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A wavelet approach towards examining dynamic association, causality and spillovers

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A B S T R A C T

This paper presents an integrated granular framework of wavelet decomposition, DCC-GARCH, ADCC-GARCH, Diks-Panchenko nonlinear Granger's causality and Diebold-Yilmaz spillover assessment techniques to understand temporal correlation, causal interplay and spillovers among volatile financial time series data exhibiting nonparametric behavior. The exercise has been carried out on daily closing observations of eight financial time series. Wavelet decomposition has been used to generate time varying components in which the other research models are applied to extract the interactive pattern of interaction to ascertain short and long run nexus. The findings rationalize the effectiveness of the presented research framework.

1. Introduction

In today's globalized world, markets have become interlinked through financial capital flows, market sentiment contagion reflecting present and expected macroeconomic prospects of different economies, information flows on political movements, trade policies and prices of essential commodities like crude oil. Time series of certain variables contain such information and a proper analysis of these time series can improve understanding and aid in policy making and also portfolio choice. This analysis can be done through estimating association among the variables, examining causality among them, and also testing for the extent of spillover. In response to worldwide events, policy formulation or portfolio realignment takes time. Thus, it is also important to examine whether the associations or spillovers are short lived or they have long term ramifications. Any adjustment is expensive, and hence it is necessary to focus on such associations which have long term effects, rather than those that die down in a short while. This paper presents a framework of analysis for examining association, causality and spill over, where the time period of the effects can also be isolated. The approach is granular whereby the time series is decomposed into various time blocks, and then the results are obtained. The exercise is performed for the Indian economy (Bhatia et al., 2018).

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Variables have differing effects on other variables, and it is important to have some basis for examining association. Macroeconomic prospects get reflected in market sentiment and also boost certain sectors like metal and capital goods. Thus, an association can be expected between stock market index and metal index. Given that India's IT companies mostly cater to the rest of the world, an association of the Dow Jones Industrial Average and the Indian IT Index can exist. As India experiences Foreign Institutional Investors (FII) inflows, any indication of volatility in other markets, in particular the US, can affect Indian stock market volatility. An association can be expected between CBOE VIX and India VIX. Crude oil imports constitute around 80% of total Indian imports. It is natural to postulate that crude oil prices will have some association with the Rs./$ exchange rate.

In this paper, we look at the above associations, and try to examine causality and spillover effects. Our framework enables us to separate long term effects from short term effects and can be used for trading, portfolio formation and churning, and also for framing policy. Financial contagion effects need to be properly understood for risk mitigation. Investors seeking portfolio diversification look for less integrated assets in the short and the long run.

There is a literature which has tried to understand and measure the degree of interrelationship among homogeneous and heterogeneous assets (Genc et al., 2017; Mensi et al., 2017; Polanco-Martinez et al., 2018), understand contagion effects (Kalbaska and Gatkowski (2012), Kazemi and Sohrabji (2012)) and ascertaining causality (Reboredo et al., 2017; Shabaz et al., 2017). The existing literature may be segregated into two strands broadly. One set deals with exploring the interplay pattern in aggregate financial time series (Kaura et al., 2018; Singhal & Ghosh, 2016). The other segment furnishes a granular level inspection of interaction in short and long run through time series decomposition by various means (Jammazi et al., 2017; Liu et al., 2017), Sen and Datta Chaudhuri (2016)). The present study attempts to contribute to the second category of literature. The key endeavor of this article is to present a granular framework for evaluating dynamic conditional correlation structure, causal network and spillover nexus in global financial markets in an integrated manner. To accomplish the research objectives, we have used Maximal Overlap Discrete Wavelet Transformation (MODWT) for decomposing time series into a series of time varying components accounting for short and long run dynamics. Subsequently, association, causal influence and spillovers are examined through Dynamic Conditional Correlation-Generalized Auto Regression Conditional Heteroscedasticity (DCC-GARCH), Asymmetric DCC-GARCH (ADCC-GARCH), Diks-Panchenko Non Linear Granger Causality Test and Dibold-Yilmaz Spillover assessment models.

The paper uses daily observations of eight time series namely, Implied Volatility of Chicago Board of Options Exchange (CBOEVIX), Implied Volatility Index of India (INDIAVIX), Crude Oil Return (CRUDEOIL), Rupee – Dollar 1 month Forward Exchange rate (FX1), Dow Jones Industrial Average Return (DJIA), BSE Information Technology Sector Return of India (IT), Bombay Stock Exchange Return (SENSEX) and Metal Sector Return of India (METAL). Pairwise association and causality analysis have been performed between the CBOEVIX-INDIAVIX, CRUDEOIL-FX1, DJIA-IT and METAL-SENSEX pairs. Lastly, spillover effects have been determined across all eight series.

The remainder of the paper is structured as follows. Previous related research is discussed in section 2. Section 3 narrates the key statistical properties of the dataset. We outline the research methodology in section 4. Section 5 explains the results of dynamic association. Outcomes of causal analysis are analyzed in Section 6, and section 7 presents the findings of spillover analysis. Section 8 concludes the paper.

2. Literature review

In this section, recent work on modelling association, causality and volatility contagion is discussed. Majority of these techniques have been conducted using advanced econometric and statistical tools in conjunction with wavelet spectrum analysis to capture inherent temporal co-movement pattern. Most of these work are empirical in nature and point out the practical implications of the findings. Kaura et al. (2018) used standard GARCH model to analyze volatility spillovers in Non-Agricultural Commodity

Market in India. The findings revealed the presence of bidirectional spillovers in majority of commodities and future returns were found to possess significant influence on spot returns. Al Refai and Hassan (2018) applied EGARCH model to measure impact of market wide volatility on time varying risk in Qatar Stock Exchange (QSE). Results implied the vulnerability of large and small sectors on overall market volatility. It was also observed that market-wide upswings lessened systematic risk of industrial sector while down-swings increased systematic risk of real estate, telecommunication and transportation sectors in Qatar. Klößner and Sekkel (2018) examines spillovers among indices of policy uncertainty of US, UK, Canada, France, Germany and Italy using Diebold Yilmaz spillover measures. It was noticed that since financial crisis of 2008-09, US and UK were responsible for large portion of spillovers while other countries were net receivers. Das et al. (2018) assessed the nexus of Asian gold spot markets of China, India, Indonesia, South Korea, Thailand and Vietnam through Wavelet Coherence (WC), Wavelet Multiple Correlation (WMC) and Wavelet Multiple Cross Correlation (WMCC) models. Strong positive co-movement structure was found and Thailand emerged as potential market leader. Das et al. (2018) used Wavelet Local Correlation (WLC) to ascertain interaction among global stock markets after global financial crisis. The outcome revealed weaker contagion effect for emerging markets in Latin America, strong contagion for European and Middle East markets and insignificant long run association after the crisis. Shahbaz et al. (2017) explored the predictive power of oil price on gold price through causality in quintiles approach. The findings displayed the evidence of weak predictive power of oil price for forecasting gold price and strong predictive power of oil for volatility of gold market. Polanco-Martinez et al. (2018) analyzed the dynamic association and causality of EU peripheral stock market indices and S&P Europe 350 (SPEURO) index during pre-crisis and crisis periods by Rolling-Window Wavelet Correlation (RWWC) and Diks-Pachenko nonlinear Granger causality test. Overall findings reported that stock indices of Portugal, Italy and Spain had strong interaction during crisis. Jammazi et al. (2017) investigated time varying nature of causal interaction of oil price change and stock returns of six oil importing countries through multiresolution analysis in wavelet decomposition framework and dynamic causality test. Significant causal links were discovered in short duration during the periods of financial crisis. Vatia et al. (2018) applied quantile causality technique to understand interrelationship among spot prices of Gold, Silver, Platinum and Palladium. Results suggested strong presence of significant causal interplay among all four metals in mean and variation of prices. Basher and Sadorsky (2016) deployed DCC-GARCH, ADCC-GARCH and generalized OGARCH (GO-GARCH) models to discover dynamic association between stock prices of emerging markets with oil, gold, VIX, and bonds and subsequently used insights gained through dynamic correlation for constructing hedge ratios. Arouri et al. (2012) employed VAR-GARCH models to study volatility transmission dynamics between European stock and oil markets. Findings implied existence of volatility spillovers between oil prices and sectoral stock returns. Sadorsky (2014) applied conventional multivariate GARCH models to evaluate volatility spillovers between emerging stock market, oil, copper and wheat prices. Findings were successfully utilized for estimating hedge ratios. Oil was found to be the cheapest hedge for emerging stock markets, while copper was the most expensive.

3. Data description

Daily closing observations of CBOEVIX, INDIAVIX, CRUDEOIL, FX1, DJIA, IT, METAL and SENSEX have been compiled from *'Metastock'* data repository during January 2013 to June 2017. Table 1 reports the key statistical properties and outcome of few statistical tests to understand behavioral characteristics. It can be observed from test statistics of Jarque-Bera and Hegazy-Green (H-G) tests that the respective series do not abide by normal distribution. Terasvirta's test hints at nonlinear behavior of CBOEVIX, INDIAVIX and METAL. On the other hand, nonlinear behavior of CBOEVIX and INDIAVIX is supported by outcome of White's test. Ljung-Box Q Statistics at lag 10 provides evidence of strong pattern of serial autocorrelation structure embedded in the considered time series. Since we shall be testing dependence structure and as some of the financial series exhibit nonlinear structure, linear association and causality tests may not reveal unambiguous interaction structure (Andries et al. (2016)).

To further explore nonlinearity, we have carried out BDS test on residuals obtained after fitting AR(1) model on aggregate series. Table 2 summarizes the outcome of the test.

Table 1
Statistical summary of concerned series

	CBOE VIX	INDIA VIX	CRUDE OIL	FX1	DJIA	IT	SENSEX	METAL
Minimum	10.32	11.565	-0.12366	53.49589	-0.03736	-0.08824	-0.04708	-0.06268
Maximum	137.15	37.705	0.167592	81.21032	0.0398	0.051708	0.046991	0.07916
Mean	15.52936	17.57355	0.000986	63.65767	0.000476	0.000754	0.000373	-0.00019
Median	14.34	16.72	0.000379	62.65301	0.000398	0.000926	0.000294	0.000198
SD	5.234391	4.049212	0.021314	3.654933	0.00799	0.01268	0.009807	0.016814
Variance	27.39885	16.39612	0.000454	13.35853	6.38E-05	0.000161	9.62E-05	0.000283
Kurtosis	297.6464	4.457116	7.292012	-0.48913	1.709831	2.890432	1.287115	1.47951
Skewness	13.37871	1.91102	0.358186	0.737074	0.184508	-0.26227	0.077566	0.052257
Jarque-Bera	454E04***	1379.008***	2170.92***	98.579***	123.11***	348.16***	67.44***	88.37***
H-G Test	0.3659***	0.259***	0.1396***	0.2366***	0.068***	0.056***	0.054***	0.07***
Terasvirta's Test	6.8245**	10.38***	0.3031#	1.629#	5.7997*	10.80***	3.5238#	7.9022**
White's Test	5.1962*	6.4279**	0.1012#	2.0091#	2.0335#	2.3467#	4.0845#	0.6311#
Ljung-Box Q Statistics	1619.225***	9027***	58.121***	9428.1***	99.222***	117.77***	118.69***	90.371***

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level, #Not significant

Table 2
BDS Test Outcome

	Dimension				
	2	3	4	5	6
AR(1): CBOEVIX	35.5581***	40.5501***	44.9967***	49.934***	56.0355***
AR(1): INDIAVIX	5.4984***	7.5719***	9.5412***	11.2257***	13.4212***
AR(1): CRUDEOIL	6.5897***	7.3706***	8.6546***	10.6084***	11.7809***
AR(1): FX1	6.252***	7.9986***	9.502***	10.9214***	14.0668***
AR(1): DJIA	3.5603***	5.4487***	6.8259***	8.3376***	9.2297***
AR(1): IT	0.358#	0.3622#	0.2774#	0.6337#	1.4956#
AR(1): SENSEX	1.0849#	3.0431***	3.581***	4.7927***	4.8564***
AR(1): METAL	2.535**	3.3591***	3.568***	3.9477***	4.3854***

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level, #Not significant

It can be clearly seen that barring IT and SENSEX on dimension 2, null hypothesis of independent and identical distribution can be rejected for rest six financial time series. Thus applying linear models on aggregate series to capture dynamic dependence may not be appropriate and could result in misleading insights. Hence, our proposed framework for assessment of association, causality and spillovers on wavelet based decomposed components is justified. We elaborate the entire research methodology to deal with these kind financial data in the next section.

4. Research methodology

4.1 Wavelet Decomposition

It is used for decomposing original time series data into a set of time varying linear and nonlinear components to enable multiresolution analysis. $y(t)$ into different time scales as follows:

$$y(t) = \sum_k s_{j,k}\varphi_{j,k}(t) + \sum_k d_{j,k}\psi_{j,k}(t) + \sum_k d_{j-1,k}\psi_{j-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t), \tag{1}$$

where father (φ) and mother (ψ) wavelets account for the low frequency and high frequency components of the series; $s_{j,k}$, $d_{j,k}$, ..., $d_{1,k}$ coefficients generated by wavelet transformation. Now, $y(t)$ can be approximated by a J-level multi-resolution decomposition analysis as:

$$y(t) = S_j(t) + D_j(t) + D_{j-1}(t) + \cdots + D_1(t) \tag{2}$$

where frequency components D_j (detailed scales) account for short, medium or long-lived variations at 2^j time scale and S_j (approximation level) is the determined residual after removing the detailed components from the original signal. Components of lower frequency range prevail for longer periods while higher frequency components prevail for shorter durations. There exist several choices for carrying out wavelet transformation. We have used MODWT which has several advantages over traditional discrete wavelet transformation (DWT) (Tiwari et al., 2015), for accomplishing the task. We have considered multi-resolution analysis of 6 levels for decomposition for comprehending association, causality and spillovers among the selected financial time series. The present paper utilizes Daubechies least asymmetric (LA) wavelet filter of length 8 for filtering. For modelling future trends through wavelet decomposition, readers may refer to Ghosh and Datta Chaudhuri (2017), Ghosh and Datta Chaudhuri (2016), Jothimoni et al. (2015), etc.

4.2 DCC & ADCC GARCH Model

DCC model as proposed by Engle (2002), determines the conditional correlation after estimating GARCH parameters.

The conditional covariance matrix for a time series data having n observations, can be expressed as:

$$H_t = D_t^T R_t D_t \tag{3}$$

where D_t is a diagonal matrix having time varying standard deviations on diagonal entries and R_t denotes conditional correlation matrix.

$$D_t = diag\left(h_{1,t}^{1/2}, \dots, h_{n,t}^{1/t}\right), \tag{3}$$

$$R_{t=}diag\left(q_{1,t}^{1/2}, \dots, q_{n,t}^{1/t}\right)Q_t diag\left(q_{1,t}^{1/2}, \dots, q_{n,t}^{1/t}\right), \tag{4}$$

where $h_{i,t}$ follows standard univariate GARCH model as given by Eq. (6).

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}. \tag{6}$$

Q_t, a symmetric positive definite matrix, is expressed as

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 z_{t-1} z_{t-1}^T + \theta_2 Q_{t-1}, \tag{7}$$

where $\bar{Q}$ represents the unconditional correlation matrix of the standardized innovations.

The two nonnegative parameters (θ_1, θ_2), used to determine the dynamic conditional correlation, account for short run and long run persistence. If $\theta_1 + \theta_2 < 1$, the DCC model is said to be exhibiting mean reverting properties. The correlation is estimated as:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}}. \tag{8}$$

Cappiello et al. (2006) hybridized the DCC model and asymmetric GARCH model of Glosten et al. (1993) by incorporating an asymmetric term to develop the Asymmetric DCC (ADCC) model.

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t-1}^2 I\left(\varepsilon_{i,t-1}\right). \tag{9}$$

The indicator function $I\left(\varepsilon_{i,t-1}\right)$ follows Eq. (10).

$$I\left(\varepsilon_{i,t-1}\right) = \begin{cases} 1 & if\, \varepsilon_{i,t-1} < 0 \\ 0 & Otherwise \end{cases} \tag{10}$$

The asymmetric or leverage term is responsible to ascertain the fact that unexpected fall in asset prices result in increased volatility than unexpected rise in prices. It implies that bad news contribute more to volatility more than good news. The modified correlation through dynamics of Q_t can be expressed as:

$$Q_t = (\bar{Q} - A^T \bar{Q} A - B^T \bar{Q} B - G^T \bar{N} G) + A^T z_{t-1} z_{t-1}^T A + B^T Q_{t-1} B + G^T n_{t-1} n_{t-1}^T G, \tag{11}$$

where *A, B* and *G* denote $n \times n$ parameter matrices, n_t represents zero-threshold standardized errors, $\bar{Q}$ and $\bar{N}$ are unconditional correlation matrices of z_t and n_t respectively. We have applied both DCC and ADCC models to capture dynamic association of four time series pairs, CBOEVIX-INDIAVIX, CRUDEOIL-FX1, DJIA-IT and METAL-SENSEX in short and long duration.

4.3 Nonlinear Granger Causality Test

The conventional Granger causality test brings out linear causal interplay among a different sets of time series data. It has been applied to examine causal structure of various financial assets in the literature. However, the major shortcoming of this statistical test is its inability to capture nonlinear causal association. Presence of structural breaks, regime shifting, volatility clustering, etc. in financial markets eventually lead to strong nonlinear behavior. To overcome the issue, researchers developed non-linear causality tests to examine bivariate nonlinear Granger causality. Baek and Brock (1992) introduced a non-parametric test to discover inherent nonlinear interconnection. Later on, Hiemstra and Jones (1994) presented an upgraded version of the test of Baek and Brock (1992) which has been successfully used in modelling financial markets. The test of Hiemstra and Jones (1994) suffered from problem of over-rejection of null hypothesis. Diks and Panchenko (2006) introduced a nonparametric pairwise nonlinear Granger causality test to take care of this challenge of over-rejection.

Granger causality test between two time series X_t and Y_t is simple carried out by examining the null hypothesis that X_t does not possess additional information about Y_{t+1}. Considering delay vectors $X_t^{l_X} = \left(X_{t-l_X+1,\dots,X_t}\right)$ and $Y_t^{l_Y} = \left(Y_{t-l_Y+1,\dots,Y_t}\right)$ where, $l_X, l_Y \geq 1$ represent the delay units of the original series, the null hypothesis can be formulated as:

$$H_o: Y_{t+1} | \left(X_t^{l_X}; Y_t^{l_Y}\right) \sim Y_{t+1} | Y_t^{l_Y} \tag{12}$$

Considering $Z_t = Y_{t+1}$ and omitting the time indices in above equation, the null hypothesis implies that the conditional distribution of *Z* given *(X, Y) = (x, y)* is actually Z given *Y = y*. The association between the joint distribution of the joint probability density function $f_{X,Y,Z}(x, y, z)$ and its marginal can be expressed in terms of the Null hypothesis as:

$$\frac{f_{X,Y,Z}(x, y, z)}{f_Y(y)} = \frac{f_{X,Y}(x, y)}{f_Y(y)} \frac{f_{Y,Z}(y, z)}{f_Y(y)}. \tag{13}$$

The equation signifies the conditional independence of *X* and *Z* in terms of *Y*. According to Diks and Panchenko, the Null hypothesis can be given by

$$q \equiv \mathbb{E}\left[f_{X,Y,Z}(X, Y, Z) f_Y(Y) - f_{X,Y}(X, Y) f_{Y,Z}(Y, Z)\right] = 0, \tag{14}$$

where, $\mathbb{E}$ stands for the expectation operator whereas the estimator for q is defined as:

$$T_n(\epsilon_n) = \frac{(2\epsilon)^{-d_X - 2d_Y - d_Z}}{n(n-1)(n-2)} \sum_i \left[\sum_{k,k\neq i} \sum_{j,j\neq i} \left(I_{ik}^{XYZ} I_{ij}^{Y} - I_{ik}^{XY} I_{ij}^{YZ} \right) \right], \tag{15}$$

where, I is an indicator function ($I_{ij}^W = I\left(\left\|W_i - W_j\right\| < \epsilon\right)$), W_i and W_j belong to d_w-variate random vector W, ϵ denotes the bandwidth and total sample size is n. The d_w-variate random vector is expressed as $\hat{f}_W(W_i) = (2\epsilon)^{-d_w}(n-1)^{-1} \sum_{j,j\neq i} I_{ij}^W$ and accordingly the T-statistic is estimated as:

$$T_n(\epsilon_n) = \frac{(n-1)}{n(n-2)} \sum_i \left[\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i) \hat{f}_{Y,Z}(Y_i, Z_i)\right], \tag{16}$$

where $\epsilon_n = Cn^{-\beta}$ with $\beta \in (1/4, 1/3)$ and $C > 0$ with $l_X = l_Y = 1$, the T-statistic asymptotically follows Gaussian distribution.

$$\sqrt{n}\frac{(T_n(\epsilon_n)-q)}{S_n}\xrightarrow{d} N(0,1)\ , \tag{17}$$

where, S_n is the estimator of variance of T_n.

We have adopted this test to identify the pairwise causality.

4.4 Diebold-Yilmaz Spillover

N-dimensional VAR(p) model can be characterized as

$$Y_t=\phi_1 Y_{t-1}+\cdots+\phi_p Y_{t-p}+\epsilon_t\ , \tag{18}$$

where ϵ_t is i.i.d innovation and the coefficients $(\phi_1 \ldots \phi_p)$ account for the dynamic interrelationships among the variables. The said system can also be formulated by moving average representation as given by

$$Y_t=\epsilon_t+A_1\epsilon_{t-1}+A_2\epsilon_{t-2}+\cdots \tag{19}$$

The information in coefficient matrices in spillover can be expressed with H-step ahead forecast error variance decompositions as:

$$Y_{t+H}-P(Y_{t+H}|Y_t,Y_{t-1})=\epsilon_t+A_1\epsilon_{t+H-1}+A_2\epsilon_{t+H-2}+\cdots+A_{H-1}\epsilon_{t+1} \tag{20}$$

where $P(Y_{t+H}|Y_t,Y_{t-1})$ denotes the H-step forecast at time t. If Σ_ϵ represents covariance matrix of ϵ and $A_0 \coloneqq I_N$, then covariance matrix of forecast's error is estimated as:

$$\Sigma_{\epsilon,H}=\sum_{h=0}^{H-1}A_h\Sigma_\epsilon A_h^T \tag{21}$$

Diebold and Yilmaz invented spillover index (SOI) to account for various spillovers measured in terms of contribution of shocks from one variable to other in forecast's error variance as:

$$SOI=100\times\frac{1}{N}\sum_{i=1}^{N}\frac{\sum_{i\neq j}\sum_{h=0}^{H-1}(A_hL)_{ij}^2}{\sum_{h=0}^{H-1}(A_h\Sigma_\epsilon A_h^T)_{ii}}=100\times\left(1-\frac{1}{N}\sum_{i=1}^{N}\frac{\sum_{h}^{H-1}(A_hL)_{ii}^2}{\sum_{h=0}^{H-1}(A_h\Sigma_\epsilon A_h^T)_{ii}}\right) \tag{22}$$

where L is the lower-triangular Cholesky factor of Σ_ϵ.

We have used this spillover analysis technique to measure the pattern of spillovers among all eight time series together across the time horizons.

5. Dynamic association

Here, we summarize the findings of DCC and ADCC GARCH models on time varying scales. However before proceeding with the outcome of these two models, we have reported the pairwise linear correlation values obtained from the original time series in Table 3.

Table 3
Pairwise correlation figures

Pairs	***INDIAVIX-CBOEVIX***	***CRUDEOIL-FX1***	***DJIA-IT***	**METAL-SENSEX**
Correlation	0.1321***	0.0048#	-0.0077#	0.6737***

***Significant at 1% level, #Not Significant

METAL and SENSEX pair exhibits strong positive association while CRUDEOIL-FX1 and DJIA-IT do not exhibit any association whatsoever. There exists significant association between INDIAVIX-

CBOEVIX pair. However the magnitude is not high enough to draw any significance on sign of association. As discussed in Section 2, due to nonlinear and nonparametric nature of the dataset drawing final judgement induces risk of unreliability. Hence, we opt for wavelet decomposition, and subsequently analyze selected decomposed components for interpreting the degree of association dynamically. We have used MODWT technique for six levels of decomposition. We have presented the graphical representation of decompositions of selected series below. Fig. 1 and Fig. 2 displays the decomposition of CRUDEOIL and DJIA.

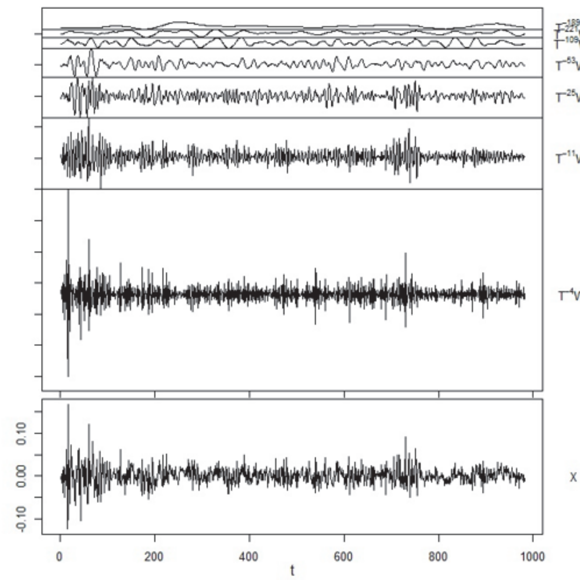

Fig. 1. MODWT Decomposition of CRUDEOIL

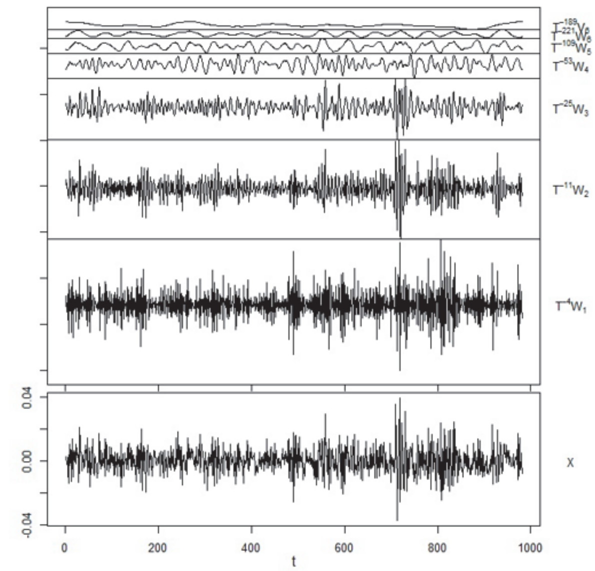

Fig. 2. MODWT Decomposition of DJIA

Table 4 represents the time interpretation of decomposed components.

Table 4
Time interpretation of different scales

Details	Wavelet Scales	Durations
D1	1	2 to 4 days (Intraweek scale)
D2	4	4 to 8 days (Weekly scale)
D3	8	8 to 16 days (Fortnightly scale)
D4	16	16 to 32 days (Monthly scale)
D5	32	32 to 64 days (Monthly to quarterly scale)
D6	64	64 to 128 days (Quarterly to biannual scale)

In this paper, we have considered D1 and D3 scales as proxy for short run whereas D6 scale as proxy for long run. Subsequently we have applied DCC and ADCC on these components of respective time series pairs and interpreted the dynamic correlation as short and long duration dynamic association. Figures 3 to 14 show the dynamic conditional correlation obtained from DCC and ADCC GARCH models scale-wise.

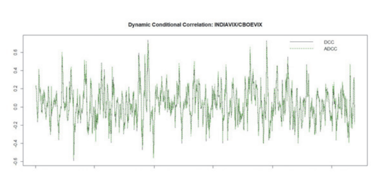

Fig. 3. Dynamic Conditional Correlation at D1 Scale

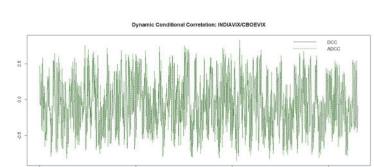

Fig. 4. Dynamic Conditional Correlation at D3 Scale

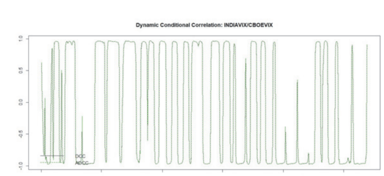

Fig. 5. Dynamic Conditional Correlation at D6 Scale

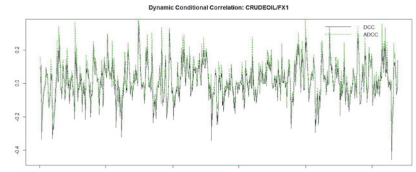

Fig. 6. Dynamic Conditional Correlation at D1 Scale

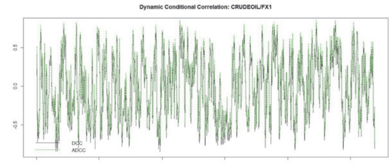

Fig. 7. Dynamic Conditional Correlation at D3 Scale

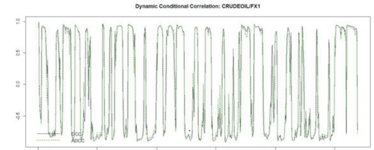

Fig. 8. Dynamic Conditional Correlation at D6 Scale

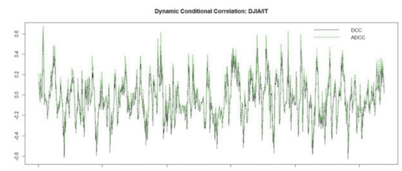

Fig. 9. Dynamic Conditional Correlation at D1 Scale

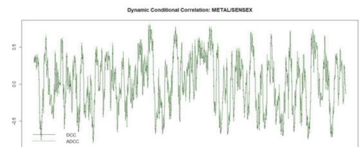

Fig. 10. Dynamic Conditional Correlation at D3 Scale

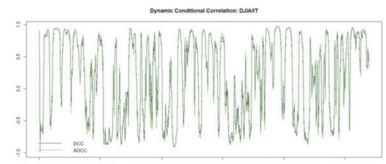

Fig. 11. Dynamic Conditional Correlation at D6 Scale

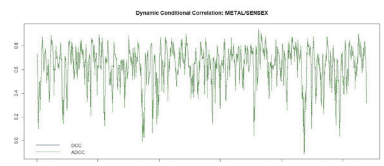

Fig. 12. Dynamic Conditional Correlation at D1 Scale

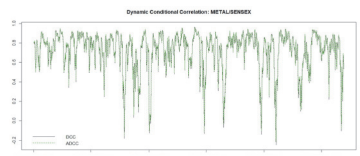

Fig. 13. Dynamic Conditional Correlation at D3 Scale

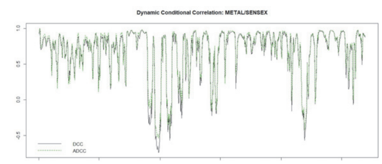

Fig. 14. Dynamic Conditional Correlation at D6 Scale

From the above figures, it can be observed that the magnitude of dynamic conditional correlation varies inside a particular scale as well. Increasing range of dynamic conditional correlation with scale implies that long run dynamics association is stronger than short run. We have estimated the scale-wise range of dynamic conditional correlation for easier understanding as summarized in Table 5 and Table 6.

Table 5
Range of dynamic conditional correlation of DCC-GARCH model

Pair	Scale					
	D1		D3		D6	
	min	max	min	Max	min	max
CBOEVIX-INDIAVIX	-0.60109	0.73635	-0.8493	0.8169	-0.9910	0.9699
DJIA-IT	-0.62739	0.65852	-0.8675	0.8982	-0.8693	0.8897
CRUDEOIL-FX1	-0.45636	0.350442	-0.8958	0.9452	-0.91706	0.9997
METAL-SENSEX	-0.19062	0.95436	-0.2457	0.9416	-0.7382	0.9995

Table 6
Range of dynamic conditional correlation of ADCC-GARCH model

Pair	Scale					
	D1		D3		D6	
	min	max	min	Max	min	max
CBOEVIX-INDIAVIX	-0.59076	0.72163	-0.84883	0.82765	-0.9743	0.9761
DJIA-IT	-0.51502	0.68252	-0.7391	0.8638	-0.8438	0.8769
CRUDEOIL-FX1	-0.33115	0.46667	-0.86670	0.99943	-0.8972	0.9830
METAL-SENSEX	-0.18722	0.93486	-0.22617	0.97446	-0.5364	0.9994

It is evident from the range figures that greater association can be observed in D6 scale, i.e. in long duration (Quarterly to biannual scale). Comparatively in D1 scale degree of volatility is much less. On contrary, again in D3 scale, the variation in dynamic association increases. As both DCC and ADCC models yield similar pattern, our findings are robust.

6. Causality exploration

We have applied the non-linear Granger causality on decomposed components of respective pairs. Findings of causality test is presented in Table 7.

Table 7
Outcome of non-linear Granger causality test

Pairs	D1	D2	D3	D4	D5	D6
CBOEVIX-INDIAVIX	–	↔**	–	↔**	–	→***
CRUDEOIL-FX1	–	–	–	↔***	↔**	↔**
DJIA-IT	–	–	–	–	↔**	–
METAL-SENSEX	–	–	↔***	↔***	↔***	←***

** Significant at 5% level, ***Significant at 1% level, The arrows (→,←: unidirectional causality; ↔: bidirectional causality) indicate the direction of causality

Significant bidirectional causality is observed in D2 and D4 scales (weekly and monthly scales). However in D6 i.e. quarterly to bi-annual duration, univariate causal influence from CBOEVIX to INDIAVIX is found. In all three scales, expanding from monthly to quarterly to bi-annual duration bidirectional causal dependence between CRUDEOIL and FX1 is evident. Significant causal nexus between DJIA and IT is discovered only in monthly to quarterly scale. No causal interaction is observed in other scales between them. In fortnightly, monthly and monthly to quarterly strong presence of bidirectional causal interrelationship between METAL-SENSEX pair can be observed. In quarterly to bi-annual scale significant unidirectional causal influence from SENSEX to METAL is discovered. We have further attempted to check how short run fluctuations of one variables, affect long run dynamics of other variables using the framework. We have restricted this exercise to CBOEVIX-INDIAVIX pair only.

Table 8
Asynchronous causality assessment

Pairs	D1-D2	D1-D3	D1-D4	D1-D5	D1-D6
CBOEVIX-INDIAVIX	–	–	↔**	–	–

Pairs	D2-D3	D2-D4	D2-D5	D2-D6
CBOEVIX-INDIAVIX	–	↔***	–	→**

Pairs	D3-D4	D3-D5	D3-D6
CBOEVIX-INDIAVIX	–	–	↔**

Pairs	D4-D5	D4-D6
CBOEVIX-INDIAVIX	–	↔**

Pairs	D5-D6
CBOEVIX-INDIAVIX	↔**

Short run variations in CBOEVIX has long run consequence for INDIAVIX. As the periods get closer, bidirectional impact can be observed. This is because of the nature of time series data. We will observe contemptuous correlation as time plays an important role.

7. Spillover analysis

To conduct spillover analysis in global context, unlike association and causality analysis, we have used all eight series together to get global insights. The findings can assist in policy formulation deeply. The following tables furnishes the findings. Each row in a table accounts for received spillovers while the columns account for imparted spillovers.

Table 9
Diebold-Yilmaz Spillover at D1 Scale

	CBOEVIX	INDIAVIX	CRUDEOIL	FX1	DJIA	IT	METAL	SENSEX	FROM OTHERS
CBOEVIX	66.23	1.72	5.78	5.46	9.36	2.08	4.80	4.56	33.76
INDIAVIX	3.92	52.82	3.40	3.38	4.78	3.45	8.43	19.81	47.17
CRUDEOIL	3.65	1.12	69.21	1.62	5.17	5.65	5.68	7.90	30.79
FX1	3.44	2.51	2.92	66.55	3.64	3.06	8.25	9.61	33.43
DJIA	5.14	1.79	2.99	1.88	73.37	4.12	5.26	5.43	26.61
IT	3.13	3.66	2.59	2.80	3.97	70.60	5.94	7.30	29.39
METAL	4.04	3.09	2.62	1.94	3.00	2.46	73.15	9.69	26.84
SENSEX	5.29	2.49	2.90	2.28	5.01	3.13	10.42	68.48	31.52
TO OTHERS	28.61	16.38	23.2	19.36	34.97	23.95	48.78	64.3	

Table 10
Diebold-Yilmaz Spillover at D2 Scale

	CBOEVIX	INDIAVIX	CRUDEOIL	FX1	DJIA	IT	METAL	SENSEX	FROM OTHERS
CBOEVIX	53.13	2.44	10.11	5.22	10.66	3.69	6.27	8.48	46.87
INDIAVIX	3.58	42.75	3.85	3.64	3.98	7.34	10.07	24.79	57.25
CRUDEOIL	2.38	2.48	68.36	4.04	4.74	5.19	5.45	7.36	31.64
FX1	2.59	2.43	3.85	60.59	3.36	3.69	8.57	14.92	39.41
DJIA	5.99	2.57	5.38	3.22	58.64	3.73	10.24	10.22	41.35
IT	3.61	1.78	5.67	2.64	3.59	59.20	11.24	12.26	40.79
METAL	5.19	6.95	3.43	2.39	3.68	6.81	58.48	15.14	43.59
SENSEX	3.63	2.18	3.99	1.72	3.47	5.97	11.38	67.66	32.34
TO OTHERS	26.97	20.83	36.28	22.87	33.48	36.42	63.22	93.17	

Table 11
Diebold-Yilmaz Spillover at D3 Scale

	CBOEVIX	INDIAVIX	CRUDEOIL	FX1	DJIA	IT	METAL	SENSEX	FROM OTHERS
CBOEVIX	50.74	3.86	6.61	4.10	6.36	3.80	10.70	13.83	49.26
INDIAVIX	5.37	39.36	5.51	2.90	5.93	6.87	11.81	22.26	60.65
CRUDEOIL	2.19	3.81	58.95	4.80	3.07	9.17	6.06	11.94	41.04
FX1	3.76	2.30	2.52	43.49	3.08	11.42	11.25	22.18	56.51
DJIA	12.07	2.83	7.39	4.87	49.44	4.09	7.34	11.97	50.56
IT	5.49	4.90	5.72	2.94	5.05	50.07	11.25	14.59	49.94
METAL	7.36	5.37	5.42	4.34	3.75	4.70	58.61	10.45	41.39
SENSEX	7.60	4.45	5.35	3.05	5.00	4.24	10.48	59.82	40.17
TO OTHERS	43.84	27.52	38.52	27	32.24	44.29	68.89	107.22	

Table 12
Diebold-Yilmaz Spillover at D4 Scale

	CBOEVIX	INDIAVIX	CRUDEOIL	FX1	DJIA	IT	METAL	SENSEX	FROM OTHERS
CBOEVIX	50.96	4.82	2.71	10.79	4.16	6.86	12.92	6.78	49.04
INDIAVIX	3.57	34.16	2.71	8.52	8.17	8.44	6.50	27.93	65.84
CRUDEOIL	2.33	5.94	43.97	26.80	4.59	5.93	3.26	7.18	56.03
FX1	5.79	6.19	3.66	62.34	3.74	2.69	5.17	10.41	37.65
DJIA	18.03	3.87	7.74	12.06	35.56	4.24	13.46	5.05	64.45
IT	2.27	3.92	4.36	6.45	11.64	46.45	14.70	10.19	53.53
METAL	9.22	6.12	8.71	2.56	5.11	11.69	48.77	7.82	51.23
SENSEX	4.22	3.44	2.27	3.16	8.09	6.45	11.91	60.46	39.54
TO OTHERS	45.43	34.3	32.16	70.34	45.5	46.3	67.92	75.36	

Table 13

Diebold-Yilmaz Spillover at D5 Scale

	CBOEVIX	INDIAVIX	CRUDEOIL	FX1	DJIA	IT	METAL	SENSEX	FROM OTHERS
CBOEVIX	32.93	20.15	2.54	2.84	6.18	14.57	7.75	13.04	67.07
INDIAVIX	1.33	49.19	3.26	5.40	3.19	4.86	9.47	23.19	50.7
CRUDEOIL	2.43	10.15	39.48	11.57	3.50	2.46	17.37	13.04	60.52
FX1	10.53	6.99	7.52	53.44	3.36	4.89	8.36	4.90	46.55
DJIA	12.58	15.93	11.12	0.82	28.58	7.26	7.76	15.95	71.42
IT	9.14	7.88	4.60	4.50	7.72	53.69	5.73	6.74	46.31
METAL	1.93	3.07	16.84	9.47	9.13	3.00	47.22	9.34	52.78
SENSEX	5.71	6.72	3.04	6.20	6.03	19.17	14.91	38.22	61.78
TO OTHERS	43.65	70.89	48.92	40.8	39.11	56.21	71.35	86.2	

Table 14

Diebold-Yilmaz Spillover at D6 Scale

	CBOEVIX	INDIAVIX	CRUDEOIL	FX1	DJIA	IT	METAL	SENSEX	FROM OTHERS
CBOEVIX	56.67	15.64	3.74	0.74	5.50	2.81	5.42	9.49	43.34
INDIAVIX	42.44	8.32	0.16	3.27	5.88	15.53	12.64	11.77	91.69
CRUDEOIL	5.27	11.47	37.37	10.80	4.09	8.63	5.76	16.60	62.62
FX1	11.38	2.58	27.40	30.62	1.38	14.45	0.68	11.50	69.37
DJIA	39.73	14.34	14.76	2.80	4.63	10.10	1.22	12.43	95.38
IT	6.28	1.20	10.06	0.93	0.74	65.38	2.49	12.91	34.61
METAL	15.25	27.20	3.52	2.54	6.40	11.47	24.14	9.49	75.87
SENSEX	3.71	14.48	1.08	0.93	5.34	15.35	8.93	50.17	49.82
TO OTHERS	124.06	86.91	60.72	22.01	29.33	78.34	37.14	84.19	

At D1 (Intraweek) scale, top two contributors of spillovers received by CBOEVIX are DJIA and CRUDEOIL i.e. in very short run DJIA and CRUDEOIL affect CBOEVIX most. This makes sense as CBOEVIX should be driven by market sentiment, DJIA. Further CRUDEOIL should also affect the volatility in USA as USA is large importer of Petroleum whereas top two gainers of its spillover are SENSEX and DJIA. This insight is important as it states that volatility in USA market affects market sentiment in India. It of course would affect market sentiment in USA. Volatility of INDIAVIX is largely driven by SENSEX and METAL apart from its own contribution. CRUDEOIL receives maximum spillover from SENSEX while it affects CBOEVIX most. FX1 has been found to be impacted by SENSEX and METAL. Spillover from DJIA affects CBOEVIX most while large portion its volatility is contributed by shock of its own volatility. IT receives significant spillovers from METAL and SENSEX. METAL and SENSEX get involved in significant bidirectional spillovers. At intraweek duration, SENSEX dominates (mostly affecting INDIAVIX) in explaining variance of forecast errors to other assets.

From Tables 9-14, we can observe that

a. If we consider volatility spillover from the US market to the Indian market, then there is a strong permanent effect as shown by the D6 component between CBOEVIX and INDIAVIX. As these are measures of implied volatility, the result indicates that in the long run if US markets are expected to turn volatile, Indian markets will turn volatile also.
b. Between CRUDEOIL and CBOEVIX there are short to medium term spillovers. That is crude oil prices affect US market volatility. But adjustments take place and thus they do not persist in the long run
c. Movement in Sensex affects INDIAVIX in the short to medium run. This is expected as when markets turn bearish, investors buy put options increasing VIX. However, this does not persist. However, INDIAVIX has a longer term effects on Sensex as expectations of increase in market volatility can turn the market bearish. Investors may like to stay away from markets.
d. In a similar vein, the impact of CBOEVIX on DJIA returns increases with time.
e. The spillover from IT sectoral returns to India VIX is present throughout across all times. The reason is that the IT sector is the largest foreign exchange earner in the services sector. If this sector does not do well due to world economic slowdown or is affected by policy measures of foreign counties, this affects foreign currency inflow in the short run generating uncertainty. If

the slowdown persists, then markets turn volatile as growth in GDP gets affected, at least in the medium run.

f. In the same logic, IT returns spill over to Sensex returns also.
g. In long run dynamics, CBOEVIX emerges as market leader in imparting volatility to other assets.

8. Concluding remarks

The findings of the paper indicate that the framework of analysis used has been able to address association, causality and spillovers of the eight variables under consideration. The granular approach enabled us to break down a time series into short, medium and long run components. We could then work out whether effects of short run shocks were temporary or had long term effects. This preceded by a study on association and causality which gave valuable insights.

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