J. Int. Financ. Markets Inst. Money 71 (2021) 101302

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Quantile connectedness in the cryptocurrency market

Elie Bouri [a,b,*], Tareq Saeed [c], Xuan Vinh Vo [d], David Roubaud [e]

[a] Adnan Kassar School of Business, Lebanese American University, Lebanon
[b] Institute of Business Research, University of Economics Ho Chi Minh City, Ho Chi Minh City, Viet Nam
[c] Nonlinear Analysis and Applied Mathematics (NAAM)-Research Group, Department of Mathematics, Faculty of Science, King Abdulaziz University, Jeddah, Saudi Arabia
[d] Institute of Business Research and CFVG -University of Economics Ho Chi Minh City, Ho Chi Minh City, Viet Nam
[e] Montpellier Research in Management, Montpellier Business School, 2300 Avenue des Moulins, 34080 Montpellier, France

ARTICLE INFO

Article history:
Received 18 February 2020
Accepted 27 January 2021
Available online 6 February 2021

Keywords:
Quantile connectedness
Return spillovers
Bitcoin
Cryptocurrency
Asymmetry
COVID-19 outbreak

ABSTRACT

In order to move beyond mean-based connectedness measures in the cryptocurrency market and capture connectedness under extreme events, this paper applies quantile-based connectedness measures based on the variance decomposition of a quantile vector autoregression model. Based on the daily price data of seven leading cryptocurrencies from August 8, 2015 to December 31, 2020, the results show that the connectedness measures in the left and right tails are much higher than those in the mean and median of the conditional distribution. This suggests that return connectedness strengthens with shock size for both positive and negative shocks, indicating that return shocks propagate more intensely during extreme events relative to calm periods. While this result shows the instability of the system of connectedness under extreme events such as the COVID-19 outbreak, it implies the need to move beyond mean-based connectedness measures to understand the return connectedness under extreme negative and extreme positive shocks. Further analyses based on rolling windows show evidence of asymmetry between the behaviour of return spillovers in lower quantiles and upper quantiles. The results are robust to several alternative choices.

1. Introduction

Interdependencies among financial variables are important to understand potential financial exposures and the overall dynamics of financial system risk. They have implications for a wide set of issues related to risk management, asset allocation, and regulatory formulation. This is very relevant for the cryptocurrency market that has emerged as a new and hot venue for many institutional and individual participants from various continents and backgrounds. It has recently remade the financial headlines after the price of Bitcoin reached new all-time highs in late December 2020. Notably, the cryptocurrency market has gradually become more complex (Antonakakis et al., 2019; Kristjanpoller et al., 2020), suggesting the need for more refined research into the system of connectedness among leading cryptocurrencies such as Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Monero, and Dash.

Previous studies have measured the direction and strength of shock spillovers in the cryptocurrency market, relying on conventional average-based estimators that can only measure the system of average shocks, such as GARCH-based processes

* Corresponding author.
E-mail addresses: elie.elbouri@lau.edu.lb (E. Bouri), tsalmalki@kau.edu.sa (T. Saeed), vinhvx@ueh.edu.vn (X.V. Vo), d.roubaud@montpellier-bs.com (D. Roubaud).

https://doi.org/10.1016/j.intfin.2021.101302
1042-4431/

(Katsiampa et al., 2019), Granger causality models (Bouri et al., 2019a), and the vector autoregression (VAR) framework of Diebold and Yilmaz (2012) (Koutmos, 2018; Corbet et al., 2018; Yi et al., 2018; Antonakakis et al., 2019; Qureshi et al., 2020). However, systemic shocks are not necessarily equal to average shocks, but can be much larger, suggesting the need to consider potential heterogenous effects across the size distribution of shocks. While these models have been extensively applied to empirical finance and economics literature, the approach of Diebold and Yilmaz (2012) has particularly shown the ability to uncover the system of connectedness in static and time-varying settings. It has been applied to several conventional assets,[1] and recently to digital assets (Corbet et al., 2018; Koutmos, 2018; Yi et al., 2018; Ji et al., 2019; Zięba et al., 2019) and Bitcoin exchange markets (Giudici and Pagnottoni, 2020). In the approach of Diebold and Yilmaz (2012), ordinary least squares are used to estimate the VAR model, which allows for inferences regarding only average shocks and their propagation within the system of connectedness. This overlooks and underestimates the potential effects of the size of the shocks on the system of connectedness.

In this paper, we determine the quantile connectedness within the network of returns of leading cryptocurrencies. To this end, we apply a quantile-based measure of connectedness within the framework of Diebold and Yilmaz (2012), through the incorporation of a quantile VAR model based on the quantile regression of Koenker and Bassett (1978). This is done by fitting VAR models at upper and lower percentiles via quantile regression, which allows us to capture the network of connectedness associated with extreme large positive and negative shocks, i.e., shocks in the 90th and 10th percentiles of the size distribution of shocks. This is more useful and informative than concentrating on the middle quantile only. Such an extended analysis helps us to better understand tail risk propagation in the cryptocurrency market, which can reflect the complexity of the system of connectedness in this controversial and highly volatile market.

We follow the related literature and consider the seven cryptocurrencies with the highest market capitalization, which are also highly liquid. Their price data is extracted from https://coinmarketcap.com for the period August 8, 2015 to December 31, 2020, covering the year 2020 during which various extreme events such as the COVID-19 outbreak have agitated the global economy and financial markets around the globe. Accordingly, our paper is related to recent studies considering the effects of the COVID-19 outbreak on financial markets (Bouri et al., 2020), including the cryptocurrency markets (e.g., Naeem et al., 2021; Shahzad et al., 2021) and thus adds to the existing literature (e.g., Corbet et al., 2018; Koutmos, 2018; Yi et al., 2018; Ji et al., 2019; Zięba et al., 2019).

The main findings indicate that, firstly, the system of return connectedness is shaped by the size of the shock, given that shocks in the upper and lower tails have a higher impact on the system of connectedness than shocks estimated at the conditional mean and median. This suggests the unsuitability of using only conditional mean-based estimators to study the return spillovers associated with extreme positive/negative events. Secondly, time-variation in the connectedness measures observed in the tails is dissimilar to that observed at the conditional mean or median. Thirdly, the time variation of the total connectedness index differs between lower tail and upper tails, indicating asymmetric behaviour. In fact, a detailed analysis involving the relative tail dependence (RTD) reveals that the difference between the tail dependence at the 90th quantile and the tail dependence at the 10th quantile differs from zero, varies with time, and mostly switches between negative and positive values. Fourthly, the total return spillovers intensified during 2020, coinciding with the COVID-19 outbreak, although they eased in the last three months of 2020 despite the new all-time high price reached by Bitcoin in late December 2020.

The findings have implications not only regarding risk management and return predictability, but regarding the stability of the system of return connectedness within the cryptocurrency market during extreme events. This important result points to the inappropriateness of restricting the analyses of return connectedness in the cryptocurrency market to models involving only average shocks.

The rest of the paper is divided into five sections. Section 2 provides a concise review of related studies dealing with interdependencies in the cryptocurrency market. Section 3 presents the empirical model, starting with the quantile regression and its extension to the quantile VAR, moving to the quantile-based measure of connectedness within the framework of Diebold and Yilmaz (2012). Section 4 describes the cryptocurrency data and its stylized facts. Section 5 presents and discusses the empirical results. Section 6 concludes.

2. Related studies

The system of connectedness and shock spillovers in the cryptocurrency market continue to induce considerable debate in the academic literature. This is mainly driven by the complexity of the system of connectedness in this controversial and highly volatile market (Stosic et al., 2019; Azqueta-Gavaldón, 2020; Gidea et al., 2020; Nie, 2020; Papadimitriou et al., 2020).

Existing studies consider multiple methodologies, including GARCH models and Granger causality tests. Katsiampa et al. (2019) use bivariate GARCH models to examine the volatility dynamics and correlations across Bitcoin, Ethereum and Litecoin.[2] They report evidence of two-way volatility flows between all the pairs of cryptocurrencies under study, and that the pairwise conditional correlations are positive and vary with time. Bouri et al. (2019a) apply a Granger causality approach

[1] This approach has been applied to various asset classes including equities and commodities (e.g. Husain et al., 2019), real estate (Gabauer and Gupta, 2020), and credit risks (e.g., Fernández-Rodríguez et al., 2016; Bekiros et al., 2019).

[2] Some other studies consider the drivers of volatility in the cryptocurrency markets using a GARCH-MIDAS approach (e.g., Walther et al., 2019).

in the frequency domain and find that Bitcoin is not the only transmitter of volatility, highlighting the importance of other large cryptocurrencies to the system of volatility spillovers. In another study, Bouri et al. (2019b) employ a jump-analysis to the price process of 12 leading cryptocurrencies based on GARCH models. They show evidence of jumps and co-jumps, with Bitcoin and other large cryptocurrencies playing central roles.

Another strand of literature involves the application of methods imported from econophysics such as multifractality (Ferreira et al., 2020; Kristjanpoller and Bouri, 2019; Kristjanpoller et al., 2020). For example, Ferreira et al. (2020) show that cryptocurrencies behave differently from the stock markets which are much closer to the efficient dynamics. Other methods used in the literature dealing with cryptocurrency markets include the theory of complex networks (Stosic et al., 2019; Azqueta-Gavaldón, 2020; Gidea et al., 2020; Papadimitriou et al., 2020), and machine learning (Lahmiri and Bekiros, 2019; Chowdhury et al., 2020; Zoumpekas et al., 2020).[3] Regarding the results of studies involving the theory of complex networks, Papadimitriou et al. (2020) use a novel Threshold Weighted-Minimum Dominating Set (TW-MDS) methodology and report evidence that large cryptocurrencies such as Bitcoin and Ethereum are not always the most dominants. This finding corroborates with Ji et al. (2019). Regarding the studies involving machine learning, they mostly indicate the ability to predict cryptocurrency prices (e.g., Chowdhury et al., 2020; Zoumpekas et al., 2020). Some other studies apply the connectedness measures of Diebold and Yilmaz (2012). Koutmos (2018) considers 18 large cryptocurrencies and finds that the spillovers are time-varying and points to the growing interdependence among cryptocurrencies, which reflects a higher degree of contagion risk. The author also reveals the central role played by Bitcoin in the network of return and volatility spillovers. Corbet et al. (2018) focus on the return and volatility spillovers among three large cryptocurrencies (Bitcoin, Ripple, and Litecoin). Using time domain connectedness measures, they find that Bitcoin returns have a significant impact on the returns of Ripple and Litecoin, whereas the feedback impact is marginal. This result indicates the dominance of Bitcoin in the network of return connectedness. However, the authors show results for volatility spillovers that are different from those of Koutmos (2018). They find that Litecoin and Ripple influence Bitcoin, while the latter has a marginal impact on Litecoin and Ripple. Furthermore, Ripple and Litecoin are strongly interconnected through both return and volatility channels. Corbet et al. (2018) also show that the three digital assets are segmented from conventional assets, pointing to their potential ability to act as diversifiers. Yi et al. (2018) study the volatility of leading cryptocurrencies to make inferences about whether Bitcoin is the dominant volatility transmitter among cryptocurrencies. Their results show that volatility spillovers are tight and vary with time, and that Bitcoin is the only influential cryptocurrency. Zięba et al. (2019) focus on the returns of several cryptocurrencies using a minimum spanning tree (MST) and VAR models (Mantegna, 1999; Wang et al., 2012). The results of the former method show the presence of hierarchical clustering within the cryptocurrency market, while the results from the latter indicate the flow of demand shocks within clusters. The authors also indicate that Bitcoin returns are isolated from the returns of other cryptocurrencies. Giudici and Polinesi (2019) employ combination of the random matrix theory approach with the MST approach and focus on the cryptocurrency markets. They show that Bitcoin exchange prices are positively correlated but are detached from conventional asset prices. However, the volatility of conventional assets has a negative but lagged effect on Bitcoin volatility. Ji et al. (2019) focus on the return and volatility series of six large cryptocurrencies. They indicate that Litecoin and Bitcoin are clear leaders in the network of returns. In contrast to the results of Corbet et al. (2018) and in line with Koutmos (2018), they show that Bitcoin is central in the network of volatility spillovers. Further results show that Dash has a very marginal role, which points to its ability to act as a diversifier. Importantly, Ji et al. (2019) differentiate between positive and negative returns, revealing that negative return spillovers are larger than positive return spillovers. They reveal that the highest receivers of negative-return shocks are Ripple and Ethereum, while very weak positive-return spillovers are reported for the case of Ethereum and Dash. In an interesting paper, Antonakakis et al. (2019) focus on the spillover effects among leading cryptocurrencies via the application of a time-varying parameter factor augmented VAR (TVP-FAVAR) model. They show that the total connectedness index fluctuates highly with time and is closely linked to levels of market uncertainty. The authors highlight the importance of Bitcoin to the system-wide connectedness measures in the cryptocurrency market, without ignoring the role of Ethereum. Qureshi et al. (2020) consider the interdependence of cryptocurrency markets across time and frequencies. They show high levels of dependency from 2016 to 2018 and evidence that the cross-wavelet transform demonstrates Ripple and Ethereum to be trivial origins of market contagion. While the above literature reveals important aspects of the average-based system of return spillovers across leading cryptocurrencies during normal periods, it overlooks the system of extreme return spillovers. In this paper, we move beyond the mean-based connectedness measures among leading cryptocurrencies, nicely complementing previous studies (e.g., Corbet et al., 2018; Koutmos, 2018; Yi et al., 2018; Bouri et al., 2019a; Ji et al., 2019, b; Katsiampa et al., 2019; Zięba et al., 2019; Giudici and Pagnottoni, 2020). Specifically, we apply an extended version of the approach of Diebold and Yilmaz (2012), where extreme upper and extreme lower quantile effects are captured and compared to the middle quantile effect. As such, we uncover the stability of the system of connectedness under extreme events, which is essential to understanding how return spillovers differ under extreme negative/positive shocks. This is important given that our sample covers the COVID-19 outbreak period and the recent rally in Bitcoin price to new all-time highs in December 2020.

[3] Some interesting machine learning techniques have used text data obtained from news and social networks. They include Cerchiello et al. (2017), Ren et al. (2018), and Ren and Wu (2018).

3. Model specification

3.1. A quantile VAR model

A quantile regression allows us to estimate the dependence of y_t on x_t at every quantile τ of the conditional distribution of y_t/x_t (Koenker and Bassett, 1978; Koenker, 2005; Furno and Vistocco, 2018). It can be represented as:

$$Q_\tau(y_t|x_t) = x_t\beta(\tau) \tag{1}$$

where Q_τ represents the τth conditional quantile function of y_t; the quantile τ lies between 0 and 1; x_t is a vector of explanatory variables; and $\beta(\tau)$ determines the dependence relationship between x_t and the τth conditional quantile of y_t. Specifically, $\beta(\tau)$ is the parameter vector estimated at the τth conditional quantile τ via the expression:

$$\widehat{\beta}(\tau) = \underset{\beta(\tau)}{a\,rgmin} \sum_{t=1}^{T} \left(\tau - 1_{\{y_t < x_t\beta(\tau)\}}\right)|y_t - x_t\beta(\tau)| \tag{2}$$

Accordingly, the n-variable quantile VAR process of pth order is:

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau)y_{t-i} + e_t(\tau), t = 1, ..., T \tag{3}$$

where y_t is the n-vector of dependent variables, $c(\tau)$ and $e_t(\tau)$ represent, respectively, n-vector of constants and residuals at quantile τ, and $B_i(\tau)$ is the matrix of lagged coefficients of the dependent valuable at quantile τ, with i = 1,. . ., p. $\widehat{B}_i(\tau)$ and $\widehat{c}(\tau)$ is estimated by assuming that the residuals conform to the population quantile restriction, $Q_\tau(e_t(\tau)|y_{t-1}, ..., y_{t-p}) = 0$. The population τth conditional quantile of response y is given in Equation (4). The latter can be estimated on an equation-by-equation at every quantile τ.

$$Q_\tau(y_t|y_{t-1}, ..., y_{t-p}) = c(\tau) + \sum_{i=1}^{p} \widehat{B}_i(\tau)y_{t-i} \tag{4}$$

3.2. The connectedness measures at various quantiles

In this section, we compute at each quantile τ several measures of return connectedness following the original work of Ando et al. (2018), which extends the mean-based measures of Diebold and Yilmaz (2012). Su (2019) has also used a quantile connectedness approch, but it does not address the issue of variable ordering.

Firstly, we rewrite Equation (3) as an infinite order vector moving average (MA) process:

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau)e_{t-s}(\tau), t = 1, \cdots, T \tag{5}$$

with:

$$\mu(\tau) = \left(\mathrm{I}_n - B_1(\tau) - \cdots - B_p(\tau)\right)^{-1} c(\tau), A_s(\tau) = \begin{cases} 0, s < 0; I_n, s = 0 \\ B_1(\tau)A_{s-1}(\tau) + \cdots + B_p(\tau)A_{s-p}(\tau), s > 0 \end{cases}$$

where y_t is given by the sum of the residuals $e_t(\tau)$.

Secondly, and unlike Su (2019), we apply of the methods of Koop et al. (1996) and Pesaran and Shin (1998) that are invariant to variable ordering. The generalized forecast error variance decomposition (GFEVD) of a variable attributable to shocks of different variables for a forecast horizon H is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_s \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_s \sum e_j\right)} \tag{6}$$

The $\theta_{ij}^{g}(H)$ denotes the contribution of the jth variable to the variance of forecast error of the variable ith at horizon H, $\sum$ is the variance matrix of the vector of errors, σ_{jj} is the jth diagonal element of the Σ matrix, and e_i is a vector with a value of 1 for the ith element and 0 otherwise.

Then, we normalize each entry of the variance decomposition matrix as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

Thirdly, using the GFEVD, we formulate at each quantile four measures of connectedness.

The total spillover index (TSI) at quantile τ is:

$$TSI(\tau) = \frac{\sum_{i=1}^{N}\sum_{j=1, i\neq j}^{N}\overset{\sim g}{\theta}_{ij}(\tau)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\overset{\sim g}{\theta}_{ij}(\tau)} \times 100 \quad (8)$$

The total directional spillover index from index i to indices j (denoted by "TO") at quantile τ is:

$$SI_{i\rightarrow j}(\tau) = \frac{\sum_{j=1, i\neq j}^{N}\overset{\sim g}{\theta}_{ji}(\tau)}{\sum_{j=1}^{N}\overset{\sim g}{\theta}_{ji}(\tau)} \times 100 = \mathrm{TO} \quad (9)$$

The total directional spillover index from indices j to index i (denoted by "FROM") at quantile τ is:

$$SI_{i\leftarrow j}(\tau) = \frac{\sum_{j=1, i\neq j}^{N}\overset{\sim g}{\theta}_{ij}(\tau)}{\sum_{j=1}^{N}\overset{\sim g}{\theta}_{ij}(\tau)} \times 100 = \mathrm{FROM} \quad (10)$$

The net total directional spillover (NSI) index at quantile τ is:

$$NSI_i(\tau) = SI_{i\rightarrow j}(\tau) - SI_{j\leftarrow i}(\tau) = \mathrm{NSI} \quad (11)$$

The empirical analyses are based on a lag order of 1, chosen according to the Akaike information criterion (AIC), and a forecast horizon of 10. To show the time variability in various spillover measures, we adopt a rolling-window approach using 200 days. The sensitivity analysis involves a window length of 250 days and a forecast horizon of 5 (see Section 5.4).

4. Cryptocurrency data

Daily price data are collected from https://coinmarketcap.com covering seven leading cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Monero, Dash[4]) from August 8, 2015 to December 31, 2020.[5] Price data are strictly dictated by their availability for the largest 20 cryptocurrencies by market capitalization for a period of at least 4 years, in order to capture the most of their dynamics during periods of booms and busts. Fortunately, the selected data comprises seven large cryptocurrencies with a total market capitalization of more than 83% of the total market capitalization of all cryptocurrencies. The price levels of the seven cryptocurrencies are shown in Fig. 1. They generally moved in tandem over the sample period, with a large spike starting in Q2 2017. Then, cryptocurrency prices were affected by the sharp correction of 2018, displaying a brusque falling pattern. After some upside movements during 2019, most of the cryptocurrencies under study experienced large corrections in Q1 2020. Afterwards, a large uptrend is noticed, especially in the price of Bitcoin, moving it to a new all-time high of nearly $29,000 in late December 2020. Persistent falling and rising patterns indicate the possibility of extreme return spillovers and call into question the suitability of considering systems of average shocks. The natural logarithmic returns $r_{i,t}$ at time t for each cryptocurrency i are computed using the closing price p as: $r_{i,t} = 100 \times ln(p_{i,t}/p_{i,t-1})$. They comprise 1972 daily return observations for each cryptocurrency. Daily returns of the seven cryptocurrencies under study are plotted in Fig. 2, while the ranking and weight of the seven cryptocurrencies are given in the Appendix in Table A1. The summary statistics for the daily returns, including statistics related to unit root, are given in Table 1 Panel A. All mean returns are positive, with Ethereum and Monero scoring the highest mean returns, while Ripple and Litecoin have the lowest mean returns. According to the standard deviations, the most risky cryptocurrency is Stellar, while the least risky is Bitcoin. Excess kurtosis is omnipresent, especially for Ripple and Stellar. Skewness is positive, except for Bitcoin. Statistics from the Jarque-Bera (JB) test show that all returns are not normally distributed. Statistics from the augmented Dickey-Fuller (ADF) test indicate that all return series are stationary. Table 1 Panel B shows that the correlation coefficients across the returns of the seven cryptocurrencies are positive. The strongest correlation is between Bitcoin and Litecoin (0.673), which is in line with previous studies (i.e., Antonakakis et al., 2019). The lowest correlation is between Ripple and Dash (0.342).

5. Results

Using the return series, the quantile VAR model presented in Equation (3) is estimated,[6] and then numerous connectedness measures are computed such as the TSI[7] (Equation (8)), the directional TO (Equation (9)), the directional FROM (Equation (10)), and the NSI (Equation (11)). Several robustness analyses are conducted.

[4] Although the top seven cryptocurrencies in term of market value have slightly changed since the date of the original submission (February 2020), we keep the original sample as the total market value remains dominated by the four largest cryptocurrencies (Bitcoin, Ethereum, Tether, and Litecoin).

[5] We exclude Tether from the sample, although its price data coverage starts before August 2015, simply because its return series are equal to zero in almost 55% of all the daily observations.

[6] The lag used is 1, selected based on the AIC.

[7] The TSI varies between 0 and 100.

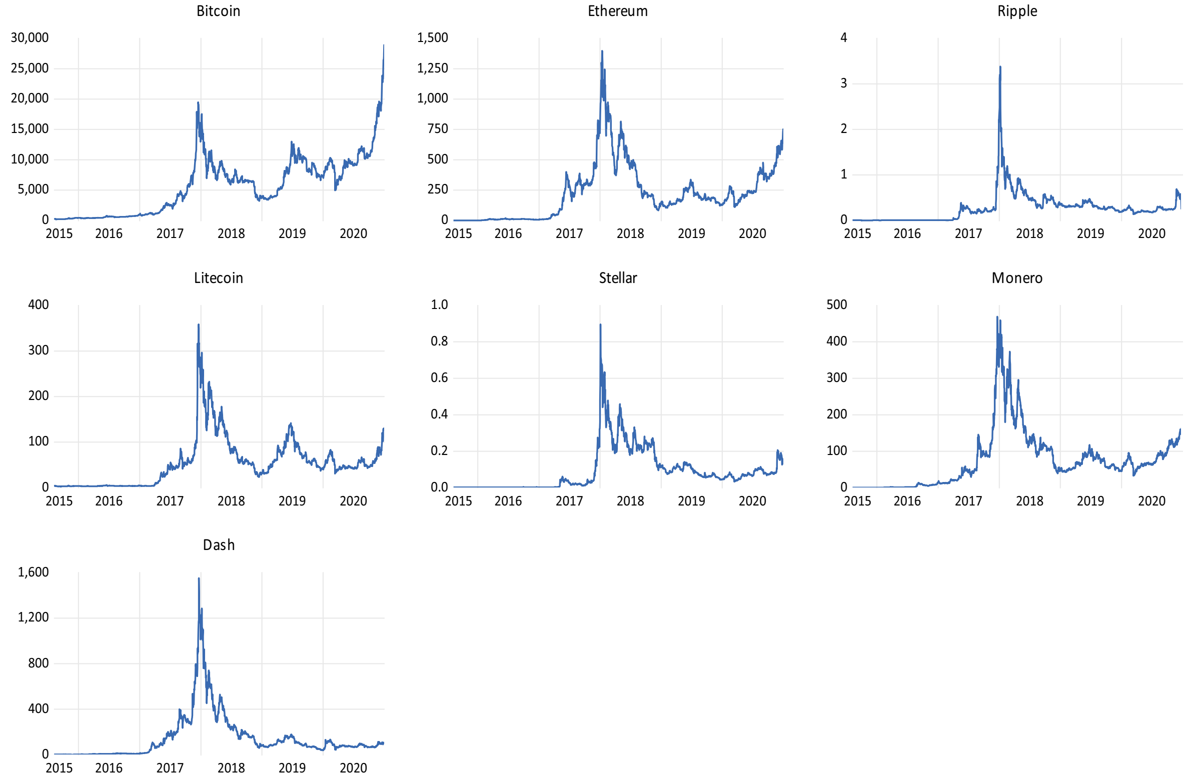

Fig. 1. Price level series.

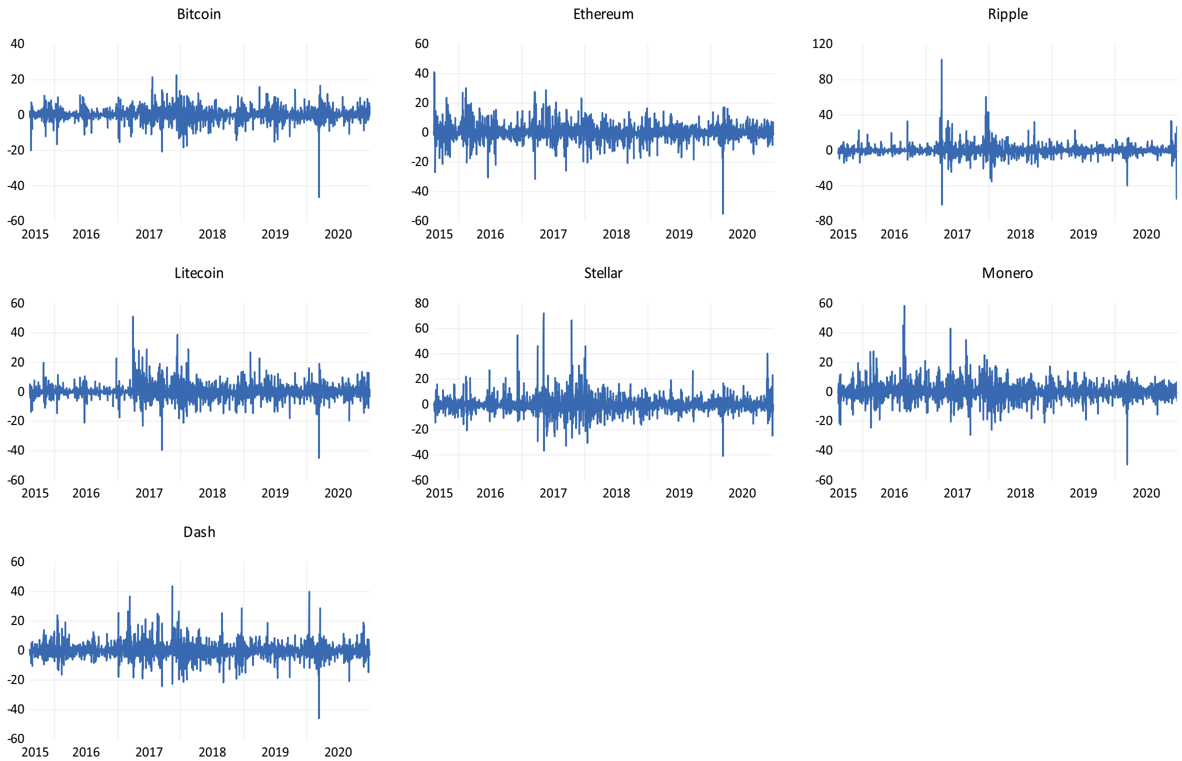

Fig. 2. Return series.

Table 1
Summary statistics and correlation matrix for daily returns.

Panel A: Selected statistics for daily returns							
	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera	ADF	
Bitcoin	0.238	3.922	−0.946	16.912	16197.24***	−45.461***	
Ethereum	0.352	6.161	0.069	11.218	5550.749***	−43.275***	
Ripple	0.162	6.761	2.462	45.304	149042.59***	−28.070***	
Litecoin	0.174	5.480	0.729	15.528	13071.06***	−44.541***	
Stellar	0.202	7.347	1.978	21.061	28087.01***	−41.932***	
Monero	0.282	6.272	0.675	13.052	8451.71***	−46.970***	
Dash	0.176	5.710	0.633	11.773	6455.30***	−45.522***	
Panel B: Pairwise Pearson correlation coefficients among returns series							
	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Monero	Dash
Bitcoin	1						
Ethereum	0.518	1					
Ripple	0.383	0.356	1				
Litecoin	0.673	0.503	0.440	1			
Stellar	0.423	0.366	0.597	0.449	1		
Monero	0.566	0.473	0.358	0.507	0.435	1	
Dash	0.544	0.477	0.342	0.524	0.374	0.532	1

Notes: The sample period is from August 8, 2015 - December 31, 2020, covering 1972 daily return observations. For Panel A: Jarque-Bera statistics of the null hypothesis test whether the return series are normally distributed. ADF is augmented Dickey Fuller statistics of the null hypothesis test on the presence of a unit root in the return series. ADF test is conducted with an intercept and lag length of models selected based on the Schwarz information criterion. *** indicates statistical significance at the 1% level.

5.1. Conditional mean spillovers versus conditional median spillovers

We first consider the connectedness measures estimated at the conditional mean[8] and the conditional median (τ = 0.5), which are used as a reference for comparing the results of the connectedness at the upper and lower tails. Comparing the estimated results of connectedness in Table 2 Panel A (at the mean) to those in Table 2 Panel B (at the median), it is clear that the various connectedness measures at the conditional mean and median exhibit a high similarity, with values of 59.27% and 58.53%, respectively. They are comparable to the total connectedness index reported in previous studies (e.g., Ji et al., 2019), although they are slightly higher, most probably due to the larger number of cryptocurrencies and the longer sample period. The strongest return spillovers are between Bitcoin and Litecoin, whereas the weakest return spillovers are between Bitcoin and Ripple. The net spillovers (see the last lines of Panels A and B) are positive for all cryptocurrencies, except Ripple, Stellar, and Dash, suggesting that these three cryptocurrencies are net receivers of return spillovers, whereas the rest are net transmitters of return spillovers.

5.2. Connectedness measures at lower quantile (τ = 0.1) and upper quantile (τ = 0.9)

The estimates of the tail connectedness measures are reported in Table 3 and Table 4, respectively, for the lower quantile (τ = 0.1) and upper quantile (τ = 0.9). Such a differentiation in the quantile connectedness between lower and upper tails allows us to distinguish between extreme negative shocks and extreme positive shocks. For both the left and right tails of the conditional distribution, the values of connectedness measures are larger than those in the mean or middle quantile. Specifically, the total return spillover index is 75.75% at the lower quantile and 77.08% at the higher quantile, compared to only 58.53% in the middle quantile (τ = 0.5). This reflects the higher impact of extreme negative/positive shocks on the system of connectedness. Furthermore, the contributions to others (labelled TO) and contributions from others (labelled FROM) in both lower and upper tails are stronger than those for the mean and median, although the net spillover across the various cryptocurrencies is low in all cases. Bitcoin appears as the cryptocurrency the most interconnected with other cryptocurrencies in both lower and upper quantiles. Given that the linkages among financial variables are stronger under stress periods than normal periods (e.g., Ang and Bekaert, 2002), stronger connectedness is expected in the left tail. However, the variation in the TSI across various quantiles (Fig. 3) shows evidence of strong connectedness in both lower and upper tails, suggesting that the intensity of return connectedness rises with shock size for both extreme positive and extreme negative shocks. This concords with previous studies on contagion showing that the spillover of extreme events (Londono, 2019). Fig. 3 shows that the TSI for the range of quantiles between 0.30 and 0.70 does not exceed 63.00%. However, when large shocks affect the network of connectedness, mutual connectedness among cryptocurrencies intensifies the propagation of risk spillover in the cryptocurrency market. At the 5th, 10th, 90th, and 95th percentiles, the TSI reaches 80.22%, 75.75%,

[8] See Diebold and Yilmaz (2012) for further details about their connectedness measures within the mean-based VAR framework.
[9] Please refer to Section 5.4 for a discussion of the choice of the window length and forecast horizon.
[10] The results for the mean-based spillover index are quite comparable to the results of Antonakakis et al. (2019) and Ji et al. (2019).

Table 2
Return spillovers estimated at the mean and median of the conditional distribution.

Panel A: Spillover measures based on the standard mean-based approach of Diebold and Yilmaz (2012)								
	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Monero	Dash	FROM others
Bitcoin	35.801	11.305	7.177	17.642	7.265	11.278	9.531	64.199
Ethereum	10.609	41.928	8.336	10.392	8.096	10.687	9.952	58.072
Ripple	7.676	9.711	43.893	9.124	14.412	8.162	7.022	56.107
Litecoin	17.904	10.923	8.427	36.562	7.955	9.590	8.640	63.438
Stellar	8.256	9.523	14.186	9.188	42.222	9.595	7.031	57.778
Monero	11.549	11.001	7.673	9.423	8.610	40.892	10.852	59.108
Dash	10.197	10.799	7.236	9.372	6.833	11.744	43.819	56.182
Contribution TO others	66.192	63.262	53.035	65.142	53.17	61.056	53.027	414.884
Contribution including own	101.994	105.191	96.928	101.703	95.392	101.948	96.845	**TSI = 59.27%**
Net spillovers	1.994	5.191	−3.072	1.703	−4.608	1.948	−3.155	
Panel B: Spillover measures based on the quantile VAR described in Section 3 (mean quantile τ = 0.5)								
	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Monero	Dash	FROM others
Bitcoin	36.582	11.173	6.889	17.78	7.011	11.183	9.383	63.418
Ethereum	10.497	42.611	8.251	10.335	7.902	10.629	9.774	57.389
Ripple	7.429	9.565	44.81	8.955	14.322	8.060	6.858	55.190
Litecoin	17.939	10.948	8.262	37.324	7.762	9.276	8.489	62.676
Stellar	7.856	9.276	14.307	8.702	43.365	9.480	7.014	56.635
Monero	11.326	11.020	7.549	9.294	8.628	41.476	10.706	58.524
Dash	10.161	10.746	7.060	9.307	6.939	11.700	44.087	55.913
Contribution TO others	65.209	62.729	52.318	64.373	52.564	60.329	52.224	409.745
Contribution including own	101.791	105.340	97.128	101.697	95.929	101.805	96.311	**TSI = 58.53%**
Net spillovers	1.791	5.340	−2.872	1.697	−4.071	1.805	−3.689	

Table 3
Return spillovers based on the quantile VAR (lower quantile τ = 0.10).

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Monero	Dash	FROM others
Bitcoin	22.617	13.234	10.675	15.689	11.343	13.652	12.791	77.383
Ethereum	13.339	24.256	11.297	12.381	11.752	13.82	13.156	75.744
Ripple	11.501	12.275	26.013	12.085	15.051	11.95	11.125	73.987
Litecoin	16.188	12.533	11.438	23.599	11.547	12.45	12.245	76.401
Stellar	12.064	12.121	14.682	12.073	24.961	12.61	11.489	75.039
Monero	13.801	13.525	11.086	12.157	12.047	23.765	13.620	76.235
Dash	13.370	13.425	10.879	12.378	11.349	14.083	24.516	75.484
Contribution TO others	80.263	77.111	70.056	76.762	73.089	78.565	74.427	530.274
Contribution including own	102.880	101.368	96.069	100.361	98.050	102.330	98.943	**TSI = 75.75%**
Net spillovers	2.880	1.368	−3.931	0.361	−1.950	2.330	−1.057	

Table 4
Return spillovers based on the quantile VAR (upper quantile τ = 0.90).

	Bitcoin	Ethereum	Ripple	Litecoin	Stellar	Monero	Dash	FROM others
Bitcoin	21.775	13.744	10.731	15.635	11.635	13.582	12.897	78.225
Ethereum	13.300	21.970	11.841	13.166	12.232	13.810	13.681	78.030
Ripple	11.303	12.705	24.696	12.619	15.457	11.825	11.395	75.304
Litecoin	15.542	13.109	11.504	22.785	12.029	12.816	12.215	77.215
Stellar	11.874	12.596	14.617	12.665	23.650	12.734	11.864	76.350
Monero	13.654	13.791	11.173	12.684	12.544	22.543	13.610	77.457
Dash	13.177	13.839	11.211	12.733	11.891	14.047	23.102	76.898
Contribution TO others	78.849	79.785	71.078	79.503	75.789	78.814	75.662	539.48
Contribution including own	100.624	101.754	95.773	102.288	99.439	101.357	98.764	**TSI = 77.08%**
Net spillovers	0.624	1.754	−4.227	2.288	−0.561	1.357	−1.236	

77.08%, and 81.21%, respectively. There seems to be a slightly symmetrical pattern in the variation in the total spillover index between extreme lower and extreme upper quantiles. Since the residual covariance matrix does not vary across quantiles, this slightly asymmetric pattern can be due to the similarities in the dynamic parameters of the quantile VAR model at $\tau = a$ and $\tau = 1 - a$, and not a general feature of the results. Notably, we conduct a rolling window analysis in the next section which shows that this slightly symmetric pattern does not hold. Our estimated results are in line with previous studies highlighting the stronger impact of large shocks as compared to small shocks (e.g., Dendramis et al., 2015).

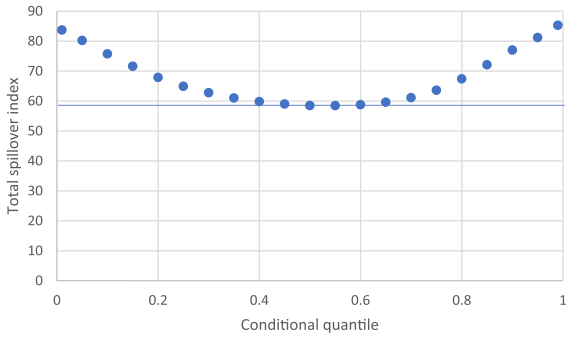

Fig. 3. Variation in the TSI across various quantiles. Note: The TSI is estimated based on Equation (12) at various quantiles τ. The horizontal line is the TSI estimated at the conditional mean.

The extreme net spillovers are shown in the last lines of Tables 3 and 4. In the lower quantile (Table 3), all cryptocurrencies are net transmitters of return spillovers, except Ripple, Stellar, and Dash which act as net receivers. In the upper quantile (Table 4), only Ripple, Dash, and Stellar are net receivers, whereas the rest of the cryptocurrencies are net transmitters of return spillovers.

5.3. Time-varying analysis

So far, we have analysed the measures of connectedness for the full sample from a static setting. In this section, we conduct a rolling analysis based on the quantile VAR in order to capture the time variability in the return spillovers not only in the mean and median of the conditional distribution but also in upper and lower quantiles. We use a fixed window length of 200 days and a 10-step forecast horizon.[9] The TSI at the conditional mean and the conditional median are given in Fig. 4 and Fig. 5, respectively. Both indices seem to follow a similar path and exhibit very large fluctuations ranging between 20% and 82%,[10] with a clear uptrend in the level of spillovers from early July to August 2017, during which time Bitcoin spiked in price and the other leading cryptocurrencies followed. Then, a year later, when Bitcoin and the other large cryptocurrencies were retracing parts of their large price gains, the TSI peaked and remained high for for most of 2019. Just before the outbreak of COVID-19 in February 2020, the TSI declined to around 73 then spiked to a new high of 82%. Afterwards, it slightly declined to below 70 at the end of the sample period. The TSI at the lower and upper tails is given in Figs. 6 and 7. Unlike the mean and the median, the TSI fluctuates in both the upper and lower tails within a smaller bound of 55–85%, with an apparent spike from around June 2017 and peaks observed in August 2018 and September 2020. The similarity in the increases in the TSI at both upper and lower quantiles suggests an increase in the sensitivity of crypto-traders to both extreme positive and extreme negative shocks. Notably, positive (negative) changes in upper tail spillovers concur with positive (negative) changes in lower tail spillovers. Accordingly, periods of rising fragility, associated with increased tendency for negative shocks to disseminate, are also periods of intensification of the dissemination of positive shocks, and vice-versa. This is probably due to the behaviour of crypto-traders. The contents of extreme events/news in either tail lead to an important proportion of crypto-traders concentrating on additional events/news happening in that tail, while taking similar notice of events/news happening in the other tail.

While Fig. 3 points to a potential symmetry in the connectedness between lower and upper quantiles, we present, in Fig. 8, the relative tail dependence RTD ($TSI_{\tau=0.90} - TSI_{\tau=0.10}$).[11] It can be seen from Fig. 8 that the slightly symmetrical pattern shown earlier in the static analysis (Fig. 3) does not hold in a time-varying analysis given that the RTD is mostly different from zero. For example, a positive peak in the value of the RTD is seen in May 2017. In fact, rising (positive) values for the relative tail dependence reflect a rise in the fragility of connectedness. However, the RTD becomes mostly negative from February 2018 till early 2020, suggesting stronger dependence in the lower quantile than the upper quantile, and thus a decrease in the fragility of the system of connectedness in the tails. After that period, the RTD turns again positive for early July 2020 and then switches between negative and positive values for the end of the sample period. Furthermore, we assess whether the result of the asymmetric pattern is sensitive to the choice of measure of spillovers in the upper and lower tails. Using more extreme quantiles, we compute the difference between the TSI at the 95th quantile and the TSI at the 5th quantile. The result presented in Fig. 9 shows that the dynamics of the RTD are quite similar to those reported in Fig. 8, although more variability is reported in Fig. 9. Overall, our result on the asymmetric pattern is insensitive to the definition of upper and lower tail dependence measures.

Fig. 10 provides the net total return spillovers estimated at the conditional median. Based on the patterns of spillovers, we notice two groups of cryptocurrencies. The first group represents net recipients of returns for most of the sample period, such as Ripple and Stellar. The second group reflects cryptocurrencies that sometimes act as net transmitters of spillovers while at

[9] Please refer to Section 5.4 for a discussion of the choice of the window length and forecast horizon.
[10] The results for the mean-based spillover index are quite comparable to the results of Antonakakis et al. (2019) and Ji et al. (2019).
[11] Through this measure, positive values reflect stronger connectedness, whereas negative values reflect weaker connectedness.

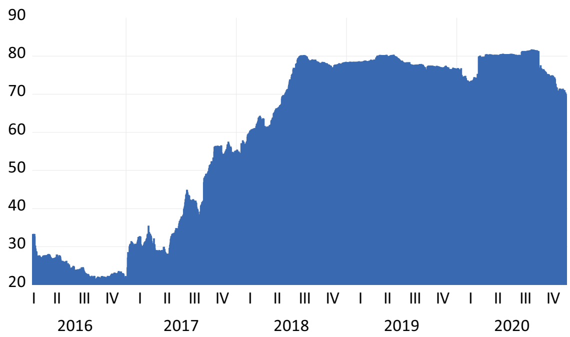

Fig. 4. TSI in the mean VAR – based on the standard approach of Diebold and Yilmaz (2012).

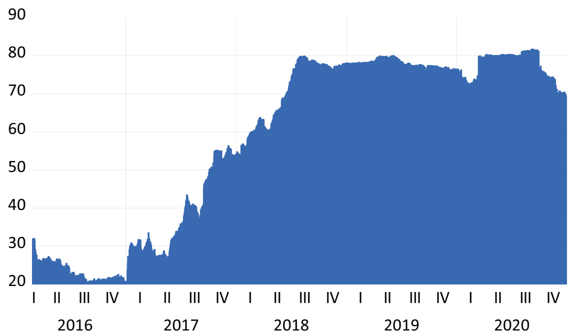

Fig. 5. TSI in the quantile VAR (mean quantile τ = 0.5).

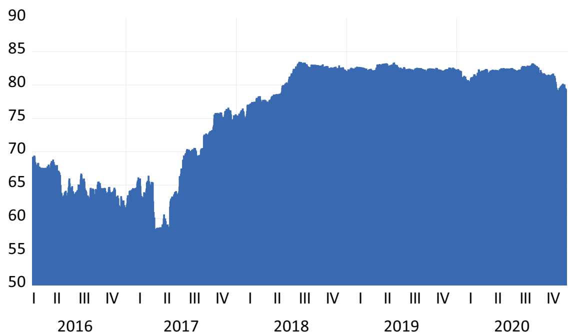

Fig. 6. TSI in the quantile VAR (lower quantile τ = 0.10).

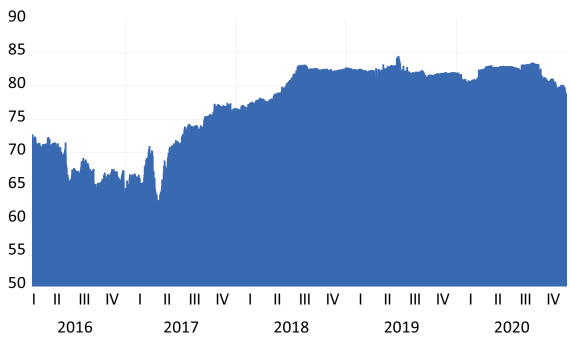

Fig. 7. TSI in the quantile VAR (upper quantile τ = 0.90).

Fig. 8. Relative tail dependence ($TSI_{\tau=0.90} - TSI_{\tau=0.10}$). Note: this figure shows the difference between the TSI at the 90th quantile and the TSI at the 10th quantile, with both indices computed based on a rolling window of 200 days.

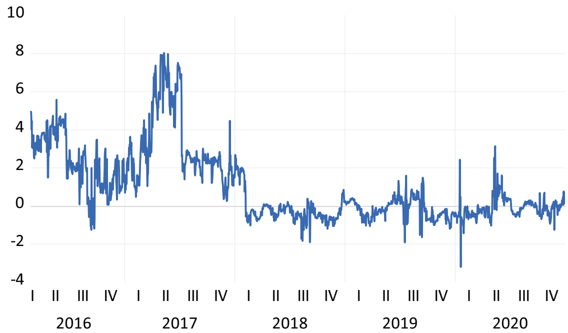

Fig. 9. Relative tail dependence ($TSI_{\tau=0.95} - TSI_{\tau=0.05}$). Note: this figure shows the difference between the TSI at the 95th quantile and the TSI at the 5th quantile, with both indices computed based on a rolling window of 200 days.

other times they are net recipients of return spillovers. Specifically, we notice Ethereum, the second largest cryptocurrency after Bitcoin, to be a net transmitter from 2018 till the end of the sample period. This result is in line with Antonakakis et al. (2019) who show that Ethereum has become a leading transmitting cryptocurrency. Further results show that Bitcoin has partially become a net recipient during the price correction of early 2018 in the cryptocurrency market, before becoming a transmitter of return shocks to the others from mid-2018-mid-209 and from early 2020 till September 2020. Interestingly, Litecoin is a net transmitter for most of 2020, Also, it is worth noting the opposite behaviour in the transmission and receipt of net spillovers between Stellar and Monero.

The net return spillovers estimated at the lower and upper tails are given in Fig. 11 and Fig. 12, respectively. Except for Ripple, which is mostly a net recipient of extreme returns spillovers in both lower and upper tails, the patterns of net extreme spillovers are mixed. This is also the case for the two largest cryptocurrencies, Bitcoin and Ethereum. However, Bitcoin, Ethereum, and Monero are mostly net transmitters of extreme returns, which could make them natural targets for monitoring by investors and regulators under extreme events, especially if their related historical patterns, underlined by the quantile-based network of connectedness, continues in the future.

The above findings add new insights regarding the propagation of extreme returns shocks within the system of connectedness of cryptocurrencies. They show evidence of asymmetry and excess return spillovers of the network system in the tails relative to the mean and median. They represent an extension to the mean-based literature on spillovers in the cryptocurrency market (Corbet et al., 2018; Koutmos, 2018; Yi et al., 2018; Bouri et al., 2019a; Ji et al., 2019; Katsiampa et al., 2019; Zięba et al., 2019), by considering for the first time the return connectedness using a quantile-based approach of Diebold and Yilmaz (2012) and the COVID-19 outbreak in 2020. The results generally concord with Ji et al. (2019) who indicate that the role of each cryptocurrency in the network of return connectedness is not a mirror image of its market value. Furthermore, we provide evidence that network of connectedness evaluated at the conditional mean is not suitable to reflect the degree of

[12] Results are not reported here for the sake of brevity. However, they are available from the authors upon request. The following site https://sites.google.com/view/davidgabauer/ can be used to compute several connectedness measures.
[13] Bearing in mind that in the previous section we show that a change in the definition of the tail dependence in lower and upper quantiles has no impact on our results.

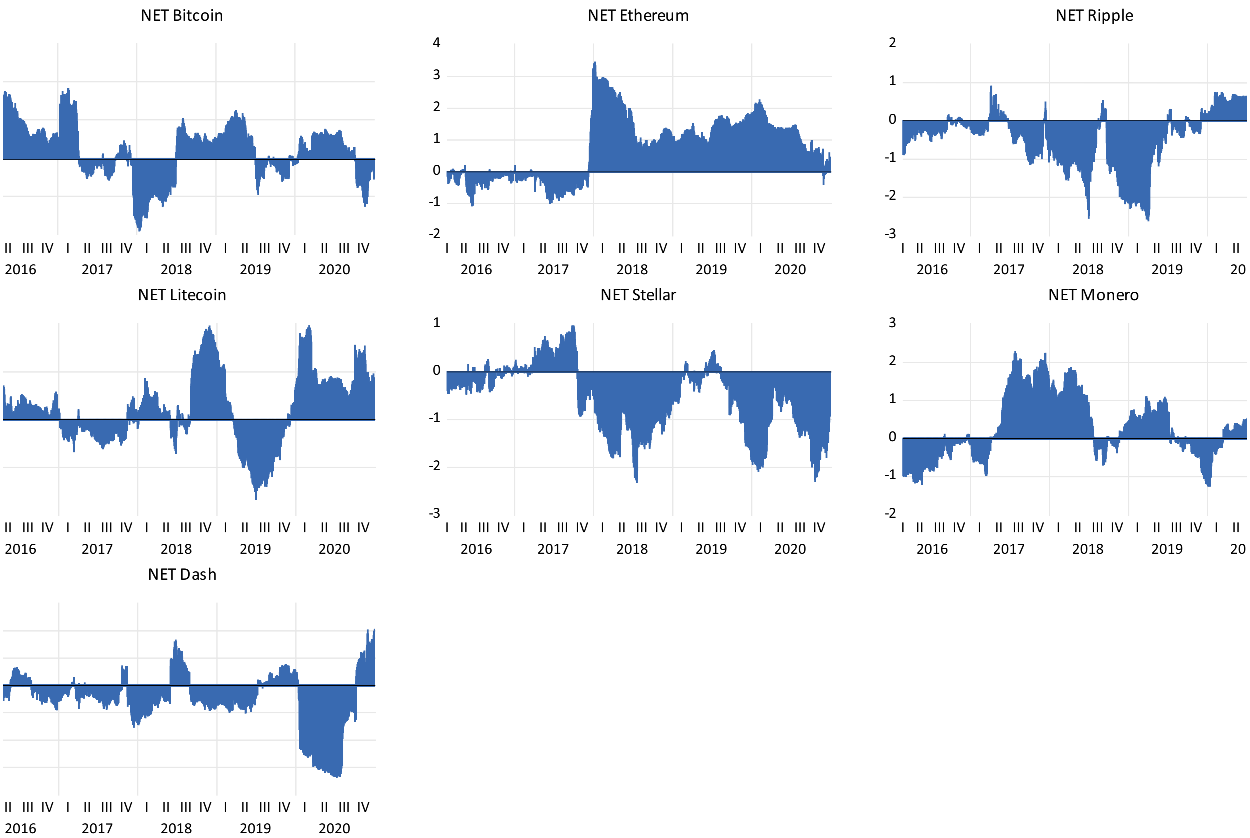

Fig. 10. Net total return spillovers in the quantile VAR (mean quantile $\tau = 0.5$).

connectedness spillovers associated with large positive/negative shocks. The fact that spillovers across cryptocurrency markets intensify during distress periods is seen in other assets, although with different methods. For example, Betz et al. (2016) emphasize the importance of tail-based dependencies in the banking sector for prudential regulatory and surveillance mechanisms.

5.4. Sensitivity analysis

To validate our analyses, we assess the sensitivity of our findings to the size of the rolling window and the selection of the forecast horizon. So far, our analyses have been conducted using a window length of 200 days and a forecast horizon of 10. Here, we consider a window length of 250 days and a forecast horizon of 5 and re-estimate the models of Section 4. The results show that the level of the TSI decreases slightly although its dynamics, which are our primary interest, remain almost the same. In fact, the same features remain when we estimate the models at the conditional mean and median (see Figs. A.1 and A.2 in the Appendix). Furthermore, total spillovers remain high in the tails, much higher than in the mean and median (see Figs. A.3 and A.4 in the Appendix). The same asymmetric feature remains present when we calculate the relative tail dependence based on a different window length.[12] All these analyses indicate that our results are not sensitive to the size of the window and the selection of the forecast horizon.[13]

6. Concluding remarks

Based on the rationale and previous evidence that interdependencies among markets are stronger under extreme events than in normal periods, we apply a quantile-based approach of connectedness to leading cryptocurrencies. The applied approach extends the mean-based VAR framework of connectedness to the quantile VAR level, allowing us to uncover the

[12] Results are not reported here for the sake of brevity. However, they are available from the authors upon request. The following site https://sites.google.com/view/davidgabauer/ can be used to compute several connectedness measures.

[13] Bearing in mind that in the previous section we show that a change in the definition of the tail dependence in lower and upper quantiles has no impact on our results.

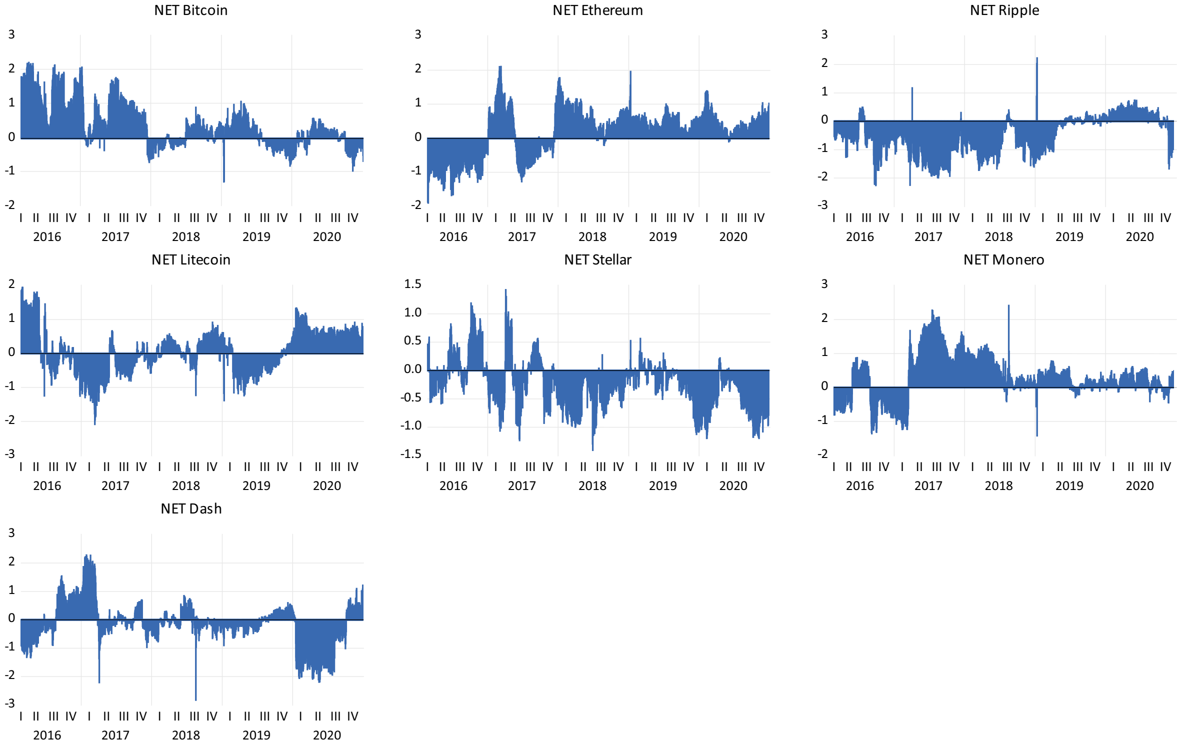

Fig. 11. Net total return spillovers in the quantile VAR (lower quantile τ = 0.10).

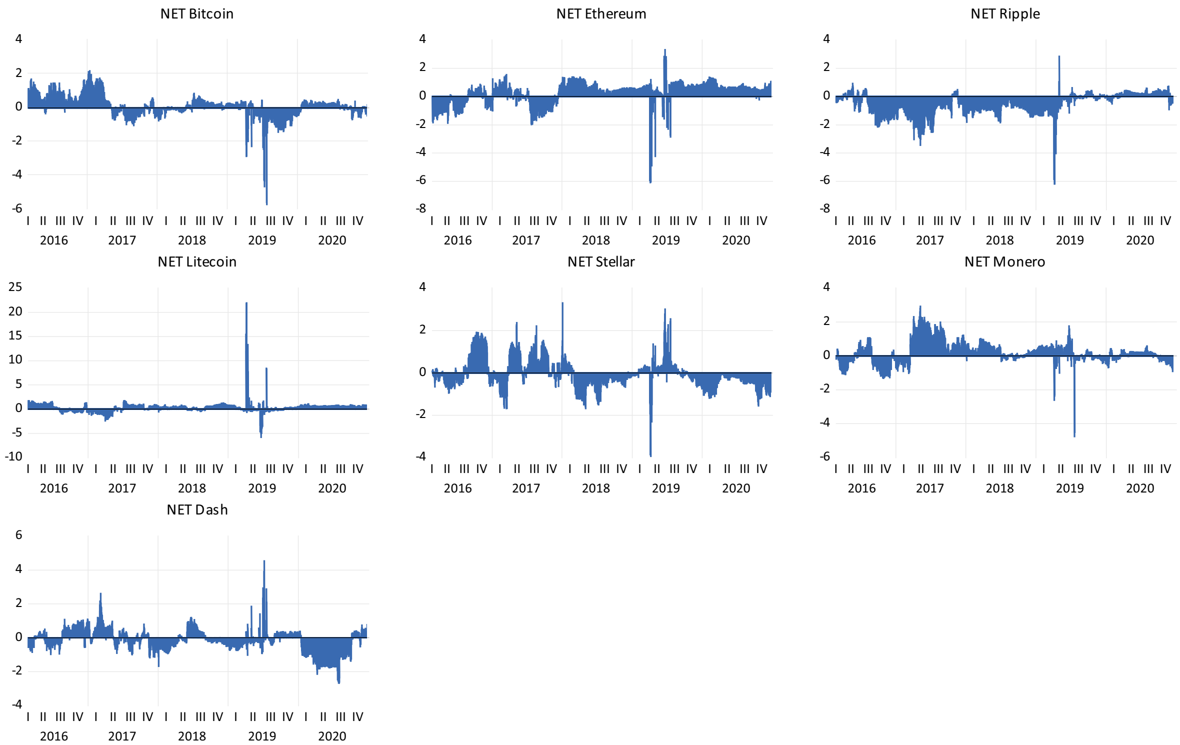

Fig. 12. Net total return spillovers in the quantile VAR (upper quantile τ = 0.90).

connectedness measures at the upper, middle, and lower quantiles of the conditional distribution. The main results show evidence of variation in the quantile structure of the system of connectedness among leading cryptocurrencies. Shocks propagate more strongly at both tails of the conditional distribution than at the conditional mean or median. The structure of spillovers at both upper and lower tails is dissimilar to that seen at the conditional mean and median, suggesting that the evolution of the dependence structure at tails is masked when connectedness measures are estimated at the conditional mean or median. Accordingly, applying quantile-based models of connectedness is recommended as a natural extension to the pervasive average-based models of connectedness. The application of a time-varying analysis shows that the degree of tail-dependence varies with time and intensifies during the COVID-19 outbreak. In fact, lower tail dependence is positively correlated with upper tail dependence, suggesting that extreme negative events are associated with an increase in stabilizing lower-tail connectedness coupled with a concurrent increase in destabilizing upper-tail connectedness. Furthermore, we uncover evidence of asymmetry between the behaviour of return spillovers in lower quantiles and upper quantiles.

The findings on extreme connectedness measures in upper and lower tails offer a nuanced view of the importance of tail risk propagation within the network system of cryptocurrencies. They point to the necessity to use the above quantile-based method as part of prudential regulatory and surveillance mechanisms. By extending our knowledge regarding the effects of the size and sign of the spillovers on the system of connectedness among leading cryptocurrencies, policymakers can use appropriate policy tools and surveillance mechanisms to manage potential adversative impacts occurring from extreme risk spillovers in the cryptocurrency market. Otherwise, a focus only on the average shocks within the system of connectedness is likely to lead to the formulation and application of inappropriate and insufficient stabilizing policies during extreme events. While most regulatory efforts focus on Bitcoin, we have shown that other leading cryptocurrencies such as Ethereum matter to the stability of the network of connectedness within the cryptocurrency market, especially during extreme negative and extreme positive returns, which suggests the need to consider cryptocurrencies other than Bitcoin in any monitoring procedures. As for crypto-traders and investors, they can refine their trading decisions and risk measures during extreme positive and extreme negative events in the highly complex and volatile cryptocurrency market. For example, they can adopt trading strategies during stress periods based on the flow and magnitude of return spillovers within the cryptocurrency market. The results regarding the asymmetry of the extreme positive returns and extreme negative returns have useful implications for crypto-traders and investors making decisions regarding short- or long-term positions in cryptocurrencies in extreme bullish/bearish markets. Regarding the time-variability in the pairwise return connectedness measures, they entail implications for investors adjusting their positions under various market conditions such as the COVID-19 outbreak period.

Further studies using the quantile system of connectedness are recommended within both conventional and conventional assets, so the return and volatility spillovers can be uncovered under extreme market events.

CRediT authorship contribution statement

Elie Bouri: Conceptualization, Methodology, Data curation, Formal analysis, Writing - original draft. **Tareq Saeed:** Methodology, Visualization, Writing - review & editing. **Xuan Vinh Vo:** Visualization, Writing - review & editing. **David Roubaud:** Data curation, Writing - review & editing.

Acknowledgement

The second author acknowledges that the Deanship of Scientific Research (DSR) at King Abdulaziz University, Jeddah, Saudi Arabia funded this project, under grant no. (FP-72-42).

Appendix A

See Table A1.
See Figs. A1–A4.

Table A1
Ranking and weight.

Ranking	Name	Weight %
1st	Bitcoin	66.45
2nd	Ethereum	8.35
3rd	Ripple	5.78
6th	Litecoin	1.54
10th	Stellar	0.57
14	Monero	0.45
18	Dash	0.28

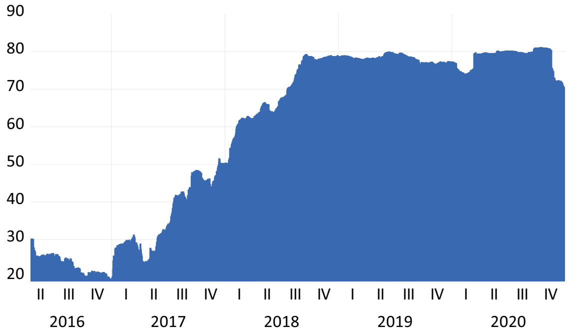

Fig. A1. TSI in the mean VAR – based on the standard approach of Diebold and Yilmaz (2012). Window length = 250 days.

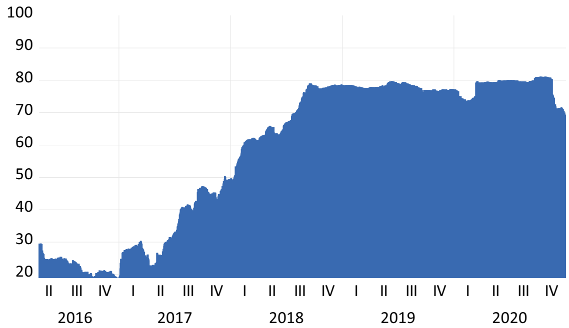

Fig. A2. TSI in the quantile VAR (mean quantile τ = 0.5). Window length = 250 days.

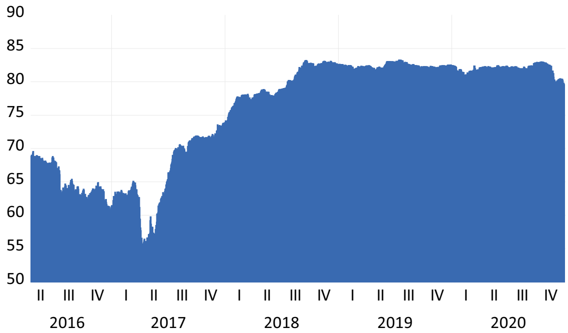

Fig. A3. TSI in the quantile VAR (lower quantile τ = 0.10). Window length = 250 days.

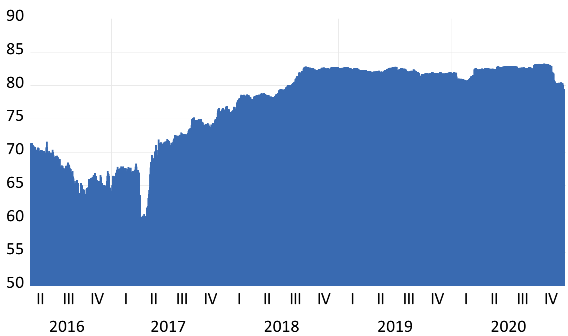

Fig. A4. TSI in the quantile VAR (upper quantile τ = 0.90). Window length = 250 days.

References

Ando, T., Greenwood-Nimmo, M., Shin, Y., 2018. Quantile connectedness: Modelling tail behaviour in the topology of financial networks. Available at SSRN 3164772.
Ang, A., Bekaert, G., 2002. International asset allocation with regime shifts. Rev. Financ. Stud. 15 (4), 1137–1187.
Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2019. Cryptocurrency market contagion: market uncertainty, market complexity, and dynamic portfolios. J. Int. Financ. Mark. Inst. Money 61, 37–51.
Azqueta-Gavaldón, A., 2020. Causal inference between cryptocurrency narratives and prices: evidence from a complex dynamic ecosystem. Physica A 537, 122574.
Bekiros, S., Shahzad, S.J., Jammazi, R., Aloui, C., 2019. Spillovers across European sovereign credit markets and role of surprise and uncertainty. Appl. Econ. https://doi.org/10.1080/00036846.2019.1659930.
Betz, F., Hautsch, N., Peltonen, T.A., Schienle, M., 2016. Systemic risk spillovers in the European banking and sovereign network. J. Financ. Stab. 25, 206–224.
Bouri, E., Roubaud, D., Lucey, B., 2019a. The volatility surprise of leading cryptocurrencies: transitory and permanent linkages. Finance Res. Lett. https://doi.org/10.1016/j.frl.2019.05.006.
Bouri, E., Cepni, B., Gabauer, D., Gupta, R., 2020. Return connectedness across asset classes around the COVID-19 outbreak. Int. Rev. Financ. Anal. https://doi.org/10.1016/j.irfa.2020.101646.
Bouri, E., Roubaud, D., Shahzad, S.J.H., 2019b. Do Bitcoin and other cryptocurrencies jump together?. Quart. Rev. Econ. Finance. https://doi.org/10.1016/j.qref.2019.09.003.
Cerchiello, P., Giudici, P., Nicola, G., 2017. Twitter data models for bank risk contagion. Neurocomputing 264, 50–56.
Chowdhury, R., Rahman, M.A., Rahman, M.S., Mahdy, M.R.C., 2020. An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning. Physica A 124569.
Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Econ. Lett. 165, 28–34.
Dendramis, Y., Kapetanios, G., Tzavalis, E., 2015. Shifts in volatility driven by large stock market shocks. J. Econ. Dyn. Control 55, 130–147.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.
Fernández-Rodríguez, F., Gómez-Puig, M., Sosvilla-Rivero, S., 2016. Using connectedness analysis to assess financial stress transmission in EMU sovereign bond market volatility. J. Int. Financ. Mark. Inst. Money 43, 126–145.
Ferreira, P., Kristoufek, L., Pereira, E.J.D.A.L., 2020. DCCA and DMCA correlations of cryptocurrency markets. Physica A 545, 123803.
Furno, M., Vistocco, D., 2018. Quantile Regression: Estimation and Simulation, Vol. 216. John Wiley & Sons.
Gabauer, D., Gupta, R., 2020. Spillovers across macroeconomic, financial and real estate uncertainties: a time-varying approach. Struct. Change Econ. Dyn. 52, 167–173.
Gidea, M., Goldsmith, D., Katz, Y., Roldan, P., Shmalo, Y., 2020. Topological recognition of critical transitions in time series of cryptocurrencies. Physica A 123843.
Giudici, P., Pagnottoni, P., 2020. Vector error correction models to measure connectedness of Bitcoin exchange markets. Appl. Stochastic Models Bus. Ind. 36 (1), 95–109.
Giudici, P., Polinesi, G., 2019. Crypto price discovery through correlation networks. Ann. Oper. Res., 1–15
Husain, S., Tiwari, A.K., Sohag, K., Shahbaz, M., 2019. Connectedness among crude oil prices, stock index and metal prices: an application of network approach in the USA. Resour. Policy 62, 57–65.
Ji, Q., Bouri, E., Lau, C.K.M., Roubaud, D., 2019. Dynamic connectedness and integration in cryptocurrency markets. Int. Rev. Financ. Anal. 63, 257–272.
Katsiampa, P., Corbet, S., Lucey, B., 2019. Volatility spillover effects in leading cryptocurrencies: a BEKK-MGARCH analysis. Finance Res. Lett. 29, 68–74.
Koenker, R., 2005. Quantile Regression (Econometric Society Monographs). Cambridge University Press. Cambridge, UK. doi:10.1017/CBO9780511754098.
Koenker, R., Bassett Jr, G., 1978. Regression quantiles. Econometrica: J. Economet. Soc., 33–50
Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Economet. 74 (1), 119–147.
Koutmos, D., 2018. Return and volatility spillovers among cryptocurrencies. Econ. Lett. 173, 122–127.
Kristjanpoller, W., Bouri, E., 2019. Asymmetric multifractal cross-correlations between the main world currencies and the main cryptocurrencies. Physica A 523, 1057–1071.
Kristjanpoller, W., Bouri, E., Takaishi, T., 2020. Cryptocurrencies and equity funds: evidence from an asymmetric multifractal analysis. Physica A 545, 123711.
Lahmiri, S., Bekiros, S., 2019. Cryptocurrency forecasting with deep learning chaotic neural networks. Chaos, Solitons Fract. 118, 35–40.
Londono, J.M., 2019. Bad bad contagion. J. Bank. Finance 108, 105652.
Mantegna, R., 1999. Hierarchical structure in financial markets. Eur. Phys. J. B-Condensed Matter Complex Syst. 11 (1), 193–197.
Naeem, M.A., Bouri, E., Peng, Z., Shahzad, S.J.H., Vo, X.V., 2021. Asymmetric efficiency of cryptocurrencies during COVID19. Physica A 565, 125562.
Nie, C.X., 2020. Correlation dynamics in the cryptocurrency market based on dimensionality reduction analysis. Physica A 124702.
Papadimitriou, T., Gogas, P., Gkatzoglou, F., 2020. The evolution of the cryptocurrencies market: a complex networks approach. J. Comput. Appl. Math. 112831.
Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58 (1), 17–29.
Qureshi, S., Aftab, M., Bouri, E., Saeed, T., 2020. Dynamic interdependence of cryptocurrency markets: an analysis across time and frequencies. Physica A. https://doi.org/10.1016/j.physa.2020.125077.
Ren, R., Wu, D., 2018. An innovative sentiment analysis to measure herd behavior. IEEE Trans. Syst. Man Cybernet. Syst.
Ren, R., Wu, D.D., Liu, T., 2018. Forecasting stock market movement direction using sentiment analysis and support vector machine. IEEE Syst. J. 13 (1), 760–770.
Shahzad, S.J.H., Bouri, E., Kang, S.H., Saeed, T., 2021. Regime specific spillover across cryptocurrencies and the role of COVID-19. Financ. Innovation 7 (1), 1–24.
Stosic, D., Stosic, D., Ludermir, T.B., Stosic, T., 2019. Exploring disorder and complexity in the cryptocurrency space. Physica A 525, 548–556.
Su, X., 2019. Measuring extreme risk spillovers across international stock markets: a quantile variance decomposition analysis. North Am. J. Econ. Finance 101098.
Walther, T., Klein, T., Bouri, E., 2019. Exogenous drivers of Bitcoin and cryptocurrency volatility: a mixed data sampling approach to forecasting. J. Int. Financ. Mark., Inst. Money 63, 101133.
Wang, G.J., Xie, C., Han, F., Sun, B., 2012. Similarity measure and topology evolution of foreign exchange markets using dynamic time warping method: evidence from minimal spanning tree. Physica A 391 (16), 4136–4146.
Yi, S., Xu, Z., Wang, G.J., 2018. Volatility connectedness in the cryptocurrency market: is Bitcoin a dominant cryptocurrency? Int. Rev. Financ. Anal. 60, 98–114.
Zięba, D., Kokoszczyński, R., Śledziewska, K., 2019. Shock transmission in the cryptocurrency market. Is Bitcoin the most influential? Int. Rev. Financ. Anal. 64, 102–125.
Zoumpekas, T., Houstis, E., Vavalis, M., 2020. ETH analysis and predictions utilizing deep learning. Expert Syst. Appl. 113866.