Time - Varying Correlations, Causality, and Volatility Linkages of Indian Commodity and Equity Markets : Evidence from DCC - GARCH

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Abstract

This empirical study explored and examined the dynamic conditional correlations, causality, and volatility linkages between the commodity and equity markets in India. In this study, we utilized the DCC - GARCH framework. The symmetric and asymmetric versions of DCC-GARCH, DCC-GJR GARCH, and DCC-EGARCH were used. Our study incorporated the major Indian equity market indices, BSE Sensex & Nifty 50 and commodity market indices, MCX Comdex & Dhaanya. Our results revealed that a mixed portfolio of commodity - equity had low and negative correlations compared to only equity or only commodity portfolios. We deployed the Granger causality test which indicated the short term integration of returns among the markets. We found a bidirectional causal relation between BSE Sensex and Nifty 50 indices. However, we noticed unidirectional causality between MCX Comdex index to Dhaanya index and Dhaanya to Nifty 50 index. The empirical evidence obtained from this study will be useful for the institutional investors, policymakers, investors, and government while framing strategies for portfolio risk diversification and hedging.

Keywords : **time - varying correlations, causality, volatility, Indian commodity and equity markets, portfolio risk management, dynamic correlations**

JEL Classification: C32, C58, C61, G11, G20

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Investigating and examining the interrelationship between markets is essential for asset allocation and diversifying a portfolio because it determines the risk. To select superior portfolios for investors, portfolio managers and risk managers estimating the correlation structure are instrumental. Markowitz (1952) demonstrated how an investor could reduce the portfolio risk through investing in uncorrelated securities. Useful modeling of dynamic conditional correlations between the commodity and equity markets will help in designing strategies for optimization of the portfolio, asset allocation, managing risk, and hedging to the investors. Sadorsky (2014) reported that combining investments in commodities that have low or negative correlations with equity assets should provide better diversification properties than a portfolio without commodity. A mixed commodity - equity portfolio may provide more expected returns and lower risk than a stock portfolio or commodity portfolio. Moreover, our study focuses on the comparative approach with various possible combinations of the equity portfolio, the commodity portfolio, and a mixed commodity - equity portfolio. The most popular commodity

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investment strategy invests in a basket of commodities in a given commodity index. The drivers of commodity prices and traditional asset prices are distinct. The commodity price dynamics are complex because various factors affect the prices of commodities directly such as weather, political conditions, supply constraints and event risks ; whereas, this is not the case for equities and bonds. Furthermore, commodities have a strong positive correlation with inflation. Hence, a long position in commodities can serve as a natural inflation hedge. Commodities or commodity-related instruments not only offer higher returns, but also help an investor to create a well-diversified portfolio.

A commodity index functions just like an equity index such as Sensex or Nifty 50. Alternatively, commodity futures contract on individual commodities and also on commodity indices, which allows the investors to take a direct exposure in the commodity sector without facing the challenges of holding the physical commodities. This facility along with the other essential benefits of financial futures make the commodity futures contracts very interesting for the investors interested in the commodity market.

The focus of our analysis is : (a) how dynamically the conditional correlations have changed between the indices of the equity portfolio, the commodity portfolio, and mixed with commodity - equity portfolio pairs in the selected time frame in recent years in India? (b) What has caused the increases or decreases in return correlations ? (c) Is there any causal relationship between the commodity and equity indices ? Is there any scope for institutional investors in Indian commodity markets ? To answer these questions, we examined possible economic mechanisms. Unlike the previous studies, we report clear evidence of varied results from various portfolio combinations for the Indian scenario.

Review of Literature

In the existing literature, the co-movements between commodity and equity prices were examined by the following authors. Jensen, Johnson, and Mercer (2000) provided evidence on the diversification benefits of commodities to the U.S. investors holding a benchmark portfolio of U.S. stocks, U.S. bonds, U.S. T-bills, and U.S. real estate. Gorton and Rouwenhorst (2006) reported that commodity returns displayed a negative correlation with equity returns over a long-term, and selected the data from 1959 to 2004. Erb and Harvey (2006) reported that commodities had only low positive return correlations with each other. Delatte and Lopez (2013) studied the dependence structure that existed between returns on commodity and equity futures and its development over the past 20 years. They found that the dependence between commodity and stock markets was time-varying. Kumar (2014) found a significant unidirectional return spillover from gold to stock sectors in India. He suggested that the stock - gold portfolio provided better diversification benefits than a stock portfolio. Sehgal and Pandey (2012) found that the commodities that offered high average returns also exhibited high - price volatility. Combining gold with the stock market index provided significant portfolio diversification benefits. Thuraisamy, Sharma, and Ahmed (2013) demonstrated the volatility spillover effects of Asian equity market and the two most dominant commodities - crude oil and gold futures. They documented strong evidence of gold price volatility influencing equity market volatility. Cheung and Miu (2010) demonstrated that the benefit of diversification to commodities is a more complicated phenomenon. Commodities may be an asset class for more adventurous investors with higher - risk tolerance. Büyükşahin, Haigh, and Robe (2012) found that correlations between equities and commodities increased greater speculator's participation. Irwin and Sanders (2012) provided the evidence that passive index investment caused a massive bubble in commodity futures prices. Silvennoinen and Thorp (2013) estimated sudden and gradual changes in correlation between stocks, bonds, and commodity futures returns. Creti, Joëts, and Mignon (2013) studied the links between price returns of 25 commodities and stocks over a period from January 2001 to November 2011. They reported that the correlations between commodity and stock markets that evolved through time were highly volatile, particularly since the 2007-2008 financial crisis. Kilian and Park (2009) reported on the results of volatility spillovers between equity and oil prices.

Hammoudeh, Nguyen, Reboredo, and Wen (2014) examined the implications of co-movements for asset allocation among commodities and the stock markets in China by using copula functions. Their results provided evidence of low and positive correlations between these markets ; hence, commodity futures were found to be a desirable asset class for portfolio diversification. Singhal and Ghosh (2016) empirically investigated the time-varying co-movements between crude - oil and the Indian stock market returns, both at the aggregate and sector level using VAR-DCC-GARCH framework. They found insignificant direct volatility spillover from the oil market to the Indian stock market at the aggregate level and significant results at sectoral levels such as auto, power, and finance sectors. Jain and Biswal (2016) investigated the dynamic linkages between crude-oil and stock markets in the Indian context by considering volatility transmissions at the market level. Adams and Glück (2015) argued that commodities have become an investment avenue for the institutional investors. The institutional investors continue to target funds into commodities ; they predicted spillovers between commodities and stock markets to remain high in the future. Bessler and Wolff (2015) found that portfolio gains greatly varied between different types of commodities and sub-periods, while aggregate commodity indices improved the performance of a stock - bond portfolio for most asset allocation strategies. Pan, Wang, and Liu (2016) reported a significant asymmetric effect in oil - stock correlations. Moreover, it was also observed that the energy price risk could be a better hedge by stocks of oil - exporting countries than stocks of oil - importing nations. Nagayev, Disli, Inghelbrecht, and Ng (2016) studied correlations between commodity markets and the Dow Jones Islamic Market World Index using MGARCH-DCC. They found that they were time - varying and highly volatile throughout the period of January 1999 - April 2015. A substantial and persistent increase was observed in the return correlations between commodities and Islamic equity during the 2008 financial crisis.

Arouri, Jouini, and Nguyen (2011) analyzed the volatility transmission between oil and stock markets in Europe and the United States at the sector-level by generalized VAR-GARCH. They found significant volatility spillover between oil and sectoral stock returns. However, the spillover was unidirectional from oil markets to stock markets in Europe, but bidirectional in the United States. Lombardi and Ravazzolo (2016) developed a time-varying Bayesian dynamic conditional correlation model. They found that joint modeling of commodity and equity prices produced accurate forecasts and led to benefits in portfolio allocation. Brooks, Fernandez - Perez, Miffre, and Nneji (2016) examined the commodity risk and cross-section of global equity returns. They suggested that when measured appropriately, commodity risk was pervasive in stocks. Jacobs Jr. and Karagozoglub (2014) identified that moving correlation structure can best track the dynamic conditional correlation estimates using a broad set of different financial time series.

Some other papers focused more specifically on co-movements of only commodity and only equity investments. Durai and Bhaduri (2011) reported a low correlation across S&P CNX Nifty with both Asian and developed nations. These low correlations provided space for the global funds to diversify risk in the Indian markets. Sclip, Dreassi, Miani, and Paltrinieri (2016) provided the evidence of high relationship between Sukuk with U.S. and EU stock markets. De Nicola, De Pace, and Hernandez (2016) studied the co-movements among the 11 major energy, agricultural, and food commodities. They found that the price returns of energy and agricultural commodities were highly correlated, and the overall level of co-movement among commodities had increased in recent years. Cabrera and Schulz (2016) found that in the long run, prices moved together and preserved the equilibrium, while correlations were mostly positive for persistent market shocks. Tang and Xiong (2012) found that prices of non-energy commodity futures in the United States became increasingly correlated with oil prices. Kang, McIver, and Yoon (2017) reported positive equicorrelations between commodity futures market returns and found that it increased sharply during the crises. They also identified bidirectional return and volatility spillovers across commodity futures markets ; gold and silver were found to be information transmitters to other commodity futures markets. Narayan, Narayan, and Sharma (2013) reported on dynamic trading strategies, and they suggested that all commodities were profitable and profits were dependent on structural breaks. Jain and Biswal (2016) emphasized upon the emergence of gold as an investment asset class among the investors. Recently, a few researchers like Bhattacharjee and Swaminathan (2016) and Vohra (2016) found the existence of comovement and integration of BSE with other markets. Patel (2017) studied the co-movements and integration among 14 countries' stock markets. The results showed that Hang Seng, FTSE-100, MXX, NASDAQ, and BVSP were positively correlated with BSE. They found a long-run relationship among the selected stock markets. Irfan and Hooda (2017) observed a long-run equilibrium relationship in commodities. Narsimhulu and Satyanarayana (2016) found that there was a long-run association between commodity spot and futures prices of Chana, Chilli, and Turmeric.

The literature has revealed the varied opinions on including commodities with other traditional asset portfolios from various countries. However, from an Indian perspective, our research will provide useful insights for the domestic and global investors. Similar to that, some researchers found that the commodity returns displayed a negative correlation with equity returns. For example, Gorton and Rouwenhorst (2006) found that the commodity returns displayed a negative correlation with equity returns over a long-term. Delatte and Lopez (2013) found that the dependence between commodity and stock markets was time-varying. Singhal and Ghosh (2016) found insignificant direct volatility spillover from the oil market to the Indian stock market at the aggregate level. However, they found a significant volatility spillover at sectoral levels, such as auto, power, and finance sectors.

Methodology

(1) The Univariate GARCH Model and Asymmetric Extensions : The GARCH model introduced by Bollerslev (1986) expressed conditional variance as a linear function of the past square values of the series. A generic GARCH (p,q) model can be described as follows:

$$R_t = \mu + \varepsilon_t \qquad \text{(Mean Equation)} \qquad (1)$$

$$\sigma^2_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j} \qquad \text{(Variance Equation)} \qquad (2)$$

where, the α_i and β_j are non negative constants and ω is a positive constant.

Since the conditional variance in equation (2) is a function of the lagged residuals and not their signs, the model enforces symmetric response of volatility to positive and negative shocks.

The exponential GARCH model is the first that investigates the leverage effects, which refers to the fact that down movements are more influential in predicting volatility than the upward movements. Nelson's (1991) EGARCH attempts to model fat tails in stock index returns by using a generalized exponential distribution in formulating the model, which can be represented as follows :

$$\log \sigma^2_t = \omega + \beta \log \sigma^2_{t-1} + a \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad (3)$$

Equation (3) allows negative values of ε_t to have different impacts on volatility. Since the coefficient γ_i is typically negative, the model claims for an asymmetric behavior in volatility.

The GJR model of Glosten, Jagannathan, and Runkle (1993) introduced an asymmetry as a function of the positive and negative parts of the past innovations, and can be defined as :

$$\sigma^2_t = \omega + \sum_{i=1}^{q} a_i \varepsilon^2_{t-i} + \gamma\varepsilon^2_{t-1} d_{t-1} + \sum_{j=1}^{p} \beta_j \sigma^2_{t-j} \tag{4}$$

where, $d_t = 1$ if $\varepsilon_t < 0$ and $d_t = 0$ otherwise.

In this model, good news ($\varepsilon_t > 0$) and bad news ($\varepsilon_t < 0$) has differential effects on the conditional variance. In particular, good news has an impact of a, while bad news has an impact of $a + \gamma$. If $\gamma > 0$, then the leverage effect exists and bad news increases volatility. The univariate GARCH models were estimated through the maximum likelihood approach of Bollorslev and Wooldridge (1992), where the log-likelihood functions are from the student's t - distribution.

(2) DCC and ADCC - GARCH Model : As we mentioned, the main purpose of the study is to analyze comparatively the dynamic conditional correlations of the commodity only, stock only, and mixed with commodity - stock only portfolios. We looked into the dynamic conditional correlation [DCC] - GARCH model introduced by Engle (2002), which is a generalization of the CCC model, which allows the correlation matrix to vary over time rather than requiring them to be constant. Cappiello, Engle, and Sheppard (2006) introduced the asymmetric version of DCC GARCH to address the impact of asymmetric information on the time - varying correlations. In the first step, residuals are GARCHED in three ways (standard, threshold, and exponential). At the second step time, varying correlations were estimated by relying on lagged values of residuals and covariance matrices. In the present study, both symmetric and asymmetric versions of DCC GARCH (Engle, 2002) and ADCC GARCH (Cappiello et al., 2006) of modelling time-varying correlations were used. The covariance matrix in DCC GARCH is (Engle, 2002) defined as :

$$H_t = D_t R_t D_t \tag{5}$$

where, H_t is the conditional covariance matrix. D_t is the $k \times k$ diagonal matrix of time - varying standard deviations from univariate GARCH models with $[\sigma^2_{i,t}]^{1/2}$ on the ith diagonal.

$$D_t = \begin{bmatrix} \sqrt{\sigma^2_{c,t}} & 0 \\ 0 & \sqrt{\sigma^2_{e,t}} \end{bmatrix} \tag{6}$$

R_t is the time varying correlation matrix.

$$R_t = \begin{bmatrix} \varepsilon_{cc,t} & \varepsilon_{ce,t} \\ \varepsilon_{ec,t} & \varepsilon_{ee,t} \end{bmatrix} = \begin{bmatrix} 1 & \varepsilon_{ce,t} \\ \varepsilon_{ec,t} & 1 \end{bmatrix} \tag{7}$$

Further, R has to be definite positive, and all the parameters should be equal to or less than one. In order to ensure this, R_t has been modeled as :

$$R_t = Q^{*-1}_{ce,t} Q_{ce,t} Q^{*-1}_{ce,t} \tag{8}$$

where,

$$Q_{ce,t} = [1 - \theta_1 - \theta_2].\, Q^* + \theta_1 [\varepsilon_{c,t-1}\varepsilon_{e,t-1}] + \theta_2 [Q_{ce,t-1}] \tag{9}$$

where, $Q_{ce,t}$ is the unconditional variance between series and I and j and follows a GARCH process, Q^* is the unconditional covariance between the series estimated in step 1, and the scalar parameters θ1 and θ2 are non-negative and satisfy $\theta 1 + \theta 2 < 1$.

Following the methodology of Engle (2002), the parameters θ1 and θ2 are estimated by maximizing the log-likelihood function. The log-likelihood function can be expressed as :

$$L(\theta) = -\frac{1}{2}\sum_{t-1}^{T}(k\log(2\pi)) + 2\log([D_t]) + \log([R_t]) + \varepsilon'_t R_t^{-1}\varepsilon_t) \quad (10)$$

As the above model, the DCC model does not allow for asymmetries and asset specific news impact parameter. The modified model of Cappiello et al. (2006) for incorporating the asymmetrical effect and asset specific news impact can be written as:

$$Q_{ce,t} = (1 - \theta_1 - \theta_2).\overline{Q} - \theta_3.\overline{\xi}_t + \theta_1[\varepsilon_{c,t-1}\varepsilon'_{e,t-1}] + \theta_2[Q_{ce,t-1}] + \theta_3(\varphi_{t-1}\varphi'_{t-1}) \quad (11)$$

where, $\overline{\xi} = E + |\overline{\varphi_{ct}\,\varphi'_{et}}|$, $\varphi_{ct} = (I[\overline{\varepsilon}_{ct} < 0]o\overline{\varepsilon}_{ct})$, and $\varphi_{ct} = 0$ otherwise. Here, θ3 is the asymmetric term which captures periods where both commodity and stock market experience bad news making $|\overline{\varphi_{ct}\,\varphi'_{et}}| = I_t$.

This model is estimated using maximum likelihood techniques based on a BFGS optimization algorithm. We adopted student - t multivariate distribution of the time series returns, which is more suitable and gives better estimation results.

Preliminary Data Analysis

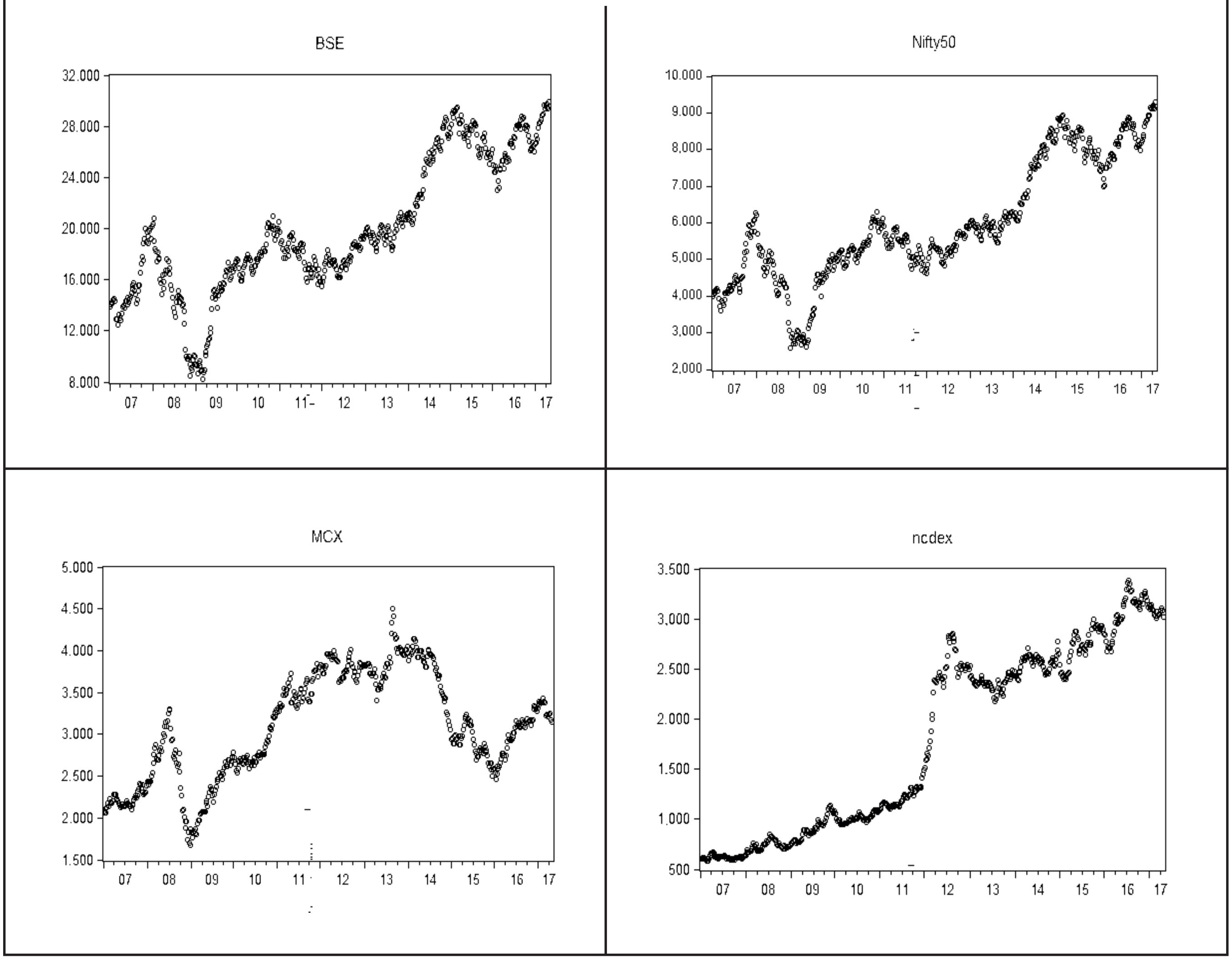
The study explores the time - varying correlations between equity and commodity markets in India, and the study uses weekly returns of the BSE Sensex, Nifty 50, MCX Comdex, and Dhaanya. The data for the above-selected indices were sourced from their official exchange websites such as Bombay Stock Exchange (BSE), National

Table 1. Descriptive Statistics of Equity and Commodity Indices : Weekly Returns

	BSE Sensex	Nifty 50	MCX Comdex	Dhaanya
Mean	0.001438	0.001586	0.000779	0.003011
Median	0.002614	0.002734	0.001125	0.002958
Maximum	0.120805	0.143568	0.112705	0.103741
Minimum	-0.173808	-0.173755	-0.120899	0.071115
Std. Dev.	0.031025	0.031133	0.023383	0.021102
Skewness	-0.361107	-0.370872	-0.572547	0.211794
Kurtosis	5.912828	6.631899	6.635228	4.505973
Jarque-Bera	200.7624 [0]*	306.3071 [0]*	323.8115 [0]*	54.55621 [0]*
ADF at level With Constant & Trend				
t-Statistic &Prob	-268.7723 [0.0001]*	-218.3784 [0.000]*	-277.9046 [0.0001]*	-160.4305 [0.0001]*
PP at level With Constant & Trend				
t-Statistic &Prob	-22.7148 [0]	-22.5081 [0]	-22.626 [0]	-19.4661 [0]
ARCH LM	0.610345 [0.4350]	0.051219 [0.8210]	0.543627 [0.4613]	0.010691 [0.9177]

Notes: Between parentheses : p - values. *denotes rejection of null hypothesis at the 1% significance level.

Figure 1. Trend of Equity and Commodity Indices



Stock Exchange (NSE), Multi Commodity Exchange (MCX), and National Commodity and Derivatives Exchange (NCDEX). First, we converted weekly prices into log returns of the two successive prices, that is, log (*Pt* / *pt*-1). The time span of the study runs from January 1, 2007 to April 30, 2017 (based on the availability, we selected the data). It also covers the impact of macroeconomic and financial factors on commodity and equity markets domestically as well as globally. The Indian stock market trading operations vary from commodity trading operations in time. Daily or monthly data is not feasible for capturing the time - varying co-movements. Hence, we considered weekly data to obtain the dynamic interactions between commodity and stock markets. The descriptive statistics reveal the characteristics of the data at a preliminary stage. The Table 1 presents the results.

The Table 1 depicts the descriptive statistics about our data. As is evident from the Table 1, Dhaanya (0.003) had the highest annualized average weekly returns followed by Nifty 50 (0.0015), the Sensex (0.0014), and MCX Comdex (0.0007). Regarding volatility, as defined by the analyzed weekly standard deviation, Nifty 50 (0.0311) had the highest volatility followed by BSE Sensex (0.0310), MCX Comdex (0.023), and Dhaanya (0.021).

All the weekly returns have asymmetric distributions as shown by the skewness and kurtosis statistics. All the distributions have a kurtosis significantly higher than 3, implying that extreme market movements in either direction (gains or losses) occurred in these commodity and equity markets with higher frequency in practice than what would be predicted by the normal distribution. The Jarque - Bera statistics confirm the non - normal distribution of all the return data series, may be due to extreme data points. We use the ADF and Phillips - Perron tests to check the stationarity of the four series. The null hypothesis of the unit root is rejected for all the return series at levels with constant, without constant, and constant with trend. The ARCH - LM test confirms the presence of no serial correlation and heteroscedasticity in all four series.

The Figure 1 depicts the trend of equity and commodity indices weekly prices from 2007 to 2017. The Figure 1 is sub-divided into 4 plots. Plot 1 represents the trend of BSE Sensex, Plot 2 shows the trend of Nifty 50, Plot 3 displays the trend of MCX Comdex, and Plot 4 represents the trend of Dhaanya.

The BSE Sensex and Nifty 50 price plots (visual inspection of Figure 1) reveal that there was significant upward movement throughout the time frame except during the global financial crisis period from 2007 - 08. However, a downward trend is noticed since 2015 because of the domestic policy changes. The MCX Comdex plot reveals that there was a significant upward movement from 2009 to 2013. However, we notice a significant downward trend since 2013. This downward trend in MCX Comdex was due to the implementation of the Commodity Transaction Tax [CTT] on non - farm commodities. There was an upward movement throughout the time frame for Dhaanya ; our observation shows that the index was not affected by the global financial crisis.

Unconditional Correlations of the Selected Indices : The Table 2 presents unconditional correlations and a summary of the results to know the relationship between the commodity and equity indices.

The Table 2 presents the unconditional correlations of the four selected indices. The results validate that BSE Sensex has a positive relationship with all other three series. Sensex shows the highest positive correlation with Nifty 50 [0.91] followed by MCX Comdex [0.16], however, it shows the least correlation with Dhaanya [0.04]. By observing Nifty50 correlations with other three series, we find the highest correlations with BSE Sensex [0.91], followed by MCX Comdex [0.18], while Dhaanya exhibits the lowest correlation [0.04]. MCX Comdex correlates positively with the other three indices. Hence, it shows the highest correlation with Nifty 50 [0.18] followed by BSE Sensex [0.168] and Dhaanya [0.162]. Finally, by observing the Dhaanya correlations, we notice that the highest positive relationship is with MCX Comdex [0.16] followed by BSE Sensex [0.048] and Nifty50 [0.045]. According to Engle (2002), "Correlations are crucial inputs for many of the essential tasks of financial management" (p.339). The static unconditional correlation represents the long-run average. Hence, unconditional correlations may not be sufficient to build an efficient model to decide the portfolio diversification. Furthermore, we have analyzed the time varying co-movements to examine and understand the correlation dynamics.

Table 2. Unconditional Correlations

	Sensex	Nifty 50	MCXComdex	Dhaanya
Sensex	1			
Nifty 50	0.9194928	1		
Comdex	0.1681786	0.18017742	1	
Dhaanya	0.0489883	0.04537656	0.1621021	1

Empirical Analysis and Results

In this section, we present and discuss the results of the univariate and bivariate parameter estimates of symmetric and asymmetric versions of DCC - GARCH, DCC - GJRGARCH, and DCC - EGARCH, the causal relationships

Table 3. Univariate Parameter Estimates of DCC- GARCH, DCC - GJR GARCH, and DCC-EGARCH

	Sensex	Nifty 50	MCX Comdex	Dhaanya
Panel-A Estimates of -GARCH				
ω	0.002294[0.0258]**	0.002357[0.0278]**	0.001530[0.0693]***	0.001997[0.0178]**
α	0.088396[0.0009]*	0.098835[0.0003]*	0.076938[0.0069]*	0.058722[0.0299]**
β	0.89733[0.0000]*	0.881678[0.0000]*	0.883662[0.0000]*	0.891706[0.0000]*
AIC	-4.374634	-4.354321	-4.876064	-4.932628
HQ	-4.358975	-4.338662	-4.860405	-4.916969
ARCH LM	0.197458[0.6570]	0.00038[0.9845]	0.575588[0.4484]	0.005053[0.9434]
Panel-B Estimates of GJR- GARCH				
	Sensex	**Nifty 50**	**MCX Comdex**	**Dhaanya**
ω	0.001706[0.1026]	0.001652[0.1186]	0.001499[0.0756]***	0.002530[0.0024]*
α	0.038265[0.1876]	0.044593[0.1389]	0.067456[0.0855]***	0.110744[0.0011]*
β	0.894664[0.0000]*	0.868148[0.0000]*	0.885376[0.0000]*	0.908606[0.0000]*
γ	0.093251[0.0271]**	0.126151[0.0039]*	0.013470[0.7408]	-0.159659[0.0001]*
AIC	-4.381482	-4.367559	-4.872575	-4.9694
HQ	-4.362692	-4.348769	-4.853785	-4.950609
ARCH LM	0.507834[0.4764]	0.051811[0.8200]	0.543627[0.4613]	0.162461[0.6871]
Panel-C Estimates of EGARCH				
	Sensex	**Nifty 50**	**MCX Comdex**	**Dhaanya**
ω	0.001636[0.1024]	0.001743[0.0864]***	0.001341[0.1070]	0.002534[0.0023]*
α	0.162493[0.0003]*	0.196872[0.0001]*	0.067456[0.0855]***	0.026329[0.5072]
β	0.985707[0.0000]*	0.977138[0.0000]*	0.885376[0.0000]*	0.945171[0.0000]*
γ	-0.054914[0.0240]**	-0.073656[0.0030]*	0.013470[0.7408]	0.117360[0.0000]*
AIC	-4.374486	-4.358814	-4.872575	-4.965853
HQ	-4.355696	-4.340024	-4.853785	-4.947062
ARCH LM	0.610345[0.4350]	0.051219[0.8210]	0.543627[0.4613]	0.010691[0.9177]

Notes: Figures in parentheses are *p* - values, *denotes significant at 1%, **denotes significant 5%, and ***denotes significant at 10%. Arch Lag Range Multiplier statistics correspond to the null of no arch effect.

(Granger causality) across the indices, and also the conditional volatility of commodity and equity indices.

The first step of the DCC model consists of fitting univariate GARCH specification of all four indices returns. We examined the stability conditions of all the four series. All the four series satisfy and meet the stability conditions. We, therefore, proceed to draw some inferences.

The Table 3 (Panel - A) represents the results of the univariate GARCH model. The coefficients ARCH (α) and GARCH (β) are positive and significant for all four series. We observed that the sum of the coefficients of α and β is close to unity, which implies that the shocks to the conditional variance are highly persistent in the long and short run. Hence, these results will help us to understand the significance levels of the persistence of shocks in the long and short run.

The Table 3 (Panel - B) presents the results of univariate GJR/TGARCH. GARCH coefficient β is positive and significant for all the series, implying that the shocks to the conditional variance are highly persistent in the long run. The ARCH coefficient α is positive and significant for MCX Comdex and Dhaanya, however, it is insignificant for BSE Sensex and Nifty50. Asymmetry term λ is positive and significant for BSE Sensex and Nifty 50, conveying that they respond positively to positive return shocks and vice versa. However, for Dhaanya, λ is negative and significant, conveying that Dhaanya reacts differently to positive and negative return shocks.

The Table 3 (Panel - C) presents the results of the univariate EGARCH model. GARCH coefficient β is positive and significant for all four series, indicating that the shocks are highly persistent in all indices in the long run. The ARCH coefficient α is positive and significant for the three series except for Dhaanya, conveying that the shocks are persistent in the short term. The EGARCH model indicates the leverage effect. It is negative and significant for Sensex and Nifty 50. Bad news generates more volatility than good news in these markets. However, it is positive and significant for Dhaanya, conveying that good news generates more volatility in agri commodity index - Dhaanya.

The ARCH LM test proves the presence of heteroskedasticity in all four series. The diagnostic criteria for the residuals reveal that all the models are correctly specified. The results of diagnostic tests show that the residuals are free from serial correlation and arch effect.

After the univariate estimates, we investigate the dynamic conditional correlations of commodity and equity pairs by using symmetric and asymmetric versions of different DCC models.

The Table 4 (Panel - A) represents the results of the DCC - GARCH. The results reveal that the coefficient θ1, which denotes the short-term persistence of shocks, is positive and significant for BSE Sensex - Nifty 50 and Nifty 50-MCX Comdex. It is negative and significant for Dhaanya - MCX Comdex. The coefficient θ2, which denotes long-term persistence of shocks, is positive and significant for all the four series except BSE Sensex - Dhaanya, which conveys that the shocks to the conditional variance are positive and highly persistent in the long run.

Table 4. Summary Results of Bivariate Parameter Estimates of DCC and ADCC - GARCH

	Sensex -Nifty50	Sensex-Comdex	Sensex-Dhaanya	Nifty50-Comdex	Nifty50-Dhaanya	Dhaanya-Comdex
Panel -A (DCC) Parameters						
θ1	0.110337 [3.89E-06] *	0.015816 [0.112093]	0.020974 [0.668655]	0.019063 [0.099487***]	-0.015783 [0.206411]	-0.03599 [0.000000]*
θ2	0.883468 [0.0000]*	0.969775 [0.0000]*	0.508269 [0.5178]	0.964034 [0.0000]*	0.974868 [0.0000]*	0.869197 [0.0000]*
θ1+θ2	<1	<1	<1	<1	<1	<1
DF	4.584833 [0.000000]	9.330653 [1.65E-06]	16.46723 [0.010069]	8.990091 [1.60E-06]	16.67697 [0.014336]	8.069412 [2.33E-07]
AIC	-11.51406	-9.266814	-9.291712	-9.248714	-9.273797	-9.833721
HQC	-11.48274	-9.235497	-9.260395	-9.217397	-9.242479	-9.802404
Panel-B (ADCC) Parameters						
θ1	0.092765 [NA]	0.013138[0.165355]	-0.030635 [NA]	0.017018[0.126199]	-0.048927 [NA]	-0.036099[0.000000]*
θ2	0.908242 [NA]	0.972063[0.0000]*	0.499586 [NA]	0.965137[0.0000]*	0.760029 [NA]	0.883382[0.0000]*
θ3	- 0.002831 [NA]	0.005029[0.485764]	0.125907 [NA]	0.004874[0.591295]	0.034475 [NA]	0.009855[0.672908]
θ1+θ 2	>1 (not met)	<1	<1	<1	<1	<1
DF	NA	9.459908 [2.39E-06]	19.52904 [NA]	9.104858 [2.40E-06]	16.90937 [NA]	8.107264 [2.64E-07]
AIC	-11.04818	-9.267845	-9.342012	-9.255221	-9.331773	-9.867794
HQC	-11.01373	-9.230265	-9.304432	-9.21764	-9.294193	-9.830213

Notes: Figures in parentheses are *p* - values, *denotes significant at 1%, **denotes significant at 5%, and ***denotes significant at 10%.

Additionally, the sum of the coefficients is close to unity, implying that shocks to conditional variance are highly persistent in the long run.

The Table 4 (Panel - B) presents the results of ADCC - GARCH model. The results indicate that the asymmetric parameter θ3 is insignificant for all pairs. However, the optimization fails for Sensex-Nifty 50, Sensex-Dhaanya, and Nifty 50-Dhaanya pairs. The point worth noticing is that Dhaanya-MCX Comdex pair's θ1 is negative and significant, conveying that the shocks to the conditional variance are persistent in the short run for this pair, while θ2 is positive and significant in case of Sensex - Comdex, Nifty50 - Comdex, and Dhaanya - Comdex pairs, which indicates that the shocks to the conditional variance are positive and highly persistent in the long run for these pairs. In case of Sensex - Nifty50, the sum of the coefficients θ1 + θ2 is greater than the 1, which violates the stability condition and rules out the possibility of considering the ADCC GARCH model.

The Table 5 (Panel -A) represents the results of the DCC- GJR - GARCH model. The estimated coefficients θ1 and θ2 are statistically significant. Short-run persistence parameter θ1 is positively significant only for Sensex - Nifty 50 and Nifty 50 - MCX Comdex pairs. For long - run persistence, θ2 is undoubtedly substantial for all the series except Sensex - Dhaanya, while the optimization fails for the Dhaanya - MCX Comdex pair. The Table 5 (Panel-B) results of the ADCC-GARCH model indicate that the ADCC parameter θ3 is negative and significant for Nifty 50-Sensex, which indicates that bad news generates more volatility than good news in the pair ; while it is positive and significant for Nifty50 - Dhaanya pair, conveying that good news generates more volatility than the bad news.

The Table 6 (Panel A) presents the results of the DCC- EGARCH model. We notice that for the coefficient θ2, long run persistence of shocks to the conditional correlations is positive and highly significant for all the series except Sensex - Dhaanya. In case of coefficient θ1, short - run persistence of shocks to the conditional correlations is positive and significant for Nifty50 - MCX Comdex and negatively significant for Dhaanya - MCX Comdex. The Table 6 (Panel - B) indicates that the ADCC EGARCH coefficient θ3 is negative and significant only for

Table 5. Summary Results of Bivariate Parameter Estimates of DCC and ADCC- GJR GARCH

	Sensex -Nifty50	Sensex-Comdex	Sensex-Dhaanya	Nifty50-Comdex	Nifty50-Dhaanya	Dhaanya-Comdex
PANEL A DCCGJR GARCH Parameters						
θ1	0.069309 (0.098110)***	0.016557 (0.102865)	0.016723 (0.703151)	0.019028 (0.099938)***	-0.016515 (0.183824)	-0.008778 (NA)
θ2	0.929005(0.0000)*	0.968852(0.0000)*	0.579716(0.3923)	0.964335(0.0000)*	0.972662(0.0000)*	1.003596(NA)
θ1+θ2	<1	<1	<1	<1	<1	<1
DF	4.816382(0.000000)	9.530034 (2.64E-06)	21.74621(0.044981)	9.274264(3.44E-06)	22.84614(0.070359)	9.261209(NA)
AIC	-11.51406	-9.266814	-9.291712	-9.248714	-9.273797	-9.833721
HQC	-11.48274	-9.235497	-9.260395	-9.217397	-9.242479	-9.802404
Panel-B ADCC GJR GARCH Parameters						
θ1	0.274622 (2.47E-12) *	0.013769(0.151004)	-0.02906(NA)	0.017014(0.122870)	-0.041321(0.321949)	-0.034796(NA)
θ2	0.624326(0.0000)	0.970941(0.0000)	0.718315(NA)	0.964494(0.0000)	-0.058471(0.8859)	0.748602(NA)
θ3	- 0.011456(0.006903)**	0.005863(0.458426)	0.100094(NA)	0.006327(0.538930)	0.120883(4.13E-14)*	-0.004479(NA)
θ1+θ 2	<1	<1	<1	<1	<1	<1
DF	4.912527(0.000000)	9.678125 (3.92E-06)	10.62103 (NA)	9.418051(5.20E-06)	22.17515(0.061099)	7.438689(NA)
AIC	-11.53031	-9.267845	-9.342012	-9.255221	-9.331773	-9.867794
HQC	-11.49273	-9.230265	-9.304432	-9.21764	-9.294193	-9.830213

Notes: Figures in parentheses are *p*-values, *denotes significant at 1%, **denotes significant at 5%, and ***denotes significant at 10%.

Table 6. Summary Results of Bivariate Parameter Estimates of DCC and ADCC- EGARCH

Panel	Sensex -Nifty50	Sensex - Comdex	Sensex-Dhaanya	Nifty50-Comdex	Nifty50-Dhaanya	Dhaanya-Comdex
Panel - A DCC EGARCH Parameters						
θ1	0.063569 (0.116013)	0.015816 (0.112093)	0.021626 (0.614847)	0.018461 (0.095919)***	-0.014392 (0.238414)	-0.037485 (0.000000)*
θ2	0.935231(0.0000)*	0.969775(0.0000)*	0.602489(0.2321)	0.966648(0.0000)*	0.972395(0.0000)*	0.858507 (0.000000)*
θ1+θ2	<1	<1	<1	<1	<1	<1
DF	4.694140 (0.000000)	9.330653 (1.65E-06)	21.7091 (0.045891)	8.839603 (1.18E-06)	21.40974 (0.053554)	8.805208 (2.02E-06)
AIC	-11.51406	-9.266814	-9.291712	-9.248714	-9.273797	-9.833721
HQC	-11.48274	-9.235497	-9.260395	-9.217397	-9.242479	-9.802404
Panel -B ADCC EGARCH Parameters						
θ1	0.300419 (1.20E-13)*	0.013813(0.140379)	-0.043446 (NA)	0.016756(0.113795)	-0.035562(NA)	-0.038034 (0.000000)*
θ2	0.575382(0.0000)*	0.972228(0.0000)*	0.689302 (NA)	0.966959(0.0000)*	0.277712 (NA)	0.901146 (0.0000)*
θ3	- 0.013774 (0.004041)*	0.005636(0.464126)	0.152098 (NA)	0.005339(0.571576)	0.125744 (NA)	0.009754 (0.514459)
θ1+θ2	<1	<1	<1	<1	<1	<1
DF	4.804141(0.000000)	9.330689 (2.29E-06)	12.17783 (NA)	8.958016 (1.79E-06)	20.994 (NA)	8.903576 (2.59E-06)
AIC	-11.53031	-9.267845	-9.342012	-9.255221	-9.331773	-9.867794
HQC	-11.49273	-9.230265	-9.304432	-9.21764	-9.294193	-9.830213

Notes: Figures in parentheses are *p* - values, *denotes significant at 1%, **denotes significant at 5%, and ***denotes significant at 10%.

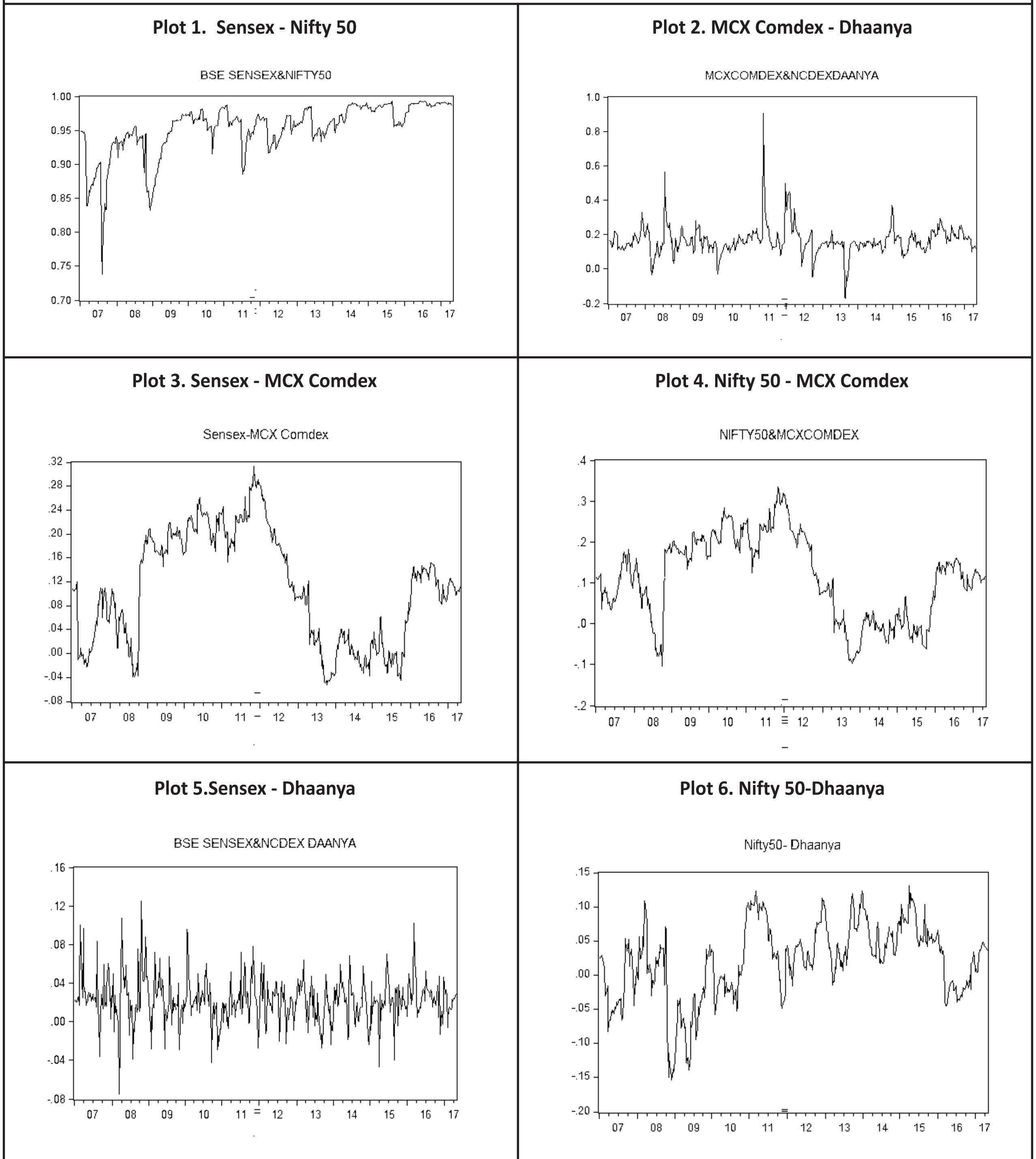
Sensex - Nifty 50. The coefficient of an asymmetric version of DCC GARCH, θ3 is negatively significant just for Sensex - Nifty 50, which conveys that bad news generates more volatility than good news for this pair. Optimization fails for Sensex - Dhaanya and Nifty 50 - Dhaanya. The coefficients of θ1+ θ2 are less than 1, which proves the stability condition of all pairs.

The Figure 2 depicts the symmetric dynamic conditional correlations of equity and commodity indices. The Figure 2 is sub-divided into 6 plots. Plot 1 represents the DCC of Sensex - Nifty 50 pair, Plot 2 shows the DCC of MCX Comdex - Dhaanya, Plot 3 shows the DCC of Sensex - MCX Comdex, Plot 4 represents the DCC of Nifty 50 - MCX Comdex, Plot 5 represents the DCC of Sensex - Dhaanya, and Plot 6 shows the DCC of Nifty 50 - Dhaanya.

Pairwise Time - Varying Conditional Correlations Co - Movements of Equity and Commodity Indices

(1) Equity Portfolio Pair : The Figure 2 (Plot 1) shows that the time-varying co-movements of Sensex - Nifty 50 are positively and highly correlated over the time frame, but in the year 2007-08, the dynamic relationships were low due to the global financial crisis. For this pair, the dynamic co-movement line touches almost the point of +1, which is .99. Hence, we conclude that only equity portfolio (Sensex - Nifty 50) provides the least diversification benefits to the investors.

Figure 2. Dynamic Conditional Correlations of Equity and Commodity Indices



Notes: *X*-axis plots the time period in weeks during 2007-2017. *Y*-axis denotes the values of time varying conditional correlations of the respective pairs.

(2) Commodity Portfolio Pair : Figure 2 (Plot 2) depicts the co-movements of MCX Comdex - Dhaanya. The correlation dynamics are seen to be low for the pair of MCX Comdex - Dhaanya (commodity portfolio) compared to the equity portfolio Sensex - Nifty 50 pair. This pair shows significant negative correlations in the year of 2007-08 (global financial crisis) and 2013-14 (Commodity Transaction Tax). Hence, there will be a scope for the investors to diversify their portfolio risk by choosing this pair.

(3) Equity - Commodity Portfolio Pair

(i) Equity & Commodity Portfolio Pair : The Figure 2 (Plots 3 & 4) display the time - varying co-movements of Sensex - MCX Comdex & Nifty 50 - MCX Comdex. These pairs show the low time - varying conditional correlations throughout the time frame for symmetric and asymmetric versions of DCC. Both the portfolio pairs exhibit similar results. The following points are worth noticing. It shows the significant negative correlations in the years of 2007- 2008 due to the global financial crisis. This pair shows low and negative correlations from 2013-15 due to the implementation of the Commodity Transaction Tax (CTT) on non-farm commodities. Shortly after the implementation of the Commodity Transaction Tax, the results show a steep decline in correlations between Sensex - Comdex and Nifty - Comdex for few years. This could be due to the herding behavior of investors, and in general, this increases when stress prevails in the market. The Indian commodity market started recovering from 2015 onwards due to the formal merger of Securities and Exchange Board of India (SEBI) with the Forwards Market Commission (FMC). Sensex - MCX Comdex pair and Nifty 50 - MCX Comdex, both have the highest correlations of 0.32 at peak. Relatively, these correlations are lower than an equity portfolio pair. While framing the strategies, these results may help in portfolio risk diversification.

(ii) Equity & Agri Commodity Portfolio Pair : Figure 2 (Plots 5 & 6) shows the dynamic correlation co-movements of Sensex - Dhaanya and Nifty 50 - Dhaanya pairs. Sensex - Dhaanya and Nifty 50 - Dhaanya pairs show very low and negative time-varying correlations, however, with high volatility throughout the time frame. It is worth noticing that agri commodities are not affected by the Commodity Transaction Tax (CTT) ; hence, the investors might have shown interest towards the agricultural commodities rather than the non-agricultural commodities. Throughout the time frame, these pairs did not cross 0.12 peaks. Portfolio managers or investors can diversify their portfolio risk by allocating resources to this pair. However, it is also essential to consider the risk of volatility.

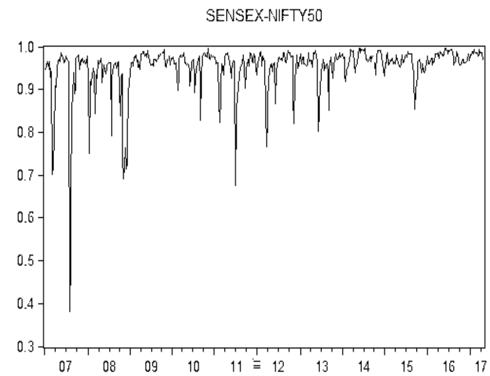
The Figure 3 depicts the asymmetric dynamic conditional correlations of equity and commodity indices. The Figure 2 is sub-divided into 6 plots. Plot 1 represents the ADCC of Sensex-Nifty 50 pair, Plot 2 shows the ADCC of MCX Comdex - Dhaanya, Plot 3 shows the ADCC of Sensex-MCX Comdex, Plot 4 represents the ADCC of Nifty 50 - MCX Comdex, Plot 5 represents the ADCC of Sensex - Dhaanya, and Plot 6 shows the ADCC of Nifty 50 - Dhaanya.

Figure 3 (Plot No.1 to Plot No.6) shows the co-movements of the asymmetric time - varying correlations between the commodities and equity pairs. We noticed similar kind of co-movements in symmetric and asymmetric versions of DCC for all pairs except Sensex - Dhaanya and Nifty 50-Dhaanya. In case of Sensex - Dhaanya and Nifty 50 - Dhaanya pairs, the ADCC co-movements are low throughout the time frame except during the global financial crisis.

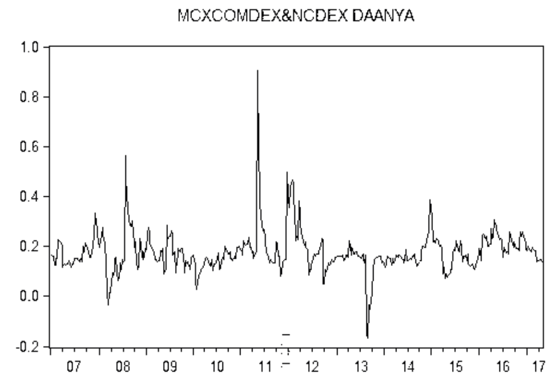
As observed from the dynamic conditional correlation co-movements, we find that the commodity with an equity portfolio shows low dynamic conditional correlations followed by commodity portfolio. However, equity portfolio exhibits high and positive relationships. The results provide evidence of the transmission of information to the cross - market correlations, which are significant and changing during policy changes.

Figure 3. Asymmetric Dynamic Conditional Correlations of Equity and Commodity Indices

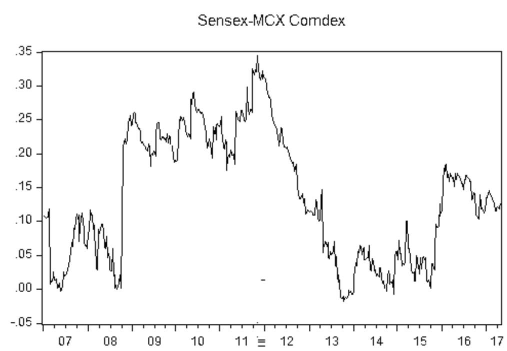
Plot 1. Sensex - Nifty 50



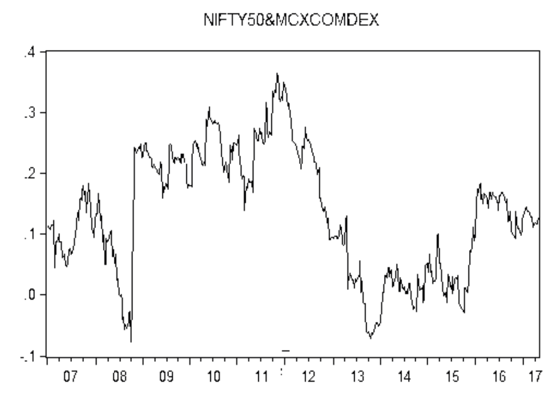
Plot 2. MCX Comdex - Dhaanya



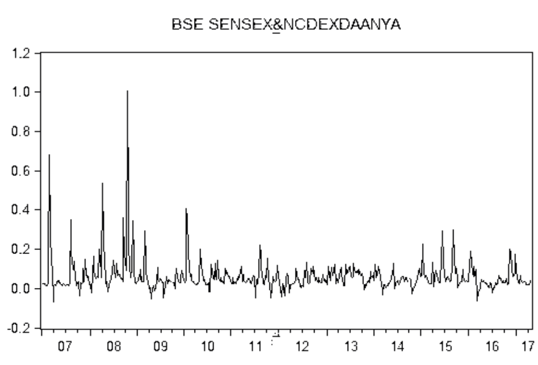
Plot 3. Sensex - MCX Comdex



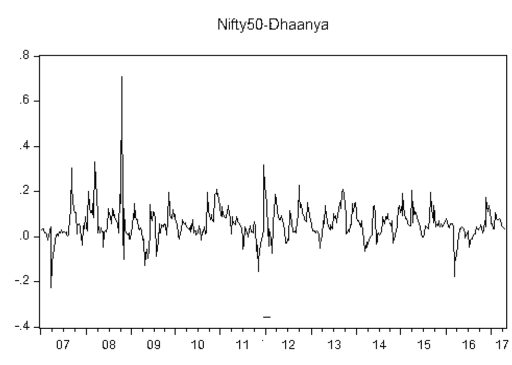
Plot 4. Nifty 50 - MCX Comdex



Plot 5. Sensex - Dhaanya



Plot 6. Nifty 50 - Dhaanya



Notes: *X*-axis plots the period in weeks during 2007 - 2017. *Y*-axis denotes the values of time - varying conditional correlations of the respective pairs.

After analyzing the correlation among the pairs, we continue to find the causal relationships between the portfolio pairs to know which index returns cause other index returns. For this analysis, we used pairwise Granger causality test. Granger causality test was suggested by Granger (1969) to test the direction of causation, bi-direction, or uni-direction between all the possible pairs by using bivariate regressions of the form :

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \ldots + \alpha_1 y_{t-1} + \beta_1 x_{t-1} + \ldots \beta_1 x_{-1} + \varepsilon_t \quad (12)$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \ldots + \alpha_1 x_{t-1} + \beta_1 y_{t-1} + \ldots \beta_1 y_{-1} + u_t \quad (13)$$

$$\beta_1 = \beta_2 = \ldots. = \beta_t = 0$$

For each equation, the null hypothesis is that x does not Granger-cause y in the first regression and that y does not Granger-cause x in the second regression.

Table 7. Summary Results of the Granger Causality Test

Null Hypothesis	*F*-statistics [Probability]
Nifty 50 returns do not Granger cause Sensex returns.	2.72899[0.0662]*
Sensex returns do not Granger cause Nifty 50 returns.	10.5025 [3.E-05] *
MCX Comdex returns do not Granger cause Sensex returns.	2.01651[0.1341]
Sensex returns do not Granger cause MCX Comdex returns.	0.28469[0.7524]
Dhaanya returns do not Granger cause Sensex returns.	1.46617[0.2317]
Sensex returns do not Granger cause Dhaanya returns.	1.53345[0.2167]
MCX Comdex returns do not Granger cause Nifty 50 returns.	1.07245[0.3429]
Nifty 50 returns do not Granger cause MCX Comdex returns.	0.26065[0.7707]
Dhaanya returns do not Granger cause Nifty 50 returns.	2.34866[0.0965]*
Nifty 50 returns do not Granger cause Dhaanya returns.	0.46180[0.6304]
Dhaanya returns do not Granger cause MCX Comdex returns.	0.88568[0.4130]
MCX Comdex returns do not Granger cause Dhaanya returns.	5.71262[0.0035]*

Note : *denotes significant at 5%.

The results of the Granger causality test are consolidated in Table 7. The Granger causality indicates the short term integration of returns among the markets (Granger, 1969). Results reveal the bidirectional causal relation between Nifty 50 and Sensex. It indicates that the predictions of the Sensex are based on its past values along with past values of Nifty 50, which are better than the predictions based only on the past values of Sensex and vice versa. We find a unidirectional causal relationship between the returns of Dhaanya with Nifty 50. It indicates that the predictions of the Nifty 50 returns are based on its past values along with the past values of Dhaanya returns, which are better than the predictions based only on the past values of Nifty 50 returns. The results also reveal the unidirectional causal relationship between MCX Comdex with Dhaanya. It conveys that the predictions of Dhaanya Index are based on its past values along with past values of MCX Comdex, which are better than the predictions based only on the past values of Dhaanya Index.

Conclusion

Our results emphasize the links between Indian commodity and stock markets. The negative and low values of estimated time - varying conditional correlations are mainly observed during periods of market turbulence and crisis, indicating the scope of portfolio diversification and hedging during these periods. Our results reveal that the mixed portfolio of commodity - equity has low or negative correlations as compared to stock only or commodity only portfolios. We observe a bidirectional causal relationship between the returns of Sensex and Nifty 50. We also observe a unidirectional causal relationship between the returns of MCX Comdex index with Dhaanya Index, and between Dhaanya returns index with Nifty 50 index.

Research Implications, Limitations of the Study, and Scope for Further Research

As investors tend to diversify their investments across different markets, the results of the study would be a crucial input for investors in portfolio diversification and hedging. There is considerable evidence of transmission of information to cross-market correlations during the Commodity Transaction Tax period. We find evidence of both positive and negative relations. It suggests that policies directed at influencing behavior in one market may have complex effects on its relationship to other markets. Shortly after the implementation of the Commodity Transaction Tax, the results show a steep decline in correlations between Sensex - Comdex and Nifty - Comdex indices for a few years. Domestic policy changes have a more significant impact on commodity and equity markets in India.

The empirical evidence of the present study provides useful insights to the institutional investors, policymakers, investors, and government while framing strategies for portfolio risk diversification and hedging. The results of the study would be important for institutional investors who tend to diversify their investments across different markets. Policy makers and investors can use the evidences to examine and understand how the transmission of information to the cross-market correlations are changing during macro economic changes and policy changes. Our study has mainly focused only on commodity - equity and inter - commodity portfolios. Hence, there will be scope for further research. Commodity with other alternative asset class portfolios can be studied. This study covered only bivariate time - varying co-movements of the commodity and equity indices. Hence, there is scope to study the co-movements of multivariate asset classes.

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