Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach

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Abstract

We use a data-driven methodology, namely the directed acyclic graph, to uncover the contemporaneous and lagged relations between Bitcoin and other asset classes. The adopted methodology allows us to identify causal networks based on the measurements of observed correlations and partial correlations, without relying on a priori assumptions. Results from the contemporaneous analysis indicate that the Bitcoin market is quite isolated, and no specific asset plays a dominant role in influencing the Bitcoin market. However, we find evidence of lagged relationships between Bitcoin and some assets, especially during the bear market state of Bitcoin. This finding suggests that the integration between the Bitcoin and other financial assets is a continuous process that varies over time. We conduct forecast error variance decompositions and find that the influence of each of the other assets on Bitcoin over a 20-day horizon does not account for more than 11% of all innovations.

JEL classifications: G11, G15

1. Introduction

Bitcoin is an electronic scheme that facilitates the transfer of value between parties. Based on peer-to-peer networking and cryptographic protocols, it allows users to make anonymous transactions, just as with cash, but through the Internet and without the need for financial intermediaries. In that sense, Bitcoin is fully decentralized without reference to third parties, such as central banks and governmental institutions, and does not make claims on anybody (Weber 2016). Interestingly, its supply is limited by the design of the protocol, with the number of coins being asymptotically capped at 21 million. While Bitcoin does not have physical representation, it can be stored directly on computers and smartphones using an online wallet (Brito and Castillo 2013).

Shortly after its proposition by an individual or group of programmers under the pseudonym Satoshi Nakamoto (2008), Bitcoin was implemented on January 3, 2009 and the first payment occurred on January, 11 2009. For more than three years, interest in this first cryptocurrency was low and limited to its strict role in e-commerce. Then the Bitcoin network started to expand, gaining widespread acceptance; and in late 2012, the transaction volume started to grow exponentially and Bitcoin's market value followed the same path. In particular, more users have emerged to profit from movements in the price of Bitcoin, given that the tradability of the unit of value possessed by Bitcoin has raised possibilities for speculation. Given the limited supply of Bitcoin, one can imply that some investors hold Bitcoin as a store of value to the detriment of its role as an alternative payment system. Baur et al. (2015) and Bouri et al. (2017a) stress the valuable role of Bitcoin as an investment. While Bitcoins are minted in a process called "mining" as a reward for confirming transactions through solving mathematical algorithms, they can be bought and sold electronically on exchange platforms using traditional currencies. As of December 2016, the Bitcoin market capitalization reached more than 15.6 billion US dollars.

Given evidence on the role of Bitcoin as an investment asset, the issue of its causal relationship with other financial assets such as equities, bonds, currencies, and commodities needs to be uncovered. In particular, increased or decreased interdependencies among Bitcoin and other financial assets have potential impacts on global investors' assets allocation decisions and on policymakers in countries that are likely to consider Bitcoin as official digital currencies or part of their foreign reserves.

Although numerous studies have so far considered the relationship between Bitcoin and other economic and financial variables, there remains scepticism on the contemporaneous and lagged causal relationship between Bitcoin and numerous financial assets, and a lack of understanding on the integration of the Bitcoin market with the markets of other financial assets. Prior studies consider the relation between Bitcoin and a few financial assets that include: UK equities, EUR/USD, GBP/USD (Dyhrberg 2016), alternative monetary systems (Rogojanu and Badea 2014), metals and currencies (Baur et al. 2015), global macro-financial development (Ciaian et al. 2016b), energy commodities (Bouri et al. 2017c), global uncertainty (Bouri et al. 2017b), and trading volume (Balcilar et al. 2017). While Brière et al. (2015) point toward the low correlation of Bitcoin with traditional assets and commodities, they simply rely on the correlation coefficient and do not account for structural breaks. Interestingly, Bouri et al. (2017a) use a correlation approach based on the dynamic conditional correlation model of Engle (2002) and consider the relation between Bitcoin returns and the returns of several international equity market indices as well as commodities. However, the authors focus only on the hedge and safe haven property of Bitcoin by employing a pairwise dynamic correlation-based model. Similarly, Bouri et al. (2017c) consider the pairwise relation between Bitcoin returns and fluctuations in commodities markets, including energy and non-energy commodities, by employing the asymmetric dynamic conditional correlation model of Cappiello et al. (2006).

Given the unique characteristics of Bitcoin returns (Brière et al. 2015) and their insignificant relationship with fluctuations of global macroeconomic aggregates (Brière et al. 2015; Polasik et al. 2015), it follows that the Bitcoin market may be weakly related to other financial assets. In fact, numerous studies have pointed toward the weak integration of the Bitcoin market by demonstrating that Bitcoin prices are affected by a unique set of non-economic and non-financial factors that include, among others, Bitcoin attractiveness indicators (Ciaian et al. 2016a, 2016b; Kristoufek 2013), attention in the news media (Lee 2014), anonymity of Bitcoin payment transactions (EBA 2014; Yermack 2013), Bitcoin use in illegal activities (Böhme et al. 2015; Yelowitz and Wilson 2015), computer programming enthusiasts (Yelowitz and Wilson 2015), cyber-attacks (Moore and Christin 2013), speculative bubbles (Cheung et al. 2015; Cheah and Fry 2015), and the cost of mining Bitcoin (Garcia et al. 2014; Hayes 2016; Li and Wang 2016).

In this study, we instead use a purely data-driven approach, namely the directed acyclic graph (DAG), to draw a complete picture representing contemporaneous and lagged causal flows among Bitcoin and a large set of financial assets (equities, bonds, currencies, and commodities). We account for the presence of structural breaks endogenously and derive forecast error decompositions. We also calculate a network centrality measure along the lines of Ahern and Harford (2014).

Our analysis provides at least four contributions. First, we use the DAG technique, which has the advantage of not requiring any prerequisite knowledge of the correct structural model. Interestingly, the DAG is a data-driven methodology that extracts the network of contemporaneous causality across a set of variables from the correlation and partial correlation structure of the data by applying logical arguments. Therefore, unlike the Granger causality approach, the DAG identifies a map that enables the causal order to be uncovered without relying on ad hoc network structures. Widely used in the scientific literature, DAG has only been recently applied to finance (Awokuse and Bessler 2003; Bessler and Yang 2003; Ji and Fan 2015; Ji and Fan 2016). To the best of our knowledge, this is the first application of the DAG method within a large set of financial assets that includes Bitcoin. Second, we derive forecast error decompositions based on the DAG results in order to consider whether Bitcoin prices are statistically exogenous or endogenous relative to each of the examined financial assets at differing forecast horizons (one and 20 days). Third, we consider a large number of financial assets that include not only conventional investments such as international equities, bonds, and currencies, but also commodities. In examining equity indices, we particularly consider Chinese equities, given evidence on the importance of Chinese users in the Bitcoin market. We focus on a general commodity index and gold price, as several studies refer to Bitcoin as a "digital" commodity or "digital" gold. Moreover, energy commodities are considered in the causality analysis since energy in the form of electricity represents the main input in Bitcoin mining. We also focus on the dollar index, given the wide acceptance and use of Bitcoin as a digital currency. Finally, given evidence that the causality estimates might be adversely affected by the presence of structural breaks, we account for these endogenously by relying on the Bai and Perron (2003) method.

Our analysis reveals interesting findings. Specifically, we reveal a complete lack of any contemporaneous causality between Bitcoin and all the financial assets under study, suggesting a complete isolation of the Bitcoin market. While the lagged causality analysis also reveals that the Bitcoin market is completely isolated during sub-period II of its bull market state, it is influenced by world and Chinese equities as well as by (energy) commodities and the US dollar in other sub-periods. In all periods, the centrality measure for the Bitcoin market is the lowest, confirming the main results that Bitcoin is the least central in the network structure.

The rest of the paper is structured as follows. Section 2 describes the data. Section 3 provides the empirical models. Section 4 presents the empirical results. Finally, section 5 concludes.

2. Methodology

In this section, the interdependence between Bitcoin price returns and fluctuations in other financial variables is modelled by employing vector autoregression (VAR) or Error correction model (ECM) models. Moreover, contemporaneous causality among the examined variables is identified using a DAG approach, and then forecast error variance decomposition is estimated based on determined contemporaneous causal ordering by DAG. Due to the wide application of VAR and ECM in the literature, we will pay particular attention to the DAG approach.

2.1 *ECM*

Let X_t denote a vector of eight selected variables. Assuming cointegration in that the variables integrated are of the same order (detailed tests are presented in Section 4), the corresponding ECM is specified as follows:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + \varepsilon_t \qquad (t = 1, 2, \ldots, T), \tag{1}$$

where Δ is the difference operator ($\Delta X_t = X_t - X_{t-1}$). Π is a coefficient matrix $\Pi = \alpha\beta'$, where β is the cointegrating vector and α indicates the speed of adjustment in response to deviation from the cointegrating relationship. Γ_i is a matrix of short-run dynamic coefficients, μ is a vector of intercepts, and ε_t is a vector of innovations.

The estimated coefficients from VAR or ECM are generally difficult to interpret, while innovation accounting is considered to be a better way to explore the dynamic structure (Sims 1980). Forecast error variance decomposition is then employed, based on ECM. However, there is a basic problem of the orthogonalization of ECM innovations that need a contemporaneous causal assumption. Previous research has often adopted Cholesky factorization, which imposes restrictions on a recursive contemporaneous causal structure. However, economic theories rarely provide guidance for contemporaneous causal ordering and most assumptions are only based on subjective settings (Ji 2012). The DAG method is relevant as a data-driven approach used to identify contemporaneous causal patterns, which overcomes the unrealistic assumption of a recursive structure in the Cholesky decomposition and the inadequacy of structural factorization (Cody and Mills 1991).

2.2 *DAG theory*

Introduced by Spirtes et al. (2000) to quantitatively determine the contemporaneous causal relations among variables, the DAG approach has been widely applied to commodity and finance markets (Awokuse and Bessler 2003; Bessler and Yang 2003; Ji and Fan 2015; Ji and Fan 2016). It is a graph structure that can be determined based on observed correlations and partial correlations. Directed edges in the DAG are used to depict the contemporaneous causal relations between variables. There are four possible edge relations in the DAG: (1) a non-directed edge (X Y) indicates that X is independent of Y; (2) an undirected edge (X—Y) indicates that the causal direction cannot be confirmed; (3) a directed edge (X→Y) indicates that the changes of X can directly influence the changes of Y; (4) a bidirectional edge (X↔Y) indicates a bidirectional causality between X and Y. In this paper, a PC algorithm proposed by Spirtes et al. (2000) is employed to build DAGs using Tetrad IV software. The PC algorithm has two main steps (Ji 2012):

First, a complete undirected graph is built in which all variables are linked. The unconditional correlation matrix is calculated and edges are removed from the undirected graph if the unconditional correlation between the variables is not statistically different from zero.

Second, first-order partial correlation is tested for the remaining edges; and edges connecting two variables whose first-order partial correlation is not statistically different from zero are removed. Edges that survive the first-order test are then tested by second-order partial correlation and so on. The algorithm continues until all the edges are removed or the $N-2$-order partial correlation test is completed for N variables.

In this process, the conditional variable(s) on removed edges are denoted as the separate set of the variables whose edges have been removed. If one edge is removed by unconditional correlation, its separate set is empty. All the remaining edges based on the above two steps can be directed using the separate set (Bessler and Yang 2003). Triples of variables are selected to be directed, considering a triple relation X—Y—Z, such that X and Y are adjacent, as are Y and Z, but X and Z are not adjacent. If Y is not in the separate set of X and Z, then X—Y—Z should be directed as X→Y←Z. Otherwise, there are three possible orientation results: X→Y→Z, X←Y→Z, or X←Y←Z. To determine the correct orientation, additional information from other identified adjacent linked triples such as Y→Z←L and an exogenous restriction such as X→Y is required. From these basic logic algorithms, all the remaining edges can be directed and the DAG is confirmed.

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

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

where n is the number of observations, $\rho(i, j|k)$ is the population conditional correlation between series i and j conditional on series k, and $|k|$ is the number of series in k. If series i, j, and k are normally distributed and $\rho_1(i, j|k)$ is the sample conditional correlation of i and j given k, then the distribution of $z(\rho(i, j|k), n) - z(\rho_1(i, j|k), n)$ is standard normal (Bessler and Yang 2003; Ji 2012).

3. Data and sample analysis

The dataset considered in this study consists of daily price index values for Bitcoin and several financial assets, namely stocks, bonds, commodities, and currencies. Depicted by the availability of Bitcoin prices, the sample period is from 19 July, 2011 to 31 January, 2017. The Bitcoin price index in US dollars is collected from CoinDesk (www.coindesk.com/price), which aggregates prices from leading Bitcoin exchanges into a reference CoinDesk Bitcoin Price Index series (Bouri et al. 2017b, 2017c). Data on other financial assets are collected from DataStream and cover the price index of MSCI World, MSCI China, Pimco investment grade bond, S&P GSCI Commodity, S&P GSCI energy, ounce of gold, and US dollar index. Statistics of the daily logarithmic price-level series for the entire sample period are summarized in Table 1. Bitcoin has the highest standard deviation, confirming the findings from Pieters and Vivanco (2017) that Bitcoin is more volatile than gold, exchange rates, and stock market prices. However, it has the second lowest mean after the Pimco's investment grade bond index. As with the MSCI world and commodity/energy indices, Bitcoin is negatively skewed. All series are normally distributed as shown by the Jarque-Bera statistics.

Table 1. Summary statistics of all the logarithm price-level time series (2010-7-19~2017-1-31)

Variables	Mean	Std. Dev	Skewness	Kurtosis	Jarque-Bera
Bitcoin	3.907	2.666	-0.890	2.763	229.579***[a]
MSCI_world	7.301	0.148	-0.381	1.706	160.314***
MSCI_China	4.114	0.098	0.396	3.764	86.097***
GSCI_commodity	8.271	0.324	-0.867	2.119	268.976***
GSCI_energy	6.695	0.429	-0.944	2.296	288.850***
Gold	7.219	0.143	0.399	2.011	114.878***
US dollar	4.444	0.094	0.517	1.795	179.278***
Investment grade	2.368	0.038	0.821	3.893	248.462***

Note: [a] *** Significant at the 1% level.

Breakpoint tests proposed by Bai and Perron (1998, 2003) are estimated for the Bitcoin price. Two breakpoints are detected, which are 2013-12-2 and 2015-1-15 (see Table 2). The first break date has been documented in prior studies (Cheah and Fry 2015; Bouri et al. 2017c) and corresponds to the Bitcoin price crash of December 2013, partially in response to new Chinese regulations against the use and acceptance of this cryptocurrency. The second break date coincides with the Bitcoin bullish reversal pattern seen in January 2015. According to the two detected breakpoints, the full sample period is divided into three sub-periods: sub-period I (2010-7-19~2013-12-2, 881 observations), sub-period II (2013-12-3~2015-1-15, 293 observations), and sub-period III (2015-1-16~2017-1-31, 533 observations). Figure 1 depicts the price of Bitcoin accounting of the two break dates.

Table 2. Multiple breakpoint tests for Bitcoin prices

Break Test	F-statistic	Scaled F-statistic	Critical value[c]
Sequential F-statistic determined breaks[a]: 2			
0 vs. 1 **[b]	46.79787	93.59575	11.47
1 vs. 2 **	15.98451	31.96902	12.95
2 vs. 3	3.589755	7.179511	14.03
Break Dates			
2013-12-2			
2015-1-15			

Note: [a] Bai-Perron tests of L+1 vs. L sequentially determined break is applied (Bai 1997; Bai and Perron 1998).

[b] ** Significant at the 5% level.

[c] Bai-Perron (2003) critical values.

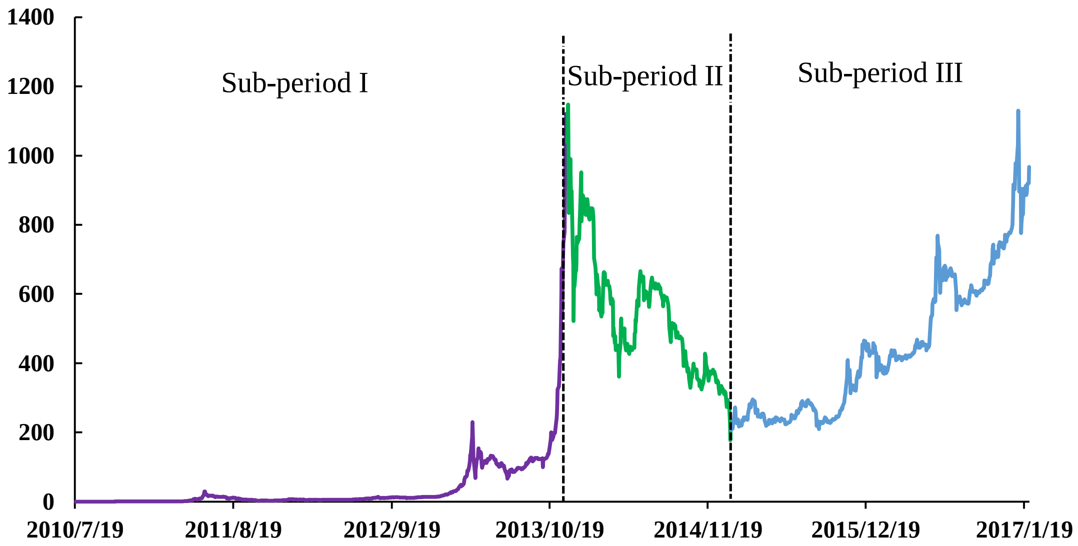

Figure 1. Historical trend of Bitcoin price

4. Empirical analysis

4.1 Sub-period I

Table 3 shows the results of unit root tests (augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS)), which indicate that all the variables under study are integrated of order one, $I(1)$. Accordingly, a VAR model is constructed and the Johansen cointegration test (Johansen and Juselius 1990) is applied. The results in Table 3 also show that the null hypothesis of no cointegration vector cannot be rejected, suggesting a lack of cointegration relationships among these variables in sub-period I. A VAR model in first differences (without cointegration) is further estimated to obtain the contemporaneous innovation correlation matrix. According to the Akaike information criterion (AIC) and Hannan-Quinn information criterion (HQ), an order of two lags is selected in the VAR model. Then, a DAG-based contemporaneous causal structure is constructed using the PC algorithm.

Table 3. Unit root tests and cointegration tests for sub-period I

Variables	ADF[b]	PP	KPSS	Variables	ADF	PP	KPSS
Bitcoin	-1.053	-1.306	0.317***[a]	ΔBitcoin	-29.358***	-29.549***	0.168
MSCI_world	-2.061	-2.082	0.520***	ΔMSCI_world	-18.379***	-26.640***	0.078
MSCI_China	-2.177	-2.278	0.434***	ΔMSCI_China	-28.494***	-28.475***	0.061
GSCI_commodity	-3.218	-3.236	0.301***	ΔGSCI_commodity	-29.594***	-29.594***	0.045
GSCI_energy	-3.127	-3.136	0.261***	ΔGSCI_energy	-29.979***	-29.978***	0.032
Gold	-1.543	-1.464	0.798***	ΔGold	-30.273***	-30.323***	0.022
US dollar	-3.019	-3.049	0.307***	ΔUS dollar	-30.118***	-30.118***	0.067
Investment grade	-1.879	-2.024	0.361***	ΔInvestment grade	-28.348***	-28.404***	0.071

Hypothesized No. of CE(s)[c]	Trace Statistic	C(5%)[d]	Max-Eigen Statistic	C(5%)	D[e]
None	147.005	159.530	45.946	52.363	F
At most 1	101.059	125.615	30.948	46.231	F
At most 2	70.110	95.754	24.998	40.078	F
At most 3	45.113	69.819	14.987	33.877	F

Note: [a] *** Significant at the 1% level.

[b] The null hypothesis of ADF and PP is that the series contain a unit root, while that of KPSS indicates that the series are stationary.

[c] The number of cointegrating vectors is tested using the trace test and max-eigenvalue test with the trend and intercept terms at 5% significance.

[d] C(5%) denote critical value of trace test and max-eigenvalue test at 5% significance.

[e] 'D' gives decision to reject (R) or fail to reject (F) at 5% significance.

Experiments reported in Spirtes et al. (2000) imply that the significance level should decrease as the sample size increases. Thus, the 1% significance level is chosen based on the sample size (881 observations) of sub-period I, as suggested by Spirtes et al. (2000). Software Tetrad IV is applied to program the PC algorithm to obtain DAG (Scheines et al. 1996). Figure 2a shows the contemporaneous causal structure by DAG, whereas Figure 2b displays the lagged causal structure by Granger causality tests for sub-period I.

The DAG contemporaneous causal structure reveals that Bitcoin is totally isolated, which can be partially explained by the absence of any governmental support for or control of Bitcoin production (Dyhrberg 2016). As for the lagged causal structure (Figure 2b), results indicate that Bitcoin is directly affected by gold and world/Chinese equities at the 5% significance level. Bouoiyour and Selmi (2015) highlight the impact of the Chinese stock market on the Bitcoin market.

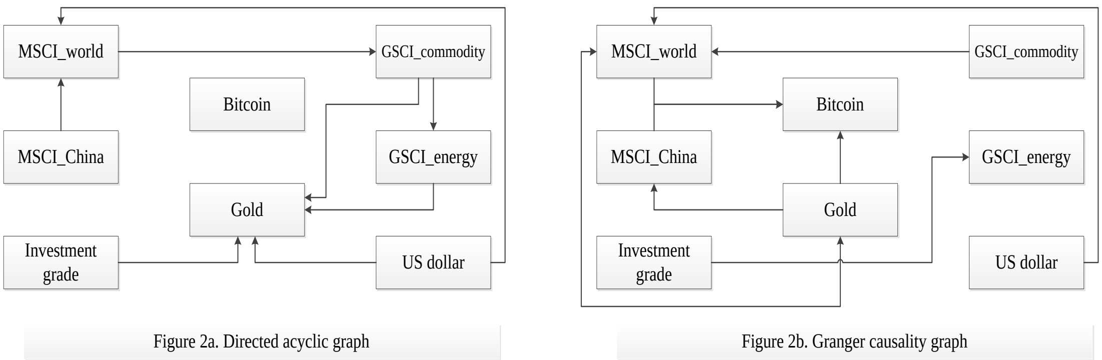

Figure 2. The contemporaneous and lagged causal structure graph for sub-period I

Table 4 presents the percentage of the forecast error in each variable that can be attributed to innovations in all the variables at the contemporaneous, 1-, and 20-day horizons in sub-period I. Table 4 shows that relative to other financial assets, Bitcoin is more independent, given that its volatility is mostly explained by itself: 86% of Bitcoin's price volatility is attributed to itself at the 20-day horizon, compared with a 100% contribution at the contemporaneous time. The volatility of the Bitcoin price can be slightly explained by seven other financial assets in both the contemporaneous and the short-term time horizons. In each case, the largest contribution made by each of the seven financial assets is roughly 5% of Bitcoin volatility.

On the other hand, except for US dollar index and Pimco investment grade bond, the variance decomposition results for other financial assets indicate the high integration of the financial system. At the 20-day horizon, 30% to 50% of the volatilities for equities and commodities can be explained by each other. Specifically, the US dollar index and MSCI world equity make the largest contributions to the volatility of other assets, behind the self-explanatory ability of each asset.

Table 4. Variance decomposition of sub-period I with the contemporaneous structure in Figure 2a

step	Bitcoin	MSCI_world	MSCI_China	GSCI_commodity	GSCI_energy	Gold	US dollar	Investment grade
				(Bitcoin)				
0	100.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	98.078	0.023	0.000	0.022	0.018	1.511	0.227	0.121
20	86.086	1.152	1.451	2.962	1.934	3.408	1.635	1.371
				(MSCI_world)				
0	0.000	56.734	11.464	0.000	0.000	0.000	31.802	0.000
1	0.051	55.969	11.191	0.141	0.043	0.812	31.791	0.000
20	2.195	49.266	12.280	1.276	2.241	2.480	29.655	0.606
				(MSCI_China)				
0	0.000	0.000	100.000	0.000	0.000	0.000	0.000	0.000
1	0.222	13.718	75.895	0.050	0.011	0.332	9.562	0.210
20	1.476	13.362	67.913	2.366	2.129	1.731	10.178	0.846
				(GSCI_commodity)				
0	0.000	18.808	3.800	66.850	0.000	0.000	10.542	0.000
1	0.151	18.840	3.804	66.384	0.016	0.088	10.486	0.232
20	2.819	18.465	4.576	56.566	2.783	2.372	10.787	1.631
				(GSCI_energy)				
0	0.000	17.819	3.601	63.337	5.254	0.000	9.988	0.000
1	0.173	17.840	3.606	62.937	5.225	0.008	9.935	0.275
20	2.896	17.493	4.582	53.591	6.716	2.503	10.723	1.495
				(Gold)				
0	0.000	1.803	0.364	6.408	6.842	78.997	3.716	1.869
1	0.256	1.925	0.425	6.497	6.802	77.113	4.775	2.207
20	2.132	4.237	2.933	7.217	7.529	67.085	5.524	3.342
				(US dollar)				
0	0.000	0.000	0.000	0.000	0.000	0.000	100.000	0.000
1	0.000	0.564	0.003	0.002	0.366	0.088	98.938	0.039
20	1.961	2.534	2.132	1.120	2.839	1.281	86.674	1.460
				(Investment grade)				
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	100.000
1	0.147	0.855	0.020	0.025	0.058	0.254	0.831	97.808
20	3.471	2.553	3.075	2.707	4.770	2.168	2.973	78.282

4.2 Sub-period II

Table 5 shows the results of unit root tests from sub-period II, which indicate that all the variables are integrated of order one, $I(1)$. Both the trace test and max-eigenvalue test show the presence of two cointegrating equations at the 5% significance level. This result suggests that there is a long-term equilibrium relationship among these variables. Accordingly, an ECM is constructed with one lag, as indicated by the Schwarz criterion (SC) and HQ. According to the cointegration results, the cointegration vector is likely to be a linear combination of a subset of the eight variables. Therefore, to further confirm the correct cointegration structure, two steps were used to re-estimate the ECM by restricting the structure of the cointegration vector (Bessler and Yang 2003):

(1) Long-run exclusion test. This test can identify whether each variable is in the cointegration vector. The ECM is re-estimated while restricting each variable's value of β to zero. From Table 6, only gold and investment grade are not in the cointegration vector, which fails to reject the null hypothesis at the 10% significance level.

(2) Weak-Exogeneity Test. This test is to examine the response to the deviation of each variable from the cointegration vector. This test places restrictions on the speed-of-adjustment parameter α. From Table 6, only MSCI world, gold, and investment grade cannot adjust after they have been disturbed by shocks.

Table 5. Unit root tests and cointegration tests for sub-period II

Variables	ADF[b]	PP	KPSS	Variables	ADF	PP	KPSS
Bitcoin	-2.755	-2.543	0.165^{**a}	ΔBitcoin	-19.842***	-19.777***	0.085
MSCI_world	-2.614	-2.508	0.292***	ΔMSCI_world	-13.873***	-13.873***	0.027
MSCI_China	-2.836	-2.821	0.186**	ΔMSCI_China	-17.423***	-17.478***	0.081
GSCI_commodity	2.424	2.181	0.473***	ΔGSCI_commodity	-21.716***	-21.247***	0.195**
GSCI_energy	2.630	2.318	0.451***	ΔGSCI_energy	-21.191***	-20.762***	0.235***
Gold	-2.310	-2.420	0.333***	ΔGold	-17.205***	-17.210***	0.089
US dollar	-0.571	-0.636	0.506***	ΔUS dollar	-20.915***	-21.132***	0.037
Investment grade	-3.040	-3.167	0.334***	ΔInvestment grade	-16.477***	-16.466***	0.101

Hypothesized No. of CE(s)[c]	Trace Statistic	C(5%)[d]	Max-Eigen Statistic	C(5%)	D[e]
None*	190.428	159.530	64.193	52.363	**R**
At most 1*	126.235	125.615	49.505	46.231	**R**
At most 2	76.730	95.754	26.891	40.078	F
At most 3	49.840	69.819	21.063	33.877	F

Note: [a] **, *** Significant at the 5% and 1% levels, respectively.

[b] The null hypothesis of ADF and PP is that the series contain a unit root, while that of KPSS indicates that the series are stationary.

[c] The number of cointegrating vectors is tested using the trace test and max-eigenvalue test with the trend and intercept terms at 5% significance.

[d] C(5%) denote critical value of trace test and max-eigenvalue test at 5% significance.

[e] 'D' gives decision to reject (R) or fail to reject (F) at 5% significance.

Table 6. Tests of exclusion of each variable from the cointegration vector and test of weak exogeneity for sub-period II (given two cointegration vectors)

Tests of exclusion[b]			Test of weak exogeneity[c]		
Variable	χ^2 Statistics	D[d]	Variable	χ^2 Statistics	D
Bitcoin	22.434***	**R**	Bitcoin	13.244***	**R**
MSCI_world	22.318***	**R**	MSCI_world	2.002	F
MSCI_China	4.668*	**R**	MSCI_China	5.876*	**R**
GSCI_commodity	15.349***	**R**	GSCI_commodity	22.998***	**R**
GSCI_energy	16.952***	**R**	GSCI_energy	22.500***	**R**
Gold	1.232	F	Gold	2.875	F
US dollar	9.385***	**R**	US dollar	21.950***	**R**
Investment grade	2.284	F	Investment grade	3.761	F

Note: [a] *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

[b] Tests are on the null hypothesis that the particular variable listed is not in the cointegration space. The test is constructed by re-estimating VECM model in which the cointegration coefficient β of the corresponding variable is restricted to zero.

[c] Tests are on the null hypothesis that the particular variable is not-responsive to deviation from previous cointegration relationship; that is, the variable's speed-of-adjustment α is zero.

[d] 'D' relates to the decision to reject (R) or fail to reject (F) the null hypothesis at 10% significance.

]

Referring to Spirtes et al. (2000), higher significance levels may improve performance at small sample sizes. Thus, the 5% significance level is chosen based on the sample size (293 observations) of sub-period II. Figure 3a and Figure 3b show respectively the contemporaneous causal structure by DAG and the lagged causal structure by Granger causality tests for sub-period II.

As in sub-period I, the DAG contemporaneous causal structure reveals that Bitcoin is totally isolated. However, the lagged causal structure indicates that Bitcoin is no longer affected by gold, as in the sub-period I. Instead, Bitcoin is directly affected by (energy) commodities, suggesting the importance of the energy cost of mining in the Bitcoin bear market state. Bouri et al. (2017c) argue that during the period that follows the Bitcoin price crash of 2013 (sub-period II), mining activities become less profitable, which makes miners simply interrupt mining on less profitable mining hardware platforms.

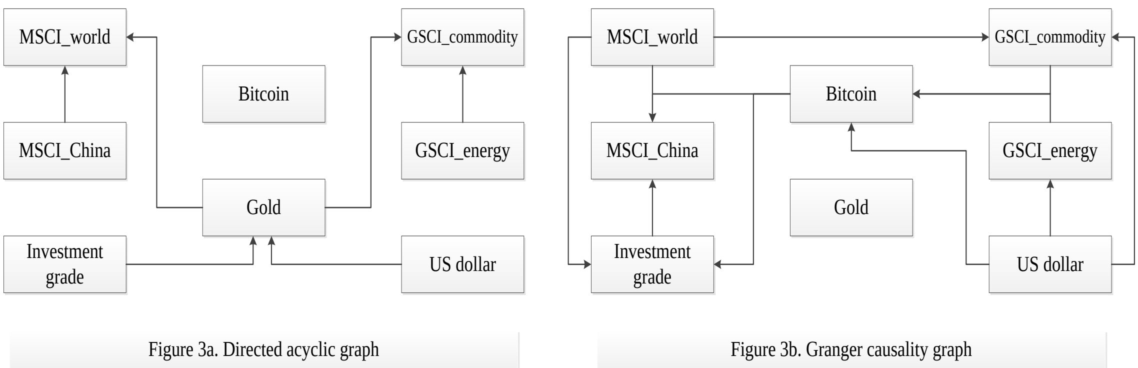

Figure 3. The contemporaneous and lagged causal structure graph for sub-period II

As shown in Table 7, the results of variance decomposition confirm the viewpoint from the Granger causality analysis presented above. That is, the volatility of Bitcoin can be better explained by other financial assets under the situation of its bear market

Table 7. Variance decomposition of sub-period II with the contemporaneous structure in Figure 3a

step	Bitcoin	MSCI_world	MSCI_China	GSCI_commodity	GSCI_energy	Gold	US dollar	Investment grade
(Bitcoin)								
0	100.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	94.939	3.529	0.117	0.211	0.366	0.504	0.215	0.119
20	49.171	9.768	6.134	10.589	6.953	5.551	5.962	5.872
(MSCI_world)								
0	0.000	94.148	2.810	0.000	0.000	2.731	0.282	0.028
1	4.538	87.192	3.128	1.331	0.007	2.215	0.227	1.363
20	8.456	56.396	7.671	8.748	2.846	3.160	6.288	6.433
(MSCI_China)								
0	0.000	0.000	100.000	0.000	0.000	0.000	0.000	0.000
1	0.695	18.036	75.708	0.977	0.052	0.156	0.070	4.307
20	4.987	14.744	47.082	8.398	4.176	6.124	5.574	8.915
(GSCI_commodity)								
0	0.000	0.000	0.000	4.799	95.136	0.059	0.006	0.001
1	1.784	3.557	0.007	8.032	84.332	0.391	0.883	1.015
20	5.775	6.607	8.281	8.587	53.419	6.511	4.965	5.855
(GSCI_energy)								
0	0.000	0.000	0.000	0.000	100.000	0.000	0.000	0.000
1	1.102	2.780	0.004	4.791	88.386	0.549	0.907	1.482
20	5.758	5.426	8.691	7.492	55.650	5.303	5.954	5.724
(Gold)								
0	0.000	0.000	0.000	0.000	0.000	89.795	9.277	0.929
1	0.445	1.697	2.585	1.168	0.023	84.097	9.062	0.922
20	5.482	8.570	7.358	8.583	9.336	45.731	9.159	5.780
(US dollar)								
0	0.000	0.000	0.000	0.000	0.000	0.000	100.000	0.000
1	2.113	1.857	3.671	0.255	2.395	0.108	89.541	0.061
20	3.572	10.082	11.819	8.992	16.681	3.624	42.586	2.644
(Investment grade)								
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	100.000
1	0.175	0.429	0.559	0.607	3.367	0.985	1.046	92.832
20	6.801	5.789	7.345	7.206	15.671	8.173	4.294	44.722

state (sub-period II) than under its bull market phase (sub-period I). At the 20-day horizon, no more than 50% of the price volatility for Bitcoin is explained by its own innovations, whereas world/Chinese equities and (energy) commodities can account for approximately 16% and 18% of total Bitcoin price volatility, respectively. Reviewing the results of other assets, the contributions for US dollar index in explaining the volatility of other assets have decreased. This finding differs from that reported in sub-period 1. It can attributed to the continuous depreciation of the US dollar during the sub-period II from 2013 to 2014 and the weak influence exerted by the US dollar on other assets. In the meantime, other assets can also explain better the volatility for the US dollar. At the 20-day horizon, world/Chinese equities and (energy) commodities can account for approximately 22% and 26% of total US dollar volatility, respectively.

Table 8. Unit root tests and cointegration tests for sub-period III

Variables	ADF[b]	PP	KPSS	Variables	ADF	PP	KPSS
Bitcoin	-2.911	-2.978	0.186**[a]	ΔBitcoin	-23.084***	-23.089***	0.027
MSCI_world	-2.317	-1.949	0.497***	ΔMSCI_world	-19.678***	-19.483***	0.065
MSCI_China	-1.306	-1.402	0.480**	ΔMSCI_China	-17.423***	-17.478***	0.081
GSCI_commodity	-1.341	-1.244	0.532***	ΔGSCI_commodity	-24.532***	-24.550***	0.089
GSCI_energy	-1.494	-1.413	0.511***	ΔGSCI_energy	-24.581***	-24.581***	0.091
Gold	-2.127	-2.111	0.334***	ΔGold	-23.309***	-23.320***	0.110
US dollar	-2.940	-3.013	0.237***	ΔUS dollar	-22.431***	-22.424***	0.047
Investment grade	-1.398	-1.496	0.456***	ΔInvestment grade	-23.289***	-23.338***	0.102

Hypothesized No. of CE(s)[c]	Trace Statistic	C(5%)[d]	Max-Eigen Statistic	C(5%)	D[e]
None*	163.883	159.530	54.058	52.363	**R**
At most 1	109.825	125.615	39.036	46.231	F
At most 2	70.7889	95.754	25.135	40.078	F
At most 3	45.654	69.819	20.081	33.877	F

Note: [a] **, *** Significant at 5% and 1% levels, respectively.
[b] The null hypothesis of ADF and PP is that the series contain a unit root, while that of KPSS indicates that the series are stationary.
[c] The number of cointegrating vectors is tested using the trace test and max-eigenvalue test with the trend and intercept terms at the 5% level.
[d] C(5%) denote critical value of trace test and max-eigenvalue test at 5% significance.
[e] 'D' gives decision to reject (R) or fail to reject (F) at 5% significance.

4.3 Sub-period III

Table 8 shows the results of unit root tests from sub-period III, which indicate that all the variables are integrated of order one, $I(1)$. Both the trace test and max-eigenvalue test show the presence of two cointegrating equations at the 5% level. This result suggests that there is a long-term equilibrium relationship among these variables.

Accordingly, an ECM is constructed with one lag, as indicated by the SC and HQ.

Both long-run exclusion tests and weak-exogeneity tests are also applied for the ECM in sub-period III. The test results in Table 9 indicate that only GSCI energy is not in the cointegration vector, whereas only gold and investment grade can respond to previous period deviations from the cointegrating relationship at the 10% significance level.

Table 9. Tests of exclusion of each variable from the cointegration vector and test of weak exogeneity for sub-period III (given one cointegration vector)

Tests of exclusion[b]			Test of weak exogeneity[c]		
Variable	χ^2 Statistics	D[d]	Variable	χ^2 Statistics	D
Bitcoin	12.967***	**R**	Bitcoin	2.392	F
MSCI_world	7.772***	**R**	MSCI_world	0.291	F
MSCI_China	11.802***	**R**	MSCI_China	1.218	F
GSCI_commodity	3.412*	**R**	GSCI_commodity	1.777	F
GSCI_energy	2.563	F	GSCI_energy	1.820	F
Gold	11.962***	**R**	Gold	7.755***	**R**
US dollar	11.687***	**R**	US dollar	2.136	F
Investment grade	7.039***	**R**	Investment grade	6.624**	**R**

Note: [a] *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

[b] Tests are on the null hypothesis that the particular variable listed is not in the cointegration space. The test is constructed by re-estimating the VECM model in which the cointegration coefficient β of the corresponding variable is restricted to zero.

[c] Tests are on the null hypothesis that the particular variable is not-responsive to deviation from the previous cointegration relationship; that is, the variable's speed-of-adjustment α is zero.

[d] 'D' relates to the decision to reject (R) or fail to reject (F) the null hypothesis at 10% significance.

For the small sample size (533 observations) of sub-period III, the 5% significance level is chosen. Figure 4a and Figure 4b show respectively the contemporaneous causal structure by DAG and the lagged causal structure by Granger causality tests for sub-period III. It can be seen from Figure 4 that there is an undirected edge between MSCI world and MSCI China, as Tetrad IV's program cannot direct this edge. Therefore, two unidirectional edges MSCI world→MSCI China and MSCI China→MSCI world are separately considered to generate two DAGs for sub-period III.

In contrast with the results in sub-periods I and II, there is no contemporaneous and lagged causality between Bitcoin and other assets in sub-period III. However, the causalities among other assets have become stronger with more significant contemporaneous and lagged edges (Figure 4).

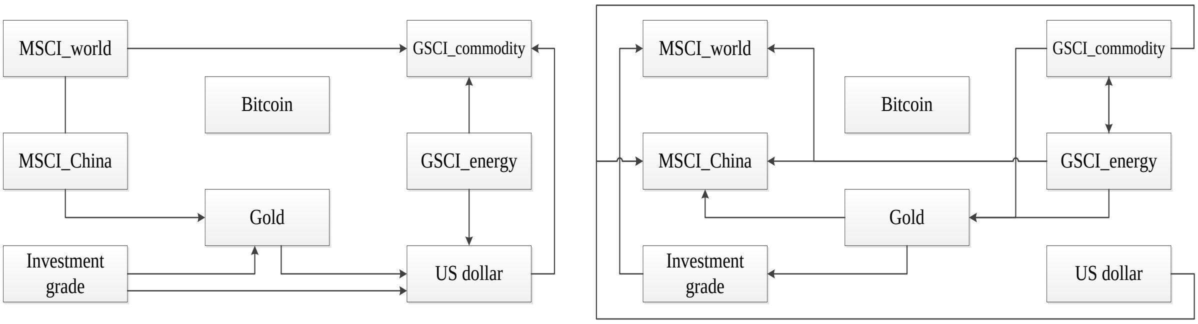

Figure 4a. Directed acyclic graph

Figure 4b. Granger causality graph

Figure 4. The contemporaneous and lagged causal structure graph for sub-period III

Table 10 and Table 11 present the results of variance decomposition in sub-period III, verifying two different contemporaneous causalities of MSCI world→MSCI China and MSCI China→MSCI world, respectively. The results of variance decomposition for Bitcoin is the same in that the volatility of Bitcoin is mainly explained by itself, remaining 80% at the 20-day horizon. Moreover, the impact of each asset on other assets is more dispersed and balanced. However, there are two clear exceptions that are within our expectations. First, at the 20-day horizon, world equity accounts for over 20% of Chinese equity's volatility (Table 10), and vice versa (Table 11). Second, the volatility of general commodity index is mostly explained by the energy commodity index, reaching approximately 95% and 69% at the contemporaneous and 20-day horizons, respectively. This result reflects the core status of energy in the commodity market system, which is also documented by Ji and Fan (2016).

Table 10. Variance decomposition of sub-period III with the contemporaneous structure in Figure 4a (if MSCI_world→MSCI_China)

step	Bitcoin	MSCI_world	MSCI_China	GSCI_commodity	GSCI_energy	Gold	US dollar	Investment grade
				(Bitcoin)				
0	100.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	97.729	0.076	0.428	1.055	0.349	0.091	0.220	0.050
20	80.994	2.390	3.481	3.625	1.973	2.203	3.091	2.243
				(MSCI_world)				
0	0.000	100.000	0.000	0.000	0.000	0.000	0.000	0.000
1	0.001	98.100	0.148	0.069	0.001	0.165	0.053	1.463
20	4.610	75.552	1.791	3.693	5.139	3.872	1.934	3.409
				(MSCI_China)				
0	0.000	27.559	72.441	0.000	0.000	0.000	0.000	0.000
1	0.000	31.716	64.943	0.187	1.407	0.006	0.235	1.506
20	4.699	25.736	52.023	3.550	5.385	3.103	1.566	3.938
				(GSCI_commodity)				
0	0.000	0.109	0.001	3.765	95.821	0.031	0.268	0.005
1	0.066	0.216	0.001	3.755	95.225	0.222	0.511	0.005
20	6.209	6.212	3.895	4.839	69.104	5.048	2.220	2.472
				(GSCI_energy)				
0	0.000	0.000	0.000	0.000	100.000	0.000	0.000	0.000
1	0.102	0.158	0.014	0.017	99.269	0.267	0.154	0.018
20	7.053	5.940	3.939	2.239	70.446	5.720	1.838	2.825
				(Gold)				
0	0.000	0.664	1.744	0.000	0.000	94.266	0.000	3.326
1	0.206	1.672	2.687	0.063	1.057	86.730	1.035	6.550
20	2.926	6.471	5.021	1.769	5.919	68.345	2.849	6.699
				(US dollar)				
0	0.000	0.071	0.187	0.000	0.702	10.112	87.372	1.555
1	0.741	2.410	0.180	0.537	0.686	9.740	84.163	1.544
20	3.322	7.645	2.104	1.695	5.971	10.452	65.371	3.440
				(Investment grade)				
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	100.000
1	0.607	2.201	0.125	0.109	0.011	0.009	0.414	96.526
20	3.780	6.632	3.034	3.184	6.836	3.439	3.996	69.098

Table 11. Variance decomposition of sub-period III with the contemporaneous structure in Figure 4a (if MSCI_China→MSCI_world)

step	Bitcoin	MSCI_world	MSCI_China	GSCI_commodity	GSCI_energy	Gold	US dollar	Investment grade
				(Bitcoin)				
0	100.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
1	97.729	0.335	0.170	1.055	0.349	0.091	0.220	0.050
20	80.994	2.932	2.939	3.625	1.973	2.203	3.091	2.243
				(MSCI_world)				
0	0.000	72.441	27.559	0.000	0.000	0.000	0.000	0.000
1	0.001	70.516	27.732	0.069	0.001	0.165	0.053	1.463
20	4.610	54.408	22.935	3.693	5.139	3.872	1.934	3.409
				(MSCI_China)				
0	0.000	0.000	100.000	0.000	0.000	0.000	0.000	0.000
1	0.000	6.442	90.217	0.187	1.407	0.006	0.235	1.506
20	4.699	6.848	70.911	3.550	5.385	3.103	1.566	3.938
				(GSCI_commodity)				
0	0.000	0.086	0.023	3.765	95.821	0.031	0.268	0.005
1	0.066	0.163	0.053	3.755	95.225	0.222	0.511	0.005
20	6.209	6.194	3.913	4.839	69.104	5.048	2.220	2.472
				(GSCI_energy)				
0	0.000	0.000	0.000	0.000	100.000	0.000	0.000	0.000
1	0.102	0.077	0.095	0.017	99.269	0.267	0.154	0.018
20	7.053	6.039	3.840	2.239	70.446	5.720	1.838	2.825
				(Gold)				
0	0.000	0.000	2.408	0.000	0.000	94.266	0.000	3.326
1	0.206	2.034	2.324	0.063	1.057	86.730	1.035	6.550
20	2.926	5.971	5.521	1.769	5.919	68.345	2.849	6.699
				(US dollar)				
0	0.000	0.000	0.258	0.000	0.702	10.112	87.372	1.555
1	0.741	1.714	0.876	0.537	0.686	9.740	84.163	1.544
20	3.322	4.584	5.164	1.695	5.971	10.452	65.371	3.440
				(Investment grade)				
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	100.000
1	0.607	2.096	0.229	0.109	0.011	0.009	0.414	96.526
20	3.780	5.686	3.980	3.184	6.836	3.439	3.996	69.98

To summarize, the overall results point toward a weak relation among Bitcoin and the different assets under study, which can be explained by the specific factors of cryptocurrencies that drive the Bitcoin price, such as its popularity and the Blockchain technology (Polasik et al. 2015; Ciaian et al. 2016). The Bitcoin literature also provides evidence of an insignificant relation between Bitcoin returns and fluctuations of major global macroeconomic aggregates (Polasik et al. 2015; Ciaian et al. 2016). Similarly, Bouri et al. (2017a, 2017c) indicate a very weak correlation between Bitcoin and conventional assets, general commodities, and energy commodities.

Finally, we follow the lines from Ahern and Harford (2014) and calculate the degree of centrality in Tables 12, 13, and 14. Degree centrality designates the importance of one market in a network relative to other markets. For the three sub-periods, the degree of centrality is the lowest for the Bitcoin market; notably, Bitcoin degree centrality is lower than that for investment grade bonds and gold. In contrast the degree of centrality is the highest for energy commodities, suggesting that the energy market is the most connected to other markets (i.e. at the center of the network structure).

Table 12. Degree centrality of sub-period I

	Bitcoin	MSCI_world	MSCI_China	GSCI_commodity	GSCI_energy	Gold	US dollar	Investment grade
Bitcoin	0	3.347	2.927	5.781	4.830	5.540	3.596	4.842
MSCI_world	3.347	0	25.642	19.741	19.734	6.717	32.189	3.159
MSCI_China	2.927	25.642	0	6.942	6.711	4.664	12.31	3.921
GSCI_commodity	5.781	19.741	6.942	0	56.374	9.589	11.907	4.338
GSCI_energy	4.830	19.734	6.711	56.374	0	10.032	13.562	6.265
Gold	5.540	6.717	4.664	9.589	10.032	0	6.805	5.51
US dollar	3.596	32.189	12.31	11.907	13.562	6.805	0	4.433
Investment grade	4.842	3.159	3.921	4.338	6.265	5.51	4.433	0
Degree centrality	4.409	15.790	9.017	16.382	16.787	6.980	12.115	4.638

Notes: This table provides degree centrality of each market. The upper 8 x 8 submatrix is an adjacency matrix where diagonal elements are zero and off-diagonal elements are the total of the pairwise volatility ties 20-day ahead. Degree centrality is the average of column sum of the off-diagonal total pairwise volatility ties.

Table 13. Degree centrality of sub-period II

	Bitcoin	MSCI_world	MSCI_China	GSCI_commodity	GSCI_energy	Gold	US dollar	Investment grade
Bitcoin	0	18.224	11.121	16.364	12.711	11.033	9.534	12.673
MSCI_world	18.224	0	22.415	15.355	8.272	11.73	16.37	12.222
MSCI_China	11.121	22.415	0	16.679	12.867	13.482	17.393	16.26
GSCI_commodity	16.364	15.355	16.679	0	60.911	15.094	13.957	13.061
GSCI_energy	12.711	8.272	12.867	60.911	0	14.639	22.635	21.395
Gold	11.033	11.73	13.482	15.094	14.639	0	12.783	13.953
US dollar	9.534	16.37	17.393	13.957	22.635	12.783	0	6.938
Investment grade	12.673	12.222	16.26	13.061	21.395	13.953	6.938	0
Degree centrality	13.094	14.941	15.745	21.632	21.919	13.245	14.230	13.786

See notes to Table 12.

Table 14a. Degree centrality of sub-period III (if MSCI_world→MSCI_China)

	Bitcoin	MSCI_world	MSCI_China	GSCI_commodity	GSCI_energy	Gold	US dollar	Investment grade
Bitcoin	0	7.000	8.180	9.834	9.026	5.129	6.413	6.023
MSCI_world	7.000	0	27.527	9.905	11.079	10.343	9.579	10.041
MSCI_China	8.180	27.527	0	7.445	9.324	8.124	3.67	6.972
GSCI_commodity	9.834	9.905	7.445	0	71.343	6.817	3.915	5.656
GSCI_energy	9.026	11.079	9.324	71.343	0	11.639	7.809	9.661
Gold	5.129	10.343	8.124	6.817	11.639	0	13.301	10.138
US dollar	6.413	9.579	3.67	3.915	7.809	13.301	0	7.436
Investment grade	6.023	10.041	6.972	5.656	9.661	10.138	7.436	0
Degree centrality	7.372	12.211	10.177	16.416	18.554	9.356	7.446	7.990

See notes to Table 12.

Table 14b. Degree centrality of sub-period III (if MSCI_China→MSCI_world)

	Bitcoin	MSCI_world	MSCI_China	GSCI_commodity	GSCI_energy	Gold	US dollar	Investment grade
Bitcoin	0	7.542	7.638	9.834	9.026	5.129	6.413	6.023
MSCI_world	7.542	0	29.783	9.887	11.178	9.843	6.518	9.095
MSCI_China	7.638	29.783	0	7.463	9.225	8.624	6.73	7.918
GSCI_commodity	9.834	9.887	7.463	0	71.343	6.817	3.915	5.656
GSCI_energy	9.026	11.178	9.225	71.343	0	11.639	7.809	9.661
Gold	5.129	9.843	8.624	6.817	11.639	0	13.301	10.138
US dollar	6.413	6.518	6.73	3.915	7.809	13.301	0	7.436

Investment grade	6.023	9.095	7.918	5.656	9.661	10.138	7.436	0
Degree centrality	7.372	11.978	11.054	16.416	18.554	9.356	7.446	7.990

See notes to Table 12.

5. Conclusions

This study contributed to the debate about the causal relationship among Bitcoin and several financial assets (equities, bonds, currencies, and commodities) using a DAG methodology and forecast error variance decompositions. Importantly, the flexibility of the DAG approach allowed us to uncover the causal order without relying on ad hoc network structures and avoiding unsubstantiated assumptions.

The main results indicated that the causal relationships among Bitcoin and most of the financial assets under study are not constant over time, but instead are relatively time variant. More importantly, we found that Bitcoin displays no evidence of any contemporaneous causality and a very weak lagged causal relationship with most of the financial assets under study, implying a quite marked isolation of the Bitcoin market with implications for portfolio diversification.

While the overall findings show that no particular asset has played a very dominant role in influencing the Bitcoin market, the (lagged) direct influences of world and Chinese equities as well as commodities on Bitcoin are relatively noticeable, as documented by Bouoiyour and Selmi (2015), Ciaian et al. (2016), and Bouri et al. (2107c). Although US regulatory bodies consider Bitcoin as a (digital) commodity, our results found very weak effects from the markets for conventional commodities on the Bitcoin price. Results from the forecast error variance decomposition highlight the marginal importance of some financial assets in affecting the price volatility of Bitcoin. Further analysis highlights the very weak degree of Bitcoin centrality in the international financial system.

While this study extended our understanding of the very weak integration of the Bitcoin market with the markets of other financial assets, it complements in particular the work of Brière et al. (2015), Baur et al. (2015), Dyhrberg (2016), and Bouri et al. (2017a, 2017c), who show evidence of a weak relationship between Bitcoin and several financial assets.

Our results are useful for global investors who are interested in considering Bitcoin as a part of their international portfolios, as well as for policymakers interested in adopting Bitcoin as an official currency.

Acknowledgements

Qiang Ji acknowledges support from the National Natural Science Foundation of China under Grant No. 91546109, No. 71203210; and Youth Innovation Promotion Association of Chinese Academy of Sciences (Grant: Y7X0231505).

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