Hindawi
Complexity
Volume 2022, Article ID 5346080, 15 pages
https://doi.org/10.1155/2022/5346080

Research Article

Impacts of COVID-19 on the Return and Volatility Nexus among Cryptocurrency Market

Xin Sui,[1] Guifen Shi,[1] Guanchong Hou,[1] Shaohan Huang,[1] and Yanshuang Li[2]

[1]*Business School of Northeast Normal University, Northeast Normal University, No. 2555 Jingyue Street, Changchun, Jilin 130117, China*
[2]*School of Applied Finance and Behavioral Science, Dongbei University of Finance and Economics, No. 217 Jianshan Street, Shahekou District, Dalian, Liaoning 116025, China*

Correspondence should be addressed to Yanshuang Li; yanshuangli668@163.com

Received 9 December 2021; Revised 1 March 2022; Accepted 16 March 2022; Published 19 May 2022

Academic Editor: Paulo Jorge Silveira Ferreira

The impacts of COVID-19 have spread rapidly to global financial markets. In this context, combining the spillover index method introduced by Diebold and Yilmaz (2012) and the complex network analysis framework, we examined the volatility connectedness and the topological structure among the top ten cryptocurrencies before and during the COVID-19 crisis. The results revealed that the total volatility connectedness of the cryptocurrency market markedly increased following the outbreak of COVID-19; statically, Bitcoin, Ethereum, Cardano, and Bitcoin Cash were the net transmitters before COVID-19, while Bitcoin, Ethereum, Ripple, Litecoin, Cardano, and Stellar became the major net transmitters in the market after COVID-19. Dynamically, the dynamic performance of different cryptocurrencies during the COVID-19 pandemic was heterogeneous, and the possible driving factors are diverse. Moreover, from network analysis, we further found that the COVID-19 crisis has significantly changed the topological structure of the cryptocurrency market. Our findings may help understand the typical dynamics in the cryptocurrency market and provide significant implications for portfolio managers, investors, and government agencies in times of highly stressful events like the COVID-19 crisis.

1. Introduction

With the continuous development of Internet technology and financial services, the cryptocurrency market has witnessed a boom. On the one hand, the traditional currency system has many disadvantages and the cryptographical technology provide a new payment system. On the other hand, global economic activities provide digitalization, networking, and intelligentisation for the innovation of cryptocurrencies. There are currently 1,006 cryptocurrencies on the market, with a combined market capitalisation in 2020 of more than $364.4 billion (data source: the cryptocurrency information in this article was sourced from the cryptocurrency exchange platform Coinbase). Further, investors focus on the fluctuations in and financial risks of cryptocurrencies [1].

The COVID-19 outbreak and its rapid spread all around the world have significantly impacted the global economy. By the 30th of January 2020, the COVID-19 outbreak was defined as a PHEIC (PHEIC: WHO identifies Public Health Emergency of International Concern as H1N1 influenza, Ebola, polio, and Zika virus (https://www.who.int/zh/)), and it has since caused the price of digital cryptocurrencies to fluctuate in the market considerably. Among them, the price

of Bitcoin (which holds the largest market value) rose from $5,012 on 12 March to $29,094 on 31 December, while Ethereum (which holds the second-largest market value) rose from $116 on 16 March to $754 on 31 December. We choose the top 10 cryptocurrencies according to the market value, and Table 1 displays the trading information for the top 10 cryptocurrencies on 31 December 2020. The top 10 cryptocurrencies account for above 80% of market value in the cryptocurrency market, and the trade volume of cryptocurrencies accounts for nearly 50% of New York Stock Exchange. Therefore, the top 10 cryptocurrencies can represent the tremendous changes in the cryptocurrency market. Consequently, it is very suitable to choose top 10 cryptocurrencies as the research object in the context of the COVID-19 pandemic. Additionally, the price change of the top 10 cryptocurrencies is given in Figure 1, from 1 January 2020 to 31 December 2020 [2]. Cryptocurrencies have a high market value and heavy trading volume; in response to the COVID-19 outbreak, the prices fluctuated significantly. Investors focus on cryptocurrency's huge profitability, volatility, and rapidly growing demand. In recent years, countries such as China have begun to study and legalize digital currencies on trial basis (on 25 October, Mu Changchun, director of the Digital Currency Research Institute of the People's Bank of China, delivered a speech on the digital yuan at the Second Bund Financial Summit), while the cryptocurrency market also needs to be regulated. Therefore, this paper examines the connectedness of cryptocurrency market, particularly over the COVID-19 period.

2. Literature Review

After the US subprime crisis, "too big to fail" translates to "too connected to fail," and that the connectedness of financial institutions would rapidly extend individual risk into systemic risk [3]. Battaglia et al. [4] pointed out that financial risk spillover means that the risk of a financial institution in the financial system will spread to other financial institutions, causing a "domino effect" in the whole financial system. Risk contagion and risk spillover effects exist in the financial market, and, therefore, it is necessary to effectively identify and avoid the characteristics of risk in the financial market [5]. Public health events have a serious impact on capital markets and economies, and this is difficult to recover from within a given period of time [6]. Al-Awadhi et al. [7] pointed out that the increasing number of confirmed COVID-19 cases and deaths had a negative impact on the stock returns of the Hang Seng Index and the Shanghai Composite Index.

Matkovsky and Jalan [8] explained that financial risks transmit from the traditional market to the cryptocurrency market, and investors then avoid investing in cryptocurrency assets under extreme pressure. Investors can use cryptocurrency to allocate asset portfolios or hedge risks under the connectedness in the cryptocurrency market. However, due to considerable differences in the technology and market environment between the emerging cryptocurrency market and the traditional financial market, the market contagion mechanism of the two markets is also different [9, 10]. Therefore, it is necessary to examine the transmission mechanism between cryptocurrencies [11]. After conducting an empirical analysis, Bouri et al. [12] concluded that the main characteristics in the cryptocurrency market are high liquidity and profitability. Many scholars believe that major media events and government regulatory policies affect the price stability of cryptocurrencies [13]. Cryptocurrency prices experience extreme fluctuations, and governments need to take measures to regulate the risks associated with this [14]. At the same time, security threats against cryptocurrency applications are frequent, which further causes concern around the security of blockchain and its development prospects.

Our work first links to a trending topic on cryptocurrency market. In the existing literature, there are many debates about the performance of cryptocurrency market under the conditions of the COVID-19 outbreak. For example, Sarkodie and Owusu [15] analyzed Bitcoin, Bitcoin Cash, Ethereum, and Litecoin and concluded that the prices of the cryptocurrencies fluctuated significantly during COVID-19. Borgards and Czudaj [16] found that Bitcoin was highly correlated with the stock market at the beginning of COVID-19. COVID-19 led to risks spreading in the financial market, which significantly affected the cryptocurrency market, and the risks gradually decreased as COVID-19 was controlled [17, 18]. The cryptocurrency market involves the herd effect, and the size of this effect predominantly depends on price changes in the market [19]. At the same time, some scholars have concluded that the cryptocurrency market differs from traditional markets such as stocks and commodities. Major events lead to high investor enthusiasm, which increases cryptocurrency market returns [20]; (Rogone & Hyde, 2020). Feng et al. [21] concluded that cryptocurrencies generally have abnormally high returns when the cryptocurrency market experiences abnormal volatility. Scholars have reached mixed conclusions about how cryptocurrency markets respond to risks. For example, during COVID-19, the cryptocurrency market was able to hedge stock market risks, while Corbet et al. [22] found that Bitcoin only amplified financial (versus hedge) risks. There are several different and interesting results of COVID-19 and cryptocurrency market. Paulo et al. [23] used DCCA and DMCA to find that the cryptocurrency market is less closer to the random walk dynamics and it is practical inefficiency.

Our work is also related to the literature on the research methods; Li Jing and Xu Liming [24] measured the market risks and spillover effects associated with Bitcoin in China and the United States by constructing the GED-GARCH model and the MGARCH-BEEK model. Kang et al. [25] found that the spillover index method was better at estimating the fluctuation spillover relationship between the different elements. Based on the vector autoregressive model, Diebold and Kamil [26] proposed the spillover index method to measure the return and volatility spillover of 19 global stock markets. Diebold et al. [27] pointed out that the spillover index method and its variables can effectively detect and measure the volatility spillover effect between financial

Table 1: Information for the top 10 cryptocurrencies (RMB).

Cryptocurrency	Market value	Price	Trade volume	Circulating supply
BTC	3,512,025,975,000	188,952.00	304,617,946,979	3,491,180,869,132
ETH	548,407,857,349	4,807.90	90,754,297,567	550,366,550,885
USDT	136,386,953,086	6.52	400,368,688,566	136,736,695,737
ADA	36,760,890,565	1.18	7,375,143,430	10,757,641,730
LTC	53,766,605,595	812.03	40,862,530,085	49,042,220,091
XRP	65,004,962,235	1.43	34,931,844,357	51,977,509,427
XLM	18,322,448,767	0.8361	3,153,623,337	18,288,287,123
LINK	29,254,396,026	73.41	7,859,964,879	29,136,493,829
BOT	54,202,739,300	60.55	17,927,694,235	42,811,317,558
BCH	41,556,750,100	2,234.13	24,639,897,782	42,850,634,867
BNB	35,160,460,410	243.48	2,632,735,451	35,080,040,943

Note. The data sample was selected for 31 December 2020.

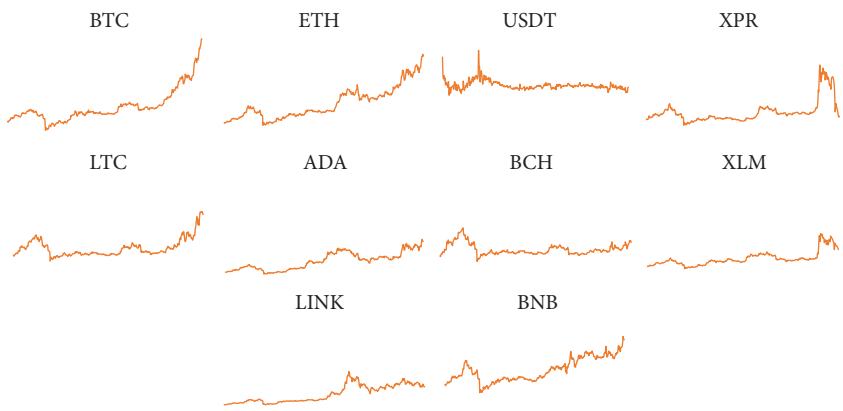


Figure 1: Price trade for the top 10 cryptocurrencies in the market.

markets. From a complex network perspective, Peron et al. [28] analyzed the relevance and stability of financial markets through changes in their network characteristics such as their topology structure, topology index of nodes, and robustness (among others). They achieved promising results, which provided the theoretical foundation for the current study.

A review of the literature has revealed that current studies in this field have predominantly focused on the impacts of natural disasters (e.g., earthquakes and tsunamis) on the financial market—few studies have focused on the impact of major public emergencies (Del Giudice & Paltrinieri, 2017). As for the COVID-19 outbreak, researchers have mainly focused on the impact of the pandemic on the stock market and traditional financial market. In addition, most studies on the response of cryptocurrencies to shocks have focused on the impact of news on Bitcoin returns and the relationship between cryptocurrencies and other assets [29]—few studies have focused specifically on relationship between cryptocurrencies. Furthermore, most of the empirical analyses of the effects of risk spillover between cryptocurrency markets are based on the GARCH model [30]. The multivariate GARCH model can only estimate the existence and direction of volatility spillover statically and involves the estimation of many parameters. The previous empirical works show that spillover index approach and its variants can effectively detect and measure the volatility connectedness or spillover effects in the cryptocurrency market.

Given the abovementioned, the current study adopted the DY spillover index method [31] to examine the correlation characteristics of the digital cryptocurrency market pre and post-COVID-19. In addition, this article approaches an understanding of the impact of COVID-19 on the cryptocurrency market both from the static and dynamic perspectives, respectively. Moreover, the complex network analysis method was combined to describe the changing characteristics of the cryptocurrency market from the perspective of the dynamic evolution of network topology structure to improve the macro-governance response mechanism and risk prevention of major public emergencies such as COVID-19.

The main contributions of the current study are as follows:

Firstly, our work focuses on how the COVID-19 crisis affected the connectedness among the cryptocurrency market and evaluates the risk transmission across the cryptocurrency market. In addition, we choose the top

10 cryptocurrencies according to the market value, which can show the role of different cryptocurrencies in the emerging cryptocurrency market. Since the COVID-19-induced crisis has brought the global economy into a new crisis period, it could bring a direct global destructive impact, raising the risk spillovers among different assets and markets and significantly changing the investor sentiment and market conditions around the world [32]. The volatility spillovers among cryptocurrency market may exhibit a differential pattern during the COVID-19 crisis, such as the rise of connectedness and the changes in spillover roles, which can provide highly informative analysis for investors.

Second, the paper combines the spillover index method of Diebold and Kamil [31] and the complex network method from the static and dynamic perspectives, respectively. We explore connectedness analysis in three different ways, including total connectedness analysis, dynamic total directional connectedness analysis, and net connectedness analysis. On the one hand, the static spillover of the risk contagion of cryptocurrency and the interaction between various cryptocurrencies in terms of global financial risk transmission were investigated. On the other hand, the dynamic evolution of the market correlation with COVID-19 was examined. Through building networks among the cryptocurrency market, we depict the risk transmission paths among cryptocurrencies, as well as the transmission intensity and the changing characteristics of the central nodes.

Finally, it shows the results of both return and volatility spillovers which can also be a robustness test of our study. These two methods also provide two perspectives of the empirical test: the difference of return and volatility connectedness among the cryptocurrency market.

Our findings may help understand the typical dynamics in the cryptocurrency market and provide significant implications for portfolio managers, investors, and government agencies in times of highly stressful events like the COVID-19 crisis.

3. Research Methods and Variable Selection

The DY [31, 33] spillover index presents the risk contagion relationship between different variables of cryptocurrencies. Diebold and Yilmaz [31, 33] first considered a covariance-stationary n-variable Var (p) process, as follows:

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t, \tag{1}$$

where $\varepsilon \sim (0, \Sigma)$ is an independent, identically distributed disturbance vector. The moving average form of equation (1) can be expressed as

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{2}$$

where $d_{\mathrm{ij}}^H = \sigma_{\mathrm{jj}}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2 / \sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)$, and the coefficient matrix of A_i is subject to the following recursive formula:

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}. \tag{3}$$

Here, A_0 is the identity matrix of N order, when $i < 0$, $A_i = 0$. The variance contribution refers to the proportion of y_i variance explained in the prediction error (y_i) variance of step H, when y_i is impacted by external factors d_{ij}^H. It reflects the extent to which changes in a variable are affected by itself or by other variables in the system. This can be expressed as

$$d_{\mathrm{ij}}^H = \frac{\sigma_{\mathrm{jj}}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)}, \tag{4}$$

where $i, j = 1, 2, \ldots, N$ is the covariance matrix of Σ; the standard deviation of ε_t, σ_{ii} represents the column vector ε_t, where the first element e_i is 0, while the other elements are all 0; H represents the prediction period; A_h is the coefficient of equation (2). Then, d_{ij}^H, the order variance decomposition matrix $N \times N$, which is composed of $D_{\mathrm{ij}}(h)$ elements, can be used to characterize the risk spillover effect among different digital cryptocurrencies. In the variance decomposition matrix $D_{\mathrm{ij}}(h)$ $(i \neq j)$, the nondiagonal elements represent the decomposition of the variance of the prediction error, reflecting the degree of risk spillover between currency i and currency j. Therefore, $D_{ij}(h)$, the sum of line I in $\sum_{\substack{j=1 \\ j \neq i}}^{N} d_{ij}^H$, represents all the others, $j = 1\ldots$, and the risk overflow of N currencies against it represents the risk tolerance of i. For example, $D_{ij}(h)$, the summed value of the first row is the prediction error variance of step h when variable 1 is impacted by other variables. Furthermore, $D_{ij}(h)$ represents the risk spillover degree of region 1 by other n-1 currencies. The sum of column$j$ in represents $\sum_{\substack{i=1 \\ j \neq i}}^{N} d_{\mathrm{ij}}^H$, its value for all other$j = 1\ldots$, and the risk spillover degree of N currencies against it represents the risk tolerance of j. For example, $D_{ij}(h)$, the sum in the first column represents the degree of spillover risk from currency 1 to the remaining $n-1$ currencies, as follows:

$$D_{\mathrm{ij}}(h) = \begin{pmatrix} d_{11} & d_{12} & \ldots & d_{1N} \\ d_{21} & d_{22} & \ldots & d_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ d_{N1} & d_{N2} & \ldots & d_{\mathrm{NN}} \end{pmatrix}. \tag{5}$$

Based on the results of the generalised prediction error variance decomposition, the net spillover (NS) effect of risk from currency j to currency i can be expressed using the following formula:

$$\mathrm{NS}_{i \leftarrow j}^H = d_{ij}^H - d_{ji}^H. \tag{6}$$

The NS effect of currency i on all other currencies can be expressed as

$$\mathrm{NS}_i^H = \sum_{\substack{i=1 \\ j \neq i}}^{N} d_{ij}^H - \sum_{\substack{j=1 \\ j \neq i}}^{N} d_{ij}^H. \tag{7}$$

Furthermore, the total risk spillover effect of each currency can be expressed as

$$\mathrm{TS}^H = \frac{1}{N} \sum_{\substack{i,j=1 \\ j \neq i}}^{N} d_{ij}^H. \tag{8}$$

The sample data in the analysis were selected from the top 10 cryptocurrencies—that is, Bitcoin, Ethereum, Cardano, Litecoin, Tether, Stellar, Ripple, Chainlink, Bitcoin Cash, and Binance Coin [2], where the sample data ranged from 1 September 2019 to 7 January 2021. We choose the date of COVID-19 as 23 January 2020 because the Chinese city Wuhan was blocked on that day when epidemic erupted.

The summary of statistical results for the ten cryptocurrencies is shown in Table 2. Referring to the distribution of volatility and return, all data indexes are negatively skewed. Additionally, all kurtosis values were higher than 3, indicating that all volatility and return series had a heavy tail and peak relative to a normal distribution. Both the kurtosis and skewness values were greater than three, indicating that the data are nonnormally distributed, peaked, and skewed. Based on the descriptive statistics, however, the data fulfilled the requirements of normality. Furthermore, the ADF tests supported the stationarity of all volatility and return series at 10% level, which confirmed that the data were stable, and the Ljung–Box test (calculated up to 20 lags) allowed the null hypothesis that there was no autocorrelation for volatility and return series and their squares. This indicates that there were significant linear and nonlinear correlations in the samples. In addition, the ARCH-Lagrange multiplier statistics (with 10 lags) showed that all sequences exhibited volatility clustering, which supports the use of the GARCH model in this study.

4. Static Spillover Analysis

We analyzed the risk spillover relationship between digital cryptocurrencies and examined the correlation between their volatility and returns from the perspective of static spillover analysis [34].

Table 3 presents the static volatility connectedness among the top ten cryptocurrencies. The estimated forecast error variance of cryptocurrency i contributing to cryptocurrency j is shown in the table's ij-element. The elements on the main diagonal represent the impact from its own disturbance, while the elements on the lesser diagonal represent the directional risk spillover effect of the pairwise interaction. Among them, "NET" represents the risk net spillover effect of cryptocurrency to other currencies, and "TOTAL" represents the total spillover effect of the cryptocurrency market. The off-diagonal column represents contributions to others ("TO"), and the row sums of the table represent the contributions from others ("FROM").

Using the static volatility spillover index, Table 3 reveals that the total connectedness index reached 68.9% before the outbreak of COVID-19, indicating that the level of the volatility connectedness in the digital currency market before the outbreak of COVID-19 is not strong. The main diagonal elements represent their own shock contributions. Among them, the volatility spillovers of Tether to itself reached 83.49%, indicating its strong stability. The stability may be due to the fact that Tether is a virtual currency that links cryptocurrency with fiat currency and functions to prevent cryptocurrency prices from fluctuating dramatically. The off-diagonal values represent the shock contributions from other cryptocurrencies, thus reflecting the magnitude of the risk spillovers between different cryptocurrencies. The volatility connectedness of the cryptocurrency market is largely due to the impact of Bitcoin. Among them, Bitcoin with an interpretation weight of more than 10% and a fluctuation weight of its external output as high as 97% was found to have a significant impact on the market fluctuations of Ethereum, Ripple, Litecoin, Cardano, Bitcoin Cash, and Stellar. This demonstrates that Bitcoin occupies a "top-tier" position in the cryptocurrency market.

According to the FROM index, Cardano is the biggest recipient of volatility connectedness or spillovers (83.89%), and Bitcoin also received a relatively high degree of risk spillover (83.19%). Conversely, Tether is the smallest recipient of risk spillover (16.51%) from others. The values of the directional connectedness of Bitcoin and Cardano were larger than others in the "TO" index, while Binance is the smallest transmitter, only 30.81%.

As for the results of the NET indicators in the table, Chainlink was the largest transmitter of volatility risk in the digital cryptocurrency market (26.07%), while Binance was found to be the largest net recipient (−33.22%). In addition, Bitcoin, Ethereum, Cardano, and Bitcoin Cash were the net transmitters, while Tether, Ripple, Litecoin, and Stellar were the net recipients in the cryptocurrency market.

Table 4 presents similar results in return spillover index of the cryptocurrency market pre-COVID-19.

In contrast, Table 5 shows that the total spillover index reached 87.3% post-COVID-19, indicating that the overall spillover of the cryptocurrency market increased under the influence of the pandemic. From the perspective of FROM, the connectedness of all samples is more than 80%, indicating that COVID-19 severely impacted the cryptocurrency market. Furthermore, Bitcoin was the biggest recipient after COVID-19. In the TO index, Stellar maintained being the biggest transmitter (104.06%), and the directional connectedness related to Bitcoin, Ethereum, Ripple, Litecoin, and Cardano was relatively high. The NET indicators revealed an increase in net risk spillover to the cryptocurrency market post-COVID-19. Bitcoin, Ethereum, Ripple, Litecoin, Cardano, and Stellar were found to be the major net transmitters in the market.

Bitcoin, Ethereum, and Cardano were found to be the major net transmitters in the market pre and post-COVID-19, all of which occupy a dominant position in the

Table 2: Descriptive statistics.

Currency	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	ADF	Q(20)	$Q^2(20)$	ARCH(10)
BTC	−0.0031	−0.0021	0.0392	2.5909	40.032	42937.11	−30.274	43.199***	160.61***	35.989***
ETH	−0.0029	−0.0020	0.0498	2.2086	31.711	25913.29	−30.369	64.372***	185.40***	67.757**
USDT	0.0000	0.0000	0.0023	−0.7359	21.991	11141.54	−16.746	125.27***	125.91***	289.663***
XPR	0.0000	−0.0004	0.0533	0.9335	28.669	20340.53	−29.773	39.224***	60.682***	106.272***
LTC	−0.0022	−0.0005	0.0521	0.7742	15.677	5008.428	−29.215	31.435***	60.526***	96.292***
ADA	−0.0027	−0.0026	0.0556	0.9869	16.067	5363.127	−30.047	37.991***	92.335***	139.105***
BCH	−0.0013	0.0001	0.0559	1.1342	24.982	14996.31	−30.023	36.217***	32.89**	23.694***
XLM	−0.0014	0.0000	0.0580	−1.3879	22.672	12120.04	−27.411	76.673***	118.370***	166.703***
LINK	−0.0053	0.0000	0.0684	0.3002	16.950	5986.531	−30.076	71.227***	104.17***	167.757***
BNB	−0.0026	−0.0023	0.0487	2.4022	31.871	26304.98	−29.783	20.065*	38.107***	28.899***

Note. $Q(10)$ $Q(10)$and $Q^2(10)$ $Q(10)$are the Ljung–Box (LB) statistics for stock index return and squared stock index return series, respectively, for the 10th lag. ***, **, and *represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 3: Total, net, and pairwise spillovers among cryptocurrencies pre-COVID-19 (volatility spillovers).

	BTC	ETH	USDT	XPR	LTC	ADA	BCH	XLM	LINK	BNB	FROM
BTC	0.1681	0.1236	0.0098	0.0859	0.1216	0.1419	0.1402	0.1052	0.0663	0.0375	0.8319
ETH	0.1313	0.1842	0.0029	0.0901	0.0955	0.1283	0.1425	0.0970	0.09392	0.0344	0.8158
USDT	0.0273	0.0041	0.8349	0.0059	0.0347	0.0169	0.0226	0.0273	0.0173	0.0091	0.1651
XPR	0.1166	0.1131	0.0030	0.2215	0.0834	0.1247	0.1203	0.1038	0.0927	0.0209	0.7786
LTC	0.1542	0.1136	0.0147	0.0713	0.2131	0.1324	0.1223	0.0950	0.0402	0.0431	0.7869
ADA	0.1387	0.1204	0.0133	0.0977	0.1031	0.1611	0.1235	0.1110	0.0916	0.0396	0.8389
BCH	0.1449	0.1369	0.0062	0.0933	0.1050	0.1252	0.1762	0.0992	0.0899	0.0235	0.8238
XLM	0.1229	0.1088	0.0069	0.0873	0.0886	0.1249	0.1053	0.1814	0.1024	0.0715	0.8186
LINK	0.0447	0.0907	0.0051	0.0393	0.0620	0.0374	0.0444	0.0365	0.6115	0.0284	0.3885
BNB	0.0905	0.0757	0.0055	0.0482	0.0649	0.1028	0.0704	0.1274	0.0549	0.3598	0.6402
TO	0.9710	0.8869	0.0675	0.6186	0.7589	0.9345	0.8914	0.8023	0.6492	0.3081	
NET	0.1391	0.0710	−0.0977	−0.1599	−0.0280	0.0957	0.0676	−0.0163	0.2607	−0.3322	
TOTAL	0.6890										

Note. This table presents the net directional spillover among the volatility of the ten cryptocurrencies based on VAR over the period September 1, 2019–January 23, 2020. FROM: row sums of the table represent the contributions from others. TO: off-diagonal column represents contributions to others. NET: spillover transmitted by each cryptocurrency to all other cryptocurrencies, where positive (negative) values indicate that the currency in question is a net transmitter (receiver) of spillovers to all other cryptocurrencies. TOTAL: total spillover index.

Table 4: Total, net, and pairwise spillovers among cryptocurrencies pre-COVID-19 (return spillovers).

	BTC	ETH	USDT	XPR	LTC	ADA	BCH	XLM	LINK	BNB	FROM
BTC	0.1453	0.1261	0.0093	0.1045	0.1072	0.1219	0.1109	0.0949	0.1229	0.0570	0.8547
ETH	0.1345	0.1643	0.0058	0.1101	0.1032	0.1364	0.1268	0.0903	0.0795	0.0490	0.8357
USDT	0.0548	0.0442	0.5222	0.0475	0.0825	0.0692	0.0667	0.0483	0.0325	0.0320	0.4778
XPR	0.1126	0.1122	0.0034	0.2091	0.0803	0.1222	0.1194	0.1110	0.1131	0.0167	0.7909
LTC	0.1309	0.1177	0.0181	0.0946	0.1747	0.1288	0.1120	0.0897	0.0833	0.0502	0.8253
ADA	0.1261	0.1358	0.0099	0.1173	0.1108	0.1559	0.1048	0.0901	0.0985	0.0507	0.8441
BCH	0.1212	0.1330	0.0086	0.1291	0.0969	0.1130	0.1596	0.0920	0.1079	0.0387	0.8404
XLM	0.1205	0.1027	0.0135	0.1373	0.0884	0.1164	0.1068	0.1684	0.0902	0.0557	0.8316
LINK	0.0868	0.0769	0.0037	0.0727	0.0602	0.0643	0.0667	0.0515	0.5089	0.0084	0.4911
BNB	0.1190	0.1038	0.0131	0.0606	0.0755	0.1141	0.0772	0.0913	0.0968	0.2487	0.7513
TO	1.0065	0.9523	0.0853	0.8737	0.8052	0.9865	0.8912	0.7592	0.8246	0.3585	
NET	0.1518	0.1166	−0.3925	0.0828	−0.0202	0.1424	0.0509	−0.0723	0.3334	−0.3929	
TOTAL	0.7540										

Note. This table presents the net directional spillover among the return of the ten cryptocurrencies based on VAR over the period September 1, 2019–January 23, 2020.

cryptocurrency market. These results confirm the findings that Bitcoin is losing its dominant role in the cryptocurrency market since 2015, and Stellar and Litecoin are the main transmitters [35]. Besides, Saba et al. [36] used wavelet-based analyses and found that Ripple and Ethereum are the main transmitters from 2016 to 2018, and investors can get long-

Table 5: Total, net, and pairwise spillovers among cryptocurrencies post-COVID-19 (volatility spillovers).

	BTC	ETH	USDT	XPR	LTC	ADA	BCH	XLM	LINK	BNB	FROM
BTC	0.1115	0.1051	0.0814	0.1026	0.1037	0.1093	0.0918	0.1125	0.0798	0.1022	0.8885
ETH	0.1011	0.1160	0.0733	0.1098	0.1082	0.1040	0.0889	0.1193	0.0799	0.0995	0.8840
USDT	0.0953	0.0962	0.1822	0.0942	0.0902	0.1025	0.0638	0.0986	0.0988	0.0781	0.8178
XPR	0.0978	0.1066	0.0713	0.1248	0.1088	0.1042	0.0914	0.1241	0.0714	0.0996	0.8752
LTC	0.0997	0.1076	0.0730	0.1106	0.1244	0.1075	0.0955	0.1182	0.0691	0.0923	0.8736
ADA	0.1049	0.1029	0.0835	0.1075	0.1054	0.1157	0.0938	0.1160	0.0748	0.0955	0.8843
BCH	0.1021	0.1028	0.0681	0.1064	0.1108	0.1097	0.1198	0.1208	0.0629	0.0967	0.8802
XLM	0.0991	0.1067	0.0697	0.1166	0.1072	0.1054	0.0932	0.1287	0.0722	0.1012	0.8713
LINK	0.0990	0.1050	0.0902	0.0967	0.1020	0.0995	0.0742	0.1122	0.1255	0.0957	0.8745
BNB	0.1075	0.1062	0.0655	0.1072	0.1004	0.1042	0.0911	0.1189	0.0829	0.1161	0.8839
TO	0.9066	0.9392	0.6761	0.9515	0.9368	0.9463	0.7836	1.0406	0.6917	0.8608	
NET	0.0181	0.0552	−0.1417	0.0764	0.0632	0.0620	−0.0966	0.1692	−0.1827	−0.0231	
TOTAL	0.8730										

Note. This table presents the net directional spillover among the volatility of the ten cryptocurrencies based on VAR over the period January 23, 2020–January 7, 2021.

term gains from them. Cardano attracted more interest from retail investors, where such interest can appear in Google searches. Following the impact of COVID-19, Stellar, Litecoin, and Ripple transformed from being risk receivers to transmitters. Stellar became the largest transmitter in the cryptocurrency market (16.92%). Stellar, as the base currency of the Stellar network and the source protocol for value exchange, contained a strong ability to resist the impact of the pandemic. Further, it has been used to build a decentralised gateway for transmission between digital and fiat currencies. Besides this, Ripple is similar to Stellar (the only common currency in Ripple network) and remained stable when the impact of the pandemic hit. The result provide a new perspective that investors should pay more attention to cryptocurrencies such as Ripple and Stellar, and these cryptocurrencies which are related in network had greater risk in COVID-19 [23]. However, Binance was found to be the main recipient pre and post-COVID-19 to a large extent. This is because of its own rule settings that destroy 20% of its annual net profit.

Following COVID-19, the results for the return series of the cryptocurrency markets exhibited no difference from the volatility series presented in Table 6. However, compared with the results before and after the outbreak of COVID-19, it can be found that there are clear changes in the cryptocurrency market, which are impacted by the COVID-19 crisis (Table 7).

5. Rolling-Window Spillover Analysis

Using the rolling-window analysis method, we revealed the changes in the cryptocurrency market during the sample period. Based on AIC and a study by Zhang et al. [37], we set the forecast horizon to 7 days and the VAR lag order to 2 days (Figure 1). Besides, we also provide other 3 results of horizon to 5, 10, and 14 days as a robustness test with lags, and the results are similar to the results we set in the paper. The total spillover index for the volatility series is shown in Figure 2.

Figure 2 shows the total volatility connectedness among the cryptocurrency market. The total spillover of cryptocurrency market fluctuates since 2015, and it can be seen that there were 5 cycles in the total spillover plot. In each cycle, the cryptocurrency market was influenced by the cryptocurrency and COVID-19 factors, and we analyzed these cycles based on the relevant events that may cause them. The first small cycle ended in November 2019. Litecoin halved in value for the second time in the previous month, and its plummeting price was the result of a collapse in its computing power. Furthermore, in the top 10 cryptocurrencies, the highest price for Bitcoin was $9804.32, and the lowest was $8370.80 on September 25. Ethereum intraday fell by 14.02%, and Bitcoin Cash fell by 20.36% in 24 hours. At the same time, the United States congress passed bills enforcing the use of blockchain. During this period, the trade conflicts between China and United States were alleviated and the market was in a bullish mood, which had an impact on cryptocurrency market.

The second cycle ended in January 2020, and the overall price of the cryptocurrency market fluctuated, with EOS falling the most, in turn leading the entire market to a rebound. Besides, when the difficulty for Bitcoin mining increased, most mining machines in mining areas encountered shutdowns. A recent slide in the yuan has raised fears of devaluations, and most of the investors may find other products to hedge, which may cause the market turbulence.

The third period ended in April 2020. The volatility spillover index experienced the most violent fluctuations in the entire sample period. The main reason for this is that since December 31, 2019, a number of COVID-19 cases appeared in Wuhan and the disease began to spread. On January 23, 2020, Wuhan took emergency lockdown measures, and on February 11, 2020, the World Health Organisation (WHO) declared the spread of COVID-19 as the new pneumonia. Since then, cases of COVID-19 have emerged in France, Germany, the United States (US), Canada, and other countries, and the number of cases worldwide has rapidly increased. The outbreak has affected investor sentiment and had an impact on the global financial system. Many mines are located in remote areas. The outbreak has slowed logistics and made it more difficult to transport machinery to those mines. The greater barrier for mining, however, is the higher return on mining

Table 6: Total, net, and pairwise spillovers among cryptocurrencies post-COVID-19 (return spillovers).

	BTC	ETH	USDT	XPR	LTC	ADA	BCH	XLM	LINK	BNB	FROM
BTC	0.1132	0.1091	0.0684	0.1007	0.1076	0.1069	0.0982	0.1080	0.0867	0.1013	0.8868
ETH	0.1020	0.1166	0.0638	0.1077	0.1095	0.1048	0.0971	0.1132	0.0828	0.1025	0.8834
USDT	0.0819	0.0996	0.2132	0.0855	0.1003	0.0873	0.0724	0.1062	0.0733	0.0803	0.7868
XPR	0.0962	0.1120	0.0580	0.1227	0.1127	0.1074	0.1007	0.1213	0.0715	0.0975	0.8773
LTC	0.1002	0.1112	0.0649	0.1104	0.1223	0.1095	0.0989	0.1127	0.0753	0.0946	0.8777
ADA	0.1045	0.1077	0.0609	0.1069	0.1111	0.1184	0.0991	0.1122	0.0790	0.1002	0.8816
BCH	0.1044	0.1080	0.0602	0.1078	0.1079	0.1054	0.1203	0.1120	0.0711	0.1028	0.8797
XLM	0.0954	0.1111	0.0659	0.1161	0.1088	0.1071	0.0998	0.1245	0.0714	0.1000	0.8755
LINK	0.1069	0.1074	0.0683	0.0905	0.0971	0.0996	0.0834	0.0987	0.1432	0.1048	0.8568
BNB	0.1039	0.1102	0.0620	0.1023	0.1010	0.1044	0.0997	0.1118	0.0865	0.1183	0.8817
TO	0.8953	0.9763	0.5723	0.9278	0.9560	0.9324	0.8493	0.9962	0.6978	0.8839	
NET	0.0085	0.0929	−0.2144	0.0504	0.0783	0.0508	0.0304	0.1207	−0.1590	0.0022	
TOTAL	0.8690										

Note. This table presents the net directional spillover among the return of the ten cryptocurrencies based on VAR over the period January 23, 2020–January 7, 2021.

Table 7: Ranking list of cryptocurrency market under COVID-19.

	Pre-COVID-19		Post-COVID-19	
	Base volatility	Base return	Base volatility	Base return
1	Chainlink	Chainlink	Stellar	Stellar
2	Bitcoin	Bitcoin	Ripple	Ethereum
3	Cardano	Cardano	Litecoin	Litecoin
4	Ethereum	Ethereum	Cardano	Cardano
5	Bitcoin Cash	Ripple	Ethereum	Ripple
6	Stellar	Bitcoin Cash	Bitcoin	Bitcoin
7	Litecoin	Stellar	Binance	Binance
8	Tether	Litecoin	Bitcoin Cash	Bitcoin Cash
9	Ripple	Tether	Tether	Chainlink
10	Binance	Binance	Chainlink	Tether

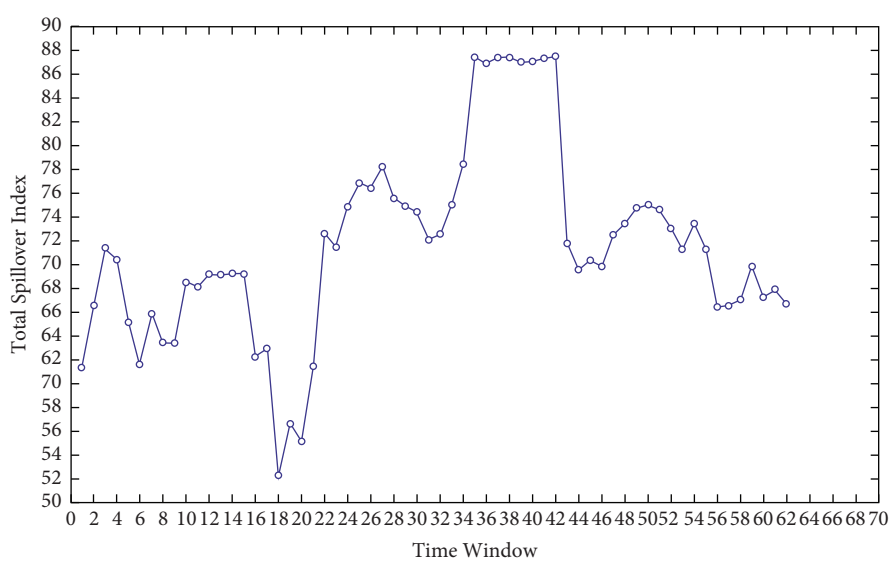


Figure 2: Total spillover index (volatility spillovers). Note: the figure shows the dynamic total connectedness based on VAR with two-day order lag length and 7-day horizon dynamic connectedness approach.

investments. During this period, the National Bank of Egypt and Ripple signed a cooperation agreement, which contained more than 300 international banks (nearly $600 billion of the market and institution share) who wished to join the RippleNet network. This also involved the national bank remit fund to set up new channels, as well as support and extend the remittance in the gulf region to the institution's liquidity management and foreign exchange. In

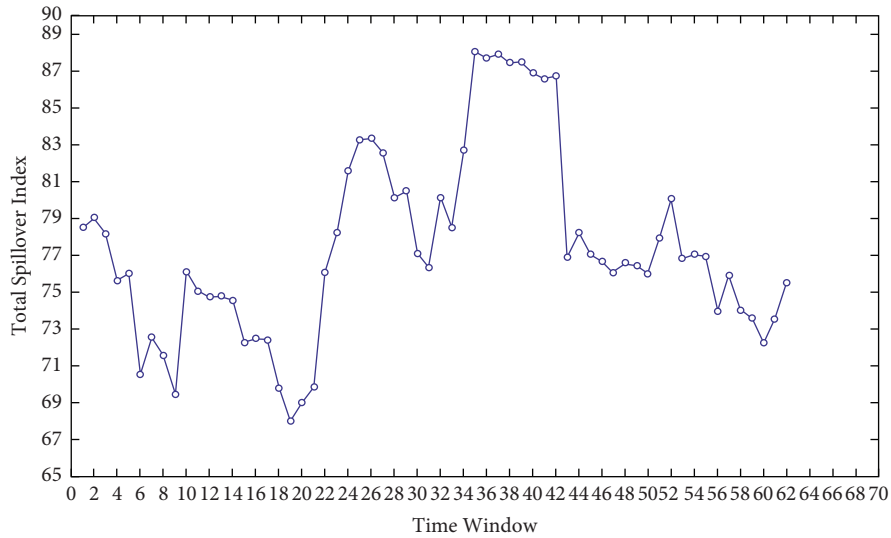


Figure 3: Total spillover index (return spillover). Note: see Figure 2.

addition, the Central Bank of China has applied for 84 patents for its plan to launch its digital currency electronic payment system DCEP, which focuses on the design of protocols to control the issuance and supply of digital RMB. This includes a focus on the framework to perform interbank settlements and the integration of CBDC with China's existing retail banking infrastructure. The heads of central banks and the Bank for International Settlements in Japan, the US, the United Kingdom (UK), Switzerland, Sweden, Canada, and other countries announced the development of their own digital currency to compete with Facebook's Libra or other digital currencies. The US Federal Reserve has reported that it is investigating the feasibility of a digital currency and plans to create a digital dollar. On February 13, 2020, blockchain concept stocks collectively increased—Jia Nan Technology soared to 82.73%, and US stocks, Hong Kong stocks, and CSI showed a obvious rise.

Following the third period, the fourth cycle rose consistently in May 2020 and ended in July 2020. The total overflow index was the highest for the entire sample period. The major events on an international scale that were involved in this period had an impact on the international financial market. First, COVID-19 spread in Europe and the US; second, the stock indexes in the US and Europe fell, and the US stock market triggered the circuit breaker mechanism many times over; and, third, the collapse of international crude oil prices caused the total spillover index in the cryptocurrency market to fluctuate at a high level. Simultaneously, Bitcoin was halved for the third time. Fewer Bitcoins will lead to higher prices, while miners will need to phase out old mining machines and buy new, more powerful devices to mine for Bitcoins.

The fifth cycle was from July 2020 to the end of the sample period. The total spillover index was stable before showing a downward trend. The reasons for this are as follows. First, the epidemic in China was stable, and all industries steadily resumed their work and production; second, all countries took measures to control the spread of the epidemic and reduced the number of new cases; third, the introduction of a COVID-19 vaccine created progress in controlling the spread of the disease. The cryptocurrency market risk contagion is closely linked to external shocks, which may lead to the "butterfly effect" [38, 39], causing the risk to expand globally at a rapid pace—with obvious "sudden," "hidden," and "infectious" characteristics. The findings for the return spillovers were found to be similar to the findings for volatility (see Figure 3). The total connectedness (volatility spillovers) among the cryptocurrency market during the COVID-19 crisis period experienced a rapid exponential rise compared to the normal period and our results are similar to the findings of some scholars [40] (Figures 4–6).

6. Net Spillover Effect Based on Network Analysis

To display the results of the net spillover network of the cryptocurrency market intuitively, we characterize the networks graphically using several devices, including node's naming convention, node's size, and edge's direction [41]. Among them, node's naming convention is short for each cryptocurrency (see Table 1). Node's size indicates the spillover intensity for each cryptocurrency, and edge's direction represents the pairwise spillover direction between different cryptocurrencies [42].

To calculate the dynamic "net directional spillover," which is used to determine the spillover transmitters or receivers of the cryptocurrencies, we use the complex network method to display the connectedness of the cryptocurrency market pre and post-COVID-19 (see Figure 4). According to the method of Lin et al. [43], the specific steps of constructing the networks are as follows: (1) measuring the time-varying directional spillovers between each pair in the cryptocurrency market; (2) selecting January 23rd, 2020, as the boundary, we divided the estimated NET index into two subperiods, before and after the outbreak of COVID-19; (3) averaging the time-varying pairwise spillover index based on each subperiod and then plotting the pairwise

Endogenous variables: X1 X10 X2 X3 X4 X5 X7 X6 X8 X9
Exogenous variables: C
Date: 02/10/22 Time: 21:39
Sample: 1 737
Included observations: 729

Lag	LogL	LR	FFE	AIC	SC	HQ
0	15301.05	NA	2.87e-31	-41.94801	-41.88503*	-41.92371
1	15503.24	400.2443	2.16e-31	-42.23111	-41.53826	-41.96378*
2	15699.74	206.8593	2.12e-31*	-42.24893*	-40.92623	-41.73859
3	15676.76	128.3393	2.32e-31	-42.15845	-40.20589	-41.40509
4	15755.42	148.4722	2.47e-31	-42.09991	-39.51748	-41.10352
5	15824.94	129.3284	2.68e-31	-42.01631	-38.80402	-40.77691
6	15878.68	98.47499	3.05e-31	-41.88938	-38.04723	-40.40695
7	15956.97	141.3302*	3.25e-31	-41.82982	-37.35781	-40.10437
8	16017.45	107.5212	3.63e-31	-41.72139	-36.61953	-39.75293

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FEE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Figure 4: VAR lag order selection criteria.

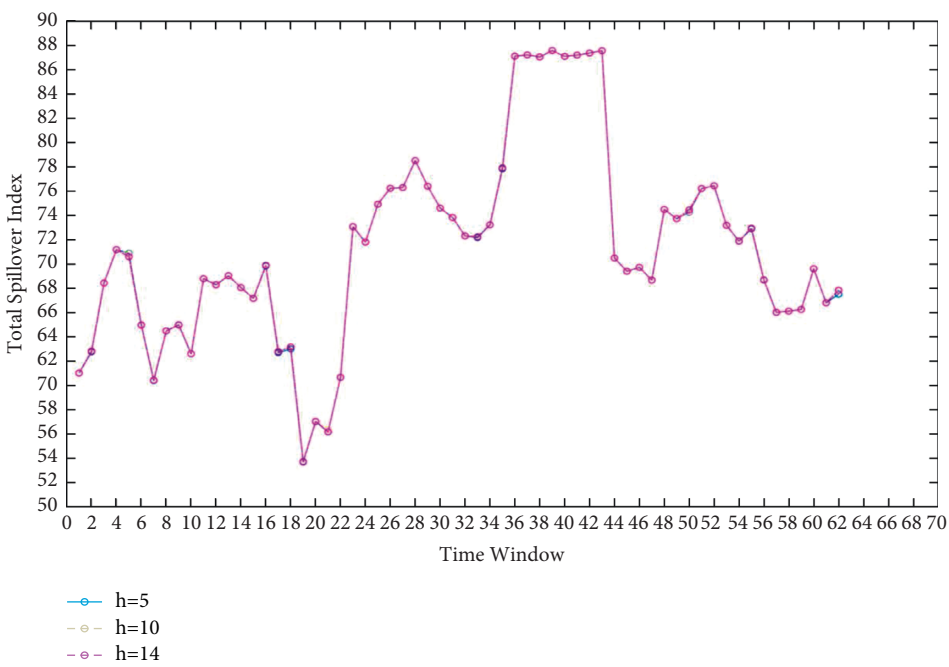


Figure 5: Total spillover index (volatility spillovers).

net spillover network of the cryptocurrency market (see Figure 4).

First, we identified that there are many differences in the pairwise net spillover network of the cryptocurrency market after the outbreak of COVID-19, especially on the edge's directions. The results we find in cryptocurrency market are similar to the results some scholars find in the stock financial market that the networks have changed during COVID-19 [40, 44]. Additionally, compared with the results of the previous studies focusing on network in the cryptocurrency market, our results support the view that the structure among the cryptocurrency market is affected strongly by the COVID-19 crisis [12, 22, 25, 43]. This means that after the outbreak of COVID-19, the risk spillover in the cryptocurrency market from one cryptocurrency to another is weakend such as Bitcion and Ethereum, while the Ripple and Stellar are strengthened. The main risk transmitters in the cryptocurrency market were Ada, Link, Bitcoin, Ethereum, and Bitcoin Cash before the outbreak of COVID-19, while the main transmitters have shifted to Stellar, Ripple,

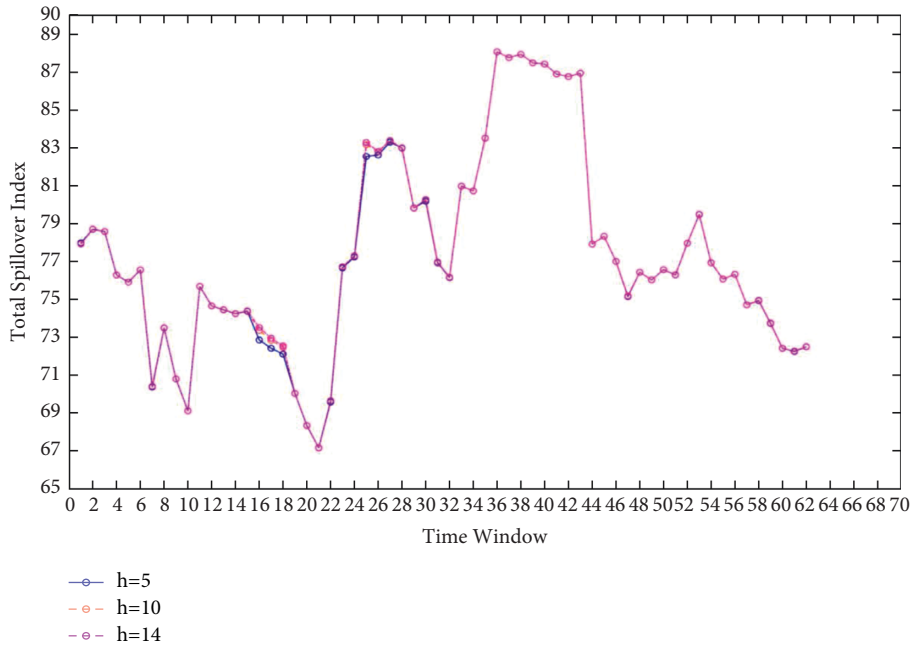
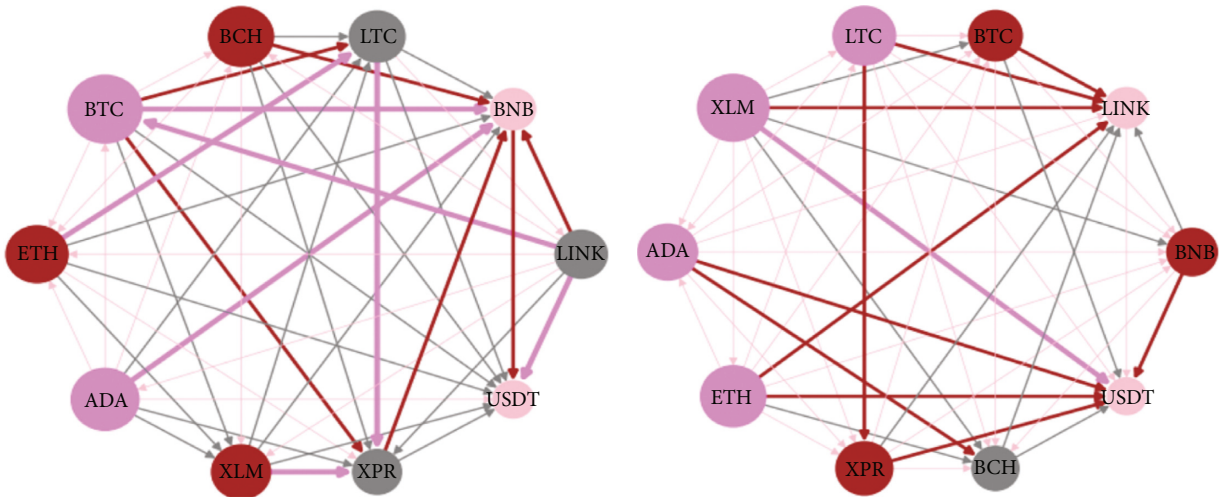


Figure 6: Total spillover index (return spillovers).



(a) (b)

Figure 7: Continued.

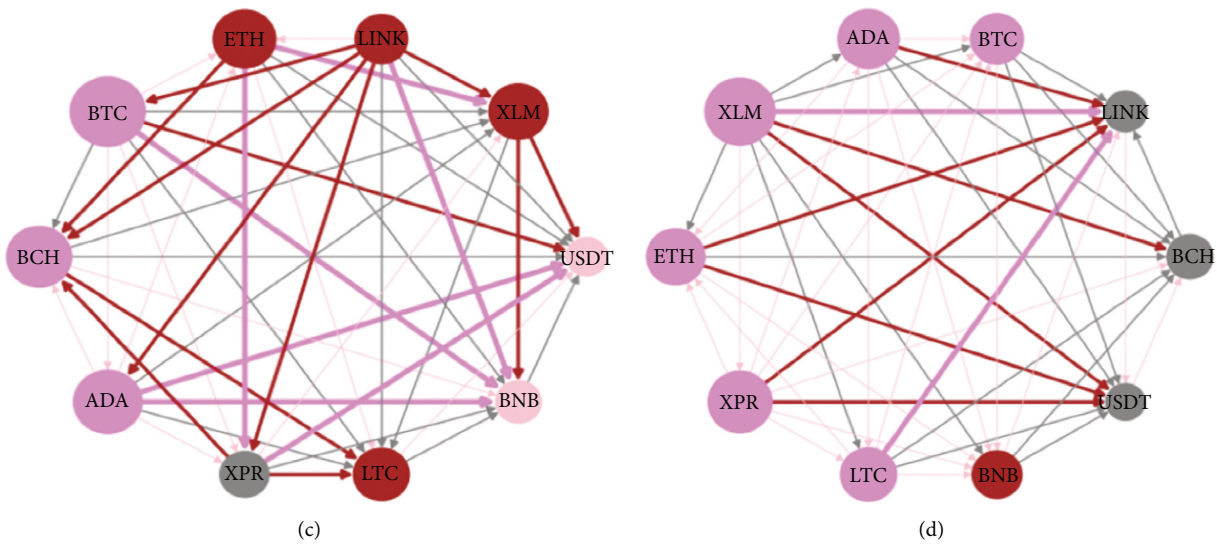


Figure 7: Net spillover network analysis of cryptocurrency market before and after COVID-19. (a) Net spillover network pre-COVID-19 (volatility spillovers). (b) Net spillover network post-COVID-19 (volatility spillovers). (c) Net spillover network pre-COVID-19 (return spillovers). (d) Net spillover network post-COVID-19 (return spillovers). Note: this figure shows the net directional connectedness among the ten cryptocurrencies' volatility and returns. The size of each node indicates the overall magnitude of spillover transmission for each cryptocurrency, which is measured by net connectedness in Table 3. Node's size indicates the spillover intensity for each cryptocurrency, and edge's direction represents the pairwise spillover direction between different cryptocurrencies.

Cardano, Ethereum, and Litecoin after the COVID-19 outbreak. Since these spillover relations are all in relatively high strength, we could conclude that the COVID-19 crisis has a structural shock on the connectedness in cryptocurrency market. The empirical results of the net spillover network revealed no significant differences for the return spillovers and volatility spillovers.

Second, according to the changing characteristics in the node's size of the net spillover network before and after the outbreak of COVID-19, it can be found that the systemic importance nodes of the cryptocurrency market network have changed after the outbreak of COVID-19. However, before COVID-19, regardless of the volatility or the returns, Bitcoin, Ethereum, and Cardano represented the center and cradle of the cryptocurrency market, where relatively larger nodes for them in the network can be seen. In addition, the three abovementioned cryptocurrencies also revealed a larger number of arrows of pairwise spillover relations among different cryptocurrencies. After COVID-19, the spillovers of Stellar, Ripple, and Litecoin are strengthened, and the relations towards others are obvious. The volatility spillover of the cross-gateway currencies such as Stellar and Ripple became the center and cradle of volatility in the cryptocurrency market by COVID-19. Most importantly, the spillover intensity of each cryptocurrency and the most directions of the net spillovers have changed, which have implications for the views of investors on the cryptocurrency market during COVID-19.

7. Conclusion

Under the influence of major events such as COVID-19, investors should pay closer attention to the analysis of connectedness and risks in the emerging cryptocurrency market. In this study, we examined the impact of the COVID-19 pandemic on the return and volatility nexus among cryptocurrency market from multiple perspectives, including measuring the effect of COVID-19 on cross-cryptocurrency linkages and analyzing the dynamic evolution of risk transmission relations and transmission paths among different cryptocurrencies. In addition, we also explored the systemic importance nodes and structural change among the cryptocurrency market before and after the outbreak of COVID-19 using the complex network analysis method.

The results of this study revealed that COVID-19 had an obvious impact on the cryptocurrency market and significantly increased its overall risk spillover effect. For single cryptocurrencies, we tested and found that the spillover effects of leading cryptocurrencies such as Bitcoin, Ethereum, and Cardano were apparent pre-COVID-19, but the spillover effects of cross-gateway currencies such as Stellar and Ripple increased significantly post-COVID-19. In view of the entire cryptocurrency market, we also found that the market as a whole contains a strong correlation. It was revealed that there were five shape changes in the different COVID-19 periods studied, which were affected by the pandemic and its own factors as a whole. The empirical results also suggest that the market net transmissions changed from Cardano, Link, Bitcoin, Ethereum, and Bitcoin Cash to Stellar, RIPPLE, Cardano, Ethereum, and Litecoin. There was also a significant shift at the center of the cryptocurrency market, from Bitcoin, Ethereum, and Cardano to Stellar, Ripple, and Litecoin. In each empirical model, the results for the volatility and return series were essentially the same [46, 47].

Our examination of the volatility connectedness between cryptocurrencies and whether cryptocurrency generates strong volatility shocks to others complements current findings in the cryptocurrency literature and offers new information to investors and miners.

First, our research contributes to the literature regarding the volatility interconnectedness between various cryptocurrencies. Our results provide support for notions that the cryptocurrency market contains strong connectedness, and this was particularly so in the midst of COVID-19. Our findings provide a reference indicator for market participants to analyze market stability and cope with unfavorable market conditions.

Second, we found differences between the cryptocurrencies. Bitcoin, Ethereum, and Cardano exhibited strong connectedness in the cryptocurrency market, and they also represented the center of the cryptocurrency market net. However, Stellar, Ripple, and Litecoin became the center of the cryptocurrency market net post-COVID-19, all playing an important function in this period.

Finally, the current research investigated the relationship between cryptocurrencies and provided a profile of both static and dynamic volatility connectedness or spillover between different currencies. This is also useful for miners in their selection and mining of cryptocurrencies, reducing potential loss due to extreme price fluctuations or declines in the competitiveness of their computing power.

In this paper, we analyzed the entire sample period into two periods, before the COVID-19 crisis period and during the COVID-19 crisis period. However, we did not study the period after COVID-19, as it is still spreading, which may be the main limitation of this study, and cryptotraders and investors can pay more attention to further changes.

In addition, we did not focus on the efficiency of the cryptocurrencies, and we did not know how long the memory of the top 10 cryptocurrencies lasted about the economics. As the cryptocurrency market evolves and matures, it is of particular interest to researchers and investors to extend our analysis by another method like DCCA. We have read the paper about the method of DCCA carefully, and we are really interested in this method. The DCCA is the cross-correlation coefficient proposed by Zebende that can investigate the dynamic linkages between COVID-19 and the cryptocurrency market, which may provide more detailed information in further research [45]. However, we have not provided deeper insights into the correlation structure of cryptocurrencies, especially the cryptocurrency return's correlation with their respective lagged returns. We can also analyze the cryptocurrencies using a multiscale network via DCCA with the intention to verify how these cryptocurrencies are related after COVID-19, compared to the situation in COVID-19.

In spite of this limitation, the study has important support for understanding the cryptocurrency market. Our finding may help investors in making portfolio selection decisions within the cryptocurrency markets during the outbreak period of COVID-19. Since Bitcoin is not the dominant player in the cryptocurrency market, gains can be achieved by traders though an allocation of Ripple and Stellar, which play a significant role in their own network. Besides, the cryptocurrencies are highly volatile, and volatility of the market mostly coincides with specific event concerning COVID-19. Consequently, investors get opportunities to gain benefits in cryptocurrency markets. Furthermore, the cryptocurrency markets remain with the problems of hacking risks, withdrawal fees, and lacking regulation, that the investors should have portfolio diversification in it by the reality and the evidence our results provided.

Data Availability

The data used to support the findings of this study have been deposited in the Wind repository.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This study was supported by grants from the National Social Science Foundation of China (grant no. 20BJY138).

References

[1] A. Mensoy, T. C. Silva, C. Shaen, and T. B. Miranda, "High-frequency return and volatility spillovers among cryptocurrencies," *Applied Economics*, vol. 53, no. 37, pp. 4310–4328, 2021.

[2] I. Najaf, F. Zeeshan, W. Guangcai, and F. Shazad, "Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market," *Elsevier*, no. 14, pp. 78-79, 2020.

[3] Z. Yang and Y. Zhou, "Quantitative easing and volatility spillovers across countries and asset classes," *Management Science*, vol. 63, no. 2, 2016.

[4] F. Battaglia and A. Gallo, "Securitization and systemic risk: an empirical investigation on Italian banks over the financial crisis," *International Review of Financial Analysis*, vol. 30, pp. 274–286, 2013.

[5] X.-L. Gong, X.-H. Liu, X. Xiong, and W. Zhang, "Financial systemic risk measurement based on causal network connectedness analysis," *International Review of Economics & Finance*, vol. 64, pp. 290–307, 2019.

[6] Z. H. Yang and Y. G. Zhou, "Global systemic financial risk spillovers and their external shocks[J]," *Social Sciences in China*, vol. 41, no. 2, pp. 26–49, 2020.

[7] A. M. Al Awadhi, L. Singh, S. Singh, P. K. Mishra, and S. K. Mishra, "Corona pandemic and stock market behaviour: empirical insights from selected asian countries," *Millennial Asia*, vol. 11, no. 3, pp. 341–365, 2020.

[8] R. Matkovskyy and A. Jalan, "From financial markets to bitcoin markets: a fresh look at the contagion effect," *Finance Research Letters*, vol. 31, pp. 93–97, 2019.

[9] R. Bhowmik and S. Wang, "Stock market volatility and return analysis: a systematic literature review," *Entropy*, vol. 22, no. 5, p. 522, 2020.

[10] G. S. Uddin and S. J. H. Shahzad, "Heterogeneous interconnections between precious metals: evidence from asymmetric and frequency-domain spillover analysis," *Resoueces Policy*, vol. 64, Article ID 101509, 2019.

[11] K. J. Forbes and R. Rigobon, "No contagion, only interdependence: measuring stock market comovements," *The Journal of Finance*, vol. 57, no. 5, pp. 2223–2261, 2002.

[12] E. Bouri, L. C. Keung Marco, S. Tareq, S. Wang, and Y. Zhao, "On the intraday return curves of Bitcoin: predictability and trading opportunities," *International Review of Financial Analysis*, vol. 76, 2021.

[13] E. Jacobs, "Bitcoin: a bit too far?[J]," *Journal of Banking and Commerce*, vol. 16, no. 2, 2011.

[14] N. A. Plassaras, "Regulating digital currencies: bring bitcoin within the reach of the IMF[J]," *Chicago Journal of International Law*, vol. 14, p. 377, 2013.

[15] S. A. Sarkodie and P. A. Owusu, "Global effect of city-to-city air pollution, health conditions, climatic & socio-economic factors on COVID-19 pandemic," *The Science of the Total Environment*, vol. 778, p. 146394, 2021.

[16] O. Borgards, L. Czudaj Robert, and H. V. Hoang Thi, "Price overreactions in the commodity futures market: an intraday analysis of the Covid-19 pandemic impact," *Resources Policy*, vol. 71, 2021.

[17] N. Iqbal, Z. Fareed, and F. Shahzad, "Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market," *International Review of Financial Analysis*, vol. 73, no. 8, p. 101613, 2021.

[18] L.-T. N. Le, Y. Larisa, and N. Muhammad Ali, "Did COVID-19 change spillover patterns between Fintech and other asset classes?" *International Business and Finance*, vol. 58, 2021.

[19] Y. Li, A. Urquhart, and P. Wang, "MAX momentum in cryptocurrency markets," *International Review of Financial Analysis*, vol. 77, Article ID 101829, 2021.

[20] Y. Liu and T. Aleh, "Risks and returns of cryptocurrency," *Review of Financial Studies*, vol. 34, no. 6, pp. 2689–2727, 2021.

[21] W. Feng, Y. Wang, and Z. Zhang, "Informed trading in the bitcoin market," *Finance Research Letters*, vol. 26, pp. 63–70, 2017.

[22] S. Corbet, P. Stephanos, A. Kyriazis Nikolaos, and G. Tzeremes Panayiotis, "Herding behaviour and price convergence clubs in cryptocurrencies during bull and bear markets," *Journal of Behavioral and Experimental Finance*, vol. 30, Article ID 100469, 2021.

[23] F. Paulo, L. Kristoufek, and E. J. de Area Leão Pereira, "DCCA and DMCA correlations of cryptocurrency markets," *Physica A*, vol. 545, 2020.

[24] J. Li and L. M. Xu, "Volatility spillover between Chinese and American Bitcion market," *Statistics and Decision*, vol. 457, pp. 156–159, 2016.

[25] S. H. Kang, A. H. Tiwari, C. T. Albulescu, and S. M. Yoon, "Exploring the time-frequency connectedness and network among crude oil and agriculture commodities V1," *Energy Economics*, vol. 84, Article ID 104543, 2019.

[26] F. X. Diebold and Y. Kamil, "Measuring financial asset return and volatility spillovers, with application to global equity markets," *Economic Journal*, vol. 119, no. 534, pp. 158–171, 2009.

[27] F. X. Diebold, L. Liu, and K. Yilmaz, "Commodity connectedness," in *Monetary Policy and Global Spillovers: Mechanisms, Effects, and Policy Measures. Bank of Chile Central Banking Series, Santiago*, E. G. Mendoza, E. Pastén, and D. Saravia, Eds., vol. 25pp. 97–136, Cambridge, 2018.

[28] T. Peron, D. F. C. Luciano, and F. A. Rodrigues, "The structure and resilience of financial market networks[J]," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 22, no. 1, pp. 13–17, 2012.

[29] S. Corbet, B. Lucey, M. Peat, and S. Vigne, "Bitcoin Futures—what use are they?" *Economics Letters*, vol. 172, 2018.

[30] Y. D. Wang, Y. Wei, and C. F. Wu, "Cross-correlations between Chinese A-share and B-share markets[J]," *Physica A: Statistical Mechanics and Its Applications*, vol. 389, no. 23, pp. 546-547, 2010.

[31] F. X. Diebold and K. Yilmaz, "On the network topology of variance decompositions: measuring the connectedness of financial firms," *Econometrics*, vol. 182, no. 1, pp. 119–134, 2014.

[32] X. He and H. Hamori, "Is volatility spillover enough for investor decisions? A new viewpoint from higher moments," *Journal of International Money and Finance*, vol. 116, Article ID 102412, 2021.

[33] F. X. Diebold and K. Yilmaz, "Better to give than to receive: predictive directional measurement of volatility spillovers," *International Journal of Forecasting*, vol. 28, no. 1, pp. 57–66, 2012.

[34] A. Ghulam, U. Bashir, S. Wang, G. Figueira Zebende, and M. Ishfaq, "The return and volatility nexus among stock market and macroeconomic fundamentals for China," *Physica A*, vol. 526, Article ID 121025, 2019.

[35] Q. Ji, E. Bouri, C. K. Marco Lau, and D. Roubaud, "Dynamic connectedness and integration in cryptocurrency markets," *International Review of Financial Analysis*, vol. 63, pp. 257–272, 2019.

[36] Q. Saba, M. Aftab, E. Bouri, and T. Saeed, "Dynamic interdependence of cryptocurrency markets: an analysis across time and frequency," *Physica A*, vol. 559, Article ID 125077, 2020.

[37] W. P. Zhang, X. T. Zhuang, and Y. S. Li, "Dynamic evolution process of financial impact path under the multidimensional spatial effect based on G20 financial network," *Physica A: Statistical Mechanics and Its Applications*, vol. 532, Article ID 121876, 2019.

[38] T. Aste, "Cryptocurrency market structure: connecting emotions and economics," *Digital Finance*, vol. 1, no. 1–4, pp. 5–21, 2019.

[39] G. Gajardo et al., "Does Bitcoin exhibit the same asymmetric multifractal cross correlations with crude oil, gold and DJIA as the euro, great British pound and yen?" *Chaos, Solitons & Fractals*, vol. 109, pp. 195–205, 2018.

[40] H. S. Syed Jawad, E. Bouri, S. H. Kang, and T. Saeed, "Regime specific spillover across cryptocurrencies and the role of COVID-19," *Financial Innovation*, vol. 7, no. 5, 2021.

[41] S. Y. Yi, Z. S. Xu, and G. J. Wang, "Volatility connectedness in the cryptocurrency market: is Bitcoin a dominant cryptocurrency?" *International Review of Financial Analysis*, vol. 60, pp. 98–114, 2018.

[42] W. P. Zhang, X. T. Zhuang, J. Wang, and Y. Lu, "Connectedness and systemic risk spillovers analysis of Chinese sectors based on tail risk network," *The North American Journal of Economics and Finance*, vol. 54, Article ID 101248, 2020.

[43] B. Lin and T. Su, "Does COVID-19 open a Pandora's box of changing the connectedness in energy commodities?" *Research in International Business and Finance*, vol. 56, Article ID 101360, 2021.

[44] A. Faheem, Y. Tariq Mohmand, P. Ferreira, B. Ahmed Memon, M. Khan, and M. Khan, "Network analysis of global stock markets at the beginning of the coronavirus disease (Covid-19) outbreak," *Borsa Istanbul Review*, vol. 20, pp. S49–S61, 2020.

[45] C. K. Peng, S. V. Buldyrev, S. Havlin et al., "Mosaic organization of DNA nucleotides[J]," *Physical Review E*, vol. 49, pp. 1685–1689, 1994.
[46] B. Podobnik and H. E. Stanley, "Detrended cross-correlation analysis: a new method for analyzing two non-stationary time series," *Physical Review Letters*, vol. 100, pp. 84–102, 2008.
[47] A. L. P. Eder Johnson de, S. F. Paulo Jorge, M. F. D Silva, J. G. Vivas Miranda, and H. B. B. Pereira, "Multiscale network for 20 stock markets using DCCA," *Physica A*, vol. 529, Article ID 121542, 2019.