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Capture the Contagion Network of Bitcoin – Evidence from Pre and Mid COVID-19

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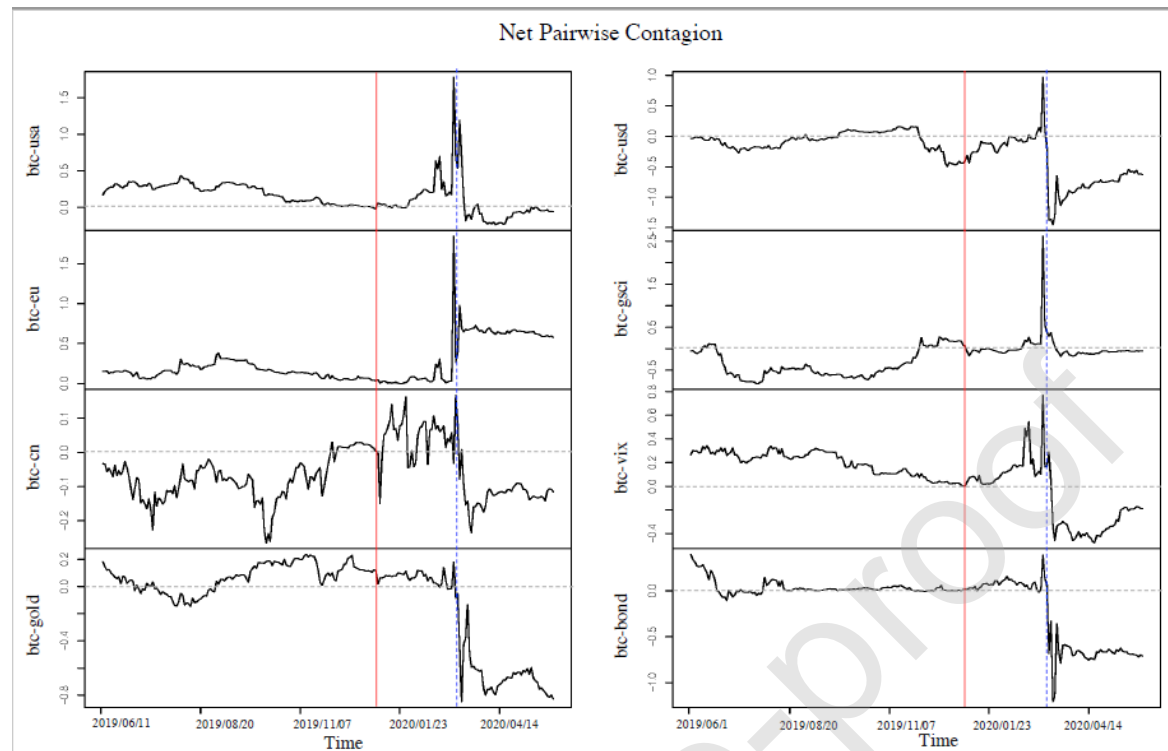
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Graphical Abstract

**Abstract**

COVID-19 is the first global scale crisis since the inception of Bitcoin. We compare the contagion phenomenon of Bitcoin and other financial markets or assets pre and during the COVID-19 shock in both contemporaneous and non-contemporaneous manner. This paper uses the directed acyclic graph (DAG), spillover index, and network topology to provide strong evidence on the directional contagion outcomes of Bitcoin and other assets. The empirical results show that the contagion effect between Bitcoin and developed markets is strengthened during the COVID-19 crisis.

Particularly, European market has a dominant role. Excluding Bitcoin's own shocks, United State and European markets are the main contagion sources to Bitcoin.

European market also works as the intermediary to deliver the infectious from United State and market fear. The findings also show that gold always has contagion effect

with Bitcoin, while gold, US dollar and bond market are the contagion receivers of Bitcoin under the shock of COVID-19. The empirical results further proved the safe haven, hedge and diversifier potential of Bitcoin in economic stable time, but also shows that the sustainability of these properties is undermined during the market turmoil.

Keywords: Bitcoin, COVID-19, Contagion, DAG, Financial Market Risk

Classification Code: G15, G01

1. Introduction

Coronavirus was first identified in late 2019 and outbreak globally in early 2020. COVID-19 has swept into many countries and has been announced as global pandemic by World Health Organization (WHO) on March 11, 2020. With the new confirmed cases rose rapidly every day, many governments started to set limits for public gathering, slow down the economic activities, and restrict international travel. The global tally for confirmed cases of COVID-19 rose to over 30 million by mid-September 2020. Financial markets also experienced extreme high and lows that the crude oil price fell rapidly, US stock market fused four times in ten days, and Bitcoin lost half of its value in two days and back to over \$10,000.

With the rapid development of economic globalization, financial shocks may transmit across countries and markets, and the global crisis will increase the risk of financial contagion or change the contagion network among different markets. COVID-19 is the first global scale crisis since the emergence of Bitcoin. It is important to investigate the change of relationships between Bitcoin and other financial assets in both economic stable time and economic crisis time. COVID-19 is an unique opportunity to reexam the financial market dynamics (Goodell, 2020). Contagion phenomenon is a key aspect to understand the interaction of different assets and markets in crisis time. It reflects the information transmission mechanisms and implies changes in fundamental linkages between markets (Yarovaya et al., 2020,

2016). One manifestation for contagion is that the shock arrives at one market, where negative returns of this market directly affect the returns in other markets (Acharya and Pedersen, 2005; Guo et al., 2011).

Before the COVID-19 crisis, numbers of papers have explored the diversifier, hedge, and safe haven properties of Bitcoin from various perspectives (Bouri et al., 2017c; Dyhrberg, 2016; Kliber et al., 2019; Selmi et al., 2018; Shahzad et al., 2020, 2019; Smales, 2019; Urquhart and Zhang, 2019). Research shows that there are weak linkages between Bitcoin and major financial markets, foreign exchange markets and macroeconomy (Bouri et al., 2017c, 2017b; Dyhrberg, 2016; Panagiotidis et al., 2019). The hedge capability towards commodity market and Asia Pacific market is obvious (Bouri et al., 2017c, 2017b; Dyhrberg, 2016). The evidences of contagion analysis and causality analysis also indicate that Bitcoin is relatively independent from major financial markets (Corbet et al., 2018; Handika et al., 2019; Ji et al., 2018). Bitcoin is categorized as somewhere between gold and US dollar (Dyhrberg, 2016). However, Bitcoin is very sensitive to political risks and regulation (Aysan et al., 2019; Wang et al., 2020), which have strong spillover effects on Bitcoin price internationally (Borri and Shakhnov, 2019). Particularly, the policy uncertainty of China largely affects the trade volume and return of Bitcoin (Borri and Shakhnov, 2019; Cheng and Yen, 2020). In general, cryptocurrency is efficient in reflecting the regulation concerns about anti-money laundry, exchange and issuance, and news about state-backed digital currency (Shanaev et al., 2020).

Compare to economic stable period, financial markets usually exhibit different properties during crisis time (Frank and Hesse, 2009). Different patterns on the linkages of global markets have been found under the influence of coronavirus pandemic, where substantial volatility, uncommon correlation and isolation occurs (Zhang et al., 2020). Total confirmed cases for COVID-19 has significant negative effect on Chinese stock market (Al-Awadhi et al., 2020). Even just companies related to the word “corona” experience abnormal negative return on stock price (Corbet et

al., 2020a). Gold is a safe haven for stock markets before the big crash of US stock markets by mid-March 2020. However, the property as a safe haven does not hold all the time (Selmi et al., 2018). Both financial and non-financial firms experienced higher conditional correlations between their stocks during the COVID-19 period (Akhtaruzzaman et al., 2020). As for Bitcoin, the properties of Bitcoin are changing very fast and dynamically. The new empirical data suggests that the level of COVID-19 causes a rise in Bitcoin price (Goodell and Goutte, 2021a), and Bitcoin and Ethereum can be short-term safe haven for stocks, however, they are also exposed to high volatilities (Dwita Mariana et al., 2021). The existing findings have not yet given a concluding remark on whether Bitcoin and other cryptocurrencies can work as a safe haven, diversifier, or a hedge. Bouri et al. (2017a) has early use quantile regression to show that Bitcoin reacts positively to uncertainty at higher quantiles, especially for short investment horizon. For crude oil market, Bitcoin can only work as a diversifier rather than a safe haven under the pandemic (Dutta et al., 2020). According to the research of Colon et al. (2020) and Conlon and McGee (2020), Bitcoin is proved to have no safe haven properties against many indices in the world at the beginning of COVID-19 pandemic and it is even likely to increase portfolio risk in the market turmoil. The research of Goodell's (2021b) also has the similar result with one exception that Tether act differently in COVID-19 period and could be a safe-haven during market turmoil.

In order to acquire better understandings of Bitcoin's properties under different economic situations, our paper compares the contagion effect between Bitcoin and other assets before and during COVID-19. In addition, existing research about financial contagion for COVID-19 period mostly explore the correlation and co-movement between different assets (eg. Akhtaruzzaman et al., 2020; Corbet et al., 2020b; Goodell and Goutte, 2021), but lack knowledge about how the risks and information has been spread between markets. In addition, cryptocurrency is a growing dynamic market subject to changes as time variant and event appeared, especially under the shock of COVID-19. The markets evolve and start to exhibit

certain new features. It is important to take consideration of the emerging event as a factor to review the cryptocurrency market behavior, so that we can test the sustainability of its safe haven, hedge and diversifier potentials when uncertainty occurs. In this paper we use methodology that can offer directional flow of contagion path between Bitcoin and other markets to answer the question. We analyze the dynamic evolution of the contagion among Bitcoin and other financial markets by Diebold and Yilmaz's (2012) model. Then, the DAG method is employed to investigate the contemporaneous causality of two periods. Finally, we visualize the net contagion networks of all assets in pre-crisis and mid-crisis time.

Our findings contribute to the existing research in the following ways. First, COVID-19 has influenced the global economy and financial market from various perspectives. Our research is an early attempt to take into consideration of the current pandemic situation by comparing pre-crisis and mid-crisis evidence, which provides existing research with up-to-date knowledge of risk contagion in terms of both traditional financial market and cryptocurrency market. We analysis and visualize the relationship of Bitcoin and other financial markets and assets from contemporaneous and non-contemporaneous perspectives. A clear comparison for the dynamic relationships between Bitcoin and other markets before and during COVID-19 crisis can help researchers to understand the changing role of cryptocurrency in both economic stable and crisis time. Further, the findings also offer new understandings to the sustainability of cryptocurrency as an alternative asset class. The empirical results indicate that COVID-19 has changed the risk and information transmission mechanism between cryptocurrency market and other major financial markets. Specifically, the contagion effect between Bitcoin and developed markets is strengthened but not the Chinese market during the COVID-19 crisis. Bitcoin is isolated from other financial markets before COVID-19 period and cannot be a safe haven during COVID-19. Gold is always the risk receiver for Bitcoin. Therefore, Bitcoin shares some similarities with gold in market properties during economic stable time, but the safe haven, hedge and diversifier property is weakened during the

crisis. The sustainability of Bitcoin properties is subjected to changes in crisis. Third, this study also contributes to the growing empirical literatures for contagion analysis in terms of methodology. To the best of our knowledge, it is the first paper to visualize the contagion path of Bitcoin with other financial markets in terms of contemporaneous and time variant manner. We employ cross-discipline research methods, including directed acyclic graph (DAG) from computer science, risk spillover framework proposed by Diebold and Yilmaz (2012), and network typology to analyze and depict the contagion effect based on different time manner. Finally, broadening the understandings for the risk features and transmission mechanism for cryptocurrency helps decision makers to better manage cryptocurrency as a new investment class, maintain financial stability, and take the best use of it as a governing tool.

The rest of this paper is organized as follows: Section 2 presents the methodology of this paper, including the DAG approach, contagion measurements and network topology; Section 3 describes the data; the findings of empirical study are discussed in Section 4; Section 5 concludes the paper.

2. Methodology

2.1 The DAG Approach

The DAG approach is introduced by Sprite et al. (2000), which combines computer science and artificial intelligence theory. The DAG is a data-driven method, which is used to determine the contemporaneous causal relationship of a set of variables by using unconditional correlation coefficient and partial correlation coefficient. The residual variance covariance matrix or residual correlation coefficient matrix of different variables can be obtained from the result from generalized vector autoregression (VAR). The results use a graph structure to show the dependency and directivity relationships of selected variables.

There are four different relationships between variables: 1) No edge (X Y); 2)

Undirected edge (X-Y), which means the direction of causal relationship is unknown;

3) Directed edge (X→Y), which means X cause Y contemporaneously; and 4) Bidirectional edge (X↔Y) indicates a bidirectional causality relationship. Two steps are involved in determining the final result. First, remove the edges. If the unconditional correlation between two variables is not significantly different from zero at a preset significance level, the edge between two variables will be removed. Then, check the remaining variables, whether their first-order partial correlations are significantly different from zero. If it is significantly different from zero, the connection is removed. For N variables, the process will repeat until it checks up to order N-2 conditional correlation. Second, decide the direction of the edges. The conditional variable(s) on the removed edges is defined as a separate set of the pairwise variables whose edge has been removed. The edge that has been removed by unconditional correlation has an empty separate set. Other remaining edges can be directed by the separate set (Bessler and Yang, 2003). For example, three variables X, Y, Z, when X is adjacent to Y, Y is adjacent to Z, and X is not adjacent to Z, that is X-Y-Z. If it is known that Y does not belong to the separate set of X and Z, then the contemporaneous causal relationship among three variables is X→Y←Z. If X→Y is known, Y is adjacent to Z, X is adjacent to Z, and the directed edge between Y and Z does not point to Y, then Y can be inferred has contemporaneous causal relationship with Z, depicting as Y→Z.

Fisher's z statistic is employed to test whether conditional correlations are significantly different from zero, formulated as follows:

$$z[\rho(i, j|k), n] = \left[\frac{1}{2} \sqrt{(n - |k| - 3)} \right] \times \ln \left\{ \frac{1 + \rho(i, j|k)}{1 - \rho(i, j|k)} \right\} \quad (1)$$

where n is the number of observations used to estimate the correlations, $\rho(i, j|k)$ is the population correlation between variables i and j conditional on series k . $|k|$ is the number of series in k . If i , j and k are normally distributed and $r(i, j|k)$ is the sample conditional correlation of i, j given k , then $z[\rho(i, j|k)n] - z[r(i, j|k)n]$ is

a normal distribution (Bessler and Yang, 2003). In this paper, we use PC algorithm in Tetrad VI software package proposed by Glymour et al. (2015) to conduct the DAG process.

2.2 Contagion Measurements

In this paper, contagion effect is measured by the framework proposed by Diebold and Yilmaz (2012). Based on this method, we use dynamic and conditional spillover to investigate the evolution of Bitcoin contagion effect, as well as the two period unconditional spillover index to compare the contagion between Bitcoin and other financial markets. This method generates directional results under a generalized VAR framework, which solve the order dependency issue of Cholesky factorization in variance decompositions (Diebold and Yilmaz, 2012, 2009).

The moving average process for VAR(p) is represented by

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \quad (2)$$

where A_i is $N \times N$ coefficient matrix in recursive pattern.

The model calculates the H-step-ahead forecast error variance decompositions by

$\theta_{ij}^g(H)$, for $H = 1, 2, 3 \dots$, there is

$$\theta_{i \leftarrow j}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i A_h \Sigma A_h' e_i)} \quad (3)$$

where $\theta_{i \leftarrow j}^g(H)$ represents the risk spillover of asset j to asset i . Σ is the variance matrix for the error vector ε , σ_{jj} is the standard deviation of the error term of asset j . e_i and e_j are $N \times 1$ selection vector with one as the i th element and zeros otherwise. The shocks to each variable are not orthogonalized, so the sum of the element contribution in each row are not necessarily equal to one. To facilitate comparison, the normalized variance decomposition matrix is given

$$\tilde{\theta}_{i \leftarrow j}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^H \theta_{ij}^g(H)} \quad (4)$$

where, $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$ and $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$.

Directional spillover from market i to market j is denote by

$$S_{\cdot i}^g(H) = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ji}^g(H)} \times 100 = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ji}^g(H)}{N} \times 100 \quad (5)$$

The spillover to market i from market j is denote by

$$S_i^g(H) = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100 \quad (6)$$

Then the net spillover is equal to

$$S_i^g(H) = S_{\cdot i}^g(H) - S_i^g(H). \quad (7)$$

This paper visualizes the contagion path using net pairwise spillover. The net pairwise spillover describe the net contagion contribution of two markets or two assets, which is helpful to identify the role of Bitcoin in relation with other financial markets and assets in a directional way.

The net pairwise spillover is

$$S_{ij}^g(H) = \left(\frac{\tilde{\theta}_{ji}^g(H)}{\sum_{i,k=1}^H \tilde{\theta}_{ik}^g(H)} - \frac{\tilde{\theta}_{ij}^g(H)}{\sum_{j,k=1}^H \tilde{\theta}_{jk}^g(H)} \right) \times 100 = \left(\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \right) \times 100 \quad (8)$$

2.3 Network Topology

Network theory has been widely used in researches of financial contagion and market connectedness (Diebold et al. 2014; Gai and Kapadia 2010; Georg 2013; Martínez-Jaramillo et al. 2010). Based on the spillover measurements of Diebold and Yilmaz (2012), this paper further combines the network topology to visualize and describe the contagion networks of Bitcoin and other financial markets.

In financial contagion network analysis, each financial institution represents a node and the interconnection between different institutions use links to define. These links are directed and weighted, reflecting the exposure of each institutions (Gai and Kapadia, 2010). Four common measurements are utilized to describe the contagion and connection between Bitcoin and other financial markets. First, the degree of node, which is the number of links to other nodes, $d_i = \sum_{j=1}^n a_{ij} = \sum_{j=1}^n a_{ji}$. In-degree measures the number of links that point into the node, $d_{in}(i) = \sum_{j=1}^n a_{ij}$. Out-degree is the number of links that point out from the node, $d_{out}(i) = \sum_{j=1}^n a_{ij}$. Second, betweenness centrality is used to measure the control of a node that has over the spread of risk and information through the network (Freeman, 1978, 1977). It is calculated as the fraction of the shortest path between nodes pairs that pass through the node of interest, $BC_i = \sum_{s \neq i \neq j} \frac{n_{st}^i}{g_{st}}$. Finally, average path length and average diameter is employed to describe the overall contagion network changes before and during COVID-19 period. The average path length of a network is defined as the average length of shortest paths for all pairs of nodes i, j . Average diameter is the average of maximum distance between any two nodes. Diameter is calculated as $S_{max} = \max_{i,j} S_{i,j}$.

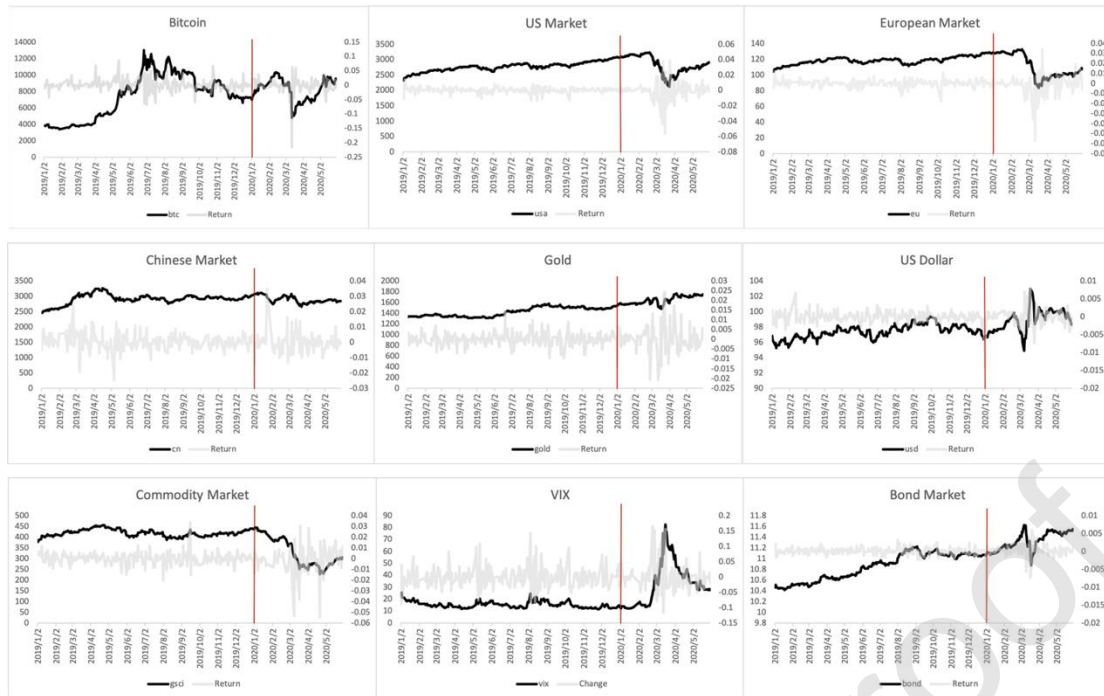
3. Data

We choose eight other variables excluding Bitcoin in this paper, which are United State (US) market, European market, Chinese market, US dollar, Gold, Commodity Market, Bond market and market fear. The three regional markets take up important positions in world economy, and they are also the major outbreak sites at the beginning of COVID-19. More specifically, MSCI USA index is used to measure United State market, since it not only covers S&P500 stocks, but also includes some mid-cap stocks (MSCI, 2020b). MSCI EUROPE index, which includes large and mid-cap stocks across 15 developed countries in Europe, is used to represent European market (MSCI, 2020a). Chinese market is denoted by Shanghai composite index. US

dollar, gold, commodity, and bond are also representative markets and assets in world economy. US Dollar, gold and commodity market are measured by the US dollar index, Comex gold future price and GSCI commodity index respectively. Bond market is explained by Vanguard Total Bond Market Index Fund Admiral Shares, which contains a wide spectrum of public, investment-grade, taxable, fixed income securities in the United States. Market fear of investors is measured by VIX, which is the implied volatility of S&P500 options. In the following figures and tables, “btc”, “usa”, “eu”, “cn”, “usd”, “gold”, “gsci”, “vix”, “bond” is used to represent Bitcoin, US market, European market, Chinese market, US dollar, gold, commodity market, VIX and bond market respectively. All data are collected from investing.com (<http://www.investing.com>).

We utilize the daily data for this empirical study, and the full sample period is from January 1, 2019 to May 31, 2020. The time period is chosen for two main reasons. First, Bitcoin price of 2019 has certain representativeness. Price of Bitcoin tends to be increasingly normalized compared to previous hype before 2020. The future market characteristics of Bitcoin will be closer to normalized market after 2018 instead of its inception stage and bubble stage. Second, it has high comparability. In two chosen periods, markets have good continuity with little other changing factors except for COVID-19 crisis.

In order to explore the change of the co-movements and linkages of Bitcoin with other financial markets and assets in different economic situation, the full sample period is divided into two sub-periods, namely pre-COVID-19 and mid-COVID-19. Since WHO received the first coronavirus case report on December 31, 2019, the outbreak time selected is right after this important event. Therefore, data of pre-COVID-19 crisis covers the whole year of 2019, and data of mid-COVID-19 ranges from January 1, 2020 to May 31, 2020. This paper uses rate of change for VIX data, and log return for the rest of markets in further analysis. We delete the missing data due to holiday difference.



Note: The red straight line separating the period before and during COVID-19.

Figure. 1 Price and Return of Selected Indices

The tendency and the descriptive statistics of all variables in terms of rate of change for VIX and log return for the rest of variables over different periods are reported in **Figure 1** and **Table 1**, respectively. There are great changes for the chosen variables in two different time periods. All assets exhibit higher volatility and negative change for average return during COVID-19 crisis. Market confidence (VIX) is relatively stable before COVID-19 crisis, but it starts to change more rapidly since February 2020. For Bitcoin, before COVID-19 crisis, it has the highest average return compared to other assets and exhibits a positive skewness, which means an inclination for positive return. However, during COVID-19 period, all indicators of Bitcoin show significant differences. Average return and skewness change from positive to negative, indicating a higher possibility for negative return and extreme negative return. Kurtosis rises almost seven times more, suggesting a heavy fat tail feature. In general, more uncertainties and extreme values characterize most markets for COVID-19 time. We also conduct augmented Dicky-Fuller test to ensure all the series

are stationary in VAR model. The results show that all series pass the stationary test.

Table 1

Descriptive Statistics for (Log) Return, nine asset classes

Panel A: Full Sample					
	Mean	Std. Dev.	Skew	Kurtosis	ADF test
btc	0.000734	0.0228	-2.4222	25.3154	-12.5438***
usa	0.000225	0.0079	-1.2466	14.6720	-12.7266***
eu	0.000021	0.0066	-2.4006	20.8674	-10.6803***
cn	0.000177	0.0056	-0.9406	6.7075	-12.8041***
gold	0.000322	0.0047	0.3859	6.7175	-12.4102***
usd	0.000031	0.0018	0.5733	3.8681	-10.3223***
gsci	-0.000342	0.0085	-1.5667	11.5916	-12.4732***
vix	-0.000492	0.0382	1.1712	3.4825	-12.5169***
bond	0.000127	0.0013	-0.9110	7.3322	-11.9748***
Panel B: Before COVID-19					
	Mean	Std. Dev.	Skew	Kurtosis	ADF test
btc	0.001146	0.0194	0.3752	3.5314	-10.4869***
usa	0.000485	0.0035	-0.7509	3.5704	-11.0132***
eu	0.000354	0.0034	-0.7547	4.3309	-10.5388***
cn	0.000370	0.0050	-0.1492	4.6731	-10.9991***
gold	0.000262	0.0032	0.1631	2.4758	-10.7638***
usd	-0.0000002	0.0013	0.5306	2.3695	-9.8553***
gsci	0.000278	0.0053	0.5172	7.0899	-12.2951***
vix	-0.001327	0.0332	0.8095	2.2561	-11.0187***
bond	0.000106	0.0009	0.0728	0.3393	-10.2353***
Panel C: Mid- COVID-19					
	Mean	Std. Dev.	Skew	Kurtosis	ADF test
btc	-0.000190	0.0302	-4.0432	27.3174	-6.7184***
usa	-0.000502	0.0140	-0.6402	3.3022	-6.5603***

eu	-0.000913	0.0114	-1.4450	6.2627	-5.2764***
cn	-0.000383	0.0068	-1.6172	6.3373	-6.505***
gold	0.000470	0.0073	0.2828	2.3298	-6.4553***
usd	0.000092	0.0026	0.4190	1.3174	-4.9312***
gsci	-0.002001	0.01361	-1.1467	3.6714	-6.0450***
vix	0.002203	0.0492	1.2585	2.5042	-6.0458***
bond	0.000172	0.0020	-1.0061	3.6327	-6.3773***

Note: Lag selection in ADF test is based on Akaike Information Criteria (AIC). *** denotes 1% level of significance.

4. Empirical Result and Discussion

4.1 Average Contagion Level for Full Sample Period

Before laying emphasis on the comparison results of two sub-sample periods, we try to depict the continuous evolution of the contagion among financial markets. This dynamic analysis can offer us a general picture of the average contagion level over the past months as well as a clear time point of the changes. We use 100 days rolling window and 10 days forecast horizon in the analysis to smooth the result and reflect the fast response in price for highly liquid market (Longstaff, 2010). Other parameters with shorter rolling windows offer a less smoothy pattern, but the result still has the same trend and features. And results with other forecast horizons also show similar patterns. In general, reasonable changes to the parameters do not impact the outcome and conclusion of this research. These results are derived from contagion measurements described in Section 2.2 under full sample VAR model. Based on Schwarz Criterion (SC) and Hannan Quinn (HQ) criteria, lag of 1 is suggested for VAR model.

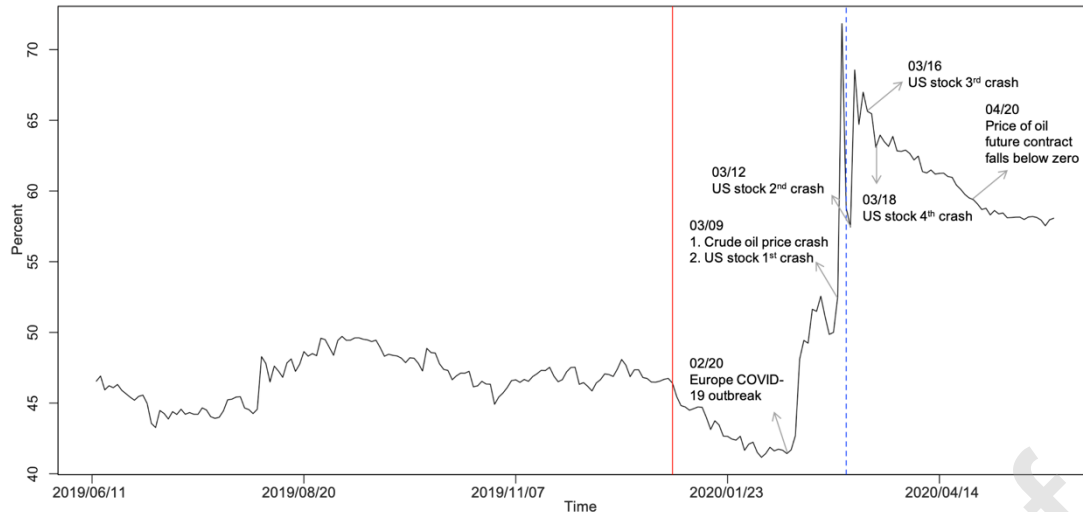


Figure. 2 Average Contagion Level, nine asset classes

Note: The straight red line and blue dash line mark the date January 1, 2020 and March 11, 2020 respectively, representing the outbreak and pandemic time point for COVID-19. The same marks are also exhibited in the following figures.

Figure 2 illustrates the average return contagion behavior of all variables for full sample period. The contagion is measured by spillover effect of one asset to another in terms of percentage. Before COVID-19 outbreak, the contagion level mostly fluctuates between forty to fifty percent. At the beginning of coronavirus outbreak, the markets were not affected by its impact, and even exhibited a declining trend of overall contagion. The reason for it is that the outbreak of COVID-19 was still regional at that time, and people did not expect the rapid spread of the virus and the severity of its influences. It is clear that the overall contagion started to have significant increase as COVID-19 were getting out of control in more countries in late February 2020. Then it spiked since 9 March (**Figure 2**). From 9 March to the end of March, the contagion level for all markets stayed at very high level. Multiple factors intertwined together during that period. On 11 March, WHO announced world pandemic of COVID-19. US market fused four time in ten days reacting to coronavirus panic and series of international instabilities, such as crude oil price fluctuation on March 9 and March 12, 2020. Meanwhile, we can also clearly see that

as the markets got used to the worsen condition, the next round fuse and crude oil crash exerted less impacts on the average contagion level between different assets. At the end of the data period, contagion effect shows a decline, as government started to take actions to react to the uncertainties that coronavirus brought to the economy and society, and Europe and East Asia began to gradually go back to normal life. Nevertheless, due to the COVID-19 pandemic and the negative economic consequences, the general level of market contagion will still stay high in the foreseeable future.

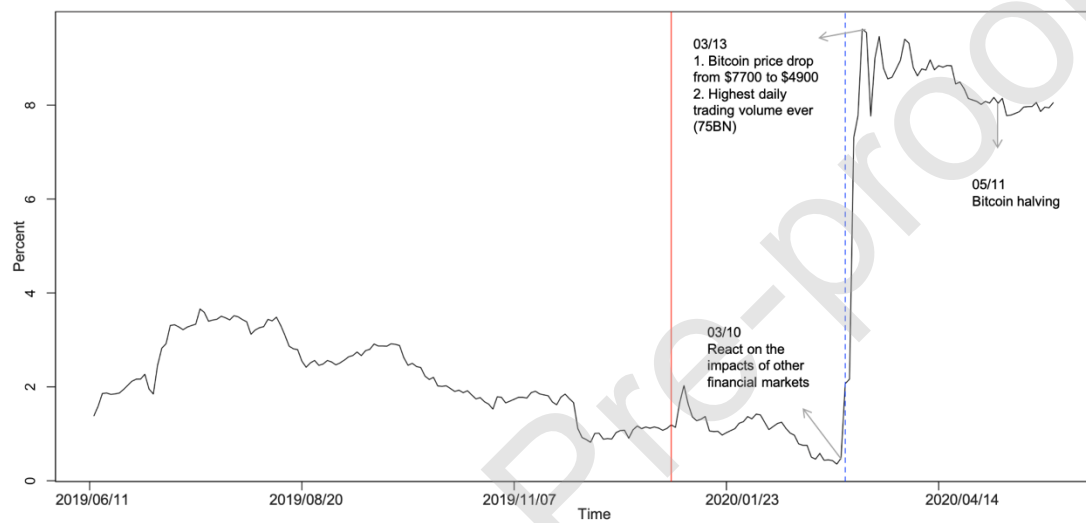


Figure. 3 Contagion from Bitcoin to Other Markets

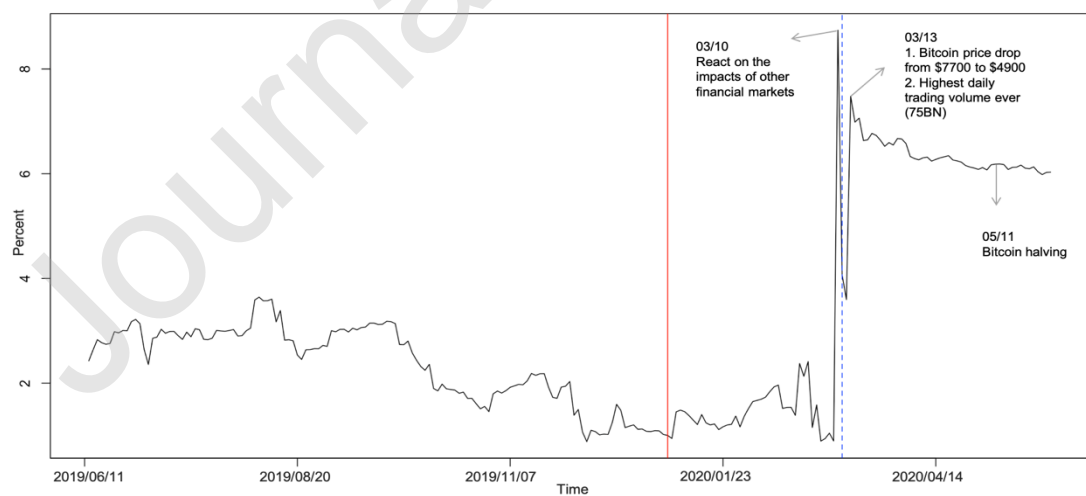
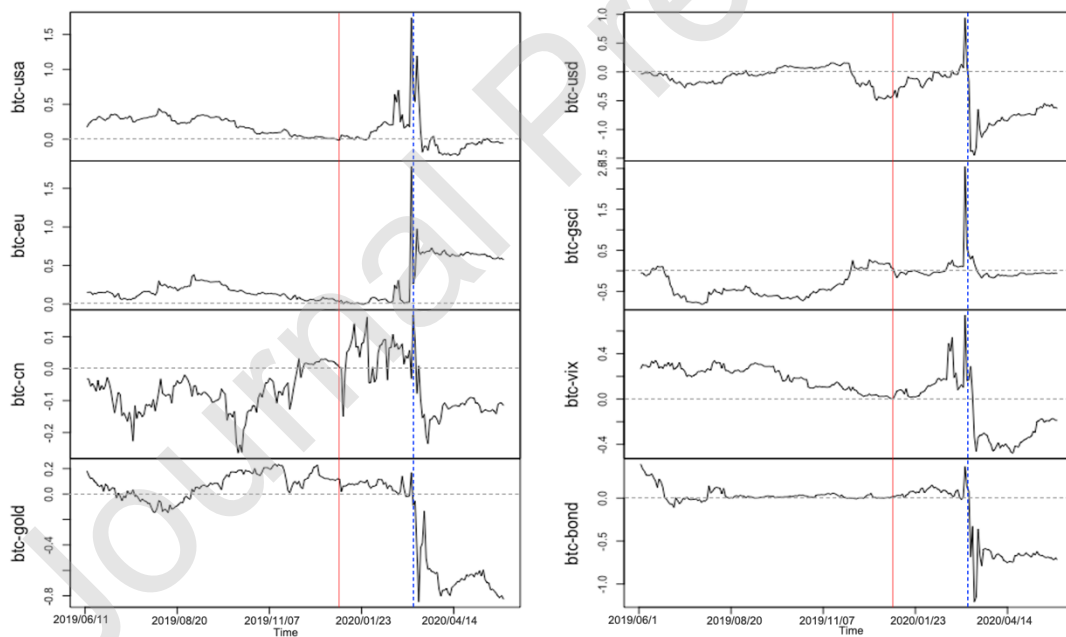


Figure. 4 Contagion from Other Markets to Bitcoin

As for Bitcoin, **Figure 3** and **Figure 4** shows the average contagion effect of Bitcoin to and from other markets over the full sample period. Both from and to Bitcoin spillover ranges from 1% to 4% before COVID-19, which is a very low level of contagion compared to the other assets. Since the world pandemic of COVID-19, Bitcoin spillover roared from less than 1% to more than 9% (**Figure 3** and **Figure 4**). This radical change is consistent with overall market response when facing COVID-19 crisis. However, the reactions to series of event from Bitcoin to other assets are slower than the opposite direction. When the crisis come, Bitcoin received dramatically increasing spillover from other financial markets first, and then follows the contagion level growth from Bitcoin to other markets. This can be partly explained by the previous finding that the extreme Bitcoin price crash has greater influences on the return co-movement between world indices (Hu et al., 2020). It also indicates that Bitcoin market has little impact on other assets before this crisis.

Figure 5 describes the net pairwise contagion from other assets to Bitcoin, where positive percentage on the Y-axis represents that the asset transmits risks to Bitcoin, and negative percentage represents the asset receives net contagion from Bitcoin. Comparably, commodity market receives the most spillover from Bitcoin and US market transmit risks to Bitcoin before COVID-19, but both effects remain small percentage in general. Other markets have very low level of contagion to and from Bitcoin. During COVID-19 crisis, contagion level from European market to Bitcoin increases substantially. While US market exerted strong effect from January to March 2020 and started to receive spillover from Bitcoin later. Gold and bond began to absorb the risks from Bitcoin market during the pandemic. Bitcoin change from the spillover receiver of VIX to a reactor of VIX, which can resonate the previous research that Bitcoin show safe haven or hedge functions before COVID-19, but the safe haven property diminished during COVID-19 period (Conlon and McGee, 2020). As for Chinese market and commodity market, there was a peak period around mid-March, however, the contagion level was gradually getting back to the previous level.

In general, contagion from other assets to Bitcoin did not rise significantly until the announcement of pandemic, which shows certain risks resistance of Bitcoin in the early time of COVID-19. The significant changes in contagion level of Bitcoin and other assets crowded in March 2020. At that time, many countries declared the suspension of economic and social activities under the pressure of coronavirus; geopolitical conflict regarding to oil dispute between Saudi Arabia and Russia exerted additional impacts on the global markets; and US stock markets, as the global benchmark, fused four times in ten days. Complex international factors overlapped and intertwined in this unstable period, causing Bitcoin lost half of its value in two days, which further cause over \$700 million liquidation of both long and short of selling Bitcoin in Bitmex. By the end of May 2020, the contagion level of Bitcoin still stood high, where the down trend for contagion from and to other markets was not obvious. Therefore, it is reasonable to expect that Bitcoin will be more related to other financial markets than before in the near future.



Note: The grey horizontal dash line indicates zero contagion level.

Figure. 5 Net Pairwise Contagion

4.2 Comparison Analysis for Bitcoin Contagion

4.2.1 Contemporaneous Contagion

To construct the DAG contemporaneous causality relationship of Bitcoin and other financial markets and assets, we first select the optimal lag for VAR model for two periods respectively. Based on SC and HQ criteria, lag of $k=1$ is suggested to both VAR models. We use innovation correlation matrix produced by VAR model to generate the DAG in the next step. Spirtes et al. (2000) suggest that the significance level should increase when sample size is small or not big enough. For example, they suggest that 0.2 significance level for samples under 100 and 0.1 significance level for 200 to 300 samples. Higher significance level avoids small sample to deliver underfit result, which includes too few edges (Bessler and Yang, 2003; Scheines et al., 1994, p. 105). Awokuse and Bessler (2003) also find that up to 30% significance level can offer a clear structural result in small sample condition. After comparing the results of different significance level of two sample periods, this research adopts 0.1 significance level for data before COVID-19 crisis (236 observations) and 0.2 significance level for data during COVID-19 crisis (90 observations) in DAG analysis.

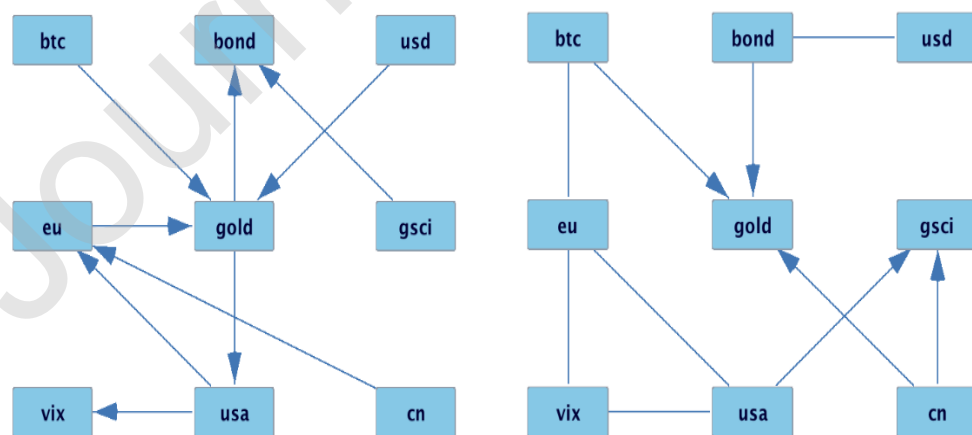
Table 2

Residual Correlation Matrix

Panel A: Innovation Correlation Matrix Before COVID-19								
btc	usa	eu	cn	gold	usd	gsci	vix	bond
1								
-0.1054	1							
-0.1036	0.7689	1						
-0.0413	0.2100	0.3059	1					
0.1927	-0.2880	-0.3402	-0.0247	1				
-0.1038	0.0839	0.1241	0.0282	-0.4293	1			
-0.0459	0.3286	0.2952	0.1609	-0.0648	-0.0440	1		

0.1140	-0.8376	-0.6510	-0.1675	0.2189	-0.0709	-0.3112	1	
0.0479	-0.4753	-0.3645	-0.0545	0.5234	-0.1807	-0.3348	0.3774	1
Panel B: Innovation Correlation Matrix During COVID-19								
btc	usa	eu	cn	gold	usd	gsci	vix	bond
1								
0.5647	1							
0.6313	0.8510	1						
0.2322	0.3676	0.3842	1					
0.3394	0.2508	0.3156	0.2559	1				
-0.0071	-0.0513	-0.1736	-0.1422	-0.2202	1			
0.3208	0.5678	0.5453	0.3679	0.2746	-0.0388	1		
-0.4536	-0.7586	-0.5942	-0.1612	0.0028	-0.1596	-0.4458	1	
0.1091	-0.1382	0.0057	-0.0474	0.2477	-0.4093	0.0515	0.1484	1

Table 2 reports the lower triangle entries for the innovation correlation matrix in two time periods. Starting from the matrices, we use PC algorithm in TETRAD VI program to conduct the DAG analysis. The process begins with a complete undirected graph with nine markets link to each other. Then, edges that are not statistically correlated are eliminated. Links are directed based on the method described in Section 2.1. The final results are illustrated in **Figure 6**.



(a) Contemporaneous causal structure graph before COVID-19 (b) Contemporaneous causal structure graph during COVID-

Figure. 6 The Contemporaneous Causal Structure Graph

Figure 6(a) shows that Bitcoin is not affected by the other markets contemporaneously before COVID-19 crisis. It is relative independent from the contagion chains. This result resonates with research findings that Bitcoin has weak relationships with financial markets and assets (Corbet et al., 2018; Ji et al., 2018). The graph also demonstrates that innovations in Bitcoin will cause the innovations in gold in a contemporaneous manner. The main reason of this phenomenon is that investors started to consider Bitcoin as an alternative for gold in certain cases (Bouri et al., 2017b; Kliber et al., 2019; Shahzad et al., 2019) but gold is still the last safe haven (Coudert and Raymond, 2011; Selmi et al., 2018).

During market turmoil of coronavirus, Bitcoin become more connected with other markets and assets. **Figure 6(b)** shows that information from Bitcoin transmits to gold market instantaneously. This contemporaneous contagion is consistent with the result shown in pre-COVID-19 period. Meanwhile, European markets start to have contemporaneous causality relationships with Bitcoin, but the impact direction is not clear. US market, VIX, and European market exhibit undirected contemporaneous causality relationship. In this way, Bitcoin is connected to the contagion network of US market and react to the fear level of VIX during COVID-19 crisis. The safe haven property of Bitcoin is weakened in the time of the shock. We can reasonably infer that large proportion of investors from those markets get in and out from the equity markets and Bitcoin market at the same time during COVID-19 period.

4.2.2 Non-contemporaneous Contagion

Our analysis focus on the Bitcoin contagion of different time periods. We assume that the COVID-19 is the event dramatically change the interrelationships between Bitcoin and other markets. To address the change, we conduct directional non-contemporaneous contagion analysis to strengthen and validate the comparison. **Table 3** and **Table 4** are the estimated contribution of the forecast error variance of Bitcoin

coming from/to innovations to/from other markets. The shocks to each variable are not orthogonalized, so the sum of the element contribution in each row is not necessarily equal to one. **Table 3** and **Table 4** show the contagions before and during COVID-19 period respectively, which imply that for all markets, it is obvious that the contagions become more active during COVID-19 period. Before COVID-19, most markets have the biggest share of impact from themselves with few other markets receive spillover effect over 5%. When COVID-19 shock hits the market, all markets receive higher proportion of contagion from other assets, the average contagion level rise from 41.38% to 58.88%.

Further, we visualize the directional transmission path of Bitcoin and other markets in both time periods. Based on **Table 3** and **Table 4**, we construct the net contagion matrices and generate contagion networks in **Figure 7**. The gross contagion is bidirectional as the two tables show, while net transmission is unidirectional, which can better depict the dominant position of each asset for information and risk transmission and contagion.

Table 3

Contagion Before COVID-19

	BTC	USA	EU	CN	GOLD	USD	GSCI	VIX	BOND	FROM
BTC	91.19	1.06	1.07	0.34	3.47	1.07	0.32	1.20	0.29	0.98
USA	0.40	35.18	20.49	1.56	3.88	1.57	3.74	24.56	8.62	7.20
EU	0.48	23.54	39.8	4.15	5.07	0.97	3.63	17.06	5.31	6.69
CN	0.75	6.94	9.06	72.37	0.53	0.98	1.97	5.98	1.40	3.07
GOLD	2.51	4.64	6.96	0.20	55.44	10.65	1.35	2.78	15.48	4.95
USD	0.88	0.80	1.24	0.08	14.72	78.61	0.29	0.67	2.71	2.38
GSCI	2.68	7.04	5.68	2.25	1.48	1.24	65.56	6.32	7.74	3.83
VIX	0.52	28.79	16.6	1.09	2.17	0.79	3.95	39.68	6.41	6.70
BOND	0.31	11.15	6.75	0.63	14.90	3.56	5.80	7.17	49.72	5.59

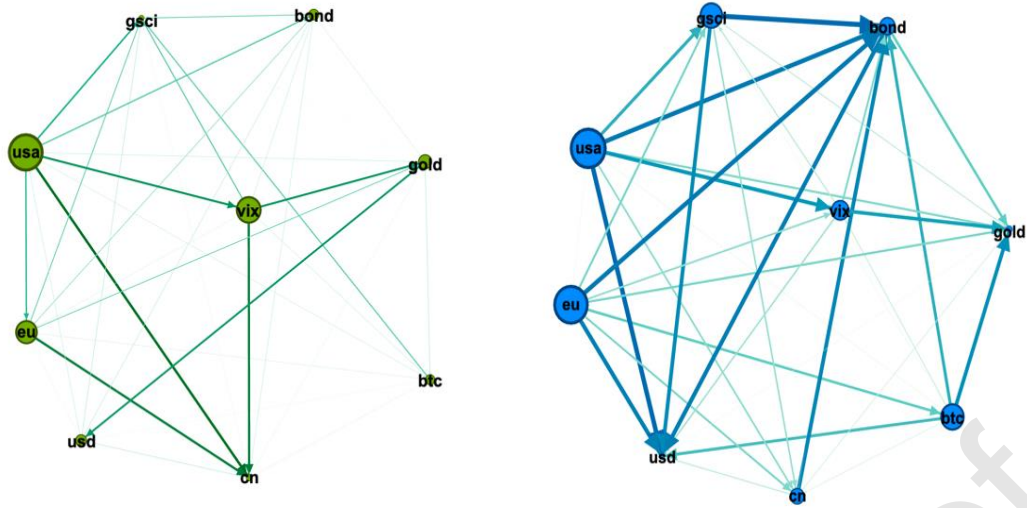
TO	0.95	9.33	7.54	1.15	5.14	2.31	2.34	7.31	5.33	41.38
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Table 4

Contagion During COVID-19

	BTC	USA	EU	CN	GOLD	USD	GSCI	VIX	BOND	FROM
BTC	44.48	14.38	18.3	2.35	5.14	1.09	4.75	8.92	0.58	6.17
USA	15.05	29.19	22.46	5.00	1.64	0.46	8.46	16.43	1.32	7.87
EU	13.21	22.96	31.73	5.20	3.19	1.66	9.84	12.04	0.17	7.59
CN	3.47	8.62	9.32	60.69	4.09	1.42	9.55	2.64	0.20	4.37
GOLD	13.16	5.71	7.48	5.44	44.51	2.86	5.41	7.25	8.19	6.17
USD	6.96	10.31	10.39	3.43	3.33	37.06	8.79	4.31	15.43	6.99
GSCI	5.33	14.98	14.13	6.20	3.46	0.56	45.33	9.74	0.27	6.07
VIX	10.64	23.97	15.59	2.35	0.16	1.27	7.53	37.37	1.12	6.96
BOND	7.12	10.37	9.26	8.64	3.08	6.57	10.06	5.14	39.74	6.70
TO	8.33	12.37	11.88	4.29	2.68	1.76	7.15	7.39	3.03	58.88

Figure 7 describes the net contagion paths between different assets. The number of assets that exert or receive net effect on the node is demonstrated by out-degree and in-degree. And size of the node is the out-degree of each variable, which indicates the influence of an asset in the network. The bigger the node is, the more markets receive spillover from the node. The thickness and color of the edge is denoted by the amount of net contagion from node asset to other assets. The more net spillover transmits out from the asset, the thicker and darker the color of the link. There are 9 nodes and 36 edges in both networks, representing the pairwise net spillover among markets.



(a) Net Contagion Network Before COVID-19

(b) Net Contagion Network During COVID-19

Figure. 7 Net Contagion Paths**Table 5**

Full Network Characteristics

	Pre COVID-19 Period	COVID-19 Period
Average Path Length	1.61	1.07
Average Weighted Degree	6.67	19.00
Weighted Average	13.33	38.01
Average Diameter	5	2

Table 6

Network Characteristics of Bitcoin

	In-Degree	Out-Degree	Weighted In-Degree	Weighted Out-Degree	Weighted Degree
Pre-COVID-19	5	3	3.08	2.79	5.87
Mid-COVID-19	1	7	5.09	24.52	29.61

Table 5 displays the full networks characteristics. For the networks, the average path

length and average diameter dropped from 1.61 and 5 to 1.07 and 2 respectively compared to pre-crisis time. The smaller the number of the two measurements, the faster and easier of the transmission process. During the COVID-19 period, one market crash will soon spread to the whole network, even for markets that are previously not closely relate to each other. Before the crisis, US dollar has the highest betweenness in the network, which is 12.5¹. It means that contagions usually go through US dollar to other assets. It has an intermediary role in this process. However, during the COVID-19 time, there is no market exhibits high betweenness, which suggests that risks and information transmission channels are equally distributed for all markets. This indicates a shorter responding time for infections, as markets do not require intermediaries to react to the uncertainties of one market in the contagion process. During the phase of crisis, US market and European market are the two biggest net contagion transmitters, which can be regarded as two of the sources causing the market contagion in COVID-19 crisis. While US dollar, gold and bond become the net receivers in the network, proving their passive positions in reacting to the negative information.

For Bitcoin, before COVID-19 crisis, it receives net contagion from five other markets, and transmits positive effects to three markets (**Table 6**). Gold has slightly positive spillover to Bitcoin and also receives the contagion from Bitcoin, thus the net effect is not obvious. While commodity market receives Bitcoin spillover but has no influence on it. In general, the contagion between each market and Bitcoin is minor, that the major influencer is itself. Impacted by COVID-19, there is a higher level of contagion from and to Bitcoin as well as the other markets. In net term, Bitcoin delivers positive effects to seven markets (**Table 6**). Gold, US dollar and bond are impacted by Bitcoin to a great extend, which works as “the last resort” for Bitcoin market. While Bitcoin is affected by one major market, which is European market. It has a dominant role for the net contagion to Bitcoin. However, we must exercise

¹ We only mention the most meaningful node in terms of betweenness. The full betweenness results for all nodes are shown in the appendix.

certain degree of caution in interpreting the result between European market and Bitcoin. First, European market also receives large proportion of spillover from US market. Second, European and US market has very high correlations historically. Third, US market has strong contagion effect to advanced markets (Dungey and Gajurel, 2014; Jayech, 2016). Forth, US market and VIX also have relatively larger spillover effects in aggregate level from **Table 4**. The origin of the contagion may come from the upper stream markets that transmit to European market. Therefore, it is reasonable to infer that European market partly works as an intermediary for US market to Bitcoin. In addition, the effect of VIX to Bitcoin indicates that a fast-increasing fear level and a dropping market confidence can drive huge price fluctuation of Bitcoin market. It is corroborated with previous study of Kurka's (2019), that there are periods of substantial shock transmission between Bitcoin and traditional assets under the shock. This also reflects the empirical study of Colon's (2020) that Bitcoin is not a safe haven in coronavirus time. These findings help to complement the undirected edges of the three markets generated from the DAG approach.

Combining **Figure 5** and the results in this section, we find that Bitcoin is shown to become the risk spiller of gold, where gold receives long lasting spillover effects from Bitcoin in the crisis. The effect between Bitcoin and gold is also strengthened during the crisis. This finding echoes the contemporaneous causality relationship shown in previous section and the research of González et al.'s (2021). The reason could be that people still consider gold as the most preferable safe haven during crisis time (Coudert and Raymond, 2011; Selmi et al., 2018) compared to Bitcoin. Apart from that, there is a significant net contagion effect change between Bitcoin and US dollar and bond in COVID-19 period (**Table 4** and **Figure 7**). Bitcoin becomes the net transmitter for these assets. The reason is that Bitcoin has higher liquidity compare to bond and US dollar, while more liquid assets usually reflect faster speed in price discovery (Longstaff, 2010). Besides, US dollar and bond are also considered to have safe haven properties in some cases (Das et al., 2020; Flavin et al., 2014; Schuknecht

et al., 2009).

We expect a strong contagion effect between Bitcoin and Chinese market followed by the empirical results of Corbet et al. (2020b) and Al-Awahdi et al. (2020). Apart from that, China is also one of the major outbreak regions for coronavirus and its activities usually has some influences over Bitcoin (Borri and Shakhnov, 2019; Cheng and Yen, 2020). However, the results do not support our hypothesis. The reasons could be that the outbreak of COVID-19 in China was early in time before the main worldwide pandemic, and the strict control over disease in China hold back the declining confidence of Chinese market. The later stage reaction of Bitcoin was mainly caused by the developed market crash and investors outside of China (Al-Awahdi et al., 2020).

5. Conclusion

The purpose of this research is to compare the contagion phenomenon between Bitcoin and other assets in pre and mid COVID-19 period. First, we examine the full period average contagion level dynamically using Diebold and Yilmaz's (2012) method. Second, we use the DAG approach to explore the contemporaneous causal relationship between Bitcoin and other markets in two periods. Third, we depict the contagion path through network analysis based on net spillover matrices. The results are robust under different methods.

The empirical results show that Bitcoin is relative independent before COVID-19 shock, that information and risk spillover from and to Bitcoin to and from other financial markets is very limited. In this regard, cryptocurrency can be chosen as an alternative investment class to diversify the risks in the portfolio during the economic stable period. This result resonates with existing research that Bitcoin is relative isolate from the major assets and holds similarities with gold (Dyhrberg, 2016; Shahzad et al., 2019). Under the shock of COVID-19, the average market contagion is higher, faster and easier. At the beginning, there is no evident stronger contagion

effect between markets. As coronavirus become out of control in more regions, the market contagion exhibits a gradual rising level since February 2020. Bitcoin starts to react until March when the world pandemic is around the corner. Both contemporaneous and non-contemporaneous findings indicate close connections between Bitcoin and gold and European market during COVID-19 crisis. Gold always receives the net contagion effect from Bitcoin. Whereas European market has a dominant role in transmitting risks and information, that it is the net contagion source to Bitcoin and contagion intermediary in the infection chain of US market. In addition, Bitcoin also reflects the fear level change during the COVID-19 period. Surprisingly, Chinese market does not have much contagion effect with Bitcoin. In the near future, cryptocurrency, especially Bitcoin might change its relationship with other financial markets compared to before. The new evidences complement the research of Kurka (2019), Ji et al. (2018), Corbet et al. (2020b, 2018), Conlon and McGee (2020), and Goodell and Goutte (2021a).

The research findings offer economic and policy implications. Due to short history and new technology nature of Bitcoin, the understandings for the capacity and feature of Bitcoin are still nascent. Taking Bitcoin into investment portfolio during economic stable time is a good choice to diversify risks and increase average return. Under the global shock, Bitcoin exhibit higher contagion effect, especially the risks and information transmission originated from developed market. Compared to other financial assets, the extreme performance and the slow recovery speed from financial contagion of Bitcoin give an alert to investors that it is highly sensitive and fragile to shocks and mostly depend on general economic environment. The sustainability of Bitcoin as a safe haven, hedge or diversifier is weakened during the market turmoil. Investors need to use it with caution to prevent extreme negative effect for their portfolio. Based on our findings, we suggest that gold, US dollar and bond could be the alternative choices for Bitcoin investment during the shock. Regulators should consider asking financial institutions to offer proper risk warning and risk assessment when individual investors try to involve in Bitcoin trading activities.

As for COVID-19 crisis, the cause of this market turmoil is different from the cause of previous financial crisis, where financial institutions were the originate reason to generate the systematic risks. This time, the primary reason for the active contagion phenomenon is the outbreak of pandemic. The effective control over disease is the solution for the recovery of economy and financial market. Government should dedicate to take actions and issue policies that can help to reduce the spread of coronavirus and maintain a good level of medical services. Of course, managing other financial policies and supplemented tools to stabilize employment and stimulate business are also necessary, but they are not the main drivers to solve this crisis from the root.

Submission declaration

I would like to declare on behalf of my co-authors that this work is original research that has not been published previously, and is not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed. And its publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out, and that, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

Authors' contributions

Xiaochun Guo conceived of the presented idea, contributing to the methodology, software, initial formal analysis and original writing of this paper. Fengbin Lu were responsible for the investigation, validation and review of the paper. Yunjie Wei further modified the manuscript, provided subsequent analysis, created the visualization of this paper and finalized the paper. The empirical discussions were the mutual work of all authors.

Declaration of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix**Table 1A**

Betweenness centrality

	Pre-COVID-19	Mid-COVID-19
btc	0.5	1
usa	5.0	1
eu	0	1
cn	10.5	0
gold	12.5	0
usd	0	0
gsci	2.3	0
vix	5.3	0
bond	1.5	0