ISSN 2063-5346

VOLATILITY SPILLOVER BETWEEN THE CRYPTOCURRENCY AND INDIAN STOCK MARKET USING BEKK - GARCH MODEL

Mohammed Riyaz[a], Harihara Sudhan R[b] and Aathy kannan[c]

Article History: Received: 01.02.2023 Revised: 07.03.2023 Accepted: 10.04.2023

Abstract

This study examines the presence of volatility spillovers between the cryptocurrency market and the Indian stock market. The analysis is based on daily data from 1st January 2015 to 31st December 2022, covering major cryptocurrencies such as Bitcoin and Ethereum along with the major stock indices of India, including the Nifty 50 and top 5 Bluechip companies. Using a multivariate BEKK - GARCH model, the results show that there exists a significant volatility spillover effect between the two markets, indicating that shocks in one market affect the volatility of the other market. Furthermore, the findings suggest that the spillover effects are asymmetric, with the impact of cryptocurrency market volatility being more significant on Indian stock market volatility than vice versa. These results have implications for investors and policymakers in understanding the interdependence between these two markets and devising appropriate risk management strategies.

[1]Student, II MBA Logistics, Hindustan Institute of Technology and Science, Chennai

[2]Assistant Professor (II), Hindustan Institute of Technology and Science, Chennai

DOI:10.31838/ecb/2023.12.s1-B.339

INTRODUCTION

Cryptocurrency is an area of Interest for most of the finance aspirants and the scholars around the globe. Volatility is the major aspect in the cryptocurrency markets. Volatility spillover refers to the transmission of volatility shocks from one financial market or asset to another. With the rise of cryptocurrencies and their increasing interaction with traditional financial markets, understanding the dynamics of volatility spillover between the two has become a crucial area of research. In this study, we investigate the volatility spillover between the cryptocurrency market and the Indian stock market using the BEKK-GARCH model. The BEKK-GARCH model is a widely used framework for estimating volatility spillover in financial markets. It allows for the estimation of both the magnitude and direction of spillovers between markets. The Indian stock market is one of the largest and most important emerging markets in the world, while cryptocurrencies have gained significant attention due to their rapid growth and high volatility. By examining the volatility spillover between these two markets, we aim to contribute to a better understanding of the potential risks and opportunities associated with investing in cryptocurrencies. In recent years, cryptocurrencies have become increasingly integrated with traditional financial markets. This integration has led to a growing interest in the potential spillover effects between the two. Overall, this study seeks to provide insights into the complex relationship between cryptocurrencies and traditional financial markets, and to inform investment decisions in these rapidly evolving markets. Volatility spillover can have significant implications for investors and policymakers alike. For investors, understanding the dynamics of spillovers can help them better manage risk and optimize their portfolios. Policymakers, on the other hand, may use this information to design effective regulatory frameworks to promote financial stability.

While previous studies have explored the volatility spillover between cryptocurrencies and other financial assets, there is still a lack of research on the spillover effects between cryptocurrencies and the Indian stock market. To address this research gap, we employ the BEKK-GARCH model to estimate the volatility spillover between the cryptocurrency market and the Indian stock market. The BEKK-GARCH model allows us to examine not only the presence of spillovers but also their magnitude and direction. We use daily data for the period January 2015 to December 2021, and our sample includes the two largest cryptocurrencies by market capitalization, Bitcoin and Ethereum, leading stock index of India, NSE Nifty and five top equity stocks. Our findings provide important insights into the nature of volatility spillover between cryptocurrencies and the Indian stock market and have important implications for investors and policymakers alike.

REVIEW OF LITERATURE

Banerjee et al. (2018) examined the volatility spillover between Bitcoin and the Indian stock market using the DCC-GARCH model. They found evidence of a bi-directional volatility spillover effect, indicating that shocks in one market could transmit to the other.

Kaur and Kaur (2019) investigated the volatility spillover between Bitcoin and the Indian stock market using the EGARCH model. They found evidence of a unidirectional volatility spillover from Bitcoin to the Indian stock market, indicating that Bitcoin's volatility could affect the stock market but not vice versa.

Mazumder and Dhar (2020) examined the volatility spillover between Bitcoin and the Indian stock market using the BEKK-GARCH model. They found evidence of a bi-directional volatility spillover effect, similar to the findings of Banerjee et al. (2018).

Saha et al. (2021) investigated the volatility spillover between cryptocurrencies (Bitcoin, Ethereum, and Ripple) and the Indian stock market using the BEKK-GARCH model. They found evidence of a unidirectional volatility spillover from Bitcoin to the Indian stock market and a bi-directional spillover between Ethereum and the stock market. They also found evidence of volatility spillover among the three cryptocurrencies themselves.

Bouri et al. (2018) investigated the volatility spillover between Bitcoin and global stock markets using the DCC-GARCH model. They found evidence of a significant spillover effect between Bitcoin and the S&P 500 index, indicating that shocks in the cryptocurrency market could affect the broader equity market.

Du et al. (2019) examined the volatility spillover between Bitcoin and the Chinese stock market using the GARCH-MIDAS model. They found evidence of a significant unidirectional spillover effect from Bitcoin to the Chinese stock market, indicating that Bitcoin's volatility could affect the stock market but not vice versa.

Al-Yahyaee and Mensi (2020) investigated the volatility spillover between Bitcoin and the Saudi Arabian stock market using the DCC-GARCH model. They found evidence of a significant unidirectional spillover effect from Bitcoin to the stock market, indicating that Bitcoin's volatility could affect the Saudi Arabian stock market but not vice versa.

Wang et al. (2021) examined the volatility spillover between Bitcoin and the US stock market using the BEKK-GARCH model. They found evidence of a significant bi-directional spillover effect between the two markets, indicating that shocks in one market could transmit to the other.

The literature on the volatility spillover between cryptocurrencies and stock markets suggests that there is a complex and dynamic relationship between these two markets. While some studies have found evidence of a unidirectional spillover effect, others have found evidence of a bi-directional spillover effect. Consequently, the major crypocurrencies in the market are considered for the study , such as Bitcoin and Ethereum, which constitute the majority of the cryptocurrency market share. The above two cryptocurrencies are compared with the Nifty Index and the top five companies contribute in the Nifty Index such as Reliance Industries, Tata Consultancy Services, HDFC Bank, ICICI Bank, and Infosys. The stocks are selected on the basis of free-float market capitalization. The objective is to study the conditional volatility spillover effects and conditional correlation between the cryptocurrency and above mentioned Index and Stocks that are traded in India. The specific nature of this relationship may depend on a variety of factors, including the specific cryptocurrency being analysed, the time period studied, and the particular stock market in question. The structure of the paper is followed the Data and methodology used and the BEKK-GARCH methodology for the study.

DATA

The data is of two types, cryptocurrency data and Indian stocks data. The data for crypto currency was obtained from www*.coinmarketcap.com* and the Indian data is obtained from the official site of National stock Exchange. The dataset consists of daily returns of Bitcoin and Ethereum from its inception to December 2022.

Table 1: List of Cryptocurrency and Selected Stocks

Sr. No.	Name of the Stock	Data from	Data to	No. of Obs.,
1	Bitcoin	01.01.2015	31.12.2022	1976
2	Ethereum	07.08.2015	31.12.2022	1828
3	Reliance Industries	01.01.2015	31.12.2022	1976
4	TCS	01.01.2015	31.12.2022	1976
5	HDFC Bank	01.01.2015	31.12.2022	1976
6	ICICI Bank	01.01.2015	31.12.2022	1976
7	Infosys Technologies	01.01.2015	31.12.2022	1976

The Prices are downloaded in Indian Rupees for both the cryptocurrency and the Indian data. The return on daily closing prices is calculated using the formula

$$Y_{i,t} = \ln\ (P_{i,t}) - \ln(P_{i,t} - 1)$$

The price of the currency is given as $Y_{i,t}$ and the I indicates the days in the t. The Augmented Dickey fuller (ADF) test and Philipp-Perron (PP) test were conducted on the level and differenced data to check the stationarity of the data. This was followed by autocorrelation analysis and the existence of volatility clustering in the data for performing the GARCH analysis. The tested data displayed the existence of ARCH effect and confirms the suitability of the data for GARCH analysis.

METHODOLOGY

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is a statistical approach that is commonly used to estimate the volatility of financial time series data, such as stock prices or exchange rates. The basic idea behind the GARCH model is to capture the time-varying nature of volatility, where volatility refers to the degree of fluctuation in the price of an asset over time.

The GARCH model is an extension of the ARCH (Autoregressive Conditional Heteroscedasticity) model, which assumes that the variance of a time series is a function of past squared error terms. The GARCH model adds an additional term to the ARCH model that captures the impact of past volatility on future volatility. This term is typically referred to as the autoregressive (AR) component of the GARCH model.

There are several variations of the GARCH model, including the BEKK-GARCH model, which is commonly used to estimate the volatility spillover between two or more time series. The BEKK-GARCH model extends the basic GARCH model to account for cross-correlations between the series being analyzed.

The volatility transmission effects between the two cryptocurrency and the Indian index and selected stock captured by the conditional covariance matrix. The conditional mean equation is given as follows

$$Y_t = c + \epsilon_t$$

The vector of price returns is denoted by yt, the vector of parameters which is estimating the mean of returns is denoted by c, the vector of errors is denoted by et.

The BEKK-GARCH methodology is deployed that was proposed by Engle and Kroner (1995). The BEKK model is an multivariate model that helps us to identify the interaction of conditional variance and covariances between the time series. Further it also helps us to identify the volatility transmission effects. The

Conditional covariance matrix (Ht) in BEKK GARCH model is given as

$$H_t = W'W + A' \epsilon_{t-1} \epsilon'_{t-1} A + B' H_{t-1} B$$

The matrices of the parameters are given by W, A and B, whereas W denotes the upper triangular matrix (Bekiros, 2014), the A and B capture the assets own shock and past volatility of the asset. It also captures the cross effect of shocks and volatility, which is denoted as shock transmission effects and volatility spillover effects.

$$h_{11,t} = w_{11}^2 + a_{11}^2 \epsilon_{1,t-1}^2 + 2a_{11}a_{21}\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{21}^2 \epsilon_{2,t-1}^2 + b_{21}^2 h_{1,t-1} + 2b_{11}b_{21}h_{1,2,t-1} + b_{21}^2 h_{2,t-1}$$

$$h_{22,t} = w_{12}^2 + w_{22}^2 + a_{12}^2\epsilon_{1,t-1}^2 + 2a_{12}a_{22}\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{22}^2 \epsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{1,2,t-1} + b_{22}^2 h_{2,t-1}$$

$$h_{12,t} = h_{21,t} = w_{12}w_{11} + a_{11}a_{12}\epsilon_{1,t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\epsilon_{1,t-1}\epsilon_{2,t-1} + a_{21}a_{22}\epsilon_{2,t-1}^2 + b_{11}b_{12} h_{11,t-1} + (b_{12}b_{21} + b_{11}b_{22}) h_{12,t-1} + b_{21}b_{22} h_{22,t-1}$$

The $h_{11,t}$ and $h_{22,t}$ denotes the assets' conditional variances and the conditional covariance is given in $h_{12,t}$. The following formula is deployed to estimate the conditional correlation between the assets.

$$r_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t}}\sqrt{h_{22,t}}}$$

ANALYSIS AND INTEPRETATION

The descriptive analysis of the stocks are as follows

Table 2: Descriptive Statistics

	BTC	ETH	NIFTY	REL	TCS	HDFC B	ICICI B	INFOSYS
Mean	0.002144	0.003465	0.000396	0.000534	0.000125	0.000272	0.000470	-0.000284
Median	0.002126	0.000131	0.000593	0.000791	0.000407	0.000494	-0.000149	0.000666
Max	0.225739	0.512698	0.084003	0.137307	0.093901	0.109747	0.137042	0.418725
Min	-0.461211	-1.362688	-0.139038	-0.698754	-0.702295	-0.686609	-0.196597	-0.684903
Std. Dev.	0.046503	0.079408	0.011135	0.024223	0.022082	0.021357	0.021575	0.049318
Skewness	-0.78428	-2.592678	-1.406065	-12.13820	-16.33777	-16.90934	-0.127468	-4.442602
Kurtosis	11.93438	55.56580	22.70101	355.6851	520.5006	545.4895	10.67977	76.93428
Jarque - Bera	6771.246	212392.7	32590.60	10284494	22126137	24312412	4858.817	456325.8
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

The above table explains the descriptive properties of the data, such as the average price returns of the cryptocurrency is ranging from 2.144% to 3.46% in cryptocurrencies, 0.039% in the Nifty Index and the -0.28% to 0.53% in the stocks. In the cryptocurrency, Ether is the most volatile cryptocurrency (0.79%) followed by the Bitcoin (0.46%) and in the stocks ranges from TCS (0.21%) to Infosys (0.49%) in the stock segment. The cryptocurrencies are having less Kurtosis when compared to stock prices means Leptokurtic distributions. The Skewness is negative in all the data indicates longer left tail indicates large negative returns is common than the large positive returns. The normality of the data is confirmed by the Jarque Bera test that rejects the null hypothesis the returns are normally distributed. The ARCH – LM test has confirmed the presence of ARCH effect in the data.

Table 3: Unit Root Test

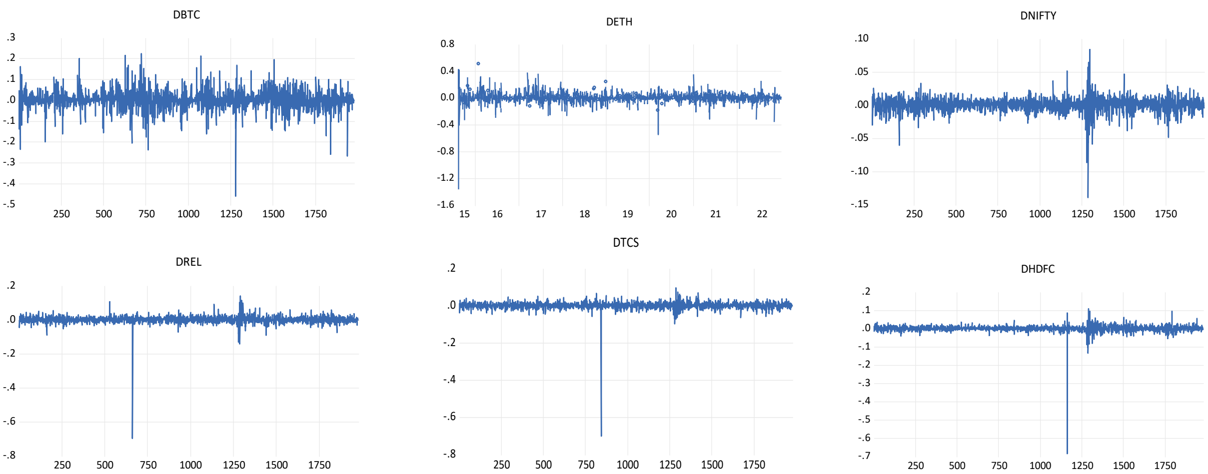
BTC		ETH		NIFTY		REL	
ADF	**PP**	**ADF**	**PP**	**ADF**	**PP**	**ADF**	**PP**
-15.5046	-45.257	-45.7326	-45.6521	-44.1127	-44.1384	-43.9819	-43.9933
0.0000**	0.0001**	0.0000**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**

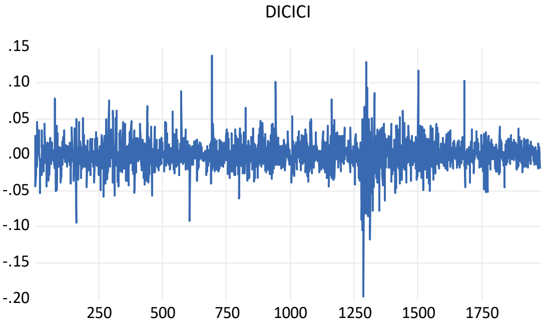
TCS		HDFC B		ICICI B		INFOSYS	
ADF	**PP**	**ADF**	**PP**	**ADF**	**PP**	**ADF**	**PP**
-44.0536	-44.052	-45.4356	-45.5751	-44.2781	-44.2863	-45.5356	-45.5751
0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**

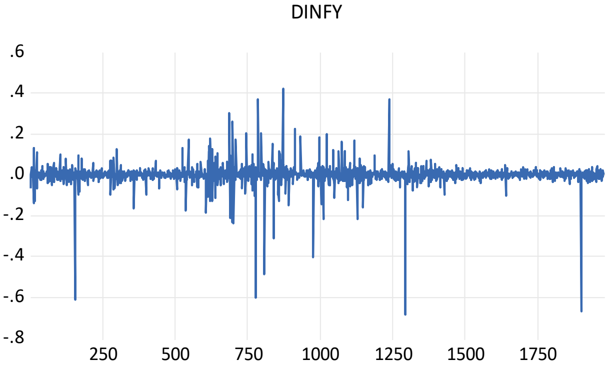
** Stationary at 1% significance levels

In the Table 3, the stationarity of the data is tested using the Augmented Dickey Fuller (ADF) test and the Phillip Perron Test (PP), the test results indicates that the prices are not stationary at level prices and stationary at 1st differencing. It Indicates the daily closing prices of all the currencies are stationary rejecting the null hypothesis of unit root at 1% significance.

CHART 1: CLUSTERING VOLATILITY EFFECT OF RETURNS







The Dataset also exhibits the volatility clustering effect in the returns data. The data is suitable for the GARCH analysis. Further the data is checked for the BEKK GARCH methodology for analysing the volatility spill over effect.

Table 3: BEKK - GARCH Results

	BTC – NIFTY	**BTC – Reliance**	**BTC – TCS**	**BTC – HDFC BANK**	**BTC – ICICI BANK**	**BTC – INFOSYS**
C1	0.002226	0.002202	0.002304	0.002208	0.002082	0.002227
	(0.0274)	(0.0317)	(0.0465)	(0.0266)	(0.0427)	(0.0312)
C2	-0.086333	-0.001557	-0.004450	-0.022307	-0.039389	-0.003699
	(0.3280)	(0.9538)	(0.9492)	(0.5854)	(0.3817)	(0.8623)
W11	0.000397	0.000113	-0.000625	0.000456	0.000423	-0.001214
	(0.0356)	(0.8799)	(0.4030)	(0.1144)	(0.3193)	(0.3275)
W12	0.011095	0.022464	0.036504	0.003159	0.006891	-0.064070
	(0.0048)	(0.1405)	(0.0069)	(0.3659)	(0.4669)	(0.0016)
W22	0.000195	0.000203	0.000210	0.000178	0.000210	0.000187
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α11	0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000
	(0.7740)	(0.5846)	(0.0897)	(0.7143)	(0.5798)	(0.9686)
α12	0.0000	0.000146	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.3032)	(0.0000)	(0.0000)	(0.0000)
α21	0.351645	0.333742	0.344019	0.333498	0.340483	0.3560456
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α22	0.032642	0.186637	0.000170	0.543835	-0.043348	0.077700
	(0.4352)	(0.0000)	(0.9984)	(0.0000)	(0.2214)	(0.0000)
β11	-0.119550	0.189575	0.175489	-0.010777	0.190741	0.001582
	(0.0054)	(0.0000)	(0.0004)	(0.8692)	(0.0000)	(0.9997)
β12	-0.402300	-0.058836	0.000134	-1.921068	0.357346	0.00000
	(0.0000)	(0.5482)	(0.9994)	(0.0000)	(0.0000)	(1.0000)

β21	0.887547	0.886003	0.881940	0.901387	0.881752	0.891862
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β22	0.939406	0.850297	0.998530	0.497804	0.949379	0.991610
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LL	9860.006	7930.903	8109.647	8616.621	8331.508	6550.447
AIC	-9.976703	-8.022191	-8.203290	-8.716941	-8.428073	-6.623553
SIC	-9.939904	-7.985392	-8.166491	-8.680142	-8.391274	-6.586754
HQ	-9.963182	-8.008670	-8.189769	-8.703420	-8.414552	-6.610032

Table 4: BEKK - GARCH Results

	ETH – NIFTY	ETH – Reliance	ETH – TCS	ETH – HDFC BANK	ETH – ICICI BANK	ETH – INFOSYS TECH
C1	0.002017	0.002239	0.002124	0.002083	0.001986	0.002046
	(0.1976)	(0.1438)	(0.1669)	(0.1878)	(0.1970)	(0.1756)
C2	-0.018315	-0.069563	0.029243	-0.012148	-0.038567	0.003763
	(0.8898)	(0.1017)	(0.7625)	(0.8887)	(0.5521)	(0.9078)
W11	0.000444	0.000245	0.000235	0.000166	0.000541	-0.0000
	(0.0210)	(0.7625)	(0.6737)	(0.5902)	(0.2218)	(0.9569)
W12	0.003860	-0.000193	0.023290	0.025940	0.004494	-0.014949
	(0.1001)	(0.9857)	(0.0000)	(0.0000)	(0.4618)	(0.4183)
W22	0.000437	0.000462	0.000491	0.000423	0.000512	0.000556
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.8505)	(0.4210)	(0.0006)	(0.9879)	(0.5385)	(0.1553)
α12	0.0000	0.000160	0.0000	0.0000	0.0000	0.000206
	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α21	0.380039	0.388576	0.404594	0.340729	0.384715	0.411212
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α22	0.068289	0.150612	0.0000	0.542733	-0.027208	-0.160164
	(0.0659)	(0.0000)	(0.9987)	(0.0000)	(0.4540)	(0.0000)
β11	0.105234	-0.034363	0.000989	0.077357	0.167726	-0.0000
	(0.0132)	(0.8607)	(0.9999)	(0.0664)	(0.0000)	(1.0000)
β12	0.404734	0.119268	0.0000	1.836912	0.363650	0.0000
	(0.0000)	(0.0377)	1.0000	(0.0000)	(0.0000)	(1.0000)
β21	0.881048	0.877440	0.868952	0.897038	0.866807	0.8586

	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β22	0.937684	0.845787	1.000391	0.511064	0.950702	0.9436
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LL	8363.288	6517.438	6749.001	7200.012	6937.556	5272.679
AIC	-9.145989	-7.124245	-7.377876	-7.871864	-7.584399	-5.760875
SIC	-9.106762	-7.085018	-7.338649	-7.832637	-7.545172	-5.721649
HQ	-9.131519	-7.109775	-7.363406	-7.857395	-7.569929	-5.746406

On the Investigation of Bitcoin and Nifty Pair, the α_{ij} values where $i \neq j$ that capture the cross-market effects between the Bitcoin and Nifty, which has a coefficient value of 0.351645 indicates that the news of Bitcoin has an impact on the prices of the Nifty that is also statistically significant, whereas the coefficient value between the Nifty and Bitcoin is 0.032642 indicates that the news of Nifty is not having an impact on the Bitcoin but has a unidirectional shock spillover from the Bitcoin to Nifty. The β_{ij} values, where $i \neq j$ that captures the conditional variance between the markets indicate, current conditional variances of Bitcoin (0.887547) have a persistent effect on the Nifty which is statistically significant. Whereas the current conditional variance of Nifty (0.939406) has a persistent effect on the Bitcoin prices. The values indicate the existence of conditional covariance is affected more by the magnitude of previous conditional variances rather than the size of innovations. There is a bidirectional volatility spillover effect from Bitcoin to Nifty. The asymmetric effect of Bitcoin over the Nifty is high as the negative shock will impact the prices of the Nifty more than the Positive shock in the Bitcoin. In Ethereum and Nifty, the coefficient (0.380039), statistically significant indicates the news of Ethereum is having an impact on the Nifty, where is negative in the vice-versa. This indicates a Unidirectional impact from Ethereum to Nifty. The conditional covariances of Ethereum and Nifty are having a positive impact on the conditional covariances of both assets. The asymmetric effect of Ethereum, is more than the positive news on the Nifty and vice versa.

The Bitcoin and Reliance pair, the coefficient value of α_{ij}, where $i \neq j$, the cross-market effects between the Bitcoin and Reliance, which has a coefficient value of 0.333742 indicates that the news of Bitcoin has an impact on the prices of the Reliance share that is also statistically significant, whereas the coefficient value between the Reliance and Bitcoin is 0.186637 indicates that the news of Reliance is having an impact on the Bitcoin, so there existence of bidirectional shock spillover from the Bitcoin to Reliance. The β_{ij} values, where $i \neq j$ that captures the conditional variance between the markets indicate, current conditional variances of Bitcoin (0.886003) has an persistent effect on the Reliance prices which is statistically significant. Whereas the current conditional variance of Reliance (0.850297) has an persistence effect on the Bitcoin prices. The values indicate the existence of conditional covariance is affected more by the magnitude of previous conditional variances rather than the size of innovations. There is a bidirectional volatility spillover effect from Bitcoin to Reliance prices. The asymmetric effect of Bitcoin over the Reliance is high as the negative shock will impact the prices of the Reliance more than the Positive shock in the Bitcoin, but there is an unidirectional impact from the Bitcoin to Reliance prices. In Ethereum and Reliance, the coefficient (0.388576), statistically significant indicates the news of Ethereum is having an impact on the Nifty and vice-versa. This indicates a bidirectional impact from Ethereum to Reliance. The conditional covariances of Ethereum and Reliance are having a positive impact on the conditional covariances of both assets. The asymmetric effect of Ethereum, is more than the positive news on the Reliance and vice versa.

The Bitcoin and TCS pair, the coefficient value of $\alpha_{ij,}$ where $i \neq j$, the cross-market effects between the Bitcoin and TCS, which has a coefficient value of 0.344017 indicates that the news of Bitcoin has an impact on the prices of the TCS share that is also statistically significant, whereas the coefficient value between the TCS and Bitcoin is 0.000170 indicates that the news of TCS is not having an impact on the Bitcoin, so there existence of unidirectional shock spillover from the Bitcoin to TCS. The β_{ij} values, where $i \neq j$ captures the conditional variance between the markets indicate that the current conditional variances of Bitcoin (0.881940) have a persistent effect on the TCS prices, which is statistically significant. Whereas the current conditional variance of TCS (0.998530) has a persistent effect on the Bitcoin prices. The values indicate the existence of conditional covariance is affected more by the magnitude of previous conditional variances rather than the size of innovations. There is a bidirectional volatility clustering spillover effect from Bitcoin to TCS prices. The asymmetric effect of Bitcoin over the TCS is high as the negative shock will impact the prices of the TCS more than the Positive shock in the Bitcoin, but there is a unidirectional impact from the Bitcoin to TCS prices, which is not statistically significant. In Ethereum and TCS, the coefficient (0.404594), statistically significant indicates the news of Ethereum is having an impact on the TCS, negative in vice-versa. This indicates a Unidirectional impact from Ethereum to TCS. The conditional covariances of Ethereum and TCS are having a positive impact on the conditional covariances of both assets. The asymmetric effect of Ethereum, is more than the positive news on the TCS and vice versa.

The Bitcoin and HDFC Bank pair, the coefficient value of $\alpha_{ij,}$ where $i \neq j$, the cross-market effects between the Bitcoin and HDFC Bank, which has a coefficient value of 0.333498 indicates that the news of Bitcoin has an impact on the prices of the HDFC Bank share that is also statistically significant, whereas the coefficient value between the HDFC bank and Bitcoin is 0.543835 indicates that the news of HDFC bank is having an impact on the Bitcoin, so there existence of bidirectional shock spillover from the Bitcoin to HDFC bank. The β_{ij} values, where $i \neq j$ captures the conditional variance between the markets indicate that the current conditional variances of Bitcoin (0.901387) have a persistent effect on the HDFC bank prices, which is statistically significant. Whereas the current conditional variance of HDFC bank (0.497804) has a persistent effect on the Bitcoin prices. The values indicate the existence of conditional covariance is affected more by the magnitude of previous conditional variances rather than the size of innovations. There is a bidirectional volatility clustering spillover effect from Bitcoin to HDFC bank prices. The asymmetric effect of Bitcoin over the HDFC Bank is having positive shock will impact the prices of the HDFC bank more than the Negative shock in the Bitcoin, but there is a unidirectional impact from the Bitcoin to HDFC bank prices, which is not statistically significant. In Ethereum and HDFC bank, the coefficient (0.340729), statistically significant indicates the news of Ethereum is having an impact on the HDFC bank prices and vice-versa. This indicates a bidirectional impact from Ethereum to HDFC bank. The conditional covariances of Ethereum and HDFC bank are having a positive impact on the conditional covariances of both assets. The asymmetric effect of Ethereum, is more than the positive news on the Nifty and vice versa, not statistically significant.

On the Investigation of Bitcoin and ICICI Bank Pair, the α_{ij} values where $i \neq j$ that capture the cross-market effects between the Bitcoin and ICICI Bank, which has a coefficient value of 0.340483 indicates that the news of Bitcoin has an impact on the prices of the ICICI Bank that is also statistically significant, whereas the coefficient value between the ICICI Bank and Bitcoin is -0.043348 indicates that the news of ICICI Bank is not having an impact on the Bitcoin but has a unidirectional shock spillover from the Bitcoin to ICICI Bank. The β_{ij} values, where $i \neq j$ that captures the conditional variance between the markets indicate, current conditional variances of Bitcoin (0.881752) have a persistent effect on the ICICI Bank which is statistically significant. Whereas the current conditional variance of ICICI Bank (0.949379) has a persistent effect on the Bitcoin prices. The values indicate the existence of conditional covariance is affected more by the magnitude of previous conditional variances rather than the size of innovations. There is a bidirectional volatility spillover effect from Bitcoin to ICICI Bank. The asymmetric effect of Bitcoin over the ICICI Bank is high as the negative shock will impact the prices of the ICICI Bank more than the Positive shock in Bitcoin. In Ethereum and ICICI bank, the coefficient (0.384715), statistically significant indicates the news of Ethereum is having an impact on the ICICI bank and vice-versa. This indicates a bidirectional impact from Ethereum to ICICI bank. The conditional covariances of Ethereum and ICICI bank are having a positive impact on the conditional covariances of both assets. The asymmetric effect of Ethereum, the negative news is having impact on the ICICI Bank and vice versa.

The Bitcoin and Infosys pair, the coefficient value of α_{ij}, where $i \neq j$, the cross-market effects between the Bitcoin and Infosys, which has a coefficient value of 0.356046 indicates that the news of Bitcoin has an impact on the prices of Infosys prices that is also statistically significant, whereas the coefficient value between the Infosys and Bitcoin is 0.077700 indicates that the news of Infosys is having an impact on the Bitcoin, so there existence of bidirectional shock spillover from the Bitcoin to Infosys. The β_{ij} values, where $i \neq j$ captures the conditional variance between the markets indicate that the current conditional variances of Bitcoin (0.891862) have a persistent effect on the Infosys prices, which is statistically significant. Whereas the current conditional variance of Infosys (0.991610) has a persistent effect on the Bitcoin prices. The values indicate the existence of conditional covariance is affected more by the magnitude of previous conditional variances rather than the size of innovations. There is a bidirectional volatility clustering spillover effect from Bitcoin to Infosys prices. The asymmetric effect of Bitcoin over Infosys is having a positive shock will impact the prices of Infosys more than the Negative shock in Bitcoin, which is not statistically significant. In Ethereum and Infosys , the coefficient (0.411212), statistically significant indicates the news of Ethereum is having an impact on Infosys prices, and vice-versa. This indicates a bidirectional impact from Ethereum to Infosys prices. The conditional covariances of Ethereum and Infosys prices are having a positive impact on the conditional covariances of both assets. The asymmetric effect of Ethereum, is more than the positive news on the Nifty, statistically significant.

Conclusion

In the application of the BEKK GARCH model to the Nifty Index and the selected stocks in India with the Bitcoin and Ethereum, this paper investigated the conditional volatility between the cryptocurrency, Nifty, and selected stocks in India, but also the asymmetric effect. It is very evident that the Nifty is closely associated and draws information from the cryptocurrency, which means the Indian traders are quite aware of the happenings from the International market, the existence of bidirectional spill over impact on the prices of the stocks. But the stocks impact is Unidirectional not bidirectional. It is evident that time varying conditional correlations between the cryptocurrency and Indian index. This results provides us strong evidence the Indian Index, Nifty is closely associated with the movements in the cryptocurrency market, supports the previous studies in the domain.

REFERENCES

1. Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets?. Journal of International Financial Markets, Institutions and Money, 54, 177-189.
2. Bouri, E., Gupta, R., & Tiwari, A. K. (2018). Does global uncertainty matter for the volatility and hedging effectiveness of Bitcoin?. Annals of Operations Research, 270(1-2), 287-313.
3. Choudhury, T., & Saha, A. K. (2021). Dynamic spillovers and volatility transmission between cryptocurrency and Indian stock market. Journal of Central Banking Theory and Practice, 10(3), 165-194.
4. Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. Econometric Theory, 11(1), 122-150.
5. Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48(5), 1779-1801.
6. Hafner, C. M., & Herwartz, H. (2006). Analyzing nonlinear time series with long memory: The case of exchange rates. Journal of International Money and Finance, 25(2), 283-302.
7. Liu, L., & Ji, Q. (2020). Asymmetric spillovers and volatility transmission between Bitcoin and stock markets: A BEKK-GARCH model. Finance Research Letters, 32, 101239.
8. Nguyen, C. V., & Nguyen, T. D. (2020). Volatility spillovers and dynamic correlations between Bitcoin and global equity markets. Journal of Risk and Financial Management, 13(6), 133.
9. Tseng, Y. H., Lin, T. W., & Hung, K. C. (2021). Dynamic relationship between Bitcoin and stock markets: Evidence from volatility spillover analyses using BEKK-GARCH model. Finance Research Letters, 38, 101862.