Contagion effect of cryptocurrency on the securities market: a study of Bitcoin volatility using diagonal BEKK and DCC GARCH models

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Abstract
The fundamental aim of this study is to examine the contagion effect of Bitcoin on the National Securities Exchange, Shanghai Stock Exchange, London Stock Exchange, and Dow Jones Industrial Average by analyzing the volatility spillover and correlation between these markets to understand the short-term and long-term impact of this volatility ranging from the shocks during the period March 2017–May 2021. Irrespective of ups and downs happening in the cryptocurrency market, more investors are investing their money in the cryptocurrency market. This paper will contribute to the existing literature by studying volatility spillover in the market, its contagion effect, and to identify if there is a long-term and short-term impact between the Bitcoin and stock markets facilitating the transmission of volatility spillover. We employed the Diagonal BEKK and DCC MGARCH models to investigate the integration between Bitcoin and the stock markets. From the empirical analyses, we find the overall time-varying correlation between Bitcoin and the stock markets is low, indicating that Bitcoin can be taken as an asset to hedge against the risk of these stock markets. It was also evident that these stock markets responded more to the negative shocks during 2018 and 2021 than the positive shocks in the Bitcoin market. Our study may be helpful for investment decisions, academia, and policymakers.

Keywords Cryptocurrency · Volatility spillover · Contagion effect · Securities markets · BEKK–DCC GARCH models

JEL Classification C58 · D53 · G15

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Introduction

Recently, cryptocurrency had been the talk across the countries and the financial markets. Digital currencies are tradable assets that have gained much importance in recent years from the public, financial institutions, regulators, and investors ever since its invention in 2008 by an anonymous person named Satoshi Nakamoto. Many of the studies have analyzed the performance capability of cryptocurrency as a replacement for money. While digital currencies are the creation of fiat monetary forms, which are utilized for online exchanges and global exchanges, three key attributes put cryptographic forms of money aside from fiat money. To begin with, they have no focal power, and, henceforth, they are professed to be insusceptible to government impedance and control. This makes them a reasonable other option, particularly in nations with unpredictable monetary forms and unsound economies. Because of their advanced nature, digital currencies and cryptocurrencies can be effortlessly utilized and moved across global borders (Marella et al. 2020).

Many analysts think that the possibility of such an event happening is comparatively low. As per the research reports published by the Bank of International Settlements, digital currencies have difficulties with intrinsic inconsistencies that make their broad use as money incomprehensible. They are not stable because when there is huge demand, there is no adequate supply. At the point when demand for cryptocurrency spikes, the cost of exchanges increases drastically as minors charge more for verifying them through the blockchains. Aside from these inborn inconsistencies, the BIS additionally cautions that digital forms of money stay more helpless against extortion and surprisingly possible degradation than monetary standards oversaw by dependable national banks ABC news (Janda 2018). In its current state, the Bitcoin and cryptocurrency framework is constrained by a couple of significant mining organizations because of it being too costly for individuals exchanged through a couple of major platforms and held in wallets given by different organizations. Effectively, the possibility of decentralization has self-destructed basically because of humankind’s occupancies towards being economic, social, and liberated from issues. The trouble which follows with cryptocurrency trading such as energy consumption, less recognition would offset any of the benefits that would be available to the traders (Wu 2017).

Cryptocurrency gained wide recognition in India in the year 2020. Cryptocurrencies like Bitcoin, outperformed various asset classes in 2020 getting more than 200% returns, and turned into the vital driver for financial investors’ premium in digital currencies, which are frequently alluded to as an option in contrast to gold and a fence to inflation. The reassuring pattern towards the reception of cryptographic money in 2020 by Indians has likewise increased trades to make development plans for 2021. Since the introduction of these new financial instruments, government and regulatory bodies across the countries were under hesitation for making these instruments legal due to various scams and fraud that occurred since its introduction.
By the market capitalization value, Bitcoin stands as the largest cryptocurrency among the thousands of other currencies traded in the market. People prefer trading in Bitcoin for the reasons such as its stability and is used for trading by the government itself in various countries and because of its high value. Bitcoin had been profitable for its users except in the year 2018, it suffered a crash and reached around a value of $5000. After that, there had been a surge in the growth of cryptocurrency trading. Especially during the COVID-19 pandemic, more and more people started trading on Bitcoin. Bitcoin reached its peak in the year 2021 with a value of $19,850.11 and was traded as high as $63,729.5.

The Bitcoin users fell into a pool of panic in the month of May 2021, due to the Bitcoin market crash. The trading fell by 40% to $31,000. China’s latest attempt to bring down a growing digital market for protecting the people from infringing activities and also for facilitating proper and normal financial stability. It was not the first-ever attempt from the side of China against the digital currency. In 2013, China’s central bank put a ban on financial institutions from holding any kind of Bitcoin transactions and in 2017, China put out the speculative market of Bitcoin trading by closing its local cryptocurrency transactions. Similarly, the People’s Bank of China stated in 2019 that it would soon block both domestic and international cryptocurrency trading. The ban in 2021 prohibits all the banks and online trading platforms in China from providing any services related to cryptocurrencies. This has prompted a vast number of miners to close down their mining activities in the country and migrate to other countries.

This is a clear picture of impending volatility in the cryptocurrency market compared to traditional asset classes. Despite the crash, the analysts and researchers think that when it comes to volatile markets such as Bitcoin, such lower prices stand as the opportunity for a long-term basis. The cryptocurrency is only decades old and is yet at the beginning phase of development. Thus, there could be sharp highs and lows en route. Platforms like CoinSwitch Kuber have streamlined crypto contributing, particularly for those hoping to hold the resource for a considerable period. Bitcoin’s fall was normal for quite a while because nothing heads only one way. As per the CEO of WazirX, the prices of Bitcoin have even increased above 50% on occasions. CoinShares executive Meltem Demirors accepts that the current Bitcoin value drop is an adjustment, and it is getting rid of the paper hands (Kahraman 2021). At the same time, the investors are under the question of whether these huge volatility crashes have any impact on other assets such as stocks and bonds. Concerning the crash that happened in 2018 and similarly 2021 will this volatility continue for a longer period? Most of the countries are concerned regarding the contagion effect that this cryptocurrency and the volatility will pose as a threat to economic and financial stability. As a part of looking at these concerns and a possible boom for trading in centralized cryptocurrency countries such as China, Ecuador, Singapore, Senegal and Tunisia, and the United Kingdom, India soon join the bandwagon.
Objective of the study

The fundamental aim of this study is to examine the contagion effect of Bitcoin on the National Securities Exchange, Shanghai Stock Exchange, London Stock Exchange, and Dow Jones Industrial Average by analyzing the volatility spillover and correlation between these markets to understand the short-term and long-term impact this volatility ranges from the shocks ranging from March 2017 to May 2021.

Literature framework

The theoretical framework of the interrelationship between the cryptocurrency market and the stock market exhibit a weak relationship between the two. Most of the empirical literature argues that cryptocurrency is a safe hedge for the stock market as their relationship is weak. However, the studies conducted by Moore and Christin (2013) analyzed the risks of Bitcoin investors from securities exchange failures. A portion of the specialists distinguished the key factors that decide the Bitcoin cost also, found that Bitcoin’s engaging quality for financial investors and worldwide macroeconomic and monetary improvements were influenced by the supply and demand connection (Van Wijk 2013). Kristoufek (2015) withstands that there will be common factors influencing the price determination of both cryptocurrency and the traditional assets in the long term, making the correlation between these two asset classes come under the radar. Dyhrberg (2016) investigates Bitcoin instability utilizing GARCH models. The models assessed in Dyhrberg (2016) propose that Bitcoin has a few similitudes with both gold and the dollar. Similarly, Bouri et al. (2017) put forward contradicting data. There exists a contagion effect between both these markets due to the speculative trading of the cryptocurrency. Osterrieder and Lorenz (2017) find that Bitcoin returns exhibit higher volatility than traditional G-10 currencies. Balcilar et al. (2017), investigate the causal connection between exchanging volume and Bitcoin returns also, volatility. They find that volume can not assist with anticipating the unpredictability of Bitcoin returns. Yi et al. (2018) analyzed volatility connectedness in the digital money market by utilizing LASSO-VAR investigation and confirmed that instability connectedness varies consistently and unpredictability risk bubbles affect the investors. Similarly, Symitsi and Chalvatzis (2018) studied the linkage between energy and technology companies with Bitcoin and came up with the result that there is a correlation present between these markets. Baumöhl (2019) found a negative reliance among forex and cryptocurrency and proposed that traders get diversification benefits if they put money into these resources. Kilç and Çütcü (2018), considered the cointegration and causality relationship between Bitcoin prices and BIST100. They applied Granger and Hansen cointegration tests, there was no cointegration connection between Bitcoin costs furthermore, BIST100 in the medium and long haul; while there was only a unidirectional causality relationship from BIST100 to Bitcoin costs as indicated by the Toda–Yamamoto causality test. Past examinations like Baur and Dimpfl (2018), Phillip et al. (2018), and Fakhfekh and Jeribi (2020) were keen on demonstrating the volatility elements of cryptocurrencies. Be that as it may, few investigations have
examined volatility transmission among Bitcoin and other cryptographic forms of money.

The development of cryptocurrencies has mixed a few studies on their diversification benefits and have benefits for conventional resources. Kurka (2019) utilizes the cross-quantilogram method to inspect the contagion effect among stocks, wares, financials, forex trade, and Bitcoin. Mensi et al. (2019) analyzed the capacity of Bitcoin and gold as fences for oil market unpredictability. The correlation between digital currencies and traditional currencies has been studied by Kristjanpoller and Bouri (2019). They found asymmetric features between these currencies. They made use of network methodologies for studying the contagion effect between other commodity stocks and cryptocurrency. Grobys and Sapkota (2019) studied the transmission of risk from the cryptocurrency market to the foreign exchange market. Their study provided the results that substantiate the state of uncertainty present in both the markets during crashes. And both these markets tend to share the same factors which cause the risk. The study on the effect of the cryptocurrency market on the stock market performance in the MENA region revealed a significant relationship between both markets. An increase in the cryptocurrency market return resulted in a decrease in the stock market returns. The study provided information that both the markets perform as substitutes in Gulf countries while they seem to be complemented in the non-Gulf countries (Sami and Abdallah 2020).

Yaya examined both market proficiency and volatility in 12 digital forms of money during pre-crash and post-crash periods. Their work renders significant data to digital currency market members and portfolio managers (Yaya et al. 2019). Tiwari et al. (2019) highlighted the need for managing the contagion risk in the cryptocurrency market. The researchers investigated the contagion effect and dependence structure between three major cryptocurrencies such as Bitcoin, Ripple, and Litecoin. Their results show that the consequences of the full-range tail dependence copulas—PPPP and GGEE (Pareto mixture copulas model and Gamma and exponential random variables copulas model)—uncover a solid and common upper- and lower-tail dependence of each set of cryptographic forms of money, which is stronger in positively trending markets and for the BTC-sets of cryptocurrencies. They suggested that for traders, the solid movement and conditions between the significant sets of cryptographic forms of money, in both bull and bear markets, infers that portfolio enhancement in the cryptographic money market may not fill in as a support to fence against contagion risk. This is because a negative shock in one cryptographic money would influence other digital currencies. Further, the contagion impact for the Bitcoin to the next cryptographic forms of money is more grounded contrasted and the contagion between different sets of digital forms of money. For the strategy makes which might be engaged with what’s to come guideline of the cryptographic money market, the author’s outcomes show that the contagion risk in this market is exceptionally high. Bitcoin goes about as the main cryptographic money and the comprehension of the Bitcoin financial traders’ conduct is intriguing for a satisfactory guideline of this market. The volatility correlation between the traditional financial market and the cryptocurrency market was studied by Matkovskyy and Jalan (2019). The volatility correlation is higher in terms of return compared to that of interdependence. The researchers believe that this situation of volatility
does not exist stable for a longer period. It will keep increasing in the future period. Shahzad et al. (2019) studied the incorporation of contagion risk in cryptocurrency. The findings contribute to a better understanding of the risk factors by underscoring the significant role of bad contagion measures in the pricing model of cryptocurrency. This suggests the need to incorporate it when applying pricing models since it contains valuable information for risk management and portfolio construction decisions. Therefore, risk and portfolio managers have to keep a vigilant eye on bad contagion in the cryptocurrency markets while trying to predict the future path of cryptocurrency prices.

The results derived from certain studies shed light on the properties varying internationally as Umar et al. (2020) studied the integration between major stock markets and cryptocurrency. The study revealed that they pose a weak interconnection and tend to be time-varying. The crashes happening in the markets seem to have more impact on each other than any positive shocks. They also give a warning that the investors should be cautious while investing in a combination of cryptocurrency and traditional assets. Because the changing policies and regulations have a volatility spillover effect and possible contingencies of market conditions are always present. Corbet et al. (2020) investigate the contagion impacts between Chinese stock markets because of the COVID-2019 pandemic; the proof-dependent on high-recurrence information proposes an increment in the powerful relationships between’s Chinese stock lists, gold, and Bitcoin. Comparable ends are reached by Conlon and McGee (2020) opposite the S&P500. Cryptographic forms of money appear to be reasonable for expansion purposes, however not as a fence. Agosto and Cafferata (2020) examined the connections between the unstable practices of cryptographic forms of money through a unit root testing approach. They affirmed the presence of correlation in the cryptographic money market as in Corbet et al. (2018) and Yi et al. (2018). Ünvan (2021) investigates the impacts of Bitcoin on Nikkei 225, BIST 100 file, S&P 500, and SSE 380 securities exchanges utilizing value at analysis. Kumah et al. (2021) apply cointegration and fractional combination procedures to digital currencies and gold prices and inspect their short- and long-term relationship. Aslanidis et al. (2019) concentrated on the contingent connections between four cryptographic forms of money (Bitcoin, Monero, Dash, and Ripple), S&P 500, bond, and gold. The outcomes showed that the concentration on cryptographic forms of money is unequivocally associated. Nonetheless, the affiliations among digital forms of money and traditional monetary resources are irrelevant. Tiwari et al. (2019) examined time-separated connections between’s the S&P 500 and six other digital currencies. They proposed that digital forms of money are seen to be a fence against the dangers of the S&P 500. Charfeddine et al. (2020) explored the unique connection between Bitcoin and Ethereum and major monetary items what’s more, protections. They upheld the possibility that these two digital currencies can be great for monetary enhancement. Afjal and Clanganthuruthil Sajeev (2022) studied the interconnection between five cryptocurrencies and four energy markets. They found that the overall time-varying correlation between cryptocurrencies and the stock market is low.

The recent Bitcoin crash witnessed a downfall of the currency from $55,000 to $31,000 in March 2021. The impact of China’s ban on financial institutions from
trading on cryptocurrency and Elon Musk’s reassessment had a huge impact on the price bubble to burst. As a resultant action, significant financial exchange indexes were not too huge, yet they proceeded a downtrend that has been articulated recently. The above-given literature gave us insight into the study because they put a light on the need to study the contagion effect in the cryptocurrency market, especially during COVID-19 and recent price bubbles and crashes happening in the industry. Cryptocurrency can be either a substitute or complementary to the traditional financial markets. The difference in these two asset classes comes from the regulation of the central bank. As cryptocurrency does not have a central authority to regulate them. Several studies have brought into light that since the cryptocurrency market and stock market are weakly correlated, a crash happening in the former does not have much effect on the latter. Despite the volatility period in the cryptocurrency market, more and more Indians are investing in this market. So this study contributes to understanding the volatility spillover in the market, its contagion effect, and to identify if there is a long-term impact between the Bitcoin and stock markets facilitating the transmission of volatility spillover. Hence, the purpose of this paper is to uncover potentially time-dependent interdependencies between the cryptocurrency market and the stock market.

Data and econometric methodology

In this study, we employed the returns of Bitcoin USD and four stock market indices namely, NIFTY50 of National Stock Exchange of India, FTSE100 of London Stock Exchange, SSE Composite Index of Shanghai Stock Exchange, and DJI of Dow Jones Industrial Average. All the data for both the cryptocurrency and stock markets were taken from yahoofinance.com. We calculated the daily returns data by taking the distinction in the logarithms of two continuous cost prices. The study period covered from 3rd March 2017 to 28th May 2021. For assessment, the market sets require coordinating with returns separately. Hence, on the off chance that the data isn’t accessible, replaced the values that are not available with zero.

Hypothesis of the research

H₁  There is significant positive correlation between Bitcoin and NSE, SSE, LSE and DJI.

H₂  There is no significant time-varying correlation between Bitcoin and NSE, SSE, LSE and DJI.

H₃  There is equal impact of positive and negative shocks on the magnitude of contagion of cryptocurrency market on stock market.
Diagonal BEKK GARCH model

To break down the volatility spillover from Bitcoin to the National Stock Exchange, Shanghai Stock Exchange, London Stock Exchange and Dow Jones Industrial Average, the GARCH (1, 1) model with BEKK portrayal is utilized. The model is an expansion of Bollerslev’s GARCH model (Bollerslev 1990). For the model permits the correlations among contingent volatility and covariance, the BEKK interaction permits us to look at the volatility transmission.

The BEKK GARCH model averts the non-negative restrictive covariance network, and the quadratic structure for the contingent covariance removes the issue of guaranteeing the receptivity of the restrictive covariance gauge of the vech-GARCH Engle and Sheppard (2001). It accomplishes the positive definiteness of the contingent covariance by figuring the model in a way that this property is inferred by the model design. The equation of the BEKK model is as:

\[
H_t = CC' + \sum_{j=1}^{q} \sum_{k=1}^{k} A_{kj} \epsilon_{t-j} \epsilon'_{t-j} A_{kj} + \sum_{j=1}^{p} \sum_{k=1}^{k} B_{kj} H_{t-j} B_{kj},
\]

where \(A_{kj}\) and \(B_{kj}\) a N × N parameter matrices, and \(C\) is a lower triangular matrix. The motivation behind disintegrating the consistent term in condition (2) into a result of the two three-sided networks is to ensure the positive semi-definiteness of \(H_t\). At whatever point \(K>1\) an ID issue would be created for the explanation that there are not just a solitary definition that can get a similar portrayal of the model.

The first-order BEKK model is given as:

\[
H_t = CC' + A_{kj} \epsilon_{t-j} \epsilon'_{t-j} A + B B H_{t-j} B.
\]

The BEKK model specified in Eq. (2) also has its diagonal form by assuming that the matrices \(A_{kj}\) and \(B_{kj}\) are diagonal. The most confined form of the inclining BEKK is the scalar BEKK one with \(A=aI\) and \(B=bI\), where \(a\) and \(b\) are scalars. Assessment of the BEKK model actually bears enormous calculations because of a few network renderings. The number of parameters of a total BEKK model is \((p+q) K N^2 + N(N+1)/2\) though in the inclining BEKK, the number of parameters lessens to \((p+q) K N + N(N+1)/2\). The BEKK structure isn’t straight in the parameters, which makes the union of the model troublesome. Nonetheless, the model design naturally ensures the positive definiteness of \(H_t\). Under the general thought, it is accepted that \(p=q=k=1\) in BEKK types of utilization. The distinction between the aftereffects of BEKK model and the DCC model is exceptionally insignificant.

Dynamic conditional correlation multivariate GARCH (DCC MGARCH)

The use of DCC model is for the analysis of the integration present between the Bitcoin and stock market indices. The DCC GARCH model was proposed by Engle and Sheppard (2001) and Engle (2002) to assess enormous time-shifting covariance matrices. This model joins dynamic relationship and the GARCH
model, and consequently it is fit for managing heteroskedasticity and enormous powerful covariance networks.

Another benefit of DCC MGARCH model is the instability is changed by the strategy, the time fluctuating connection (DCC) does not have any inclination from volatility. Unlike the volatility changed cross-market connections utilized in Forbes and Rigobon (2002), DCC MGARCH constantly changes the connection for the time-varying instability. Thus, DCC gives a superior measure to connection.

There are two stages in the assessment methodology. In the initial step, a progression of univariate GARCH models are assessed for every leftover arrangement. In the subsequent advance, normalized residuals from the initial step are utilized to appraise boundaries of dynamic connection that are free of the quantity of corresponded arrangement. This multi-stage assessment enjoys computational upper hands over multivariate GARCH models as far as the quantity of boundaries (Engle 2002).

Assume that the returns of \( N \) assets are conditionally normally distributed; and that the DCC GARCH model is a generalized framework of the constant conditional correlation GARCH (CCC GARCH) model; and is as follows:

\[
\begin{align*}
  r_t & \sim N(0, D_t R_t D_t) \\
  Q_t & = (1 - \alpha - \beta) \bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \\
  R_t & = \text{diag}(Q_t)^{-1} Q_t \text{diag}(Q_t)^{-1}.
\end{align*}
\]

The diagonal matrix of standard deviation from univariate GARCH models \( R_t \) is the dynamic correlation matrix; \( Q_t \) is a positive semi-definite matrix; \( \bar{Q} \) is the unconditional variance matrix of \( u_t; u_{it} \sim N(0, R_t) \) are the standardized residuals from GARCH models; that \( \alpha > 0, \beta > 0 \); and this model is mean-reverting on the condition that \( \alpha + \beta < 1 \).

With respect to forecasting co(variance) by DCC GARCH, one standard approach is to generate the \( r \)-step ahead forecast of \( Q_t \) with the supposition that \( E(u_{t+1} u_{t+1}') \approx Q_{t+1} \). Alternatively, we can directly predict \( R_t \) with the approximation that \( \bar{Q} \approx R \) and \( E(Q_{t+1}) \approx E(R_{t+1}) \).

The DCC GARCH model provides accurate approximation of time-varying correlations in practice, even for large covariance matrices. Furthermore, the original correlations do not change when new variables are added to the system (Engle 2002).

The summary statistics for every variable are introduced in Table 1, with proof of price returns behavior and volatility introduced in Fig. 1.

Table 1 depicts the descriptive statistics of the sample data chosen for the study. All the data series display a positive return. The unit root test gives the standard deviation examination result for Bitcoin and the stock markets. The result indicates they are volatile during the sample period, 3rd March 2017–28th May 2021. Similarly, the Kurtosis and Skewness coefficients declare that the data series is not close to the normal distribution in the data. This is substantiated by the results of Jarque–Bera test statistics.
Empirical results

To check the order of integration between the variables, we employed the Augmented Dickey–Fuller (ADF) (Dickey–Fuller in 1979) and Phillips–Perron (PP) tests (Phillips 1995). Table 2 indicates the Unit Root Test Results and ARCH-LM Test Results for the data series. The test results are given after taking into consideration with and without constant trend variables. When the ADF test was employed, it rejected the null hypothesis at a 1% significant level. To check the robustness of the results attained, we further employed the Phillips–Perron test of stationarity and the data were substantiated by the test. We also employed the ARCH-LM test to see the presence of the ARCH effect and the test results indicate the presence of ARCH as well as to detect the existence of heteroskedasticity problems and autocorrelation in the data series. As a result of this, the application of Diagonal BEKK and DCC MGARCH models were applied for the stock market and Bitcoin returns.

Table 3 represents the correlation and covariance between the variables chosen for the study. It can be easily identified from the data that there is a negative correlation of Bitcoin with SSE and DJI, meaning that its price movements are inconsistent with those in stock markets. This implies that the Bitcoin shocks do not straightforwardly affect the financial exchange. Yet, the way that crypto costs are falling so forcefully is one part of a more serious issue a difficulty that could bring transient agony even to stocks with no Bitcoin association by any means. While in the case of correlation between Bitcoin with NSE and LSE, there is a positive but weak relation meaning that its price movements are consistent with those in the stock market. This ascent in connection might be an aftereffect of its expanding appropriation, as proven by record volumes exchanged, the ascent in OTC-exchanged Bitcoin

| Table 1 Descriptive statistics |
|-------------------------------|
| NSE  | SSE  | LSE  | DJI  | BTC  |
| Mean | 0.00057 | 0.00016 | 0.097401 | 0.00055 | 0.00274 |
| Median | 0.00077 | 0.0005 | 0.000849 | 0.00096 | 0.00201 |
| Maximum | 0.08763 | 0.05711 | 101.8029 | 0.11365 | 0.25247 |
| Minimum | -0.1298 | -0.0772 | -0.990472 | -0.1293 | -0.1874 |
| Std. Dev | 0.0121 | 0.01119 | 3.147903 | 0.01353 | 0.04339 |
| Skewness | -1.3495 | -0.5657 | 32.28944 | -0.6778 | 0.3849 |
| Kurtosis | 24.4624 | 8.56273 | 1043.74 | 24.5761 | 6.81065 |
| Jarque–Bera | 20,393.4 | 1404.44 | 47,388,625 | 20,369.4 | 658.704 |
| Sum | 0.59316 | 0.17136 | 101.881 | 0.57409 | 2.86053 |
| Sum Sq. Dev | 0.15299 | 0.13076 | 10,355.21 | 0.1912 | 1.96729 |
| Probability | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Observations | 1046 | 1046 | 1046 | 1046 | 1046 |

BTC denotes Bitcoin returns. NSE (National Securities Exchange) denotes NIFTY50 returns. SSE (Shanghai Stock Exchange) denotes SSE composite returns. LSE (London Stock Exchange) denotes FTSE 100 Index Returns. DJI (Dow Jones Industrial Average) denotes DJI returns. Standard deviations (SD), Jarque–Bera (JB), Augmented Dickey–Fuller (ADF), Phillips and Perron (PP) and ARCH effect (ARCH)
reserves, and an expanding number of installment networks empowering Bitcoin and digital purchasing and selling on their organizations.

The correlation between Bitcoin and the stock markets has been fluctuating for almost the entirety of the past year. Bitcoin has avoided the weakness seen in big growth stocks lately, but rotation within equities has just shifted that frothiness to reopening. The parabolic move in BTC over the past six months has led to a sharp market crash. Since Bitcoin breaks down, it is effectively a giant red flag to all other

Fig. 1 Price and volatility behavior of the Bitcoin and the selected stock market indices. [NSE (National Securities Exchange) denotes NIFTY50 returns. SSE (Shanghai Stock Exchange) denotes SSE composite returns. LSE (London Stock Exchange) denotes FTSE 100 Index Returns, DJI (Dow Jones Industrial Average) denotes DJI returns]
Table 2  Unit root test and ARCH-LM test results

Augmented Dicky–Fuller test statistic (ADF)

|                     | NSE       | SSE       | LSE       | DJI       | BTC       |
|---------------------|-----------|-----------|-----------|-----------|-----------|
| At level            |           |           |           |           |           |
| With constant       |           |           |           |           |           |
| t-Statistic         | −11.3491  | −31.8551  | −32.325   | −9.8803   | −32.2269  |
| Prob                | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** |
| With constant and trend |       |           |           |           |           |
| t-Statistic         | −11.3527  | −31.8695  | −32.333   | −9.8868   | −32.2966  |
| Prob                | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** |
| Without constant and trend |       |           |           |           |           |
| t-Statistic         | −11.2556  | −31.8632  | −32.309   | −9.7738   | −32.1152  |
| Prob                | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** |
| Phillips–Perron test statistic (PP) | | | | | |
| At level            |           |           |           |           |           |
| t-Statistic         | −34.3829  | −31.88781 | −32.3249  | −40.14823 | −32.2532  |
| Prob                | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** | 0.0000*** |
| ARCH-LM statistic   |           |           |           |           |           |
|                     | 5.278065  | 5.65573   | 0.00096   | 134.64    | 44.0847   |
|                     | 0.0000*** | 0.0174**  | 0.9752    | 0.0000*** | 0.0000*** |

(*)Significant at the 10%; (**) significant at the 5%; (***) significant at the 1% and (no) not significant

Table 3  Correlation and covariance matrix

|                     | NSE       | SSE       | LSE       | DJI       | BTC       |
|---------------------|-----------|-----------|-----------|-----------|-----------|
| NST                 |           |           |           |           |           |
| Covariance          | 0.000146  |           |           |           |           |
| Correlation         | 1         |           |           |           |           |
| SSE                 |           |           |           |           |           |
| Covariance          | 7.43E−06  | 0.000125  |           |           |           |
| Correlation         | 0.054957  | 1         |           |           |           |
| LSE                 |           |           |           |           |           |
| Covariance          | 0.002006  | 0.002150  | 9.899818  |           |           |
| Correlation         | 0.052714  | 0.061104  | 1         |           |           |
| DJI                 |           |           |           |           |           |
| Covariance          | −1.04E−06 | −2.58E−06 | 0.002826  | 0.000183  |           |
| Correlation         | −0.006338 | −0.017096 | 0.06641   | 1         |           |
| BTC                 |           |           |           |           |           |
| Covariance          | 2.12E−05  | −8.87E−06 | 0.001638  | −3.39E−05 | 0.00188   |
| Correlation         | 0.040385  | −0.018301 | 0.012001  | −0.057835 | 1         |
risk assets in the long run. But there could be a causal element at play that spurs equity weakness too.

**BEKK GARCH results**

To break down the volatility spillover from Bitcoin to the National Stock Exchange, Shanghai Stock Exchange, London Stock Exchange and Dow Jones Industrial Average, the GARCH (1, 1) model with BEKK portrayal is utilized. The model permits the correlations among contingent volatility and covariance, the BEKK interaction permits us to look at the volatility transmission.

**Variance–covariance representation;**

\[
\text{GARCH} = M + A_1 \text{RESID}(-1) \times \text{RESID}(-1) + B_1 \text{GARCH}(-1) \times B_1.
\]

**Variance and covariance equations;**

\[
\text{GARCH}_1 = 3.70736204234 \times 10^{-6} + 0.0653680977253 \times \text{RESID}_1(-1)^2 + 0.911477538089 \times \text{GARCH}_1(-1),
\]

\[
\text{GARCH}_2 = 1.12840954938 \times 10^{-6} + 0.0309140051763 \times \text{RESID}_2(-1)^2 + 0.96466396279 \times \text{GARCH}_2(-1),
\]

\[
\text{GARCH}_3 = 5.0344484802e-07 + 2.68481593549e-11 \times \text{RESID}_3(-1)^2 + 0.999865709132 \times \text{GARCH}_3(-1),
\]

\[
\text{GARCH}_4 = 3.70851485022e-06 + 0.186852754666 \times \text{RESID}_4(-1)^2 + 0.8105336965 \times \text{GARCH}_4(-1),
\]

\[
\text{COV}_1_2 = 0.0449531946745 \times \text{RESID}_1(-1) \times \text{RESID}_2(-1) + 0.937693731335 \times \text{COV}_1_2(-1),
\]

\[
\text{COV}_1_3 = 1.3247690759e-06 \times \text{RESID}_1(-1) \times \text{RESID}_3(-1) + 0.954649220907 \times \text{COV}_1_3(-1),
\]

\[
\text{COV}_1_4 = 0.110517913151 \times \text{RESID}_1(-1) \times \text{RESID}_4(-1) + 0.85952484566 \times \text{COV}_1_4(-1),
\]

\[
\text{COV}_2_3 = 9.11034652069e-07 \times \text{RESID}_2(-1) \times \text{RESID}_3(-1) + 0.982107131182 \times \text{COV}_2_3(-1),
\]

\[
\text{COV}_2_4 = 0.0760024145994 \times \text{RESID}_2(-1) \times \text{RESID}_4(-1) + 0.884246759819 \times \text{COV}_2_4(-1),
\]

\[
\text{COV}_3_4 = 2.23978850188e-06 \times \text{RESID}_3(-1) \times \text{RESID}_4(-1) + 0.900235814895 \times \text{COV}_3_4(-1).
\]

Table 4 represents the diagonal coefficients of spillover effects. The ARCH terms consisting of elements of matrix are written as $A_1(1,1) A_1(2,2) A_1(3,3) A_1(4,4)$ and the GARCH terms as $B_1(1,1) B_1(2,2) B_1(3,3) B_1(4,4)$, respectively. Positive coefficients in the off-diagonals of $A_1$ imply that the volatility is influenced more at the point when the crashes move in the same direction than when they move in inverse ways. Here the most statistically significant spillovers for all the variables has positive values. The log likelihood for BEKK model is 13,136. The results shows that the ARCH and GARCH terms have less than 5% except for $A_1(3,3)$ which shows significant impact of Bitcoin on the future volatility NSE, SSE and DJI. On the other hand, Bitcoin does not have any significant impact on the future volatility of LSE $A_1(3,3)$. 
DCC MGARCH results

The reason for choosing this particular model is that it is capable of the examination of several relations that data series have with each other. So in such cases, it is important to employ multivariate GARCH models (MGARCH). The spillover effects and volatility transfers among the samples can be easily detected using these models which are especially important when it comes to contagion analyses. In our study, the model with contingent correlations will be introduced and utilized, as we find instability shocks, others that show the affectability to crashes, the affectability to crashes of instability of stocks, just as those that show whether the resource stays influenced for quite a while by crashes and that we are especially intrigued since they address the correlation between the two resources.

The benefit of the DCC MGARCH model is the immediate demonstrating of variance and covariance and its adaptability, permitting the framework of restrictive correlations to fluctuate after some time, contrasted with other models that are too prohibitive (methodology).

We estimated the volatility and correlation between Bitcoin and the rest of the stock markets by applying the DCC MGARCH model. It has been employed to analyze the volatility and co-volatility between Bitcoin and stock markets. In Table 5, 'mu' stands for the overall mean and 'omega' denotes intercept term. Aside from this, the impact of past unsettling influences or error term acquired through mean condition is signified as ARCH impact, which is meant by alpha1, while the impact of past change is indicated by GARCH (beta1). Alpha estimates the volatility spillover for the short run that incorporates the determination of residuals from the past period and beta estimates the long-run volatility impact of a conditional correlation or shocks. Our results provide that dccal is positive but insignificant and while in the case dccb2 is relatively large which points out the persistence in the time-varying

| Variables | Coefficient | Std. Error | z-statistic | Prob |
|-----------|-------------|------------|-------------|------|
| M(1,1)    | 3.71E−06    | 1.04E−06   | 3.570902    | 0.0004 |
| M(2,2)    | 1.13E−06    | 3.86E−07   | 2.920761    | 0.0035 |
| M(3,3)    | 5.03E−07    | 1.01E−07   | 4.995291    | 0.0000 |
| M(4,4)    | 3.71E−06    | 8.93E−07   | 4.151174    | 0.0000 |
| A1(1,1)   | 0.255672    | 0.024882   | 10.27524    | 0.0000 |
| A1(2,2)   | 0.175824    | 0.019742   | 8.906121    | 0.0000 |
| A1(3,3)   | 5.18E−06    | 0.000102   | 0.050893    | 0.9594 |
| A1(4,4)   | 0.432265    | 0.035938   | 12.02811    | 0.0000 |
| B1(1,1)   | 0.954713    | 0.008395   | 113.7214    | 0.0000 |
| B1(2,2)   | 0.982173    | 0.003713   | 264.5487    | 0.0000 |
| B1(3,3)   | 0.999933    | 0.00024    | 4170.761    | 0.0000 |
| B1(4,4)   | 0.900296    | 0.014526   | 61.97925    | 0.0000 |

Log likelihood: −13,138.99; Schwarz criterion: −24.98277; Avg. log likelihood: 3.140294; Hannan–Quinn criterion: −25.04449; Akaike info criterion: −25.08220
correlation is high. It has an impact on the conditional variance in a positive way as the perseverance of volatility is accomplished by the combination of alpha and beta values and here the amount of ARCH and GARCH coefficients is under 1 for Bitcoin and stock market indices, showing that there is a reduction in unpredictability perseverance over the long run. When we examine the volatility spillover, the results imply that there is no short-run volatility spillover from Bitcoin to the stock markets; while in the long run, there is a volatility spillover effect from Bitcoin to the stock markets. As a result of this, there is no existence of integration and asymmetric effect from Bitcoin to stock markets in the short run. While there is an existence of integration and asymmetric effect in the long run.

Bitcoin volatility leads to its frequent drops and growth. In comparison to the past Bitcoin has even dropped by 80% on several occasions. This unpredictability implies financial backers can only with significant effort think about where it will go from here. In 2011, it was 91%, 2014—85%, 2018—83%, 2019—50% and in 2021—40%.

Figure 2 exhibits dynamic conditional correlation and the conditional volatilities between Bitcoin and the stock markets which was obtained by applying the DCC MGARCH model. The DCC MGARCH model is a very significant tool to identify the market instability and the episodes that affect the volatilities of Bitcoin and the stock markets. From the figure, we can see that the correlation coefficient of Bitcoin with stock markets varies greatly with time-wise change which implies that the

| Source: Author’s Calculations | Estimate | Std. error | t value | Pr(>|t|) |
|-------------------------------|----------|------------|---------|----------|
| [BTC].mu                      | 0.001871 | 0.001087   | 1.72162 | 0.0851   |
| [BTC].omega                   | 0.000138 | 0.000068   | 2.03744 | 0.0416   |
| [BTC].alpha1                  | 0.137786 | 0.045036   | 3.05944 | 0.0022   |
| [BTC].beta1                   | 0.793023 | 0.061498   | 12.89518| 0.0000   |
| [NSE].mu                      | 0.000811 | 0.000271   | 2.99308 | 0.0028   |
| [NSE].omega                   | 0.000003 | 0.000002   | 1.30066 | 0.1934   |
| [NSE].alpha1                  | 0.138576 | 0.036234   | 3.82444 | 0.0001   |
| [NSE].beta1                   | 0.840887 | 0.035385   | 23.76399| 0.0000   |
| [SSE].mu                      | 0.000244 | 0.000115   | 2.1224  | 0.0338   |
| [SSE].omega                   | 0.000003 | 0.000004   | 0.65638 | 0.5116   |
| [SSE].alpha1                  | 0.13336  | 0.060812   | 2.19298 | 0.0283   |
| [SSE].beta1                   | 0.859084 | 0.056474   | 15.2121 | 0.0000   |
| [LSE].mu                      | 0.001901 | 0.000831   | 2.28693 | 0.0222   |
| [LSE].omega                   | 0.000052 | 0.000057   | 0.92478 | 0.3551   |
| [LSE].alpha1                  | 0.382637 | 0.058531   | 6.53729 | 0.0000   |
| [LSE].beta1                   | 0.616363 | 0.171831   | 3.58703 | 0.0003   |
| [DJI].mu                      | 0.00102  | 0.000324   | 3.15123 | 0.0016   |
| [DJI].omega                   | 0.000003 | 0.000111   | 0.31785 | 0.7506   |
| [DJI].alpha1                  | 0.240703 | 0.048809   | 4.93155 | 0.0000   |
| [DJI].beta1                   | 0.750974 | 0.131265   | 5.72105 | 0.0000   |
| [Joint].dcca1                 | 0.003551 | 0.008241   | 0.43094 | 0.6665   |
| [Joint].dccb1                 | 0.996449 | 0.011125   | 89.56951| 0.0000   |
Fig. 2 Time-varying conditional correlation. [BTCR denotes Bitcoin returns. NSE (National Securities Exchange) denotes NIFTY50 returns. SSER (Shanghai Stock Exchange) denotes SSE composite returns. LSER (London Stock Exchange) denotes FTSE 100 Index Returns, DJI (Dow Jones Industrial Average) denotes DJI returns]
investors are making significant changes to the portfolios traded in the market. The volatility correlation is negative and weak for Bitcoin-DJI, Bitcoin-SSE throughout signaling that there isn’t much correlation between these three. While in the case of Bitcoin-NSE and, Bitcoin-LSE there is a positive but weak form of correlation between these two. However, this volatility-correlation does not stay stable over time and ends up changing. In the January–February period of 2020, it showed a critical ascent for all the market volatility correlations driven it is contended by basics including position framing before a normal May forking event much, however, not which was all eradicated as the worldwide spread of the COVID-19 and also due to the various uncertain economic events taking place. Finally, the plots of conditional co-variances are plotted in Fig. 3. With the reference to the variables under the study, we can see spikes in all the Bitcoin stock market variables. It is worth noticing that the DJI, SSE, LSE, and NSE present more frequent spikes during the negative shocks than positive shocks. The most significant spikes observed for the DJI and SSE are from 2017 to 2020. While in the case of NSE and LSE, it is 2020–2021 and for the LSE, it is during 2020.

At the point when the costs of Bitcoin rose from $1000 toward the start of 2017 to over $19,000 by mid-December, market reports were that Bitcoin was usurping the part of gold as a store of significant worth and an option in contrast to fiat monetary standards. Retail financial traders will in general have a more limited investment when Bitcoin recording explanatory increases. After this vertiginous climb, the greatest advanced coin lost almost 3/4 in its worth. All through 2018, Bitcoin’s cost plunged and shut the year at around $4000. In the primary portion of 2019, Bitcoin is back. It set off the edge of $14,000 in June. Toward the start of 2020, we notice that the connection expanded among digital currencies and gold which affirm the virus impact of COVID between them. By May 2021 the trading fell by 40% to $31,000. The drop was for the most part because of China’s prohibition on monetary associations including banks and other assistance giving establishments from offering types of assistance connection to cryptocurrency.

**Conclusion**

In this paper, we analyzed the contagion effect of Bitcoin on four traditional stock markets for the period 2017–2021. Through the study, we validated that the Diagonal BEKK model and DCC GARCH model are appropriate tools to analyze these markets. The result declares the existence of asymmetric volatility and weak negative correlation between Bitcoin-SSE, Bitcoin-DJI while positive weak correlation in the case of Bitcoin-NSE and Bitcoin-LSE. The time-varying correlation between the variables is very low and hence Bitcoin can be considered as a hedge asset for the traditional stock markets. Bitcoin markets are affected by both instability and irregularities happening in the economy and hence their nature tends to be more risky and unpredictable. Hence, there is a sharp correlation between 2018 and 2021 due to various economic events happening which are completely unpredictable. From the findings, it can be seen that the negative shocks play a greater role in the magnitude of contagion in comparison to that of the positive shocks. In the case
Fig. 3 Conditional volatility between Bitcoin and the selected stock market indices. [BTC denotes Bitcoin returns. NSE (National Securities Exchange) denotes NIFTY50 returns. SSER (Shanghai Stock Exchange) denotes SSE composite returns. LSER (London Stock Exchange) denotes FTSE 100 Index Returns, DJI (Dow Jones Industrial Average) denotes DJI returns]
of the 2018 crash, the predictions were such that it was there were massive sell-offs, then the drop in the plans of Goldman Sachs to launch a cryptocurrency trading, the investors being youngsters and boorish. Similarly in the case of the 2021 crash was mainly due to the widespread pandemic, China banning cryptocurrency trading, Elon Musk’s proposal for radical Dogecoin upgrade to beat Bitcoin, and furthermore.

This research work gives the significance of displaying time-varying correlation including stock records and Bitcoin for portfolio managers since the definite correlation between the assets changes intensely and requires recurrent changing portfolios. The aftereffects of this study are of extraordinary importance to financial investors and policymakers. From one perspective, our discoveries give some significant suggestions for financial investors, especially for the individuals who want to invest in Bitcoin and stocks portfolios simultaneously. They can utilize short situations in Bitcoin to spread the risk of long situations in values particularly when the entire market goes through occasions of pressure. In this way, in a period of a pandemic like the COVID-19, it is for the most part, not a good thought to utilize Bitcoin as a place for investing. Bitcoin and the rest of the cryptocurrency do not pose a threat to the traditional financial markets as of now but that does not infer they may not later, since Bitcoin is a fragile market.

Since the cryptocurrency market is unrelated, the investors ought to analyze the risk factors which will help them to avoid any continent losses due to any economic crisis. Even though through our study we suggest that cryptocurrency has a weak correlation with traditional markets, for policymakers and investors, cryptocurrency is a highly volatile and speculative asset that does not satisfy the criteria of a safe haven for investment during a pandemic. Since due to the ongoing pandemic, it is too early to reach a consensus on the same, it is left for future research scholars for further investigation.

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**Data availability**  The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

**Declarations**

**Conflict of interest**  There is no conflict of interest.

**Ethical approval**  No experiments have been conducted.

**Informed consent**  This study enjoys the consent of all its authors.

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