Received 9 January 2021
Revised 21 February 2021
Accepted 17 March 2021

Cryptocurrency connectedness nexus the COVID-19 pandemic: evidence from time-frequency domains

Onur Polat
Department of Public Finance, Bilecik Seyh Edebali University, Bilecik, Turkey, and
Eylül Kabakçı Günay
Department of Economics, İzmir Demokrasi University, İzmir, Turkey

Abstract

Purpose – The purpose of this study is to investigate volatility connectedness between major cryptocurrencies by the virtue of market capitalization. In this context, this paper implements the frequency connectedness approach of Barunik and Krehlik (2018) and to measure short-, medium- and long-term connectedness between realized volatilities of cryptocurrencies. Additionally, this paper analyzes network graphs of directional TO/FROM spillovers before and after the announcement of the COVID-19 pandemic by the World Health Organization.

Design/methodology/approach – In this study, we examine the volatility connectedness among eight major cryptocurrencies by the virtue of market capitalization by using the frequency connectedness approach over the period July 26, 2017 and October 28, 2020. To this end, this paper computes short-, medium- and long-cycle overall spillover indexes on different frequency bands. All indexes properly capture well-known events such as the 2018 cryptocurrency market crash and COVID-19 pandemic and markedly surge around these incidents. Furthermore, owing to notably increased volatilities after the official announcement of the COVID-19 pandemic, this paper concentrates on network connectedness of volatility spillovers for two distinct periods, July 26, 2017–March 10, 2020 and March 11, 2020–October 28, 2020, respectively. In line with the related studies, major cryptocurrencies stand at the epicenter of the connectedness network and directional volatility spillovers dramatically intensify based on the network analysis.

Findings – Overall spillover indexes have fluctuated between 54% and 92% in May 2018 and April 2020. The indexes gradually escalated till November 9, 2018 and surpassed their average values (71.92%, 73.66% and 74.23%, respectively). Overall spillover indexes dramatically plummeted till January 2019 and reached their troughs (54.04%, 57.81% and 57.81%, respectively). Etherium catalyst the highest sum of volatility spillovers to other cryptocurrencies (94.2%) and is followed by Litecoin (79.8%) and Bitcoin (76.4%) before the COVID-19 announcement, whereas Litecoin becomes the largest transmitter of total volatility (89.5%) and followed by Bitcoin (89.3%) and Etherium (88.9%). Except for Etherium, the magnitudes of total volatility spillovers from each cryptocurrency notably increase after – COVID-19 announcement period. The medium-cycle network topology of pairwise spillovers indicates that the largest transmitter of total volatility spillover is Litecoin (89.5%) and followed by Bitcoin (89.3%) and Etherium (88.9%) before the COVID-19 announcement. Etherium keeps its leading role of transmitting the highest sum of volatility spillovers (89.4%), followed by Bitcoin (88.9%) and Litecoin (88.2%) after the COVID-19 announcement. The largest transmitter of total volatility spillovers is Etherium (95.7%), followed by Litecoin (81.2%) and Binance Coin (75.5%) for the long-cycle connectedness network in the before-COVID-19 announcement period. These nodes keep their leading roles in propagating volatility spillover in the latter period with the following sum of spillovers (Etherium-89.5%, Bitcoin-88.9% and Litecoin-88.1%, respectively).

Research limitations/implications – The study can be extended by including more cryptocurrencies and high-frequency data.

JEL classification – C58, F37, G10

Studies in Economics and Finance
Vol. 38 No. 5, 2021
pp. 946-963

1086-7376
DOI 10.1108/SEF-01-2021-0011

Originality/value – The study is original and contributes to the extant literature threefold. First, this paper identifies connectedness between major cryptocurrencies on different frequency bands by using a novel methodology. Second, this paper estimates volatility connectedness between major cryptocurrencies before and after the announcement of the COVID-19 pandemic and thereby to concentrate on its impact on the cryptocurrency market. Third, this paper plots network graphs of volatility connectedness and herewith picture the intensification of cryptocurrencies due to a major financial distress event.

Keywords Cryptocurrencies, Frequency connectedness, Overall spillovers, Network analysis

Paper type Research paper

1. Introduction

The cryptocurrency market has attracted overwhelming attention by investors, scholars and policymakers since the initiation of Bitcoin in 2009 and the market capitalization of the cryptocurrency market dramatically rose from \$10.62bn in 2013 to \$237.1bn in 2019, more than 2,200% (Szmigiera, 2020). With a total market value of almost 0.3% of the world's total gross domestic product in 2019, and in the light of the digitalization process of financial markets, regulators and policymakers have focused on the price developments of the cryptocurrency market.

It is worth mentioning that, the monumental price inflation of cryptocurrencies has been accompanied by excess volatility inherent to the nature of the market. For example, Baek and Elbeck (2015) found that Bitcoins are 26 times more volatile than S&P500. Additionally, scholars have reported asymmetric volatility effects for cryptocurrencies unlike traditional financial markets (Baur and Dimpfl, 2018; Cheikh *et al.*, 2020). Likewise, Hafner (2020) indicated that the evolution of cryptocurrencies is prone to extreme volatility and specified by bubble-like behavior. Thereupon, volatility dynamics play an essential role in understanding the price movements of cryptocurrencies and provide valuable insight into their characteristics.

Cryptocurrencies are peer-to-peer digital cash systems designed to allow direct electronic payments between parties without a financial intermediary. Unlike major financial assets, the value of cryptocurrency is not based on a tangible asset, contrariwise, it is determined by a cryptographic hash function. Furthermore, the cryptocurrency market is mainly de-regulated, which leads to decentralized control as opposed to centralized central banking systems and digital currency (Corbet *et al.*, 2019).

Bitcoin is the first initiated cryptocurrency and has the highest market capitalization close to \$772bn on January 08, 2021. The market capitalization of Bitcoin has markedly surged from \$11.9bn in November 2016 to \$364.6bn in November 2020 while its price skyrocketed from \$745 to \$19,625[1]. Accordingly, the return on the investments for Bitcoin gained almost 227% per year, which cannot be obtained by any other financial assets.

Despite the short existence of the cryptocurrency market in the financial system, it has attracted investors and stakeholders, particularly in the recent past. As extensively reported by the recent literature the cryptocurrency market is subject to speculative bubbles, herding behavior dominates the position of investors in the market and may conduce contagion (da Gama Silva *et al.*, 2019). For this purpose, a strand of studies examines return and volatility spillovers among cryptocurrencies (Koutmos, 2018; Yi *et al.*, 2018; Canh *et al.*, 2019; Katsiampa *et al.*, 2019; Qiao, 2020). Most of these studies detected moderate or strong spillovers among cryptocurrencies and found a dominant role of Bitcoin in transmitting return and volatility spillovers.

It should be noted that the cryptocurrency market is tightly interdependent to commodity markets (Ji *et al.*, 2019; Panagiotidis *et al.*, 2019), derivative markets (Akyildirim *et al.*, 2020), bond and foreign exchange markets (Corbet *et al.*, 2018). Furthermore, Bitcoin futures have been traded in Chicago Mercantile Exchange and the Chicago Board Options Exchange since December 2017 and these innovative products have raised interest by investors (Lee *et al.*, 2020). Thus, a shock stemmed in the cryptocurrency market can spread to the financial markets with its detrimental effects. Besides, contagion across financial markets tends to escalate around financial/political upheavals and the COVID-19 pandemic sets an example of this (Corbet *et al.*, 2020).

Nonetheless, some studies failed to detect such a strong relationship. For example, Gurrib (2019) constructed an energy blockchain-based crypto index and an energy commodity price index as representatives of the commodity and crypto markets and found both not to be robust forecasters of each other.

As extensively investigated by scholars, contagion and connectedness between financial markets tend to amplify around financial/political imbalances. In compliance with that, return and volatility spillovers across global financial markets have notably risen since the emergence of the COVID-19 outbreak (Bouri, Cepni, Gabauer, and Gupta *et al.*, 2020). The new type of coronavirus emerged in the Chinese municipality Wuhan in December 2019 and expeditiously dispersed across the globe. As of February 19, 2021, the number of total cases has approached 110,000,000, globally with a total number of deaths 2,424,060 and keeps its increasing trend[2]. Despite fiscal/monetary stimulus implemented by the authorities, the COVID-19 pandemic has severely hit the global economy, it is arguably the worst economic downturn since the 2008 global financial crisis (the GFC).

In this study, we analyze the impact of COVID-19 on the cryptocurrency volatility connectedness. For this purpose, we use the frequency connectedness methodology of Baruník and Křehlík (2018) and compute volatility connectedness between nine major currencies by the virtue of market capitalization. To this end, we estimate cryptocurrency connectedness on the $(\pi,\pi/4)$, $(\pi/4,\pi/10)$ and $(\pi/10,0)$ frequency bands. In doing so, we identify short-, medium- and, long-term connectedness between the realized volatilities of cryptocurrencies.

Our study contributes to the extant literature is threefold. First, we identify connectedness between major cryptocurrencies on different frequency bands by using a novel methodology. Second, we estimate volatility connectedness among major cryptocurrencies before and after the official announcement of the COVID-19 as a pandemic, and thereby concentrate on its impact on the cryptocurrency market. Furthermore, we focus on the network analysis of cryptocurrency connectedness and depict pairwise spillovers during these two epochs. We proceed with the work as follows: Section 2 reviews studies on cryptocurrencies, financial contagion and frequency connectedness. Section 3 presents the data and empirical framework of the study. In Section 4, the empirical findings of the study are discussed. Finally, Section 5 discusses the main findings and provides key policy implications of the study.

2. Literature review

2.1 The evolution of cryptocurrency market

The notion, *cryptocurrency*, which emerged by the virtue of search for a new monetary system, particularly after the GFC, is considered as the strongest candidate to substitute today's monetary system. The leading cryptocurrency, bitcoin was initiated by Satoshi Nakamoto in his/her seminal paper. Nakamoto defined the bitcoin as a peer-to-peer version of electronic cash and transactions of electronic coins as a chain of digital signatures. Nakamoto offered a system for electronic transactions without relying on trust (Nakamoto, 2008).

As of January 8th, 2020, there are 8,212 different types of cryptocurrencies circulating in the market and the total volume is $1,094,287,133.608[3]. This spectacular price increase has faced periods of high volatility inherent to the market due to *regulatory disorientation* and *cybercriminality* (Corbet *et al.*, 2019). Additionally, the cryptocurrency market is prone to speculative bubbles (Fry and Cheah, 2016; Fry, 2018; Geuder *et al.*, 2019; Kyriazis *et al.*, 2020).

Unlike conventional financial assets, cryptocurrencies are subject to exponential price spikes, known as price explosivity (Bouri *et al.*, 2019). The spectacular price inflation of the cryptocurrency market is distinctive and cannot be explained by the economic dynamics. Moreover, major cryptocurrencies tend to have price explosivity simultaneously (co-explosivity) and a strand of studies reported evidence for co-explosivity. In this vein, Agosto and Cafferata (2020) found a significant explosive relationship between five main cryptocurrencies, namely, Bitcoin, Etherium, Ripple, Litecoin and Stellar in 2017 and 2018. Likewise, Bouri, Roubaud, and Shahzad *et al.* (2020) investigated co-jumps in the return series for 12 cryptocurrencies and detected noteworthy jumps for all cases, particularly for Ripple, Bitcoin and Litecoin. Along similar lines, Bouri *et al.* (2021) analyzed return equicorrelation for 12 large cryptocurrencies between August 8, 2015 and February 28, 2019 and found evidence for time-varying equicorreletion. Bouri, Lucey, and Roubaud *et al.* (2020) examined linkages between surprise (unexpected) volatilities of eight leading cryptocurrencies and found evidence of causality linkages between volatility surprises.

As reported by the recent literature, the COVID-19 pandemic has vehemently hit the global economy has confronted with the worst economic upheaval since the GFC. The detrimental effects of the pandemic have quickly spilled to the global financial markets and conduced excessive volatilities (Ali *et al.*, 2020; Ashraf, 2020; Baker *et al.*, 2020; Zhang *et al.*, 2020; Albulescu, 2021). Likewise, a body of studies has analyzed the impact of the pandemic on the cryptocurrency market. For example, Shahzad *et al.* (2021) examined daily return spillover between 18 cryptocurrencies for the low and high volatility regimes, and by considering the COVID-19 outbreak. The authors found that the total spillover index suddenly uprises following the COVID-19 outbreak. Similarly, Naeem *et al.* (2021) analyzed the asymmetric efficiency of four leading cryptocurrencies, namely, Bitcoin, Etherium, Litecoin and Ripple. The findings of the study indicate that the COVID-19 outbreak negatively affected the efficiency of cryptocurrencies.

The tremendous increase in transaction volumes in the cryptocurrency market has propelled an increase in their potential impacts on financial markets via different channels, such as trade, derivatives, commodity, bond, stock and foreign exchange markets. Departing from this phenomenon, we concentrate on nine top cryptocurrencies by their market capitalization and those which have the longest price data[4]. Table 1 presents major 11 cryptocurrencies (CoinMarketCap, 2020).

As shown in Table 1, the cryptocurrencies with the highest market value are Bitcoin, Ethereum, XRP, Tether, Bitcoin Cash, Bitcoin SV, Litecoin, Binance Coin, Eos, Cardano and Tezos. As seen in Table 1, bitcoin is the leading cryptocurrency (1 bitcoin = $9,438) with the highest volume ($32.8bn) and the highest market cap ($173.5bn). Ethereum ranks 2nd in terms of the market capitalization around 15% of the market value of Bitcoin with $24.5bn. Ripple follows Ethereum with a market capitalization of $8.7bn. Bitcoin keeps its leading role since the emergence of the cryptocurrency market in 2009. Furthermore, the annual price growth rates of Bitcoin for the past three years are 1,336.6%, −71.85% and 187.3%, whereas those rates for Etherium are 9,457%, −81% and −7%, and for Ripple are 37,531%, −555.1% and −47.1%. Notice that the annual price growth rate for cryptocurrencies in 2018 is negative due to the 2018 cryptocurrency crash and only the annual return on the investment for Bitcoin in 2018 is positive among those three cryptocurrencies.

2.2 Financial contagion and cryptocurrency connectedness

The globalization of the financial system has entailed rapid risk spillovers between financial markets and has led to financial contagion, accordingly. As extensively reported by the scholars, financial contagion tends to escalate during times of financial distress owing to strongly connected financial markets.

Financial contagion has been the focus of quantitative studies and different econometric models have been used by the scholars, such as multivariate generalized autoregressive conditional heteroskedasticity (Jaworski and Pitera, 2014; Hemche *et al.*, 2016; Bonga-Bonga, 2018; Gomez-Gonzalez and Rojas-Espinosa, 2019), causality analysis (Zhang, 2017; Gharib *et al.*, 2020), the Kalman Filter (Shen *et al.*, 2015) and the vector autoregression (VAR) (Bouvet *et al.*, 2013; Le and David, 2014; Georgoutsos and Moratis, 2017; Boutabba, 2019; Akhtaruzzaman *et al.*, 2020).

It should be noted that financial contagion and financial connectedness are closely linked. Consequently, researchers have measured spillovers among financial markets during financial calm and turmoil times. Among them, Diebold and Yilmaz (2009) introduced a pioneering approach, henceforth, the DY, by which directional, total and net spillovers are computed based on the H-step ahead forecast error variance decompositions of a standard vector autoregression (VAR) model. The study estimated return and volatility spillovers among stock markets of 19 countries by using the DY approach. Diebold and Yilmazcomputed spillovers between various markets by using the DY approach (Diebold and Yilmaz, 2012, 2015).

The DY approach has been popular in financial connectedness studies and scholars have estimated spillovers among financial markets. Studies have calculated connectedness in various markets, such as FX markets connectedness (Bubák *et al.*, 2011; Antonakakis, 2012; Baruník and Křehlík, 2018), stock markets connectedness (Tsai, 2014; Guimarães-Filho and Hong, 2016), debt markets connectedness (Antonakakis and Vergos, 2013; Le *et al.*, 2020), cryptocurrency markets connectedness (Yi *et al.*, 2018; Andrada-Félix *et al.*, 2020; Bagheri and Ebrahimi, 2020).

Despite the literature on the cryptocurrency market connectedness is scant and relatively new, a body of studies has attempted to gauge cryptocurrency connectedness by using the DY approach. Among them, Corbet *et al.* (2018) analyzed connectedness between Bitcoin, Litecoin, Ripple and six financial indicators (Cboe volatility index, bond, gold, fx and S&P 500) by using the DY approach in 2013 and 2017. The findings of the study suggest that cryptocurrencies are isolated from other financial markets and closely linked. Likewise, Ji *et al.* (2019) investigated

Rankings	Name	Symbol	Market cap (Bn$)	Price($)	Circulating supply (bn)	Volume (bn $)
1	Bitcoin	BTC	173.5	9,438	1.839 BTC	32.8
2	Ethereum	ETH	24.5	220.6	11.116 ETH	12.2
3	Ripple	XRP	8.7	0.19	44.11 XRP	1.4
4	Tether	USDT	8.8	1	8.8 USDT	36.7
5	Bitcoin Cash	BCH	4.3	251.3	1.842 BCH	3.3
6	Bitcoin SV	BSV	3.5	201.8	1.842 BSV	1.5
7	Litecoin	LTC	2.8	44.6	6.485 LTC	2.6
8	Binance Coin	BNB	2.6	17	15.554 BNB	0.3
9	EOS	EOS	2.4	2.6	93.309 EOS	2.01
10	Tezos	XTZ	1.7	2.4	71.222 XTZ	0.07
11	Cardano	ADA	1.6	0.06	25.93 ADA	0.3

Table 1. Top 11 cryptocurrencies by the market capitalization

return and volatility connectedness among six major cryptocurrencies between August 8, 2015 and August 7, 2018. The findings of the study indicate that Litecoin and Bitcoin stand at the epicenter of the connected network and return shocks caused by Litecoin and Bitcoin have the largest effects on other cryptocurrencies. Additionally, the authors indicate that connectedness through negative returns is higher than the one via positive returns. Along similar lines, Yi *et al.* (2018) focused on volatility connectedness between eight cryptocurrencies by implementing the vector autoregression (VAR) models. Their findings indicate that connectedness oscillates and has markedly surged since the end of 2016. Antonakakis *et al.* (2019) examined connectedness between nine major cryptocurrencies by implementing a time varying parameter – factor augmented vector autoregression connectedness method between August 8, 2015 and May 31, 2018. The study found that the total connectedness between various cryptocurrencies fluctuates between 25% and 75% over the analyzed period. Aslanidis *et al.* (2020) analyzed return and volatility connectedness among 17 major cryptocurrencies by means of their market capitalization by implementing the DY approach. The authors detected a sudden upward trend in total connectedness around March 2020 due to the COVID-19 pandemic. Likewise, Li *et al.* (2020) examined risk connectedness among seven cryptocurrencies in August 7, 2015 and February 15, 2020 by using the DY and the BK methodologies. The results of the study indicate that the direction of spillovers are highly correlated with the market capitalizations of cryptocurrencies, spillovers under a downward tendency are stronger than those under a upward tendency and heterogeneity dominates the average and range of spillover at different time frequencies.

Baruník and Křehlík (2018) proposed a seminal approach, *frequency connectedness*, henceforth the BK, which estimates connectedness in different cycles based on the spectral representation of the vector autoregression (VAR) model. According to the frequency connectedness method, the connectedness of assets can be computed by Fourier transforms of the impulse response functions on a given frequency band. This novel methodology is superior to mainframe connectedness measures and has gained overwhelming attention from scholars. More recent studies have concentrated on connectedness in several financial markets by using the frequency connectedness approach (Polat, 2019; Maghyereh *et al.*, 2019; Le *et al.*, 2020; Owusu Junior *et al.*, 2020; Polat, 2020; Fousekis and Tzaferi, 2021).

3. Methodology

3.1 Data

The data set is comprising 8 out of 10 largest cryptocurrencies by market capitalization, namely, Bitcoin, Etherium, Ripple, Tether, Bitcoin Cash, Litecoin, Binance Coin, EOS and span from July 26, 2017 and October 28, 2020[5].

3.2 Empirical framework

Baruník and Křehlík (2018) specified the frequency connectedness methodology based on the spectral representation of a M-variable *vector autoregression (VAR)*(p):

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-1} + \mu_t \tag{1}$$

herein, x_t, $M \times 1$ vector of variables, μ, $M \times 1$ vector of i.i.d. error terms and $\mu_t \sim N(0,\Omega)$.

The MA representation of the *vector autoregression (VAR)*(p) can be given as $x_t = \psi(\mathrm{L})\varepsilon_t$, where $\psi(\mathrm{L})$ is the matrix of infinite lag polynomials and can be introduced as $\varphi(L) = [\psi(\mathrm{L})]^{-1}$.

Hereinafter, the frequency response function is defined as $\psi(e^{-iw}) = \sum_h e^{-iwh}\ \psi_h$ is the Fourier transform of the coefficients ψ_h.

The spectral density of x_t at frequency w is introduced as the Fourier transform of MA (∞) filtered series as:

$$S_X(W) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-iwh} = \ \psi(e^{-iw})\ \Omega\ \psi'(e^{+iw}) \tag{2}$$

$$\zeta(w)_{j,k} = \frac{\sigma_{kk}^{-1} |\ \psi(e^{-iw})\ \Omega|_{j,k}^2}{\left(\psi(e^{-iw})\ \Omega\ \psi'(e^{+iw})_{jj}\right.} \tag{3}$$

where $\sigma_{kk} = (\Omega)_{kk}$.

Scaled generalized variance decompositions on the frequency band $d = (a,b){:}a,b \in (-\pi,\pi), a < b$ is defined as $(\tilde{\varphi}_d)_{j,k} = (\varphi_d)_{j,k} / \sum_k (\varphi_\infty)_{j,k}$, where

$$(\tilde{\varphi}_d)_{j,k} = \frac{1}{2\pi} \int_a^b \frac{\left(\psi(e^{-iw})\Omega\psi'(e^{+iw})\right)_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\psi(e^{-i\lambda})\Omega\psi'(e^{+i\lambda})_{jj} d\lambda\, (\zeta(w))_{j,k} dw\right.} \tag{4}$$

and

$$(\varphi_\infty)_{j,k} = \frac{1}{2\pi} \int_{-\pi}^{\pi} \frac{\left(\psi(e^{-iw})\Omega\psi'(e^{+iw})\right)_{jj}}{\int_{-\pi}^{\pi}\left(\psi(e^{-i\lambda})\Omega\psi'(e^{+i\lambda})_{jj} d\lambda\right.} \tag{5}$$

The within connectedness on d is defined as:

$$C_d^w = 100.\left(1 - \frac{Tr(\tilde{\varphi}_d)}{\sum \tilde{\varphi}_\infty}\right) \tag{6}$$

The frequency connectedness on d is defined as:

$$C_d^f = 100.\left(\frac{\sum \tilde{\varphi}_d}{\sum \tilde{\varphi}_\infty} - \frac{Tr(\tilde{\varphi}_d)}{\sum \tilde{\varphi}_\infty}\right) = C_d^w \frac{\sum \tilde{\varphi}_d}{\sum \tilde{\varphi}_\infty} \tag{7}$$

herein, $Tr\{.\}$ Is the trace operator, $\sum \tilde{\varphi}_d$ is the sum of all elements of the φ_d.

Following Garman and Klass (1980), Diebold and Yilmaz (2015) and Ji *et al.* (2019), we use the daily range-based realized volatility estimations in the empirical model. As stated in Alizadeh *et al.* (2002), range-based volatility estimations provide highly efficient estimations of stochastic volatility models, and thus, suitable for our empirical model. Daily range-based volatility estimations for cryptocurrencies are presented as:

$$\begin{aligned} \mathrm{RV} = {} & 0.511(H-L)^2 - 0.019\left[(C-O)(H+L-2O) - 2(H-0)(L-O)\right] \\ & - 0.383(C-O)^2 \end{aligned} \tag{8}$$

where H, L, C and O correspond to log of daily high price, low price, close price and open price, respectively.

3.3 VAR-LASSO model

Tibshirani (1996) introduced the least absolute shrinkage and selection operator (LASSO) regression based on Breiman's algorithm (Breiman, 1995), which adds a penalty to the least squares minimization problem represented by the L_1 norm of the model's coefficient vector indexed by the multiplicative positive factor λ (penalty or tuning parameter), given as follows:

$$Q(\beta) = (y_t - \beta_0 - X_t\beta)'(y_t - \beta_0 - X_t\beta) + \lambda\,\beta \tag{9}$$

herein, y_t is the dependent variable, X_t is the vector of regressors, β_0 is constant and β is the vector of coefficients.

The penalty parameter can be chosen based on the information criterion or cross-validation. However, the cross-validation provides a set of coefficients that allow more robust predictions, as the information criterion only minimizes the in-sample variance of a forecasting error adjusted by the number of parameters.

4. Results

4.1 Historical daily prices of cryptocurrencies

Figure 1 exhibits historical prices for eight cryptocurrencies in July 26, 2017 and October 28, 2020.

As shown in Figure 1, all cryptocurrency price series remarkably surged between July, 2017 and December, 2017, sharing a common trend. Six out of nine cryptocurrencies peaked in December, 2017 or in January, 2018. Bitcoin, Tether, Bitcoincash and Litecoin peaked in December, 2017, while Etherium, Ripple reached their peak values in January, 2018. On the other hand, Binance coin and Eos peaked in April, 2018.

Figure 2 shows the daily range-based volatilities of cryptocurrencies computed by the equation (8) in July 26, 2017 and October 28, 2020.

Daily range-based volatilities of cryptocurrencies excessively fluctuated between mid-2017 and early-2018 and notably on March 11, 2020 (except Bitcoincash), which coincides with the official announcement of COVID-19 as a pandemic by the World Health Organization (WHO)[6]. In view of noticeable amplified volatilities after the COVID-19 announcement, in the next step, we concentrate on cryptocurrency volatility connectedness before and after the COVID-19 announcement.

4.2 Overall spillover index

In this section, we compute the overall connectedness between realized volatilities by using the BK approach. We estimate the overall connectedness with a moving window of 300 days using 100-day forecast error variance decompositions of *vector autoregression (VAR)*(1). Herewith, the overall spillover indexes on the (π,π/4), (π/4,π/10) and (π/10,0)[7] frequency bands are estimated by carrying out VAR-LASSO estimations with an automatic penalty parameter selection. Figure 3 depicts overall spillover indexes on different frequency bands.

Overall spillover indexes have fluctuated between 54% and 92% in May 2018 and April 2020. The indexes gradually escalated till November 9, 2018 and surpassed their average values (71.92%, 73.66% and 74.23%, respectively). Overall spillover indexes dramatically plummeted till January 2019 and reached their troughs (54.04%, 57.81% and 57.81%, respectively). In line with the finding in Aslanidis *et al.* (2020), after slightly surging to their average levels, the indexes skyrocketed in March, 2020 with the official announcement of COVID-19 as a pandemic by the World Health Organization (WHO) and they surpassed 90%.

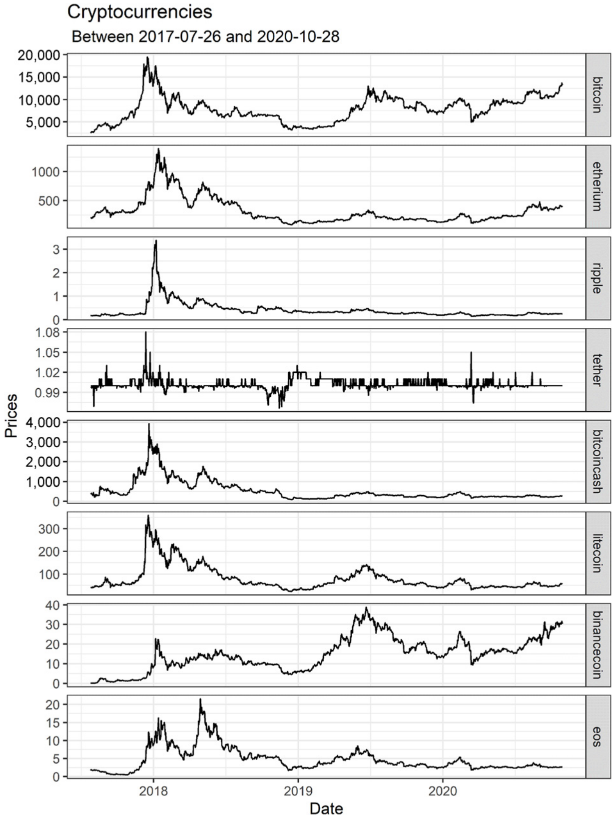

Figure 1.
Historical daily prices of cryptocurrencies in July, 2017–October, 2020

4.3 Network analysis

Owing to markedly surged connectedness between realized volatilities of cryptocurrencies after March 11, 2020, we focus on the network topology of pairwise spillovers for two distinct periods, July 26, 2017 and March 10, 2020 (before the COVID-19 announcement) and March 11, 2020 and October 28, 2020 (after the COVID-19 announcement). Network topologies consist of pairwise spillovers that are larger than a threshold value[8] to better visualize the network connectedness[9]. Furthermore, the size of each node exhibits the magnitude of spillovers, reflecting total FROM spillovers. The thickness of the arrow reflects the strength of the spillover connecting a pair of nodes. Figure 4 depicts network graphs of pairwise spillovers estimated on the (π,π/4), (π/4,π/10) and (π/10,0) frequency bands for those two distinct periods, respectively.

As clearly shown in Figure 4 that the pairwise spillovers dramatically intensify after the official announcement of the COVID-19 as a pandemic by the World Health Organization (WHO). Notice that the total spillover indexes for short-, medium- and long-cycle before the COVID-19 announcement are 53.48%, 56.57% and 58.04%, respectively, while those indexes after the COVID-19 announcement are 85.76%, 86.03% and 86.06%)[10]. This may be explained by the herding behavior of cryptocurrencies during turbulent times (Kallinterakis and Wang, 2019).

Several results can be drawn from short-cycle network topologies. First, Etherium catalyst the highest sum of volatility spillovers to other cryptocurrencies (94.2%) and is

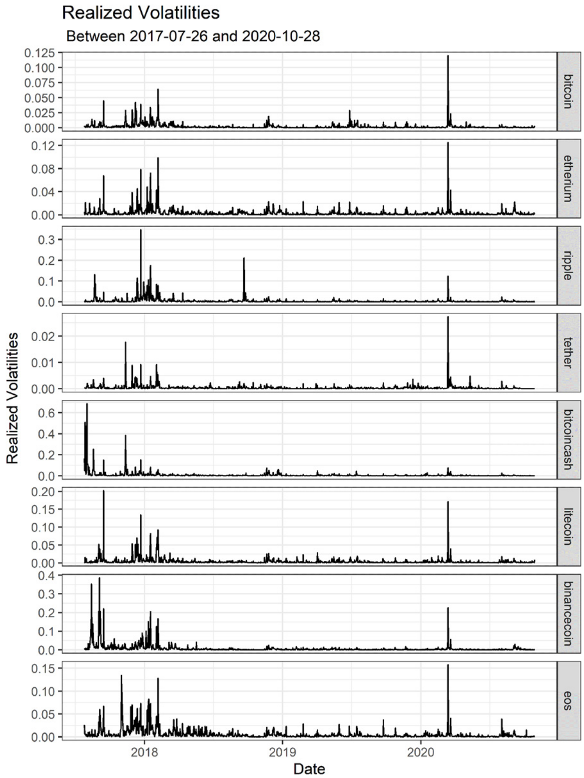

Figure 2.
Daily range-based volatilities for cryptocurrencies in July, 2017–October, 2020

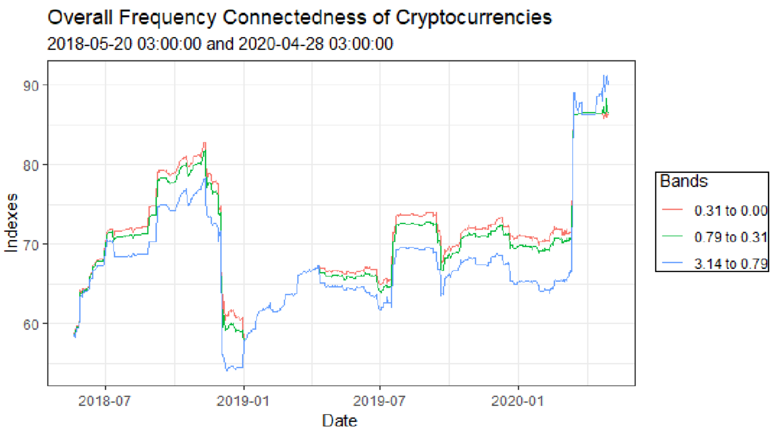

Figure 3.
Overall spillover indexes for the short-, medium- and long-cycle connectedness

followed by Litecoin (79.8%) and Bitcoin (76.4%) before the COVID-19 announcement, whereas Litecoin becomes the largest transmitter of total volatility (89.5%) and followed by Bitcoin (89.3%) and Etherium (88.9%). This result is consistent with the study of Ji *et al.* (2019). Second, except for Etherium, the magnitudes of total volatility spillovers from each

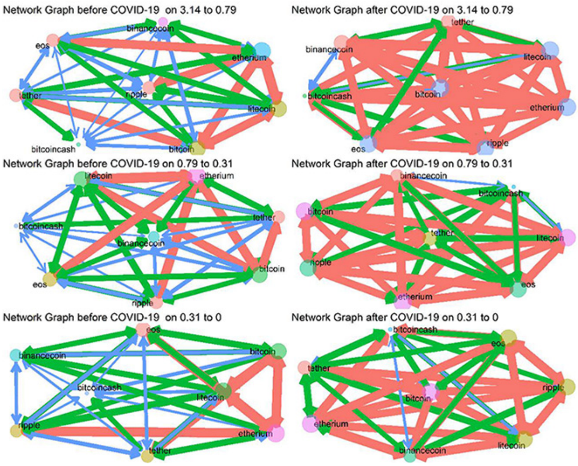

Figure 4.
Network graphs of pairwise spillovers before and after the COVID-19 announcement

cryptocurrency notably increase after- COVID-19 announcement period. The pair Etherium/Litecoin has the strongest connectedness before the COVID-19 announcement, whereas the pair Bitcoin/Tether has the tightest connectedness in the latter period.

The Medium-cycle network topology of pairwise spillovers indicates that the largest transmitter of total volatility spillover is Litecoin (89.5%) and followed by Bitcoin (89.3%) and Etherium (88.9%) before the COVID-19 announcement. Therefore, the largest nodes of transmitting total volatility spillovers are the same for both short- and medium-cycle connectedness networks. Etherium keeps its leading role of transmitting the highest sum of volatility spillovers (89.4%), followed by Bitcoin (88.9%) and Litecoin (88.2%) after the COVID-19 announcement. Etherium/Litecoin pair has the highest pairwise spillovers in the former period, and the pair Bitcoin/Tether has the strongest connectedness in the latter period.

The largest transmitter of total volatility spillovers is Etherium (95.7%), followed by Litecoin (81.2%) and Binance Coin (75.5%) for the long-cycle connectedness network in the before-COVID-19 announcement period. These nodes keep their leading roles in propagating volatility spillover in the latter period with the following sum of spillovers (Etherium-89.5%, Bitcoin-88.9% and Litecoin-88.1%, respectively). Sharing a common feature with the short- and medium-cycle connectedness network, the pairs Etherium/Litecoin and Bitcoin/Tether have the strongest connectedness in the former and latter periods, respectively.

5. Conclusion

The world economy has witnessed acute financial/political upheavals since the 1929 great depression, yet the most severe ones are the GFC and the COVID-19 pandemic. The recent pandemic sorely hit the global economic system and the detrimental effects of it have continued to spread across the globe since its first emergence. Despite fiscal/macroeconomic stimulus packages launched by the authorities, the COVID-19 pandemic has adversely affected global financial markets.

Thanks to remarkably increased cryptocurrency volatilities following the official announcement of the COVID-19 pandemic by the World Health Organization (WHO), in this study, we examine the volatility connectedness of nine main cryptocurrencies before and after the COVID-19 announcement. To this end, we use the frequency connectedness approach and compute volatility spillovers among major cryptocurrencies. Furthermore, we focus on the short-, medium- and long-cycle connectedness networks, which consist of pairwise volatility spillovers among cryptocurrencies.

In line with the previous studies (Aslanidis *et al.*, 2020; Iqbal *et al.*, 2021), we found that the volatility connectedness among cryptocurrencies markedly intensifies, particularly after March 11, 2020, which coincides with the official announcement of the COVID-19 pandemic. This result is probably because of the herding behavior in the cryptocurrency market.

Network analysis for two distinct periods, namely, before- and after- the official announcement of the COVID-19 pandemic provides valuable insights for volatility transmissions among cryptocurrencies during calm and turbulent times. First, total spillover indexes dramatically surge in the latter period, indicating a significant impact of the COVID-19 pandemic on the cryptocurrency market. Second, consistent with the study of Ji *et al.* (2019), we detected that major cryptocurrencies, such as Bitcoin, Etherium and Litecoin stand at the epicenter of the networks. Moreover, Etherium is the largest node of transmitting the total amount of volatility spillovers in short-, medium- and long-cycle connectedness networks reflecting before the official announcement of the COVID-19 pandemic.

Tight interdependence between major cryptocurrencies based on the network analysis influence the decisions of investors, regulators and researchers. However, consistent with the related literature, large cryptocurrencies transmit/receive diverse amounts of volatility spillovers, which shortens the diversification in the cryptocurrency market. Furthermore, our study asserts a significant impact on the COVID-19 pandemic on the cryptocurrency volatility connectedness. Notwithstanding the fact this can provide a profit opportunity for investors, regulators should closely monitor the price developments in the cryptocurrency market to pretend the economic system from an unprecedented shock stemmed from the cryptocurrency market.

Notes

1. See https://coinmarketcap.com/currencies/bitcoin/historical-data/
2. See, https://covid19.who.int/table
3. See, https://coinmarketcap.com/
4. The cryptocurrencies used in the study are as follows: Bitcoin, Etherium, Ripple, Tether, Bitcoincash, Litecoin, Binancecoin and Eos.
5. We collect the price series for cryptocurrencies from https://coinmarketcap.com/
6. See www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19−−11-march-2020
7. $(\pi, \pi/4)$, $(\pi/4, \pi/10)$ and $(\pi/10, 0)$ reflect approximately 1 days to 4 days, 4 days to 10 days and 10 days to infinity days, respectively.
8. ρ_x:= (max(*FROM directional spillovers*) $\times$ β), where $\beta = 0.1$.
9. We provide the spillovers tables in the Appendix.
10. See Appendix.

References

Agosto, A. and Cafferata, A. (2020), "Financial bubbles: a study of co-explosivity in the cryptocurrency market", *Risks*, Vol. 8 No. 2, p. 34.

Akhtaruzzaman, M., Boubaker, S. and Sensoy, A. (2020), "Financial contagion during COVID–19 crisis", *Finance Research Letters*, Vol. 38, p. 101604.

Akyildirim, E., Corbet, S., Katsiampa, P., Kellard, N. and Sensoy, A. (2020), "The development of bitcoin futures: exploring the interactions between cryptocurrency derivatives", *Finance Research Letters*, Vol. 34, p. 101234.

Albulescu, C.T. (2021), "COVID-19 and the United States financial markets' volatility", *Finance Research Letters*, Vol. 38, p. 101699.

Ali, M., Alam, N. and Rizvi, S.A.R. (2020), "Coronavirus (COVID-19) – an epidemic or pandemic for financial markets", *Journal of Behavioral and Experimental Finance*, Vol. 27, p. 100341.

Alizadeh, S., Brandt, M.W. and Diebold, F.X. (2002), "Range-based estimation of stochastic volatility models", *The Journal of Finance*, Vol. 57 No. 3, pp. 1047-1091.

Andrada-Félix, J., Fernandez-Perez, A. and Sosvilla-Rivero, S. (2020), "Distant or close cousins: connectedness between cryptocurrencies and traditional currencies volatilities", *Journal of International Financial Markets, Institutions and Money*, Vol. 67, p. 101219.

Antonakakis, N. (2012), "Exchange return co-movements and volatility spillovers before and after the introduction of euro", *Journal of International Financial Markets, Institutions and Money*, Vol. 22 No. 5, pp. 1091-1109.

Antonakakis, N. and Vergos, K. (2013), "Sovereign bond yield spillovers in the Euro zone during the financial and debt crisis", *Journal of International Financial Markets, Institutions and Money*, Vol. 26, pp. 258-272.

Antonakakis, N., Chatziantoniou, I. and Gabauer, D. (2019), "Cryptocurrency market contagion: market uncertainty, market complexity, and dynamic portfolios", *Journal of International Financial Markets, Institutions and Money*, Vol. 61, pp. 37-51.

Ashraf, B.N. (2020), "'Stock markets' reaction to COVID-19: cases or fatalities?", *Research in International Business and Finance*, Vol. 54, p. 101249.

Aslanidis, N., Bariviera, A.F. and Perez-Laborda, A. (2020), "Are cryptocurrencies becoming more interconnected?", *Economics Letters*, Vol. 199, p. 109725.

Baek, C. and Elbeck, M. (2015), "Bitcoins as an investment or speculative vehicle? A first look", *Applied Economics Letters*, Vol. 22 No. 1, pp. 30-34.

Bagheri, E. and Ebrahimi, S.B. (2020), "Estimating network connectedness of financial markets and commodities", *Journal of Systems Science and Systems Engineering*, Vol. 29 No. 5, pp. 572-589.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M. and Viratyosin, T. (2020), "The unprecedented stock market reaction to COVID-19", *The Review of Asset Pricing Studies*, Vol. 10 No. 4, pp. 742-758.

Baruník, J. and Křehlík, T. (2018), "Measuring the frequency dynamics of financial connectedness and systemic risk", *Journal of Financial Econometrics*, Vol. 16 No. 2, pp. 271-296.

Baur, D.G. and Dimpfl, T. (2018), "Asymmetric volatility in cryptocurrencies", *Economics Letters*, Vol. 173, pp. 148-151.

Bonga-Bonga, L. (2018), "Uncovering equity market contagion among BRICS countries: an application of the multivariate GARCH model", *The Quarterly Review of Economics and Finance*, Vol. 67, pp. 36-44.

Bouri, E., Lucey, B. and Roubaud, D. (2020), "The volatility surprise of leading cryptocurrencies: transitory and permanent linkages", *Finance Research Letters*, Vol. 33, p. 101188.

Bouri, E., Roubaud, D. and Shahzad, S.J.H. (2020), "Do Bitcoin and other cryptocurrencies jump together?", *The Quarterly Review of Economics and Finance*, Vol. 76, pp. 396-409.

Bouri, E., Shahzad, S.J.H. and Roubaud, D. (2019), "Co-explosivity in the cryptocurrency market", *Finance Research Letters*, Vol. 29, pp. 178-183.

Bouri, E., Vo, X.V. and Saeed, T. (2021), "Return equicorrelation in the cryptocurrency market: analysis and determinants", *Finance Research Letters*, Vol. 38, p. 101497.

Bouri, E., Cepni, O., Gabauer, D. and Gupta, R. (2020), “Return connectedness across asset classes around the COVID-19 outbreak”, *International Review of Financial Analysis*, Vol. 73, p. 101646.

Boutabba, I. (2019), “An empirical validation of financial contagion by a multivariate VAR model”, *International Journal of Business and Economics*, Vol. 18 No. 2, pp. 221-244.

Bouvet, F., Brady, R. and King, S. (2013), “Debt contagion in Europe: a panel-vector autoregressive (VAR) analysis”, *Social Sciences*, Vol. 2 No. 4, pp. 318-340.

Breiman, L. (1995), “Better subset regression using the nonnegative garrote”, *Technometrics*, Vol. 37 No. 4, pp. 373-384.

Bubák, V., Kočenda, E. and Žikeš, F. (2011), “Volatility transmission in emerging European foreign exchange markets”, *Journal of Banking and Finance*, Vol. 35 No. 11, pp. 2829-2841.

Canh, N.P., Wongchoti, U., Thanh, S.D. and Thong, N.T. (2019), “Systematic risk in cryptocurrency market: evidence from DCC-MGARCH model”, *Finance Research Letters*, Vol. 29 No. 29, pp. 90-100.

Cheikh, N.B., Zaied, Y.B. and Chevallier, J. (2020), “Asymmetric volatility in cryptocurrency markets: new evidence from smooth transition GARCH models”, *Finance Research Letters*, Vol. 35 No. 35, p. 101293.

CoinMarketCap (2020), “Today’s cryptocurrency prices by market cap”, available at: https://coinmarketcap.com (accessed 29 May 2020).

Corbet, S., Larkin, C. and Lucey, B. (2020), “The contagion effects of the COVID- 19 pandemic: evidence from gold and cryptocurrencies”, *Finance Research Letters*, Vol. 35, p. 101554.

Corbet, S., Lucey, B., Urquhart, A. and Yarovaya, L. (2019), “Cryptocurrencies as a financial asset: a systematic analysis”, *International Review of Financial Analysis*, Vol. 62, pp. 182-199.

Corbet, S., Meegan, A., Larkin, C., Lucey, B. and Yarovaya, L. (2018), “Exploring the dynamic relationships between cryptocurrencies and other financial assets”, *Economics Letters*, Vol. 165, pp. 28-34.

da Gama Silva, P.V.J., Klotzle, M.C., Pinto, A.C.F. and Gomes, L.L. (2019), “Herding behavior and contagion in the cryptocurrency market”, *Journal of Behavioral and Experimental Finance*, Vol. 22, pp. 41-50.

Diebold, F.X. and Yilmaz, K. (2009), “Measuring financial asset return and volatility spillovers, with application to global equity markets”, *The Economic Journal*, Vol. 119 No. 534, pp. 158-171.

Diebold, F.X. and Yilmaz, K. (2012), “Better to give than to receive: predictive directional measurement of volatility spillovers”, *International Journal of Forecasting*, Vol. 28 No. 1, pp. 57-66.

Diebold, F.X. and Yilmaz, K. (2015), “Trans-Atlantic equity volatility connectedness: US and European financial institutions, 2004– 2014”, *Journal of Financial Econometrics*, Vol. 14 No. 1, pp. 81-127.

Fousekis, P. and Tzaferi, D. (2021), “Returns and volume: frequency connectedness in cryptocurrency markets”, *Economic Modelling*, Vol. 95, pp. 13-20.

Fry, J. (2018), “Booms, busts and heavy-tails: the story of Bitcoin and cryptocurrency markets?”, *Economics Letters*, Vol. 171, pp. 225-229.

Fry, J. and Cheah, E.T. (2016), “Negative bubbles and shocks in cryptocurrency markets”, *International Review of Financial Analysis*, Vol. 47, pp. 343-352.

Garman, M.B. and Klass, M.J. (1980), “On the estimation of security price volatilities from historical data”, *The Journal of Business*, Vol. 53 No. 1, pp. 67-78.

Georgoutsos, D. and Moratis, G. (2017), “Bank-sovereign contagion in the Eurozone: a panel VAR approach”, *Journal of International Financial Markets, Institutions and Money*, Vol. 48, pp. 146-159.

Geuder, J., Kinateder, H. and Wagner, N.F. (2019), “Cryptocurrencies as financial bubbles: the case of Bitcoin”, *Finance Research Letters*, Vol. 31 No. 31, pp. 179-184.

Gharib, C., Mefteh-Wali, S. and Jabeur, S.B. (2020), "The bubble contagion effect of COVID-19 outbreak: evidence from crude oil and gold markets", *Finance Research Letters*, Vol. 38, p. 101703.

Gomez-Gonzalez, J.E. and Rojas-Espinosa, W. (2019), "Detecting contagion in Asian exchange rate markets using asymmetric DCC-GARCH and R-vine copulas", *Economic Systems*, Vol. 43 Nos 3/4, p. 100717.

Guimarães-Filho, R. and Hong, G.H. (2016), "Dynamic connectedness of Asian equity markets", IMF Working Papers. No.16/57.

Gurrib, I. (2019), "Can energy commodities affect energy blockchain-based cryptos?", *Studies in Economics and Finance*, Vol. 36 No. 4, pp. 682-699.

Hafner, C.M. (2020), "Testing for bubbles in cryptocurrencies with time-varying volatility", *Journal of Financial Econometrics*, Vol. 18 No. 2, pp. 233-249.

Hemche, O., Jawadi, F., Maliki, S.B. and Cheffou, A.I. (2016), "On the study of contagion in the context of the subprime crisis: a dynamic conditional correlation–multivariate GARCH approach", *Economic Modelling*, Vol. 52, pp. 292-299.

Iqbal, N., Fareed, Z., Wan, G. and Shahzad, F. (2021), "Asymmetric nexus between COVID-19 outbreak in the world and cryptocurrency market", *International Review of Financial Analysis*, Vol. 73, p. 101613.

Jaworski, P. and Pitera, M. (2014), "On spatial contagion and multivariate GARCH models", *Applied Stochastic Models in Business and Industry*, Vol. 30 No. 3, pp. 303-327.

Ji, Q., Bouri, E., Lau, C.K.M. and Roubaud, D. (2019), "Dynamic connectedness and integration in cryptocurrency markets", *International Review of Financial Analysis*, Vol. 63, pp. 257-272.

Kallinterakis, V. and Wang, Y. (2019), "Do investors herd in cryptocurrencies–and why?", *Research in International Business and Finance*, Vol. 50, pp. 240-245.

Katsiampa, P., Corbet, S. and Lucey, B. (2019), "Volatility spillover effects in leading cryptocurrencies: a BEKK-MGARCH analysis", *Finance Research Letters*, Vol. 29, pp. 68-74.

Koutmos, D. (2018), "Return and volatility spillovers among cryptocurrencies", *Economics Letters*, Vol. 173, pp. 122-127.

Kyriazis, N., Papadamou, S. and Corbet, S. (2020), "A systematic review of the bubble dynamics of cryptocurrency prices", *Research in International Business and Finance*, Vol. 54, p. 101254.

Le, C. and David, D. (2014), "Asset price volatility and financial contagion: analysis using the MS-VAR framework", *Eurasian Economic Review*, Vol. 4 No. 2, pp. 133-162.

Le, T.L., Abakah, E.J.A. and Tiwari, A.K. (2020), "Time and frequency domain connectedness and spill-over among Fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution", *Technological Forecasting and Social Change*, Vol. 162, p. 120382.

Lee, S., El Meslmani, N. and Switzer, L.N. (2020), "Pricing efficiency and arbitrage in the bitcoin spot and futures markets", *Research in International Business and Finance*, Vol. 53, p. 101200.

Li, Z., Wang, Y. and Huang, Z. (2020), "Risk connectedness heterogeneity in the cryptocurrency markets", *Frontiers in Physics*, Vol. 8, p. 243.

Maghyereh, A.I., Abdoh, H. and Awartani, B. (2019), "Connectedness and hedging between gold and Islamic securities: a new evidence from time- frequency domain approaches", *Pacific-Basin Finance Journal*, Vol. 54, pp. 13-28.

Naeem, M.A., Bouri, E., Peng, Z., Shahzad, S.J.H. and Vo, X.V. (2021), "Asymmetric efficiency of cryptocurrencies during COVID19", *Physica A: Statistical Mechanics and Its Applications*, Vol. 565, p. 125562.

Nakamoto, S. (2008), "Bitcoin: a peer-to-peer electronic cash system", available at: https://Bitcoin.org/Bitcoin.pdf/ (accessed 29 May 2020).

Owusu Junior, P., Adam, A.M. and Tweneboah, G. (2020), "Connectedness of cryptocurrencies and gold returns: evidence from frequency-dependent quantile regressions", *Cogent Economics and Finance*, Vol. 8 No. 1, p. 1804037.

Panagiotidis, T., Stengos, T. and Vravosinos, O. (2019), "The effects of markets, uncertainty and search intensity on bitcoin returns", *International Review of Financial Analysis*, Vol. 63, pp. 220-242.

Polat, O. (2019), "Systemic risk contagion in FX market: a frequency connectedness and network analysis", *Bulletin of Economic Research*, Vol. 71 No. 4, pp. 585-598.

Polat, O. (2020), "Frequency connectedness and network analysis in equity markets: evidence from G-7 countries", *Akdeniz İİBF Dergisi*, Vol. 20 No. 2, pp. 221-226.

Qiao, X., Zhu, H. and Hau, L. (2020), "Time-frequency co-movement of cryptocurrency return and volatility: evidence from wavelet coherence analysis", *International Review of Financial Analysis*, Vol. 71, p. 101541.

Shahzad, S.J.H., Bouri, E., Kang, S.H. and Saeed, T. (2021), "Regime specific spillover across cryptocurrencies and the role of COVID-19", *Financial Innovation*, Vol. 7 No. 1, pp. 1-24.

Shen, P.L., Li, W., Wang, X.T. and Su, C.W. (2015), "Contagion effect of the European financial crisis on China's stock markets: interdependence and pure contagion", *Economic Modelling*, Vol. 50, pp. 193-199.

Szmigiera, M. (2020), "Cryptocurrency market value 2013-2019", available at: www.statista.com/statistics/730876/cryptocurrency-maketvalue/ (accessed 20 May 2020).

Tibshirani, R. (1996), "Regression shrinkage and selection via the lasso", *Journal of the Royal Statistical Society: Series B (Methodological)*, Vol. 58 No. 1, pp. 267-288.

Tsai, I.C. (2014), "Spillover of fear: evidence from the stock markets of five developed countries", *International Review of Financial Analysis*, Vol. 33, pp. 281-288.

Yi, S., Xu, Z. and Wang, G.J. (2018), "Volatility connectedness in the cryptocurrency market: is Bitcoin a dominant cryptocurrency?", *International Review of Financial Analysis*, Vol. 60, pp. 98-114.

Zhang, D. (2017), "Oil shocks and stock markets revisited: measuring connectedness from a global perspective", *Energy Economics*, Vol. 62, pp. 323-333.

Zhang, D., Hu, M. and Ji, Q. (2020), "Financial markets under the global pandemic of COVID-19", *Finance Research Letters*, Vol. 36, p. 101.

Corresponding author
Onur Polat can be contacted at: onur.polat@bilecik.edu.tr

Appendix: Spillover tables

Table A1.
Short-cycle spillover table before the COVID-19 announcement

	Bitcoin	Etherium	Ripple	Tether	Bitcoincash	Litecoin	Binancecoin	Eos	FROM
Bitcoin	35.88	17.41	6.08	12.54	2.14	15.94	3.13	6.88	8.02
Etherium	15.65	30.93	12.04	7.36	0.91	17.87	4.50	10.75	8.63
Ripple	7.89	17.38	45.56	6.21	1.12	12.34	3.18	6.32	6.80
Tether	16.19	11.02	6.42	45.62	4.96	8.89	2.12	4.78	6.80
Bitcoincash	4.83	2.31	1.90	8.25	76.60	4.13	0.64	1.34	2.92
Litecoin	15.69	19.71	9.34	6.50	1.88	34.16	5.29	7.43	8.23
Binancecoin	6.35	9.59	4.39	2.69	0.55	10.04	58.64	7.75	5.17
Eos	9.85	16.81	6.82	4.64	0.81	10.67	5.62	44.77	6.90
TO	9.56	11.78	5.87	6.02	1.55	9.99	3.06	5.66	TSI = 53.48%

Table A2.
Short-cycle spillover table after the COVID-19 announcement

	Bitcoin	Etherium	Ripple	Tether	Bitcoincash	Litecoin	Binancecoin	Eos	FROM
Bitcoin	13.79	12.54	12.75	12.83	10.39	13.00	12.49	12.21	10.78
Etherium	12.61	13.80	12.43	11.76	11.31	12.71	12.70	12.68	10.77
Ripple	12.85	12.45	13.92	12.02	10.09	13.24	12.34	13.09	10.76
Tether	13.49	12.35	12.54	14.45	11.29	12.30	11.55	12.03	10.69
Bitcoincash	12.18	13.18	11.74	12.42	15.90	11.65	10.46	12.48	10.51
Litecoin	12.96	12.60	13.10	11.66	9.92	13.79	12.97	12.99	10.78
Binancecoin	12.93	13.09	12.68	11.41	9.41	13.46	14.37	12.65	10.70
Eos	12.35	12.75	13.14	11.53	10.78	13.18	12.35	13.92	10.76
TO	11.17	11.12	11.05	10.45	9.15	11.19	10.61	11.02	TSI = 85.76%

Table A3.
Medium-cycle spillover table before the COVID-19 announcement

	Bitcoin	Etherium	Ripple	Tether	Bitcoincash	Litecoin	Binancecoin	Eos	FROM
Bitcoin	29.71	17.47	6.44	10.93	2.34	15.83	7.09	10.19	8.79
Etherium	14.70	27.39	11.64	6.92	1.05	18.10	6.69	13.52	9.08
Ripple	8.47	18.00	40.12	6.23	1.12	12.62	3.68	9.77	7.49
Tether	16.19	11.02	6.42	45.62	4.96	8.89	2.12	4.78	6.80
Bitcoincash	5.07	2.57	2.01	8.32	74.84	4.47	1.18	1.54	3.15
Litecoin	14.91	19.59	9.22	6.29	1.70	30.07	7.11	11.10	8.74
Binancecoin	6.52	9.89	4.50	2.78	0.56	10.18	57.09	8.48	5.36
Eos	9.87	16.73	6.83	4.62	0.81	10.92	7.62	42.61	7.17
TO	9.47	11.91	5.88	5.76	1.57	10.13	4.44	7.42	TSI = 56.57%

	Bitcoin	Etherium	Ripple	Tether	Bitcoincash	Litecoin	Binancecoin	Eos	FROM
Bitcoin	13.56	12.64	12.61	12.79	11.13	12.81	12.19	12.27	10.80
Etherium	12.55	13.71	12.33	11.87	11.97	12.55	12.35	12.66	10.79
Ripple	12.77	12.57	13.63	12.08	10.82	13.03	12.08	13.02	10.80
Tether	13.49	12.35	12.54	14.45	11.29	12.30	11.55	12.03	10.69
Bitcoincash	12.18	13.18	11.74	12.42	15.90	11.65	10.46	12.48	10.51
Litecoin	12.83	12.73	12.86	11.82	10.94	13.39	12.50	12.92	10.83
Binancecoin	12.79	13.15	12.49	11.68	10.76	13.06	13.42	12.65	10.82
Eos	12.33	12.85	12.88	11.71	11.68	12.90	11.99	13.66	10.79
TO	11.12	11.18	10.93	10.55	9.82	11.04	10.39	11.00	TSI = 86.03%

Table A4. Medium-cycle spillover table after COVID-19 announcement

	Bitcoin	Etherium	Ripple	Tether	Bitcoincash	Litecoin	Binancecoin	Eos	FROM
Bitcoin	27.28	17.47	6.56	10.26	2.35	15.76	8.95	11.36	9.09
Etherium	14.29	26.25	11.31	6.72	1.07	17.75	7.95	14.67	9.22
Ripple	8.75	18.26	37.32	6.23	1.12	12.80	4.26	11.26	7.84
Tether	16.19	11.02	6.42	45.62	4.96	8.89	2.12	4.78	6.80
Bitcoincash	5.28	2.79	2.12	8.39	73.39	4.74	1.58	1.71	3.33
Litecoin	14.54	19.46	9.11	6.17	1.62	28.30	8.34	12.45	8.96
Binancecoin	6.62	10.05	4.57	2.82	0.57	10.26	56.23	8.88	5.47
Eos	9.87	16.68	6.83	4.61	0.81	11.08	8.88	41.24	7.35
TO	9.44	11.97	5.87	5.65	1.56	10.16	5.26	8.14	TSI = 58.04%

Table A5. Long-cycle spillover table before the COVID-19 announcement

	Bitcoin	Etherium	Ripple	Tether	Bitcoincash	Litecoin	Binancecoin	Eos	FROM
Bitcoin	13.54	12.65	12.60	12.78	11.21	12.79	12.16	12.27	10.81
Etherium	12.54	13.71	12.32	11.88	12.05	12.54	12.31	12.66	10.79
Ripple	12.76	12.58	13.59	12.09	10.90	13.01	12.05	13.01	10.80
Tether	13.49	12.35	12.54	14.45	11.29	12.30	11.55	12.03	10.69
Bitcoincash	12.18	13.18	11.74	12.42	15.90	11.65	10.46	12.48	10.51
Litecoin	12.82	12.75	12.84	11.84	11.04	13.35	12.45	12.91	10.83
Binancecoin	12.78	13.16	12.47	11.70	10.87	13.02	13.34	12.65	10.83
Eos	12.33	12.86	12.86	11.73	11.77	12.87	11.96	13.63	10.80
TO	11.11	11.19	10.92	10.55	9.89	11.02	10.37	11.00	TSI = 86.06%

Note: TSI-Total Spillover Index

Table A6. Long-cycle spillover table after the COVID-19 announcement