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

Qiang Ji[a,b], Elie Bouri[c,*], Rangan Gupta[d], David Roubaud[e]

[a] Center for Energy and Environmental Policy Research, Institutes of Science and Development, Chinese Academy of Sciences, Beijing, 100190, China
[b] School of Public Policy and Management, University of Chinese Academy of Sciences, Beijing, 100049, China
[c] USEK Business School, Holy Spirit University of Kaslik, P.O. Box 446, Jounieh, Lebanon
[d] Department of Economics, University of Pretoria, Pretoria, 0002, South Africa
[e] Montpellier Research in Management, Montpellier Business School, 2300 Avenue des Moulins, 34080, Montpellier, France

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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.

1. Introduction

With the emergence of Bitcoin as an investment asset (see Baur, Hong, & Adrian, 2017; Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017a), an increasing number of international participants have become involved in this market, which is the largest of today's cryptocurrencies. Recent spikes in transaction and trading volumes evidence this trend. Furthermore, Bitcoin's market capitalisation has increased exponentially, from 4.5 billion USD at the end of 2014, to more than 41.6 billion USD as of June 2017. Despite the rising scholarly interest in the economics and finance of Bitcoin, the extent to which the Bitcoin market has integrated into the markets of other asset classes remains largely unexplored. Specifically, there is a perceived threat that the Bitcoin market represents a potential source of financial instability, which suggests the need to monitor its integration into the global financial system (European Central Bank, 2012). Additionally, we must enhance our limited understanding of Bitcoin's market integration with other financial assets for several other reasons. First, it affects the design and implementation of policies for maintaining financial stability. Second, it influences the decisions of policy makers in countries that are likely to consider Bitcoin as an official digital currency or as part of their foreign reserves. Third, it affects investor inferences regarding asset allocation and risk management.

The few existing studies considering the relations between Bitcoin and other economic and financial assets have mostly relied on unconditional correlations (e.g. Baur et al., 2017; Brière, Oosterlinck, & Szafarz, 2015) or are limited to the hedging ability of Bitcoin (e.g. Bouri et al., 2017a; Bouri, Jalkh, Molnár, & Roubaud, 2017c). In the present study, we offer a broad view of contemporaneous causal flows (see Awokuse & Bessler, 2003) between Bitcoin and several asset classes (i.e. equities, bonds, currencies and commodities) via the use of a purely data-driven approach, called the directed acyclic graph (DAG). We endogenously detect structural breaks and derive the forecast error variance decompositions (FEVDs). We also calculate network centrality (i.e., the importance of one market in a network relative to other markets), based on the work of Ahern and Harford (2014).

Our research contribution arises from two main aspects. First, the application of the DAG approach allows us to map the causal order without relying on ad-hoc network structures while avoid-

* Corresponding author.
E-mail addresses: jqwxnjq@163.com (Q. Ji), eliebouri@usek.edu.lb (E. Bouri), rangan.gupta@up.ac.za (R. Gupta), d.roubaud@montpellier-bs.com (D. Roubaud).

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ing unsubstantiated assumptions. Second, the enrichment of the discussion concerning the relationship between the largest cryptocurrency – Bitcoin – and other financial assets provides new empirical evidence under different market situations. Interestingly, our methodological approach allows for uncovering significant differences in the relationship across three sub-periods, with less levels of segmentation shown during the bear-market state. Such findings extend our limited understanding of Bitcoin integration by revealing a time-varying nature of market integration that seems to contradict the general view in the current empirical literature that Bitcoin is isolated from the global financial system.

In our empirical analyses, we consider several financial assets, including the more conventional investments, such as international equities, bonds, and currencies, as well as commodities. In choosing these financial assets, we refer to prior studies that consider the relationship between Bitcoin and key asset classes from the global financial system (Baur et al., 2017; Bouri et al., 2017a,c), which can provide useful implications for the stake of investors and policy makers. In examining the equity market, we consider a global equity index and pay particular attention to Chinese equities, given that Chinese investors and users represent an important group of stakeholders in the Bitcoin market (Bouoiyour & Selmi, 2015; Bouri et al., 2017a). We focus on a general commodity index and on gold prices, as several studies refer to Bitcoin as a 'digital commodity' or 'digital gold' (Baur et al., 2017; Dyhrberg, 2016). We also include energy commodities in the empirical analysis, because energy, particularly in the form of electricity, represents the main input in Bitcoin mining (Li & Wang, 2017; Bouri et al., 2017c; Hayes, 2017). Investment-grade bonds are also part of the analysis because their role as a proxy for sovereign risk might contradict with the role of Bitcoin as new asset class independent from sovereign authorities (Brière et al., 2015; Baur et al., 2017; Bouri et al., 2017a). We also focus on the US Dollar Index given the use of Bitcoin as a (digital) currency (Baur et al., 2017; Bouri et al., 2017a; Polasik, Piotrowska, Wisniewski, Kotkowski, & Lightfoot, 2015).

We structure the remainder of this paper as follows: Section 2 discusses Bitcoin and a selection of its related literature, Section 3 describes the materials and methods, Section 4 provides the empirical results, and Section 5 summarises the conclusions.

2. Bitcoin and asset classes

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 this sense, Bitcoin is fully decentralised without the intervention of third parties, such as central banks or government financial agencies (Weber, 2016). Interestingly, the design of its protocols limits its supply, with the number of Bitcoins asymptotically capped at 21 million. While Bitcoins do not have any physical representations, user can store them directly on computers and smartphones using an online wallet (Brito & Castillo, 2013).

An individual or group of programmers, operating under the pseudonym Satoshi Nakamoto (2008) proposed Bitcoin, and its implementation began on 3 January 2009, with its first payment occurring on 11 January 2009. For more than three years following its inception, interest in this first cryptocurrency was low and its use was strictly limited to e-commerce. Then, in 2012, the Bitcoin network started to expand and gain widespread acceptance; by the end of that year, the transaction volume had grown exponentially, along with Bitcoin's market value. Given the limited supply of Bitcoins, one can infer that some investors regard them as a store of value, to the detriment of Bitcoin's role as an alternative payment system. The minting of Bitcoins occurs through a process called 'mining', as a reward for confirming transactions by solving mathematical algorithms. Users can also buy and sell them electronically on exchange platforms with traditional currencies.

Existing literature considers the individual relations between Bitcoin and a few financial assets and recognises Bitcoin's value as an investment asset (see Baur et al., 2017; Bouri et al., 2017a). These other assets include: UK equities, EUR/USD and GBP/USD (Dyhrberg, 2016); alternative monetary systems (Rogojanu & Badea, 2014); metals and currencies (Baur et al., 2017); global macro-financial development (Ciaian, Rajcaniova, & Kancs, 2016b); energy commodities (Bouri et al., 2017c); global uncertainty (Bouri, Gupta, Tiwari, & Roubaud, 2017b; Bouri, Gupta, Lau, & Roubaud, 2018); and trading volume (Balcilar, Bouri, Gupta, & Roubaud, 2017). While Brière et al. (2015) highlights the low correlation between Bitcoin and traditional assets and commodities, they only rely on the correlation coefficient and do not account for structural breaks. Bouri et al. (2017a) use a correlation approach based on Engle (2002) dynamic conditional correlation model in their examination of the relations 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 properties of Bitcoin, employing a pairwise dynamic correlation-based model. Similarly, Bouri et al. (2017c) consider the pairwise relations between Bitcoin returns and fluctuations in commodity markets, including energy and non-energy commodities, by applying Cappiello, Engle, and Sheppard, 2006 model of asymmetric dynamic conditional correlation.

Given the unique characteristics of Bitcoin returns (see Brière et al., 2015) and their insignificant relationships with fluctuations in the global macroeconomy (see also Polasik et al., 2015), the Bitcoin market may be weakly related to most asset classes. A unique set of non-economic and non-financial factors affect Bitcoin prices. These factors include Bitcoin's attractiveness indicators (2016b, Ciaian, Rajcaniova, & Kancs, 2016a; Kristoufek, 2013), the attention Bitcoin generates in the news (Lee, 2014), the anonymity of Bitcoin payment transactions (EBA, 2014; Yermack, 2013), Bitcoin use in illegal activities (Böhme, Christin, Edelman, & Moore, 2015; Yelowitz & Wilson, 2015), computer-programming enthusiasts (Yelowitz & Wilson, 2015), cyber-attacks (Moore & Christin, 2013), speculative bubbles (Cheah & Fry, 2015; Cheung, Roca, & Su, 2015) and the cost of mining Bitcoin (Garcia, Tessone, Mavrodiev, & Perony, 2014; Hayes, 2017; Li & Wang, 2017).

3. Materials and methods

We studied the interdependence between Bitcoin prices and the other financial variables through the application of the vector autoregression (VAR) and error correction model (ECM) techniques. We use the DAG approach to identify the contemporaneous causality among the examined variables, and then we estimate the FEVDs based on the causal order we determined from the DAG results. Due to the wide application of VAR/ECM techniques in the empirical literature, we paid special attention to the DAG approach in the following subsections.

3.1. ECM

Assuming cointegration is present, in that the variables integrated are of the same order (Section 4 presents detailed tests), the corresponding ECM is as follows:

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

Table 1
A summary of statistics for the daily logarithmic price-level series (19/07/2010–31/01/2017).

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] *** Significance level of 1%.

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

It is worth noting that in the cointegration equation, the cointegration vector is likely a linear combination of a subset of the eight variables. Therefore, to confirm the correct cointegration structure, we further conduct two tests to re-estimate the ECM by restricting the structure of the cointegration vector (see Bessler & Yang, 2003). First is the long-run exclusion test. This test can identify whether each variable is in the cointegration vector by restricting each variable's value of β to zero. If the value of β is significant different from zero, it indicates the corresponding variable is indeed in the cointegration vector; otherwise, its coefficient should be restricted to zero. Second is the weak exogeneity test. This test examines the response to each variable's deviation from the cointegration vector by placing restrictions on the speed-of-adjustment parameter α. Similarity, if the value of α is significant different from zero, it indicates the corresponding variable can adjust the deviation from the cointegrating relationship.

Generally, the estimated coefficients in the ECM are difficult to interpret, while many consider innovation accounting a better way to explore the dynamic structure (Sims, 1980). Based on this, we conduct FEVDs; however, there is a basic problem arising from the orthogonalisation of vectors related to ECM innovations, which requires the assumption of contemporaneous causality. Previous research often adopts Cholesky factorisation, which imposes restrictions on recursive, contemporaneous causal structures, yet economic theories rarely provide guidance for contemporaneous causal ordering and most assumptions are based in subjective settings (Ji, 2012). In this context, the DAG emerges as a useful method for identifying contemporaneous causal patterns, as it is a data-driven approach that overcomes both the unrealistic assumption of a recursive structure in the Cholesky decomposition and the inadequacy of structural factorisation (Cody & Mills, 1991).

3.2. The DAG approach

Spirtes, Glymour, and Scheines (2000) introduced the DAG approach, intending to quantitatively determine the contemporaneous causal relations among a set of variables, and researchers now widely apply it to commodity and financial markets (Awokuse & Bessler, 2003; Bessler & Yang, 2003; Ji & Fan, 2015, 2016). The DAG is a graph structure based on observed and partial correlations, in which directed edges 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) indicating that X is independent of Y, (2) an undirected edge (X–Y) indicating that the causal direction cannot be confirmed, (3) a directed edge (X→Y) indicating that the changes of X can directly influence the changes of Y, and (4) a bidirectional edge (X ↔ Y) indicating a bidirectional causality between X and Y. In the present study, we used a PC algorithm proposed by Spirtes et al. (2000) to build DAGs using the Tetrad IV software package.

According to Ji (2012), the PC algorithm has two main steps. First, we build a complete undirected graph in which we link all variables. We calculate the unconditional correlation matrix, and we remove edges from the undirected graph if the unconditional correlation between the variables is not statistically different from zero. Second, we test the first-order partial correlation in the remaining edges, and we remove edges connecting two variables whose first-order partial correlations are not statistically different from zero. We then test edges that survive the first-order test for second-order partial correlations, and so on. The algorithm continues until we remove all the edges or we complete the *N*-order partial correlation test for *N* variables.

Through this process, we consider the conditional variable(s) on removed edges to be a separate set of variables with removed edges. If we remove one edge due to unconditional correlation, the separate set is empty. All the remaining edges, based on the above two steps, can be directed using the separate set (Bessler & Yang, 2003). We select triples of variables, referring to the relations between X—Y—Z, for direction, 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, we require additional information from other adjacently linked triples identified, such as Y→Z⟵L, and an exogenous restriction, such as X→Y. From these basic logic algorithms, we direct all the remaining edges, thereby completing the DAG.

In application, we use Fisher's *z*-statistic to test whether conditional correlations are significantly different from zero, as follows:

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

where n is the number of observations, $\rho(i, j|k)$ is the sample conditional correlation between the series i and the 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 (see Bessler & Yang, 2003; Ji, 2012).

3.3. Data and sample analyses

The dataset we consider in the present study consists of daily index values for Bitcoin and several asset classes (i.e. stocks, bonds, commodities and currencies). As the availability of Bitcoin prices depicts, the sample period ranges from 19 July 2010 to 31 January 2017. We collect the Bitcoin price index in USD from CoinDesk (www.coindesk.com/price). The latter aggregates prices from leading Bitcoin exchanges into a reference, the CoinDesk Bitcoin Price Index series (Bouri et al., 2017b, 2017c, 2018). Furthermore, we

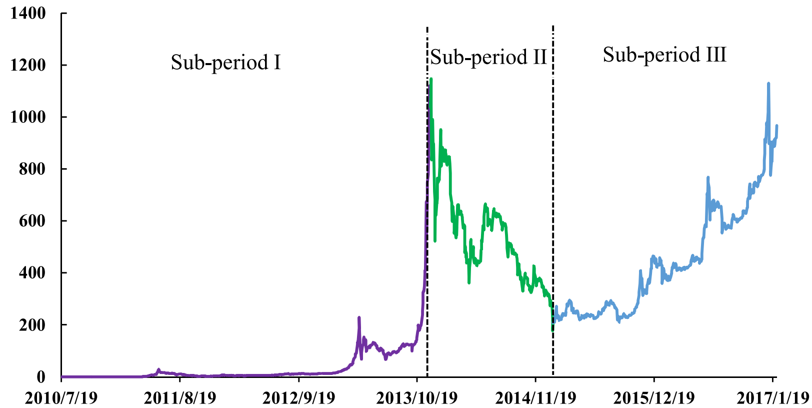

Fig. 1. Historical trends in Bitcoin's price.

collect data on other financial assets from DataStream and cover the price indices of MSCI World, MSCI China, PIMCO Investment-Grade Corporate Bonds, S&P GSCI Commodity, S&P GSCI Energy, an ounce of gold and the USD dollar index. Table 1 summarises statistics for the daily logarithmic price-level series during the entire sample period. As evidenced, Bitcoin has the highest standard deviation (confirming Pieters and Vivanco (2017) findings that Bitcoin is more volatile than gold, exchange rates and stock market prices); however, it also has the second-lowest mean after the PIMCO Investment-Grade Corporate Bond index. Along with the MSCI World and S&P GSCI Commodity/Energy indices, Bitcoin is negatively skewed. The results from a Jarque–Bera test reject the assumption of normal distribution within the data.

Breakpoint tests, proposed by Bai and Perron (1998), 2003), were conducted on the price of Bitcoin. These tests detect two breakpoints, which occurred on 2 December 2013 and 15 January 2015 (see Table 2). Prior studies (e.g. Bouri et al., 2017c; Cheah & Fry, 2015) document in the first breakpoint, which corresponds to the Bitcoin price crash of December 2013. New Chinese regulations against the use and acceptance of this cryptocurrency partially led to this crash. The second breakpoint coincides with the bullish reversal pattern seen in January 2015. Considering these two detected breakpoints, we divide the full sample period into three sub-periods: sub-period I (i.e. 19/07/2010–02/12/2013; 881 observations), sub-period II (i.e. 03/12/2013–15/01/2015; 293 observations) and sub-period III (i.e. 16/01/2015–31/01/2017; 533 observations). Fig. 1 depicts the price of Bitcoin, accounting for the two breakpoints. Furthermore, unreported results from three unit root tests (i.e. the augmented Dickey–Fuller [ADF], the Phillips–Perron [PP] and the Kwiatkowski–Phillips–Schmidt–Shin [KPSS]) indicate that all the variables under study are integrated of order one, I(1).

Table 2
Multiple breakpoint tests on Bitcoin prices.

Sequential F-statistic determined breaks[a]: 2			
Break Test	F-statistic	Scaled F-statistic	Critical value[c]
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]The Bai–Perron tests of L + 1 vs. L sequentially determined breaks were applied (Bai & Perron, 1998).
[b]** Significance level of 5%.
[c]Bai and Perron (2003) critical values.

4. Results and discussion

4.1. Sub-period I

We construct a VAR model and apply the Johansen cointegration test (Johansen & Juselius, 1990). Results in Table 3 Panel A show that the null hypothesis (i.e. no cointegrating vectors) cannot be rejected, suggesting a lack of cointegration among these variables during sub-period I. We further estimate a VAR model in first differences (i.e. without cointegration) to obtain the contemporaneous correlation matrix of innovations. According to the Akaike information criterion (AIC) and the Hannan–Quinn (HQ) information criterion, we select an order of two lags for the VAR model.

The experiments reported in Spirtes et al. (2000), imply that the significance level should decrease as the sample size increases; thus, we chose a significance level of 1% based on the sample size of sub-period I (881 observations). Fig. 2a shows the contemporaneous causal structure via the DAG, whereas Fig. 2b displays the lagged causal structure via the Granger causality tests for sub-period I. The contemporaneous causal structure reveals that Bitcoin is totally isolated, which the absence of any governmental support or control in Bitcoin production can partially explain (Dyhrberg, 2016). As for the lagged causal structure (see Fig. 2b), the results indicate that gold and global/Chinese equities direct affect Bitcoin at a significance level of 5%. Bouoiyour and Selmi (2015) highlight the impact of the Chinese stock market on the Bitcoin market.

Table 4 presents the percentage of forecast error for each variable, which is attributable to innovations in all variables at the contemporaneous time point and the 1-/20-day horizons during sub-period I. As Table 4 shows, Bitcoin is more independent than other financial assets, given that its volatility is mostly self-explanatory (e.g. 86% contribution at the 20-day horizon compared with a 100% contribution at the contemporaneous time point). The influence of other assets at both the contemporaneous time point and the short-term horizons partially explains Bitcoin's price volatility. This is also the case for gold, yet gold slightly affects Bitcoin more than the USD. In all cases, the largest contribution made by each of the seven financial assets accounts for roughly 4% of Bitcoin's total volatility.

In contrast, the FEVD results indicate that the financial system is highly integrated, except for Bitcoin. At the 20-day horizon, 30%–50% of the volatility in the equity and commodity markets contribute to the volatility of each other. Specifically, the USD and MSCI World equities make the largest contributions to the volatility of other assets, after the self-explanatory contributions.

Table 3
Cointegration tests.

Hypothesized No. of CE(s)[a]	Trace Statistic	C(5%)[b]	Max-Eigen Statistic	C(5%)	D[c]
Panel A: sub-period I (19/07/2010–02/12/2013)					
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
Panel B: sub-period II (03/12/2013–15/01/2015)					
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
Panel C: sub-period III (16/01/2015–31/01/2017)					
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] The number of cointegrating vectors were tested using the trace test and the maximum eigenvalue test, with the trend and intercept terms, at a 5% significance level.
[b] 'C(5%)' denotes a critical value of the trace and maximum eigenvalue tests at a significance level of 5%.
[c] 'D' relates to the decision to reject (R) or fail to reject (F) at a significance level of 5%.

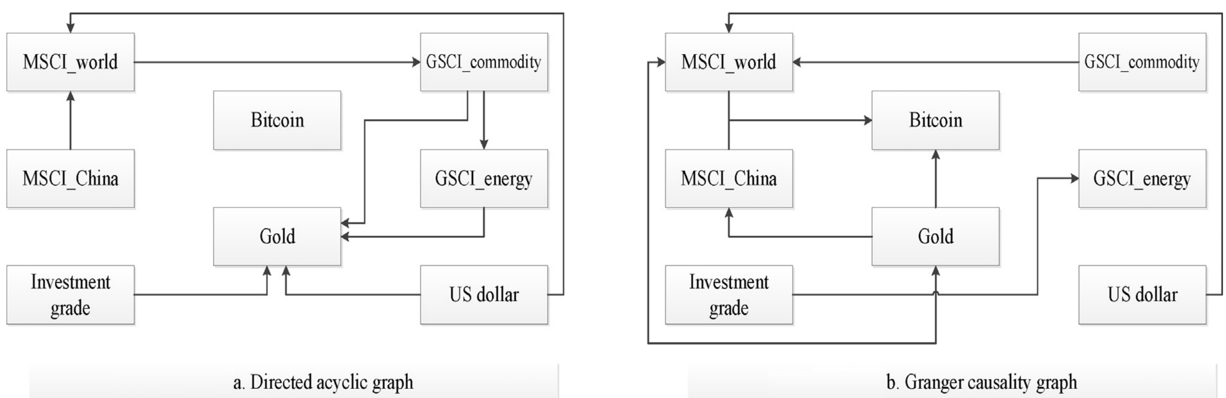

Fig. 2. The contemporaneous and lagged causal structure graph for sub-period I.

4.2. Sub-period II

As Table 3 Panel B shows, both the trace test and the maximum eigenvalue test reveal the presence of two cointegrating equations at a significance level of 5%. This result suggests a long-run equilibrium relationship exists between the eight variables. Accordingly, we construct an ECM with one lag, as the HQ information criterion indicates.

We examine the long-run exclusion and weak exogeneity tests to the ECM of sub-period II. The results of long-run exclusion tests in Table 5 show that gold and PIMCO Investment-Grade Corporate Bonds are not in the cointegration vector, which fails to reject the null hypothesis at a significance level of 10%. The weak exogeneity test results show that MSCI World, gold and PIMCO Investment-Grade Corporate Bonds were unable to adjust after being disturbed by economic shocks.

Referring to Spirtes et al. (2000), higher significance levels may improve performance in small sample sizes. Thus, we choose a significance level of 5% based on the sample size of sub-period II (293 observations). Figs. 3a and b, respectively, show the contemporaneous causal structure via the DAG and the lagged causal structure via the Granger causality tests for sub-period II. The contemporaneous causal structure reveals that Bitcoin is totally isolated, as in sub-period I; however, unlike in sub-period I, the lagged causal structure indicates that gold no longer affects Bitcoin. Instead, (energy) commodities directly affect Bitcoin, suggesting the importance of the energy cost in Bitcoin mining during the bear-market state. Bouri et al. (2017c) argue that during the period that followed the Bitcoin price crash of 2013 (i.e. sub-period II), mining activities become less profitable, which makes miners simply stop mining on less profitable hardware platforms.

The FEVD results (see Table 6) show that the innovations of other financial assets under the bear-market state (i.e. sub-period II) can better explain the volatility of Bitcoin than those under the bull-market phase (i.e. sub-period I). At the 20-day horizon, its own innovations explain no more than 50% of Bitcoin's price volatility, whereas world and Chinese equities account for approximately 10% and 6%, respectively, commodities (energy) accounts for approximately 11% (7%), and USD and gold accounts for 6% each. We notice that the contributions of the USD towards the volatility of other assets (excluding Bitcoin) have decreased compared to sub-period I. The USD's continuous depreciation during sub-period II, specifically from 2013 to 2014, and USD's weak influence USD on other assets contribute to this decrease. Innovations of other assets can also explain the volatility of the USD during sub-period II. At the 20-day horizon, world and Chinese equities account for approximately 10% and 12%, respectively, whereas commodities (energy) account for 9% (17%).

4.3. Sub-period III

Both the trace test and the maximum eigenvalue test (Table 3 Panel C) indicate the presence of two cointegrating equations at a significance level of 5%. This result suggests a long-run equilibrium

Table 4
FEVD results for sub-period I from the contemporaneous structure in Fig. 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	5.254	63.337	0.000	9.988	0.000
1	0.173	17.840	3.606	5.225	62.937	0.008	9.935	0.275
20	2.896	17.493	4.582	6.716	53.591	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

Table 5
Long-run exclusion and weak exogeneity tests on each variable in the cointegration vector 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***[a]	**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] *, **, *** Significance levels of 10%, 5%, and 1%, respectively.
[b] Tests were operating on the null hypothesis (i.e. the variable listed is not in the cointegration vector). The test was constructed by re-estimating the VAR/ECM model, in which the cointegration coefficient β of the corresponding variable was restricted to zero.
[c] Tests were operating on the null hypothesis (i.e. the variable is not responsive to deviations from the previous cointegration relationship); in other words, 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 a significance level of 10%.

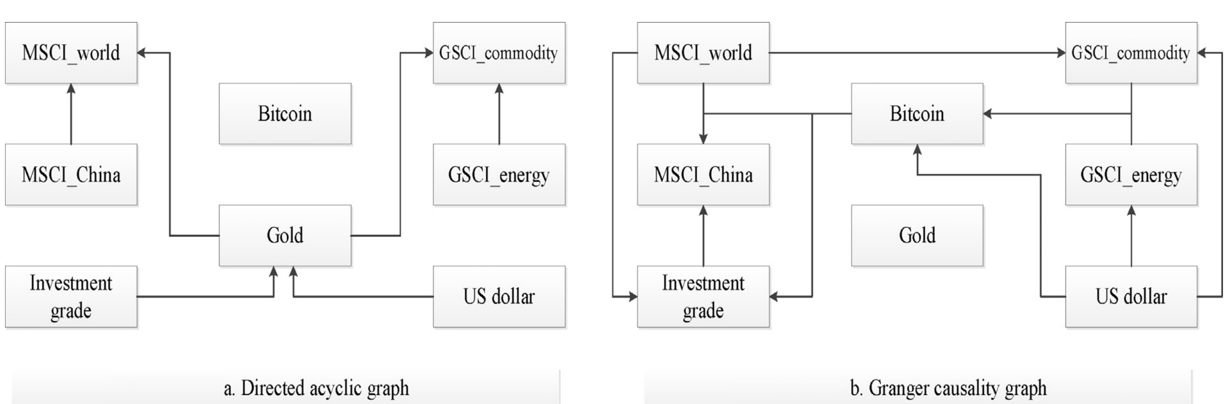

Fig. 3. The contemporaneous and lagged causal structure graph for sub-period II.

Table 6
FEVD results for sub-period II from the contemporaneous structure in Fig. 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	95.136	4.799	0.059	0.006	0.001
1	1.784	3.557	0.007	84.332	8.032	0.391	0.883	1.015
20	5.775	6.607	8.281	53.419	8.587	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

Table 7
Long-run exclusion and weak exogeneity tests on each variable in the cointegration vector 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^{***a}	**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: $^{a\,*}$, **, *** Significance levels of 10%, 5%, and 1%, respectively.
[b] Tests were operating on the null hypothesis (i.e. the variable listed is not in the cointegration vector). The test was constructed by re-estimating the VAR/ECM model, in which the cointegration coefficient β of the corresponding variable was restricted to zero.
[c] Tests were operating on the null hypothesis (i.e. the particular variable is not responsive to deviations from the previous cointegration relationship); in other words, 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 a significance level of 10%.

relationship between the variables. Accordingly, we construct an ECM with one lag, as the HQ information criterion indicates.

We apply both the long-run exclusion and weak exogeneity tests to the ECM of sub-period III. The test results (see Table 7) indicate that only GSCI Energy was not found in the cointegration vector, and only gold and PIMCO Investment-Grade Corporate Bonds can respond to previous deviations from the cointegrating relationship, with a significant level of 10%.

Considering the small sample size of sub-period III (533 observations), we chose a significance level of 5%. Fig. 4a and b, respectively, show the contemporaneous causal structure via the DAG and the lagged causal structure via the Granger causality tests for sub-period III. As seen here, there is an undirected edge between MSCI World and MSCI China, as the Tetrad IV software package cannot direct this edge. Therefore, we consider two unidirectional edges (i.e. MSCI World→MSCI China and MSCI China→MSCI World) separately to generate the two DAGs for sub-period III.

In contrast with the results from sub-periods I and II, we found no contemporaneous nor lagged causality between Bitcoin and other assets during sub-period III. However, causality among the other assets did strengthen, with more significant contemporaneous and lagged edges (see Fig. 4).

Tables 8 and 9 present the FEVD results for sub-period III, verifying that two different contemporaneous causal relationships (i.e. MSCI World→MSCI China and MSCI China→MSCI World, respectively) exist. The FEVD results for Bitcoin are the same in that its own innovations are mostly responsible for its volatility, remaining 81% at the 20-day horizon. Moreover, the impact of each asset on another asset is more dispersed and balanced. There are two clear exceptions, however, which are within our expectations. First, at the 20-day horizon, world equities account for over 20% of the volatility in Chinese equities (see Table 8), and vice versa (see Table 9). Second, the volatility of the energy commodity index explains the volatility of the general commodity index, reaching

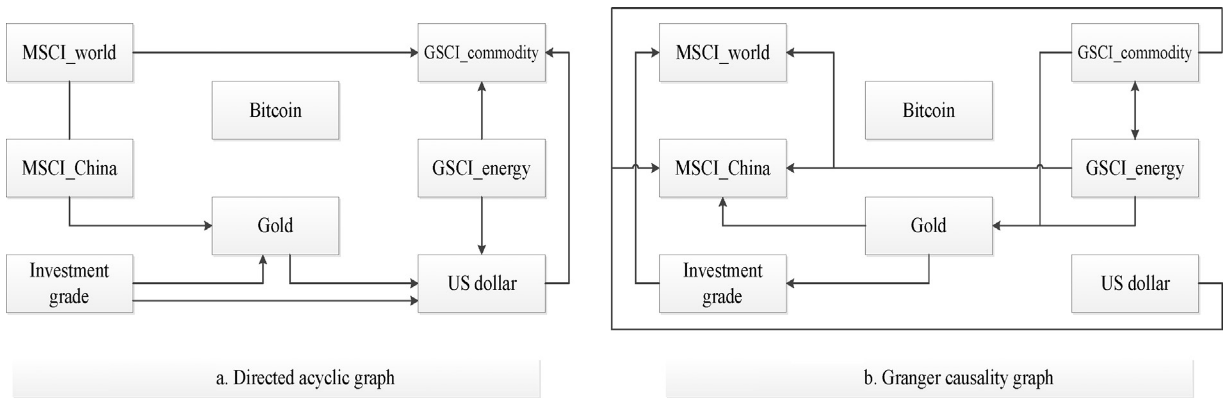

Fig. 4. The contemporaneous and lagged causal structure graph for sub-period III.

Table 8
FEVD results for sub-period III from the contemporaneous structure in Fig. 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	95.821	3.765	0.031	0.268	0.005
1	0.066	0.216	0.001	95.225	3.755	0.222	0.511	0.005
20	6.209	6.212	3.895	69.104	4.839	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

approximately 95% and 69% at the contemporaneous time point and the 20-day horizon, respectively. This result reflects the core status of energy within the commodity market, which Ji and Fan (2016) also document.

In summary, the results indicate relatively weak relations between Bitcoin and the other financial assets under study, which can be explained by the specific factors driving up Bitcoin's price, such as its popularity and the blockchain technology (Polasik et al., 2015; Ciaian et al., 2016a,b). The literature on Bitcoin also provides evidence of an insignificant relation between Bitcoin returns and fluctuations in the global macroeconomy (e.g. Polasik et al., 2015; Ciaian et al., 2016a,b). Similarly, Bouri et al. (2017a), (2017c) suggest very weak correlations between Bitcoin, conventional assets, general commodities and energy commodities; however, we find that these relations are not constant across the three sub-periods, with less levels of segmentation shown during the bear-market state (i.e. sub-period II).

Finally, we follow Ahern and Harford (2014) when calculating the degree of centrality (see Tables 10–12). Centrality designates the importance of one market in a network relative to other markets. Across the three sub-periods, the degree of centrality is lowest for the Bitcoin market, which is notably lower than that of PIMCO Investment-Grade Corporate Bonds and gold. In contrast, energy commodities have the highest degree of centrality, suggesting that the energy market is the most connected to other markets (i.e. it is at the centre of the network structure).

5. Conclusions

The present study contributes to the debate surrounding the causal relationships between Bitcoin and several financial assets (i.e. equities, bonds, currencies and commodities) using a DAG-based approach and FEVDs.

Table 9
FEVD results for sub-period III from the contemporaneous structure in Fig. 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	95.821	3.765	0.031	0.268	0.005
1	0.066	0.163	0.053	95.225	3.755	0.222	0.511	0.005
20	6.209	6.194	3.913	69.104	4.839	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	

Table 10
Degree of centrality during 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

Note: This table provides the degree of centrality for each market. The upper 8-x-8 submatrix is an adjacency matrix, in which the diagonal elements are equal to zero and the off-diagonal elements are the total of the pairwise volatility at the 20-day horizon. The degree of centrality is represented by the average of the column with off-diagonal pairwise volatility values.

Table 11
Degree of centrality for 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

Note: See notes under Table 10.

Focusing on the contemporaneous causality between Bitcoin and all the asset classes under study, empirical results suggest the isolation of the Bitcoin market. However, based on the time-lagged causality structure, the causal relationships seem to be time-variant. Specifically, there is evidence of time-lagged causal relations between Bitcoin and other asset classes during the bearish state of the Bitcoin market (sub-period II). This latest finding extends our limited understanding of the variability in the integration of the Bitcoin market and nicely complements the works of Brière et al. (2015); Baur et al. (2017); Dyhrberg (2016) and Bouri et al. (2017a), (2017c) that provide evidence of a weak relationship between Bitcoin and several financial assets. While financial

Table 12
Degree of centrality for sub-period III.

	Bitcoin	MSCI_world	MSCI_China	GSCI_commodity	GSCI_energy	Gold	US dollar	Investment grade
Panel A: if MSCI_World→MSCI_China								
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
Panel B: if MSCI_China→MSCI_World								
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

Note: See notes under Table 10.

regulatory bodies in the US consider Bitcoin to be a (digital) commodity, FEVD results highlight the marginal effect of commodities on Bitcoin's price volatility.

Our findings are useful for global investors interested in making Bitcoin a part of their international portfolios. The fact that the Bitcoin market presents a relatively independent price behaviour in specific periods has important implications regarding portfolio diversification and risk management inferences. However, there are potentially lower diversification benefits during the Bitcoin bear market, suggesting that investor should have a close look at Bitcoin during its bear state. Our findings have also implications for policy makers keen to adopt Bitcoin as an official currency or are concerned about the stability the global financial system (European Central Bank, 2012). The fact that the Bitcoin market is not strongly related to the global financial system implies that Bitcoin does not represent an eminent source of financial instability. However, given our empirical evidence on the time-varying relationship between Bitcoin and most of the financial assets under study, it appears that the integration of the Bitcoin market is a continuous process and thus varies over time. Accordingly, there is a need for a continuous monitoring of the Bitcoin's integration into the global financial system (European Central Bank, 2012), so regulators and policy makers will be able to react in a timely manner to threats that can potentially destabilize the financial system or have adverse consequences on its respective participants.

Further research should examine whether specific events (i.e., political and macroeconomic events) can have an impact on the network causality structures.

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