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Causal relation and volatility spillover between commodity market and equity market of India using VAR Granger Causality and BEKK-GARCH Model

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ABSTRACT

The financial markets play a discerning role in accentuating the growth of industry and commerce whereas, a volatile market has whopping reverberations on economic and financial stability of a country. The interconnectedness and reciprocity among the financial markets in economies are veraciously liable for the pricing of securities and provide investors, hedgers and speculators with copious opportunities for portfolio diversification. In this context, the study has been taken up to explore the relationship between the commodity and stock markets of India. The study has used the daily closing prices of MCX iComdex composite index, BSE Sensex and NSE Nifty 50 index from 1st January 2016 to 31st December 2022. The Johansen's cointegration test estimates the absence of cointegration between the indices under study. The results of VAR Granger Causality Tests substantiate a bi-directional causality between the equity and commodity market of India. Whereas, it refutes any causal relationship between the Sensex and Nifty index. The estimates of BEKK-GARCH model confirm a significant volatility spillover between the two markets. The empirical outcomes of the study have poignant implications for all the stakeholders such as individual and institutional investors, policymakers, government agencies, traders, hedgers and other participants in the financial markets.

Key Words: Financial Stability, Portfolio Diversification, Cointegration, Causality, Volatility Spillover.

INTRODUCTION

In this era of globalization, the financial markets across the world are often marked by high unpredictability and pronounced price volatility. The financial markets play an imperious role for accelerating the growth of industry and commerce where as a volatile market has massive repercussions on economic and financial stability of a country (Narayan and Narayan, 2007). Huo and Ahmed (2017) predicted that the volatility spillover effect is quite prominent across and within the financial markets of many nations. There are considerable global and domestic factors that contribute to volatility transmission between the equity and commodity markets of a country. The interdependence and interconnectedness among the financial markets in economies are overtly responsible for pricing of securities and provide investors, hedgers, and speculators with ample opportunities to escalate their earnings through portfolio diversification. After, the global financial crisis the commodity and equity markets have experienced significant interrelationships and excessive price volatility (Delatte and Lopez, 2013; Creti et al., 2013). The financial markets experienced higher price returns and volatility spillover during the financial crisis and less returns and volatility spillover during the non-financial crisis period (Umm et al, 2020). Many studies assert that financial stress and crisis, such as the recent Covid-19 pandemic and the global financial crisis, primarily affect the degree of connectedness and correlation across the financial markets (Youssef et al., 2021). The constant interdependence among the financial markets like equity, bond, commodity, stock, etc. propagate intensification of the financialization and enhanced price volatility (Parab & Reddy, 2020). Multiple alternatives are available for the investors to diversify their investment portfolios because of financialization of securities (Domanski & Heath, 2007; Dwyer, Gardner & Williams, 2011; Vivian & Wohar, 2012; Silvennoinen & Thorp, 2013). In order to boost their portfolios' risk adjusted incomes, many portfolio managers started introducing commodities and stocks in their holdings (Jain and Biswal, 2016). Investors worldwide are hysterically interested about volatility transmission across financial markets as they are required to regularly observe and adjudge dynamics in market linkages to avail the benefits of risk- sharing and portfolio diversification (Jung and Maderitsch, 2014; Kocaarslan et al., 2017). During the last two and a half decades, commodities have been developed as a distinguished trading asset class like equity, currency, debt, foreign exchange etc. Indian commodity market has registered a remarkable hike in terms of value and volume of contracts traded particularly after the establishment of commodity exchanges in the country and has reached a level where they can be compared with top commodity exchanges of the world (Gupta & Bhardwaj, 2021). Therefore, it is evident that the knowledge and awareness about the market relationships and the volatility spillover effect are critical for managing price risk as well as formulating viable portfolio strategies (Cao and Wen, 2019). Several studies support the argument that equity investors are becoming more and more interested in commodities as most of these commodities can be a way to diversification, hedging, or safe haven for both conventional and contemporary financial assets, particularly during economic crises (Ji et al., 2020; Shaikh, 2021; Adekoya and Oliyide, 2021). Thus, both equities and commodities are significant for portfolio allocation. Therefore, in this context the present study attempts to investigate the causality linkage and volatility spillover between the equity and commodity markets of India.

Review of literature

In recent years, the degree of market linkages, interdependencies, and volatility transmission among the financial markets have piqued the curiosity of the researchers around the world. Many studies have investigated the market linkages between commodity and equity markets (He and Chen, 2011; Kumar et al, 2012; Du et al, 2011; Kumar, and Pandey, 2010; Yilmaz, 2010; Hassan and Malik, 2007; Singh et al, 2010;).Most of the studies have analyzed the cointegration and volatility spillovers between the developed equity and commodity markets. These studies have received scant attention in developing countries like India. During the study period comprising of five years from 2017 to 2022, Vimal et al. (2023) investigated the causal trends and volatility spillover across the NIFTY 50 and commodity market indices. The researchers verify the stationarity of the data by using ADF (Augmented Dickey Fuller) test and also examine the volatility spillover by applying GARCH Model. Furthermore, researchers analyze correlation by using Karl Pearson coefficient of correlation between the two market segments. The study has confirmed the stationarity of the data and exhibit the existence of high volatility throughout the study period in the indices of both the markets. The outcomes of the study revealed the existence of significant and positive correlation between the two markets and further concluded that the India's commodity and equity markets are closely linked with each other. Kaura et al. (2022) explored the causality and volatility spillover across the commodity and stock markets in India. They undertake Nifty index of NSE and commodity market indices of MCX in their study to determine the relationship. The results of the study indicate the presence of strong relationship between commodity market indices and Nifty. The researchers deployed the VAR (Value at risk) model which reveals the presence of cause-and-effect relationship. The outcomes of DCC-GARCH model manifest notable volatility spillover between the conditional variances of all the commodity market indices and Nifty. Besides this, the study further concludes that any fluctuation in one market made the other market more volatile. Miklesh et al (2020) in their study also investigated the volatility spillovers from the Indian equity markets to commodity futures markets. Granger causality is employed to determine the direction of information flow. The results of the study found the absence of bi-directional causality from the equity markets to commodity markets and reveal that there is a possibility of volatility transmission between equity to commodity markets in the long run. Sharma and Mishra (2017) investigated the volatility spillover across the equity and currency markets in India. The researchers employed unit root tests, ARCH model, Johansen's cointegration test, VECM and Diagonal VECH model to analyze data. The results of the research reveal a bi-directional volatility transmission between the two markets. The findings of the study also noticed that both the markets move in conjunction with each other and reveals a significant long-run relationship between the two market segments. In another recent study, Mishra et al. (2022) examined the volatility spillover across India and four leading Asian countries including Japan, Singapore, Hong Kong and China and two global equity markets of the United States and the United Kingdom. They applied a multivariate GARCH-BEKK model to measure correlation and volatility transmission during the pre- and post- global crisis. The findings of the study noticed the co-movement of Indian equity market index with the equity market indices of the Hong Kong and the United States. The study further found that the volatility transmission from Indian to Asian markets was relatively bigger compared to the US and UK. Bhardwaj and Gupta (2022) empirically investigated the conditional volatility, causality linkages and lead lag relationship in futures and spot markets of crude oil. The researchers have used the daily average futures and spot prices of crude oil from 2006 to 2020 taken from MCX for estimation and employed GARCH (1.1) model for determination of conditional volatility in time series with volatility clustering and found the evidences of time varying conditional volatility and persistence of volatility shocks in the crude oil prices. The estimates reveal that the spot and future markets in crude oil are cointegrated in the long run by using Johansen's test which is an improved version of Granger Model whereas the findings of VECM Granger causality test manifest the presence of a bidirectional cause and effect relationship. The overall results of the study also disprove any lead-lag link between futures and spot markets of crude oil and demonstrate the crucial role of spot market in determining the equilibrium price. Maitra and Dawar (2019) also investigated volatility transmission among exchange rate markets, equity, and commodity markets. The researchers applied Vector Auto Regression together with Granger Causality test to examine the causality of returns and used multivariate volatility model to check the co-movement of different financial assets. The results of the study noticed a unidirectional return spillover from MCX to exchange rates and equity market indices. The study concluded that one financial market has a significant volatility spillover effect on the other financial market. It is evident that commodity indices possess more volatility spillover effects on stocks. Kim and Ryu (2014) by applying VAR (1)-asymmetric BEKK-MGARCH model found a strong market connection between the spot index. While, futures exhibit a volatility spillover effect. The results of their study indicate that the futures return impulse influences the spot market more than the spot, though there exists a two-way causal relationship between the spot and futures markets. Adrangi et al., (2014) studied the co-movements among equity, commodity and exchange rates and found a very weak relationship between equity and commodity in India. Umm et al., (2020).

OBJECTIVES OF THE STUDY

In order to fathom the dynamic market linkages and the phenomenon of volatility spillover across the India's equities and commodity markets the study predominantly tries to achieve the following objectives:

1. To study cointegration between the commodity and equity market of India.
2. To examine the causality linkages among the commodity and equity market of India.
3. To estimate the volatility transmission across commodity and equity market of India.

HYPOTHESES

Based on the literature reviewed, the study proposes the following hypotheses:

H_1: The commodity and equity markets of India are cointegrated in the long-run.

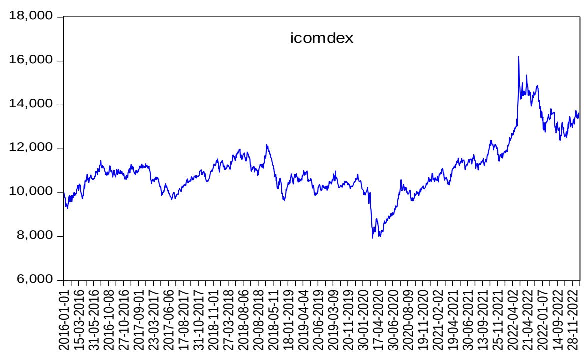
H_2: There exists a significant causality relationship between the commodity and equity market of India.

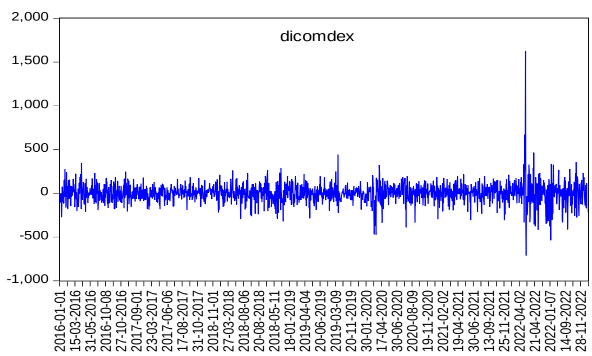
H_3: Volatility transmission takes place across the two markets.

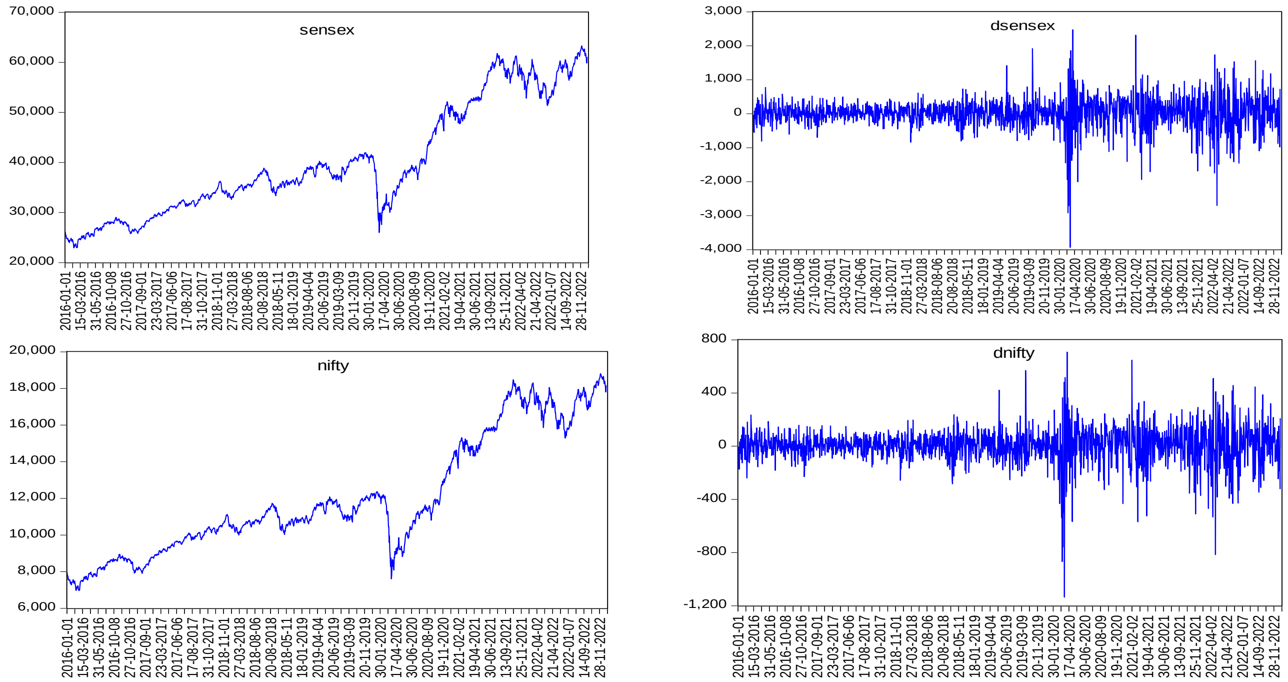
H_{3a}: Volatility transmission takes place from commodity to equity market of India.

H_{3b}: Volatility transmission takes place from equity to commodity market of India.

Figure 1: Graphical Representation of Non-Stationary Data and Stationary Data







Descriptive Statistics

The descriptive statistics are the first statistical information enabling the presentation and interpretation of the data in a more meaningful and comprehensive manner. It is the simplest way of classifying and summarizing the information thus helping the researchers in better understanding of a dataset. The return series of the dataset has been used in the study for measuring central tendency, dispersion and normality and the results are presented in *Table 1*.

Table 1: Descriptive Statistics

	iComdex	**Sensex**	**Nifty**
Mean	11040.79	40128.60	12051.99
Median	10814.58	37165.16	11073.45
Maximum	16201.73	63284.19	18812.50
Minimum	7926.930	22951.83	6970.600
Std. Dev.	1272.608	11135.31	3229.648
Skewness	0.937480	0.563485	0.602975
Kurtosis	4.440279	2.064187	2.119737
Jarque-Bera	401.7724	154.2300	160.2223
Probability	0.000000	0.000000	0.000000
Sum	19045363	69221840	20789680
Sum Sq. Dev.	2.79E+09	2.14E+11	1.80E+10
Observations	1725	1725	1725

*Note: Significant at *0.01 and **0.05 Level*

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Estimating Stationarity

In order to perform any time series analysis, the data must be stationary to avoid absurd interpretations. The autocorrelation, variance and mean in a stationary time series remain constant over a period of time which is a necessary prerequisite for the time series analysis. The following tests have been used in the study to estimate stationarity in the dataset.

Augmented Dickey-Fuller (ADF) Test

ADF test is considered as an authentic tool for estimating the stationarity in the data due to its ability to incorporate general ARIMA (p, q) with uncertain orders.

Augmented Dickey-Fuller Test

$$\Delta Y_t = \mu + \delta Y_{t-1} + \sum^{n} i\alpha_i \Delta Y_{t-1} + \varepsilon_t$$

Null hypothesis (H_0) is δ=0, i.e. the series has a unit root or is not stationary.

Alternate hypothesis (H_1) δ<0, i.e. the series do not have a unit root or is stationary.

According to *Table 2,* the test estimates of ADF test has found that the null hypothesis of a unit autoregressive root, which means an integration of the order 1(1) in the data series of the indices taken for the study. The study noticed that the null hypothesis of an autoregressive root, i.e. integration of order 1(1), could not be rejected for all the indices taken for the study. ADF test suggests that the price series of iComdex, Nifty and Sensex are stationary at their first difference.

Table 2: Estimates of ADF Test

Indices	**ADF Test**	**t-statistic**	**Critical Value**	**P-Value**
iComdex	Level	-1.480843	-3.433940	0.5433
	First Difference	-39.23387	-3.433942	0.0000
Sensex	Level	-0.260221	-3.433940	0.9281
	First Difference	-41.44206	-3.433942	0.0000
Nifty	Level	-2.120058	-3.963375	0.5337
	First Difference	-41.33261	3.963378	0.0000

*Note: Significant at *0.01 and **0.05 Level*

Phillip-Perron Test

The following equation can be used to express Phillips and Perron test (1988) for estimating stationarity in a time series data and can be expressed as

$$\Delta Y_t = \delta Y_{t-1} + \varepsilon_t$$

Null hypothesis (H_0) is δ=0, the series has a unit root or is not stationary.

Alternate hypothesis (H_1) δ<0, the series do not have a unit root or is stationary.

According to *Table 3,* similar interpretations are given by PP Test as given by ADF test. The null hypothesis (H_0), i.e., the data are stationary is accepted which means that the data are not stationary.

Table 3: Estimates of Phillips-Perron (PP) Test

Indices	PP Test	t-statistic	Critical Value	P-Value
iComdex	Level	-2.023245	-3.963375	0.5876
	First Difference	-39.16516	-3.963378	0.0000
Sensex	Level	-2.425152	-3.963375	0.3662
	First Difference	-41.45929	-3.963378	0.0000
Nifty	Level	-3.963375	-3.963375	0.4698
	First Difference	-41.36509	-3.963378	0.0000

*Note: Significant at *0.01 and **0.05 Level*

Johansen Cointegration Test

The extensive literature reviewed in the study has found that the Johansen Cointegration Test is most authentic and widely used estimate to analyze cointegration of time series data. Therefore, to examine the cointegration in metal markets Johansen Cointegration Test (Johansen, 1991) has been employed as below.

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma \Delta Y_{t-1} + Bx_t + \varepsilon_t$$

Where $\Delta Y t = Y_t - Y_{t-1}$, ε_t is error term or white noise, T_i and Π is the co-efficient matrix. The lag length k can be selected by SIC lag length criteria.

Table 4: Estimates of Johansen's Cointegration Test

Indices	Lags	H_0: R	Trace Statistics		Max-Eigen Statistics		Decision
			λ trace	Prob.	λ trace	Prob.	
iComdex Sensex	4	0	8.3947	0.4242	8.1094	0.3677	R=0 accept non-cointegration
		1	0.2853	0.5932	0.2853	0.5932	
iComdex Nifty	4	0	8.9702	0.3681	8.6465	0.3168	R=0 accept non-cointegration
		1	0.3237	0.5694	0.5694	0.5694	
Sensex Nifty	4	0	2.5723	0.9829	2.4391	0.9769	R=0 accept non-cointegration
		1	0.1332	0.7151	0.1332	0.7151	

*Note: Significant at *0.01 and **0.05 Level*

The study has employed Johansen's Cointegration Test to estimate long-run cointegration between the two markets. The test was carried at lag length 4. According to *Table 4,* the test results of Johansen λ trace and λ max test predicts that null hypothesis of non-cointegration (R=0) has been accepted at 0.05 level of significance. The alternate hypothesis (R=1) has been accepted, predicting the absence of long-run cointegration between the commodity and equity market of India. This means that both the markets are not cointegrated in the long run. *Hence, H_1 is rejected.*

VAR Model

The vector autoregressive (VAR) is a multivariate time series model that tries to find the linkage between the current and lagged values of one time series with the current and lagged values of other time series. The study has employed VAR Granger Causality/Block Exogeneity Wald Tests to estimate the causal relationship between the time series.

Table 5: Showing the estimates VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable: DICOMDEX			
Excluded	**Chi-sq**	**df**	**Prob.**
DSENSEX	11.66764	6	0.0698
DNIFTY	10.45165	6	0.0106
Dependent variable: DSENSEX			
DICOMDEX	12.59975	6	0.0499
DNIFTY	3.071401	6	0.7998
Dependent variable: DNIFTY			
DICOMDEX	13.28880	6	0.0387
DSENSEX	3.715598	6	0.7151

*Note: Significant at *0.01 and **0.05 Level*

If only one series cause other it is unidirectional causality but if both the series cause each other it is known as bi-directional or feedback causality. Estimates in *Table 5,* predict that there is a two-way causality between Sensex index and iComdex index as well as between Nifty index and the iComdex index. In both the cases the probability value is less than 5% level of significant thus rejecting the null hypothesis of no cause-and-effect relationship between the indices. *Hence, H_2 is accepted.* As per the estimates of VAR Granger Causality/Block Exogeneity Wald Tests no causal relation has been notices between the Sensex and Nifty index. *Hence, H_2 is rejected.*

Estimating Volatility Transmission

Volatility transmission between the Indian stock market and commodity market is a complex and multifaceted phenomenon as it determines how price in one market is correlated to other causing unanticipated price fluctuations. The data series has been analyzed for heteroscedasticity i.e ARCH (q) effect before running diagonal BEKK-GARCH Model.

ARCH Effect

The model for testing of ARCH (1) effects is as;

$$\hat{u}_t^2 = b_0 + b_1\hat{u}_{t-1}^2 + e_t$$

Where, Null Hypothesis $b_1 = 0$ (homoscedastic) and Alternate Hypothesis $b_1 \neq 0$ (heteroscedastic)

Table 6: Estimates of Heteroscedasticity Test: ARCH Effect

Indices	**F-statistics**	**Prob.**	**R^2**	**Prob.**
iComdex	23.85084	0.0000	23.55216	0.0000
Sensex	66.52907	0.0000	64.12740	0.0000
Nifty	66.55538	0.0000	64.15182	0.0000

*Note: Significant at *0.01 and **0.05 Level*

Developed by Robert F. Engle III, ARCH model is used to analyze volatility in time series to estimate future volatility. As shown in *Table 6***,** the values of F-stat, R^2 and Prob. shows heteroscedasticity in the dataset of iComdex, Sensex and Nifty indices and confirm an ARCH effect in all the indices. Thus, satisfying the basic condition for volatility estimation. It also confirms volatility clustering in the indices as visible from the graphical presentation of the dataset.

Diagonal BEKK-GARCH Model

The multivariate Diagonal BEKK GARCH Model introduced by Baba, Engle, Kraft, and Kroner in 1991, is an extension of the traditional GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model used to estimate conditional mean function and the conditional volatility function of high dimensional relationship in order to investigate volatility spillover effect among multiple time series.

Table 7: Estimates of Diagonal BEKK-GARCH Model

Mean Equation						
	iComdex Sensex		**iComdex Nifty**		**Sensex Nifty**	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C(1)	0.000232	0.2698	0.000256	0.2326	0.000708	0.0002
C(2)	0.012534	0.5147	0.008972	0.6443	0.052012	0.0199
C(3)	0.000467	0.0154	0.000409	0.0356	0.000698	0.0003
C(4)	0.064187	0.0101	0.076498	0.0013	0.056268	0.0130
Variance Equation Coefficients						
C(5)	5.23E-06	0.0000	5.09E-06	0.0000	4.39E-06	0.0000
C(6)	1.99E-07	0.4264.	2.05E-08	0.9186	4.39E-06	0.0000
C(7)	2.54E-06	0.0000	2.70E-06	0.0000	4.47E-06	0.0000
C(8)	0.301587	0.0000	0.098969	0.0000	0.243582	0.0000
C(9)	0.021590	0.5359	0.005779	0.5208	0.234928	0.0000
C(10)	0.104173	0.0048	0.017811	0.0200	0.252742	0.0000

C(11)	0.404419	0.0000	0.005218	0.7558	0.262194	0.0000
C(12)	0.919197	0.0000	0.034888	0.0293	0.924515	0.0000
C(13)	0.942914	0.0000	0.186636	0.0000	0.924566	0.0000
Transformed Variance Coefficients						
M(1,1)	5.23E-06	0.0000	5.09E-06	0.0000	4.39E-06	0.0000
M(1,2)	1.99E-07	0.4264	2.05E-08	0.9186	4.39E-06	0.0000
M(2,2)	2.54E-06	0.0000	2.70E-06	0.0000	4.47E-06	0.0000
A1(1,1)	0.301587	0.0000	0.098969	0.0000	0.243582	0.0000
A1(1,2)	0.187836	0.0000	0.005779	0.5208	0.688804	0.0000
A1(2,2)	0.021590	0.5359	-0.017811	0.0200	0.234928	0.0000
D1(1,1)	0.104173	0.0048	0.005218	0.7558	0.252742	0.0000
D1(1,2)	0.260933	0.0000	0.034888	0.0293	0.102346	0.0000
D1(2,2)	0.404419	0.0000	0.186636	0.0000	0.262194	0.0000
B1(1,1)	0.919197	0.0000	0.918432	0.0000	0.924515	0.0000
B1(1,2)	0.912645	0.0000	0.918432	0.0000	0.920135	0.0000
B1(2,2)	0.942914	0.0000	0.894053	0.0000	0.924566	0.0000

*Note: Significant at *0.01 and **0.05 Level*

The estimates presented in *Table 7*, show that all the parameters of mean and variance equations are significant, confirming a volatility spillover effect across the indices taken for the study i.e. icomdex, senex and Nifty. M1(1,2), (2,1), (2,2) signify that there is a long-term co-variance between all the indices taken for study. It has been noted that A1 (1.1), (1,2), (2,2) is significant, which predict that the impact of news on one index is further affecting the conditional covariance in other indices. As B1(1,1), (1,2), (2,2) are significant, confirming persistence level in all the indices which is further causing co-variance in other indices. The parameters of asymmetric terms D (1,1), (1,2), (2,2) are also significant, meaning that negative shocks in one index further increase the co-variance in other indices. The result confirms a significant bi-directional volatility spillover across the commodity market and equity market of India during the study period. *Hence,* H_{3a} *and* H_{3b} *are accepted.*

Conclusion

The empirical outcomes of the study will have poignant implications for several stake holders such as individuals, institutional investors, policy makers, government agencies, traders, and other participants of the financial markets at national and international level. The study is significant and pertinent for academicians, research scholars and financial institutions to give fresh insights into various other important aspects of stock and commodity markets of India. The study found that besides efforts from the regulator’s volatility spillover across the equity and commodity markets is a normal phenomenon and our findings propound that resource allocation decisions by the investors between the stock or commodity market must be taken after extensive analysis. The findings of the study have important implications for portfolio management to formulate effective hedging strategies.

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