touched its lowest value in the mid 2013 and this incident was not unveiled from the unconditional correlation. Similarly, while studying conditional correlation between commodity index and gold price (see figure 4.(b)), we notice a huge ups and downs in 2013. Even this phenomenon was not revealed from the unconditional correlation. The correlation between the two prior to the financial crisis, was overestimated in the case of unconditional correlation. So is the case for correlation between commodity index and stock price in 2013-14. The reason behind this imprecise exploration of market co-movements is ignorance of heteroskedasticity and conditional behavior of the daily return series. When a series is conditional upon its past value, it evidently captures all information available till that time period; and hence it is appropriate to consider conditional correlation for the analysis of financial contagion or optimal portfolio selection.

Table 5 below displays results of an analysis of financial contagion. Here we have estimated equation (9) using ordinary least squares technique. Coefficients of volatilities of commodity in all four cases are found to be negative, implies that conditional correlation between commodity and other assets decreases when volatility increases in the commodity market. When considered along with commodity market volatility, exchange rate, Gsec and stock returns volatilities show significant positive impact on their respective correlations with commodity returns. This signifies that when volatilities increase in these markets, correlations with commodity market also increase and gives evidence in favour of existence of financial contagion between commodity market and other asset markets. Other than commodity market, financial contagion is seen to exist between Forex and gold markets, gold and stock markets and between Gsec and stock markets. Here adjusted R^2 or $\bar{R}^2$ measures the degree of financial contagion. If we consider the financial contagion of commodity market vis-à-vis other asset markets, it is maximum with gold and least with Gsec market.

Table:5 Existence and Extent of Financial Contagion

	Constant	h_i	h_j	$\bar{R}^2$
Commodity Index--Exchange Rate	-0.10389*** (-23.4061)	-2.89009*** (-7.58788)	1.68713* (1.772027)	0.018096
Commodity Index--Gold Price	0.307556*** (82.23817)	-5.42061*** (-16.1191)	7.371216*** (17.57908)	0.105327
Commodity Index--Government Security Index	-0.03878*** (-14.3265)	-0.78929*** (-3.01081)	0.554739* (1.905327)	0.003193
Commodity Index-- Stock Index	0.13161*** (34.81747)	-3.54792*** (-9.08991)	3.19809*** (10.50074)	0.039686
Exchange Rate--Gold Price	0.004291 (1.114111)	8.40891*** (10.94734)	2.61516*** (6.825251)	0.088954
Exchange rate--Government security Index	5.39E-05 (0.020323)	-1.24489** (-2.18553)	-0.26431 (-1.04439)	0.001818
Exchange Rate--Stock Index	-0.32353*** (-106.339)	-11.9391*** (-18.4748)	-1.09063*** (-5.40649)	0.137271
Gold Price--Government Security Index	0.023325*** (7.694132)	-3.1611*** (-11.1614)	-0.71761*** (-2.84467)	0.050364
Gold Price--Stock Index	-0.00048 (-0.10891)	-3.35088*** (-6.20017)	7.13E-01** (2.107381)	0.013707
Government Security Index--Stock Index	0.008113*** (3.01803)	2.365752*** (7.797846)	1.57747*** (7.400784)	0.059226

Note: (a) t-statistics are mentioned in parentheses.
(b)*** implies significance at 1% level, ** implies significance at 5%, and * implies significance at 10% level.

Thus we expect to find high volatility spillover between commodity market and gold market and relatively low volatility spillover between commodity market and Gsec market. The above feature can also be observed from the figure 5 where conditional correlations between commodity index and other assets are plotted along with conditional volatilities. It gives a pictorial representation of financial contagion. From the figure, it can be seen that in these markets, whenever a spike is seen in conditional volatilities, i.e. whenever volatilities increase, conditional correlations also seen to be in upright.

However, the degree of financial contagion may not be constant over time. To understand the time-varying nature of financial contagion we have estimated 200 day rolling regression and reported the R^2 values. From figure 6.(a), it can be seen during financial crisis contagion between commodity and forex markets increased. However, highest contagion effect is seen during the rupee depreciation of 2013-14. If we consider financial contagion between commodity and gold markets in figure 6.(b) significant contagion is seen during financial

Figure 5: Conditional Volatility and Conditional Correlation

Figure 5(a)

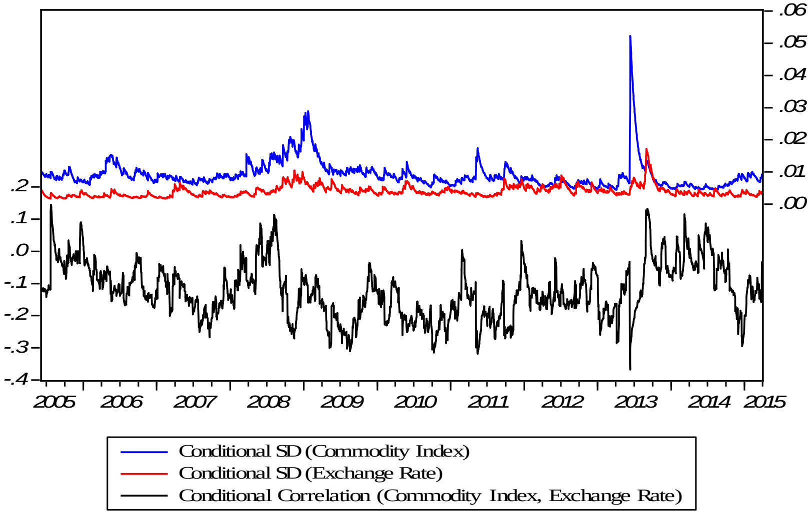


Figure 5(b)

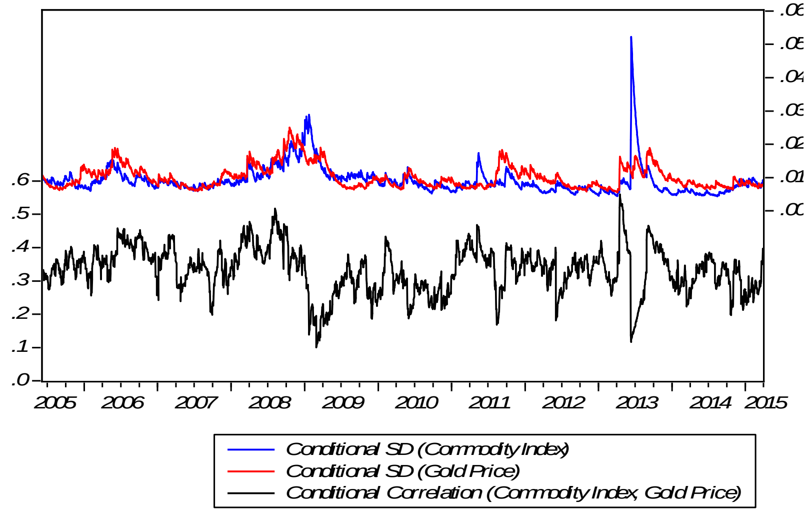


Figure 5(c)

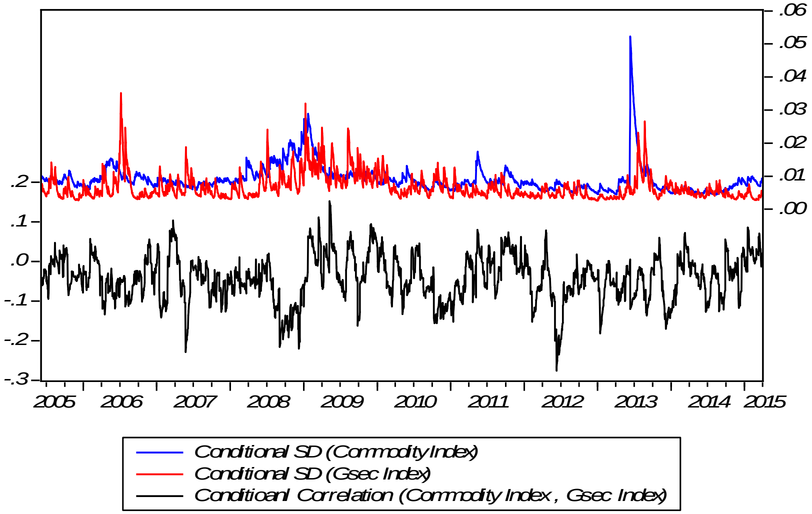


Figure 5(d)

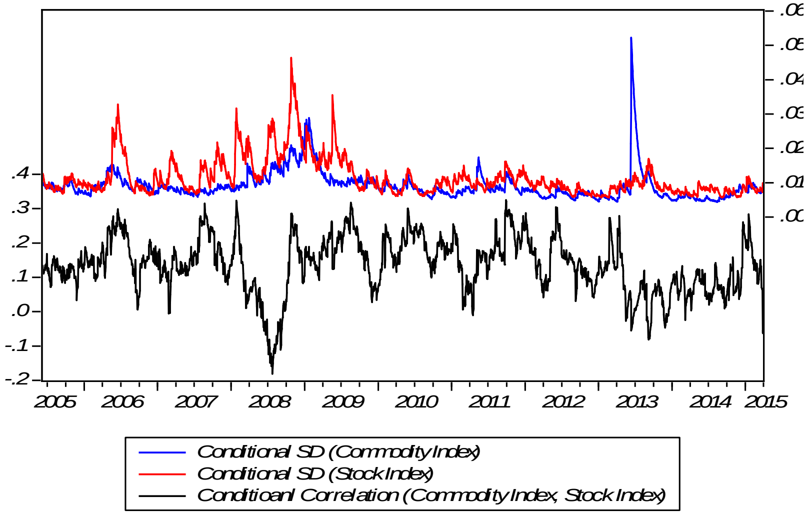


Figure 6 Financial Contagion

Figure 6.(a)

Degree of Financial Contagion between Commodity and Forex Markets

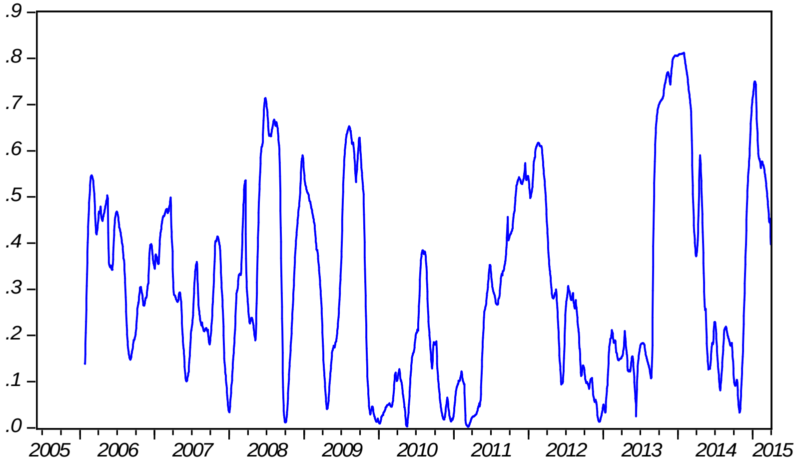


Figure 6.(b)

Degree of Financial Contagion between Commodity and Gold Market

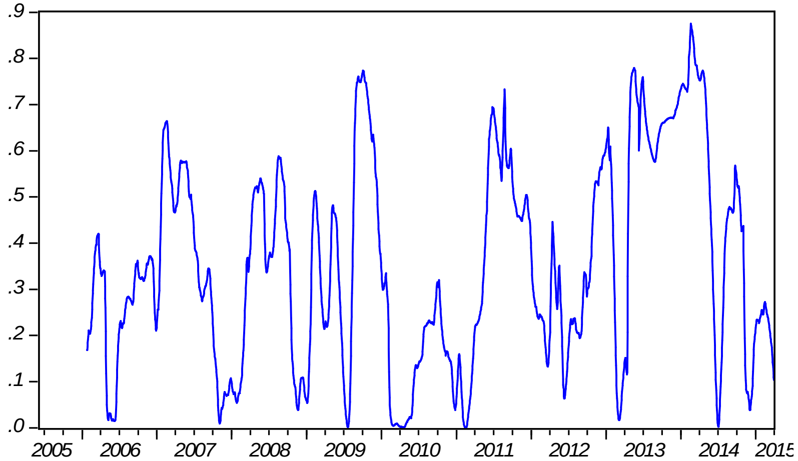


Figure 6.(c)

Degree of Financial Contagion Between Commodity and GSec Markets

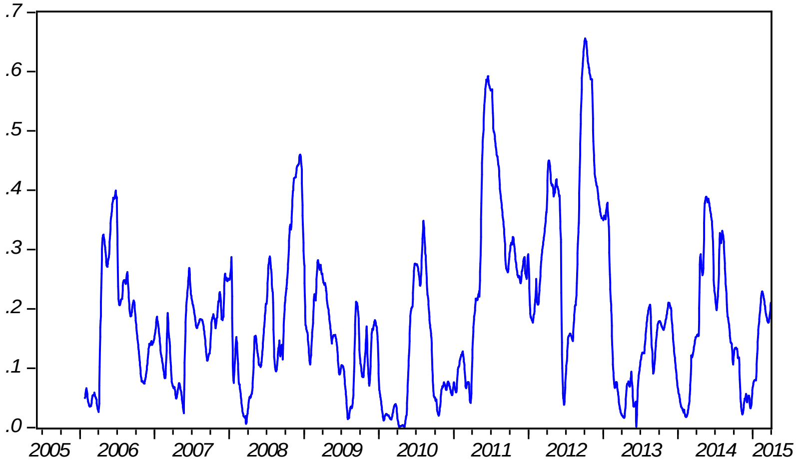
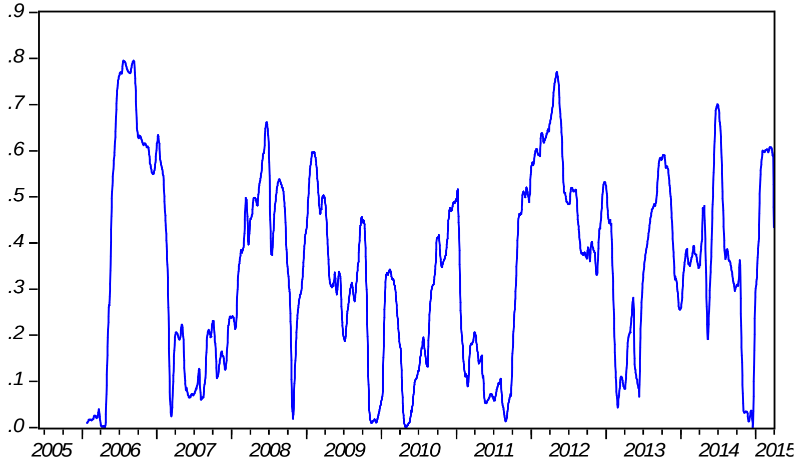


Figure 6.(d)

Degree of Financial Contagion between Commodity and Stock Markets



crisis, second phase of Eurozone crisis and then during the period of large rupee depreciation. However, the contagion between commodity and Gsec markets was not high during the financial crisis as was seen for other markets (see figure 6.(c)). The contagion between these two markets was mostly seen during the Eurozone crisis. Lastly, in figure 6.(d) we show contagion between commodity and stock markets. It was significantly high throughout the period of study except for the interim period of 2010-11. Thus we have found significant financial contagion between commodity market and other asset markets especially during two crises and period of large rupee depreciation. Here we should put a caveat that this dynamic analysis of financial contagion is sensitive to the selection of rolling window. However, there is no other technique available to check the extent of financial contagion considering conditional volatilities and conditional correlations.

4.3 Analysis of Volatility Spillover

4.3.1 Unconditional Patterns: the Full Sample Volatility Spillover Analysis

Table 6 below shows the volatility spillovers among different asset markets. We have calculated forecast error variance and hence volatility spillover indices on the basis of VAR of order 2 and generalized variance decomposition of 10 day ahead volatility forecast errors[14]. In the table, jth 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 ith market to all other markets and total volatility spillovers measured from all other markets to ith market respectively. Net volatility spillovers are calculated simply by subtracting "FROM spillover" from "To spillover". It measures total contributions of ith market in the total volatility spillover. Total spillover index is also shown in the table. It is approximately the grand off diagonal column sum (or grand off diagonal row sum) relative to the grand column sum including 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. Transmission of volatility is highest for stock market (15.45%) followed by forex market (14.49%) and Gold market (14.35%).

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

Table 6: Volatility Spillover (unconditional)

	Commodity Index	Exchange Rate	Gold Price	Government security Index	Stock Price	From others
Commodity Index	83.601	1.081	13.049	0.092	2.177	16.399
Exchange Rate	0.839	85.302	1.017	0.16	12.682	14.698
Gold Price	10.128	0.894	88.724	0.208	0.046	11.276
Government security Index	0.542	0.041	0.189	98.677	0.551	1.323
Stock Price	1.864	12.473	0.091	0.415	85.157	14.843
To others	13.373	14.489	14.346	0.875	15.455	Total Volatility
Contribution Including own	96.975	99.791	103.07	99.552	100.613	=58.539 =11.708%
Net Volatility spillover	-3.026	-0.209	3.07	-0.448	0.612	

On the other hand, the last column labeled "from others" shows the acquiescence of volatility by each of the five asset markets. Commodity market receives highest volatility from other markets (16.4%), followed by stock market (14.84%) and forex market (14.7%). It is noteworthy that stock market transmits maximum volatility to other markets and also receives high amount of volatility from other markets; and thus one may infer that stock market is most bustling market. At the same time, Gsec market due to its risk free nature, is the most inactive market. The net spillover is obtained by subtracting contributions "from others" from contribution "to others". As for the net directional volatility spillover, the largest is of gold market followed by commodity market and stock market. It is conspicuous that commodity, forex and Gsec markets are net receivers of volatility whereas gold and stock markets are net transmitters of volatility. Next consider the total (non-directional) volatility spillover, which is a distillation of the various directional volatility spillovers into a single index. It measures, on average, across the entire sample 11.71% of the volatility forecast error variance in all five asset markets comes from spillovers.

Now, we are doing a comparative analysis between degree of financial contagion and the extent of volatility spillover in commodity market. If we consider the first row of table 5, it shows volatility transmitted from other markets to the commodity market. The commodity market receives maximum volatility from the gold market and minimum volatility from Gsec market. Similarly, if we consider the first column, then it shows volatility transmitted from commodity market to other markets. From commodity market maximum volatility is dispatched to the gold market and least to the Gsec market. This information is taken in column 3 and 4 in table 6 below and also the total spillovers are calculated in column 5.

Table:6 Financial Contagion and Volatility Spillover, a Comparison

	Degree of Financial Contagion	**Rank**	**Volatility Spillover from i to j**	**Volatility Spillover from j to i**	**Total Volatility Spillover Between i and j**	**Rank**
	(1)	(2)	(3)	(4)	(5)	(6)
Commodity Index--Exchange Rate	1.8096%	3	0.839%	1.081%	1.92%	3
Commodity Index--Gold Price	10.5327%	1	10.128%	13.049%	23.177%	1
Commodity Index--Government Security Index	0.3193%	4	0.542%	0.092%	0.634%	4
Commodity Index-- Stock Index	3.9686%	2	1.864%	2.177%	4.041%	2

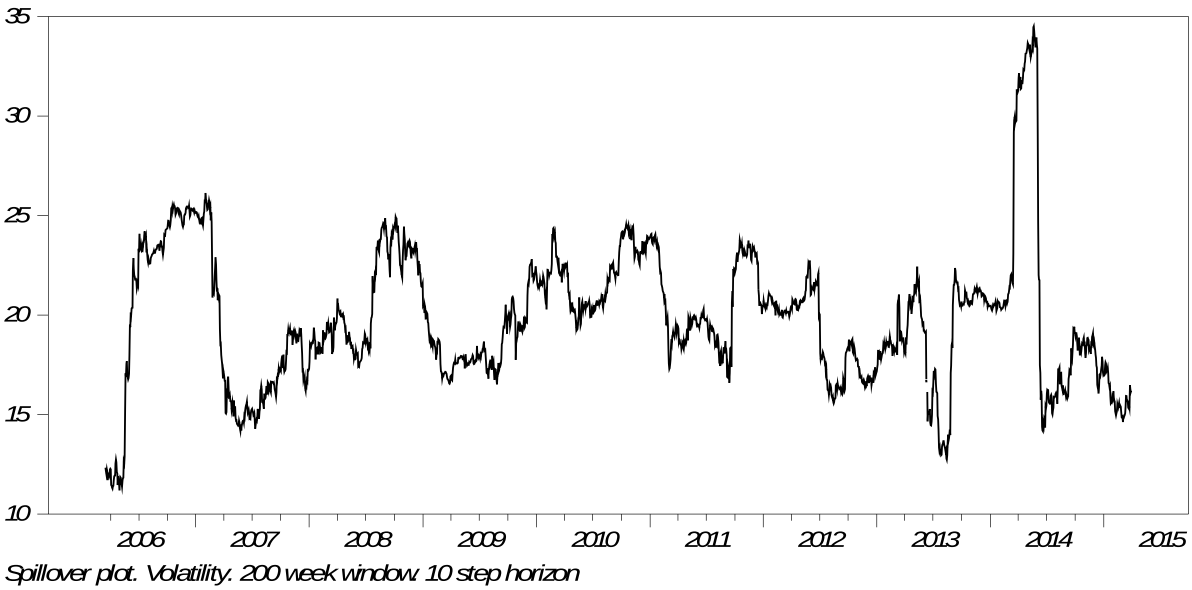
Note: (a) Degrees of financial contagion, which is adjusted R^2 expressed as percentages, are taken from table 5.
(b) Volatility Spillover estimates in row 3 and 4 are taken from the first column and first row, respectively, of table 6.
(c) Total volatility spillover is the sum of digits in column 3 and 4.
(d) Ranks in column 2 and column 6 are on the basis of column 1 and column 5 respectively

It can be seen that the ranking on the basis of degree of financial contagion certainly matches with the ranking of total volatility spillover; and hence more the degree of financial contagion more is the evidence of volatility spillover.

4.3.2 Conditional and Dynamic Spillover analysis

Since our sample period includes some phases of financial market evolution and turbulence, it seems unrealistic that any single fixed parameter model would apply over the entire sample. 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, we now estimate volatility spillovers using 200-day rolling samples, and assess the extent and nature of the spillover variation over time via the corresponding time series of spillover indices, which we examine graphically in the figure 7 below.

Figure 7: Total Volatility spillovers, five asset markets



Starting at a value below 12%, total volatility spillover goes over 25% at the end of 2006 and beginning of 2007 and then in the mid of 2007 it again comes down to below 15%. Since 2008 these markets show almost similar volatility spillover till 2013 and then a sudden leap pushes it to near 35%. We believe that it is due to the large rupee depreciation of 2013-14. From this we can draw an inference that Indian asset markets are more vulnerable to internal shocks than external shocks. In figure 8 and figure 9 (see Appendix 2) we have shown volatility spillover “FROM others” and “TO others” respectively for each asset class. However, here we shall analyze the net directional spillover and net pairwise directional spillover vis-à-vis commodity market to understand the dynamic nature of volatility spillover. From figure 10, where the net directional spillovers are represented, we see that commodity market for most of the sample time period remain a receiver of volatility. The nature changed during the financial crisis, second phase of Eurozone crisis, and during the depreciation of 2013-14. The nature of net volatility spillovers of Forex market and gold market are of opposite nature in the sense that from 2010 onwards the Forex market became a net transmitter of volatility whereas prior to 2010 gold market was a transmitter of volatility. There is not any clear trend of volatility transmission for the Gsec market; but it is seen to receive a huge volatility during the financial crisis and after rupee depreciation of 2013-14. The nature of volatility transmission also does not show any particular trend.

Figure 10: Net Directional Volatility Spillover

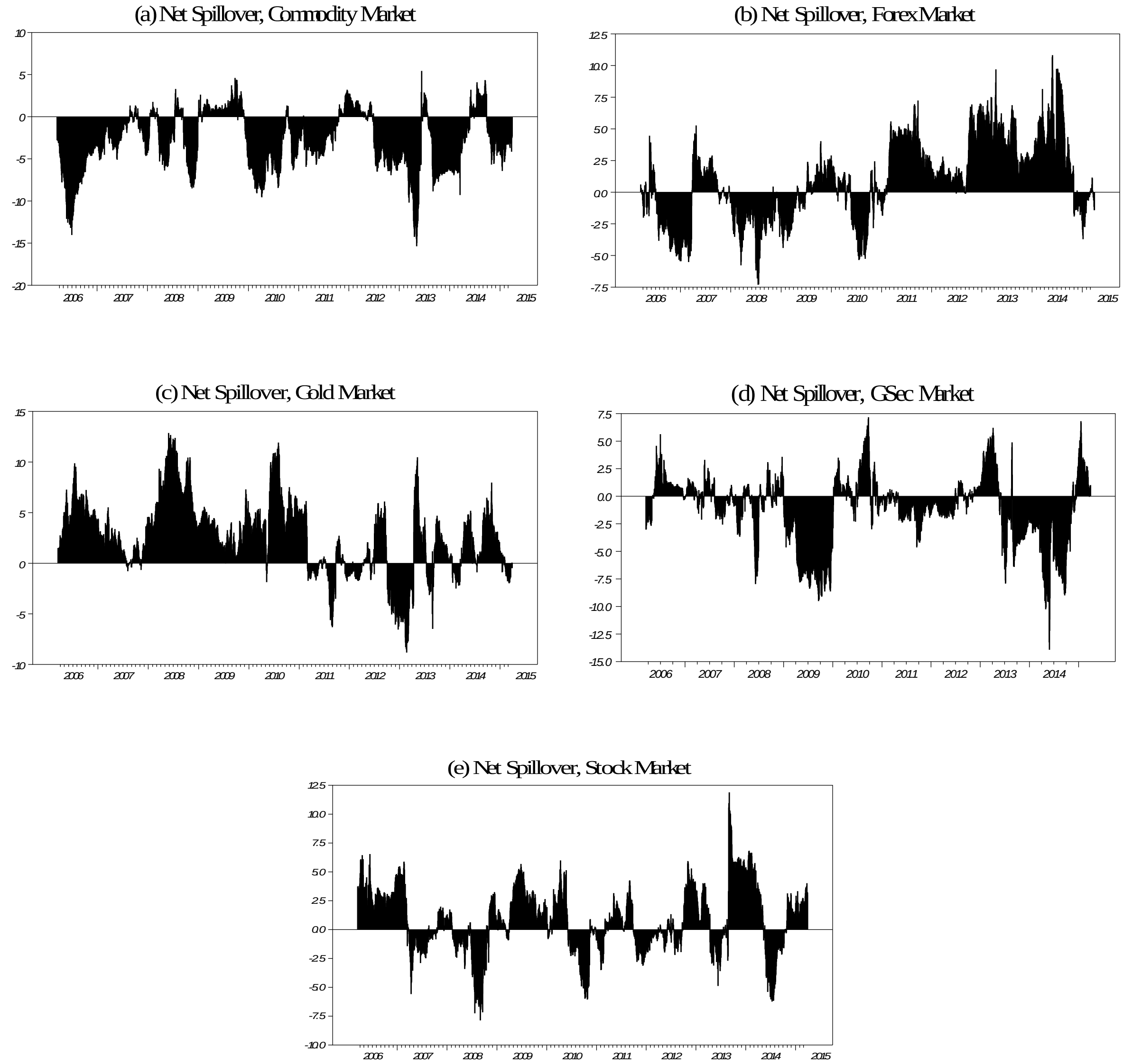
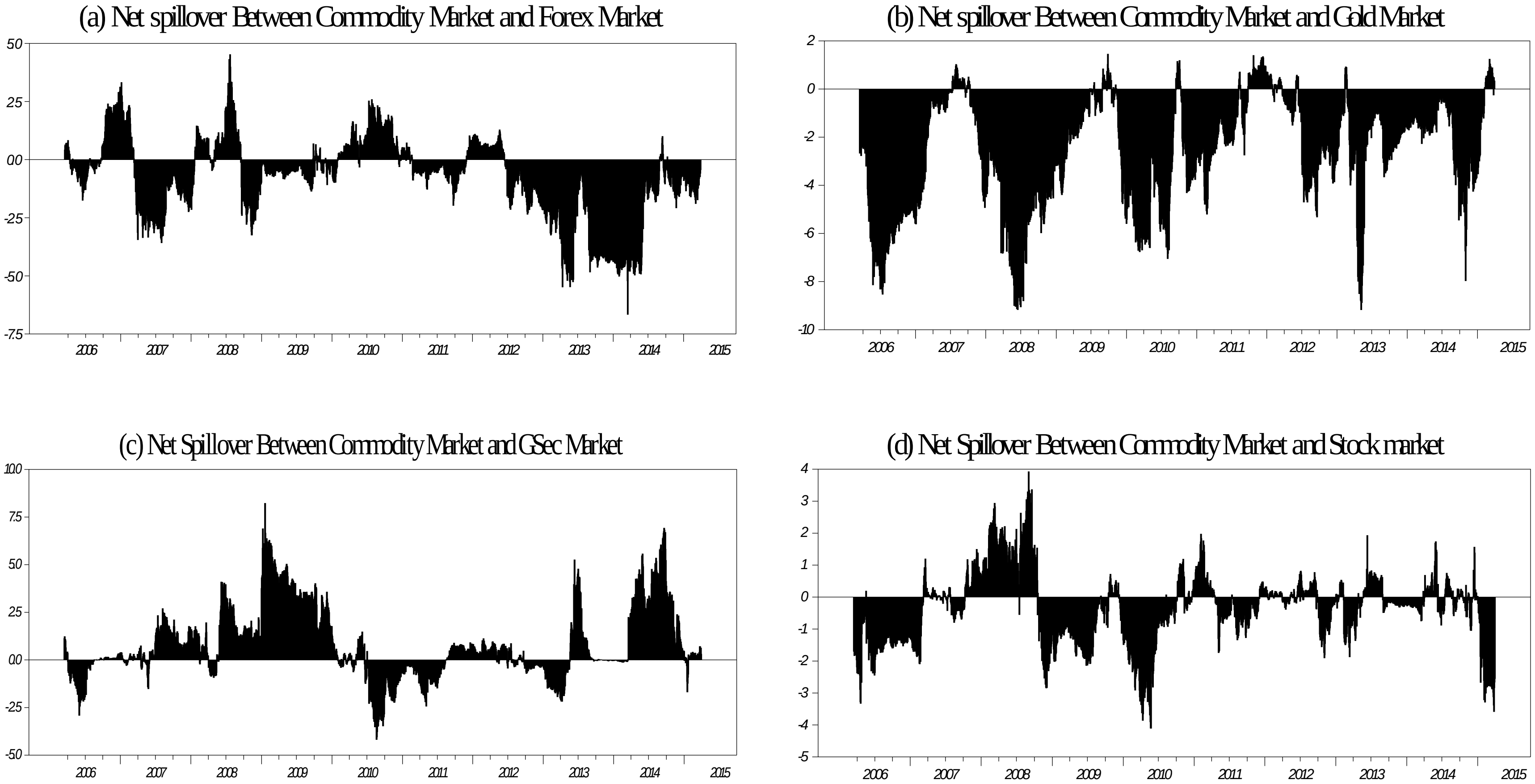


Figure 11 below shows the nature of net pairwise directional spillover vis-à-vis commodity market. Since 2012, huge volatility has been transmitted from the Forex market to the commodity market. On the other hand, for the entire sample period, the commodity market remained a net receiver of volatility with respect to the gold market. The commodity market received maximum volatility from the gold market only. During the financial crisis and rupee depreciation period, huge volatility got transmitted from the commodity market to the Gsec market and with respect to Gsec market, commodity market remained a net transmitter of volatility. Except for the first half of the financial crisis and small time points thereafter, for t the most of the sample period, the commodity market remained a receiver of volatility from

Figure 11: Net Directional Volatility Spillover



the stock market. The extent of volatility spillover between the stock market and the commodity market is seen to significantly decrease after 2010. This just the opposite for the Forex market as the volatility spillover is seen to increase in magnitude after 2012. Thus we can safely conclude that the commodity market, on an overall basis, is a receiver of volatility from other markets.

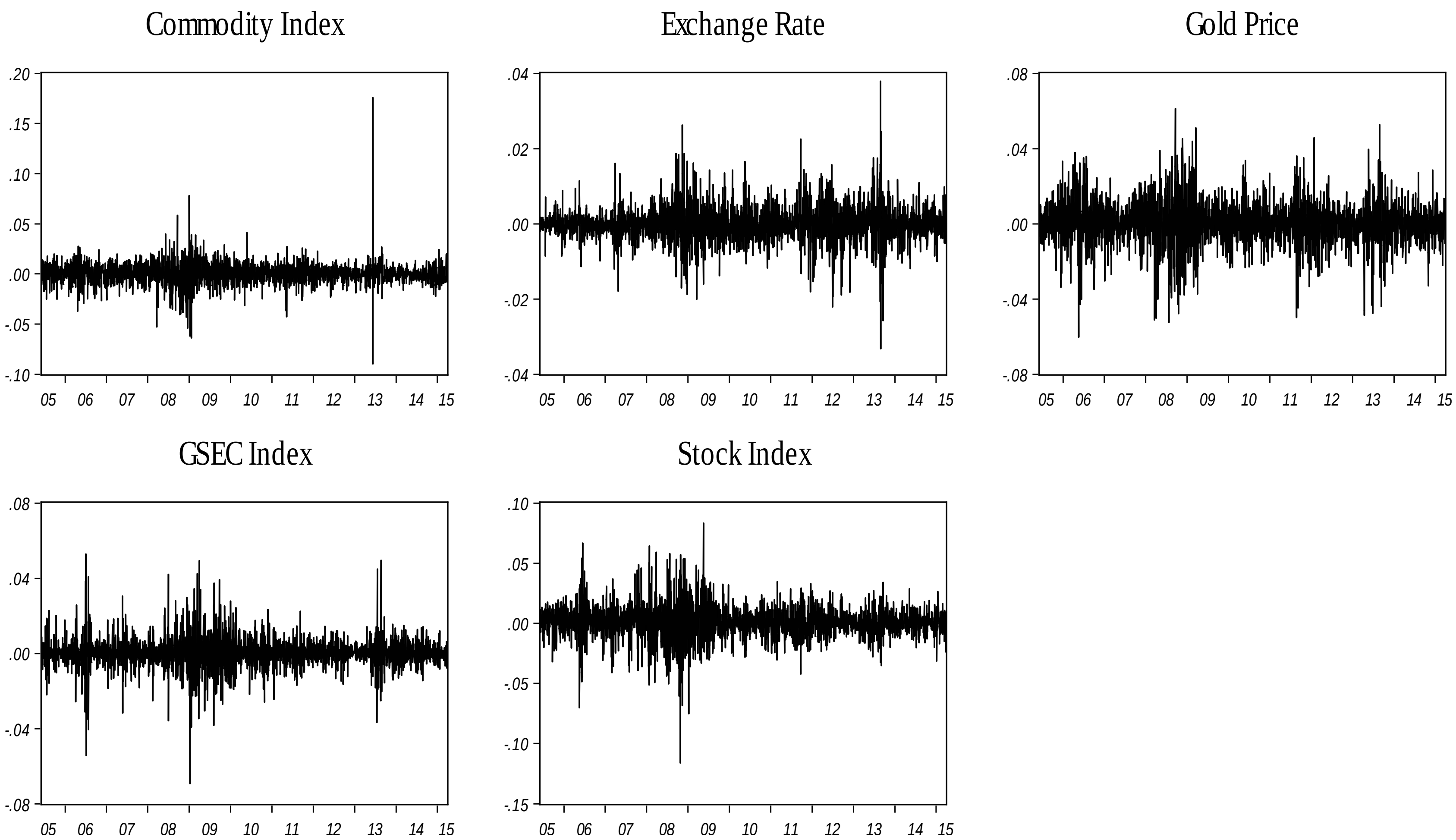
5. CONCLUSION

Considering commodity as an asset class, we have estimated extent of financial contagion in Indian asset markets. Commodity market is found to have significant contagion with other asset markets. When the Indian commodity market is found to be most contagious to Indian gold market, it is least contagious to Gsec market. In this study, we have investigated the dynamic correlations between commodity, currency, gold, Gsec and stock returns as the degree of financial contagion dependence on the dynamic conditional correlation between two asset returns, and hence its nature changes over time. During financial crisis, Eurozone crisis and mostly at the time of rupee depreciation, contagion of Indian commodity market is seen to increase with other asset markets. Correlation between two asset returns and hence extent of contagion between two asset markets play an important role in the process of optimal portfolio selection. The dynamic correlation analysis infers, except for the crises periods, commodities can be considered as hedge against exchange rate and Gsec; and as a diversifier in the presence of gold and stocks. Markets are called “safe haven” if they provide protection for each other during high volatilities. From our analysis it is evident that commodities should not be treated as a “safe haven” when the portfolio consists of gold and foreign currency. This conclusion has been strengthened by our analysis of volatility spillover. We have found that firstly, the commodity market is a net receiver of volatility from Forex, gold and stock markets. Secondly, the volatility transmission increases during the period of stress. We have also done a comparative analysis between financial contagion and volatility spillover to check whether there is any one to one connection. We see that for the commodity market a high degree of financial contagion leads to higher volatility spillover and vice versa. Our results have serious implications for optimal portfolio selection especially when commodity is held as an asset in portfolio.

Appendices

Appendix1

Figure 2 Return Series



Appendix 2

Figure 8: Directional Volatility Spillover, FROM five Financial Markets

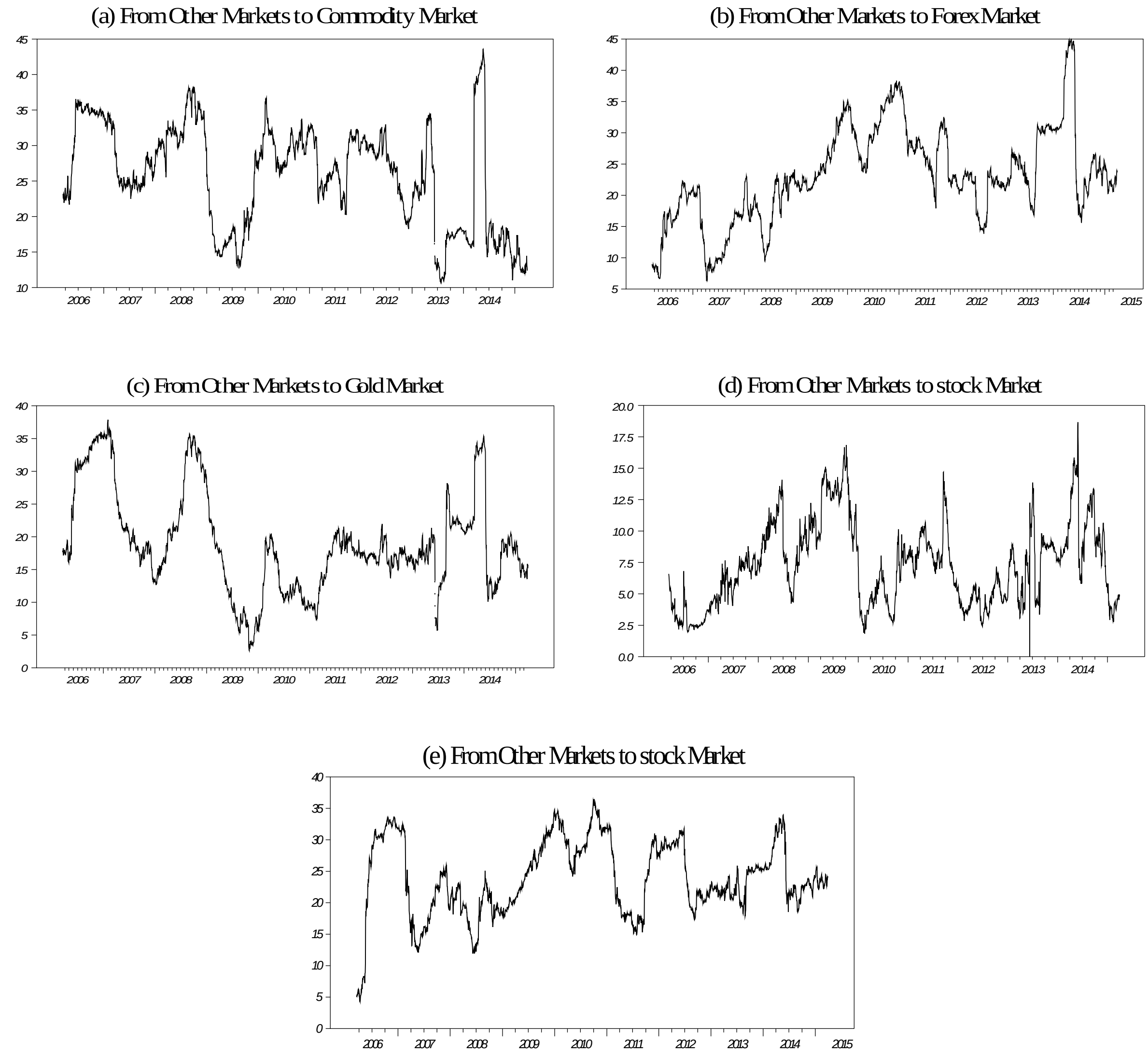
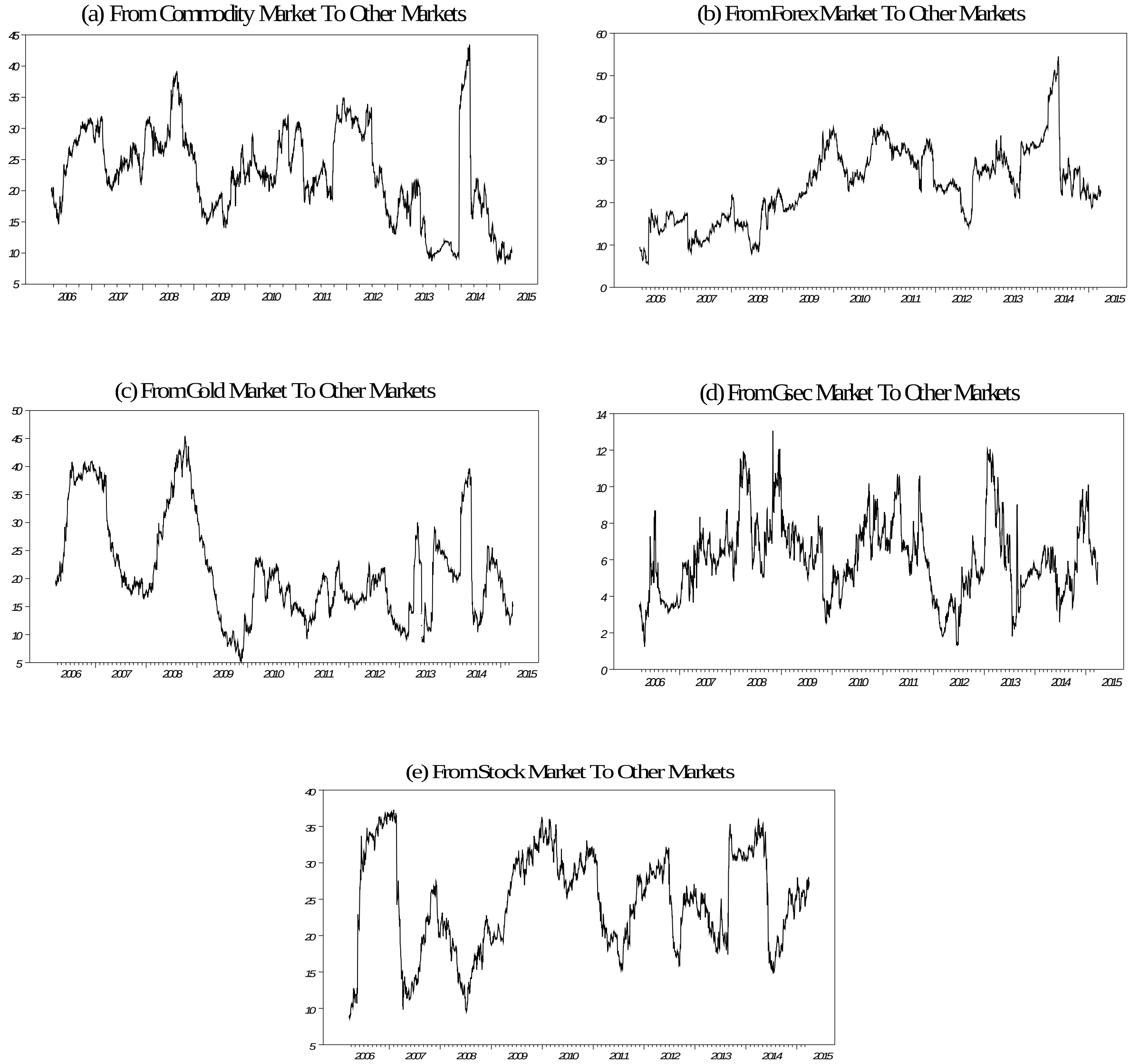


Figure 9: Directional Volatility Spillover, TO five Financial Markets



REFERENCES

Acharya, V, and Pedersen, L. H. (2005). Asset Pricing with Liquidity Risk, Journal of Financial Economics 77(2), 375–410.

Ahmed, W, Seghal, S. and Bhanumurthy, N.R. (2013). Eurozone crisis and BRIICKS stock markets: contagion or market interdependence .Economic Modelling. 33, 209-225.

Ahmed, W., Seghal, S. and Bhanumurthy, N. R. (2014). The Eurozone crisis and its contagion effects on the European stock markets. Studies in Economics and Finance. 31 (3), 325-352.

Allen, F and Gale, D. . (2004). Financial Intermediaries and Markets.Econometrica. 72 (4), 1023–1061.

Aloui, R., Ben Aissa, M. S., and Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: the role of economic structure? Journal of Banking and Finance 35(1), 130–141.

Ang, A., and Bekaert, G. (1999). International asset allocation with time-varying correlations. NBER Working Paper , No. 7056.

Ankrim, A. E and Hensel, C. R. (1993). Commodities in Asset Allocation: A Real-Asset Alternative to Real Estate?. Financial Analyst Journal. 49 (3), 20-29.

Arouri, M.E.H., Jouini, J. and Nguyen D.K. (2011). Volatlity spillovers between oil prices and stock sector returns:Implications for Portfolio Management . Journal of International Money and Finance . 30 , 1387-1405.

Bae K., Karolyi, A.G. and Stulz, R. M. (2003). A New Approach to Measuring Financial Contagion, The Review of Financial Studies 16(3), 717–763.

Baig, T., and Ilan, G. (1999). Financial market contagion in the Asian crisis. IMF Staff Papers , 46 , 167–95.

Bauwens, L., Laurent, S. and Rombouts, J.V.K. (2006). Multivariate GARCH models: A survey. Journal of Applied Economics. 21, 79-109.

Bekaert, G. and. Harvey, C. R. (2000). Foreign speculators and emerging equity markets. Journal of Finance 55(2), 565−613.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics. 31 (3), 307-327.

Boyer, B. H., Kumagai, T and Yuan, K. (2006). How Do Crises Spread? Evidence from Accessible and Inaccessible Stock Indices. Journal of Finance . 61 (2), 957–1003.

Brunnermeier, M. K., and L. H. Pedersen. (2005). Predatory Trading. Journal of Finance 60:1825–63.

Brunnermeier, M. K., S. Nagel, and L. H. Pedersen. (2009). Carry Trades and Currency Crashes, in Daron Acemoglu, Kenneth Rogoff, and Michael Woodford (eds.), NBER Macroeconomics Annual 2008, vol. 23. Cambridge, MA: MIT Press.

Cappiello, L., Engle, R., and Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. Journal of Financial Econometrics 4(4), 537-572.

Chan, K., Tse, Y. and Williams, M. (2011). The Relationship between Commodity Prices and Currency Exchange Rates: Evidence from the Futures Markets. In: Ito, T. and Rose, A. K Commodity Prices and Markets, East Asia Seminar on Economics. London: University of Chicago Press. 47-71.

Chiang, T.C., Jeon, N. B., and Li, H. (2007). Dynamic correlation analysis of financial contagion:Evidence from Asian markets . Journal of International Money and Finance . 26, 1206-1228.

Chong, J., Miffre, J. and Stevenson, S. (2009). Conditional Correlations and Real Estate Investment Trusts. Journal of Real Estate Portfolio. 15 (2), 173-184.

Claessens, S., Dornbusch, R. and Park, Y. (2001). Contagion: Why Crises Spread and How This Can Be Stopped.” In Claessens, S. and Forbes, K. 32 (Eds.), International Financial Contagion. Boston: Kluwer Academic Publishers, pgs. 19- 41.

Collins, D and Biekpe, N. (2003). Contagion and interdependence in african stock markets. South African Journal of Economics. 71 (1), 181–194.

Corsetti, G., Pericoli, M., and Sbracia, M. (2005). Some contagion, some interdependence: More pitfalls in tests of financial contagion. Journal of International Money and Finance 24(8), 1177−1199.

Creti, A., Joets, M. and Mignon, V. (2013). On the links between stock and commodity markets' volatility. Energy Economics. 37, 16-28.

Dornbusch, R., Park, Y., and Claessens, S. (2000). Contagion: understanding how it spreads. The World Bank Research Observer 15(2), 177–197.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. journal of Business and Economic Statistics. 20 (3), 339-350.

Forbes, K. J and Rigobon, R. (2002). No Contagion, Only Interdependence: Measuring Stock Market Comovements. Journal of Finance . 57 (5), 2223–2261.

Franklin, A. and Gale, D. (2000), Financial Contagion, Journal of Political Economy 108(1), 1–33.

Hansen, P.R. and Lunde, A. (2005). A forecast comparison of volatility models: does anything beat a GARCH(1,1)?. Journal of Applied Econometrics. 20 (7), 873–889.

Jeon, J. Q., and Moffett, C. M. (2010). Herding by foreign investors and emerging market equity returns: Evidence from Korea. International Review of Economics and Finance 19 (4), 698−710.

Kaminsky, L. G., Reinhardt, C., and Vegh, C. (2003). The unholy trinity of financial contagion. Journal of Economic Perspectives 17(4), 51–74.

Kim, S. J., Moshirian, F., and Wu, E. (2005). Dynamic stock market integration driven by the European Monetary Union: An empirical analysis. Journal of Banking and Finance 29(10), 2475-2502.

Kiyotaki, N. & Moore, J. (2002). Liquidity and Asset Pricing, ESE Discussion Papers 116, Edinburgh School of Economics, University of Edinburgh.

Kyle, A. S and Xiong, W. (2001). Contagion as a Wealth Effect. The Journal of Finance. 56 (4), 1401–1440.

Lessard, D. R. (1973). International portfolio diversification: Multivariate analysis for a group of Latin American countries. Journal of Finance 28(3), 619−633.

Longin, F., and Solnik, B. (1995). Is the correlation in international equity returns constant: 1960–1990?. Journal of International Money and Finance 14 (1), 3−26.

Longstaff, A. F. (2010). The subprime credit crisis and contagion in financial markets. Journal of Financial Economics. 97, 436-450.

Mantu, M. K., Acharya, D. and Suresh Babu, M. (2010). Price discovery and volatility spillovers in futures and spot commodity markets : Some Indian evidence. Journal of Advances in Management Research. 11 (2).

Marçal E F., Periera. V. L. P., and Martin, L.M.D. (2011). Evaluation of contagion or interdependence in the financial crises of Asia and Latin America, considering the macroeconomic fundamentals. Applied Economics 43(19), 2365-2379.

Mensi, W., Beljid, M., Boubaker, A. and Managi, S. (2013). Correlations and Volatility Spillover across Commodity and Stock Markets:Linking Energies, Food and Gold. Economic Modelling. 32, 15-22.

Phylaktis, K., and Ravazzolo, F. (2005). Stock market linkages in emerging markets: implications for international portfolio diversification. Journal of International Financial Markets, Institutions and Money 15(2), 91-106.

Samarakoon, P. L. (2011). Stock market interdependence, contagion, and the U.S financial crisis: The case of emerging and frontier markets. International Financial Markets, Institutions and Money 21(5), 724–742.

Silvennoinen, A. and Terasvirta, T. (2009). Multivariate GARCH models. Handbook of Financial Time Series. 201-229.

Silvennoinen, A. and Thorp, S.. (2013). Financialization, crisis and commodity correlation dynamics. Jornal of International Finance, Markets, Institutions & Money. 24, 42-65.

Solnik, B. (1974). Why not diversify internationally rather than domestically?. Financial Analysts Journal 30 (4), 48−54.

Suardi, S. (2012). When the US sneezes the world catches cold: are worldwide stock markets stable? Applied Financial Economics 22(23), 1961-1978.

Syllignakis, M. N., and Kouretas, G. P. (2011). Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. International Review of Economics and Finance 20(4), 717–732.

Syllignakis, M. N., and Kouretas, G. P. (2011). Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. International Review of Economics and Finance 20(4), 717–732.