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Connectedness among major cryptocurrencies in standard times and during the COVID-19 outbreak

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A R T I C L E I N F O

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A B S T R A C T

The cryptocurrency markets are perceived as being dominated by Bitcoin leading the overall system dynamics. Although the previous empirical evidence points towards strong connections among selected cryptocurrencies or, from the other side, weak dependence between Bitcoin and traditional financial assets, a focused study on the dynamics of return and volatility connectedness among a wider range of cryptocurrencies is lacking, and more so, one directed towards the very first actual critical period of the global economy coinciding with relevant crypto-markets. Using data for the 10 most capitalized cryptocurrencies between 1st October 2017 and 5th January 2021, we examine how cryptocurrencies interact and whether they have a clear leader, with a special focus on differences with respect to investment horizons and how the relationship structure evolves in time. We uncover a structural change in the connectedness evolving in 2020 as the market restructures in reaction to the unprecedented monetary injections as a counter to the COVID-19-induced economic standstill. The structural change is shown not only for cryptocurrencies considered separately but also when we jointly examine them with traditional assets.

1. Introduction

Following the release of Bitcoin in 2009 and the adoption of its blockchain technology, many cryptocurrencies have been enabled (e.g., Ethereum, Litecoin, Stellar, and Cardano)[1] and mostly used for investment purposes rather than as a means of payment. As a new digital asset class, cryptocurrencies provide a very appealing return that overshadows traditional financial assets (see, among others, Ji et al., 2019; Kristjanpoller et al., 2020). Some of the investors view cryptocurrencies as an uncertainty hedge or an asset capable of

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[1] Figures from December 2019 indicate the existence of more than 2,200 traded cryptocurrencies with a total market value exceeding $237.1 billion. These cryptocurrencies are traded in more than 258 exchanges around the globe, with BKEX being the largest cryptocurrency exchange with a trading volume of $3.73 billion.

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preserving their wealth in times of market turmoil. Cryptocurrencies are often perceived as a 'safe haven' not only because they are uncorrelated with conventional assets but also because they perform well during stress periods (Corbet et al., 2018; Shahzad et al., 2019).

In the wake of the economic shock of the COVID-19 outbreak in early 2020, cryptocurrencies are again in the news as most fiat currencies are in danger of losing value due to the quantitative easing measures announced by many central banks to revive fading economic activity[2]. If cryptocurrencies are considered a new asset, they deserve particular attention during turbulent periods in regard to their price co-movements for the sake of investors and portfolio managers who are keen to understand the connectedness among markets not only in general but during turbulent periods such as the COVID-19 outbreak. In fact, the COVID-19 global recession has emerged abruptly as the most economically costly outbreak in the recent one hundred years, disturbing financial markets across the globe. As cryptocurrencies play an important role for an increasing number of institutional investors[3] also, it is of relevance whether such economic shocks and the following policies influence the overall dynamics and connections within the crypto-market. As cryptocurrencies are often characterized by a dominant role of speculative capital, it is essential to account for the heterogeneous behaviour of market participants (e.g., long-term investors versus short-term speculators and traders) with respect to their various investment horizons and risk preferences (Kang et al., 2019; Bouri et al., 2020). To the best of our knowledge, no previous studies have considered these issues and thereby the following research questions. Are the return and volatility connectednesses among large cryptocurrencies dissimilar across various investment horizons? How shocks and policies emanating from the COVID-19 period influence the overall dynamics and connections not only within the cryptocurrency markets but also between cryptocurrencies and other financial assets? We hypothesize that the presence of heterogeneous market participants (e.g., long-term investors versus short-term speculators and traders) in the cryptocurrency markets would lead to a dissimilarity in the connectedness between the short- and long-term and that the financial markets reaction to the unprecedented monetary injections as a counter to the COVID-19-induced economic standstill has led to a structural change in the connectedness among cryptocurrencies around early 2020.

Against this background, in this study, we examine the spillovers[4] among the returns and volatility of leading cryptocurrencies over a full sample period and a sub-period corresponding to the COVID-19 outbreak. We do it for connectedness between cryptocurrencies and other traditional financial assets also. Methodologically, we apply the frequency-based connectedness approach of Baruník and Křehlík (2018), which allows us to uncover return spillovers while accounting for the investment horizons of market participants that often vary across frequencies. Such an analysis is useful and informative as it allows traders, investors, risk managers, arbitragers, and miners to better understand the information transmission in the highly debated digital asset class, and thereby facilitate effective decision making. Notably, our analysis presents measures of spillover for various investment horizons ranging from days to months, which helps the heterogeneous market participants adjust their portfolios and risk management strategies according to their investment horizons. Furthermore, it considers the turbulent period of COVID-19, during which most traditional assets lost a large part of their charm.

Our study offers several contributions. Firstly, we extend the existing literature arguing that spillovers across cryptocurrencies vary with the time horizon (e.g., Ciaian et al., 2018; Ji et al., 2019; Wajdi et al., 2020; Zeng et al., 2020)[5] by expanding the dataset to 10 crypto-assets and studying in detail the interconnections using the novel methodology of Baruník and Křehlík (2018) which distinguishes between high, middle, and low frequency bands that can reflect various investment horizons. This is important as investors in the cryptocurrency market have long-term investment horizons[6] that are reflected in low frequencies, whereas speculators and crypto-traders have short-term trading horizons that are reflected in high frequencies (Bouri et al., 2020). Secondly, we provide a discussion of the events of 2020 and how they translate into the system dynamics. We argue that it is not necessarily COVID-19 itself that led to the structural change but rather the reaction to it – an unprecedented monetary expansion. Stretching the dataset to early January 2021, our analysis covers enough data to show the changes. Thirdly, and partly as a limitation of our study, the spillover effects might remain hidden at higher frequencies (e.g., hour or minute frequencies) of data granularity. We discuss this briefly. Fourthly, we show that the cryptocurrency markets became strongly connected with the traditional financial assets in 2020, both during the increasing uncertainty due to globally spreading pandemic and as a reaction to the unprecedented quantitative easing that came after. Overall, the whole crypto-market provides a fascinating and ever-evolving system worthy of further examination.

The next section presents a brief review of related studies dealing with the market linkages among cryptocurrencies. Section 3 describes the data and frequency-based connectedness measures. Section 4 presents the main empirical results and discusses them in the light of previous studies. The final section concludes.

2. Brief literature review

The dazzling growth of the cryptocurrency markets over the last four years has led to emerging strands of literature dealing with

[2] If we compare the performance of cryptocurrencies with other assets during the COVID-19 outbreak, cryptocurrencies are the second-best performing, after gold. Furthermore, the trading volume of cryptocurrencies increased by 61% in first quarter of 2020 compared to the same quarter of 2019 (bitcoin.com).

[3] Momtaz (2021) points to "The soaring development of the ICO market has already attracted more than 600 institutional investors …..".

[4] We use the terms "spillover" and "connectedness" interchangeably.

[5] These studies mostly highlight that the spillover effect among cryptocurrencies varies with time horizon by classifying the data only into short-run and long-run time frames.

[6] Notably, the number of fund managers investing in cryptocurrencies has climbed over the past months of 2020.

cryptocurrencies. Many consider the spillover effect among traditional assets classes such as bonds, equities, commodities, and fiat currencies and the largest cryptocurrency, Bitcoin (e.g., Baur et al., 2018; Klein et al., 2018; Selmi et al., 2018; Guesmi et al., 2019; Kristjanpoller and Bouri, 2019; Charfeddine et al., 2020; Zeng et al., 2020), while others consider the modelling techniques of the conditional volatility of leading cryptocurrencies (Cerqueti et al., 2020). However, empirical evidence on the linkages across cryptocurrencies is less developed. Fry and Cheah (2016) analyse the spillover effect between Bitcoin and XRP using econophysics models and find a spillover from XRP to Bitcoin. Corbet et al. (2018) use the spillover index approach to understand the relationship across Bitcoin, XRP and Litecoin. They find a high level of connectedness among the three cryptocurrencies. Using a similar methodology, Yi et al. (2018) examine the static and dynamic volatility connectedness of eight leading cryptocurrencies and find that connectedness increases during market stress. Ciaian et al. (2018) examine the interdependencies between Bitcoin and 16 other cryptocurrencies for the period 2013 to 2016. They find a stronger price relationship between Bitcoin and the other cryptocurrencies under consideration in the short run than the long run. Aslanidis et al. (2019) examine the conditional correlation among major cryptocurrencies using the generalized DCC class model and find a time varying positive correlation among them. Similar findings are reported by Omane-Adjepong and Alagidede (2019) and Celeste et al. (2019) who explore Granger causal linkages and market coherencies among major cryptocurrencies using wavelet-based methods. Beneki et al. (2019) test the volatility spillovers and hedging ability between Bitcoin and Ethereum and find a time-varying correlation among them. Using a sample of 12 cryptocurrencies over a sample period of four years from 2015 to 2019, Ji et al. (2019) study return and volatility linkages across six leading cryptocurrencies from 2015 to 2018 and find that Litecoin and Bitcoin are central to the network of returns, while, for volatility spillovers, Bitcoin emerges as the most influential cryptocurrency. Antonakakis et al. (2019) focus on the spillover effects among leading cryptocurrencies in the time domain. They highlight the importance of Bitcoin to the stability of the cryptocurrency market, without ignoring the role of Ethereum in the transmission of shocks. Katsiampa (2019) explores the volatility dynamics of five major cryptocurrencies and finds a time varying conditional correlation among them. Tiwari et al. (2020) study the dependence across Bitcoin, Litecoin and Ripple using mixture of copulas from 2013 to 2018 and indicate strong dependency between each pair of cryptocurrencies. Ferreira et al. (2020) use the detrended cross-correlations of cryptocurrency markets and indicate the presence of long-range cross-correlations. Wajdi et al. (2020) employ vector autoregression (VAR) and GARCH-based models to examine the time-varying interactions among leading cryptocurrencies. Their results show evidence of an asymmetric effect and a strong return spillover as well as long-term dynamic volatility linkages between cryptocurrencies. Ji et al. (2021) apply connectedness measures in the time domain and study the dynamics of volatility spillovers across major Bitcoin exchanges. They show that Coinbase is the leading exchange whereas Binance stands at a weaker position in the system of connectedness. Balli et al. (2020) argue that the connectedness among cryptocurrencies is stronger in the short-term than in the medium- and long-term. They indicate an inverse relationship between economic uncertainty and the level of connectedness, suggesting the potential hedging ability of cryptocurrencies against economic uncertainty. Kosc et al. (2019) examine momentum and contrarian effects among 100 cryptocurrencies with the highest market capitalization and find evidence of a strong short-term contrarian effect that dominates the momentum effect. Borgards (2021) supports the momentum effect in cryptocurrency markets using data on twenty cryptocurrencies and proposes a momentum trading strategy. Bouri et al. (2021) use a time-varying measure of volatility connectedness among fifteen major cryptocurrencies, extracted from a dynamic conditional correlation-generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model, and highlight the importance of investor happiness to the dynamics of volatility connectedness. Using quantile regressions, they report evidence that lower quantiles of investor happiness move in tandem with all levels of connectedness, but the opposite is noticed at higher quantiles of investor happiness. Their results imply that cryptocurrencies represent a hedging instrument when investor sentiment is weak. Demiralay and Golitsis (2021) show that the equicorrelation dynamics among major cryptocurrencies intensified over time, especially during the pandemic, and indicate that Bitcoin trading volume and economic and financial uncertainties can drive the cryptocurrency market integration. Fousekis and Tzaferi (2021) use a frequency connectedness approach to examine the lag-lead relationship of returns and trading volume among large cryptocurrencies. Their results show evidence of a bi-directional Granger causality and an asymmetry regarding the scale of frequencies. Moratis (2021) studies the interconnectedness and shock spillovers among major cryptocurrencies using a Bayesian VAR model and reports evidence of an increasing interconnectedness to external drivers over time.

The above brief literature review points to two research gaps. First, there is inconclusive evidence regarding the return and volatility spillovers among leading cryptocurrencies, which is crucial to any investment decisions regarding portfolio diversification and hedging strategies. Second, there is a lack of evidence on the return and volatility spillovers among leading cryptocurrencies during the catastrophic event of the COVID-19 outbreak. Third, most of the above-mentioned studies use autoregressive distributed lag (ARDL), VAR, multivariate GARCH, or copula models (e.g., Ciaian et al., 2018; Aslanidis et al., 2019; Katsiampa, 2019; Ji et al., 2021; Tiwari et al., 2020; Wajdi et al., 2020; Zeng et al., 2020; Bouri et al., 2021; Moratis, 2021). However, those methods are not suitable to study return and volatility spillovers in a time-varying setting while differentiating between short- and long-term investment horizons. The same applies to other studies considering the connectedness measures of Diebold and Yilmaz (2012) in the time domain only (Yi et al., 2018; Antonakakis et al., 2019; Ji et al., 2019). Interestingly, a recent study conducted by Bouri et al. (2020) uses wavelet-based methods to examine the safe-haven property of Bitcoin against stock market indices and compare it with that of gold and the commodity index, however, its focus does not extend to the universe of cryptocurrencies that continues to attract the attention of investors and policymakers. We extend the above line of research by uncovering for the first time the time and frequency connectedness across the returns and volatility of 10 leading cryptocurrencies while using the approach of Baruník and Křehlík (2018) that accounts for the investment horizons of market participants that often vary across frequencies. Notably, we consider the period of the COVID-19 outbreak, an unexplored research area. This is especially important when we know that the pandemic strongly influenced the cryptocurrency market (Iqbal et al., 2020).

Table 1
Descriptive statistics for daily data.

Currency name	Mean (%)	Standard deviation	Ex. kurtosis	Skewness	J-B Test statistic	ADF test statistic	QP test statistic
Descriptive statistics for returns							
Bitcoin	0.1719	4.1445	15.867	−1.0915	12751***	−35.14***	−3.90***
Ethereum	0.0960	5.1234	13.015	−1.1551	8685***	−22.78***	−6.08***
XRP	0.0119	6.3387	20.475	0.9719	21026***	−21.83***	−2.47**
Litecoin	0.0764	5.5441	9.2082	0.3936	4246***	−34.84***	−3.92***
Bitcoin Cash	−0.0084	6.8051	10.493	0.1054	5461***	−33.97***	−2.85***
EOS	0.1048	6.6114	7.273	0.1276	2632***	−35.29***	−3.95***
Binance Coin	0.2331	6.0067	13.844	0.1509	9531***	−33.56***	−4.76***
Bitcoin SV	0.0687	6.8752	46.876	2.1169	110118***	−36.08***	−5.45***
Tron	0.1968	8.0319	22.614	2.1276	26320***	−15.99***	−1.88*
Descriptive statistics for volatility							
Bitcoin	2.8331	2.3747	14.297	2.9581	11899***	−8.45***	−2.80***
Ethereum	3.6272	2.7022	17.630	3.2415	17539***	−9.52***	−2.22**
XRP	4.1355	4.2706	22.688	3.9939	28760***	−5.62***	−2.05**
Litecoin	4.1287	3.1051	20.083	3.4091	22360***	−9.82***	−1.84*
Bitcoin Cash	4.6500	3.8201	25.908	3.6945	36080***	−9.65***	−2.30**
EOS	4.6385	3.7180	8.9233	2.4709	5172***	−8.16***	−2.65***
Binance Coin	4.5094	3.7931	19.051	3.5075	20488***	−7.22***	−3.83***
Bitcoin SV	3.2051	4.6406	27.422	4.1154	40757***	−7.13***	−2.29**
Tron	5.5312	6.7612	17.528	3.5870	17830***	−6.17***	−2.19**

Note: We present the descriptive statistics of returns and volatility of the 10 cryptocurrencies. The sample period is 1st October 2017 to 5th January 2021. JB: Jarque–Bera. Augmented Dickey–Fuller (ADF) and Qu-Perron (QP) tests are conducted with intercept. *, **, and *** indicate significance at the 90, 95, and 99% levels, respectively.

3. Data and methodology

3.1. Data

Our study covers 10 large and liquid cryptocurrencies that constitute the benchmark for the cryptocurrency market - Crypto 10. As of April 2020, the 10 constituents are Bitcoin, Ethereum, Ripple, Litecoin, Bitcoin Cash, EOS, Binance Coin, Tether, Bitcoin SV, and Tron[7]. We exclude Tether (USDT) as its stablecoin nature does not make it appealing for connectedness or correlation-based studies in general. Our sample period is 1st October 2017 to 5th January 2021, dictated by data availability[8]. Notably, the sample period allows us to examine the frequency connectedness during the full sample period (1st October 2017 to 5th January 2021) and the COVID-19 outbreak period (1st January 2020 to 5th January 2021). All the daily price data are extracted from https://coinmarketcap.com. We compute cryptocurrency daily logarithmic returns. Daily volatility is the square root of the Garman-Klass variance estimator (Garman and Klass, 1980) that is a highly efficient range-based (open, close, high, low) estimator of variance when obtaining high-frequency data is problematic[9].

Descriptive statistics of the daily logarithmic returns and daily volatility are given in Table 1. The highest daily average return is provided by Binance Coin (0.23%) followed by Tron and Bitcoin, while Bitcoin Cash has the lowest and actually negative daily average return, likely reflecting its late split from Bitcoin SV and recent split from Bitcoin ABC. Tron is the most volatile of the cryptocurrencies while the others have similar levels of volatility. All series are leptokurtic, i.e., with frequent extreme events. Even though the returns series show different levels of skewness, with Bitcoin and Ethereum being negatively skewed, the levels remain rather close to zero. The volatility series are positively skewed, as expected. None of the series are close to Gaussian distributions, which is confirmed by the Jarque-Bera test. Furthermore, all the return series are stationary as indicated by the statistics of the augmented Dickey–Fuller (ADF) (Dickey and Fuller, 1979) and Qu-Perron (QP) (Qu and Perron, 2007) tests.

3.2. Methodology

The traditional understanding of connections in financial systems through simple correlations and related measures turns out to be insufficient to explain the systemic dynamics of the complicated networks that the financial markets are. Following Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), we study the connectedness of the cryptocurrencies through the generalized vector autoregression (VAR) framework and implied forecast error variance decompositions forming a numerical spillover score among a system of variables, which can be defined as a proxy for systematic risk (Belke et al., 2018). Baruník and Křehlík (2018) extend the original

[7] April 2020 is the date of the original submission. Even though the Top 10 with respect to market capitalization have changed since then, we keep the original sample as the total market capitalization remains dominated by the Top 3 – Bitcoin, Ethereum, and Tether.

[8] Although Bitcoin Cash data are available from November 2018 onwards, it joins our sample period from that date.

[9] For cryptocurrencies with lower liquidity, obtaining high-frequency (intra-day) data might be an issue, more so when put together with the most liquid cryptocurrencies being traded on many exchanges with different time zones and respective volumes.

framework to frequency bands to distinguish between the effects of specific investment horizons or types of economic agent in the financial markets' narratives. Diebold and Yilmaz (2012)[10] derive the procedure from the standard VAR model:

$$x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \cdots + \Phi_p x_{t-p} + \varepsilon_t \tag{1}$$

where $\Phi_1,..,\Phi_p$ are coefficient matrices and ε_t is the residual term. Assuming that the roots of $|\Phi_{(z)}|$ are outside the unit-circle, the VAR process is standardly represented through the MA(∞) process as $x_t = \psi(L)\varepsilon_t$, where $\psi(L)$ is a matrix of infinite lag polynomials.

In such systems, the interaction between variables is often numerically represented through the forecast error variance decomposition, i.e., what proportion of a given variable's variability can be forecast by another (or itself through its autocorrelation structure) and how the shocks to one variable are reflected in the others (or again itself). As the shocks often do not occur orthogonally, i.e., the shocks can be common, the standard Cholesky factorization, which needs to order the system variables with respect to how the shocks are expected to propagate in the system, is not viable. Therefore, we use the generalized identification that is invariant to such ordering. Building on the infinite moving average representation of the VAR model, the generalized forecast error variance decomposition (GFEVD) is given by:

$$(\Phi_H)_{j,k} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}\left((\Psi_h \sum)_{j,k}\right)^2}{\sum_{h=0}^{H}\left((\Psi_h \sum \Psi_h^{'})_{i,j}\right)} \tag{2}$$

where $\Psi_h^{'}$ is a (N × N) matrix of moving average coefficients at lag h, $\sigma_{k,k} = (\Phi_H)_{j,k}$ is the contribution of the k^{th} variable for the forecast error variance of the element j for H horizon, and Σ is the variance matrix of residuals. For highly correlated systems such as the one we examine, the matrix Σ input is diagonal so that the whole connectedness is not driven and dominated by the (zero-lag) correlations which might give a false impression that the system is connected in the sense of causal relationships when in fact there is only standard correlation and common shocks to the system. Given that the rows of the Φ_H matrix may fail to add up to one, each entry is normalized as:

$$(\Phi_H)_{j,k} = \frac{(\Phi_H)_{j,k}}{\sum_{k=1}^{N}(\Phi_H)_{j,k}} \tag{3}$$

Following Diebold and Yilmaz (2012), the spillover measure is given by:

$$C_H = 100 \times \frac{\sum_{j\neq k}(\Phi_H)_{j,k}}{\sum \Phi_H} = 100 \times \left(1 - \frac{Tr\{\Phi_H\}}{\sum \Phi_H}\right) \tag{4}$$

where $Tr\{\cdot\}$ is the trace operator, and the total of all elements of Φ_H matrix is shown in the denominator. Baruník and Křehlík (2018) identify that the degree of persistence of the shock associated with different frequency responses varies. Thus, they use the different frequency bounds of impulse response functions to obtain a specific spillover measure for a specified time horizon. Within the generalized form to measure connectedness, Baruník and Křehlík (2018) use a frequency response function $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h}\Psi_h$ that is obtained from the Fourier transform of the coefficients Ψ. Here i is an imaginary constant.

Accordingly, the generalized causation spectrum over frequencies $\omega \in (-\pi,\pi)$ is given by:

$$\left(f_{(\omega)}\right)_{j,k} = \frac{\sigma_{kk}^{-1}\left|\Psi((e^{-i\omega})\sum)_{j,k}\right|^2}{(\Psi(e^{-i\omega})\sum\Psi^{'}(e^{+i\omega}))_{j,j}} \tag{5}$$

where $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h}\Psi_h$ is the Fourier transform of the impulse response of $\Psi_h^{'}$ within columns in the generalized VAR process of forecast error variance decompositions. $\left(f_{(\omega)}\right)_{j,k}$ is the portion of the spectrum of the j^{th} variable at a frequency ω on account of shocks transmitted by the k^{th} variable, which is considered as the quantity within frequency causation. To get a decomposition of the original GFEVD to frequencies, the weights $\left(f_{(\omega)}\right)_{j,k}$ are used. The weighting function is given by:

$$\Gamma_j(\omega) = \frac{(\Psi(e^{-i\omega})\sum\Psi^{'}(e^{+i\omega}))_{j,j}}{\frac{1}{2\pi}(\Psi(e^{-i\lambda})\sum\Psi^{'}(e^{+i\lambda}))_{j,j}d\lambda} \tag{6}$$

where $\Gamma_j(\omega)$ denotes the power of the j^{th} variable at a given frequency. The Fourier transform of the impulse response is quantified using the generalized causation spectrum. The GFEVD on a frequency band d is given by:

[10] The reader can refer to Diebold and Yilmaz (2012) for more detail about their time-domain model.

Table 2
Spillover measures for returns over the entire sample period (October 2017 to January 2021).

x (↓), y (→)	Bitcoin	Ethereum	XRP	Litecoin	Bitcoin Cash	EOS	Binance Coin	Bitcoin SV	Tron	From ABS	From WTH
Panel 2A: Diebold and Yilmaz (2012) spillover											
Bitcoin	48.16	12.52	6.82	7.87	5.96	7.11	3.51	3.34	4.82		5.76
Ethereum	9.90	57.38	5.00	7.14	4.55	5.78	2.71	3.95	3.59		4.74
XRP	9.76	13.16	37.26	9.28	9.84	10.79	3.08	1.80	5.03		6.97
Litecoin	10.98	10.75	4.85	49.15	5.18	8.37	4.32	2.95	3.45		5.65
Bitcoin Cash	8.29	8.88	5.66	7.57	48.46	9.07	3.69	4.04	4.33		5.73
EOS	9.82	13.84	4.28	8.37	5.81	46.45	3.28	2.49	5.66		5.95
Binance Coin	10.65	11.78	6.16	11.95	7.48	8.41	35.12	2.48	5.97		7.21
Bitcoin SV	3.67	8.55	2.99	3.80	7.06	3.71	2.70	65.99	1.52		3.78
Tron	9.84	13.19	6.31	14.53	10.67	8.90	3.97	2.07	30.53		7.72
To WTH	8.10	10.30	4.67	7.84	6.37	6.90	3.03	2.57	3.82		53.50
Panel 2B: For a short-term time horizon of 1–7 days as per Baruník and Křehlík (2018)											
BTC	39.72	9.44	6.54	6.50	4.90	5.91	3.15	2.95	3.93	4.81	6.02
ETH	8.31	48.87	4.52	4.54	3.88	4.15	2.28	3.44	2.92	3.78	4.73
XRP	7.61	9.53	30.40	7.08	6.29	7.55	2.25	1.66	4.57	5.17	6.46
LTC	9.30	7.64	4.32	37.47	4.11	6.07	3.95	2.26	2.77	4.49	5.61
BCH	6.69	6.67	4.67	4.43	41.42	7.28	3.15	3.09	4.04	4.45	5.56
EOS	8.44	8.76	4.01	5.85	5.23	38.35	3.02	2.06	5.17	4.73	5.91
BNB	9.60	6.68	6.00	7.96	6.17	6.29	31.10	2.16	5.36	5.58	6.98
BSV	3.42	6.54	2.91	2.56	6.00	3.34	2.49	56.84	1.38	3.18	3.98
TRX	6.92	7.80	5.09	8.13	6.98	5.53	2.57	1.73	25.47	4.97	6.21
To ABS	6.70	7.01	4.23	5.23	4.84	5.13	2.54	2.15	3.35	41.17	
To WTH	8.37	8.76	5.28	6.53	6.05	6.41	3.17	2.69	4.19		51.45
Panel 2C: For a medium-term time horizon of 7–30 days as per Baruník and Křehlík (2018)											
BTC	6.37	2.45	0.14	0.74	0.42	0.81	0.27	0.37	0.35	0.62	4.50
ETH	1.22	6.89	0.29	1.45	0.63	0.62	0.40	0.46	0.64	0.63	4.62
XRP	1.59	1.73	6.08	1.16	2.47	0.94	0.64	0.08	0.43	1.01	7.33
LTC	1.33	1.99	0.39	8.26	0.83	1.15	0.32	0.67	0.28	0.77	5.63
BCH	1.29	0.86	0.67	2.62	5.47	1.01	0.51	0.89	0.21	0.90	6.53
EOS	1.27	1.98	0.14	1.99	0.42	4.80	0.23	0.34	0.48	0.76	5.55
BNB	0.92	2.34	0.11	1.73	0.99	0.70	3.46	0.28	0.44	0.83	6.07
BSV	0.22	1.72	0.03	1.12	1.03	0.32	0.18	7.45	0.13	0.53	3.85
TRX	2.42	3.23	1.17	4.25	2.78	0.58	1.19	0.29	4.40	1.77	12.88
To ABS	1.14	1.81	0.33	1.67	1.06	0.68	0.41	0.37	0.33	7.81	
To WTH	8.30	13.19	2.38	12.20	7.76	4.97	3.02	2.73	2.39		56.95
Panel 2D: For a long-term time horizon of 30 days to ∞ as per Baruník and Křehlík (2018)											
BTC	2.07	0.64	0.14	0.62	0.53	0.38	0.09	0.02	0.54	0.33	5.25
ETH	0.38	1.62	0.20	1.15	0.05	1.00	0.03	0.06	0.03	0.32	5.11
XRP	0.56	1.90	0.79	1.04	1.09	2.30	0.19	0.05	0.03	0.79	12.69
LTC	0.35	1.13	0.14	3.41	0.24	1.15	0.06	0.02	0.41	0.39	6.17
BCH	0.32	1.35	0.32	0.53	1.57	0.78	0.03	0.06	0.08	0.39	6.15
EOS	0.11	3.11	0.13	0.54	0.15	3.31	0.03	0.09	0.00	0.46	7.38
BNB	0.13	2.75	0.05	2.26	0.31	11.42	0.57	0.04	0.17	0.79	12.68
BSV	0.04	0.29	0.06	0.12	0.02	0.04	0.03	1.70	0.01	0.07	1.07
TRX	0.50	2.17	0.05	2.16	0.91	2.78	0.22	0.05	0.65	0.98	15.67
To ABS	0.26	1.48	0.12	0.93	0.37	1.10	0.07	0.04	0.14	4.52	
To WTH	4.22	23.66	1.94	14.92	5.85	17.48	1.18	0.69	2.23		72.17

Notes: This table shows the estimated spillover from one cryptocurrency to other cryptocurrencies using the approach of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). The spillover measure given in a cell explains the spillover impact of (y) cryptocurrency captioned in the column on (x) cryptocurrency captioned in the row. WTH refers to total spillover estimated within the system while ABS refers to absolute spillover.

$$(\theta_d)_{j,k} = \frac{1}{2\pi}\int_d \Gamma_j(\omega)[f(\omega)]_{j,k} d\omega \tag{7}$$

The scaled generalized variance decomposition on the frequency band $d = (a, b)$: $a, b \in (-\pi \text{ to } \pi)$, $a < b$ is given by $\left(\theta_d\right)_{j,k} = \frac{(\theta_d)_{j,k}}{\sum_k (\theta_\infty)_{j,k}}$ and the within connectedness on the frequency band d is:

$$C_d^w = 100 \times \left(1 - \frac{Tr\left\{\theta_d\right\}}{\sum \theta_d}\right) \tag{8}$$

The frequency connectedness for the frequency band d can be expressed as:

$$C_d^F = 100 \times \left(\frac{\sum \overline{\theta}_d}{\sum \theta_\infty} - \frac{Tr\{\overline{\theta}_d\}}{\sum \theta_\infty} \right) = C_d^w \times \frac{\sum \theta_d}{\sum \theta_\infty} \tag{9}$$

where $Tr\{\cdot\}$ is the trace operator, and the total of all elements of Φ_d matrix is shown in the denominator. The within connectedness measure, C_d^w reflects the connectedness within the frequency band. The frequency connectedness separates the original connectedness into various components that add up to the original connectedness measure[11].

4. Empirical results

In this section, we present the results of the connectedness measures both from the global perspective (Diebold and Yilmaz, 2012) and from the perspective of various investment horizons (Baruník and Křehlík, 2018). We first focus on the pairwise spillovers between the 10 studied cryptocurrencies and follow up with an inspection of the time evolution of overall and horizon specific connectedness. Finally, we inspect the specifics of the COVID-19 period and the follow-up events.

4.1. Global spillover perspective

We study the connectedness among the 10 major cryptocurrencies (together with tokens, to be precise) focusing on spillovers in both returns and volatility. The sample period covers almost 3.5 years between 1st October 2017 and 5th January 2021 (1,193 observations). Along with the global connectedness, we also inspect the investment horizon specific connectedness between the assets. We follow the industry standard for the daily data and split the spectrum into three bands – short-term (one day up to one week), medium-term (one week up to one month), and long-term (one month and above). As cryptomarkets function on a 24/7 basis, a trading week is 7 days and a trading month is 30 days, unlike the standards of traditional financial assets where the trading week is usually 5 days and the trading month 20 days. This gives us the bands of 1–7, 7–30, and 30+ days. The original VAR estimate with lags is based on the Akaike information criterion (AIC) and the GFEVD is built on 100-day ahead forecasts.

The results for return spillovers in time and frequency are presented in Table 2. Panel 2A presents the results of Diebold and Yilmaz (2012) which indicate the spillover in the time domain, i.e., over all frequency bands. Panels 2B-3D show the spillovers for the short-term, medium-term, and long-term frequency bands, following Baruník and Křehlík (2018). Each panel contains a data matrix of size 10 × 10 wherein each cell (*x*,*y*) presents the contribution to the forecast error variance of cryptocurrency × (row vector) by the cryptocurrency *y* (column vector). The forecast error of each cryptocurrency can be logically divided into two parts – own contribution (which can be seen as parallel to an auto-correlation effect) and contribution of the other assets (parallel to a cross-correlation effect). Each spillover measure lies between 0 and 100. For example, in Panel 2A, cell (1,1) shows the spillover effect of Bitcoin due to its own contribution to be 48.16%, whereas cell (1,2) shows that the portion of forecast error variance explained by shocks coming from Ethereum to Bitcoin is 12.52%. The abbreviations ABS and WTN refer to absolute and within, respectively. The total spillover index, shown in the last cell of the matrix, is 53.50%, indicating a fairly sizable overall level of spillover in the time domain. The dynamic is apparently dominated by auto-correlation structures, and shocks, at least from this global perspective, do not seem to present much of a pairwise structure, even though the highest interactions and spillovers can be observed for the set of the three biggest cryptocurrencies – Bitcoin, Ethereum, and XRP. The "from" here represents "shocks from others", and "to" represents "shocks to others". Now, even though the variability is not strong, we see that Ethereum comes out as spillover leader, or the source of spillovers. This might well be attributed to the fact that even though Bitcoin is usually the headline, Ethereum shows much higher gains during the year 2017 (Bitcoin started the at around $1,000 and reached its, back-then, all-time-high of around $20,000 but Ethereum started below $10 and reached its still current all-time-high of around $1,400 in January 2018, i.e., gains of almost one order of magnitude higher). Tether turns out to be the least influential which is expected as it is a stablecoin.

Panels 2B-2D show the connectedness and spillover split between the frequency bands. Note that the pairwise spillovers for the frequency bands sum to the global spillovers in Panel 2A. The clearest result here is the dominance of the highest frequency (short-term horizons) in the spillover dynamics. This accounts for 41.17 (the position of To ABS and From ABS in the panel) of the overall 53.50 spillover index, i.e., almost 80% of the total. Other details remain rather similar. Firstly, Ethereum is the leader over all three frequency bands, which concords with previous findings that challenge the dominance of Bitcoin in the system of relationship among cryptocurrencies (Bouri et al., 2020). It can be explained by the fact that Ethereum is not only the second largest cryptocurrency after Bitcoin, but it is highly liquid yet more volatile than Bitcoin. Furthermore, Ethereum has a larger number of transaction count[12], which makes it a leading cryptocurrency in the universe of cryptocurrencies. In fact, empirical evidence by Beneki et al. (2019) shows that "an innovation in Ethereum's volatility triggers a higher impact on Bitcoin's volatility than the other way around". Much recent evidence from early 2021 suggests the ability of Ethereum to experience a prolonged spike in its price exceeding the 300% mark compared to an increase of less than 50% for Bitcoin. Secondly, Tron seems to be the cryptoasset most influenced and driven by the others regardless of the horizon. Thirdly, in the short-term, Ethereum mostly leads the other two of the three most capitalized cryptocurrencies.

Results for the volatility spillovers, shown in Table 3 split into four panels as with the returns, tell a similar story, even though the

[11] For further details, the reader can refer to Baruník and Křehlík (2018).

[12] https://www.theblockcrypto.com/data/on-chain-metrics/comparison-bitcoin-ethereum.

Table 3
Spillover measures for volatility over the entire sample period (October 2017 to January 2021).

x (↓), y (→)	Bitcoin	Ethereum	XRP	Litecoin	Bitcoin Cash	EOS	Binance Coin	Bitcoin SV	Tron	From ABS	From WTH
Panel 3A: Diebold and Yilmaz (2012) spillover											
BTC	36.17	30.44	3.70	8.58	7.61	3.91	2.73	3.74	3.14		7.09
ETH	8.70	53.76	6.08	7.68	7.58	4.42	3.26	3.77	4.74		5.14
XRP	8.27	27.58	30.27	12.48	7.87	4.08	3.66	1.41	4.39		7.75
LTC	7.72	27.54	4.84	34.09	10.16	3.95	3.41	3.39	4.91		7.32
BCH	6.08	21.34	7.17	6.39	37.26	8.56	3.35	4.32	5.53		6.97
EOS	9.56	26.97	7.26	4.86	8.24	32.57	2.42	1.93	6.19		7.49
BNB	8.22	23.45	7.34	10.41	11.98	6.52	22.95	2.84	6.29		8.56
BSV	4.32	10.15	3.50	4.03	3.66	9.57	2.08	61.06	1.63		4.33
TRX	7.73	26.62	9.19	5.36	10.95	9.70	3.50	2.09	24.86		8.35
To ABS	6.73	21.57	5.45	6.64	7.56	5.63	2.71	2.61	4.09		63.00
Panel 3B: For a short-term time horizon of 1–7 days as per Baruník and Křehlík (2018)											
BTC	17.40	2.35	1.57	3.34	3.25	1.61	1.81	1.05	1.87	1.87	4.74
ETH	4.78	25.90	2.23	3.85	3.03	2.11	2.08	1.41	3.19	2.52	6.38
XRP	5.85	3.76	15.76	3.76	3.78	1.79	2.20	0.62	3.43	2.80	7.09
LTC	5.09	4.45	2.00	19.62	4.09	2.38	2.38	1.37	3.24	2.78	7.03
BCH	3.41	4.29	2.00	3.82	20.18	2.82	2.04	1.18	2.81	2.49	6.30
EOS	3.13	4.06	1.71	2.84	1.75	18.96	1.52	0.89	2.66	2.06	5.23
BNB	3.76	4.60	2.26	3.56	4.73	1.94	14.29	0.95	2.84	2.74	6.93
BSV	2.23	1.58	0.65	1.52	1.36	0.67	1.42	24.93	0.34	1.08	2.75
TRX	2.71	4.26	2.08	2.26	3.72	2.14	2.55	0.71	12.85	2.27	5.75
To ABS	3.44	3.26	1.61	2.77	2.86	1.72	1.78	0.91	2.26	20.61	
To_WTH	8.71	8.26	4.08	7.02	7.24	4.35	4.50	2.30	5.73		52.19
Panel 3C: For a medium-term time horizon of 7–30 days as per Baruník and Křehlík (2018)											
BTC	6.26	2.81	1.10	1.78	2.29	1.16	0.73	0.96	1.03	1.32	6.91
ETH	3.23	11.24	1.83	0.92	1.64	1.26	0.97	1.13	1.40	1.38	7.22
XRP	1.27	2.13	6.29	0.95	1.32	0.55	1.01	0.35	0.34	0.88	4.61
LTC	1.65	1.88	1.43	5.17	2.90	0.96	1.01	0.96	1.19	1.33	6.98
BCH	2.39	1.49	3.21	0.75	8.98	3.43	1.22	1.85	1.37	1.75	9.15
EOS	4.71	1.73	1.78	0.66	2.17	4.67	0.69	0.55	1.72	1.56	8.16
BNB	4.20	2.45	1.14	1.32	1.52	0.67	5.65	0.62	0.79	1.41	7.40
BSV	0.67	1.66	1.84	1.39	0.47	0.80	0.33	13.95	0.60	0.86	4.52
TRX	2.32	2.11	1.75	0.96	1.44	0.83	0.45	0.67	4.59	1.17	6.13
To ABS	2.27	1.80	1.56	0.97	1.53	1.07	0.71	0.79	0.94	11.65	
To TH	11.90	9.46	8.21	5.09	8.01	5.63	3.74	4.13	4.92		61.08
Panel 3D: For a long-term time horizon of 30 days to ∞ as per Baruník and Křehlík (2018)											
BTC	12.50	25.27	1.03	3.46	2.06	1.13	0.19	1.73	0.23	3.90	9.42
ETH	0.69	16.62	2.02	2.91	2.91	1.04	0.21	1.24	0.15	1.24	3.00
XRP	1.15	21.68	8.21	7.77	2.77	1.74	0.45	0.44	0.61	4.07	9.82
LTC	0.99	21.22	1.40	9.30	3.16	0.61	0.02	1.06	0.48	3.22	7.76
BCH	0.29	15.56	1.96	1.82	8.10	2.31	0.10	1.28	1.35	2.74	6.61
EOS	1.72	21.18	3.77	1.35	4.33	8.94	0.21	0.49	1.81	3.87	9.34
BNB	0.27	16.41	3.93	5.53	5.73	3.91	3.01	1.28	2.67	4.41	10.65
BSV	1.41	6.92	1.02	1.12	1.82	8.10	0.34	22.18	0.69	2.38	5.74
TRX	2.70	20.26	5.36	2.14	5.80	6.73	0.50	0.71	7.42	4.91	11.85
To ABS	1.02	16.50	2.28	2.90	3.18	2.84	0.22	0.92	0.89	30.74	
To WTH	2.47	39.81	5.49	7.00	7.66	6.86	0.54	2.21	2.14		74.19

Note: See notes to Table 2.

details differ. The overall connectedness level is of a similar size at 63 and the dominant cryptoasset is Ethereum rather than Bitcoin. However, the most dominant horizon is the long-term one forming around 50% of the overall spillover index. Nevertheless, most of the dynamic is again driven by the auto-correlation patterns. Such a similarity of connectedness between assets in their returns and volatility is not standardly observed for ordinary financial assets where most of the connectedness emerges among volatilities while returns are much less connected or, from the frequency perspective, returns are characterized by short-term connectedness and volatility by long-term connectedness (Baruník and Křehlík, 2018; Ellington and Barunik, 2020; Ferrer et al, 2018; Zhang and Hamori, 2021). Cryptocurrencies thus show a distinct feature of their dynamics compared to other financial assets most likely driven by their much more volatile nature. As the shocks into cryptocurrency market are of much higher magnitudes than in the standards markets, abrupt changes occur both at the level of stochastic trends as well as the level of volatilities. The dynamics of the system is then remarkably similar in both returns and volatilities.

4.2. Evolution of connectedness and spillovers over time

As the next step, we inspect whether the connectedness of the system remains stable over time. Following Baruník and Křehlík

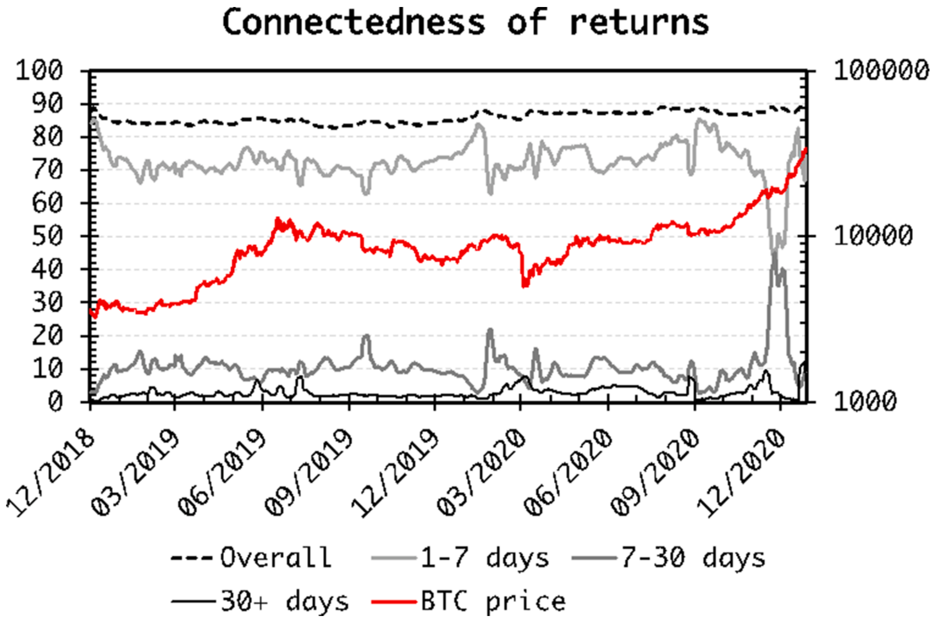

Fig. 1. Connectedness of returns, Notes: Overall connectedness following Diebold and Yilmaz (2012) is shown with a dashed line and the horizon-specific series based on Baruník and Křehlík (2018) are shown in shades of grey. For perspective, Bitcoin price is shown in red (right vertical axis).

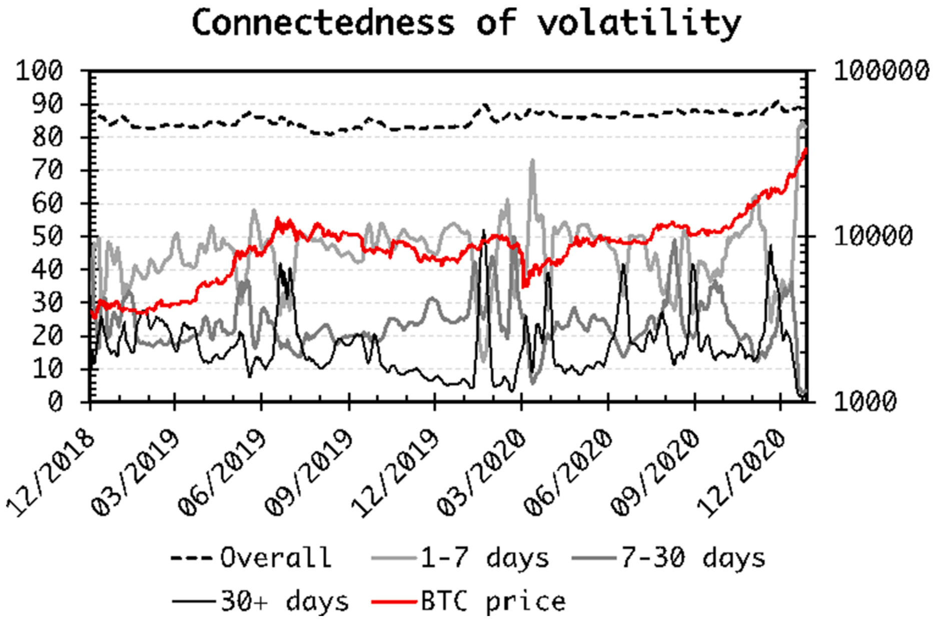

Fig. 2. Connectedness of volatility, Note: See notes to Fig. 1.

(2018), we present moving-window estimates of the overall connectedness as well as the frequency-based connectedness. The estimation window is set at one trading year (365 days) with a moving window step of a single day[13]. In each step, the original VAR is estimated using the automatic lag selection procedure based on the AIC minimization. The GFEVD is based on 100-day ahead forecasts.

[13] We have experimented with alternative window sizes as robustness checks. For the estimation window, we have altered the default 365 days to 180 days (half year) and 730 days (2 years) and a moving window step of 7 days (trading week). Unreported results show that the basic dynamics of spillovers are preserved even though the expected effects (smoother curves for longer estimation window and coarser ones for the sorter window as well as a bit less stable behavior for the moving window of 7 days due to general dynamics of the connectedness measure, mostly at the different frequencies levels) emerge.

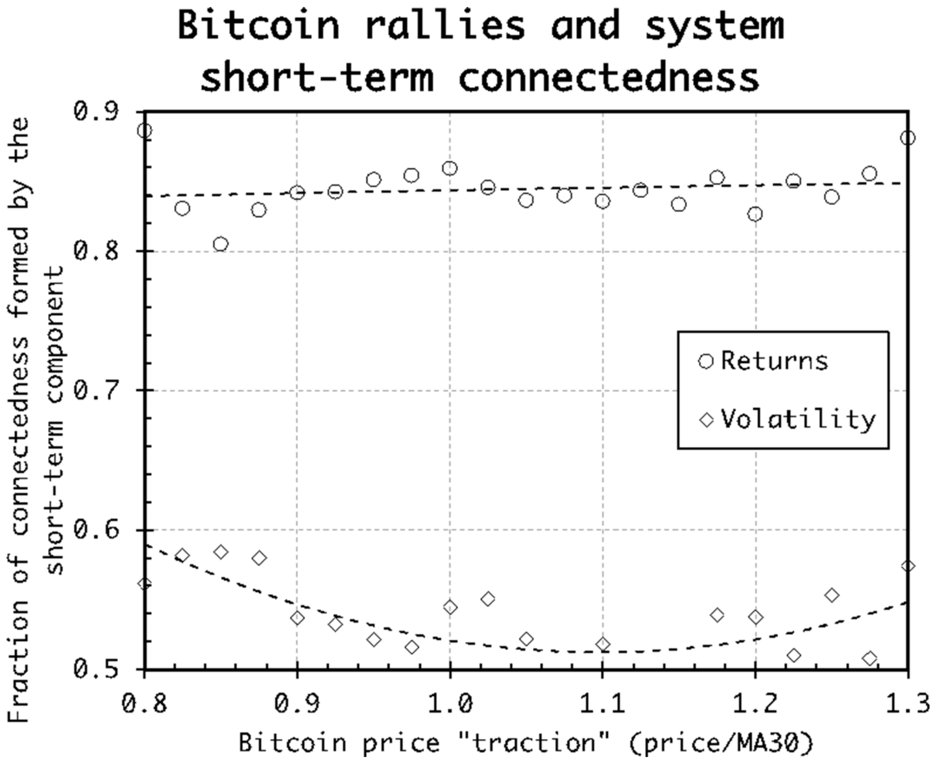

Fig. 3. Bitcoin rallies and system short-term connectedness, Notes: Bitcoin price traction (horizontal axis) represents the ratio between the current price and its 30-day moving average. The traction is binned between 0.8 and 1.3 with a step of 0.2. The short-term connectedness (vertical axis) shows the conditional mean.

The results for returns and volatility are illustrated in Figs. 1 and 2, respectively. Overall, connectedness is remarkably stable over time for both returns and volatility. To better understand the dynamics and evolution of the system connectedness, the Figures also show Bitcoin price. An interesting pattern emerges as Bitcoin price corrections are reflected in decreasing short-term spillovers in returns but higher spillovers in volatility. Therefore, these negative shocks arrive simultaneously and affect all cryptoassets at once; or, alternatively, our frequency resolution is not high enough, i.e., high-frequency data might be necessary to see the spillover patterns more clearly. Issues and caveats with high-frequency data are discussed above. Either way, the result from the global connectedness gets at least partially translated to the local dynamics as the returns spillovers are dominated by the short-term horizon which is weaker for volatility spillovers. However, the long-term component is not as dominant for volatility as it was for the global connectedness shown in Section 4.1.

The relationship between the short-term connectedness and Bitcoin price or dynamics is not clear to the naked eye. In Fig. 3, we show conditional means of the short-term connectedness portion of the overall connectedness with respect to recent Bitcoin price dynamics. The "traction" here is defined as the ratio of the current price to the past 30-day moving average. The figure presents a clear picture – a monotonous and positive relationship between traction and short-term connectedness dominance for returns and a convex relationship for volatility. In a bull market, the short-term spillovers in returns become more dominant, and in a bear market, the longer-term components become more important. For volatility, the short-term spillovers rule when the markets quickly rise or quickly fall.

4.3. Spillovers and connectedness in the COVID-19 period

Even though the results in the previous section hint that the overall connectedness is quite stable over time, the difference between the global connectedness given in Section 4.1 and the moving window estimates given in Section 4.2 suggests that the global spillover values might have been dragged down by the connectedness at the very beginning of the sample period, which is underrepresented in the moving window analysis due to the specifications of the procedure (moving window size and GFEVD forecasting window). In fact, the results for the period between January 2020 and January 2021 summarized in Tables 4 and 5 confirm this. The overall connectedness for returns jumps from 40 to almost 90 and similarly for volatility from 48 to almost 90 again. This signifies an intensification of the connectedness during critical and turbulent periods, which is in line with previous studies of fiat currencies (e.g., Greenwood-Nimmo et al., 2016) and cryptocurrencies (e.g., Yi et al., 2018). However, as the saying goes, the devil is in the detail. Foremost, the structure of the connectedness completely changes when compared to the complete sample. We see much weaker autocorrelation structures and actual relevant spillovers emerge. However, these are quite uniformly distributed. Surprisingly, Bitcoin Cash

Table 4
Spillover measures for returns over the COVID-19 period (January 2020 to January 2021).

x (↓), y (→)	Bitcoin	Ethereum	XRP	Litecoin	Bitcoin Cash	EOS	Binance Coin	Bitcoin SV	Tron	From ABS	From WTH
Panel 4A: Diebold and Yilmaz (2012) spillover											
BTC	8.04	10.75	15.49	13.17	22.59	11.58	6.19	5.76	6.42		10.22
ETH	7.33	11.40	12.40	11.47	23.21	16.69	5.99	5.34	6.18		9.84
XRP	5.40	8.84	18.11	8.67	23.78	18.49	5.67	4.18	6.86		9.10
LTC	6.26	10.87	16.09	12.90	20.95	14.27	5.96	5.74	6.97		9.68
BCH	7.06	10.98	13.84	14.17	21.32	14.29	5.93	5.55	6.85		8.74
EOS	6.80	10.08	12.80	10.52	22.13	18.88	6.52	5.71	6.55		9.01
BNB	6.68	9.37	16.54	13.20	19.70	15.50	6.53	5.35	7.13		10.39
BSV	7.11	10.41	12.19	14.28	23.14	13.96	6.20	6.43	6.28		10.40
TRX	8.53	9.62	15.46	11.39	20.23	14.59	7.00	5.19	8.00		10.22
To WTH	6.13	8.99	12.76	10.76	19.53	13.26	5.50	4.76	5.92		87.60
Panel 4B: For a short-term time horizon of 1–7 days as per Baruník and Křehlík (2018)											
BTC	6.59	9.53	12.79	11.40	18.96	10.28	5.56	4.62	5.96	8.79	10.22
ETH	5.39	10.37	8.79	9.81	21.18	15.43	5.51	4.31	5.68	8.45	9.83
XRP	3.68	8.47	14.49	7.57	20.69	16.97	5.35	3.32	6.57	8.07	9.38
LTC	5.14	9.97	14.39	11.91	19.04	13.56	5.46	4.93	6.59	8.79	10.22
BCH	5.50	10.32	10.57	12.77	19.43	13.10	5.52	4.67	6.44	7.65	8.90
EOS	5.11	9.33	8.93	9.18	20.94	17.17	6.12	4.76	6.19	7.84	9.12
BNB	3.97	8.64	12.60	10.59	15.99	13.89	6.17	4.54	6.54	8.53	9.92
BSV	5.53	9.54	9.35	12.19	20.89	12.20	5.74	5.70	5.93	9.04	10.51
TRX	5.12	8.52	7.87	9.26	17.18	12.25	6.35	3.66	7.51	7.80	9.07
To ABS	4.38	8.26	9.48	9.19	17.21	11.96	5.07	3.87	5.55	74.96	
To WTH	5.10	9.60	11.02	10.69	20.01	13.91	5.89	4.50	6.45		87.16
Panel 4C: For a medium-term time horizon of 7–30 days as per Baruník and Křehlík (2018)											
BTC	1.23	0.79	2.25	1.42	2.19	1.17	0.52	1.00	0.35	1.08	10.09
ETH	1.66	0.93	3.16	1.27	1.19	1.16	0.43	0.97	0.43	1.14	10.70
XRP	1.00	0.28	1.90	0.78	0.69	0.76	0.19	0.73	0.29	0.52	4.91
LTC	0.91	0.60	1.38	0.37	1.34	0.59	0.40	0.74	0.26	0.69	6.48
BCH	1.24	0.55	2.76	1.02	1.35	1.13	0.38	0.86	0.32	0.92	8.59
EOS	1.31	0.68	3.25	0.98	0.99	1.51	0.36	0.92	0.31	0.98	9.18
BNB	1.79	0.52	2.85	1.63	2.26	1.40	0.34	0.80	0.53	1.31	12.27
BSV	1.27	0.74	2.17	1.79	1.90	1.64	0.42	0.71	0.30	1.14	10.66
TRX	2.46	0.91	6.18	1.27	2.35	1.98	0.60	1.44	0.48	1.91	17.91
To ABS	1.30	0.56	2.67	1.13	1.44	1.09	0.37	0.83	0.31	9.69	
To WTH	12.14	5.29	25.00	10.57	13.46	10.24	3.45	7.76	2.90		90.80
Panel 4D: For a long-term time horizon of 30 days to ∞ as per Baruník and Křehlík (2018)											
BTC	0.22	0.43	0.46	0.36	1.44	0.14	0.11	0.15	0.11	0.35	10.63
ETH	0.28	0.09	0.45	0.39	0.84	0.10	0.05	0.05	0.08	0.25	7.45
XRP	0.71	0.10	1.72	0.32	2.41	0.76	0.13	0.13	0.00	0.51	15.21
LTC	0.22	0.29	0.32	0.61	0.56	0.12	0.10	0.07	0.11	0.20	5.99
BCH	0.31	0.11	0.51	0.39	0.54	0.06	0.03	0.02	0.09	0.17	5.12
EOS	0.38	0.07	0.62	0.36	0.20	0.20	0.04	0.03	0.04	0.19	5.82
BNB	0.91	0.22	1.10	0.98	1.44	0.20	0.02	0.02	0.05	0.55	16.45
BSV	0.32	0.13	0.66	0.30	0.34	0.12	0.04	0.01	0.05	0.22	6.57
TRX	0.94	0.19	1.41	0.86	0.70	0.36	0.05	0.09	0.01	0.51	15.30
To ABS	0.45	0.17	0.61	0.44	0.88	0.21	0.06	0.06	0.06	2.95	
To WTH	13.60	5.11	18.45	13.22	26.46	6.23	1.81	1.84	1.82		88.55

Note: See notes to Table 2.

comes out as the most influential cryptocurrency during this period. We attribute this to the Bitcoin SV split in November 2018 which led to a Bitcoin Cash price crash. Over time, it regained some of its value but never back to a par or the stable ratio it used to have with Bitcoin. Again, one might assume that a more detailed picture could be obtained from high-frequency (hour or minute) data analysis. In addition, we again see dominance of the short-term horizon for returns but also for volatility which makes the period more short-term driven than the full sample period. Tether remains unique in the same way as for the full sample and holds its position as a market follower rather than a market setter.

From an economic and financial perspective, the year 2020 was not only the year of COVID-19 but also the year of policymakers' reactions to it. As shown by Kristoufek (2020), Bitcoin, and one might easily argue that the whole cryptomarket, did not respond to the early COVID-19 threat positively. In fact, it followed the fear and uncertainty of the traditional financial assets and reached lows levels below $4,000. The central banks reacted to the threat of economic catastrophe the same way they reacted to the global financial crisis, i.e., by massive monetary emission and a new wave (or waves) of quantitative easing. Even though we still need to wait to see the eventual effect, it certainly seems that some of the monetary injections actually have gone, and continue to go, into cryptoassets. The safe haven position against financial risk seems to be off the table, but as a hedge against future inflation or fiat currency devaluation, cryptocurrencies seem to have established their position. Our results show that these injections have come as a common shock to the

Table 5
Spillover measures for volatility over the COVID-19 period (January 2020 to January 2021).

x (↓), y (→)	Bitcoin	Ethereum	XRP	Litecoin	Bitcoin Cash	EOS	Binance Coin	Bitcoin SV	Tron	From ABS	From WTH
Panel 5A: Diebold and Yilmaz (2012) spillover											
BTC	3.34	14.95	9.29	9.30	41.60	14.46	4.78	1.59	0.69		10.74
ETH	3.04	13.32	11.34	9.88	39.87	15.59	4.85	1.47	0.64		9.63
XRP	3.35	18.97	10.93	8.33	40.54	11.32	3.09	2.81	0.64		9.90
LTC	2.92	15.01	10.78	8.65	40.02	16.58	4.41	1.13	0.49		10.15
BCH	2.49	17.81	12.80	8.85	32.73	18.34	5.70	0.86	0.42		7.47
EOS	2.71	17.21	11.78	8.16	36.44	17.28	4.90	1.10	0.42		9.19
BNB	3.46	16.51	6.88	9.53	48.12	8.11	3.98	2.87	0.54		10.67
BSV	2.50	16.60	13.48	9.07	32.46	18.97	5.53	0.95	0.43		11.01
TRX	3.29	15.21	9.98	8.93	40.69	15.25	4.52	1.48	0.65		11.04
To WTH	2.64	14.70	9.59	8.01	35.53	13.18	4.20	1.48	0.47		89.80
Panel 5B: For a short-term time horizon of 1–7 days as per Baruník and Křehlík (2018)											
BTC	3.12	14.45	8.97	8.99	40.81	14.00	4.35	1.31	0.54	10.38	10.72
ETH	2.66	12.85	10.88	9.57	38.73	15.05	4.43	1.22	0.51	9.23	9.53
XRP	2.52	18.50	10.02	7.71	40.23	10.23	2.66	2.51	0.50	9.43	9.74
LTC	2.83	14.49	10.73	8.53	38.98	16.09	4.23	1.00	0.41	9.86	10.19
BCH	2.39	17.44	12.72	8.75	31.98	17.84	5.55	0.77	0.38	7.32	7.56
EOS	2.52	16.89	11.64	8.03	35.99	16.97	4.77	0.94	0.37	9.02	9.31
BNB	2.95	15.96	6.54	9.07	47.70	7.69	3.47	2.58	0.44	10.33	10.67
BSV	2.42	16.25	13.38	8.99	31.61	18.58	5.37	0.83	0.39	10.78	11.13
TRX	2.85	14.73	9.64	8.69	40.02	14.71	4.12	1.25	0.44	10.67	11.02
To ABS	2.35	14.30	9.39	7.75	34.90	12.69	3.94	1.29	0.39	87.01	
To WTH	2.43	14.77	9.70	8.01	36.05	13.11	4.07	1.33	0.41		89.87
Panel 5C: For a medium-term time horizon of 7–30 days as per Baruník and Křehlík (2018)											
BTC	0.21	0.45	0.31	0.25	0.59	0.40	0.33	0.23	0.09	0.30	11.84
ETH	0.32	0.43	0.46	0.25	0.85	0.50	0.40	0.20	0.12	0.35	13.85
XRP	0.70	0.45	0.72	0.39	0.10	0.43	0.39	0.23	0.09	0.31	12.36
LTC	0.06	0.49	0.05	0.05	0.66	0.26	0.15	0.07	0.04	0.20	7.86
BCH	0.07	0.33	0.08	0.05	0.56	0.38	0.12	0.08	0.03	0.13	5.04
EOS	0.14	0.30	0.15	0.07	0.32	0.23	0.12	0.14	0.03	0.14	5.67
BNB	0.41	0.48	0.31	0.32	0.33	0.39	0.41	0.25	0.08	0.29	11.47
BSV	0.05	0.30	0.09	0.04	0.68	0.34	0.13	0.10	0.03	0.18	7.40
TRX	0.32	0.47	0.31	0.17	0.44	0.44	0.32	0.19	0.14	0.30	11.85
To ABS	0.23	0.36	0.19	0.17	0.44	0.35	0.22	0.15	0.06	2.18	
To WTH	9.25	14.54	7.78	6.85	17.69	14.04	8.67	6.21	2.30		87.32
Panel 5D: For a long-term time horizon of 30 days to ∞ as per Baruník and Křehlík (2018)											
BTC	0.02	0.05	0.01	0.07	0.20	0.05	0.11	0.04	0.05	0.06	9.30
ETH	0.06	0.04	0.00	0.06	0.29	0.04	0.02	0.05	0.01	0.06	8.27
XRP	0.13	0.02	0.19	0.23	0.21	0.66	0.04	0.08	0.06	0.16	22.75
LTC	0.03	0.03	0.00	0.06	0.38	0.24	0.03	0.06	0.04	0.09	13.08
BCH	0.03	0.04	0.00	0.05	0.19	0.12	0.03	0.01	0.01	0.03	4.65
EOS	0.04	0.02	0.00	0.06	0.13	0.08	0.01	0.03	0.01	0.03	4.92
BNB	0.10	0.07	0.02	0.14	0.08	0.03	0.10	0.04	0.01	0.05	7.85
BSV	0.02	0.05	0.02	0.05	0.17	0.04	0.03	0.02	0.01	0.04	6.26
TRX	0.12	0.02	0.02	0.07	0.24	0.09	0.08	0.04	0.06	0.08	10.86
To ABS	0.06	0.03	0.01	0.08	0.19	0.14	0.04	0.04	0.02	0.61	
To WTH	8.49	4.85	1.38	11.59	27.06	20.27	5.56	5.60	3.15		87.95

Note: See notes to Table 2.

market, leading to uniformly spread spillover effects and increased overall levels of connectedness.

4.4. Spillovers and connectedness among cryptocurrencies and other asset classes

We also study the connectedness among cryptocurrencies and other asset classes to provide a more complex picture of the overall market dynamics. To make the analysis more tractable and presentable, we select the three major cryptocurrencies – Bitcoin, Ethereum, and XRP – and add the representatives of other asset classes. Specifically, we include the S&P500 and NASDAQ stock indices to represent the universe of stocks in the largest economy (the US), and gold and crude oil to represent commodities. The examination period remains the same and we keep the daily frequency. The data were obtained from the finance.yahoo.com website. The results for the whole period are summarized in Tables A1 and A2 for returns and volatility, respectively, and we follow the same logic used in the cryptocurrency-only analysis, thus presenting the results for the original Diebold and Yilmaz (2012) framework as well as the split into short-term, medium-term, and long-term horizons with respect to Baruník and Křehlík (2018). Panel A1a shows the global picture for returns without splitting it into horizons. We see strong auto-correlation patterns in all assets with the levels being mostly above 70% of the whole forecast error variance. Focusing on the connectedness and interactions between different asset classes, we observe that the

Table A1
Spillover measures for returns of other asset classes over the entire sample period (October 2017 to January 2021).

x (↓), y (→)	Bitcoin	Ethereum	XRP	S&P500	NASDAQ	Gold	Crude Oil	From ABS	From WTH
Panel A1A: Diebold and Yilmaz (2012) spillover									
BTC	76.08	3.92	3.30	7.63	6.87	1.24	0.96		3.42
ETH	2.37	79.94	3.12	5.96	6.26	0.90	1.45		2.87
XRP	4.65	9.74	79.43	2.78	2.37	0.30	0.74		2.94
S&P500	1.61	1.20	0.25	76.04	14.91	1.56	4.42		3.42
NASDAQ	1.86	0.90	0.29	13.33	79.78	0.85	3.00		2.89
Gold	1.33	1.64	0.58	16.18	11.30	66.28	2.69		4.82
Crude Oil	1.48	2.67	0.52	11.00	6.83	2.00	75.49		3.50
To ABS	1.90	2.87	1.15	8.13	6.93	0.98	1.89		23.85
Panel A1B: For a short-term time horizon of 1–7 days as per Baruník and Křehlík (2018)									
BTC	62.61	2.82	3.18	6.45	5.26	1.12	0.79	2.80	3.65
ETH	1.60	66.35	2.98	4.97	4.59	0.80	1.25	2.31	3.01
XRP	4.40	8.45	62.71	2.48	1.53	0.23	0.65	2.54	3.30
S&P500	1.19	1.10	0.23	65.67	9.21	1.19	3.46	2.34	3.05
NASDAQ	1.52	0.81	0.23	9.95	55.31	0.73	2.45	2.24	2.92
Gold	1.26	0.87	0.30	9.68	5.99	47.01	1.73	2.83	3.69
Crude Oil	0.69	2.11	0.27	10.00	6.49	1.50	51.09	3.01	3.92
To ABS	1.52	2.31	1.03	6.22	4.72	0.80	1.48	18.07	
To WTH	1.98	3.01	1.34	8.10	6.15	1.04	1.92		23.55
Panel A1C: For a medium-term time horizon of 7–30 days as per Baruník and Křehlík (2018)									
BTC	8.81	0.71	0.05	0.88	1.17	0.11	0.16	0.44	2.48
ETH	0.56	11.80	0.14	0.65	1.06	0.07	0.19	0.38	2.15
XRP	0.24	1.12	11.97	0.21	0.54	0.06	0.07	0.32	1.82
S&P500	0.38	0.08	0.02	9.85	4.77	0.32	0.80	0.91	5.12
NASDAQ	0.33	0.05	0.03	2.50	17.00	0.11	0.42	0.49	2.76
Gold	0.07	0.67	0.16	5.33	4.20	16.13	0.75	1.60	9.01
Crude Oil	0.34	0.28	0.19	0.97	0.32	0.40	17.13	0.36	2.01
To ABS	0.27	0.42	0.09	1.51	1.72	0.15	0.34	4.50	
To WTH	1.54	2.34	0.48	8.49	9.71	0.85	1.93		25.35
Panel A1D: For a long-term time horizon of 30 days to ∞ as per Baruník and Křehlík (2018)									
BTC	4.66	0.39	0.07	0.31	0.43	0.01	0.01	0.17	3.14
ETH	0.21	1.79	0.00	0.33	0.62	0.03	0.01	0.17	3.13
XRP	0.00	0.17	4.76	0.08	0.30	0.00	0.01	0.08	1.46
S&P500	0.04	0.02	0.01	0.52	0.93	0.05	0.17	0.17	3.16
NASDAQ	0.02	0.03	0.03	0.88	7.46	0.01	0.13	0.16	2.85
Gold	0.01	0.10	0.12	1.17	1.11	3.15	0.20	0.39	7.00
Crude Oil	0.46	0.28	0.06	0.04	0.03	0.10	7.28	0.14	2.48
To ABS	0.11	0.14	0.04	0.40	0.49	0.03	0.08	1.28	
To WTH	1.91	2.58	0.72	7.28	8.86	0.53	1.36		23.24

stock indices S&P500 and NASDAQ influence Bitcoin and Ethereum much more than the other way around (connectedness around 6–7% compared to below 2%, respectively). XRP is more detached with spillovers from the stock indices below 3%. Even though the two cryptocurrencies are affected by the stock markets, the levels are markedly lower than for gold and crude oil, with spillovers from the stock indices between 7% and 16%. The spillovers from gold and crude oil to cryptocurrencies are weak. Looking at the horizon split in Panels A1b-A1d, we see that the short-term horizon (1–7 days) dominates the dynamics. Moving towards volatility spillovers, Table A2 shows a bit different story. XRP remains rather detached from the system, but BTC and ETH are not much affected by increasing uncertainty in the stock markets. Quite the opposite – the uncertainly in Bitcoin and Ethereum spill over to the stock indices and not really to the two commodity markets. The cryptocurrency markets thus seem to react faster to upcoming uncertainty or incorporate the coming uncertainty into its dynamics faster than the stock markets. Horizon-wise, the connectedness does not seem to be driven as much by one specific horizon as was the case for returns but the least dominant horizon is the medium-term one.

Focusing now on the evolution of connectedness among markets of various asset classes, Figs. 3 and 4 present connectedness dynamics in time, both overall and split into the horizons. The evolution is more interesting than for the cryptocurrency-only set. Up till early 2020, the connectedness among the whole system was rather week at levels mostly below 20% and 30% for returns and volatility, respectively. At the break of Q1 and Q2 of 2020, the connectedness started to shoot up. It is important to see that it is not a jump in one or two observations that could have been caused by an outlier in data but rather it was the results of a swift increase, yet still not jump, in the connectedness up to level above 80% for returns and close to 90% for volatility. The cryptocurrency and traditional markets thus became strongly connected and co-moved strongly during the period. The connectedness remained very high for returns until the end of the examined period and even though it corrected for volatility, the levels at the end of the examined period are still higher that before the rapid increases. This coincides with the wave of quantitative easing as a reaction to the pandemic and the connectedness dynamics indicate that an important amount of such "new money" entered not only the traditional financial markets but also the cryptocurrency markets. However, the quick increase of the connectedness suggests that it was not only the gains that cryptocurrencies and stock markets shared through the monetary injections but also the fear and losses due to the pandemic spreading.

Table A2
Spillover measures for volatility of other asset classes over the entire sample period (October 2017 to January 2021).

x (↓), y (→)	Bitcoin	Ethereum	XRP	S&P500	NASDAQ	Gold	Crude Oil	From ABS	From WTH
Panel A2A: Diebold and Yilmaz (2012) spillover									
BTC	80.37	7.42	5.74	2.07	2.83	0.69	0.89		2.80
ETH	9.26	76.16	7.82	2.56	2.62	0.49	1.09		3.41
XRP	12.72	6.63	74.27	4.01	1.54	0.41	0.42		3.68
S&P500	4.88	9.01	1.25	68.34	6.47	9.44	0.61		4.52
NASDAQ	7.89	12.62	1.20	27.62	41.76	8.10	0.81		8.32
Gold	1.99	3.26	0.66	11.73	8.53	70.85	2.99		4.16
Crude Oil	3.08	3.26	0.48	33.03	7.96	12.86	39.33		8.67
To ABS	5.69	6.03	2.45	11.57	4.28	4.57	0.97		35.56
Panel A2B: For a short-term time horizon of 1–7 days as per Baruník and Křehlík (2018)									
BTC	31.03	0.99	0.56	1.53	1.49	0.22	0.83	0.80	2.43
ETH	2.24	42.82	0.98	1.89	1.75	0.13	0.80	1.11	3.37
XRP	4.58	1.82	34.58	1.85	1.19	0.21	0.14	1.40	4.24
S&P500	0.51	0.54	0.18	15.66	1.49	0.51	0.32	0.51	1.53
NASDAQ	0.53	0.62	0.15	1.70	16.70	0.23	0.52	0.54	1.63
Gold	0.86	1.24	0.41	3.13	5.42	28.05	2.20	1.89	5.73
Crude Oil	1.14	0.62	0.23	0.69	0.73	0.54	14.60	0.56	1.71
To ABS	1.41	0.83	0.36	1.54	1.72	0.26	0.69	6.82	
To WTH	4.27	2.52	1.09	4.67	5.22	0.80	2.08		20.65
Panel A2C: For a medium-term time horizon of 7–30 days as per Baruník and Křehlík (2018)									
BTC	14.54	1.29	1.26	0.22	1.08	0.26	0.05	0.59	2.91
ETH	0.64	26.94	1.77	0.22	0.68	0.16	0.22	0.53	2.59
XRP	0.81	0.54	15.07	0.14	0.02	0.04	0.08	0.23	1.13
S&P500	1.52	1.29	0.60	8.27	3.50	1.02	0.21	1.16	5.68
NASDAQ	1.82	2.30	0.53	2.48	19.12	1.11	0.25	1.21	5.92
Gold	0.24	0.21	0.08	1.60	1.72	17.66	0.12	0.57	2.78
Crude Oil	0.67	0.27	0.07	0.88	0.52	0.96	8.07	0.48	2.35
To ABS	0.81	0.84	0.62	0.79	1.07	0.51	0.13	4.78	
To WTH	3.98	4.12	3.01	3.87	5.26	2.48	0.65		23.36
Panel A2D: For a long-term time horizon of 30 days to ∞ as per Baruník and Křehlík (2018)									
BTC	34.80	5.13	3.92	0.31	0.26	0.21	0.00	1.41	3.02
ETH	6.38	6.40	5.07	0.44	0.18	0.20	0.07	1.76	3.79
XRP	7.33	4.27	24.61	2.02	0.32	0.16	0.20	2.04	4.39
S&P500	2.86	7.18	0.48	44.41	1.48	7.91	0.08	2.86	6.14
NASDAQ	5.53	9.71	0.51	23.44	5.95	6.76	0.04	6.57	14.12
Gold	0.90	1.81	0.17	6.99	1.39	25.13	0.66	1.70	3.66
Crude Oil	1.27	2.37	0.18	31.46	6.72	11.36	16.66	7.62	16.38
To ABS	3.47	4.36	1.47	9.24	1.48	3.80	0.15	23.97	
To WTH	7.45	9.36	3.17	19.86	3.18	8.16	0.33		51.50

The role of cryptocurrencies as safe-havens against risks in the traditional markets and stock markets specifically is not corroborated by this latest shock to the financial stability which concords with the results of Shahzad et al. (2019), Conlon and McGee (2020), Kristoufek (2020), Rubbaniy et al. (2021), Chemkha et al. (2021), Choi and Shin (2021), and Jiang et al. (2021).Fig. 5.

5. Conclusion

We uncover the time and frequency connectedness among the returns and volatility of 10 major cryptocurrencies. We do this for the full sample period (1st October 2017 to 5th January 2021) and the COVID-19 outbreak period (1st January 2020 to 5th January 2021). Considering the time domain, the total connectedness intensifies during the COVID-19 outbreak period, indicating the sensitivity of return connectedness in the cryptocurrency markets to exogenous shocks, even though such shocks might be the aftermath or a reaction to the pandemic situation in the form of new waves of quantitative easing. These findings add to previous studies indicating that cryptocurrencies are mostly sensitive to factors related to the Bitcoin and cryptocurrency markets in general, such as Bitcoin popularity (Kristoufek and Scalas, 2015), hashing difficulty (Hayes, 2017) and cyber-criminality (Corbet et al., 2019). Accordingly, our results contradict the wide strand of literature arguing that Bitcoin and other leading cryptocurrencies are independent of the global financial system and thus are immune to shocks related to the global economy (Baur et al., 2018). Considering various time bands corresponding to short-, medium- and long-term horizons, the results show that the returns connectedness is highest over short-time horizons of one day to one week, which is intensified during the COVID-19 outbreak. For volatility connectedness, short-term connectedness increases significantly during the COVID-19 period, while over medium- and long-term horizons the connectedness eases. These findings suggest that the connectedness of the return and volatility of these cryptocurrencies is more sensitive to crisis periods over short time horizons than over longer horizons. Accordingly, crypto-traders with short investment horizons should worry more about turbulent periods when making trading decisions. Further results show that Bitcoin is not the dominant cryptocurrency, which concords with Corbet et al. (2018) and Yi et al. (2018). In our case, Ethereum is shown to be an influential cryptocurrency over the entire sample period. It

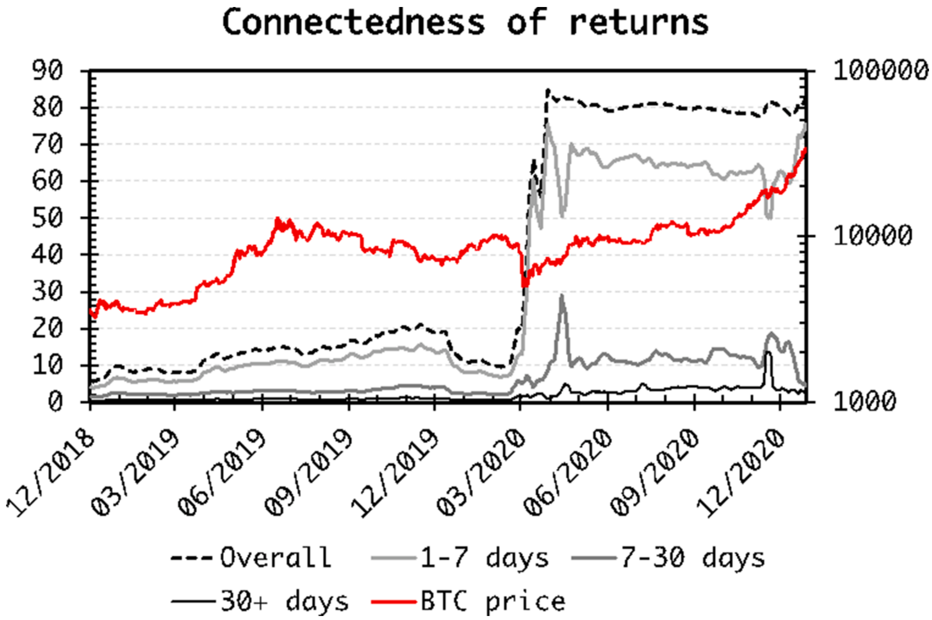

Fig. 4. Connectedness of returns (cryptocurrencies and other asset classes), Note: See notes to Fig. 1.

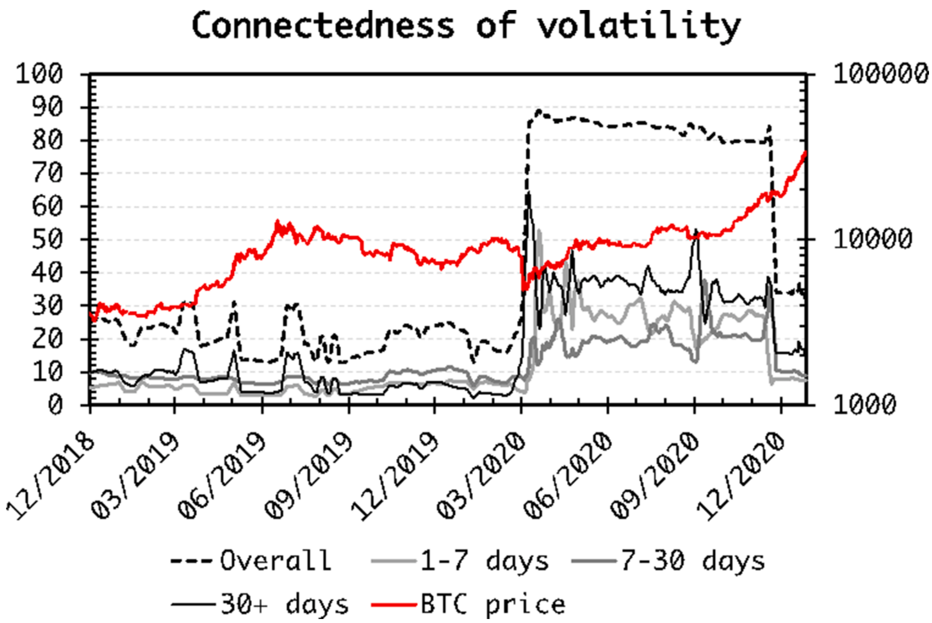

Fig. 5. Connectedness of volatility (cryptocurrencies and other asset classes), Note: See notes to Fig. 1.

passes its shocks on to the other cryptocurrencies but is comparatively less impacted by other cryptocurrency shocks. This can offer investors in Ethereum better and less volatile returns. However, the important role of Bitcoin Cash during the COVID-19 outbreak cannot be ignored. The findings imply that the various participants in the cryptocurrency markets should monitor not only Bitcoin but also Ethereum and Bitcoin Cash when making trading and investment decisions. With respect to the potential safe-haven properties of the studied cryptocurrencies, they do not come up as a relevant factor within the scope of the analysis which supports some other previous findings studying such properties during the latest financial markets turmoil.

The richness of the cryptocurrency markets and its specific statistical and dynamic properties invite for a deeper study of spillovers and general connectedness through network structures and other alternative methodological approaches (Antonakakis et al., 2020, Ellington and Barunik, 2020). Our findings are useful for various types of market participants in the highly debated cryptocurrency markets. Accordingly, crypto-traders and crypto-investors can tailor their trading and investment decisions in general, and during the unprecedentedly unstable period of the COVID-19 outbreak in particular. Still, it is worth noting that it is not necessarily COVID-19 itself that led to the change in the dynamics of connectedness in the cryptocurrency market but rather the reaction to the COVID-19 with an unprecedented monetary expansion. Future studies could examine in a more explicit way how spillovers and connectedness among major cryptocurrencies are affected by quantitative easing in response to the reaction to COVID-19. Such an extension would be possible when suitable data about monetary aggregates become available at the daily frequency. Policymakers and regulators might consider our findings while adopting or crafting a new cryptocurrency that best suits the global financial system and exhibits a low sensitivity to the universe of most of cryptocurrencies that continue to be highly volatile and unstable. A final extension would be uncovering the frequency connectedness among the return and volatility of cryptocurrencies using higher frequency (hour or minute) data to uncover potential hidden spillovers for the sake of high-frequency traders.

CRediT authorship contribution statement

Ashish Kumar: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft. **Najaf Iqbal:** Validation, Visualization, Writing – review & editing. **Subrata Kumar Mitra:** Methodology, Writing – original draft. **Ladislav Kristoufek:** Data curation, Formal analysis, Methodology. **Elie Bouri:** Supervision, Visualization, Methodology, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intfin.2022.101523.

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