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Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency?

Shuyue Yi[a,1], Zishuang Xu[a,1], Gang-Jin Wang[a,b,*]

[a] Business School, Hunan University, Changsha 410082, China
[b] Center for Finance and Investment Management, Hunan University, Changsha 410082, China

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ABSTRACT

Using the spillover index approach and its variants, we examine both static and dynamic volatility connectedness among eight typical cryptocurrencies. The results reveal that their connectedness fluctuates cyclically and has shown an obvious rise trend since the end of 2016. In the variance decomposition framework, we further construct a volatility connectedness network linking 52 cryptocurrencies using the LASSO-VAR for estimating high-dimensional VARs. We find that these 52 cryptocurrencies are tightly interconnected and "mega-cap" cryptocurrencies are more likely to propagate volatility shocks to others. However, some unnoticeable cryptocurrencies (e.g., Maidsafe Coin) are also significant net-transmitters of volatility connectedness and even have larger contribution of volatility spillovers to others.

1. Introduction

The last decade has witnessed a boom in the cryptocurrency market. Cryptocurrencies which are completely decentralized have captured the interests of the public. The most creative difference between cryptocurrency and traditional flat currency is that the former establishes a new distributed payment system on the basis of cryptographical protocols which can ensure the anonymity, low cost and fast speed of peer-to-peer transactions.

Currently in the cryptocurrency market the most notable currency is Bitcoin, which was created by Satoshi Nakamoto in 2009. By 1 April 2018, the market capitalization of Bitcoin has surpassed 116 billion US dollars (USD) according to coinmarketcap.com. The market capitalization of cryptocurrencies has jumped to 295 billion USD, and the total number of cryptocurrencies has surpassed 1600. A number of new cryptocurrencies appear and most of them are developed further on the basis of blockchains, including Ethereum (ETH) and Ripple (XRP). ETH uses powerful specialized hardware in the network and reduces the transaction processing time. Ripple can support the free payment of different currencies on the premise that the payment gateway and foreign exchange market are fully effective. Although there is no significant change in the basic technology of these currencies, different features of each currency will influence their prices and stability as well as relationships among various cryptocurrencies. Many other factors such as market uncertainty and investors' emotion and expectation also may lead to violent fluctuations. A great deal of literature has focused on the categories or the performance of cryptocurrencies. However, most of literature focuses on Bitcoin only and pays little attention to the relationship, especially volatility connectedness or spillovers, among different cryptocurrencies (Corbet, Lucey, Urquhart, & Yarovaya, 2018).

Investigating volatility connectedness or spillovers among cryptocurrencies contributes to understanding the information transmission mechanism in the cryptocurrency market and provides useful information for market participants (e.g., investors and miners). In general, a high level of volatility connectedness or spillovers among cryptocurrencies can limit the benefits of diversification. If investors have the knowledge on the information transmission mechanism in the cryptocurrency market, they can use it to adjust asset portfolios or create investment or hedging strategies when the market is in a high level of volatility connectedness. Traditional theories focusing on volatility connectedness or spillovers and related information transmission mechanism can be divided into two groups. The first one refers to visible transmission mechanism, which holds the view that the correlation between economic fundamentals and global capital allocation leads to the co-movement of asset prices (Adler & Dumas, 1983; McQueen & Roley, 1993). The other group is invisible transmission mechanism, including market inefficiency, the psychological

* Corresponding author at: Business School of Hunan University, 11 Lushan South Road, Yuelu District, Changsha 410082, China.
E-mail address: wanggangjin@hnu.edu.cn (G.-J. Wang).

[1] These authors contributed equally to this work.

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expectation and behaviors of investors. Supporters of this mechanism consider that investors will seek investment or hedging opportunities in a certain market by assessing other markets' performance, thereby causing contagion through a correlated information channel (Forbes & Rigobon, 2002). However, in the emerging cryptocurrency market, such mechanisms may be different since the underlying technology and market environment of cryptocurrencies differ from traditional financial assets (e.g., stock, bond, currency, and futures). Therefore, to explore how volatility shocks transmit from one cryptocurrency to another is important for market participants. In particular, some investors employ cryptocurrencies as a hedge against stocks or a speculative asset. When they face macroeconomic uncertainty, information about volatility spillovers among cryptocurrencies would help them to choose a suitable cryptocurrency to adjust their asset portfolio based on their risk preference. Large costs of hardware purchase and power consumption would make less cryptocurrency miners be willing to participate in mining process when the cryptocurrency price falls. If miners, especially small miners (e.g., individual miner and small-scale institutional miners),[2] have the information of volatility connectedness or spillovers among different cryptocurrencies, they can select and mine part of less interconnected cryptocurrencies to diversify risks that come from extreme price fluctuations in the cryptocurrency market.

Our work here aims to fill this gap by evaluating volatility connectedness or spillover effects among cryptocurrencies at a system-wide level. In addition, it seems that Bitcoin plays a dominant role in the cryptocurrency market now, thus we also want to figure out whether there is a dominant cryptocurrency. In empirical analysis, first, to get a preliminary cognition of the market, we select eight cryptocurrencies with long-term trading data according to their market capitalization and estimate their volatility connectedness. We also point out relevant events that may lead to changes of connectedness. Through this step we find that the total volatility connectedness has shown an upward trend since the ending of 2016, thus we do a deep research over the period from December 2016 to April 2018. To capture more information, we expand the number of our sample cryptocurrencies from eight to 52 and analyze their volatility connectedness from a network view.

Using the spillover index approach and its variants (Diebold & Yilmaz, 2009, 2012, 2014), we measure both total and directional volatility connectedness (spillovers) across the eight cryptocurrencies during the period from 4 August 2013 to 1 April 2018. The variants of the spillover index approach proposed by Diebold and Yilmaz (2012, 2014) are based on the generalized VAR framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) for obtaining order-independent results. To avoid overlooking changes not evident over the whole sample period, we also conduct full-sample and rolling-sample volatility connectedness or spillovers. In the analysis of high-dimensional data (in our sample, including 52 cryptocurrencies), we exploit the least absolute shrinkage and selection operator (LASSO) method to reduce dimensionality and shrink the sample when estimating VAR parameters, where the LASSO is a regression analysis method to increase the prediction accuracy and interpretability of the statistical model through variable selection and regularization. The results of volatility connectedness or spillovers across the 52 cryptocurrencies are shown in the intuitive network diagram.

Our work focusing on the volatility connectedness in the cryptocurrency market has the following contributions. First, our paper complements the existing research on cryptocurrencies by using the volatility spillover index and variants. Much previous research has focused on the classification of cryptocurrency or on their reactions to relevant external shocks. But there is a lack of research on the interconnectedness among different cryptocurrencies. To the best of our knowledge, this is the first attempt to fill this gap by evaluating the volatility transmission across a number of cryptocurrencies and explaining their relationships from the network perspective. Meanwhile, our investigation also enriches the literature on measuring the volatility connectedness in terms of high-dimensional data, by adopting the LASSO-VAR (Nicholson, Matteson, & Bien, 2017) to select and shrink variables when estimating VAR parameters. Second, we provide empirical evidence on the patterns of volatility connectedness (including total connectedness and directional connectedness) in the cryptocurrency market, finding that the total volatility connectedness among eight cryptocurrencies with different market capitalization fluctuated over the period from 2013 to 2018 with obvious cyclicity and usually rose when the international situation is unstable. Empirical results on volatility connectedness among either eight or 52 cryptocurrencies show that even if the market capitalization of Bitcoin greatly exceeds that of other cryptocurrencies, Bitcoin is not the dominant player of volatility connectedness in the cryptocurrency market. Our findings provide new information for investors who have interest in investment or hedging strategies in Bitcoin and other cryptocurrencies.

The structure of this paper is as follows. In Section 2, we give a review of related literature, including cryptocurrencies and volatility connectedness. In Section 3, we present an introduction of the methods we adopt. In Section 4, we describe the data set and show the empirical results of eight representative currencies and discuss our main findings. In Section 5, we expand our sample and do the further study on a volatility connectedness network made up of 52 cryptocurrencies. In Section 6, we draw conclusions.

2. Literature review

Our work first links to the increasingly hot topic on the Bitcoin and cryptocurrency market. Corbet, Lucey et al. (2018) conduct an excellent and systematic review on the research of cryptocurrencies as a financial asset. In the existing literature there are many debates about the nature of cryptocurrencies and discussions on whether cryptocurrencies are classified as a medium of exchange or a speculative investment. Frisby (2014) holds the view that Bitcoin seems to possess the characteristics of money and even perform better: its mining process and limited supply allow it to function as a store of value. Its durability, divisibility, portability, higher liquidity and lower transaction costs enable it to circulate in the market. Dyhrberg (2016a) obtains similar conclusions in the GARCH model of Bitcoin and gold. Her results indicate that Bitcoin possesses allied hedging capabilities, and therefore it can be defined as a hybrid between a currency and a commodity. Demir, Gozgor, Lau, and Vigne (2018) examine the relation between Bitcoin and the economic policy uncertainty index using quantile-on-quantile regressions and conclude that Bitcoin can be employed as a hedging tool against uncertainty. While some papers point out that the speculative bubbles and little intrinsic value of cryptocurrencies bring many uncertain factors and reduce the price stability, thereby weakening its function. Urquhart (2016) argues that Bitcoin is an inefficient market during the investigated sample period and finds that Bitcoin shows evidence of becoming more efficient after the middle of 2013. Fry and Cheah (2016) find that the fundamental price of Bitcoin is estimated to be zero. Greatly higher volatility and little correlation between Bitcoin and flat currencies as well as gold indicate that Bitcoin is difficult to play as a traditional currency or a hedging asset. Glaser, Zimmermann, Haferkorn, and Siering (2014) also find that new Bitcoin users are more likely to use it on a speculative investment intention.

Alongside the behaviors of cryptocurrencies are paid more attention. Some studies focus on the reactions of cryptocurrencies to other shocks. An econometric investigation by Cheung, Roca, and Su (2015) proves that bubbles exist in the Bitcoin market and the huge bubble burst over the 2011–2013 period, which is consistent with the bankruptcy of the Mt. Gox Bitcoin Exchange. Corbet, Larkin, Lucey, and

[2] In the current Bitcoin market, Mega Bitcoin miners (e.g., Bitmain and Bitfury) are threatening to squeeze the smaller miners out of the picture according to a Bloomberg report by Kharif (2018), because the former own more computing power in analysis of Bitcoin's hash rate than the latter.

Yarovaya (2018) examine the relationship between macroeconomics news announcements and Bitcoin returns, and find that news relating to unemployment and durable goods has a significant impact on Bitcoin returns while news about GDP and CPI seems to have no statistically significant relationship with Bitcoin. Corbet, Larkin, Lucey, and Yarovaya (2017) evaluate the reactions of a number of cryptocurrencies to two specific events: the US Federal Fund interest rate adjustments and the quantitative easing (QE) announcements. They divide their sample into three portfolios: currency, protocol and decentralized application, finding (i) that the reactions of cryptocurrencies are linked to their types and (ii) that currency-based digital assets are more susceptible to monetary policy shocks. Glaser et al. (2014) find that the Media reports also play a big role in influencing the price volatility of cryptocurrencies.

Another strand of literature concentrates on linkages among cryptocurrencies as well as other assets. A growing research emerges on relationships between Bitcoin and other traditional assets and assessment whether Bitcoin can be used as a safe-haven, a diversifier, or a hedging asset (see, e.g., Baur, Dimpfl, & Kuck, 2018; Baur, Hong, & Lee, 2018; Bouri, Gupta, Tiwari, & Roubaud, 2017; Bouri, Jalkh, Molnár, & Roubaud, 2017; Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017; Bouri, Das, Gupta, & Roubaud, 2018; Brière, Oosterlinck, & Szafarz, 2015; Corbet, Larkin et al., 2018; Dyhrberg, 2016b; Feng, Wang, & Zhang, 2018; Giudici & Abu-Hashish, 2018; Ji, Bouri, Gupta, & Roubaud, 2018; Symitsi & Chalvatzis, 2018). However, only few studies pay attention to relations between different cryptocurrencies. For example, Gandal and Halaburda (2016) study the competition in the cryptocurrency market by examining changes of exchange rates of several cryptocurrencies, and analyze the influence of network effects on cryptocurrency market. They find that the performance of Bitcoin and other cryptocurrencies in the period from 1 May 2014 to 1 July 2014 is consistent with network effects and winner-take-all dynamics. Fry and Cheah (2016) use econophysics models to measure the spillover effect between the two largest cryptocurrencies: Bitcoin and Ripple. They investigate the effects of several events (e.g., the closure of the Silk Road website and the People's Bank of China's ban from using Bitcoin). Their results support the existence of a negative bubble between these two currencies after 2014. The influence of related events is found to be mixed, which means that the impact of some events is imperceptible due to speculative bubbles in Bitcoin. Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018) use the spillover index approach and its variants for examining relations among three popular cryptocurrencies (Bitcoin, Ripple and Litecoin) and other traditional financial assets (the foreign exchange, stock, VIX, gold and bond). Their empirical results show that the three popular cryptocurrencies are relatively isolated from other financial assets and thus cryptocurrencies benefit risk diversification for investors. Our work is also closely related to Ciaian, Rajcaniova, and Kancs (2018), however, who focus on studying price interdependencies between Bitcoin and 16 altcoins (cryptocurrencies other than Bitcoin) both in the short- and long-run. Their empirical findings indicate that Bitcoin and altcoins are interdependent in the short-run while the interdependencies between Bitcoin and altcoins in the long-run cannot be proven because Bitcoin cannot drive up the prices of altcoins in the long-run. In summary, although much effort has been devoted to examining the price behavior and the influence factors of Bitcoin and other cryptocurrencies, little attention is paid to the cross-correlations, e.g., volatility connectedness or spillover effects, among different currencies in the cryptocurrency market. Thus our study using the spillover index approach and its variants to analyze the volatility connectedness across major cryptocurrencies will fill this gap.

Our work is also related to the literature on the spillover index approach and its variants. Based on the vector autoregressive (VAR) model and Cholesky-based variance decompositions of Sims (1980), Diebold and Yilmaz (2009) propose the spillover index approach for measuring the return and volatility spillovers among 19 global equity markets. Using the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), Diebold and Yilmaz (2012) then further extend the spillover index framework to overcome the limitation that the forecast variance decompositions may rely on the variable orderings. Based on this model, to make the elusive concept–spillover–more intuitive, Diebold and Yilmaz (2014) develop a population connectedness measure to estimate network connectedness. They calculate rolling connectedness of 13 major US financial institutions' share return volatilities and present their connectedness in network diagrams. Although the improved method can be effective in the analysis of small sample, there are some problems when discussing the connectedness among large sample individuals since its heavy parameterization reduces its applicability. To this end, Demirer, Diebold, Liu, and Yilmaz (2018) extend the spillover index framework into high-dimensional environments by using LASSO method for shrinking variables when estimating VAR parameters. They empirically investigate the network connectedness among 96 banks around the world. The spillover index approach and its variants are becoming popular and extensively-used methods for studying the return or volatility connectedness or spillover effects in different markets, e.g., stock markets (Tsai, 2014; Yarovaya, Brzeszczyński, & Lau, 2016a,b; Zhou, Zhang, & Zhang, 2012), foreign exchange markets (Antonakakis, 2012; Baruník, Kočenda, & Vácha, 2017), commodity markets (Antonakakis & Kizys, 2015; Batten, Ciner, & Lucey, 2015; Diebold, Liu, & Yilmaz, 2017; Lucey, Larkin, & O'Connor, 2014), crude oil markets (Zhang & Wang, 2014), cross-markets (Antonakakis, Chatziantoniou, & Filis, 2017; Wang, Xie, Jiang, & Eugene Stanley, 2016) and the banking system (Demirer et al., 2018; Wang, Xie, Zhao, & Jiang, 2018). The previous empirical works show that the spillover index approach and its variants can effectively detect and measure the volatility connectedness or spillover effects across different financial agents, which motivate us to use the spillover index approach for investigating the volatility connectedness in the cryptocurrency market.

3. Methodology

3.1. Variance decompositions for connectedness measurement

The spillover index approach and its variants build on variance decompositions on a p-th order VAR with N-variable, i.e., VAR$_N(p)$. Let $\{y_t\}_{t=1}^{T}$ denote an N dimensional vector time series. It may be expressed as

$$\boldsymbol{y}_t = \boldsymbol{\nu} + \sum_{i=1}^{p} \boldsymbol{\Phi}_i \boldsymbol{y}_{t-i} + \boldsymbol{u}_t, \tag{1}$$

where $\boldsymbol{\nu}$ is an N-dimensional constant intercept vector, each $\boldsymbol{\Phi}_i$ denotes an $N \times N$ coefficient matrix, and $\boldsymbol{u}_t \sim (\boldsymbol{0}, \boldsymbol{\Sigma})$. We transform the VAR model into the moving average (MA) representation, i.e., $\boldsymbol{y}_t = \boldsymbol{w} + \sum_{i=0}^{\infty} \boldsymbol{A}_i \boldsymbol{u}_{t-i}$ where $\boldsymbol{A}_i$ satisfies the recursion $\boldsymbol{A}_i = \sum_{j=1}^{p} \boldsymbol{\Phi}_j \boldsymbol{A}_{i-j}$ and $\boldsymbol{A}_0$ is an $N \times N$ identity matrix, $\boldsymbol{A}_i = 0$ for $i < 0$.

Following Diebold and Yilmaz (2012), we use the generalized variance decomposition framework of Koop et al. (1996) and Pesaran and Shin (1998), which is invariant to ordering. Thus we denote $\theta_{ij}^{g}(H)$ as cryptocurrency j's contribution to cryptocurrency i's H-step-ahead generalized forecast error variance, i.e.,

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\boldsymbol{e}_i' \boldsymbol{A}_h \boldsymbol{\Sigma} \boldsymbol{e}_j)^2}{\sum_{h=0}^{H-1} (\boldsymbol{e}_i' \boldsymbol{A}_h \boldsymbol{\Sigma} \boldsymbol{A}_h' \boldsymbol{e}_j)}, \quad H = 1, 2, \ldots, \tag{2}$$

where $\boldsymbol{\Sigma}$ is the covariance matrix of the disturbance vector $\boldsymbol{u}_t$, σ_{jj} denotes the standard deviation of the disturbance of j-th equation, and $\boldsymbol{e}_j$ is the selection vector with one as the j-th element and zeros otherwise.

Because of the method we used, the variance shares do not necessarily add to 1, i.e., $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. Thus we normalize each entry of the generalized variance decomposition matrix by the row sum

$$\widetilde{\theta}_{ij}^{g}(H)=\frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)}. \tag{3}$$

For the convenience of notation, let $C_{i\leftarrow j}^{H}$ denote the *pairwise directional connectedness* from cryptocurrency j to cryptocurrency i, which equals to $\widetilde{\theta}_{ij}^{g}(H)$. We further introduce three *total directional volatility connectedness* measures: (i) *from-connectedness*, i.e., the total directional connectedness *from other* cryptocurrencies j to cryptocurrency i, is defined as

$$C_{i\leftarrow \bullet}^{H}=\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(H), \tag{4}$$

(ii) *to-connectedness*, i.e., the total directional connectedness from cryptocurrency i *to other* cryptocurrencies j, is defined as

$$C_{\bullet\leftarrow i}^{H}=\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ji}^{g}(H), \tag{5}$$

and (iii) *net-connectedness*, i.e., the net total directional connectedness of cryptocurrency i, is defined as

$$C_{i}^{H}=C_{\bullet\leftarrow i}^{H}-C_{i\leftarrow \bullet}^{H}. \tag{6}$$

To measure the system-wide connectedness, we introduce the *total volatility connectedness* (TVC) index, C^H, which is defined as

$$C^{H}=\frac{1}{N}\sum_{i,j=1,i\neq j}^{N}\widetilde{\theta}_{ji}^{g}(H). \tag{7}$$

3.2. LASSO-VAR

As noted before, to discuss connectedness using the spillover index approach and its variants, we should estimate VAR model firstly. In the VAR, parameter space grows quadratically with the number of variables, leading to rapid running out the available degrees of freedom. Because of $N=52$ variables in the second part of our empirical analysis with an expanded sample (see Section 5), N^2p+p regression parameters will need to be estimated in the VAR. When the VAR lag $p=3$ and the number of variables $N=52$, for example, there are 8115 regression parameters. This heavy parametrization is the major drawback of the VAR and this limits its applicability. The traditional estimation approaches used in Diebold and Yilmaz (2012, 2014) fail to estimate multivariable VAR parameters in a high dimensional context. This is also the reason why Diebold and Yilmaz (2014) are forced to limit their research on volatility spillover network of financial institutions to a small number of US financial institutions (actually, only 13 financial institutions). Thus an urgent problem that needs to be addressed is how to estimate VAR parameters in a high dimensional environment. To this end, Demirer, Diebold, Liu, and Yilmaz (2018) propose the use of the LASSO-VAR for fixing high dimensionality in the VAR when estimating network connectedness among 96 banks around the world, because the LASSO-VAR applies the scalar regression regularization technique to a vector time series, which can reduce the parameter space greatly. Here we follow Demirer et al. (2018) and use the extension of LASSO-VAR, i.e., the VARX-L framework developed by Nicholson et al. (2017), for selecting and shrinking variants. Specially, we consider applying the Lag Sparse Group LASSO penalty proposed by Simon, Friedman, Hastie, and Tibshirani (2013), which is a regularized model for linear regression with ℓ_1 and ℓ_2 penalties. It can sparse the model space both on a group and within group level. Using the algorithm of accelerated generalized gradient descent fits the model.

Apply the Lag Sparse Group LASSO penalty to the convex least squares objective function

$$\min_{\boldsymbol{\nu},\boldsymbol{\Phi}}\sum_{t=1}^{T}\left\|\boldsymbol{y}_t-\boldsymbol{\nu}-\sum_{i=1}^{p}\boldsymbol{\Phi}_i\boldsymbol{y}_{t-i}\right\|_F^2+\lambda\left((1-\alpha)N\sum_{i=1}^{p}\|\boldsymbol{\Phi}_i\|_F+\alpha\,\|\boldsymbol{\Phi}\|_1\right), \tag{8}$$

where $\|\boldsymbol{A}\|_F=\sqrt{\sum_{i,j}\boldsymbol{A}_{ij}^2}$ is the Frobenius norm of a matrix $\boldsymbol{A}$, $\|\boldsymbol{A}\|_1=\sum_{jk}|\boldsymbol{A}_{jk}|$ is the ℓ_1 norm, and $0<\alpha<1$ is an additional turning parameter, which indicates the within-group sparsity. Note that $\alpha=0$ gives the Lag Group LASSO-VAR, $\alpha=1$ gives the LASSO-VAR fit. As an alternative to estimating via cross-validation (jointly over α and λ), we set $\alpha=1/(N+1)$. $\lambda>0$ is the optimal penalty parameter, which is chosen by minimizing h-step ahead mean-square forecast error (MSFE), and h denotes the desired forecast horizon. Here we follow Nicholson et al. (2017) and set $h=1$. Nicholson et al. (2017) divide the data into three periods: initialization, training, and forecast evaluation. Each period is set on third of sample period, i.e., $T_1=\frac{T}{3}$, $T_2=\frac{2T}{3}$. $\widehat{\lambda}$ is selected from a grid of values $\lambda_1,\lambda_2,\ldots,\lambda_n$. $\hat{y}_{t+h}^{\lambda_i}$ is the h-step ahead forecast based on all observations from $1,\ldots,t$. We choose $\widehat{\lambda}$ as the minimizer of

$$\mathrm{MSFE}(\lambda_i)=\frac{1}{(T_2-T_1-h+1)}\sum_{t=T_1}^{T_2-h}\|\hat{y}_{t+h}^{\lambda_i}-y_{t+h}\|_F^2. \tag{9}$$

4. Data and empirical analysis

4.1. Data used in the analysis

In the analysis, we use eight cryptocurrencies from 4 August 2013 to 1 April 2018. These cryptocurrencies include Bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Peercoin (PPC), Namecoin (NMC), Feathercoin (FTC), Novacoin (NVC) and Terracoin (TRC). We obtain the data including high, low, closing and opening prices for each cryptocurrency from coinmarketcap.com. The beginning date of the sample is determined by Ripple because it started trading on 4 August 2013. We choose the ending date of the sample because the market capitalization rank of cryptocurrencies is updated on a week-by-week basis and the latest ranking date that we have accessed is 1 April 2018. There are two reasons why we choose these eight cryptocurrencies. On the one hand, cryptocurrencies emerge and disappear continually, while our selected eight currencies have been publicly-traded for almost five consecutive years. A large sample length could make our analysis more convincing. On the other hand, our sample includes three tier currencies as in Gandal and Halaburda (2016). Bitcoin, Ripple and Litecoin, whose market capitalizations stay in the world's top five cryptocurrencies, are "top-tier" cryptocurrencies.[3] Peercoin and Feathercoin are two "second-tier" cryptocurrencies, representing "middle cryptocurrency" in terms of market capitalization. Novacoin and Terrcoin are two cryptocurrencies with small market capitalization, which ranked 499th and 597th by market capitalization as of 1 April 2018, respectively. These two currencies are a representative "minor cryptocurrency" according to market capitalization. Thus our selected sample including different tier currencies by market capitalization would make our analysis more reliable, and it would also benefit to asset diversification for investors. In Table 3 we report these eight cryptocurrencies' symbols, market capitalizations (MCs) and rankings of MCs as of 1 April 2018.

Following Diebold and Yilmaz (2014) and Demirer et al. (2018), we

[3] In our sample, we also take into consideration another top cryptocurrency, Ethereum, which started trading on on 7 August 2015 and ranked second only to Bitcoin as of 1 April 2018. We investigate the volatility connectedness among nine cryptocurrencies by adding Ethereum in our sample. Both static and dynamic analyses on volatility connectedness show that the results based on nine cryptocurrencies are consistent with those by eight cryptocurrencies. Due to a relatively short investigated period by considering Ethereum in our sample, here we do not report the results for nine cryptocurrencies that include Ethereum, but they can be available upon request.

Table 1
Volatility summary statistics for the eight cryptocurrencies during the period from 4 August 2013 to 1 April 2018.

	BTC	XRP	LTC	PPC	NMC	FTC	NVC	TRC
Mean (%)	0.1825	0.4182	0.3818	0.5982	0.6240	1.6176	0.7383	4.0178
Median (%)	0.0436	0.0550	0.0664	0.1658	0.1680	0.5967	0.1637	1.1242
Maximum (%)	14.702	29.988	24.543	41.668	31.316	49.229	80.803	431.41
Minimum (%)	0.0002	0.0005	0.0001	0.0044	0.0032	0.0061	0.0011	0.0034
Std. dev. (%)	0.5772	1.5459	1.2871	1.8802	1.9113	3.3011	3.3381	16.021
Skewness	13.341	10.266	10.582	12.013	8.7330	5.9130	15.505	16.305
Kurtosis	277.01	145.29	155.00	208.56	100.25	53.460	307.95	359.05
ADF	−7.0704	−25.580	−6.3233	−23.748	−8.4998	−16.347	−33.288	−23.034

Notes: all ADF statistics are significant at the 1% level, suggesting that all sample series are stationary.

Table 2
Volatility connectedness table for eight cryptocurrencies during the period from 4 August 2013 to 1 April 2018.

	BTC	XRP	LTC	PPC	NMC	FTC	NVC	TRC	From others
BTC	42.28	10.93	23.24	6.92	10.94	4.88	0.53	0.27	57.72
XRP	13.83	61.56	13.06	2.73	6.10	2.03	0.43	0.27	38.44
LTC	14.25	7.28	44.88	7.01	17.63	4.86	3.63	0.46	55.12
PPC	9.33	3.35	11.85	56.75	13.18	2.65	2.69	0.20	43.25
NMC	11.28	5.14	18.68	8.19	44.24	4.08	7.69	0.70	55.76
FTC	7.81	2.20	7.78	2.79	7.36	69.53	1.60	0.93	30.47
NVC	1.36	0.73	3.56	2.94	7.23	0.79	83.36	0.02	16.64
TRC	0.29	0.59	0.59	0.15	0.82	0.81	1.71	95.03	4.97
To others	58.14	30.22	78.76	30.74	63.25	20.11	18.29	2.84	TVC index
Net	0.43	−8.21	23.65	−12.50	7.49	−10.37	1.65	−2.13	37.79

Notes: the TVC index represents the total volatility connectedness index.

Table 3
8 Cryptocurrencies and their symbols, market capitalizations (MCs) and rankings of MCs (as of 1 April 2018).

Cryptocurrency	Symbol	MC ($1 Mil)	Rank by MC
Bitcoin	BTC	116,890	1
Ripple	XRP	19,620	3
Litecoin	LTC	6441	5
Peercoin	PPC	38	183
Feathercoin	FTC	37	188
Novacoin	NVC	7	499
Terracoin	TRC	4	597

use daily range-based volatility of Garman and Klass (1980) to estimate daily volatility of each cryptocurrency. For cryptocurrency i on day t, we have

$$V_{it}^{GK} = 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2 \quad (10)$$

where H_{it}, L_{it}, C_{it}, and O_{it} are the natural logarithms of high, low, closing and opening prices of cryptocurrency i on day t, respectively. Each volatility series comprises 1702 observations.

4.2. Cryptocurrency market volatility data

We show the daily volatility series of eight cryptocurrencies in Fig. 1. In general, Bitcoin is relatively stable, while Terracoin whose max daily volatility exceeds 4 is most volatile. All cryptocurrencies had a comparatively high volatility in the last quarter of 2013, June 2017 and the first quarter of 2018.

In Table 1, we show the summary statistics of volatility series for the eight cryptocurrencies during the entire period. Bitcoin's volatility was below 2% for the most time in the sample period. Although it went through a relatively high volatility in the last quarter of 2013, the volatility of Bitcoin is the lowest, compared with others at the same time. The standard deviation of Litecoin volatility is 1.287% and it is the second smallest in eight samples, showing that Litecoin moves comparatively slight. Fig. 1 shows that Litecoin experienced three major periods of volatility. The first one extends from the last quarter of 2013 to January 2014, during which the volatility of Litecoin increased to nearly 25% and suddenly declined to 0.49%. After the calm era from March 2014 to May 2015, the volatility suddenly soared to 20% in July 2015. The third wave occurred since December 2017 and sustained to the end of the sample period. The volatility curve of Ripple is extremely similar to Litecoin. The volatile periods of Peercoin, Namecoin and Novecoin are consistent with Litecoin, but their volatility levels are even larger than that of Litecoin. Among these three currencies, Novacoin is the most volatile one. Although the fluctuation of Feathercoin is not as large as Novacoin, it fluctuates more frequently, and is up to almost once a year. The fluctuation of Terracoin is frequent and large. Its volatility is over 1% more than half of time, and more than 5% in the one fifth of the sample period. This indicates that small-cap cryptocurrencies may be easier to be affected by exogenous shocks and more unstable. We also carry out the ADF tests for each volatility series. All ADF statistics are significant at the 1% level, suggesting that the eight volatility series are suitable for VAR modeling.

4.3. Static analysis

Table 2 is the volatility connectedness table for the full sample. We estimate volatility connectedness at the forecast horizon $H = 10$ and the lag order $p = 3$. The estimated forecast error variance of cryptocurrency i contributed by innovations to cryptocurrency j is shown in table's ij-th element. The off-diagonal column and row sums of the table are contributions to others and contributions from others, respectively. In addition, the row sum is 100%, and the volatility connectedness (or contribution) from others equals to 1 minus the diagonal element. The difference between "to" and "from" is equal to net connectedness. The total volatility connectedness (TVC) index is the off-diagonal column sum (or row sum) divided by the column sum including diagonal elements (or row sum including diagonal elements).

The total connectedness index indicates that 37.79% of the volatility forecast error variance in eight cryptocurrencies comes from spillovers. The diagonal elements, which represent own connectedness, are the largest individual elements in the table and all are above 40%. Among

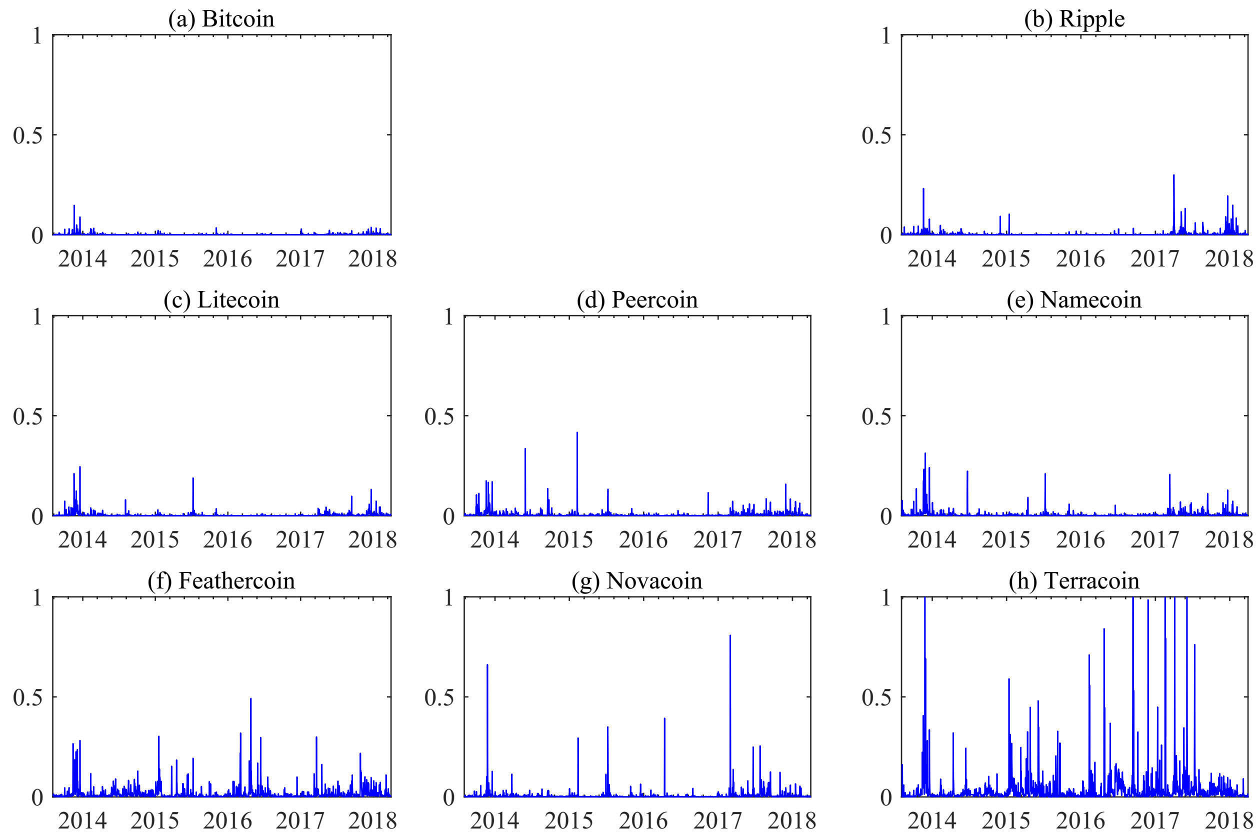

Fig. 1. Daily cryptocurrency volatility series for (a) Bitcoin (BTC), (b) Ripple (XRP), (c) Litecoin (LTC), (d) Peercoin (PPC), (e) Namecoin (NMC), (f) Feathercoin (FTC), (g) Novacoin (NVC) and (h) Terracoin (TRC) during the period from 4 August 2013 to 1 April 2018. Notes: the values of volatility series for Terracoin range from 3.4287e − 05 to 4.3141, here we only plot volatility series whose values are no greater than 1.

them the largest element is 95.03% (Terracoin's own connectedness). Terracoin is both the smallest transmitter and recipient of volatility connectedness or spillovers. In addition, the values of total directional connectedness of Bitcoin, Litecoin and Namecoin in both "from" and "to" are larger than the other five cryptocurrencies obviously. Bitcoin, Litecoin, Novacoin and Namecoin on average are the net transmitters, while the others are the net recipients.

To figure out how volatility shocks transmitted across cryptocurrencies, we discuss the off-diagonal elements which represent the pairwise directional connectedness. The largest one is from Litecoin to Bitcoin (23.24%). In return, the pairwise directional connectedness from Bitcoin to Litecoin is the fourth largest (14.25%). The net pairwise connectedness from Litecoin to Bitcoin is 8.99%, which is the largest element of the net pairwise connectedness. The second largest pairwise directional connectedness is from Litecoin to Namecoin (18.68%). In return, the pairwise directional connectedness from Namecoin to Litecoin is the second largest (17.63%), but the net pairwise connectedness from Litecoin to Namecoin is only 1.05%. More than 80% of volatility shocks of Novacoin and Terracoin come from themselves. The pairwise directional connectedness coming from Litecoin to Ripple is 13.06%.[4] It is worth noting (i) that 61.56% of volatility connectedness of Ripple can be explained by itself rather than being transmitted from others, which are significantly larger than those of other two "top-tier" cryptocurrencies (i.e., Bitcoin and Litecoin), and (ii) that the from-connectedness and to-connectedness of Ripple are 38.44% and 30.22%, respectively, which are obviously lower than those of the other two "top-tier" cryptocurrencies. Ripple's differences with other mega-cap cryptocurrencies indicate that volatility connectedness among cryptocurrencies does not necessarily depend on their size. A potential explanation for the Ripple exception is that Ripple displays some centralization features and permits the exchange between Ripple and flat money, thus increasing its stability.

4.4. Dynamic analysis I: total volatility connectedness

The full-sample and unconditional analysis provides a good characterization for volatility connectedness from average and static perspective. However, there are many changes in the cryptocurrency market during our sample from 4 August 2013 to 1 April 2018. For example, cryptocurrencies caught more interest of the mainstream media, and new cryptocurrencies appear and disappear constantly. Different reactions of countries also influenced the performance of cryptocurrencies.

With the consideration of these, some information like important cyclical movements would be ignored by single fixed-parameter model. Therefore, we plot total connectedness over 100-day rolling-sample windows (i.e., $w = 100$ days) to measure its long-term trend and periodic fluctuation. Like in Section 4.3, we set the forecast horizon H at 10 days and the VAR lag order p at 3 days. Note that in Section 4.6, we provide a robustness assessment for each parameter. The rolling total volatility connectedness plot is shown in Fig. 2 and presents some patterns.[5]

[4] Bouri, Gupta, and Roubaud (2018) argue that there is co-explosivity between Litecoin and Ripple, which means that the presence of explosivity in Litecoin increases the probability of producing explosivity in Ripple. The reason causing co-explosivity is that market participants tend to invest in other more attractive cryptocurrencies with a better risk-reward profile after a price appreciation occurring in one cryptocurrency.

[5] Note that we also apply the LASSO-VAR estimation approach to examining volatility connectedness among the eight cryptocurrencies. The dynamic total volatility connectedness index estimated by the LASSO-VAR approach shows

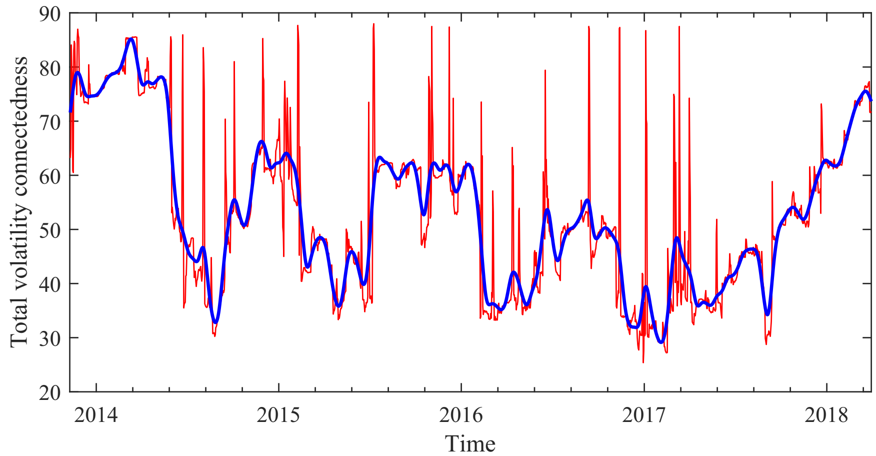

Fig. 2. Rolling total volatility connectedness index, eight cryptocurrencies. Notes: the blue line is the smooth curve for the time-varying total connectedness index using the smooth spline estimation.

We can identify some cycles in the total spillover plot and we will analyze these cycles with relevant events that may cause them.

The first cycle ended in August 2014. The total volatility connectedness was over 70% in mid-November 2013 and reached the highest point at 84% in March 2014, followed by a significant downward movement from March 2014 to the end of August 2014. It should be noticed that in the same era, the volatility series of each cryptocurrency experienced a wide fluctuation. Several events may exert influence on cryptocurrencies and promote their connectedness. In August 2013, Germany became the first country to recognize the legal status of Bitcoin and incorporated it into the national regulatory system. This announcement reflects to a certain extent that the monetary function and asset characteristic of cryptocurrency represented by Bitcoin are affirmed, and it can be regarded as good news for the cryptocurrency market. While in October 2013, FBI closed the Silk Road website which provided a platform for people making illegal transactions mainly paid by Bitcoin. Besides, the People's Bank of China's banned the Chinese financial institutions from using Bitcoin in end-2013. In early 2014, the suspension of trading on the Mt. Gox Bitcoin exchange due to technical issues and the cyberattack on the Canada-based Bitcoin bank Flexcoin, also brought exogenous shocks to the cryptocurrency market. These events reveal the uncertainty of relevant policies and flaws in keeping account security, which may reduce the public confidence in cryptocurrencies and cause the sell-off, therefore pushing up the volatility connectedness.

After hitting the lowest point in September 2014, the total volatility connectedness went through three similar but relatively small cycles until the end of 2016. The first cycle lasted from September 2014 to April 2015; the second from April 2015 to April 2016; and the third from May 2016 to the end of 2016. An interesting part of the plot is that the index increased from 32% at the middle of May 2015 to 67% by August 2015. This coincides with the high volatility in the cryptocurrency market at the same time. In May 2015, the Justice Department and the Federal Reserve announced to fine six major banks over 5.8 billion USD for their manipulating foreign exchange. These illegal and unsafe conducts of the famous banks may lead to investors' doubts on the transparency of traditional currencies, and consequently they pay more attention to cryptocurrencies that are decentralized and difficult to manipulate. In addition, the total volatility connectedness experienced a slight but constant upward trend in mid-2016, which may be linked to British exit from the EU. Bitcoin can take a role in risk management like gold and hedging instrument (Dyhrberg, 2016a). The unclear prospect of Europe caused rising risk aversion thereby increasing volatility and its connectedness in the cryptocurrency market.

Following the first four cycles, the total volatility connectedness rose consistently from December 2016 onwards, with two waves. The first one started from February to April in 2017. The figure jumped by 20% in February and went back down in April. In this period, Microsoft Excel enabled Bitcoin support and Japan passed the Virtual Currency Act gave Bitcoin legal tender status. These events may provoke investors' positive attitudes towards bitcoin whose increasing volatility will interfere with other markets. Another wave happened since September 2017, after which the index climbed from 30% to 58%. The movement coincided with China's ban on initial coin offerings. The growing spillover effect across cryptocurrencies in 2017 lasts in Q1 2018, and the total volatility connectedness still keeps an upward trend to 73%. This may be associated with a series of negative information about cryptocurrencies. In January 2018, the Coincheck exchange, one of the largest cryptocurrency exchanges in Japan, suffered from hacker attack, resulting in that units of the cryptocurrency New Economy Movement (NEM) worth 660 million USD were stolen. At the same time, a regulation that all cryptocurrency accounts should be traded with real identities was enacted in South Korea, the world's third largest market in Bitcoin (source: https://www.coinhills.com/market/currency/). These events lead people to be suspicious of the security and anonymity of cryptocurrencies in the future.

4.5. Dynamic analysis II: total directional volatility connectedness

The rolling-sample gross directional volatility connectedness analysis shows the amount of volatility shocks transmitted across individual cryptocurrency markets and its changes over the full sampling time. To get a better understanding, we further estimate dynamic directional connectedness for every eight cryptocurrencies over the 2013–2018 period.

In Fig. 3, we present the dynamic directional volatility connectedness from each of the eight cryptocurrencies to others (corresponding to the "directional to others" row in Table 2). It can be seen that the to-connectedness or spillovers from each cryptocurrency maintain between 30% and 80% most of the time. However, the directional spillover fluctuates widely during violent times and sometimes increases over 200%. The large fluctuations mainly occurred in 2014 and 2015 as well as the first half of 2017.

Fig. 4 presents the dynamic directional volatility connectedness from the others to each eight cryptocurrencies (corresponding to the "directional from others" column in Table 2). They vary noticeably over

(*footnote continued*)
the same pattern with that using the traditional VAR estimation approach. The detailed results can be available upon request.

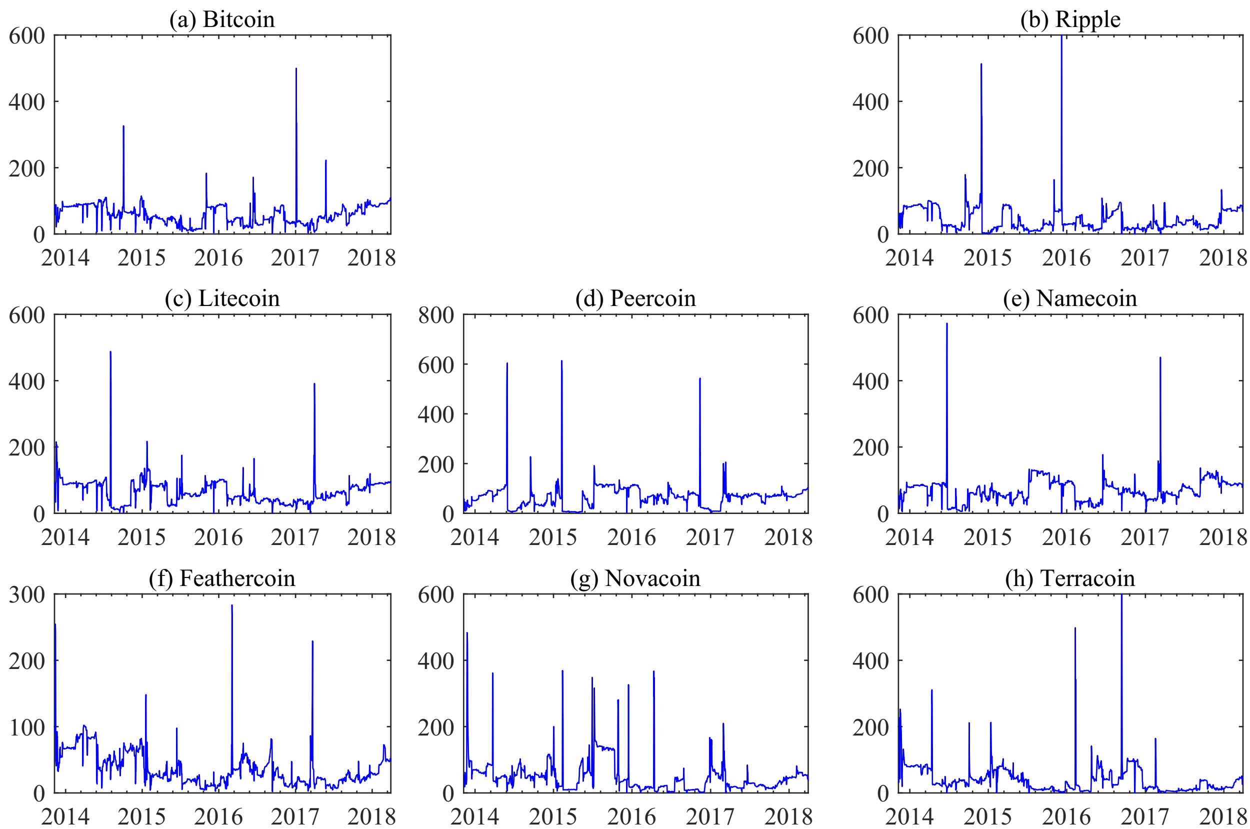

Fig. 3. Total directional volatility connectedness, To others (i.e., to-connectedness).

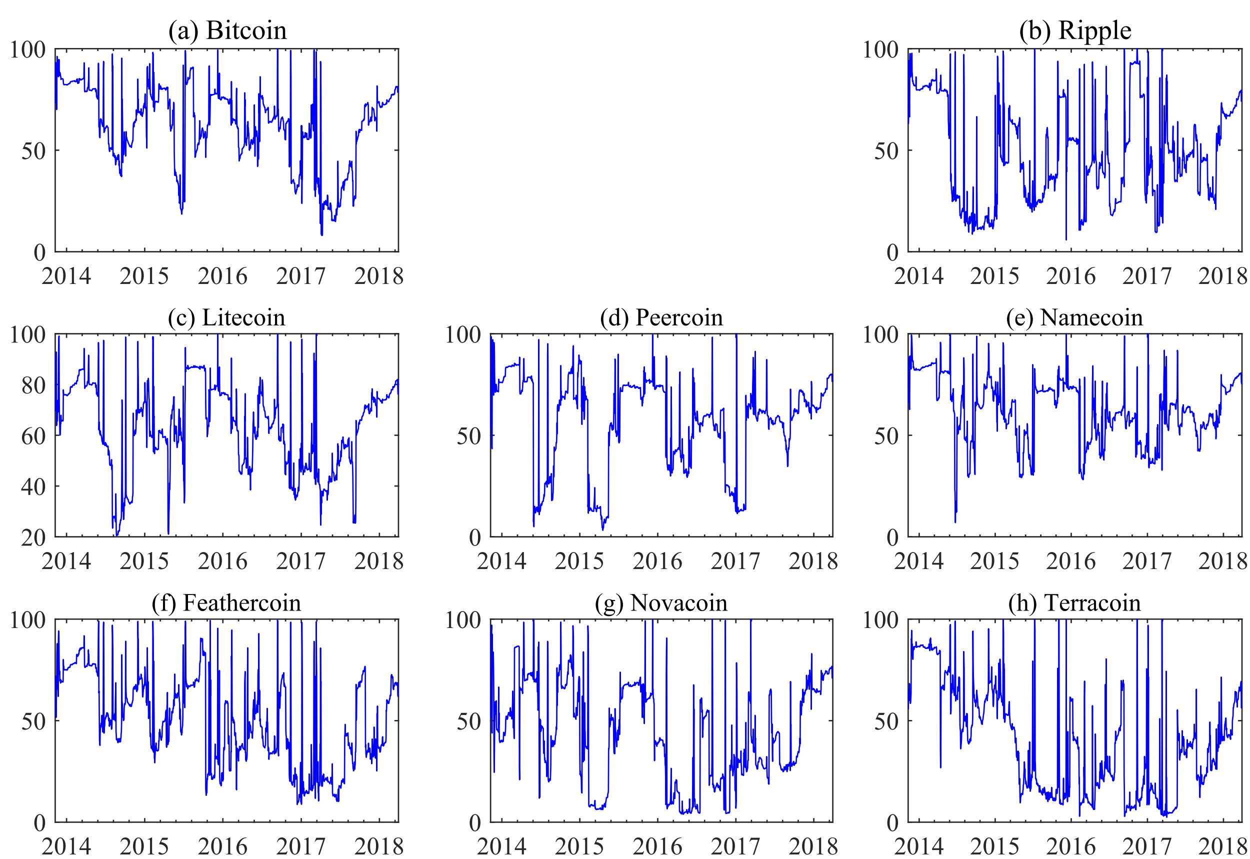

Fig. 4. Total directional volatility connectedness, From others (i.e., from-connectedness).

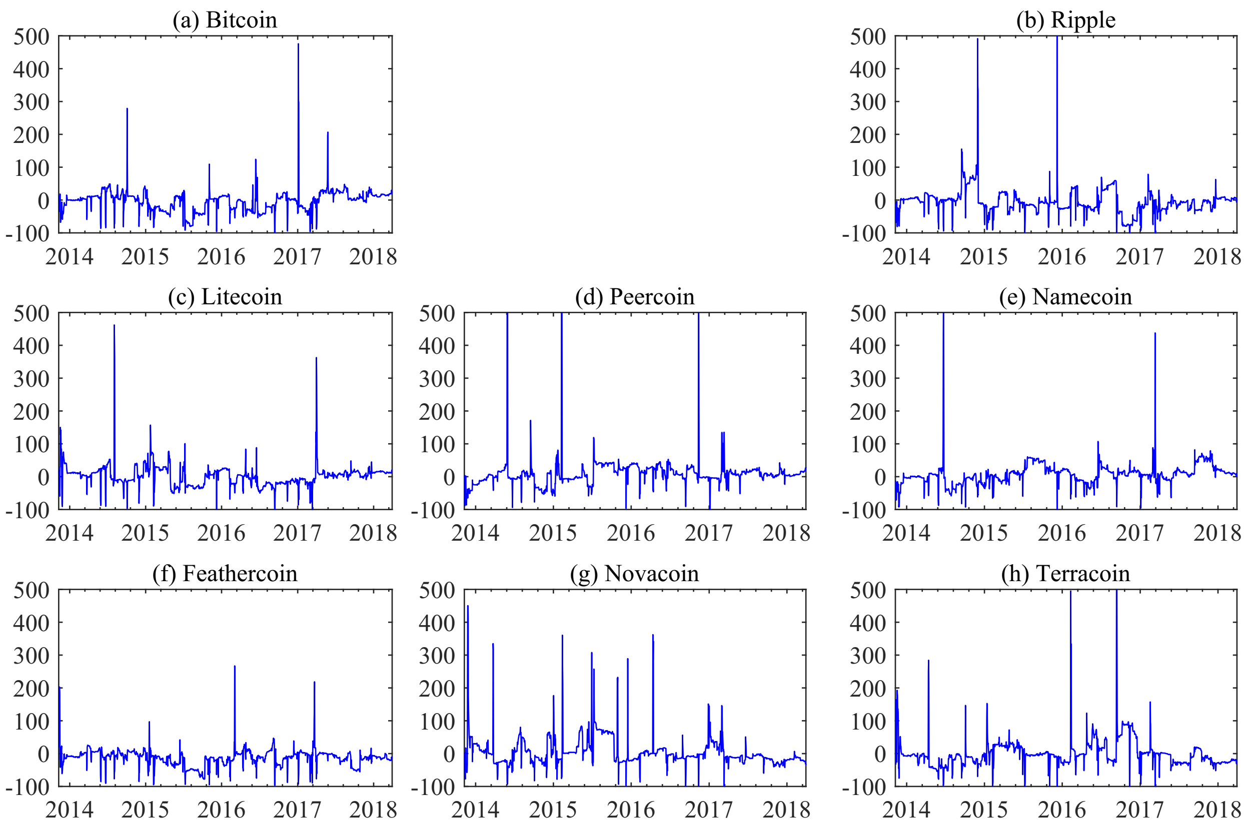

Fig. 5. Total directional volatility connectedness, Net (i.e., net-connectedness).

time and also fluctuate violently.

One of the things one notices between Figs. 3 and 4 is their substantial differences, which can be called "net-connectedness," and its dynamic results are presented in Fig. 5. Although the to-connectedness and from-connectedness or spillovers "to" and "from" others varied over the rolling-sample windows, the variation in the plot for net-connectedness resembles that for to-connectedness during the 2013–2018 period. This is because unlike the to-connectedness, the from-connectedness is relatively stable without huge mutations. The volatile fluctuation shows that cryptocurrencies influence each other and the effect is unstable.

In order to better understand the dynamic behavior of the total directional volatility connectedness for each cryptocurrency, we rank the eight cryptocurrencies based on to-connectedness, from-connectedness and net-connectedness in Figs. 6–8, respectively, where the colors from red to blue represent the rankings from 1 to 8. Note that the difference between to-connectedness and from-connectedness is equal to net-connectedness. Here we focus our attention on the rankings of Bitcoin according to to-connectedness, from-connectedness and net-connectedness. From Figs. 6 and 8, we observe that these two pictures are similar to each other, suggesting that the dynamic rankings between to-connectedness and net-connectedness have something in common. Specifically, in these two plots, the ranking of Bitcoin was relatively low from 2015 to 2017, because during this period its color is dominated by yellow or blue, representing a low ranking in to-connectedness and net-connectedness; while Bitcoin's ranking has risen since the beginning of 2018, because during this period its major color is red or orange, which represents a high ranking in to-connectedness and net-connectedness. However, the from-connectedness ranking of Bitcoin in Fig. 7 is different, because instead of yellow or blue, red or orange is its major color during the period from 2015 to 2017. This finding indicates that Bitcoin is more vulnerable to the volatility shocks transmitted from other seven cryptocurrencies. A similarity between Figs. 6 and 7 is the rankings of FTC (Feathercoin), NVC (Novacoin) and TRC (Terrcoin), i.e., they all ranked in the bottom three at most of time. This means that these three cryptocurrencies are neither major recipients nor major transmitters of volatility shocks. These three cryptocurrencies are all relatively small-cap assets (whose market capitalization are below 50 million USD) and are not "major cryptocurrency," and thus they are comparatively insulated from volatility shocks to other cryptocurrencies.

We now focus on net-connectedness ranking in Fig. 8, where three episodes of net-connectedness can be spotted. The first extends from the beginning of the sample to the middle of 2015. In this period, Litecoin, which was supported by Mt. Gox in July 2013, ranked high in terms of net-connectedness. A possible explanation is that it improved the basic algorithm of Bitcoin to help people pay for daily consumption, thereby complementing the bitcoin market. As a result, Litecoin seemed to attract more investors and dominated the market in this period. This situation is consistent with substitution effect found by Gandal and Halaburda (2016). As the sample moves out to 2016, the volatility transmission from Peercoin to others increased compared with other cryptocurrencies. During the period from 2017 to April 2018, there is a trend that the net-connectedness of Bitcoin outperformed other currencies and became a net-transmitter of volatility shocks to others broadly. It took place with the heat of the Bitcoin market in 2017. This may be explained for several reasons. Dyhrberg (2016a) holds the view that Bitcoin possesses similarities to both currency and gold. This suggests that Bitcoin can be used as a medium for exchange and a store of value for hedging. Therefore, a series of events like Fed rate increases, European Union's gradual withdrawal of the quantitative easing (QE), and Trump's political uncertainty bring economic shocks to the global markets and cause the rising volatility of Bitcoin. The price change of Bitcoin can be seen as a signal of market attitude towards the cryptocurrency market, and further affects the performance of this market. Another reason is related to investors' expectations. As Bitcoin is gradually accepted by the public and accounted for the majority of market capitalization, it has become the representative of cryptocurrencies. Hence there is a reinforcement effect that people believe it will win the winner-take-all race against others,

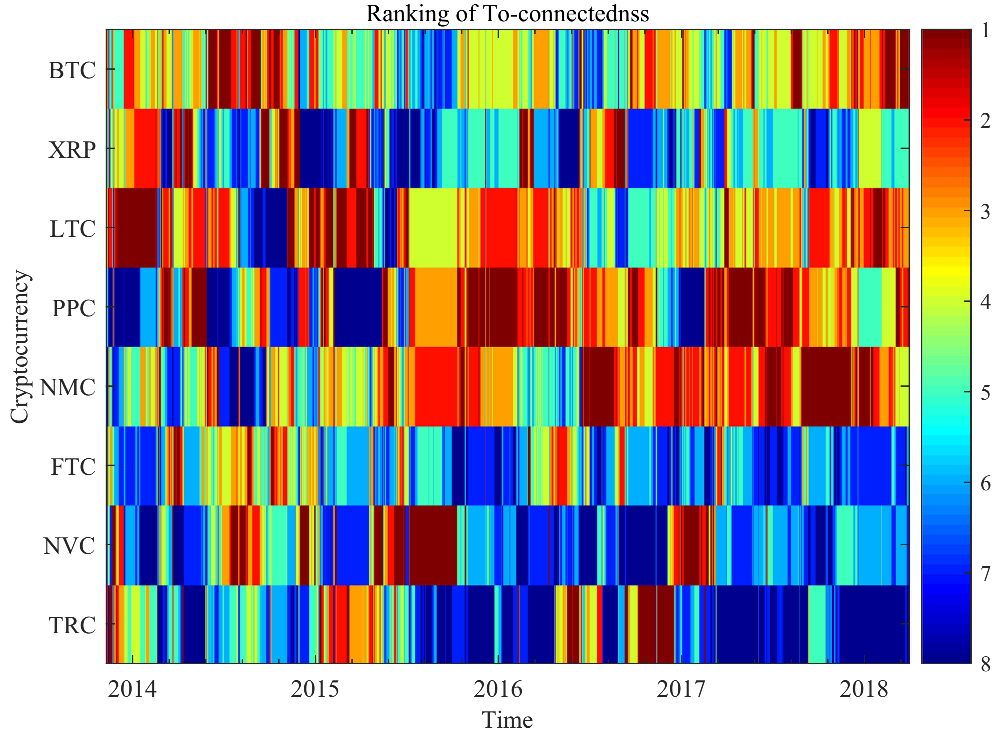

Fig. 6. Dynamic ranking of to-connectedness for the eight cryptocurrencies. Notes for this and the following two figures: the colors from red to blue represent the rankings from 1 to 8.

thereby increasing demand for Bitcoin. Consequently, its price soared and Bitcoin exerted more influences on others. It should be noticed that Bitcoin has always been the biggest net-transmitter of volatility connectedness or spillovers in Q1 2018, which indicates that the fluctuation of Bitcoin affects other cryptocurrencies significantly.

4.6. *Robustness analysis*

Our results about dynamic volatility connectedness based on the spillover index approach and its variants are related to several parameters, including the window width w, the forecast horizon H, the VAR lag p, and volatility estimator V. Here we discuss the robustness of our

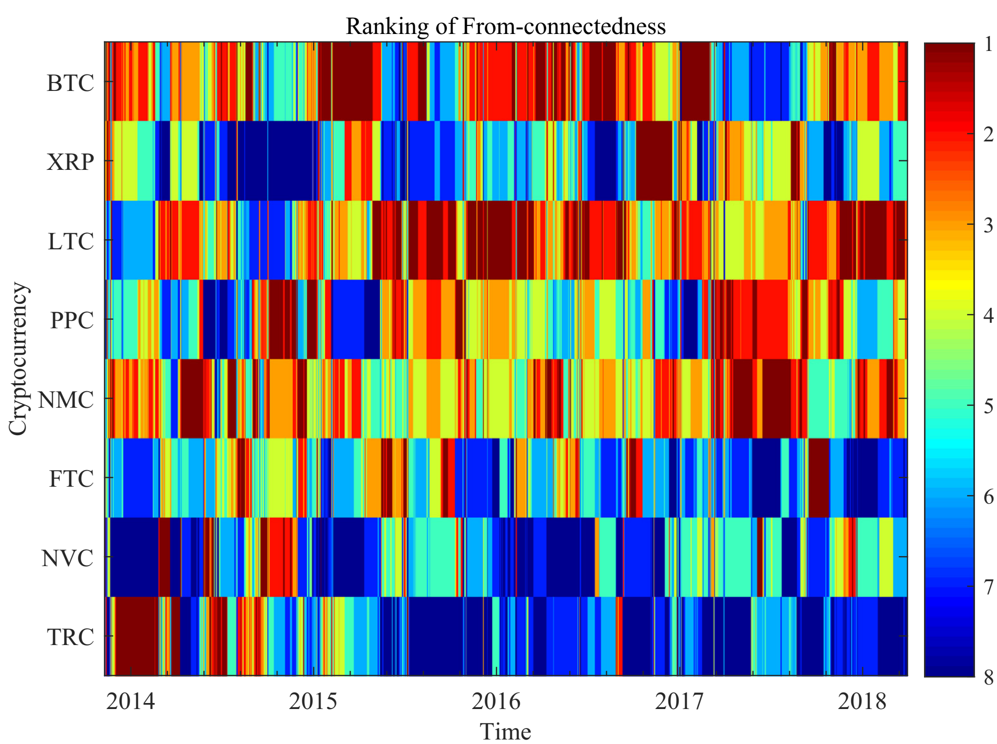

Fig. 7. Dynamic ranking of from-connectedness for the eight cryptocurrencies.

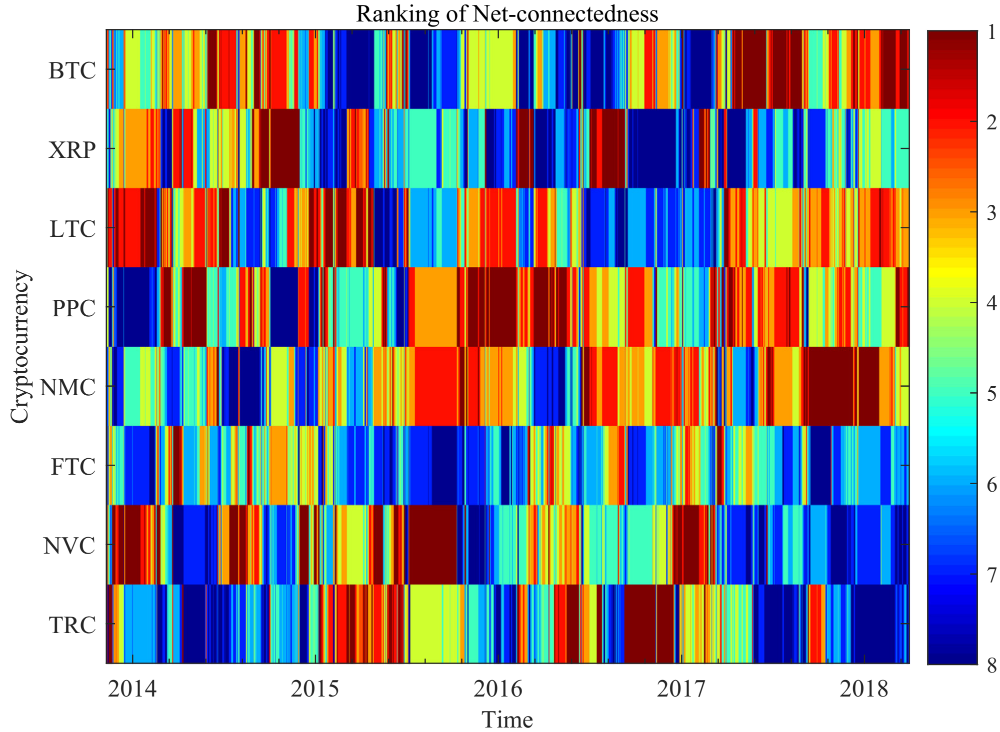

Fig. 8. Dynamic ranking of net-connectedness for the eight cryptocurrencies.

results to the choice of the parameters in the spillover index approach and its variants. We plot dynamic total volatility connectedness for alternative window widths, forecast horizons, VAR lags and volatility estimators in Figs. 9–11. Because there are four parameters in our used approach, it is difficult to compare four parameters at the same time. For convenience of comparison, in each figure we only pay attention to one or two parameters' varying and control other remaining parameters unchanged. In Table 4 we show a guide on the values of the four parameters in each robustness checking figure (i.e., Figs. 9–11).

In Fig. 9, we plot the total volatility connectedness for different window width (in addition to $w = 100$ days, we consider 80 and 120 days), and for different forecast horizons (in addition to $H = 10$ days, we consider 8 days and 12 days). Fig. 9 shows that the window width and the choice of forecast horizon exert little influence on the pattern, indicating that our results are robust to the choice of the window width and the forecast horizon. In Fig. 10, we set the VAR lag order varying from 1 to 6. The six curves of total volatility connectedness have the same trend, indicating that the choice of the VAR lag order has little impact on the pattern of the total volatility connectedness, and thus verifying that our results are robust to the VAR lag order. For investigating the robustness of the choice of range-based volatility estimators, we consider other three estimation methods including V^P of Parkinson (1980), V^{RS} of Rogers and Satchell (1991) and V^{YZ} of Yang and Zhang (2000). They are respectively defined by:

$$V_{it}^{P} = \frac{1}{4\ln 2}(H_{it} - L_{it})^2, \tag{11}$$

$$V_{it}^{RS} = (H_{it} - O_{it})(H_{it} - C_{it}) + (L_{it} - O_{it})(L_{it} - C_{it}), \tag{12}$$

$$V_{it}^{YZ} = V_o + kV_c + (1 - k)V_{it}^{RS}, \tag{13}$$

where V_o and V_c denote variances of normalized opening and closing prices, respectively, and the constant k is given by

$$k = \frac{0.34}{1.34 + (n + 1)/(n - 1)}. \tag{14}$$

Fig. 11 shows that the qualitative features of three curves using the three alternative range-based volatility estimators are similar to the curve using the range-based volatility estimator V^{GK}, suggesting that the pattern of total volatility connectedness is not sensitive to the range-based volatility estimators. In summary, the curves for the total volatility connectedness move almost the same in the sample period, suggesting that our results are not sensitive to the choice of window width, forecast horizon, VAR lag order, and range-based volatility estimator.

5. Expanded cryptocurrency network connectedness

From the analysis in Section 4, it is notable that the connectedness among the eight currencies has increased since December 2016. At the same time, however, a number of new cryptocurrencies have appeared and the market capitalization of cryptocurrencies has extraordinarily increased. For example, there are 1548 cryptocurrencies and their total market capitalization surpassed 259 billion USD as of 1 April 2018. Therefore, the volatility connectedness behavior of more cryptocurrencies is worth discussing, so we expand our sample cryptocurrencies and analyze their relationships from a network connectedness perspective.

5.1. Data and sample period

We select 52 cryptocurrencies from 1 December 2016 to 1 April 2018. To ensure the persuasion and integrity of the sample, we firstly choose cryptocurrencies in world's top 200 (by market capitalization on 1 April 2018) that were publicly-traded throughout the sample period. On the basis of these 200 currencies, we exclude 148 that consecutive missing data days are more than 10 days. Among the remaining 52 currencies, there are 48 without data loss (data records are available for daily transactions), SaluS, ARDOR missing one data, Enigma missing two data and ION missing ten data. For SaluS, ARDOR, Enigma and ION, their missing data (including the high, low, opening and closing prices) in one trading day are complemented by the relevant prices of

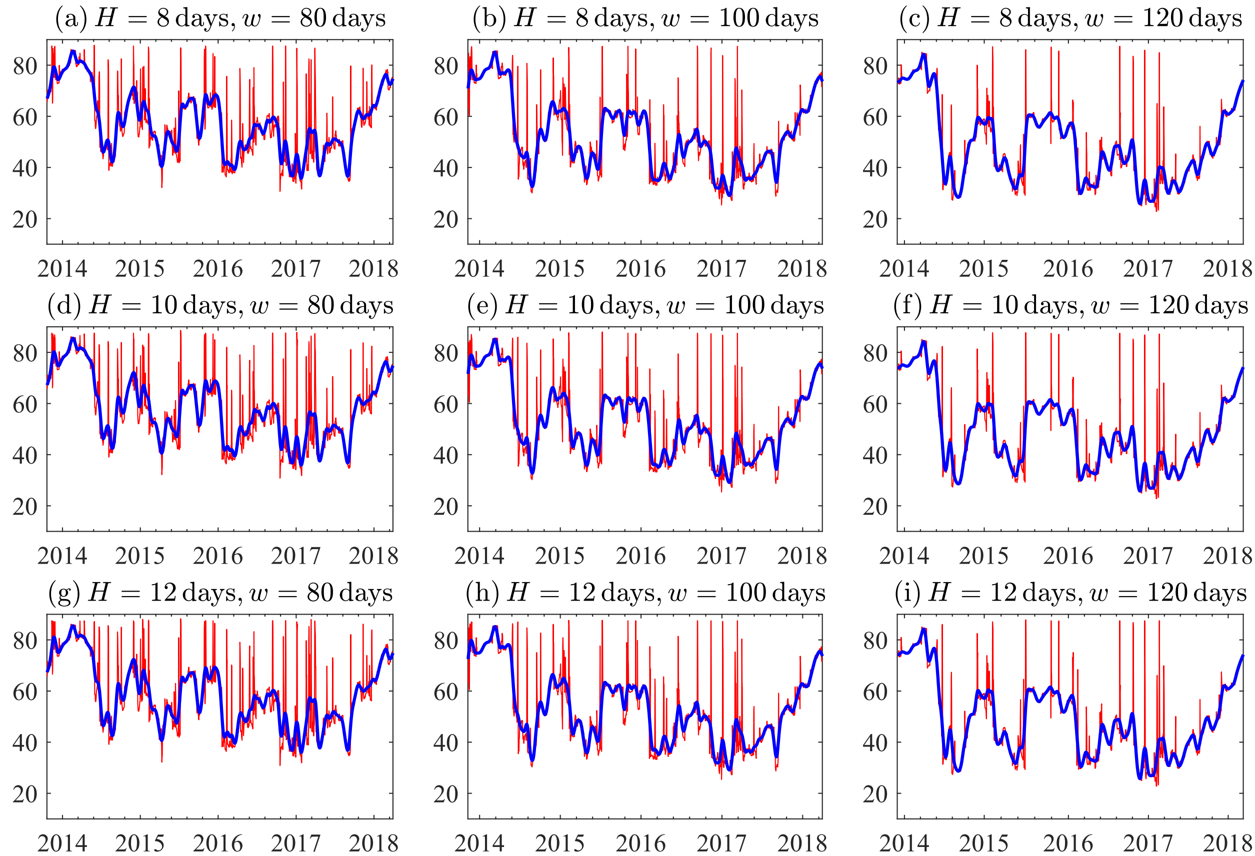

Fig. 9. Robustness of total volatility connectedness index based on varying forecast horizons *H* and window widths *w*.

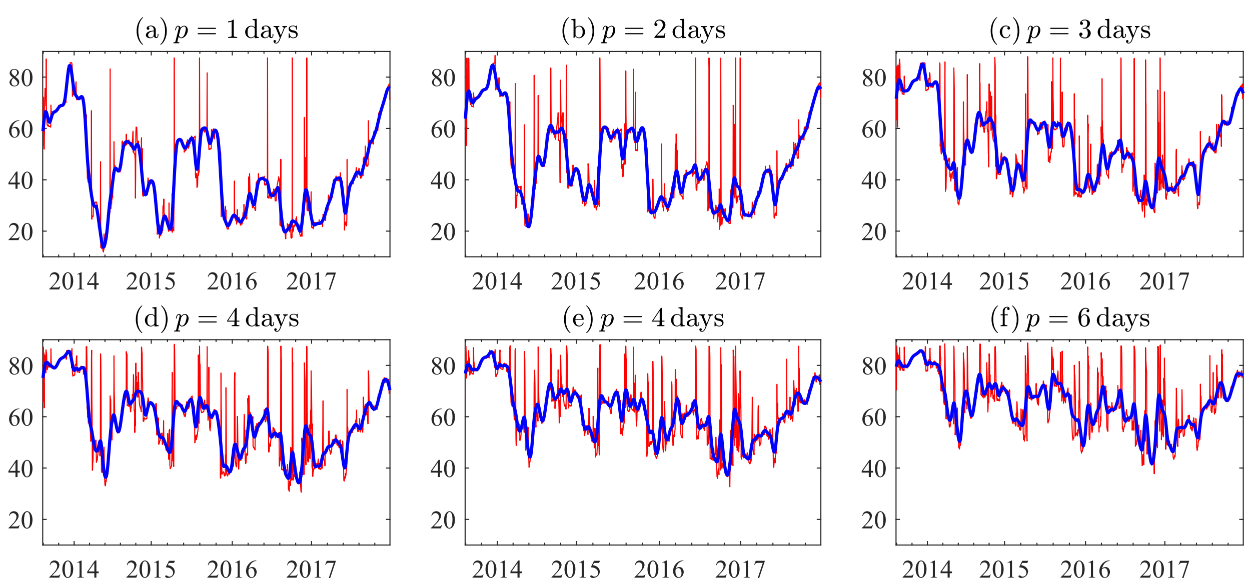

Fig. 10. Robustness of total volatility connectedness index based on varying VAR lag orders *p*.

the previous trading day. In Table 5, we show the 52 cryptocurrencies and their symbols, market capitalizations (MCs), and rankings based on MCs as of 1 April 2018.

We also use daily range-based volatility estimator V^{GK} to compute daily volatility series. Each volatility series comprises 487 observations. Since our expanded sample including 52 cryptocurrencies is a type of high-dimensional variable setting, we first estimate VARs for 52 volatility series using the Lag Sparse Group LASSO (see Section 3.2), and then calculate variance decompositions and relevant volatility connectedness using the estimated VAR parameters.[6]

[6] Note that we have tried to use traditional VAR estimation approach as in Diebold and Yilmaz (2012, 2014) to compute the volatility connectedness among 52 cryptocurrencies. But the traditional VAR estimation approach fails to obtain the estimation results.

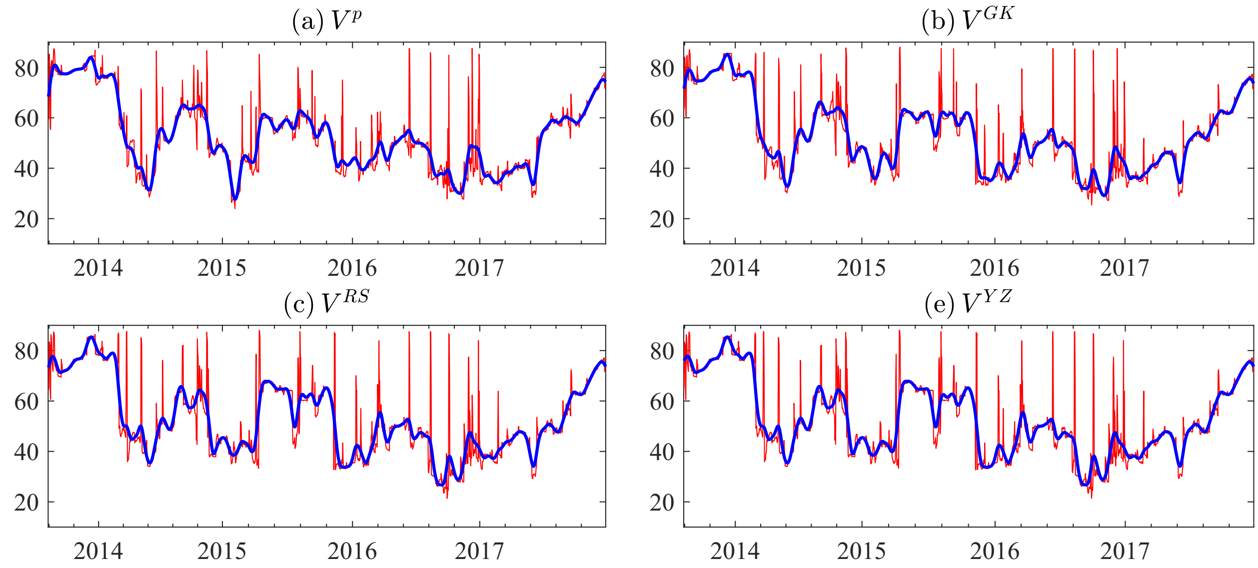

Fig. 11. Robustness of total volatility connectedness based on different range-based volatility estimators: (a) V^P of Parkinson (1980), (b) V^{GK} of Garman and Klass (1980), (c) V^{RS} of Rogers and Satchell (1991), and (d) V^{YZ} of Yang and Zhang (2000).

Table 4
A guide on the values of the four parameters (i.e., window width w, forecast horizon H, VAR lag p and volatility estimator V) in each robustness checking figure.

	Window width w	Forecast horizon H	VAR lag p	Volatility estimator V
Fig. 9	80, 100, 120	8, 10, 12	3	V^{GK}
Fig. 10	100	10	1, 2, ⋯, 6	V^{GK}
Fig. 11	100	10	3	V^P, V^{GK}, V^{RS}, V^{YZ}

Notes: the volatility estimators include V^{GK} of Garman and Klass (1980) [Eq. (10)], V^P of Parkinson (1980) [Eq. (11)], V^{RS} of Rogers and Satchell (1991) [Eq. (12)], and V^{YZ} of Yang and Zhang (2000) [Eq. (13)].

5.2. Network visualization of high-dimensional variance decompositions

To display the results of high-dimensional network intuitively, we characterize the networks graphically using several devices. These devices include node's naming convention, node's size, and edge's direction.

Node's naming convention is short for each cryptocurrency (see Table 3). Node's size indicates the size of their relative market capitalization. We divide the sample currencies into several ranges according to the size of their market capitalization. For example, Bitcoin, the only cryptocurrency whose market value surpassed 100 billion USD, is marked red. The colors for the remaining currencies also indicate the relative size of their market values, including blue (indicating a

Table 5
52 Cryptocurrencies and their symbols, market capitalizations (MCs) and rankings of MCs (as of 1 April 2018).

#	Cryptocurrency	Symbol	MC ($1 Mil)	Rank by MC	#	Cryptocurrency	Symbol	MC ($1 Mil)	Rank by MC
1	Bitcoin	BTC	116,890	1	27	DigiByte	DGB	174	64
2	Ethereum	ETH	38,417	2	28	Golem	GNT	165	65
3	Ripple	XRP	19,620	3	29	Factom	FCT	164	66
4	Litecoin	LTC	6441	5	30	Syscoin	SYS	142	72
5	Stellar	XLM	3822	8	31	ZCoin	XZC	129	80
6	NEO	NEO	3194	9	32	ReddCoin	RDD	111	83
7	Monero	XMR	2819	11	33	Nxt	NXT	111	84
8	Dash	DASH	2404	12	34	Enigma	ENG	105	87
9	NEM	XEM	1963	15	35	MaidSafeCoin	MAID	104	89
10	Ethereum Classic	ETC	1424	16	36	Emercoin	EMC	93	99
11	Lisk	LSK	773	22	37	Nexus	NXS	84	106
12	Zcash	ZEC	669	25	38	Iconomi	ICN	73	114
13	Verge	XVG	577	26	39	Vertcoin	VTC	72	119
14	DigixDAO	DGD	475	29	40	GameCredits	GAME	70	122
15	Bytecoin	BCN	389	31	41	BitcoinDark	BTCD	68	126
16	Steem	STEEM	384	32	42	Blocknet	BLOCK	66	130
17	Stratis	STRAT	359	33	43	NavCoin	NAV	53	145
18	Waves	WAVES	358	34	44	SaluS	SLS	52	148
19	Siacoin	SC	349	37	45	DigitalNote	XDN	45	165
20	BitShares	BTS	329	38	46	ION	ION	45	166
21	Dogecoin	DOGE	315	40	47	Pura	PURA	41	173
22	Decred	DCR	278	47	48	Peercoin	PPC	38	183
23	Augur	REP	277	48	49	Feathercoin	FTC	37	188
24	Ardor	ARDR	219	53	50	BitBay	BAY	36	192
25	PIVX	PIVX	199	58	51	Einsteinium	EMC2	34	198
26	MonaCoin	MONA	181	62	52	SingularDTV	SNGLS	34	200

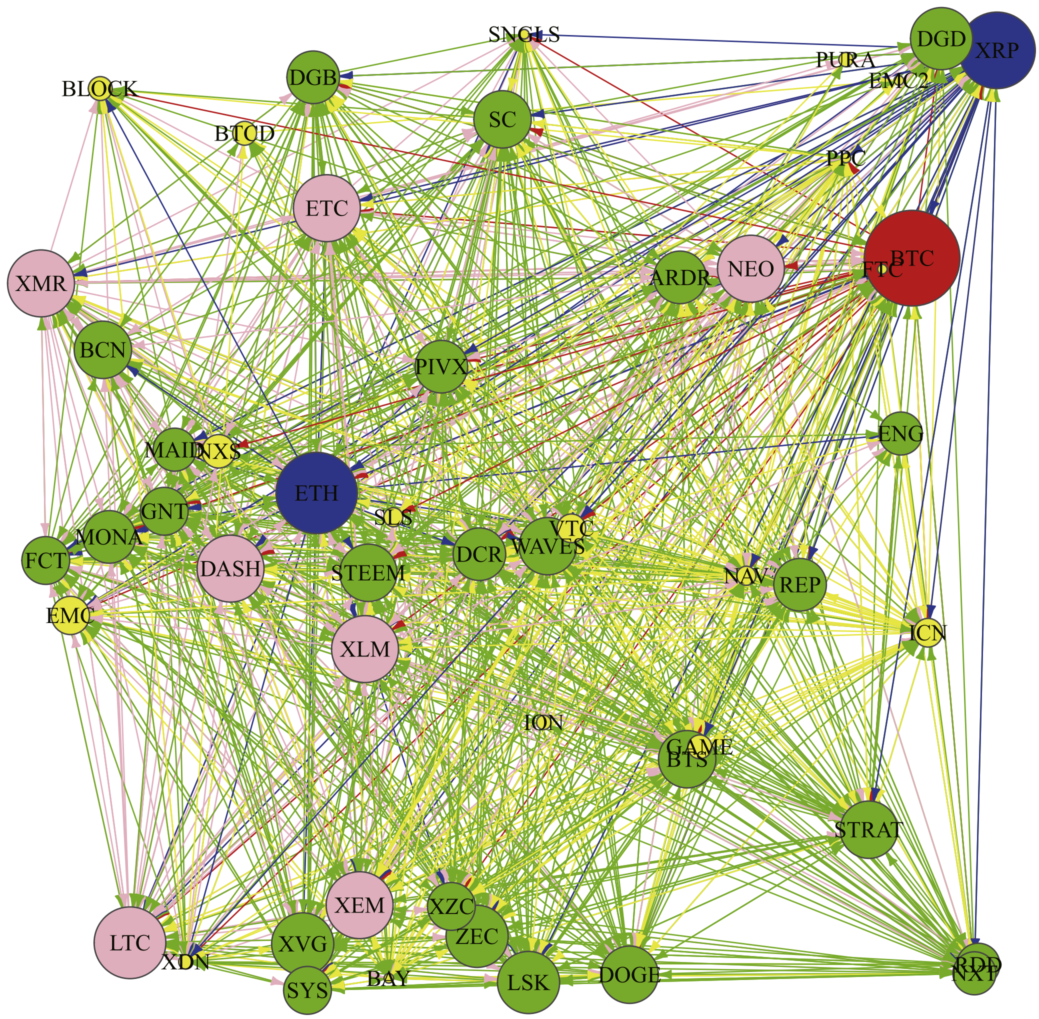

Fig. 12. Snapshot of volatility connectedness network linking 52 cryptocurrencies. Note that the edges whose volatility pairwise directional connectedness or spillover strength from one cryptocurrency to another less than 0.01 are not shown in the plot. The full name of each cryptocurrency is presented in Table 5. The node's size corresponds to the relative size of the corresponding cryptocurrency in terms of market capitalization. The node's color is set as: (i) red if the market capitalization of a cryptocurrency is above 100 billion USD (only Bitcoin), (ii) blue if the market capitalization ranges from 10 billion to 100 billion USD (only ETH and XRP), (iii) pink if market capitalization ranges from 1 billion to 10 billion USD, (iv) green if market capitalization ranges from 100 million to 1 billion USD, and (v) yellow if market capitalization below 100 million USD. The directed edge's color follows its starting node's color.

currency's market value between 10 and 100 billion USD), pink (between 1 and 10 billion USD), green (between 100 million and 1 billion USD), and yellow (below 100 million USD); for a detailed description see the caption of Fig. 12. The direction of an edge shows the pairwise directional connectedness from one cryptocurrency to another. The directed edge's color is the same as the starting node's color.

The network snapshot of the pairwise directional connectedness for these 52 currencies is shown in Fig. 12. Note that Fig. 12 only shows the edges from one cryptocurrency to another such that their pairwise directional connectedness values are greater than 0.01. We observe that Bitcoin generates substantial and widespread connectedness since it transmits volatility shocks to almost all other cryptocurrencies (i.e., nodes in the network with other four colors), but it is also affected by other currencies. Table 6 shows the top ten largest net-emitters ranked by net-connectedness, consisting of (i) Bitcoin whose market capitalization is the largest, (ii) four top ten cryptocurrencies in terms of market capitalization (i.e., ETH, ETC, LTC, and XMR), (iii) three "second-tier" cryptocurrencies (i.e., MAID, FTC, and DOGE) whose market capitalizations ranking in the middle and (iv) one cryptocurrency (i.e., GAME) with relatively low market capitalization. This finding suggests that the intensity of connectedness between pairwise cryptocurrencies is not fully determined by market capitalization. The

Table 6
Top ten cryptocurrencies ranked by their Net-connectedness and PageRank centrality in the network (see Fig. 12).

Rank	Net-connectedness		PageRank centrality	
	Cryptocurrency	Value	Cryptocurrency	Value
1	MAID	72.3169	MAID	0.0442
2	ETC	59.3724	ETC	0.0420
3	ETH	50.5564	LTC	0.0393
4	LTC	50.1359	BTC	0.0384
5	DOGE	48.1778	ETH	0.0381
6	BTC	47.1961	DOGE	0.0378
7	FCT	44.8679	FCT	0.0377
8	XMR	42.4903	XMR	0.0368
9	SC	38.3000	GAME	0.0340
10	GAME	35.8898	SC	0.0334

cryptocurrency market fluctuated frequently and unstably and is prone to be interfered with by exogenous shocks. Although most of cryptocurrencies with high market capitalization (e.g., Bitcoin) show high "from" and "to" connectedness, some cryptocurrencies at the same level (e.g., Ripple) do not stand out in terms of directional connectedness. In

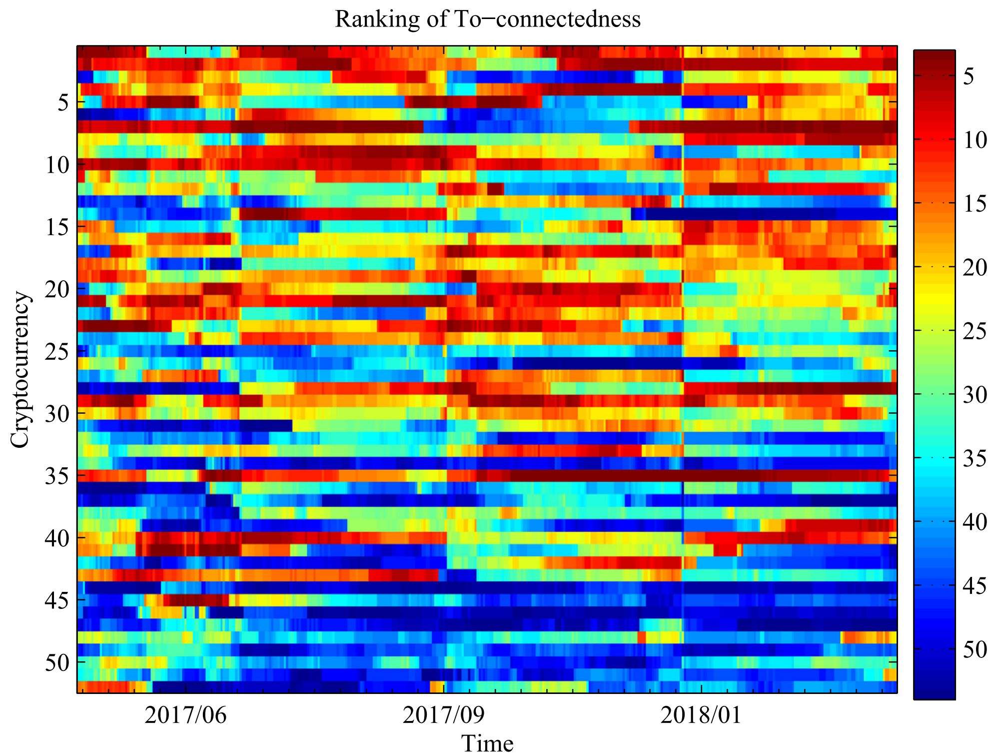

Fig. 13. Rolling rankings of to-connectedness for 52 cryptocurrencies. We set the rolling window width $w = 100$, the prediction horizon $H = 10$, and the VAR lag order $p = 3$. Notes: in the color bar (see the legend in the right hand side), each color stands for a ranking of to-connectedness, varying from 1 to 52. The label order for each cryptocurrency in the left hand side (i.e., y-axis) is shown in Table 5.

addition, other cryptocurrencies with low market capitalization also take an important role in volatility connectedness for the whole market.

In Table 6, what surprised us is that MAID is the largest net-emitter in the period from December 2016 to April 2018. To further examine relative influence of cryptocurrencies in the network (see Fig. 12), we also employ a widely-used centrality structure in the network topology analysis, i.e., the PageRank centrality to calculate their rankings. PageRank used in Google is a method to solve how to rank pages in link analysis (Brin & Page, 1998). The principle is that when a web page is linked by more pages, it ranks better. High-ranked web pages have greater voting power, meaning that the importance of a web page is increased if it is linked to a high ranking one. From Table 6, we find that the rankings based on the PageRank centrality are similar to those using the net-connectedness results, and confirm that MAID is truly the center node of the network.

Considering that the time span of the sample period is relatively long, the results may be caused by some special events in a certain period. Therefore, in Fig. 13 we plot the dynamic rankings of each currency's to-connectedness, so as to evaluate the significance of their volatility spillovers.

Fig. 13 shows that the volatility spillover effects of MAID (number 35) is strong in the whole sample period, especially since Q4 2017. Another two important volatility transmitters, ETC (number 10) and ETH (number 2), ranked high after September 2017. By contrast, the rankings of the rest of cryptocurrencies in Table 6 vary more frequently, showing instability and discontinuity.

6. Conclusions

To summarize, we have provided static and dynamic analyses of volatility connectedness (including the total connectedness and directional connectedness) among eight typical cryptocurrencies from 4 August 2013 to 1 April 2018, using the volatility spillover index and its variants. We also have tested the robustness of results in terms of the choice of related parameters (including the VAR lag order, the prediction horizon, the rolling window width and the range-based volatility estimator). We further used the LASSO to shrink and estimate VAR parameters in the high-dimensional variable context for building volatility connectedness network during the special period with a rising connectedness (i.e., the period from 1 December 2016 to 1 April 2018). The network is linked to 52 publicly-traded cryptocurrencies in world's top 200 (by market capitalization on 1 April 2018).

We find that the total volatility connectedness among eight cryptocurrencies fluctuated periodically over the sample period, and increased when the market is experiencing unstable economic conditions or unpredictable exogenous shocks. In particular, the total volatility connectedness increased constantly after December 2016, indicating that at present the changes of the cryptocurrency market are frequent and uncertain. Another interesting finding is that the volatility connectedness or spillover effect is not necessarily linked to market capitalization. In most cases, cryptocurrencies with high market capitalization (e.g., Bitcoin, Litecoin and Dogecoin) propagate large volatility shocks, while small-cap cryptocurrencies are more likely to receive volatility shocks from others. However, some small cryptocurrencies are also important emitters of volatility shocks (e.g., MAID, FCT and GAME). More importantly, the largest emitter of volatility shocks in the cryptocurrency market is MAID, which catches less attention of the public. Although Bitcoin truly plays an important role and generates strong volatility shocks to other cryptocurrencies, it does not dominate the whole market. This unexpected result is in line with Corbet, Meegan et al. (2018), who find that cryptocurrencies are highly connected to each other while for volatility spillovers Bitcoin is not a clear leader. Moreover, the non-dominant position of Bitcoin reinforces the conclusion got by Ciaian et al. (2018) that the prices of altcoins are not driven by the development of Bitcoin in the long-run.

The transmission mechanism of volatility spillovers among cryptocurrencies are more inclined to be invisible, which refers to market imperfections or the behaviors and sentiments of investors. This is because most of cryptocurrencies have many similarities in their underlying technology and trading rules, and importantly differ from "classic" financial assets (e.g., stocks) that are more susceptible to international or national economic fundamentals or the operating situations of corporations. Besides, herding is also a possible channel to transmit volatility spillovers. Evidence of herding in the cryptocurrency market shows that cryptocurrency traders are likely to follow the decisions of other investors, especially as uncertainty increases (Bouri, Gupta et al., 2018). Such investor behaviors have a negative impact on market efficiency.

Our investigation on volatility connectedness among cryptocurrencies and examining which cryptocurrency generates strong volatility shocks to others complement the literature on cryptocurrency and provide new information for investors and miners.

First, our research contributes to the literature regarding the volatility interconnectedness among various cryptocurrencies. Our results provide supports to the existing literature that in the cryptocurrency market Bitcoin is not the clear leader in terms of volatility connectedness.

Second, we find that the total volatility connectedness index reflects the stability of the whole cryptocurrency market to some degree, because it shows an upward trend when cryptocurrency markets experience unpredictable events or suffer losses. Therefore, it supplies a reference indicator for market participants to analyze the market stability and cope with unfavorable market conditions.

Third, much previous research shows that Bitcoin can be used as a hedge, a safe-haven, or a diversifier against traditional financial assets (e.g., stock, bond, commodity and USD) for investors. Our work further investigates the relationship among crytocurrencies and provides the profile of both static and dynamic volatility connectedness or spillovers among different cryptocurrencies. It is helpful for investors or portfolio managers to choose various cryptocurrencies, instead of narrowly focusing on Bitcoin. It is also useful for miners to select and mine part of cryptocurrencies, reducing the potential losses due to extreme price fluctuations or the declining competitiveness of their computing power.

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