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High-frequency connectedness between Bitcoin and other top-traded crypto assets during the COVID-19 crisis

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ABSTRACT

In this paper, we analyse co-movements and correlations between Bitcoin and thirty-one of the most-tradable crypto assets using high-frequency data for the period from January 2019 to December 2020. We apply the Diagonal-BEKK model to data from the pre-COVID and COVID-19 periods, and identify significant changes in patterns of co-movements and correlations during the pandemic period. We also employ the Minimum Spanning Tree (MST) and Planar Maximally Filtered Graph (PMFG) methods to study the changes of the crypto asset network structure after the COVID-19 outbreak. While the influential role of Bitcoin in the digital asset ecosystem has been confirmed, our novel findings reveal that due to recent developments in the blockchain ecosystem, crypto assets that can be categorised as dApps and protocols have become more attractive to investors than pure cryptocurrencies.

1. Introduction

Since the introduction of Bitcoin, cryptocurrency markets have substantially evolved. However, the absence of standardised classification of digital assets causes confusion among market participants and creates an obstacle to financial literacy in the digital age. Although Bitcoin awareness has recently improved due to the increased public attention to this pioneer cryptocurrency that hit the $63,000 mark in April 2021, it might still be tricky to distinguish the differences in the behaviour of the most recent innovations in digital asset ecosystems, such as altcoins, stablecoins, dApps, and DeFi, among others. Besides, in the literature only a few empirical papers have demonstrated an attempt to account for the type of cryptocurrencies in their analysis (see, e.g., Corbet et al., 2020a; Benedetti & Nikbakht, 2021; Yarovaya & Zieba, 2022), while the majority of studies simply refer to cryptocurrency names when reporting their results.

As of March 2022, there are more than 9,000 digital assets traded according to coinmarketcap.com. The digital assets can be classified into three distinctive categories: (i) protocols; (ii) currencies; and (iii) decentralised applications (Corbet et al., 2020a). Protocols are digital assets offering a platform - such as Ethereum - on which other applications can be built and the main function of the blockchain protocol is data transfer. A protocol is a foundation layer enabling the network to function. Currencies constitute a category of digital assets that are most often described as cryptocurrencies. These are digital assets which primarily function as money transfer, and a classic example of a currency is Bitcoin, which is a peer-to-peer system used for payments. Finally, decentralised applications, or dApps, are digital assets that may have any other functionality apart from decentralised transfer of money from peer to

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peer. This classification corresponds with Benedetti and Nikbakht (2021) who categorised digital tokens in five groups: currency, utility, protocol, security, and asset. Yarovaya and Zięba (2022) considered additional unique characteristics of digital assets, such as the origin of the founder, consensus algorithm, and geographical location of headquarters, among others. Similarly to Corbet et al. (2020a), they also distinguished between mineable and non-mineable cryptocurrencies, and showed that the results of empirical tests would be influenced by the unique heterogeneous characteristics of each type of digital asset.

During the COVID-19 pandemic, decentralised finance (DeFi) and decentralised applications (dApps) in particular experienced a rapid increase in popularity and growth in market share. These innovations attracted attention from policy makers and financial regulators and originated debates on whether these new digital assets cause a threat to financial stability, or can offer a cure against the financial effects of the pandemic, similarly to stablecoins, i.e., digital tokens with in-built stability mechanisms, which might be helpful for hedging the risk of the pandemic (Jalan et al., 2021). The COVID-19 crisis also spiked interest in cryptocurrency markets among retail investors, accessing financial markets from their homes via Fintech trading platforms such as Robinhood, and institutional investors. This attention and increased accessibility of digital assets further increased intraday trading activity in cryptocurrency markets. Furthermore, the recent introduction of the long-awaited Polkadot and Cosmos ecosystems have enabled crypto asset holders to conduct cross-blockchain transactions, which had not been possible before. Therefore, in this paper we aim to analyse the high-frequency co-movements and correlations between top-tradable crypto assets during the COVID-19 pandemic, and identify how their patterns have changed in comparison to the pre-pandemic period.

Heterogeneity in crypto asset characteristics should be taken into account in analyses of co-movements and inter-relationships between digital assets, since crypto assets from different categories can respond to common shocks in a different manner and have different patterns of interconnectedness with other digital and traditional assets. Lucey et al. (2021) argued that different cryptocurrencies can be susceptible to different types of uncertainty, and the impact of uncertainty may be time-varying and can change with increased institutional interest in these assets. Therefore, analysis of co-movements between crypto assets during times of increased uncertainty, such as the COVID-19 pandemic crisis, can provide an important contribution to policy making and practice.

To account for heterogeneous characteristics of crypto assets and changes brought by the COVID-19 pandemic, this paper empirically analyses high-frequency co-movements and correlations between top-traded cryptocurrencies for the period from January 2019 to December 2020 using the Diagonal-BEKK model as well as the Minimum Spanning Tree (MST) and Planar Maximally Filtered Graph (PMFG) methods. We specify three research hypotheses and discuss the results in relation to the following groups, similar to Corbet et al.'s (2020a) classification of digital assets: (i) Cryptocurrencies that are used primarily for money transfer; (ii) Protocols that offer their users features of complex digital contracts facilitating a secure exchange of not only money, but any other data or information; (iii) Decentralised Apps (dApps) that are built on protocols and offer any other functionality beyond money transfer. This simple categorisation allows quick and efficient analysis of a large number of digital assets, and will enable researchers and practitioners to make a better sense of empirical results obtained using large datasets.

We show that, although Bitcoin still has strong power to affect the movements of prices of other types of crypto assets, it remains one of not-too-many pure cryptocurrencies which are attractive to investors. On the other hand, we observe that dApps and protocols are becoming increasingly popular among cryptocurrency market investors. Our findings also confirm that crypto asset co-movements increased during the COVID-19 pandemic period. Indeed, our results provide strong evidence suggesting that during the pandemic period altcoins, and in particular, Ether became more influential in comparison to the pre-pandemic period. Our results further reveal that several new crypto assets (such as Iost and Wrapped Ether) became particularly popular during the COVID-19 pandemic.

Our results contribute to the previous literature that utilised high-frequency cryptocurrency data (e.g., Aslan & Sensoy, 2020; Chu et al., 2020; Gradojevic & Tsiakas, 2021; Wang & Wang, 2020), and more specifically to existing studies on interdependencies between crypto assets (e.g., Hu et al., 2019; Katsiampa et al., 2019; Nguyen et al., 2020; Yousaf & Ali, 2020), as well as to the literature that analysed the dominant power of Bitcoin in the digital asset ecosystem (Wang & Ngene, 2020; Zięba et al., 2019). We also contribute to the literature on the impact of the COVID-19 pandemic on financial markets and in particular on cryptocurrency markets (e.g., Corbet et al., 2020b; Vidal-Tomás, 2021; Yarovaya et al., 2021).

The remainder of this paper is organised as follows. Section 2 specifies our research hypotheses and further explains the motivation of this paper. Section 3 describes the data and methodology employed. Section 4 discusses the empirical results and their practical implications, while Section 5 concludes. This paper further contains extensive supplementary materials that will be available as a separate online Appendix.

2. Hypotheses development

We derive our theoretical framework from the vast body of the financial contagion literature. The interconnectedness between financial markets has been thoroughly and widely examined in financial integration research (Patel et al., 2022), since it has strong implications for portfolio diversification and for the maintenance of global financial stability. Financial contagion is the phenomenon that manifests itself via increased degrees of co-movements between financial markets after a crisis shock has occurred in one of the markets. While contagion could be detected at a smaller set of markets, i.e. through the spillover effect from one market to another, in some cases, when a crisis reaches systemic proportions, financial contagion can have a global magnitude adversely affecting financial markets across the globe simultaneously. There are numerous definitions of financial contagion available in the literature (e.g., Allen & Gale, 2002; Forbes & Rigobon, 2002; Morales & Andreosso-O'Callaghan, 2014). However, a notable study by Forbes and Rigobon (2002) criticised the existing contagion research arguing that a large body of contagion literature assessed the "interdependence" between financial markets rather than the contagion phenomenon.

According to the survey of the COVID-19 literature developed by Yarovaya et al. (2020), the term '*connectedness*' tends to be employed more frequently than '*contagion*' or '*spillover effect*' in the early literature on the financial effects of the COVID-19 pandemic. For example, So et al. (2021) employed rolling-window Granger-causality tests to assess the causal linkages between the pandemic network connectedness and the financial network connectedness, showing the strong leading effect of the COVID-19 pandemic on the systemic risk in financial markets. However, the term '*contagion*' has been used by Iwanicz-Dorozdowska et al. (2021), who examined the financial contagion caused by various past crisis events and claimed that the COVID-19 pandemic has been the most widespread source of contagion. While the plethora of terms and definitions in this literature might be confusing (spillover effect, financial contagion, connectedness, co-movements, causality, dynamic linkages, to name but a few), it is worth clarifying why we use the term '*connectedness*' instead of '*contagion*' or '*spillover effect*' in this paper. The main goal of our research is to analyse co-movements and correlations between Bitcoin and thirty-one of the most-tradable cryptocurrency in the pre- and COVID-19 periods to see whether the COVID-19 pandemic has caused any changes. Since the COVID-19 shock has not originated in crypto asset markets, and we do not use any COVID-19 specific variables as a main source (catalysts) of the financial contagion or spillover effect, the term '*connectedness*' would be the most appropriate to use. Furthermore, we do not aim to examine the causal patterns between Bitcoin and other crypto assets but we appreciate that this could be examined in future research and could have some important implications for predictability. Our main goal is to assess the patterns of connectedness, i.e. correlations, between Bitcoin, Ether, and other most-tradable crypto assets to show how these have changed during the COVID-19 pandemic, which justify the choice of the 'connectedness' and 'co-movements' terms used in this paper. Nevertheless, this paper will contribute to the contagion literature since it explores important channels of information transmission through which spillover effects may take place. More notably, an increased degree of co-movements between digital assets will not always suggest 'negative' financial contagion effects. On the contrary, it could show that the increase in the return of one digital asset can cause an increase in the return of another digital asset, the so-called 'positive contagion'.

In this paper, we employ high-frequency data, hence, our research has also been informed by the growing body of the cryptocurrency literature that uncovers numerous 'stylised facts' for high-frequency crypto data. The majority of the papers, however, are focused mainly on Bitcoin. For example, Bariviera et al. (2017) compared Bitcoin with fiat currencies using both daily and intraday data and discussed a number of stylised facts of the Bitcoin price dynamics using the Hurst exponent. Later, Zhang et al. (2019) extended the assessment of Bitcoin's stylised facts to other popular crypto assets, such as Ether, Litecoin, and Ripple. The authors used two different approaches to compute the Hurst exponent, namely the DFA method and the R/S method, and found that the DFA method is more robust and preferable for high-frequency cryptocurrency data. Quiroga-Garcia et al. (2022) assessed the price clustering for the same three crypto assets and demonstrated that clustering at round numbers is more important for high-frequency crypto asset prices with higher trading volumes. Chan et al. (2022) performed an extreme value analysis of return-volume tail relationships using high-frequency Bitcoin and Ether data, and found only weakly positive correlation between return and trading volume in the left and right distribution tails. Cryptocurrency research is one of the most dynamic literature fields in contemporary Finance[1]. In order to shed light on the rapidly changing patterns of co-movements and correlations between digital assets, we specify the following three original research hypotheses.

Hypothesis 1. *Intraday relations between top-tradable cryptocurrencies have increased during the COVID-19 pandemic.*

This is the first, and the main, research hypothesis formulated to assess the impact of the COVID-19 pandemic crisis on the cryptocurrency market as a whole. In the literature, only a few studies have employed high-frequency data when analysing the behaviour of cryptocurrency markets during the COVID-19 pandemic (e.g., Yousaf & Ali, 2020; Davidovic, 2021; Wang and Wang, 2021). However, these studies provide evidence for a very limited number of digital assets and do not offer comprehensive assessment of pandemic-driven changes in co-movements among crypto assets. To address this literature gap, our paper assesses the impact of the COVID-19 pandemic on the patterns of connectedness between crypto assets with the highest trading volume, accounting for 90% of the total cryptocurrency market capitalisation as of January 2019 and for 60% of the total cryptocurrency market trading volume in the 2019–2020 period. The scale of this study determines the practical implications of the results reported as well as potential usefulness for policy developments.

Furthermore, we aim to investigate the relationships between Bitcoin and other crypto assets, and show how these have been altered by the COVID-19 pandemic crisis. We specify Hypotheses 2a and 2b motivated by the literature that has analysed the dominant role of Bitcoin in cryptocurrencies' price formation (e.g., Corbet et al., 2018; Wang & Ngene, 2020). While Corbet et al. (2018) showed that Bitcoin is the most influential currency in the interconnected system of digital assets, Wang and Ngene (2020) analysed the dynamic linkages of cryptocurrencies reporting that intraday correlations between Bitcoin and other cryptocurrencies are insignificant.

Hypothesis 2a. *Co-movements and correlations between Bitcoin and altcoins have been amplified by the COVID-19 pandemic.*

Hypothesis 2b. *Bitcoin remains a cryptocurrency market leader and exhibits the highest degree of co-movements and correlations with other digital assets.*

These hypotheses are particularly important to test considering the continuous complexity of Bitcoin mining, energy consumption, and debates on ethicality and sustainability of Bitcoin. We could expect that potentially other digital assets that are built on alternative

[1] The majority of past studies have been discussed in a systematic literature review by Corbet et al. (2019), while the most recent literature on interconnectedness between cryptocurrency markets during the COVID-19 pandemic has been discussed by Yarovaya et al. (2022). Therefore, in this section, we explain the rationale behind our research design and research hypotheses using only key relevant literature.

and less energy intensive algorithms might attract further attention from investors, as the most recent technological innovation in this area. For example, protocols may exhibit any unique co-movement patterns within their digital asset class category, and in comparison to other crypto assets in our sample, while dApps might become more influential during the pandemic period. Thus, not only the influential power of Bitcoin in the digital assets' ecosystem may change in the post-COVID-19 outbreak period, but also one of the other major altcoins, particularly Ether, might become a new dominant force in this interconnected system.

3. Data and methodology

3.1. Data

Our dataset consists of hourly closing prices in US Dollars from 1st January 2019 at 12:00 a.m. to 31st December 2020 at 11:00 p.m. We pre-select the top fifty most traded digital assets, with a trading volume exceeding 20 million US Dollars, during the 2019–2020 period and restrict them to those that were in existence as of 1st January 2019. We further exclude stablecoins from our analysis due to their in-built stability mechanisms.[2] All in all, our sample accounts for 90% of the total cryptocurrency market capitalisation as of January 2019 and for 60% of the total cryptocurrency market trading volume during the analysed period. Our sample purposely does not cover the most recent period of Bitcoin's price explosivity, which started in the beginning of 2021, since this bubble-like behaviour has been driven by interest from specific Tech Giants, such as Tesla, and might not be attributed to the COVID-19 pandemic, and would therefore be out of scope of this study. The dataset thus comprises daily closing prices for Bitcoin and thirty-one major altcoins with 17,544 observations for each digital asset. Table 1 presents the digital assets included in our dataset and indicates the type of each crypto asset, whereas Figure A1 (Appendix) illustrates the hourly closing prices of the thirty-two crypto assets considered in our study over the entire sample period. The data were collected from Coinpaprika.com.

We calculate the hourly price returns of each cryptocurrency as the first logarithmic closing price difference in two consecutive hours. Figure A2 (Appendix) plots the hourly price returns, signifying the presence of volatility clustering in all considered crypto assets. To examine how the patterns of connectedness of cryptocurrencies have changed during the COVID-19 pandemic period, we split our sample period into two sub-periods of equal size: i) from 1st January 2019 at 12:00 a.m. to 31st December 2019 at 11:00 p.m., referred to as the pre-COVID period; and ii) from 1st January 2020 at 12:00 a.m. to 31st December 2020 at 11:00 p.m., referred to as the COVID-19 period. We generate our results using hourly data.[3]

3.2. Diagonal BEKK model

Given the large number of digital assets in our dataset and the fact that our interest lies mainly in their volatility co-movements and correlations, similar to Corbet et al. (2018) and Katsiampa et al. (2019), among others, we employ the following simple specification for the conditional mean equation of the crypto assets' return series:

$$R_t = c + \varepsilon_t \tag{1}$$

where R_t denotes the price return vector, c represents a vector of parameters estimating the mean values, and ε_t is the vector of residuals with a conditional variance–covariance matrix denoted as H_t given the information set, I_{t-1}, at a given time.

As for the conditional variance–covariance matrix, we employ a multivariate GARCH (MGARCH) model. The two most widely used classes of MGARCH models are the Baba-Engle-Kraft-Kroner (BEKK) model of Baba et al. (1990) and Engle and Kroner (1995) and the Dynamic Conditional Correlation (DCC) model of Engle (2002). As noted by Caporin and McAleer (2012), the former is employed to forecast conditional covariances but can be employed to forecast conditional correlations indirectly as well, whereas the latter is employed to forecast conditional correlations solely, even though its structure may be used to forecast conditional covariances.[4] Although in several empirical applications it seems that the DCC model is preferred to the BEKK model due to the curse of dimensionality linked to the latter, Caporin and McAleer (2012) contended that this constitutes a misconception regarding the appropriateness of each model in practice and that the parameter dimension for the DCC model without targeting is similar to that of the BEKK model.

Yet, BEKK models may be superior to other MGARCH models, including the DCC model of Engle (2002) (Boldanov et al., 2016; Broadstock and Filis, 2014; Caporin and McAleer, 2012). Indeed, several MGARCH models lack structural and statistical properties (McAleer et al., 2008). In particular, although the DCC model can be estimated using a two-step procedure[5], a fact that has helped overcome some numerical challenges encountered when estimating MGARCH models, and even though it has been widely used in empirical applications, a number of key issues regarding its representation have been disregarded in the literature (Caporin and McAleer, 2013).[6] These include the imposition of strong parametric restrictions on the conditional correlations, with the impact of

[2] Finally, we exclude Bitball (BTB) from our dataset since it was not found to exhibit ARCH effects over the sample period.

[3] Yarovaya and Zięba (2020) compared the results of correlation analysis and Granger Causality tests applied to return and trading volume data of the top-30 most-tradable cryptocurrencies using 5-, 10-, 20-, 40-min, and hourly data, and showed that results are not sensitive to changes of the high-frequency sampling interval; however, there are differences between intraday data and daily and weekly data.

[4] A comprehensive discussion of the differences between BEKK and DCC models can be found in Caporin and McAleer (2012).

[5] The DCC model estimates the conditional variances in the first step and the conditional correlations in the second step.

[6] Caporin and McAleer (2013) and McAleer (2019a) discuss in detail several critical issues related to the representation and use of the DCC model.

Table 1
List of cryptocurrencies used and categorisation.

Cryptocurrency	Ticker	Founder country	Type of crypto asset
Bitcoin	BTC	Unknown	Cryptocurrency
Ether	ETH	Russia / Canada	Protocol
Litecoin	LTC	USA	Cryptocurrency
EOS	EOS	Cayman Islands	Protocol
Ripple	XRP	West USA	Cryptocurrency
Bitcoin Cash	BCH	West USA	Cryptocurrency
Ethereum Classic	ETC	West USA	Protocol
Tron	TRX	China	Protocol
Bitcoin SV	BSV	Australia	Cryptocurrency
Neo	NEO	China	Protocol
Dash	DASH	West USA	Cryptocurrency
Chainlink	LINK	West USA	Protocol
Qtum	QTUM	China	Protocol
Binance coin	BNB	China	Protocol
Stellar	XLM	USA	Protocol
Zcash	ZEC	West USA	Cryptocurrency
Cardano	ADA	West USA	Protocol
Omg network	OMG	Singapore	dApp
Monero	XMR	Unknown	Cryptocurrency
Huobi token	HT	China	dApp
Ontology	ONT	China	Protocol
VeChain	VET	China	dApp
Dogecoin	DOGE	West USA	Cryptocurrency
Basic attention token	BAT	USA	dApp
Waves	WAVES	Russia	Protocol
ABBC Coin*	ABBC	Dubai (UAE)	Cryptocurrency
Tezos	XTZ	France	Protocol
Zilliqa	ZIL	Singapore	Protocol
0x	ZRX	West USA	dApp
Wrapped Ether	WETH	Unknown	dApp
Nem	XEM	Singapore	Protocol
Iost	IOST	China	Protocol

Notes: Out of 32 total assets analysed there are 10 cryptocurrencies, 15 protocols, and 7 dApps. * previously known as Alibaba coin.

these restrictions when they do not hold being undetermined (McAleer et al., 2008), as well as the fact that it does not strictly formulate a dynamic conditional correlation (Boldanov et al., 2016; Broadstock and Filis, 2014; Caporin and McAleer, 2013). Moreover, the underlying stochastic process to derive the DCC model has not yet been determined, rendering the derivation of asymptotic properties of the Quasi-Maximum Likelihood Estimators (QMLE) complicated (McAleer, 2017). In fact, the consistency and asymptotic normality of the estimated DCC model parameters have not yet been established (Caporin and McAleer, 2012, 2013; McAleer, 2019a), and therefore the reliability of inferential procedures is questionable (Caporin and McAleer, 2013).[7] In contrast, Aielli (2013) proved the inconsistency of the two-step estimator of the DCC model parameters and showed that the conventional interpretation of its dynamic correlation parameters can lead to reaching incorrect conclusions, given that the DCC model cannot be interpreted as a linear MGARCH model. Other critical issues related to the DCC model include the fact that it has no moments or testable regularity conditions and, as a result, it has been argued that the DCC specification could be appropriate as a filter or as a diagnostic check but it is not a model (see, e.g., Caporin and McAleer, 2013; McAleer, 2019a). Furthermore, unlike the BEKK model, the DCC model does not constitute a special case of the GARCC model, which has testable regularity conditions as well as standard asymptotic properties (Caporin and McAleer, 2013; McAleer, 2019a). In contrast, Comte and Lieberman (2003) proved consistency and asymptotic normality of the QMLE for the BEKK model parameters under the assumption of the existence of moments of order eight, while later Hafner and Preminger (2009) derived strong consistency of the QMLE under mild regularity conditions and asymptotic normality under the assumption of the existence of sixth-order moments of a process following the VEC model, which includes the BEKK model as a special case.

Nevertheless, the BEKK model has been subject to criticism as well. For instance, Allen and McAleer (2018) found evidence of significant biases in the full BEKK coefficient estimates. On the other hand, several studies (e.g., Allen and McAleer, 2018; Chang and McAleer, 2019; McAleer, 2019b) have discussed the advantages of the Diagonal BEKK model, which is a restrictive version of the BEKK model where the number of parameters to be estimated is significantly reduced, thus overcoming the curse of dimensionality issue while maintaining the positive definiteness of *Ht* (Baur, 2006), compared to the full BEKK model. The Diagonal BEKK model therefore has the advantage that interpretation of the parameters is easier and that the parameters' net impact on future conditional variances and covariances is straightforwardly discerned (Katsiampa, 2019). In addition, the statistical properties of the Diagonal BEKK model

[7] The existence of the model's underlying stochastic processes, regularity conditions, and asymptotic properties are necessary for the existence of the likelihood function and reliability of the statistical analysis of the parameter estimates.

parameter estimates can be established straightforwardly (McAleer, 2017). Specifically, the Diagonal BEKK model has an underlying stochastic process that leads to its specification, thus satisfying the regularity conditions, and the QMLE of its model parameters are consistent and asymptotically normal (McAleer, 2019b). Statistical inference on testing hypotheses is therefore valid.[8] Consequently, to model the conditional variance–covariance matrix in our study, we employ the Diagonal BEKK model.[9]

In the Diagonal BEKK model, the conditional variance–covariance matrix, H_t, is given as:

$$H_t = W'W + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{2}$$

where W, A and B are parameter matrices, with W being an upper triangular matrix, whereas A and B are diagonal matrices. We estimate the parameters of the conditional mean, variance and covariance equations simultaneously under maximum likelihood using the BFGS algorithm.

The diagonal elements of H_t, $h_{i,t}$, represent the conditional variances, given as:

$$h_{i,t} = w_{ii} + {a_{ii}}^2{\varepsilon_{i,t-1}}^2 + {\beta_{ii}}^2 h_{i,t-1} \tag{3}$$

whereas the off-diagonal elements of H_t, $h_{i,j,t}$, for $i \neq j$, correspond to conditional covariances between cryptocurrencies i and j, given as:

$$h_{i,j,t} = \widetilde{w}_{ij} + a_{ii}a_{jj}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta_{ii}\beta_{jj}h_{i,j,t-1} \tag{4}$$

where $\widetilde{w}_{ij}$ is the ij^{th} element of $W'W$. Finally, we calculate the conditional correlations between two cryptocurrencies i and j, $r_{i,j,t}$, as:

$$r_{i,j,t} = \frac{h_{i,j,t}}{\sqrt{h_{i,t}}\sqrt{h_{j,t}}} \tag{5}$$

3.3. Correlation-based networks

Correlation-based networks constitute a commonly used method for studying financial markets, since they enable us to filter out the most important information from the network. Among the most frequently applied methods are the Minimum Spanning Tree (MST) (Mantegna, 1999) and the Planar Maximally Filtered Graph (PMFG) (Tumminello et al., 2005). These, and other similar methods, are often applied when analysing the structure of stock markets and have recently also found applications in cryptocurrency markets, for example, in network analyses (Chemkha et al., 2021; Vidal-Tomás, 2021; Zięba et al., 2019). In general, a Minimum Spanning Tree of an undirected, weighted graph is a tree that spans the graph while minimising the total weight of the edges (their sum) in the tree. By convention, weights are calculated based on cross-correlation coefficients, $\rho_{i,j}$, in this case between the i^{th} and j^{th} crypto assets, which are then converted into distance metrics calculated as $d_{i,j} = \sqrt{2(1-\rho_{i,j})}$. Therefore, small (large) values of $d_{i,j}$ correspond to large (small) values of $\rho_{i,j}$. Moreover, the MST has to fulfil three axioms: i)$d_{i,j} = 0 \Leftrightarrow \mathrm{i} = \mathrm{j}$; ii) $d_{i,j} = d_{j,i}$; and iii) $d_{i,j} \leq d_{i,k} + d_{k,j}$.

The idea behind the PMFG is to obtain a graph that retains the same hierarchical properties of the MST but which allows a greater number of links and more complex topological structures than the MST, such as loops and cliques (Tumminello et al., 2007). In the MST, the number of links equals $n-1$, while in the PMFG $3(n-2)$, where n is the number of assets under consideration. As a result of this property, it is possible to extract more information about the network with the PMFG. Moreover, in the MST, if there is a connection between crypto assets A and B and between A and C, the connection between B and C is not allowed (i.e., the weakest connection among those three is rejected). However, in the PMFG such loops (cliques) are allowed. In general, a clique of k elements (k-clique) is a subgraph of k elements where each element is linked to each other. Based on Kuratowski's theorem (West, 2001), only 3-cliques and 4-cliques are allowed in the PMFG.

In our study, first we present the MST calculated using Pearson and Kendall's correlation methods based on the correlation matrix of crypto asset log-returns. This is the conventional procedure at the preliminary stage of the empirical analysis of the network of assets. At this stage, we analyse the change of the hierarchical structure in the network over the two sub-periods.

Then, in order to more clearly test our research hypotheses, we draw on the PMFG methodology, which by construction not only contains its corresponding MST but also allows us to extract more information from the complex network. Following the estimation of the DBEKK model, in order to further investigate the estimated time series of conditional correlations, $r_{i,j,t}$, for each pair of crypto assets i and j, we calculate the average conditional correlations, $r_{i,j\,\bar{}} = \frac{\sum_{t=1}^{T} r_{i,j,t}}{T}$, and convert the matrices of average conditional correlations into the corresponding distance matrices. Considering the complexity of the PMFG, we do not present the full graphs in our article.[10] Instead, we summarise the results by grouping the considered crypto assets into five categories, namely Bitcoin, Ether, protocols, cryptocurrencies, and dApps (analogical to, e.g., sectors in the traditional financial market or types of assets such as commodities,

[8] For a more detailed discussion of the advantages of the Diagonal BEKK model over the full BEKK model, see, e.g., Allen and McAleer (2018) and Chang and McAleer (2019).

[9] It is worth noting that another BEKK model that has found several applications is the Scalar BEKK model. Interestingly, Caporin and McAleer (2008) established sufficient conditions for the (indirect) DCC model to be consistent with the Scalar BEKK representation. However, the Scalar BEKK model is the most restricted version of the Diagonal BEKK model (Silvennoinen and Teräsvirta, 2009).

[10] These are available from the authors upon request.

stocks, and forex), and then calculating an average degree (number of connections) for each category, in order to study the changes of importance of those groups in the network over the two analysed periods.

However, although the MST and PMFG are the most commonly used methods for the analysis of correlation networks, Massara et al. (2017) argued that these methods are not performing well in the case of large and frequently-updated datasets and proposed a Triangular Maximally Filtered Graph (TMFG) as an alternative and better-performing method than the PMFG in particular. The total number of nodes in the TMFG is the same as in the PMFG and equals $3(n - 2)$. Among several technical advantages of the TMFG over the PMFG (see Massara et al., 2017), the most important one, being less execution time, could be visible in the case of datasets of higher frequency and wider time frame than the one used in this study. Therefore, comprehensive analysis with the use of the TMFG is beyond the scope of this research, since it would require a dynamic analysis of the crypto asset network, with frequent updating of the dataset and analysing the changes in the network structure over a particular period. Nevertheless, according to Massara et al. (2017), it is natural to compare the results of the PMFG with those of the TMFG. Therefore, as a robustness check of our PMFG results, we further employ the TMFG method and compare the results from the TMFG and PMFG for each sub-period with regard to i) the total number of edges that repeat in both the PMFG and TMFG; ii) the differences in the degree level of each crypto asset between the PMFG and TMFG; and iii) the average degree level of each crypto asset class category in the PMFG and TMFG.

4. Empirical results

4.1. Descriptive statistics

Tables 2 and 3 report the descriptive statistics for the returns of the cryptocurrencies considered in this study for the pre-COVID and COVID-19 sub-periods, respectively. For the majority of crypto assets we can observe an increase in mean hourly returns during the COVID-19 period, specifically, an average 0.012% increase in comparison to the pre-COVID period, ranging from 0.01% increase in mean returns (e.g., Bitcoin) to 0.05% increase (e.g., Zilliqa). On the other hand, for 9 out of 32 crypto assets mean intraday returns have not changed after the COVID-19 shock, and only for Tezos the descriptive statistics show 0.01% decrease in hourly returns. However, the standard deviation, and thus variability, of all crypto assets also increased by 0.11% on average during the COVID-19 period. The values of the increase in standard deviation vary significantly across digital assets, i.e. from 0.02% to as high as 0.57%. Only five assets displayed decline in standard deviations in comparison to the pre-COVID period. For example, among cryptocurrencies the standard deviation of Dogecoin decreased by 0.02% and that of the ABBC coin (former Alibaba coin) by 1.49%, while protocols Chainlink and Iost experienced 0.28% and 0.50% decline in standard deviations, respectively. However, descriptive statistics do not display clear patterns that can be attributed to the crypto asset categorisation used.

Analysis of skewness reveals that the vast majority of return series experience declines in skewness during the COVID-19 period becoming negatively skewed. A few exceptions are Ripple and Dash cryptocurrencies as well as OMG and 0x dApps that become positively skewed in the COVID-19 period, indicating increased opportunity to receive additional returns for investors during the pandemic period. Comparing the kurtosis in pre- and during- COVID periods, we can observe that those digital assets that had very large values of kurtosis in the pre-COVID period demonstrated a decline in their kurtosis value during the COVID-19 period. Examples include Bitcoin SV and ABBC cryptocurrencies, VeChain dApp, and Chainlink protocol. Alternatively, several digital assets displayed increases in kurtosis during the COVID-19 period, where the most substantial increases are evident for Bitcoin and Dash cryptocurrencies. Finally, the Jarque-Bera (JB) test results suggest the rejection of the null hypothesis of normal returns for all crypto assets in both periods. Yet, both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests suggest the rejection of the null hypothesis of a unit root, thus confirming the stationarity of all the return series in both the pre-COVID and COVID-19 periods.[11]

4.2. Helicopter view on pre- and post- COVID-19

At the stage of preliminary analysis we present the network results based on the Minimum Spanning Tree methodology using two types of cross-correlation matrices, i.e. Pearson and Kendall, of the log-returns of the crypto assets considered. Similar analysis for the crypto asset network during the COVID-19 period has been performed by Drożdż et al. (2020) and Vidal-Tomás (2021).

The analysis of Pearson's correlations (see Figs. 1 and 2) indicates that the structure of the market has not changed much after the COVID-19 outbreak, where Ether is positioned as a central node in the network in both periods. It can also be observed that Bitcoin forms a cluster with Dogecoin, Monero, and ABBC cryptocurrencies in both periods. On the other hand, the analysis of the network based on Kendall's correlations (see Figs. 3 and 4) indicates that there is indeed a change in the structure of the network over the analysed periods. Specifically, in the pre-COVID period there are two main clusters, namely one formed around Ether and one formed around Bitcoin. In the COVID-19 period, however, there is one main central node - Ether - with one major cluster formed around it. Similar structure might as well be observed in the work of Drożdż et al. (2020). The difference in our analysis is that we do not include stablecoins (particularly USDT), as consistent with the DBEKK model analysis. At the same time, we notice that removing USDT from the network has not changed the structure, as the large cluster formed around Ether is present both in our analysis and in Drożdż et al.'s (2020) study. Moreover, according to the proposed classification of crypto assets, we may also observe that the nodes being closest to Ether are other smart contract protocols and dApps, while pure cryptocurrencies are either much farther from Ether or closely

[11] We have also tested for ARCH effects using the ARCH tests in both sub-periods and the results are highly statistically significant for all crypto assets considered.

Table 2
Descriptive statistics of price returns (pre-COVID period).

	Mean	Median	Minimum	Maximum	Std. Dev	Skewness	Kurtosis	JB	ADF	PP
BTC	0.0001	0.0001	−0.0725	0.0950	0.0067	0.3771	31.9201	305447.8***	−66.6111***	−88.7484***
ETH	0.0000	−0.0001	−0.1324	0.0786	0.0078	−0.9178	29.3947	255489.2***	−89.3082***	−89.4125***
LTC	0.0000	−0.0002	−0.1432	0.0978	0.0091	0.0211	24.8182	173733.8***	−91.1301***	−91.2271***
EOS	0.0000	0.0000	−0.1645	0.0848	0.0095	−1.5691	36.9923	425295.0***	−91.329***	−91.3624***
XRP	−0.0001	−0.0001	−0.1162	0.0744	0.0074	−0.4434	28.7242	241792.3***	−94.1829***	−94.2202***
BCH	0.0000	−0.0001	−0.1303	0.1191	0.0101	0.0203	23.7963	157839.9***	−92.4796***	−92.656***
ETC	0.0000	0.0000	−0.1711	0.0929	0.0089	−1.2233	34.1383	356046.3***	−94.1498***	−94.1677***
TRX	0.0000	−0.0001	−0.1415	0.1131	0.0100	−0.4099	24.7764	173312.4***	−94.0033***	−94.0341***
BSV	0.0000	−0.0003	−0.1542	0.4421	0.0130	5.5024	187.9958	12534324***	−93.8312***	−93.8495***
NEO	0.0000	0.0000	−0.1058	0.1181	0.0097	0.2826	18.0513	82794.65***	−89.8766***	−89.8246***
DASH	−0.0001	0.0000	−0.0977	0.0737	0.0075	−0.5760	20.4027	111012.9***	−88.387***	−88.4568***
LINK	0.0002	0.0000	−0.2230	0.4245	0.0165	4.0406	114.8201	4587173. ***	−48.5863***	−98.1074***
QTUM	0.0000	0.0000	−0.1335	0.1368	0.0110	0.0388	23.6273	155286.9***	−95.2445***	−95.3085***
BNB	0.0001	0.0000	−0.0944	0.0952	0.0086	−0.2884	15.8550	60431.44***	−96.3438***	−96.3326***
XLM	−0.0001	−0.0001	−0.0937	0.0958	0.0093	0.1062	16.0260	61941.73***	−98.3767***	−98.5209***
ZEC	−0.0001	−0.0002	−0.2155	0.0800	0.0089	−1.6560	51.6433	867558.2***	−96.3781***	−96.5851***
ADA	0.0000	0.0000	−0.1429	0.0653	0.0095	−0.8911	20.7195	115749.0***	−69.1712***	−92.9932***
OMG	−0.0001	0.0000	−0.1293	0.0731	0.0103	−0.8301	17.9717	82811.55***	−93.5629***	−93.6101***
XMR	0.0000	0.0001	−0.0880	0.0813	0.0080	−0.4779	16.3149	65035.23***	−91.8392***	−91.8263***
HT	0.0001	0.0000	−0.1007	0.0721	0.0086	0.0619	14.2357	46078.49***	−70.4651***	−97.9481***
ONT	0.0000	0.0000	−0.1518	0.1086	0.0117	0.0101	19.4252	98461.42***	−94.8683***	−94.9397***
VET	0.0000	0.0000	−0.0938	0.3611	0.0120	3.4003	105.3305	3838551. ***	−73.6485***	−100.0278***
DOGE	0.0000	0.0000	−0.1699	0.2241	0.0115	0.8619	69.2529	1603051. ***	−19.8732***	−112.6496***
BAT	0.0000	0.0000	−0.0852	0.2273	0.0114	1.6493	40.4850	516783.8***	−71.8874***	−96.2679***
WAVES	−0.0001	0.0000	−0.0947	0.1340	0.0105	0.5904	19.5248	100167.8***	−99.5127***	−101.1804***
ABBC	0.0001	−0.0005	−0.3213	0.8368	0.0278	5.7151	150.4780	7985435.***	−75.6218***	−114.0108***
XTZ	0.0001	0.0000	−0.1072	0.2350	0.0119	1.3756	30.9084	287020.2***	−94.2135***	−94.3186***
ZIL	−0.0002	0.0000	−0.1171	0.0889	0.0108	−0.5641	15.5771	58194.83***	−95.1923***	−95.224***
ZRX	−0.0001	0.0000	−0.0877	0.0782	0.0101	−0.1040	12.4821	32828.96***	−95.4596***	−95.671***
WETH	0.0000	0.0000	−0.2088	0.2028	0.0128	0.0232	56.7753	1055380.***	−108.3324***	−108.7401***
XEM	−0.0001	−0.0001	−0.0990	0.1479	0.0102	1.2620	30.1322	270990.4***	−70.698***	−100.3152***
IOST	0.0000	0.0000	−0.1762	0.3000	0.0126	0.9169	58.9181	1142391.***	−94.1657***	−94.2688***

Note: *** significant at the 1% level.

Table 3
Descriptive statistics of price returns (COVID-19 period).

	Mean	Median	Minimum	Maximum	Std. Dev	Skewness	Kurtosis	JB	ADF	PP
BTC	0.0002	0.0001	−0.1830	0.1510	0.0076	−1.5343	96.1420	3178292. ***	−18.6872***	−97.8308***
ETH	0.0002	0.0002	−0.1936	0.1408	0.0092	−1.5102	53.3369	930606.6***	−96.0787***	−96.1417***
LTC	0.0001	0.0000	−0.1812	0.1205	0.0104	−0.8747	29.7357	262705.5***	−98.0154***	−98.0637***
EOS	0.0000	0.0000	−0.2165	0.1454	0.0106	−2.7178	67.7963	1547309. ***	−101.0361***	−101.0567***
XRP	0.0000	0.0000	−0.1726	0.2412	0.0119	0.0310	52.4103	893444.9***	−57.8419***	−96.9296***
BCH	0.0001	0.0000	−0.2010	0.1457	0.0110	−1.5571	48.7774	770441.6***	−58.0554***	−97.4092***
ETC	0.0000	0.0000	−0.1726	0.1137	0.0112	−1.5744	36.0388	403095.6***	−97.6108***	−97.6124***
TRX	0.0001	0.0002	−0.1807	0.1086	0.0108	−1.1756	35.2926	383649.7***	−96.729***	−96.9459***
BSV	0.0001	−0.0002	−0.2772	0.3540	0.0133	1.4414	103.7033	3714280. ***	−18.8373***	−96.1212***
NEO	0.0001	0.0000	−0.1587	0.1593	0.0111	−0.5873	24.7952	174345.8***	−94.9259***	−94.9744***
DASH	0.0001	0.0000	−0.1318	0.3563	0.0116	3.3077	120.2560	5047567. ***	−69.822***	−95.1475***
LINK	0.0002	0.0000	−0.1888	0.1500	0.0137	−0.3231	20.4771	111934.1***	−69.9867***	−97.8575***
QTUM	0.0000	0.0000	−0.2701	0.2109	0.0123	−1.2364	56.1314	1035316. ***	−99.785***	−100.0602***
BNB	0.0001	0.0000	−0.2265	0.0966	0.0103	−2.3926	63.2075	1334958. ***	−19.463***	−100.3691***
XLM	0.0001	0.0001	−0.1652	0.1261	0.0120	−0.0065	25.0351	177688.9***	−99.6811***	−99.7432***
ZEC	0.0001	0.0000	−0.1988	0.2203	0.0119	−0.0080	40.7895	522605.7***	−94.6035***	−94.7501***
ADA	0.0002	0.0001	−0.1777	0.0964	0.0115	−0.7939	21.4147	125019.8***	−98.5359***	−98.5534***
OMG	0.0002	0.0000	−0.2423	0.3595	0.0160	1.3342	55.5334	1012562. ***	−19.2348***	−98.6913***
XMR	0.0001	0.0003	−0.1794	0.1456	0.0096	−0.9046	39.8385	497831.9***	−36.4627***	−94.0357***
HT	0.0001	0.0000	−0.1648	0.1210	0.0086	−0.7834	44.5454	632548.7***	−21.7632***	−103.2274***
ONT	0.0000	0.0002	−0.2435	0.1191	0.0121	−1.9172	48.0305	747450.1***	−97.4575***	−97.4575***
VET	0.0001	0.0002	−0.2077	0.1954	0.0158	−0.2065	18.3438	86220.61***	−106.118***	−106.5378***
DOGE	0.0001	0.0000	−0.1843	0.1618	0.0113	0.0091	61.7803	1264431. ***	−51.169***	−107.8245***
BAT	0.0000	0.0003	−0.1942	0.1155	0.0114	−1.2318	32.5582	321953.3***	−96.9425***	−97.0476***
WAVES	0.0002	0.0000	−0.1849	0.1514	0.0128	0.2501	21.5222	125641.9***	−68.0773***	−92.1255***
ABBC	0.0001	0.0000	−0.1462	0.2943	0.0129	2.1080	53.4927	939521.7***	−58.5476***	−85.1395***
XTZ	0.0000	0.0000	−0.1823	0.1900	0.0135	−0.0029	24.4868	168956.6***	−59.0012***	−101.6827***
ZIL	0.0003	0.0002	−0.2257	0.1869	0.0147	−0.2958	22.3642	137352.3***	−98.5478***	−98.5208***
ZRX	0.0001	0.0001	−0.1702	0.1658	0.0134	0.3855	23.0978	148036.5***	−99.5393***	−99.6583***
WETH	0.0002	0.0004	−0.1744	0.1349	0.0130	−1.5606	27.5094	223399.9***	−18.2853***	−105.1123***
XEM	0.0002	0.0001	−0.1270	0.1665	0.0150	0.3080	14.5988	49371.83***	−61.9568***	−109.547***
IOST	0.0002	0.0001	−0.1830	0.1510	0.0076	−1.5343	96.1420	3178292. ***	−36.7942***	−96.8976***

Note: *** significant at the 1% level.

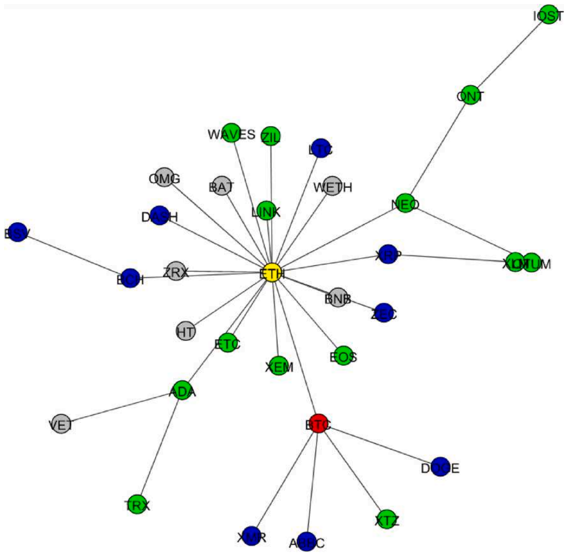


Fig. 1. Minimum-Spanning tree for log-returns based on Pearson correlation matrix (pre-COVID period). Note: Colours of nodes correspond to particular groups of crypto assets: Bitcoin – red; Ether – yellow; cryptocurrencies – blue; protocols – green; dApps - grey. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

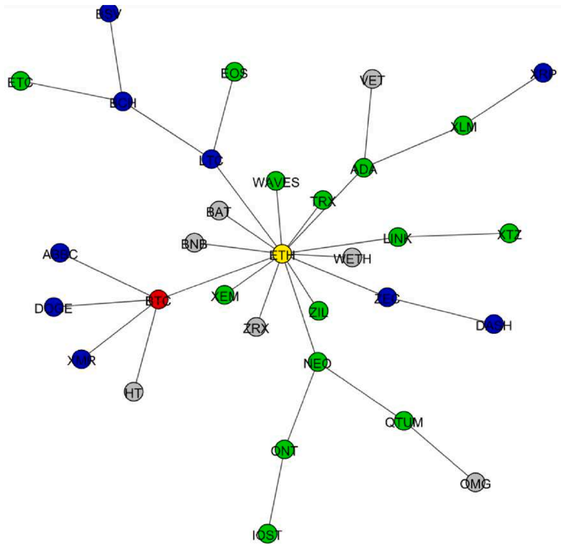


Fig. 2. Minimum-Spanning tree for log-returns based on Pearson correlation matrix (COVID-19 period). Note: Colours of nodes correspond to particular groups of crypto assets: Bitcoin – red; Ether – yellow; cryptocurrencies – blue; protocols – green; dApps - grey. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

connected to Bitcoin. To some extent, these findings bring evidence against our Hypothesis 2b, considering that, particularly after the COVID-19 outbreak, Ether starts playing a more important role in the network than Bitcoin. This might indicate that, even though Bitcoin movements usually instigate the movement of the rest of the market, the majority of the crypto assets co-move with Ether afterwards. We will revisit this finding in the following analysis.

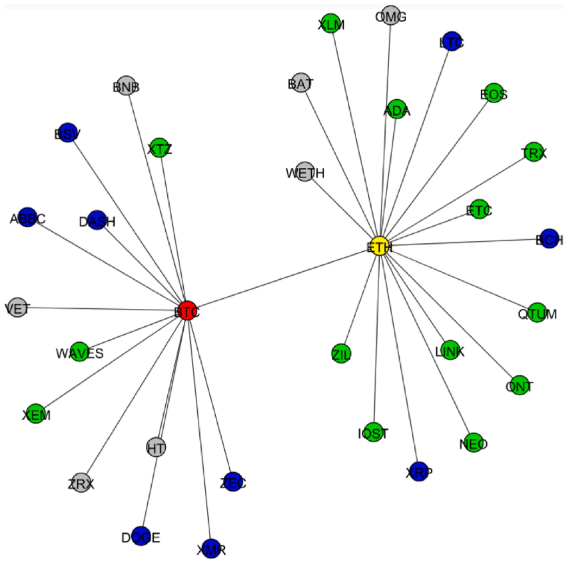


Fig. 3. Minimum-Spanning tree for log-returns based on Kendall correlation matrix (pre-COVID-19 period). Note: Colours of nodes correspond to particular groups of crypto assets: Bitcoin – red; Ether – yellow; cryptocurrencies – blue; protocols – green; dApps - grey. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

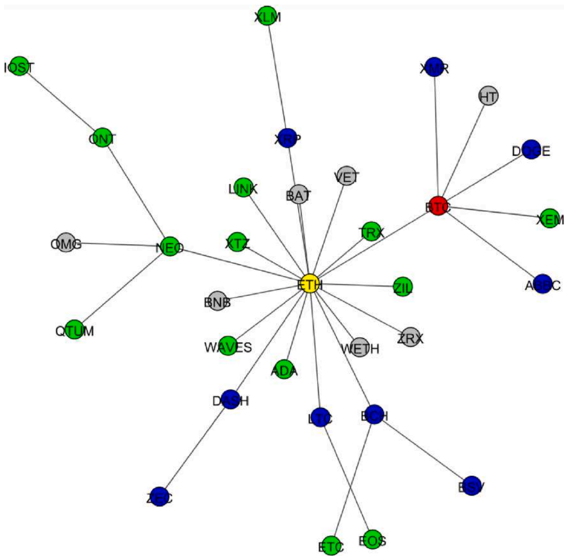


Fig. 4. Minimum-Spanning tree for log-returns based on Kendall correlation matrix (COVID-19 period). Note: Colours of nodes correspond to particular groups of crypto assets: Bitcoin – red; Ether – yellow; cryptocurrencies – blue; protocols – green; dApps - grey. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.3. Volatility dynamics

In this section, we present the estimation results from the Diagonal BEKK model for the pre-COVID and COVID-19 periods. The results are reported in Table 4.[12] The results reveal that, unlike the estimated parameters of the conditional mean equations, the estimates of all the diagonal elements of matrices W, A, and B are statistically significant at the 1% level in both periods.

[12] Given the evidence of non-normal crypto asset price returns, provided by the kurtosis statistic as well as the Jarque-Bera test results in both the pre-COVID and COVID-19 periods, the model parameters were estimated under the multivariate Student's t error distribution. In the interest of brevity, we report the estimation results only for the diagonal parameters in Table 4. Estimates of the off-diagonal parameters, w_{ij}, are presented in Tables 6 and 9. The results on their statistical significance are available upon request.

Table 4
Diagonal BEKK model parameter estimates.

	pre-COVID period				COVID-19 period			
	c_{ii}	w_{ii}	α_{ii}	β_{ii}	c_{ii}	w_{ii}	α_{ii}	β_{ii}
BTC	−0.0000	0.0000***	0.1261***	0.9860***	−0.0000	0.0000***	0.1417***	0.9866***
	(0.0000)	(0.0000)	(0.0016)	(0.0003)	(0.0000)	(0.0000)	(0.0017)	(0.0002)
ETH	−0.0001**	0.0000***	0.1231***	0.9843***	0.0000	0.0000***	0.1332***	0.9872***
	(0.0000)	(0.0000)	(0.0018)	(0.0003)	(0.0000)	(0.0000)	(0.0017)	(0.0002)
LTC	−0.0001*	0.0000***	0.1171***	0.9848***	−0.0001***	0.0000***	0.1255***	0.9884***
	(0.0001)	(0.0000)	(0.0021)	(0.0005)	(0.0001)	(0.0000)	(0.0017)	(0.0002)
EOS	−0.0001	0.0000***	0.1106***	0.9849***	−0.0002***	0.0000***	0.1178***	0.9872***
	(0.0001)	(0.0000)	(0.0020)	(0.0005)	(0.0001)	(0.0000)	(0.0018)	(0.0003)
XRP	−0.0002***	0.0000***	0.1234***	0.9836***	−0.0001**	0.0000***	0.1484***	0.9842***
	(0.0000)	(0.0000)	(0.0022)	(0.0005)	(0.0000)	(0.0000)	(0.0019)	(0.0003)
BCH	−0.0002***	0.0000***	0.1207***	0.9856***	−0.0002***	0.0000***	0.1152***	0.9893***
	(0.0001)	(0.0000)	(0.0019)	(0.0004)	(0.0001)	(0.0000)	(0.0016)	(0.0002)
ETC	−0.0002***	0.0000***	0.1244***	0.9826***	−0.0002***	0.0000***	0.1204***	0.9879***
	(0.0001)	(0.0000)	(0.0025)	(0.0006)	(0.0001)	(0.0000)	(0.0018)	(0.0003)
TRX	−0.0001*	0.0000***	0.1378***	0.9804***	−0.0001	0.0000***	0.1298***	0.9863***
	(0.0001)	(0.0000)	(0.0026)	(0.0006)	(0.0001)	(0.0000)	(0.0018)	(0.0003)
BSV	−0.0003***	0.0000***	0.1358***	0.9811***	−0.0003***	0.0000***	0.1214***	0.9876***
	(0.0001)	(0.0000)	(0.0022)	(0.0004)	(0.0001)	(0.0000)	(0.0018)	(0.0003)
NEO	−0.0002***	0.0000***	0.1288***	0.9839***	−0.0002***	0.0000***	0.1260***	0.9879***
	(0.0001)	(0.0000)	(0.0023)	(0.0005)	(0.0001)	(0.0000)	(0.0019)	(0.0003)
DASH	−0.0002***	0.0000***	0.1178***	0.9839***	−0.0002***	0.0000***	0.1272***	0.9879***
	(0.0000)	(0.0000)	(0.0026)	(0.0007)	(0.0001)	(0.0000)	(0.0016)	(0.0002)
LINK	0.0000	0.0000***	0.1711***	0.9789***	−0.0001	0.0000***	0.1405***	0.9872***
	(0.0001)	(0.0000)	(0.0030)	(0.0007)	(0.0001)	(0.0000)	(0.0023)	(0.0003)
QTUM	−0.0002***	0.0000***	0.1288***	0.9821***	−0.0002**	0.0000***	0.1132***	0.9888***
	(0.0001)	(0.0000)	(0.0027)	(0.0007)	(0.0001)	(0.0000)	(0.0021)	(0.0004)
BNB	0.0001 (0.0001)	0.0000***	0.1447***	0.9836***	−0.0000	0.0000***	0.1339***	0.9871***
		(0.0000)	(0.0030)	(0.0006)	(0.0001)	(0.0000)	(0.0023)	(0.0003)
XLM	−0.0002***	0.0000***	0.1691***	0.9777***	−0.0001**	0.0000***	0.1475***	0.9844***
	(0.0001)	(0.0000)	(0.0027)	(0.0006)	(0.0001)	(0.0000)	(0.0022)	(0.0004)
ZEC	−0.0003***	0.0000***	0.1267***	0.9823***	−0.0002***	0.0000***	0.1266***	0.9864***
	(0.0001)	(0.0000)	(0.0028)	(0.0007)	(0.0001)	(0.0000)	(0.0022)	(0.0004)
ADA	−0.0002**	0.0000***	0.1342***	0.9826***	−0.0001	0.0000***	0.1521***	0.9842***
	(0.0001)	(0.0000)	(0.0027)	(0.0006)	(0.0001)	(0.0000)	(0.0022)	(0.0004)
OMG	−0.0002***	0.0000***	0.1122***	0.9850***	−0.0002**	0.0000***	0.1294***	0.9876***
	(0.0001)	(0.0000)	(0.0029)	(0.0007)	(0.0001)	(0.0000)	(0.0022)	(0.0003)
XMR	−0.0001	0.0000***	0.1241***	0.9845***	0.0000	0.0000***	0.1269***	0.9878***
	(0.0001)	(0.0000)	(0.0028)	(0.0007)	(0.0001)	(0.0000)	(0.0023)	(0.0004)
HT	−0.0000	0.0000***	0.1367***	0.9868***	−0.0000	0.0000***	0.1400***	0.9852***
	(0.0001)	(0.0000)	(0.0029)	(0.0004)	(0.0000)	(0.0000)	(0.0026)	(0.0005)
ONT	−0.0003***	0.0000***	0.1273***	0.9847***	−0.0002***	0.0000***	0.1227***	0.9876***
	(0.0001)	(0.0000)	(0.0025)	(0.0005)	(0.0001)	(0.0000)	(0.0020)	(0.0003)
VET	−0.0001	0.0000***	0.1485***	0.9800***	−0.0002**	0.0000***	0.2012***	0.9729***
	(0.0001)	(0.0000)	(0.0032)	(0.0008)	(0.0001)	(0.0000)	(0.0028)	(0.0006)
DOGE	−0.0001*	0.0000***	0.1833***	0.9770***	−0.0001	0.0000***	0.1637***	0.9831***
	(0.0001)	(0.0000)	(0.0033)	(0.0007)	(0.0000)	(0.0000)	(0.0019)	(0.0003)
BAT	0.0001	0.0000***	0.1702***	0.9763***	−0.0001	0.0000***	0.1355***	0.9859***
	(0.0001)	(0.0000)	(0.0033)	(0.0008)	(0.0001)	(0.0000)	(0.0023)	(0.0004)
WAVES	−0.0001**	0.0000***	0.1752***	0.9792***	−0.0000	0.0000***	0.1587***	0.9843***
	(0.0001)	(0.0000)	(0.0030)	(0.0006)	(0.0001)	(0.0000)	(0.0023)	(0.0004)
ABBC	−0.0003**	0.0000***	0.1094***	0.9944***	−0.0001	0.0000***	0.1875***	0.9811***
	(0.0001)	(0.0000)	(0.0017)	(0.0001)	(0.0001)	(0.0000)	(0.0027)	(0.0004)
XTZ	−0.0001	0.0000***	0.0900***	0.9957***	−0.0002**	0.0000***	0.1300***	0.9883***
	(0.0001)	(0.0000)	(0.0016)	(0.0001)	(0.0001)	(0.0000)	(0.0026)	(0.0004)
ZIL	−0.0001	0.0000***	0.1536***	0.9766***	0.0001	0.0000***	0.1405***	0.9889***
	(0.0001)	(0.0000)	(0.0029)	(0.0008)	(0.0001)	(0.0000)	(0.0023)	(0.0003)
ZRX	−0.0002**	0.0000***	0.1567***	0.9794***	−0.0001*	0.0000***	0.1531***	0.9832***
	(0.0001)	(0.0000)	(0.0033)	(0.0008)	(0.0001)	(0.0000)	(0.0025)	(0.0004)
WETH	−0.0001	0.0000***	0.2148***	0.9669***	0.0001	0.0000***	0.1523***	0.9855***
	(0.0001)	(0.0000)	(0.0025)	(0.0006)	(0.0001)	(0.0000)	(0.0018)	(0.0002)
XEM	−0.0002***	0.0000***	0.1419***	0.9801***	0.0000	0.0000***	0.1785***	0.9786***
	(0.0001)	(0.0000)	(0.0026)	(0.0007)	(0.0001)	(0.0000)	(0.0033)	(0.0007)
IOST	−0.0001	0.0000***	0.1229***	0.9823***	−0.0001*	0.0000***	0.1217***	0.9875***
	(0.0001)	(0.0000)	(0.0031)	(0.0008)	(0.0001)	(0.0000)	(0.0022)	(0.0004)
v(d.o.f.)	5.0717***	LL	1037239.		v(d.o.f.)	4.6888***	LL	1,057,267
	(0.0698)					(0.0709)		

Notes: *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively. Standard errors in brackets. The variance specification is presented as $h_{i,t} = \widetilde{w}_{ii} + {a_{ii}}^2 {\varepsilon_{i,t-1}}^2 + {\beta_{ii}}^2 h_{i,t-1}$ and the covariance specification is presented as $h_{i,j,t} = \widetilde{w}_{ij} + a_{ii}a_{jj}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta_{ii}\beta_{jj}h_{i,j,t-1}$.

Cryptocurrencies' current conditional variances were therefore significantly affected by both past squared errors and past conditional volatility in both the pre-COVID and COVID-19 sub-periods.

Table 5 presents the conditional variance equations with substituted coefficients for the two sub-periods. An inspection of the substituted coefficients in the conditional variance equations reveals that in the first period the estimated values of the ARCH coefficient ranged from 0.0081 for Tezos protocol to 0.0461 for Wrapped Ether dApp, suggesting that prior to the COVID-19 outbreak cryptocurrency traders paid the least attention to news related to Tezos and the most attention to news related to Wrapped Ether. On the other hand, during the COVID-19 period the least attention was paid to news related to Qtum protocol, whereas the most attention to news about VeChain dApp, as indicated by the estimated values of the ARCH coefficient, which ranged between 0.0128 for Qtum and 0.0405 for VeChain.

As for the results of the GARCH coefficient, we find high values of the estimated GARCH coefficient in all crypto assets both in the pre-COVID and COVID-19 periods, thus suggesting high persistence of volatility over time in all the digital assets considered in our study and in both periods. Specifically, when inspecting the estimated GARCH coefficients in each period, we notice that in the pre-COVID period the estimated value of the GARCH coefficient ranges from 0.9349 for Wrapped Ether dApp to 0.9914 for Tezos protocol, indicating that shocks in the Wrapped Ether market persisted the least, while shocks in the Tezos market persisted the most prior to the COVID-19 outbreak, whereas during the COVID-19 period shocks in VeChain dApp persisted the least, while shocks persisted the most in Bitcoin Cash cryptocurrency, as revealed by the estimated values of the GARCH coefficient which ranged from 0.9465 (VeChain) to 0.9786 (Bitcoin Cash) in the latter period.

The plots of the conditional variances of the price returns of the crypto assets considered in the pre-COVID and COVID-19 periods are illustrated in Figs. 5 and 6, respectively. During the pre-COVID period (Fig. 5) we notice several spikes in the conditional volatility of three cryptocurrencies (Bitcoin SV, Dogecoin, and Alibaba coin), three dApps (VeChain, Basic Attention Token, and Wrapped Ether) and one protocol (Chainlink). On the other hand, in the COVID-19 period (Fig. 6), we notice distinct spikes in all crypto assets' conditional variances in mid-March 2020, which seem to coincide with the lockdown announcements of several governments.

4.4. Bitcoin vs Ether

Table 6 reports the conditional covariance equations of Bitcoin with altcoins with substituted coefficients for the two periods. We find that Bitcoin's conditional covariances with altcoins are significantly affected by both cross products of past error terms and past conditional covariance terms both in the pre-COVID and COVID-19 periods. Similar results are obtained for the altcoins' conditional covariances in both periods.[13] This finding is in line with previous studies that report the strong linkages between crypto assets (e.g., Corbet et al., 2018; Yi et al., 2018; Katsiampa et al., 2019).[14]

The conditional covariances of Bitcoin with the considered altcoins before and during the COVID-19 crisis are plotted in Figs. 7 and 8, respectively. The plots illustrate the time-varying and mostly positive conditional covariances between Bitcoin and altcoins during both periods. Again, we observe distinct spikes in the conditional covariances of Bitcoin with all crypto assets around mid-March 2020. The figures thus provide some support for the contention in our Hypothesis 2a that intraday crypto asset co-movements increased during the COVID-19 pandemic period. This is especially true around the announcements of several countries' first national lockdown. Notably, though, Bitcoin's conditional covariances, and thus its co-movements, with altcoins soon reverted back to their pre-pandemic levels.

Further, the conditional correlations between Bitcoin and the considered altcoins in the pre-COVID and COVID-19 periods are plotted in Figs. 9 and 10, accordingly. The figures confirm Bitcoin's time-varying and mostly positive conditional correlations with altcoins during both periods.

Yet, Table 7 reports the unconditional correlations and the mean conditional correlations between Bitcoin and the considered altcoins in the pre-COVID and COVID-19 periods. It can be noticed that all the unconditional and average conditional correlations are positive. When comparing the correlations between the two sub-periods, we notice that all unconditional correlations between Bitcoin and altcoins, except for Ripple, Dash, and Zcash cryptocurrencies, Omg network dApp, and Nem protocol, increased during the COVID-19 pandemic period, which supports Hypothesis 2a. In particular, we observe that the increase of Bitcoin's unconditional correlations with Chainlink protocol and ABBC cryptocurrency exceeded 100% in the second sub-period (115.62% and 129.44%, respectively), probably due to the larger attention around Chainlink and ABBC during that time. Similarly, the average conditional correlations between Bitcoin and altcoins increased during the COVID-19 period, with the only exceptions now being Bitcoins' conditional correlations with the Omg network dApp and Nem protocol. Specifically, the change in the average conditional correlations of Bitcoin in

[13] The results are provided in Table S1 (Supplementary material).

[14] It is worth noting, however, that although the estimates of all the off-diagonal elements of W'W are statistically significant at the 1% level in the COVID-19 period, in the pre-COVID period we find that several off-diagonal elements of *W'W* that correspond to the conditional covariances of the Alibaba coin cryptocurrency with altcoins are less significant, and even insignificant in the case of Chainlink protocol. Similarly, we find that the element of *W'W* that corresponds to the conditional covariance between Huobi token dApp and Tezos protocol is insignificant at any conventional level of statistical significance.

Table 5
Diagonal BEKK model conditional variance equations - substituted coefficients.

	pre-COVID period	COVID-19 period
BTC	$h_{1,t}$ = 1.9252e-07 + 0.0159*$\varepsilon_{1,t-1}{}^2$ + 0.9721*$h_{1,t-1}$	$h_{1,t}$ = 1.8016e-07 + 0.0201*$\varepsilon_{1,t-1}{}^2$ + 0.9734*$h_{1,t-1}$
ETH	$h_{2,t}$ = 5.0595e-07 + 0.0152*$\varepsilon_{2,t-1}{}^2$ + 0.9689*$h_{2,t-1}$	$h_{2,t}$ = 3.9128e-07 + 0.0177*$\varepsilon_{2,t-1}{}^2$ + 0.9747*$h_{2,t-1}$
LTC	$h_{3,t}$ = 7.9578e-07 + 0.0137*$\varepsilon_{3,t-1}{}^2$ + 0.9698*$h_{3,t-1}$	$h_{3,t}$ = 3.7592e-07 + 0.0158$\varepsilon_{3,t-1}{}^2$ + 0.9770*$h_{3,t-1}$
EOS	$h_{4,t}$ = 8.2814e-07 + 0.0122*$\varepsilon_{4,t-1}{}^2$ + 0.9701*$h_{4,t-1}$	$h_{4,t}$ = 5.7683e-07 + 0.0139*$\varepsilon_{4,t-1}{}^2$ + 0.9745*$h_{4,t-1}$
XRP	$h_{5,t}$ = 4.9104e-07 + 0.0152*$\varepsilon_{5,t-1}{}^2$ + 0.9675*$h_{5,t-1}$	$h_{5,t}$ = 4.6112e-07 + 0.0220*$\varepsilon_{5,t-1}{}^2$ + 0.9687*$h_{5,t-1}$
BCH	$h_{6,t}$ = 7.3697e-07 + 0.0146*$\varepsilon_{6,t-1}{}^2$ + 0.9714*$h_{6,t-1}$	$h_{6,t}$ = 3.8297e-07 + 0.0133*$\varepsilon_{6,t-1}{}^2$ + 0.9786*$h_{6,t-1}$
ETC	$h_{7,t}$ = 9.3801e-07 + 0.0155*$\varepsilon_{7,t-1}{}^2$ + 0.9655*$h_{7,t-1}$	$h_{7,t}$ = 5.2912e-07 + 0.0145*$\varepsilon_{7,t-1}{}^2$ + 0.9760*$h_{7,t-1}$
TRX	$h_{8,t}$ = 1.2280e-06 + 0.0190*$\varepsilon_{8,t-1}{}^2$ + 0.9612*$h_{8,t-1}$	$h_{8,t}$ = 5.0769e-07 + 0.0168*$\varepsilon_{8,t-1}{}^2$ + 0.9729*$h_{8,t-1}$
BSV	$h_{9,t}$ = 1.2646e-06 + 0.0184*$\varepsilon_{9,t-1}{}^2$ + 0.9626*$h_{9,t-1}$	$h_{9,t}$ = 6.5358e-07 + 0.0147*$\varepsilon_{9,t-1}{}^2$ + 0.9753*$h_{9,t-1}$
NEO	$h_{10,t}$ = 8.8637e-07 + 0.0166*$\varepsilon_{10,t-1}{}^2$ + 0.9680*$h_{10,t-1}$	$h_{10,t}$ = 6.1178e-07 + 0.0159*$\varepsilon_{10,t-1}{}^2$ + 0.9759*$h_{10,t-1}$
DASH	$h_{11,t}$ = 7.0955e-07 + 0.0139*$\varepsilon_{11,t-1}{}^2$ + 0.9682*$h_{11,t-1}$	$h_{11,t}$ = 3.7770e-07 + 0.0162*$\varepsilon_{11,t-1}{}^2$ + 0.9760*$h_{11,t-1}$
LINK	$h_{12,t}$ = 3.0055e-06 + 0.0293*$\varepsilon_{12,t-1}{}^2$ + 0.9582*$h_{12,t-1}$	$h_{12,t}$ = 9.8942e-07 + 0.0197*$\varepsilon_{12,t-1}{}^2$ + 0.9745*$h_{12,t-1}$
QTUM	$h_{13,t}$ = 1.4363e-06 + 0.0166*$\varepsilon_{13,t-1}{}^2$ + 0.9646*$h_{13,t-1}$	$h_{13,t}$ = 8.5038e-07 + 0.0128*$\varepsilon_{13,t-1}{}^2$ + 0.9778*$h_{13,t-1}$
BNB	$h_{14,t}$ = 8.8079e-07 + 0.0209*$\varepsilon_{14,t-1}{}^2$ + 0.9676*$h_{14,t-1}$	$h_{14,t}$ = 5.1719e-07 + 0.0179*$\varepsilon_{14,t-1}{}^2$ + 0.9745*$h_{14,t-1}$
XLM	$h_{15,t}$ = 1.1445e-06 + 0.0286*$\varepsilon_{15,t-1}{}^2$ + 0.9560*$h_{15,t-1}$	$h_{15,t}$ = 8.4260e-07 + 0.0218*$\varepsilon_{15,t-1}{}^2$ + 0.9691*$h_{15,t-1}$
ZEC	$h_{16,t}$ = 1.0573e-06 + 0.0161*$\varepsilon_{16,t-1}{}^2$ + 0.9649*$h_{16,t-1}$	$h_{16,t}$ = 9.4864e-07 + 0.0160*$\varepsilon_{16,t-1}{}^2$ + 0.9729*$h_{16,t-1}$
ADA	$h_{17,t}$ = 1.0055e-06 + 0.0180*$\varepsilon_{17,t-1}{}^2$ + 0.9655*$h_{17,t-1}$	$h_{17,t}$ = 8.5780e-07 + 0.0231*$\varepsilon_{17,t-1}{}^2$ + 0.9686*$h_{17,t-1}$
OMG	$h_{18,t}$ = 1.3218e-06 + 0.0126*$\varepsilon_{18,t-1}{}^2$ + 0.9702*$h_{18,t-1}$	$h_{18,t}$ = 1.3264e-06 + 0.0167*$\varepsilon_{18,t-1}{}^2$ + 0.9754*$h_{18,t-1}$
XMR	$h_{19,t}$ = 7.9524e-07 + 0.0154*$\varepsilon_{19,t-1}{}^2$ + 0.9692*$h_{19,t-1}$	$h_{19,t}$ = 5.7026e-07 + 0.0161*$\varepsilon_{19,t-1}{}^2$ + 0.9758*$h_{19,t-1}$
HT	$h_{20,t}$ = 5.8381e-07 + 0.0187*$\varepsilon_{20,t-1}{}^2$ + 0.9738*$h_{20,t-1}$	$h_{20,t}$ = 5.2625e-07 + 0.0196*$\varepsilon_{20,t-1}{}^2$ + 0.9706*$h_{20,t-1}$
ONT	$h_{21,t}$ = 1.2677e-06 + 0.0162*$\varepsilon_{21,t-1}{}^2$++0.9697*$h_{21,t-1}$	$h_{21,t}$ = 8.4644e-07 + 0.0151*$\varepsilon_{21,t-1}{}^2$ + 0.9754*$h_{21,t-1}$
VET	$h_{22,t}$ = 2.0800e-06 + 0.0221*$\varepsilon_{22,t-1}{}^2$++0.9605*$h_{22,t-1}$	$h_{22,t}$ = 3.2709e-06 + 0.0405$\varepsilon_{22,t-1}{}^2$ + 0.9465*$h_{22,t-1}$
DOGE	$h_{23,t}$ = 1.3512e-06 + 0.0336*$\varepsilon_{23,t-1}{}^2$++0.9545*$h_{23,t-1}$	$h_{23,t}$ = 3.9375e-07 + 0.0268*$\varepsilon_{23,t-1}{}^2$ + 0.9665*$h_{23,t-1}$
BAT	$h_{24,t}$ = 2.4243e-06 + 0.0290*$\varepsilon_{24,t-1}{}^2$++0.9532*$h_{24,t-1}$	$h_{24,t}$ = 8.4683e-07 + 0.0184*$\varepsilon_{24,t-1}{}^2$ + 0.9720*$h_{24,t-1}$
WAVES	$h_{25,t}$ = 1.3771e-06 + 0.0307*$\varepsilon_{25,t-1}{}^2$++0.9589*$h_{25,t-1}$	$h_{25,t}$ = 1.0501e-06 + 0.0252*$\varepsilon_{25,t-1}{}^2$ + 0.9689*$h_{25,t-1}$
ABBC	$h_{26,t}$ = 3.3990e-07 + 0.0120*$\varepsilon_{26,t-1}{}^2$++0.9887*$h_{26,t-1}$	$h_{26,t}$ = 1.3397e-06 + 0.0352*$\varepsilon_{26,t-1}{}^2$ + 0.9626*$h_{26,t-1}$
XTZ	$h_{27,t}$ = 1.5442e-07 + 0.0081*$\varepsilon_{27,t-1}{}^2$++0.9914*$h_{27,t-1}$	$h_{27,t}$ = 1.0344e-06 + 0.0169*$\varepsilon_{27,t-1}{}^2$ + 0.9768*$h_{27,t-1}$
ZIL	$h_{28,t}$ = 2.1678e-06 + 0.0236*$\varepsilon_{28,t-1}{}^2$++0.9538*$h_{28,t-1}$	$h_{28,t}$ = 8.8767e-07 + 0.0197*$\varepsilon_{28,t-1}{}^2$ + 0.9780*$h_{28,t-1}$
ZRX	$h_{29,t}$ = 1.6416e-06 + 0.0245*$\varepsilon_{29,t-1}{}^2$++0.9591*$h_{29,t-1}$	$h_{29,t}$ = 1.5035e-06 + 0.0235*$\varepsilon_{29,t-1}{}^2$ + 0.9666*$h_{29,t-1}$
WETH	$h_{30,t}$ = 1.9624e-06 + 0.0461*$\varepsilon_{30,t-1}{}^2$++0.9349*$h_{30,t-1}$	$h_{30,t}$ = 7.1816e-07 + 0.0232*$\varepsilon_{30,t-1}{}^2$ + 0.9712*$h_{30,t-1}$
XEM	$h_{31,t}$ = 1.3497e-06 + 0.0201*$\varepsilon_{31,t-1}{}^2$++0.9606*$h_{31,t-1}$	$h_{31,t}$ = 2.9754e-06 + 0.0319*$\varepsilon_{31,t-1}{}^2$ + 0.9576*$h_{31,t-1}$
IOST	$h_{32,t}$ = 2.2947e-06 + 0.0151*$\varepsilon_{32,t-1}{}^2$++0.9649*$h_{32,t-1}$	$h_{32,t}$ = 1.0308e-06 + 0.01480*$\varepsilon_{32,t-1}{}^2$ + 0.9752*$h_{32,t-1}$

Note: The variance specification is presented as $h_{i,t} = \widetilde{w}_{ii} + a_{ii}{}^2\varepsilon_{i,t-1}{}^2 + \beta_{ii}{}^2h_{i,t-1}$.

the two sub-periods ranges from −16.33% with Nem to 72.48% with Chainlink.

To further investigate differences in the conditional correlations of Bitcoin with altcoins after the COVID-19 outbreak, we also perform t-tests to test whether the dynamic correlations are different in the pre-COVID and COVID-19 periods. Table 8 reports the test results which suggest the rejection of the null hypothesis that the mean of Bitcoin's dynamic correlations are the same in the two periods for all crypto assets, except for Qtum and Cardano protocols, in favour of the alternative hypothesis that the mean of Bitcoin's dynamic correlations with altcoins increased in the COVID-19 period. These results therefore provide additional support for our Hypothesis 2a asserting that co-movements and correlations between Bitcoin and altcoins have been amplified by the COVID-19 pandemic.

Similarly, Table 9 presents the conditional covariance equations of Ether with the other altcoins with substituted coefficients for the two periods. Similar to Bitcoin's conditional covariances with altcoins, Ether's conditional covariances are also significantly affected by both cross products of previous error terms and conditional covariance terms in both the pre-COVID and COVID-19 periods.

Figs. 11 and 12 further plot the conditional covariances of Ether with the other altcoins in the period before and during the COVID-19 crisis, respectively. Ether's conditional covariances with altcoins are also time-varying and mostly positive during both periods. Distinct spikes around mid-March 2020 are also observed in all of Ether's conditional covariances with altcoins. These figures therefore provide further support for the assertion in our Hypothesis 1 that intraday cryptocurrency co-movements have increased during the COVID-19 pandemic, and especially around the first national lockdown announcements, which however soon reverted back to the pre-pandemic levels.

Accordingly, Figs. 13 and 14 illustrate the conditional correlations between Ether and each altcoin in the pre-COVID and COVID-19 periods, further depicting time-varying and mostly positive conditional correlations between Ether and altcoins during both periods.

A comparative analysis of unconditional and mean conditional correlations of Ether with the altcoins in the two sub-periods is presented in Table 10. Similar to the results for Bitcoin, all Ether's unconditional and average conditional correlations are found positive. With regard to the unconditional correlations, we find that, with the exception of Ripple and Dash cryptocurrencies, Cardano and Nem protocols, and Omg network dApp, Ether's unconditional correlations with all other altcoins increased during the COVID-19 pandemic period, with the increase of Ether's unconditional correlations with Chainlink protocol and the previously known as Alibaba

Fig. 5. Diagonal BEKK model conditional variances (pre-COVID period).

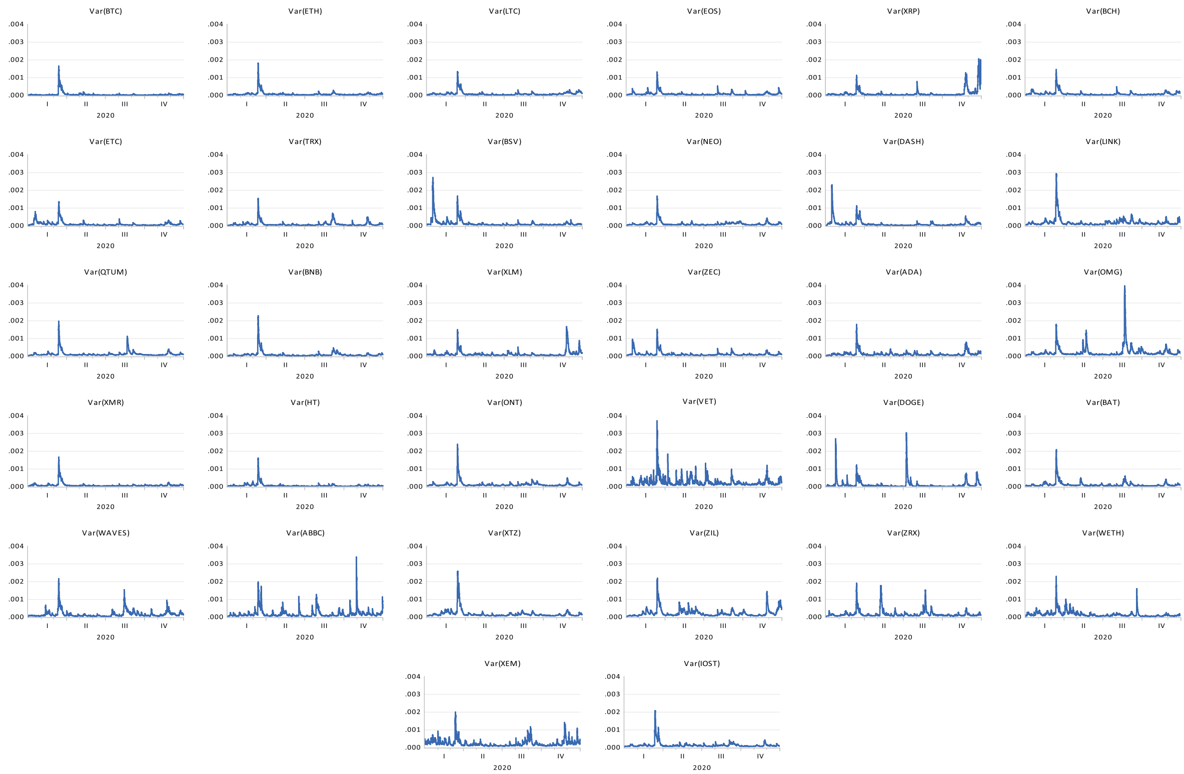


Fig. 6. Diagonal BEKK model conditional variances (COVID-19 period).

Table 6
Diagonal BEKK model conditional covariance equations of Bitcoin with altcoins - substituted coefficients.

	pre-COVID period	COVID-19 period
ETH	$h_{1,2,t} = 2.2044\text{e-}07 + 0.0155^*\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.9705^*h_{1,2,t-1}$	$h_{1,2,t} = 1.8934\text{e-}07 + 0.0189^*\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.9740^*h_{1,2,t-1}$
LTC	$h_{1,3,t} = 2.4198\text{e-}07 + 0.0148^*\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.9709^*h_{1,3,t-1}$	$h_{1,3,t} = 1.6835\text{e-}07 + 0.0178^*\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 0.9752^*h_{1,3,t-1}$
EOS	$h_{1,4,t} = 2.3185\text{e-}07 + 0.0140^*\varepsilon_{1,t-1}\varepsilon_{4,t-1} + 0.9711^*h_{1,4,t-1}$	$h_{1,4,t} = 1.8717\text{e-}07 + 0.0167^*\varepsilon_{1,t-1}\varepsilon_{4,t-1} + 0.9739^*h_{1,4,t-1}$
XRP	$h_{1,5,t} = 1.8022\text{e-}07 + 0.0156^*\varepsilon_{1,t-1}\varepsilon_{5,t-1} + 0.9698^*h_{1,5,t-1}$	$h_{1,5,t} = 1.7642\text{e-}07 + 0.0210^*\varepsilon_{1,t-1}\varepsilon_{5,t-1} + 0.9710^*h_{1,5,t-1}$
BCH	$h_{1,6,t} = 2.1620\text{e-}07 + 0.0152^*\varepsilon_{1,t-1}\varepsilon_{6,t-1} + 0.9718^*h_{1,6,t-1}$	$h_{1,6,t} = 1.7335\text{e-}07 + 0.0163^*\varepsilon_{1,t-1}\varepsilon_{6,t-1} + 0.9760^*h_{1,6,t-1}$
ETC	$h_{1,7,t} = 2.1678\text{e-}07 + 0.0157^*\varepsilon_{1,t-1}\varepsilon_{7,t-1} + 0.9688^*h_{1,7,t-1}$	$h_{1,7,t} = 1.6196\text{e-}07 + 0.0171^*\varepsilon_{1,t-1}\varepsilon_{7,t-1} + 0.9747^*h_{1,7,t-1}$
TRX	$h_{1,8,t} = 2.5497\text{e-}07 + 0.0174^*\varepsilon_{1,t-1}\varepsilon_{8,t-1} + 0.9666^*h_{1,8,t-1}$	$h_{1,8,t} = 1.7919\text{e-}07 + 0.0184^*\varepsilon_{1,t-1}\varepsilon_{8,t-1} + 0.9731^*h_{1,8,t-1}$
BSV	$h_{1,9,t} = 2.3150\text{e-}07 + 0.0171^*\varepsilon_{1,t-1}\varepsilon_{9,t-1} + 0.9673^*h_{1,9,t-1}$	$h_{1,9,t} = 1.8549\text{e-}07 + 0.0172^*\varepsilon_{1,t-1}\varepsilon_{9,t-1} + 0.9743^*h_{1,9,t-1}$
NEO	$h_{1,10,t} = 2.3153\text{e-}07 + 0.0162^*\varepsilon_{1,t-1}\varepsilon_{10,t-1} + 0.9701^*h_{1,10,t-1}$	$h_{1,10,t} = 1.8795\text{e-}07 + 0.0179^*\varepsilon_{1,t-1}\varepsilon_{10,t-1} + 0.9746^*h_{1,10,t-1}$
DASH	$h_{1,11,t} = 2.0946\text{e-}07 + 0.0149^*\varepsilon_{1,t-1}\varepsilon_{11,t-1} + 0.9701^*h_{1,11,t-1}$	$h_{1,11,t} = 1.5513\text{e-}07 + 0.0180^*\varepsilon_{1,t-1}\varepsilon_{11,t-1} + 0.9747^*h_{1,11,t-1}$
LINK	$h_{1,12,t} = 2.1200\text{e-}07 + 0.0216^*\varepsilon_{1,t-1}\varepsilon_{12,t-1} + 0.9651^*h_{1,12,t-1}$	$h_{1,12,t} = 1.8933\text{e-}07 + 0.0199^*\varepsilon_{1,t-1}\varepsilon_{12,t-1} + 0.9739^*h_{1,12,t-1}$
QTUM	$h_{1,13,t} = 2.5413\text{e-}07 + 0.0162^*\varepsilon_{1,t-1}\varepsilon_{13,t-1} + 0.9684^*h_{1,13,t-1}$	$h_{1,13,t} = 1.7954\text{e-}07 + 0.0160^*\varepsilon_{1,t-1}\varepsilon_{13,t-1} + 0.9756^*h_{1,13,t-1}$
BNB	$h_{1,14,t} = 1.7675\text{e-}07 + 0.0182^*\varepsilon_{1,t-1}\varepsilon_{14,t-1} + 0.9698^*h_{1,14,t-1}$	$h_{1,14,t} = 1.4864\text{e-}07 + 0.0190^*\varepsilon_{1,t-1}\varepsilon_{14,t-1} + 0.9739^*h_{1,14,t-1}$
XLM	$h_{1,15,t} = 2.3386\text{e-}07 + 0.0213^*\varepsilon_{1,t-1}\varepsilon_{15,t-1} + 0.9640^*h_{1,15,t-1}$	$h_{1,15,t} = 1.7887\text{e-}07 + 0.0209^*\varepsilon_{1,t-1}\varepsilon_{15,t-1} + 0.9712^*h_{1,15,t-1}$
ZEC	$h_{1,16,t} = 2.3742\text{e-}07 + 0.0160^*\varepsilon_{1,t-1}\varepsilon_{16,t-1} + 0.9685^*h_{1,16,t-1}$	$h_{1,16,t} = 2.1077\text{e-}07 + 0.0179^*\varepsilon_{1,t-1}\varepsilon_{16,t-1} + 0.9731^*h_{1,16,t-1}$
ADA	$h_{1,17,t} = 2.3840\text{e-}07 + 0.0169^*\varepsilon_{1,t-1}\varepsilon_{17,t-1} + 0.9688^*h_{1,17,t-1}$	$h_{1,17,t} = 1.9893\text{e-}07 + 0.0215^*\varepsilon_{1,t-1}\varepsilon_{17,t-1} + 0.9710^*h_{1,17,t-1}$
OMG	$h_{1,18,t} = 2.3152\text{e-}07 + 0.0141^*\varepsilon_{1,t-1}\varepsilon_{18,t-1} + 0.9712^*h_{1,18,t-1}$	$h_{1,18,t} = 1.9089\text{e-}07 + 0.0183^*\varepsilon_{1,t-1}\varepsilon_{18,t-1} + 0.9744^*h_{1,18,t-1}$
XMR	$h_{1,19,t} = 2.0479\text{e-}07 + 0.0157^*\varepsilon_{1,t-1}\varepsilon_{19,t-1} + 0.9707^*h_{1,19,t-1}$	$h_{1,19,t} = 1.6965\text{e-}07 + 0.0180^*\varepsilon_{1,t-1}\varepsilon_{19,t-1} + 0.9746^*h_{1,19,t-1}$
HT	$h_{1,20,t} = 1.0086\text{e-}07 + 0.0172^*\varepsilon_{1,t-1}\varepsilon_{20,t-1} + 0.9730^*h_{1,20,t-1}$	$h_{1,20,t} = 1.2972\text{e-}07 + 0.0198^*\varepsilon_{1,t-1}\varepsilon_{20,t-1} + 0.9720^*h_{1,20,t-1}$
ONT	$h_{1,21,t} = 2.2222\text{e-}07 + 0.0161^*\varepsilon_{1,t-1}\varepsilon_{21,t-1} + 0.9709^*h_{1,21,t-1}$	$h_{1,21,t} = 1.9714\text{e-}07 + 0.0174^*\varepsilon_{1,t-1}\varepsilon_{21,t-1} + 0.9744^*h_{1,21,t-1}$
VET	$h_{1,22,t} = 2.3922\text{e-}07 + 0.0187^*\varepsilon_{1,t-1}\varepsilon_{22,t-1} + 0.9663^*h_{1,22,t-1}$	$h_{1,22,t} = 3.6478\text{e-}07 + 0.0285^*\varepsilon_{1,t-1}\varepsilon_{22,t-1} + 0.9598^*h_{1,22,t-1}$
DOGE	$h_{1,23,t} = 1.6928\text{e-}07 + 0.0231^*\varepsilon_{1,t-1}\varepsilon_{23,t-1} + 0.9633^*h_{1,23,t-1}$	$h_{1,23,t} = 1.4867\text{e-}07 + 0.0232^*\varepsilon_{1,t-1}\varepsilon_{23,t-1} + 0.9699^*h_{1,23,t-1}$
BAT	$h_{1,24,t} = 2.2507\text{e-}07 + 0.0215^*\varepsilon_{1,t-1}\varepsilon_{24,t-1} + 0.9626^*h_{1,24,t-1}$	$h_{1,24,t} = 1.7850\text{e-}07 + 0.0192^*\varepsilon_{1,t-1}\varepsilon_{24,t-1} + 0.9727^*h_{1,24,t-1}$
WAVES	$h_{1,25,t} = 1.8490\text{e-}07 + 0.0221^*\varepsilon_{1,t-1}\varepsilon_{25,t-1} + 0.9655^*h_{1,25,t-1}$	$h_{1,25,t} = 1.5541\text{e-}07 + 0.0225^*\varepsilon_{1,t-1}\varepsilon_{25,t-1} + 0.9711^*h_{1,25,t-1}$
ABBC	$h_{1,26,t} = 5.4846\text{e-}08 + 0.0138^*\varepsilon_{1,t-1}\varepsilon_{26,t-1} + 0.9804^*h_{1,26,t-1}$	$h_{1,26,t} = 1.5446\text{e-}07 + 0.0266^*\varepsilon_{1,t-1}\varepsilon_{26,t-1} + 0.9680^*h_{1,26,t-1}$
XTZ	$h_{1,27,t} = 5.1216\text{e-}08 + 0.0113^*\varepsilon_{1,t-1}\varepsilon_{27,t-1} + 0.9817^*h_{1,27,t-1}$	$h_{1,27,t} = 1.7553\text{e-}07 + 0.0184^*\varepsilon_{1,t-1}\varepsilon_{27,t-1} + 0.9751^*h_{1,27,t-1}$
ZIL	$h_{1,28,t} = 2.7679\text{e-}07 + 0.0194^*\varepsilon_{1,t-1}\varepsilon_{28,t-1} + 0.9629^*h_{1,28,t-1}$	$h_{1,28,t} = 1.4220\text{e-}07 + 0.0199^*\varepsilon_{1,t-1}\varepsilon_{28,t-1} + 0.9757^*h_{1,28,t-1}$
ZRX	$h_{1,29,t} = 2.1835\text{e-}07 + 0.0198^*\varepsilon_{1,t-1}\varepsilon_{29,t-1} + 0.9656^*h_{1,29,t-1}$	$h_{1,29,t} = 2.0024\text{e-}07 + 0.0217^*\mathrm{R}\ \varepsilon_{1,t-1}\varepsilon_{29,t-1} + 0.9700^*h_{1,29,t-1}$
WETH	$h_{1,30,t} = 2.6776\text{e-}07 + 0.0271^*\varepsilon_{1,t-1}\varepsilon_{30,t-1} + 0.9533^*h_{1,30,t-1}$	$h_{1,30,t} = 1.8191\text{e-}07 + 0.0216^*\varepsilon_{1,t-1}\varepsilon_{30,t-1} + 0.9723^*h_{1,30,t-1}$
XEM	$h_{1,31,t} = 2.1322\text{e-}07 + 0.0179^*\varepsilon_{1,t-1}\varepsilon_{31,t-1} + 0.9664^*h_{1,31,t-1}$	$h_{1,31,t} = 2.4198\text{e-}07 + 0.0253^*\varepsilon_{1,t-1}\varepsilon_{31,t-1} + 0.9655^*h_{1,31,t-1}$
IOST	$h_{1,32,t} = 2.4253\text{e-}07 + 0.0155^*\varepsilon_{1,t-1}\varepsilon_{32,t-1} + 0.9685^*h_{1,32,t-1}$	$h_{1,32,t} = 1.9509\text{e-}07 + 0.0172^*\varepsilon_{1,t-1}\varepsilon_{32,t-1} + 0.9743^*h_{1,32,t-1}$

Note: The covariance specification is presented as $h_{i,j,t} = \widetilde{w}_{ij} + a_{ii}a_{jj}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta_{ii}\beta_{jj}h_{i,j,t-1}$.

coin cryptocurrency even exceeding 100% in the second sub-period (121.29% and 132.34%, respectively). Notably, these increases are even higher than the corresponding ones observed for Bitcoin, which provide some evidence against Hypothesis 2b. As for the mean conditional correlations between Ether and other altcoins, these also increased during the COVID-19 period, with the only exceptions including Ether's conditional correlations with Nem (-13.47%) and Cardano (-1.16%) protocols, and Omg network (-8.47%) dApp. On the other hand, Ether's conditional correlation with Tezos protocol increased by 109.86% in the COVID-19 period.

Table 11 further presents the results of the performed t-tests when further investigating the differences of Ether's dynamic correlations with altcoins between the pre-COVID and COVID-19 periods. The results suggest the rejection of the null hypothesis that the mean of Ether's dynamic correlations are the same before and during the COVID-19 periods in favour of the alternative hypothesis that the mean of Ether's dynamic correlations increased in the COVID-19 period in all cases. These findings thus provide further support for our Hypothesis 1, stating that intraday cryptocurrency relations increased during the COVID-19 pandemic period, but also potential evidence against Hypothesis 2b, since an alternative crypto asset seems to have become more dominant during the pandemic period.

To further assess Hypothesis 2b, we compare Bitcoin and Ether's correlations with altcoins (Tables 7 and 10, respectively). The comparison reveals that Ether exhibits overall higher unconditional correlations with altcoins than Bitcoin in both sub-periods. The only exceptions to this constitute Monero, Dogecoin, and ABBC cryptocurrencies in both periods as well as Tezos protocol in the pre-COVID period and Huobi token dApp in the COVID-19 period. This result is overall in contrast with Hypothesis 2b which contends that Bitcoin remains a cryptocurrency market leader and exhibits the highest degree of co-movements with other digital assets. On the other hand, only half of Ether's average conditional correlations with altcoins are higher than the corresponding ones for Bitcoin in the first sub-period. Interestingly, though, in the second sub-period Ether's average conditional correlations with altcoins are higher than Bitcoin's corresponding average conditional correlations. The only exceptions to this are Monero, Dogecoin, and ABBC cryptocurrencies, Huobi token dApp, and Nem protocol. The latter result is again in contrast to Hypothesis 2b, as it shows that Ether gains in prominence. It is worth noting that Yi et al. (2018) further found that, although Bitcoin plays an important role transmitting strong volatility shocks to other digital assets, it does not dominate the entire cryptocurrency market.

4.5. Co-movements and correlations of other crypto assets

We further calculate mean conditional correlations for all other pairs of crypto assets in the pre-COVID and COVID-19 periods. The results, presented in Table S2 (supplementary material), show that all correlations increased during the COVID-19 period. Notably, the

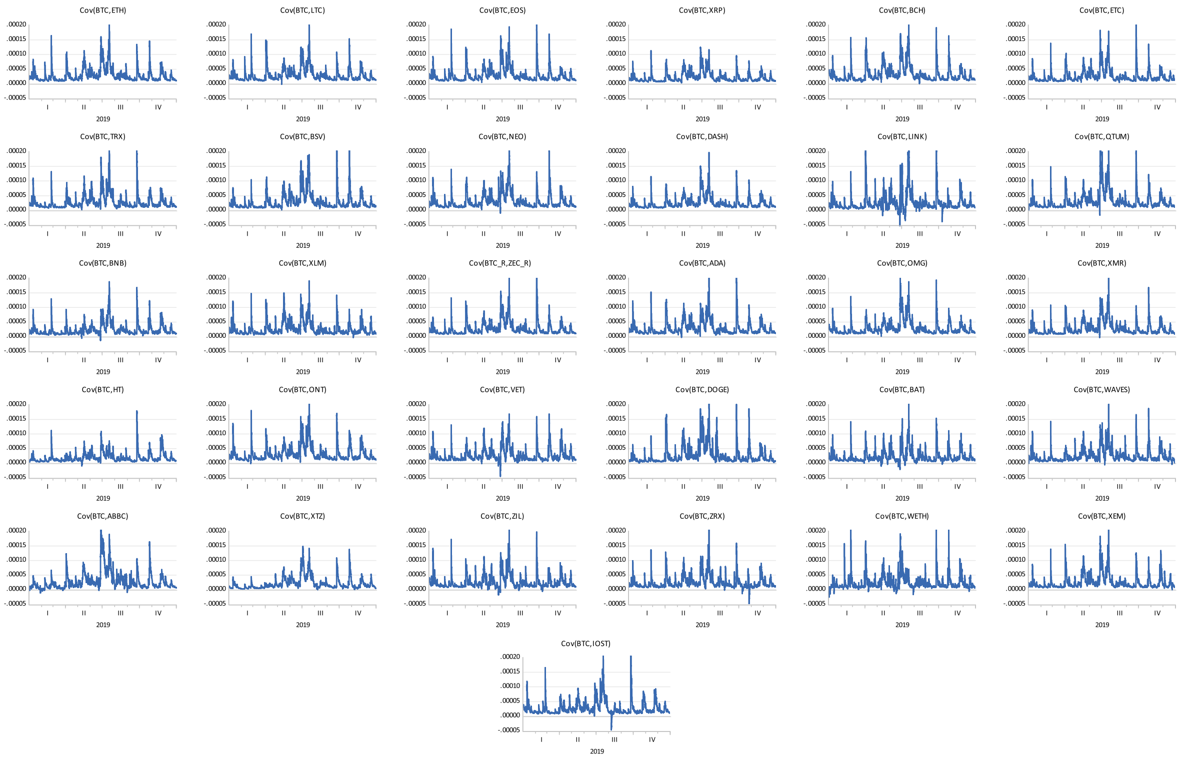


Fig. 7. Diagonal BEKK model conditional covariances of Bitcoin with altcoins (pre-COVID-19 period).

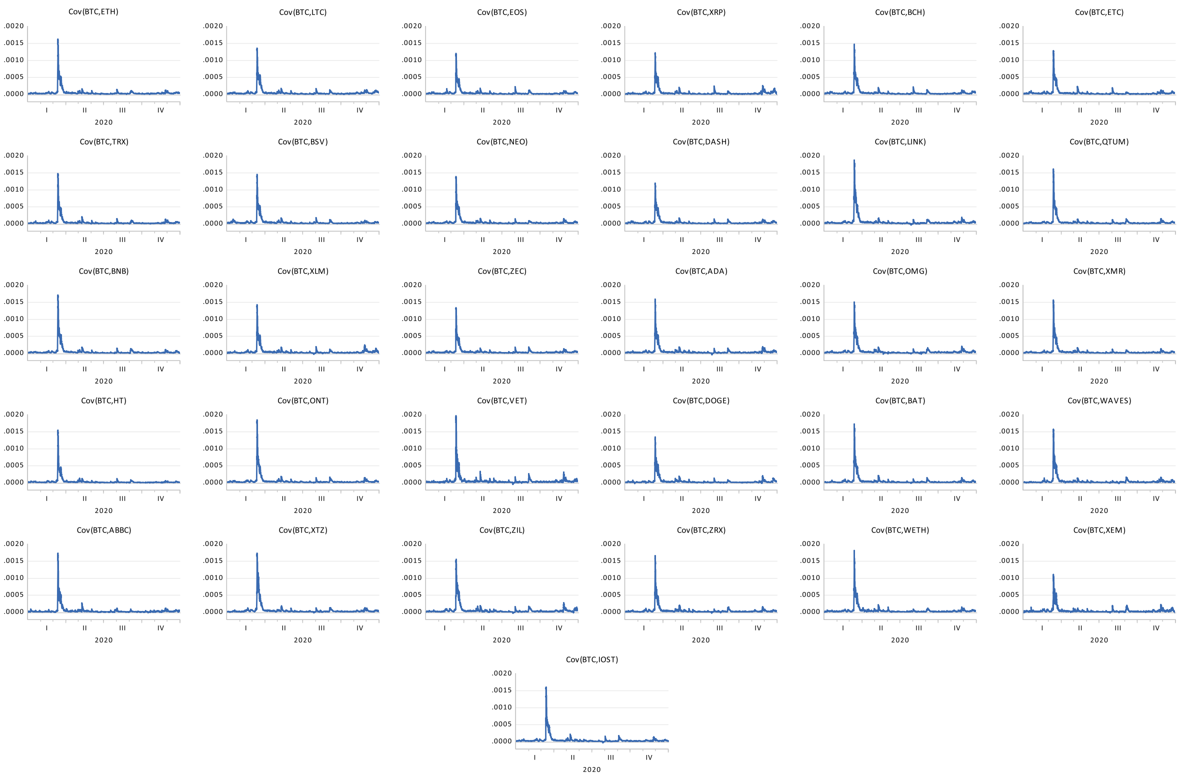


Fig. 8. Diagonal BEKK model conditional covariances of Bitcoin with altcoins (COVID-19 period).

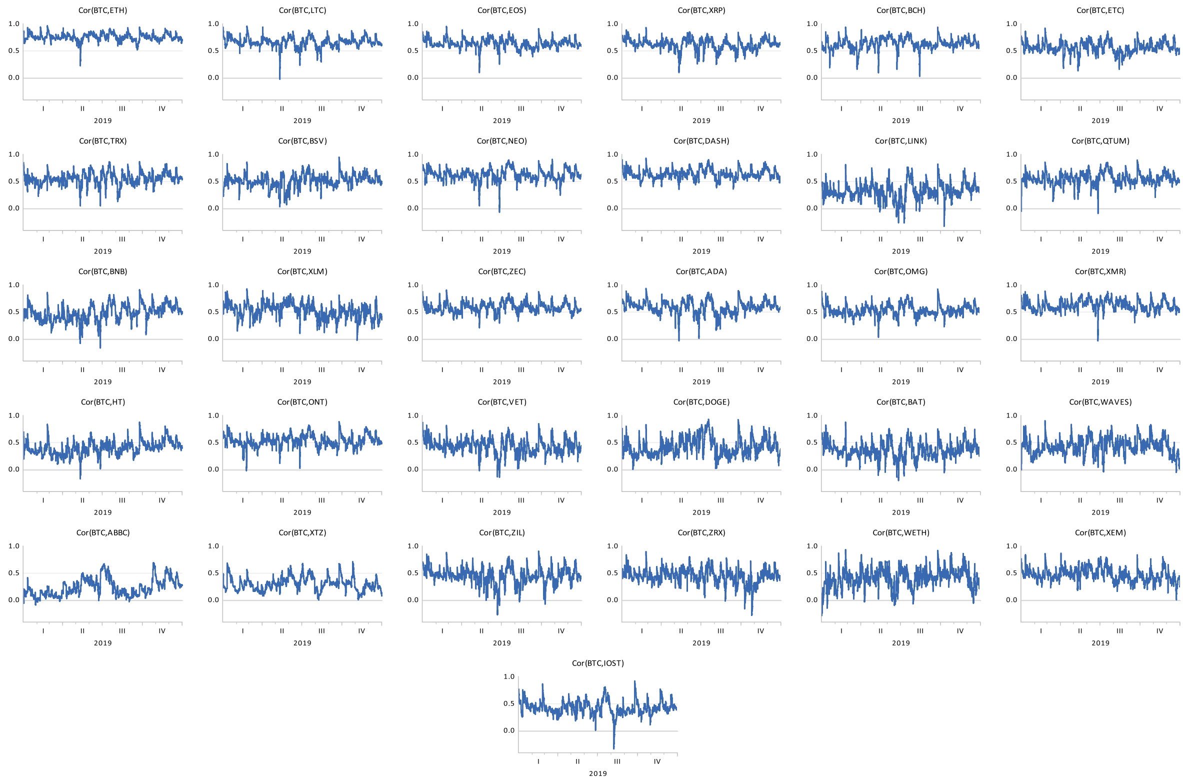


Fig. 9. Diagonal BEKK model conditional correlations of Bitcoin with altcoins (pre-COVID period).

increase in most correlations of Tezos and Chainlink protocols with altcoins exceeded 100%, with the increase in the correlation between the two protocols reaching 436%. These results provide supporting evidence for Hypothesis 1, showing that for the majority of crypto asset pairs the degree of co-movements and correlations has been amplified during the COVID-19 pandemic. These findings can be explained by the increased uncertainty during the COVID-19 crisis, and increased attention to crypto assets from both institutional and retail investors.

We also investigate the average conditional covariances and average conditional correlations across both time and digital assets for each analysed crypto asset (Table 12). All in all, it can be noticed that in all but one case (the change in the average conditional correlation of Nem protocol) both the average conditional correlations and average conditional covariances increased after the COVID-19 outbreak. The most notable changes with regard to average conditional correlations are Tezos (137.5 %) and Chainlink (99.5%) protocols, while the most notable changes with regard to average conditional covariances include Iost protocol (121.5%), Bitcoin Cash cryptocurrency (110%), and 0x dApp (107.5 %), among others.

What is also striking is that Bitcoin, besides exhibiting one of the highest correlations and the highest covariance in both periods, is the most stable crypto asset in our sample over the analysed period, having the lowest change in average conditional covariance and one of the lowest changes in conditional correlations after the COVID-19 outbreak. This finding shows the stable dominance of Bitcoin in the cryptocurrency market.

4.6. PMFG analysis of conditional correlations between different types of crypto assets

Next, we use all the conditional correlations estimated from the DBEKK model to further examine the hierarchical structure of the cryptocurrency market, similar to the results discussed in section 4.2 for the unconditional correlations. In this section, however, we use the Planar Maximally Filtered Graph, which enables us to extract more information from the analysed network than the MST.[15] Since the PMFG is a much more sophisticated network than the MST, making the graphs hardly readable, we decide to aggregate the results of the PMFG analysis by calculating average degree levels (numbers of connections) for each of the categories according to the proposed classification. Thus, we analyse the change in the importance (in terms of the number of strong connections, i.e., the ones included in the graph) of particular categories of crypto assets over the two considered periods with regard to the measure of similarity, i.e., the conditional correlation.

[15] We also applied the MST methodology to the conditional correlations. The corresponding Figures are provided in the supplementary material. However, these graphs paint a rather incomplete picture as discussed earlier.

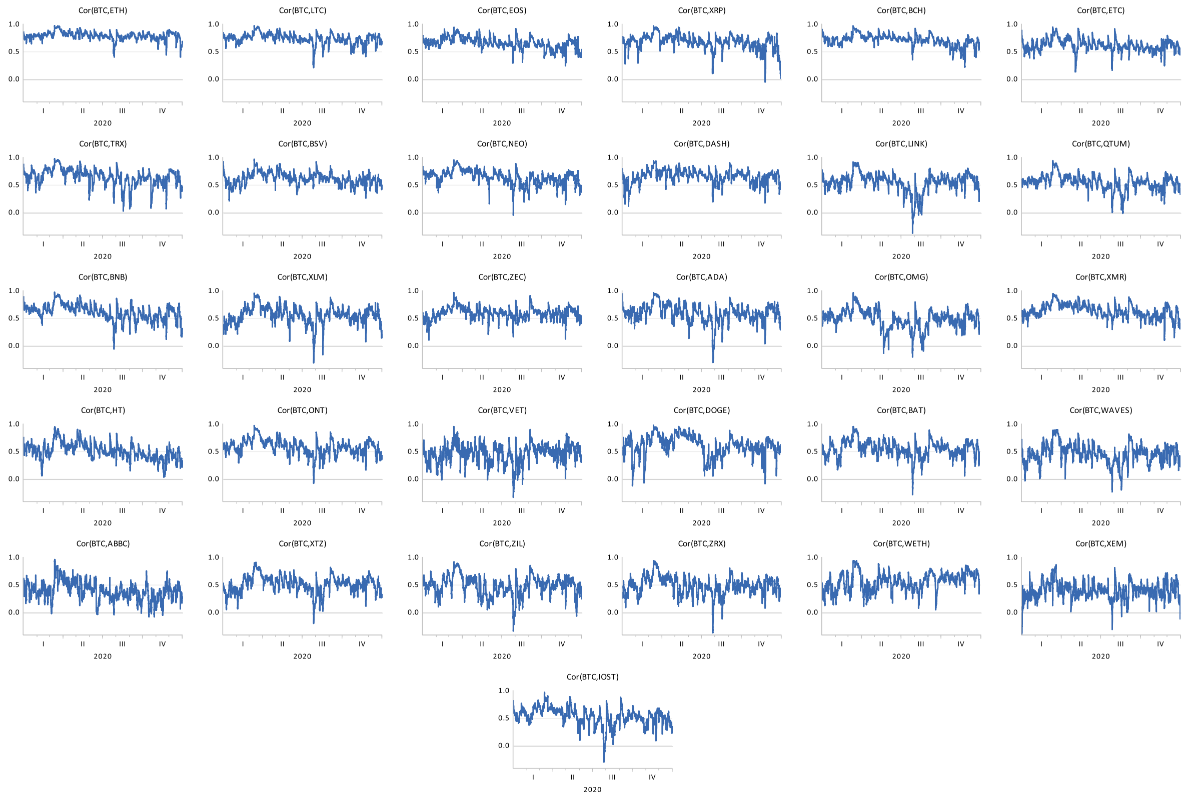


Fig. 10. Diagonal BEKK model conditional correlations of Bitcoin with altcoins (COVID-19 period).

The results, presented in Fig. 15, show several important findings. First, the analysis of the structure of the PMFG based on conditional correlations reveals that, interestingly, Bitcoin and Ether are the least important crypto assets in the network both in the pre-COVID and COVID-19 periods. These findings provide further evidence against Hypothesis 2b. However, it is worth confronting the results of the PMFG based on conditional correlations (henceforth CC PMFG) with the preliminary results of the MST based on the unconditional correlation matrix (henceforth UC MST). Specifically, it can be observed that while Bitcoin and Ether are the most important crypto assets in the UC MST network, they are the least important ones in the CC PMFG network. This finding can be explained based on the case of Ether, which is the most important crypto asset in the UC MST network, considering that the number of edges connected to Bitcoin is similarly low in both UC MST and CC PMFG. Particularly, the majority of the crypto assets that Ether is connected with in the UC MST network, on the one hand, are not directly connected with Ether in the CC PMFG network, while on the other hand, these crypto assets are directly connected with one another in the CC PMFG network. For instance, considering both networks in the pre-COVID period, Ether is directly connected with crypto assets such as Ethereum Classic and Binance coin in the UC MST network but not connected with them in the CC PMFG network, while Ethereum Classic and Binance coin are directly connected with each other in the CC PMFG network. This finding is particularly interesting considering that dApps (tokens) issued on Binance Smart Chain (a platform behind the Binance coin) are fully compatible and transferrable with the Ethereum platform. In other words, if the token is created on the Ethereum platform, it can be transferred to the Binance Smart Chain using the so-called Trust Wallet and be used on the Binance platform (which is more efficient and cost-effective than Ethereum at the moment). It is then particularly interesting that the connection between these platforms is reflected in the data as well. Similar findings can be observed during the COVID-19 period. Specifically, in the UC MST network Ether is connected, for example, with Litecoin, Nem, Zilliqa, Basic attention token, and Waves, among others, while only connected with Dash, Wrapped Ether, and Iost in the CC PMFG network. However, in the CC PMFG network Litecoin is connected with Zilliqa and Wrapped Ether, Basic attention token is connected with Waves and Zilliqa, and Waves is connected with Basic attention token and Nem. Overall, these findings support our argument that the connections between Ether and other crypto assets visible in the UC MST network, in many cases, are not because Ether is strongly connected with them directly but because Ether, being a major player in the cryptocurrency market, is loosely connected with almost all crypto assets and the strength of the connections comes from the direct connections between these other crypto assets themselves. This finding emphasises that when conducting a network analysis on the cryptocurrency market, it is important to combine such analysis with results obtained using non-linear methods, such as the DBEKK model used in our paper, since the analysis of simple unconditional correlations may lead to an incomplete picture of the market.

Furthermore, the aggregated results presented in Fig. 15 imply that, both during the pre-COVID and COVID-19 periods, protocols (which also include Ether) and dApps are much more important in the structure of the crypto asset market network than pure

Table 7
Comparative analysis of unconditional and conditional correlations of Bitcoin with altcoins.

	Unconditional correlations			Average conditional correlations		
	pre-COVID period	COVID-19 period	% difference	pre-COVID period	COVID-19 period	% difference
ETH	0.7837	0.8455	7.8857	0.7571	0.7904	4.3984
LTC	0.6907	0.7952	15.1296	0.6644	0.7398	11.3486
EOS	0.6903	0.7170	3.8679	0.6371	0.6599	3.5787
XRP	0.6191	0.6019	−2.7782	0.6206	0.6764	8.9913
BCH	0.6603	0.7596	15.0386	0.6346	0.7139	12.4961
ETC	0.6222	0.6769	8.7914	0.5655	0.6186	9.3899
TRX	0.5817	0.6784	16.6237	0.5540	0.6474	16.8592
BSV	0.4921	0.6191	25.8078	0.5143	0.6200	20.5522
NEO	0.6596	0.6966	5.6095	0.6247	0.6423	2.8174
DASH	0.7241	0.6303	−12.9540	0.6345	0.6562	3.4200
LINK	0.2952	0.6365	115.6165	0.3190	0.5502	72.4765
QTUM	0.6209	0.6440	3.7204	0.5492	0.5501	0.1639
BNB	0.5073	0.7327	44.4313	0.4876	0.6135	25.8203
XLM	0.5357	0.6171	15.1951	0.5221	0.5618	7.6039
ZEC	0.6585	0.6450	−2.0501	0.5839	0.5912	1.2502
ADA	0.6285	0.6652	5.8393	0.5920	0.5944	0.4054
OMG	0.6212	0.5127	−17.4662	0.5333	0.4861	−8.8506
XMR	0.7280	0.7637	4.9038	0.6218	0.6336	1.8977
HT	0.4229	0.6603	56.1362	0.4021	0.5144	27.9284
ONT	0.5706	0.6976	22.2573	0.5341	0.5849	9.5113
VET	0.4413	0.5303	20.1677	0.4328	0.4641	7.2320
DOGE	0.4458	0.5576	25.0785	0.4200	0.6089	44.9762
BAT	0.3843	0.6661	73.3281	0.3606	0.5509	52.7732
WAVES	0.4478	0.5276	17.8205	0.4300	0.4604	7.0698
ABBC	0.1977	0.4536	129.4385	0.2361	0.3887	64.6336
XTZ	0.3743	0.6312	68.6348	0.3055	0.5124	67.7250
ZIL	0.4980	0.5605	12.5502	0.4534	0.4850	6.9696
ZRX	0.4804	0.5502	14.5296	0.4459	0.4811	7.8941
WETH	0.3532	0.5849	65.6002	0.4061	0.5573	37.2322
XEM	0.5313	0.4501	−15.2833	0.4715	0.3945	−16.3309
IOST	0.4838	0.6445	33.2162	0.4267	0.5336	25.0527

cryptocurrencies. This finding is also in line with the observation from the UC MST network, where protocols and dApps are placed closer to the centre of the network than pure cryptocurrencies. Such a finding might be, in fact, not that surprising considering that dApps and protocols are part of the so-called Blockchain 2.0 (or even Blockchain 3.0) technology which has always been predicted to become a key implementation of the blockchain technology, while pure cryptocurrencies are only its first implementation. We can also notice that dApps became more important in the COVID-19 period than the other considered groups of crypto assets. One of the possible explanations is that due to the COVID-19 social isolation measures retail investors have been forced to stay home, which may have motivated them to explore new developments in the crypto asset market, such as dApps. Furthermore, COVID-19 isolation and restrictions demonstrated the importance and potential of decentralised finance among both retail and institutional investors, and hence increased attention to these assets. With the expectation of further development of these blockchain-based platforms, i.e., protocols and dApps, investors could believe that investing in useful and successful projects will bring them high returns in the future.[16] Alternatively, dApps could be also considered by market participants as more sustainable assets in terms of their energy consumption. In contrast to Bitcoin, which is infamous for its extreme energy usage (Corbet et al., 2021), Ethereum announced a plan to move to a consensus mechanism called proof-of-stake (PoS), which should decrease the energy consumption of the network, making applications that are based on it more appealing for responsible investors.

Moreover, after investigating the individual degree levels of the analysed crypto assets[17], it turns out that Iost is connected with the largest number of other crypto assets in the sample in both analysed periods, specifically with twenty-one crypto assets in the pre-COVID period and twenty-two crypto assets during the COVID-19 period, while the second most important digital asset in both periods, Wrapped Ether, is connected with thirteen crypto assets in the pre-COVID period and nineteen crypto assets during the COVID-19 period. Overall, it can be noticed that the results obtained from the PMFG analysis of conditional correlations are consistent between the two analysed periods. This would imply that the structure of the market has not drastically changed after the COVID-19-related turmoil and that the market behaved collectively in a similar manner over both periods.

[16] However, it is worth noting that one might not necessarily imply the other, i.e., successful blockchain-based projects might not necessarily provide any extraordinarily high returns for external investors. In many cases, the movements of the market are dictated by market-makers, the so-called whales, i.e., likely the long-time miners who decide at particular times when to flood the market with more money and then when to burst the bubble.

[17] Detailed results are provided in the supplementary material.

Table 8
t-test for the equality in the conditional correlations of Bitcoin with altcoins in the two sub-periods.

	pre-COVID period		COVID-19 period		t-statistic
	Mean	Variance	Mean	Variance	
ETH	0.7571	0.0046	0.7904	0.0050	−31.7595***
LTC	0.6644	0.0081	0.7398	0.0087	−54.4535***
EOS	0.6371	0.0069	0.6599	0.0107	−16.0580***
XRP	0.6206	0.0102	0.6764	0.0179	−31.1528***
BCH	0.6346	0.0111	0.7139	0.0096	−51.7224***
ETC	0.5655	0.0108	0.6186	0.0119	−32.9430***
TRX	0.5540	0.0122	0.6474	0.0224	−47.1146***
BSV	0.5143	0.0137	0.6200	0.0117	−61.9995***
NEO	0.6247	0.0110	0.6423	0.0162	−10.0127***
DASH	0.6345	0.0083	0.6562	0.0147	−13.3979***
LINK	0.3190	0.0239	0.5502	0.0274	−95.5044***
QTUM	0.5492	0.0117	0.5501	0.0174	−0.4785
BNB	0.4876	0.0216	0.6135	0.0201	−57.7434***
XLM	0.5221	0.0190	0.5618	0.0244	−17.8435***
ZEC	0.5839	0.0085	0.5912	0.0112	−4.8246***
ADA	0.5920	0.0148	0.5944	0.0255	−1.1439
OMG	0.5333	0.0102	0.4861	0.0289	22.3957***
XMR	0.6218	0.0101	0.6336	0.0158	−6.8640***
HT	0.4021	0.0160	0.5144	0.0220	−53.9526***
ONT	0.5341	0.0119	0.5849	0.0189	−27.0973***
VET	0.4328	0.0192	0.4641	0.0290	−13.3647***
DOGE	0.4200	0.0268	0.6089	0.0362	−70.5342***
BAT	0.3606	0.0212	0.5509	0.0219	−85.8704***
WAVES	0.4300	0.0219	0.4604	0.0302	−12.5013***
ABBC	0.2361	0.0259	0.3887	0.0266	−62.3701***
XTZ	0.3055	0.0162	0.5124	0.0228	−98.1534***
ZIL	0.4534	0.0217	0.4850	0.0324	−12.7276***
ZRX	0.4459	0.0194	0.4811	0.0264	−15.4096***
WETH	0.4061	0.0307	0.5573	0.0269	−58.9917***
XEM	0.4715	0.0144	0.3945	0.0226	37.4898***
IOST	0.4267	0.0167	0.5336	0.0249	−49.0689***

Notes: t-statistic for testing H$_0$: $\mu_{r_t}^{pre-COVIDperiod} - \mu_{r_t}^{COVID-19period} = 0$, against H$_a$: $\mu_{r_t}^{pre-COVIDperiod} - \mu_{r_t}^{COVID-19period} < 0$, assuming unequal variances. *** indicates statistical significance at the 1% level.

4.7. Robustness check of the PMFG results using the TMFG

Finally, in order to check the robustness of our PMFG results, we employ the TMFG method and compare the results from the TMFG and PMFG for each sub-period.[18] Specifically, the following properties of the graphs are compared: i) The total number of edges that repeat in both the PMFG and TMFG; ii) The differences in the degree level of each crypto asset between the PMFG and TMFG, for which the distribution of differences is presented (see Table 13); and iii) The average degree level of each crypto asset class category in the PMFG and TMFG (see Table 14).

According to the results, the total number of edges in the PMFG and TMFG is the same, equal to $3n - 6$ (Massara et al., 2017), resulting in 90 edges in our sample of thirty-two crypto assets. There were 56 and 57 identical edges in both the PMFG and TMFG in the pre-COVID and COVID-19 periods, respectively[19], indicating a quite satisfactory robustness of our results.

Moreover, the analysis of the differences in the degree level of each particular crypto asset in the sample (Table 13) indicates that approximately one third of the considered crypto assets has the same vertex degree level in each sub-period. It can be also observed that the similarity of the TMFG and PMFG is stronger in the COVID-19 period, considering that twenty-three out of the thirty-two considered crypto assets do not differ or differ only by one in terms of the degree level. Although this may seem counterintuitive from the economic standpoint (as a crisis such as the COVID-19 pandemic crisis indicates larger turbulence), from the econophysics standpoint the nodes (i.e. crypto assets) are in a less free-floating mode during the crisis, as the crypto assets move more collectively together than in the non-crisis period, so the graph is more connected during the COVID-19 period (robust to method of computation).

The robustness of our PMFG results is further confirmed when analysing the average degree level for each category of crypto asset. Similar to the PMFG results, the TMFG results also show that protocols and dApps are more important in the networks than pure

[18] Comprehensive analysis with the use of the TMFG, enabling the examination of dynamic topological properties, would require extending the dataset and applying dynamic updating with data of higher frequency than those used in this study. Considering that the aim of this research is to capture and compare two states of the crypto asset market, i.e. the period before the COVID-19 outbreak and the period during the COVID-19 crisis, the effective analysis based on the TMFG is outside the scope of this study.

[19] The results are available from the authors upon request.

Table 9
Diagonal BEKK model conditional covariance equations of Ether with other cryptocurrencies - substituted coefficients.

	pre-COVID period	COVID-19 period
LTC	$h_{2,3,t} = 3.9949\text{e-}07 + 0.0144*\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.9693*h_{2,3,t-1}$	$h_{2,3,t} = 2.5646\text{e-}07 + 0.0167*\varepsilon_{2,t-1}\varepsilon_{3,t-1} + 0.9758*h_{2,3,t-1}$
EOS	$h_{2,4,t} = 3.9992\text{e-}07 + 0.0136*\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 0.9695*h_{2,4,t-1}$	$h_{2,4,t} = 2.8601\text{e-}07 + 0.0157*\varepsilon_{2,t-1}\varepsilon_{4,t-1} + 0.9746*h_{2,4,t-1}$
XRP	$h_{2,5,t} = 2.8549\text{e-}07 + 0.0152*\varepsilon_{2,t-1}\varepsilon_{5,t-1} + 0.9682*h_{2,5,t-1}$	$h_{2,5,t} = 2.6210\text{e-}07 + 0.0198*\varepsilon_{2,t-1}\varepsilon_{5,t-1} + 0.9717*h_{2,5,t-1}$
BCH	$h_{2,6,t} = 3.5762\text{e-}07 + 0.0149*\varepsilon_{2,t-1}\varepsilon_{6,t-1} + 0.9702*h_{2,6,t-1}$	$h_{2,6,t} = 2.5665\text{e-}07 + 0.0154*\varepsilon_{2,t-1}\varepsilon_{6,t-1} + 0.9766*h_{2,6,t-1}$
ETC	$h_{2,7,t} = 3.5272\text{e-}07 + 0.0153*\varepsilon_{2,t-1}\varepsilon_{7,t-1} + 0.9672*h_{2,7,t-1}$	$h_{2,7,t} = 2.4950\text{e-}07 + 0.0160*\varepsilon_{2,t-1}\varepsilon_{7,t-1} + 0.9753*h_{2,7,t-1}$
TRX	$h_{2,8,t} = 4.1498\text{e-}07 + 0.0170*\varepsilon_{2,t-1}\varepsilon_{8,t-1} + 0.9650*h_{2,8,t-1}$	$h_{2,8,t} = 2.6575\text{e-}07 + 0.0173*\varepsilon_{2,t-1}\varepsilon_{8,t-1} + 0.9738*h_{2,8,t-1}$
BSV	$h_{2,9,t} = 3.4718\text{e-}07 + 0.0167*\varepsilon_{2,t-1}\varepsilon_{9,t-1} + 0.9657*h_{2,9,t-1}$	$h_{2,9,t} = 2.7034\text{e-}07 + 0.0162*\varepsilon_{2,t-1}\varepsilon_{9,t-1} + 0.9750*h_{2,9,t-1}$
NEO	$h_{2,10,t} = 3.5052\text{e-}07 + 0.0159*\varepsilon_{2,t-1}\varepsilon_{10,t-1} + 0.9685*h_{2,10,t-1}$	$h_{2,10,t} = 2.7651\text{e-}07 + 0.0168*\varepsilon_{2,t-1}\varepsilon_{10,t-1} + 0.9753*h_{2,10,t-1}$
DASH	$h_{2,11,t} = 3.0243\text{e-}07 + 0.0145*\varepsilon_{2,t-1}\varepsilon_{11,t-1} + 0.9685*h_{2,11,t-1}$	$h_{2,11,t} = 2.2474\text{e-}07 + 0.0169*\varepsilon_{2,t-1}\varepsilon_{11,t-1} + 0.9753*h_{2,11,t-1}$
LINK	$h_{2,12,t} = 3.2458\text{e-}07 + 0.0211*\varepsilon_{2,t-1}\varepsilon_{12,t-1} + 0.9635*h_{2,12,t-1}$	$h_{2,12,t} = 2.9250\text{e-}07 + 0.0187*\varepsilon_{2,t-1}\varepsilon_{12,t-1} + 0.9746*h_{2,12,t-1}$
QTUM	$h_{2,13,t} = 3.9576\text{e-}07 + 0.0159*\varepsilon_{2,t-1}\varepsilon_{13,t-1} + 0.9667*h_{2,13,t-1}$	$h_{2,13,t} = 2.7233\text{e-}07 + 0.0151*\varepsilon_{2,t-1}\varepsilon_{13,t-1} + 0.9762*h_{2,13,t-1}$
BNB	$h_{2,14,t} = 2.6094\text{e-}07 + 0.0178*\varepsilon_{2,t-1}\varepsilon_{14,t-1} + 0.9682*h_{2,14,t-1}$	$h_{2,14,t} = 2.1623\text{e-}07 + 0.0178*\varepsilon_{2,t-1}\varepsilon_{14,t-1} + 0.9746*h_{2,14,t-1}$
XLM	$h_{2,15,t} = 3.3504\text{e-}07 + 0.0208*\varepsilon_{2,t-1}\varepsilon_{15,t-1} + 0.9624*h_{2,15,t-1}$	$h_{2,15,t} = 2.7263\text{e-}07 + 0.0196*\varepsilon_{2,t-1}\varepsilon_{15,t-1} + 0.9719*h_{2,15,t-1}$
ZEC	$h_{2,16,t} = 3.4557\text{e-}07 + 0.0156*\varepsilon_{2,t-1}\varepsilon_{16,t-1} + 0.9669*h_{2,16,t-1}$	$h_{2,16,t} = 3.0300\text{e-}07 + 0.0169*\varepsilon_{2,t-1}\varepsilon_{16,t-1} + 0.9738*h_{2,16,t-1}$
ADA	$h_{2,17,t} = 3.8311\text{e-}07 + 0.0165*\varepsilon_{2,t-1}\varepsilon_{17,t-1} + 0.9672*h_{2,17,t-1}$	$h_{2,17,t} = 2.8695\text{e-}07 + 0.0203*\varepsilon_{2,t-1}\varepsilon_{17,t-1} + 0.9716*h_{2,17,t-1}$
OMG	$h_{2,18,t} = 3.6995\text{e-}07 + 0.0138*\varepsilon_{2,t-1}\varepsilon_{18,t-1} + 0.9696*h_{2,18,t-1}$	$h_{2,18,t} = 2.6230\text{e-}07 + 0.0172*\varepsilon_{2,t-1}\varepsilon_{18,t-1} + 0.9750*h_{2,18,t-1}$
XMR	$h_{2,19,t} = 2.7592\text{e-}07 + 0.0153*\varepsilon_{2,t-1}\varepsilon_{19,t-1} + 0.9691*h_{2,19,t-1}$	$h_{2,19,t} = 2.2397\text{e-}07 + 0.0169*\varepsilon_{2,t-1}\varepsilon_{19,t-1} + 0.9752*h_{2,19,t-1}$
HT	$h_{2,20,t} = 1.5989\text{e-}07 + 0.0168*\varepsilon_{2,t-1}\varepsilon_{20,t-1} + 0.9714*h_{2,20,t-1}$	$h_{2,20,t} = 1.7902\text{e-}07 + 0.0187*\varepsilon_{2,t-1}\varepsilon_{20,t-1} + 0.9726*h_{2,20,t-1}$
ONT	$h_{2,21,t} = 3.6369\text{e-}07 + 0.0157*\varepsilon_{2,t-1}\varepsilon_{21,t-1} + 0.9693*h_{2,21,t-1}$	$h_{2,21,t} = 3.0064\text{e-}07 + 0.0163*\varepsilon_{2,t-1}\varepsilon_{21,t-1} + 0.9750*h_{2,21,t-1}$
VET	$h_{2,22,t} = 3.4112\text{e-}07 + 0.0183*\varepsilon_{2,t-1}\varepsilon_{22,t-1} + 0.9647*h_{2,22,t-1}$	$h_{2,22,t} = 5.1052\text{e-}07 + 0.0268*\varepsilon_{2,t-1}\varepsilon_{22,t-1} + 0.9605*h_{2,22,t-1}$
DOGE	$h_{2,23,t} = 2.1692\text{e-}07 + 0.0226*\varepsilon_{2,t-1}\varepsilon_{23,t-1} + 0.9617*h_{2,23,t-1}$	$h_{2,23,t} = 1.7823\text{e-}07 + 0.0218*\varepsilon_{2,t-1}\varepsilon_{23,t-1} + 0.9706*h_{2,23,t-1}$
BAT	$h_{2,24,t} = 3.5279\text{e-}07 + 0.0209*\varepsilon_{2,t-1}\varepsilon_{24,t-1} + 0.9610*h_{2,24,t-1}$	$h_{2,24,t} = 2.5748\text{e-}07 + 0.0181*\varepsilon_{2,t-1}\varepsilon_{24,t-1} + 0.9733*h_{2,24,t-1}$
WAVES	$h_{2,25,t} = 2.6195\text{e-}07 + 0.0216*\varepsilon_{2,t-1}\varepsilon_{25,t-1} + 0.9639*h_{2,25,t-1}$	$h_{2,25,t} = 2.1947\text{e-}07 + 0.0211*\varepsilon_{2,t-1}\varepsilon_{25,t-1} + 0.9718*h_{2,25,t-1}$
ABBC	$h_{2,26,t} = 9.8647\text{e-}08 + 0.0135*\varepsilon_{2,t-1}\varepsilon_{26,t-1} + 0.9788*h_{2,26,t-1}$	$h_{2,26,t} = 1.8632\text{e-}07 + 0.0250*\varepsilon_{2,t-1}\varepsilon_{26,t-1} + 0.9686*h_{2,26,t-1}$
XTZ	$h_{2,27,t} = 7.9466\text{e-}08 + 0.0111*\varepsilon_{2,t-1}\varepsilon_{27,t-1} + 0.9801*h_{2,27,t-1}$	$h_{2,27,t} = 2.7172\text{e-}07 + 0.0173*\varepsilon_{2,t-1}\varepsilon_{27,t-1} + 0.9757*h_{2,27,t-1}$
ZIL	$h_{2,28,t} = 4.2030\text{e-}07 + 0.0189*\varepsilon_{2,t-1}\varepsilon_{28,t-1} + 0.9613*h_{2,28,t-1}$	$h_{2,28,t} = 2.0382\text{e-}07 + 0.0187*\varepsilon_{2,t-1}\varepsilon_{28,t-1} + 0.9763*h_{2,28,t-1}$
ZRX	$h_{2,29,t} = 3.1183\text{e-}07 + 0.0193*\varepsilon_{2,t-1}\varepsilon_{29,t-1} + 0.9640*h_{2,29,t-1}$	$h_{2,29,t} = 2.9823\text{e-}07 + 0.0204*\varepsilon_{2,t-1}\varepsilon_{29,t-1} + 0.9706*h_{2,29,t-1}$
WETH	$h_{2,30,t} = 5.5568\text{e-}07 + 0.0264*\varepsilon_{2,t-1}\varepsilon_{30,t-1} + 0.9518*h_{2,30,t-1}$	$h_{2,30,t} = 3.5660\text{e-}07 + 0.0203*\varepsilon_{2,t-1}\varepsilon_{30,t-1} + 0.9729*h_{2,30,t-1}$
XEM	$h_{2,31,t} = 2.9837\text{e-}07 + 0.0175*\varepsilon_{2,t-1}\varepsilon_{31,t-1} + 0.9647*h_{2,31,t-1}$	$h_{2,31,t} = 3.0788\text{e-}07 + 0.0238*\varepsilon_{2,t-1}\varepsilon_{31,t-1} + 0.9661*h_{2,31,t-1}$
IOST	$h_{2,32,t} = 3.6585\text{e-}07 + 0.0151*\varepsilon_{2,t-1}\varepsilon_{32,t-1} + 0.9669*h_{2,32,t-1}$	$h_{2,32,t} = 2.8595\text{e-}07 + 0.0162*\varepsilon_{2,t-1}\varepsilon_{32,t-1} + 0.9749*h_{2,32,t-1}$

Note: The covariance specification is presented as $h_{i,j,t} = \widetilde{w}_{ij} + a_{ii}a_{jj}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta_{ii}\beta_{jj}h_{i,j,t-1}$.

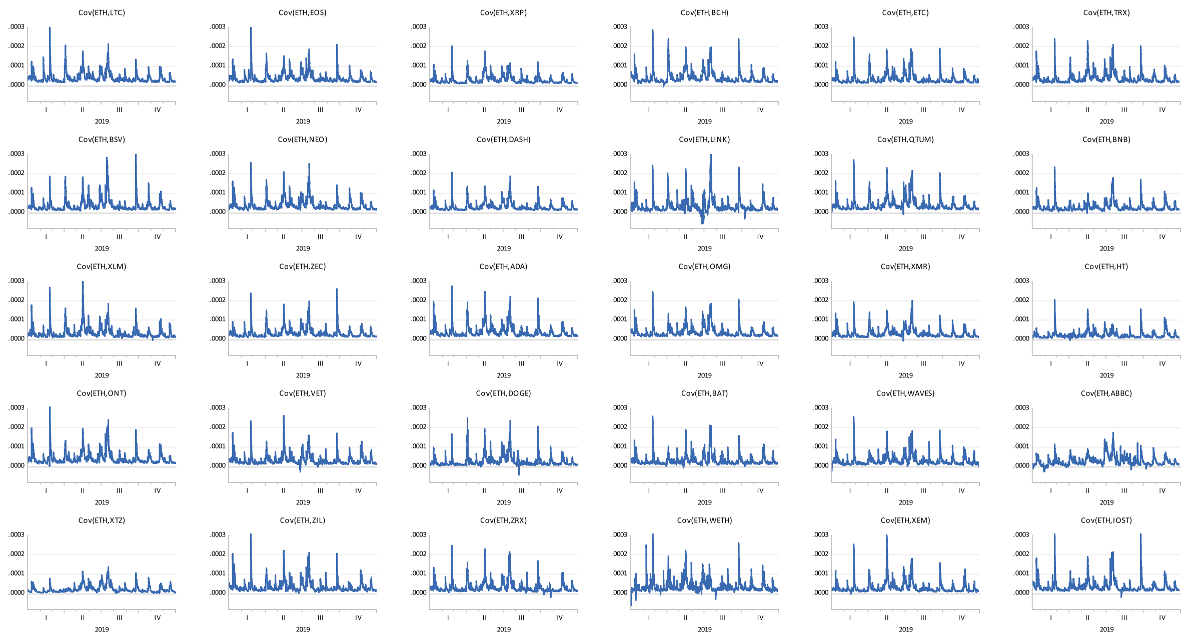


Fig. 11. Diagonal BEKK model conditional covariances of Ether with altcoins (pre-COVID period).

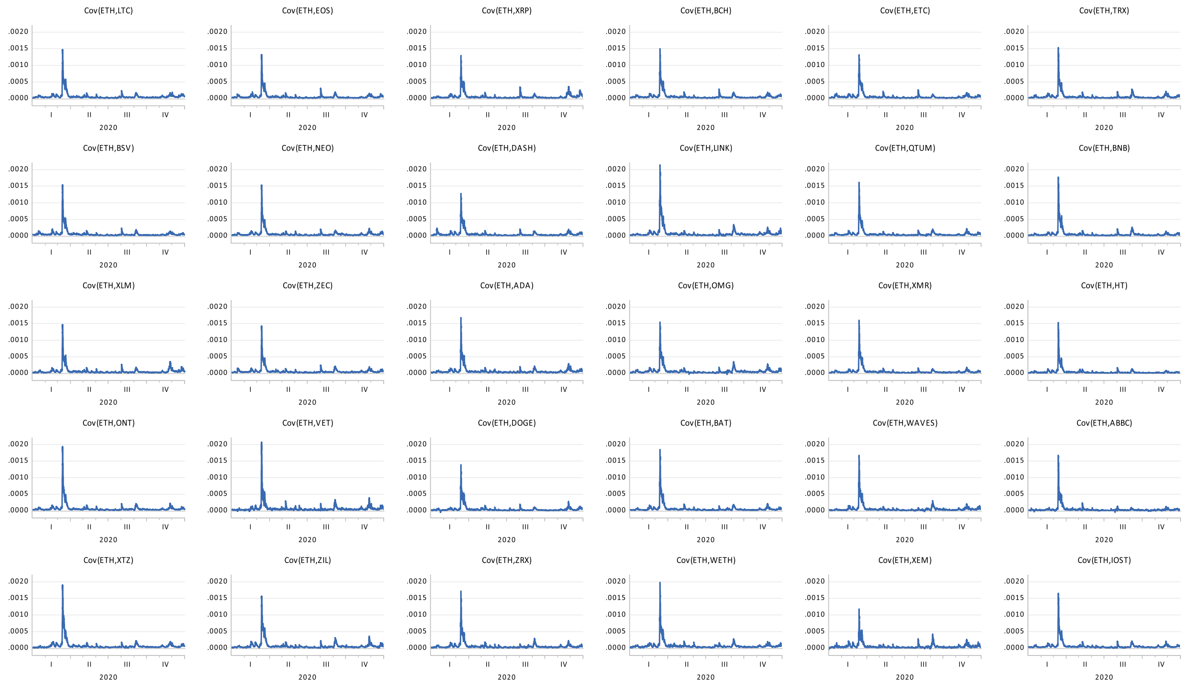


Fig. 12. Diagonal BEKK model conditional covariances of Ether with altcoins (COVID-19 period).

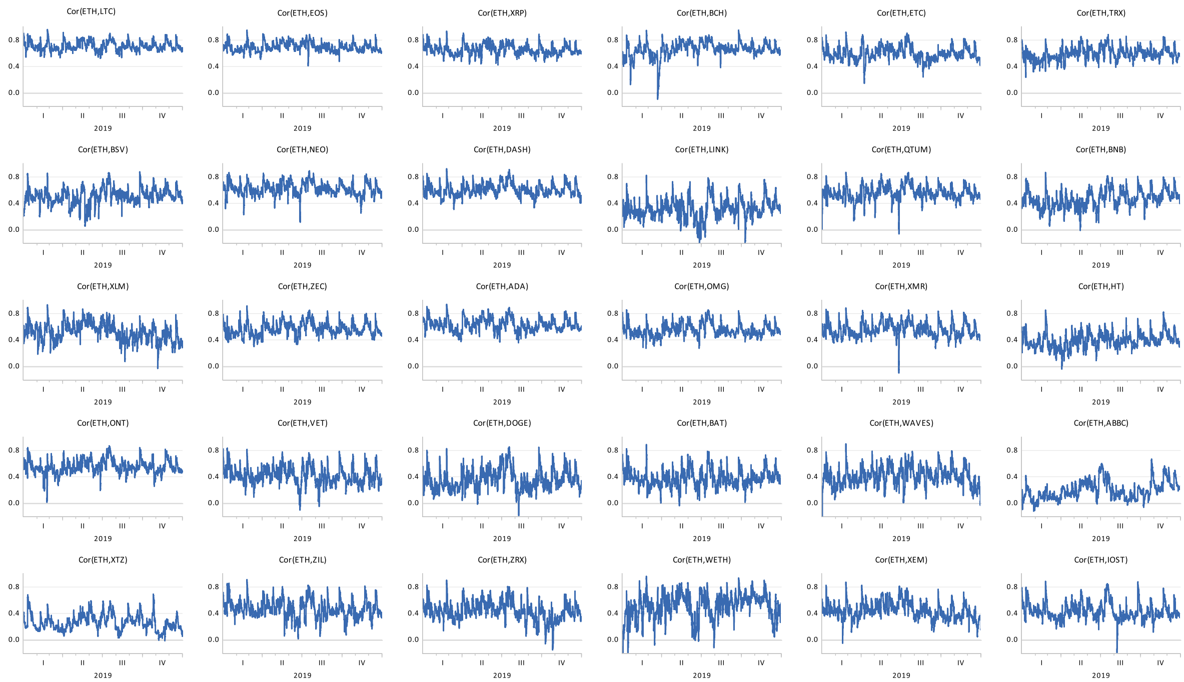


Fig. 13. Diagonal BEKK model conditional correlations of Ether with altcoins (pre-COVID period).

cryptocurrencies. However, in the pre-COVID period protocols have a larger average degree level than dApps in the PMFG, whereas dApps have a larger average degree level than protocols in the TMFG and vice versa for the COVID-19 period.

5. Conclusion

This paper analyses high-frequency co-movements and correlations between thirty-two most-tradable crypto assets in the pre-

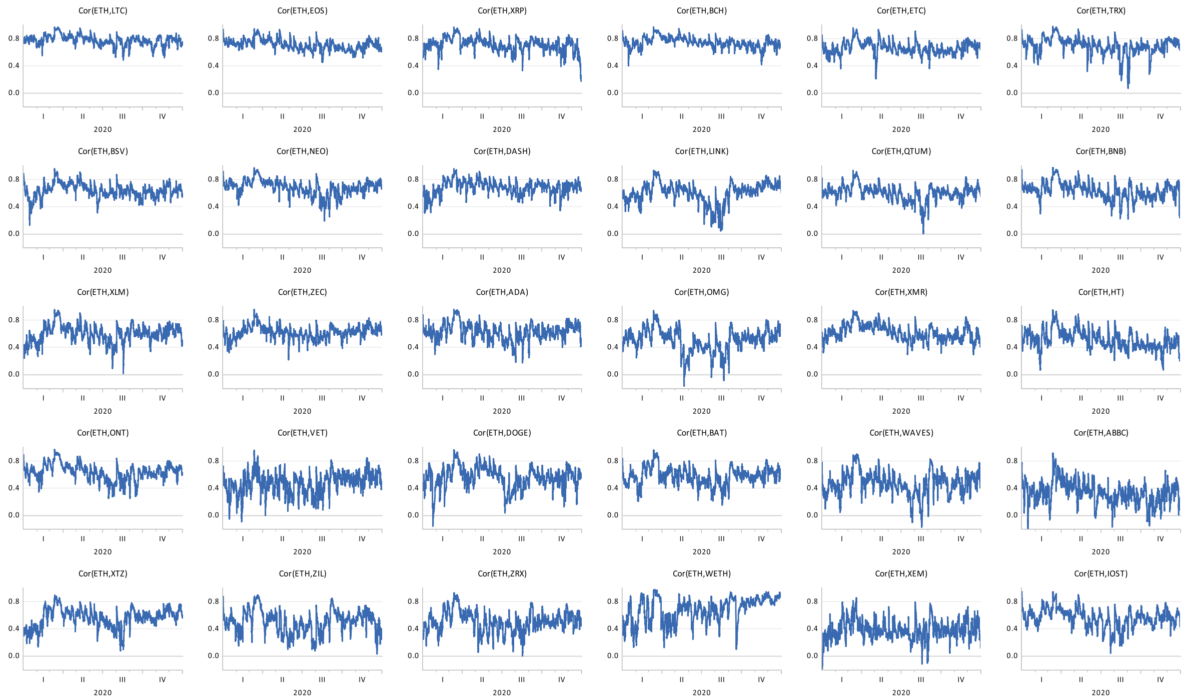


Fig. 14. Diagonal BEKK model conditional correlations of Ether with altcoins (COVID-19 period).

Table 10
Comparative analysis of unconditional and conditional correlations of Ether with altcoins.

	Unconditional correlations			Average conditional correlations		
	pre-COVID period	COVID-19 period	% difference	pre-COVID period	COVID-19 period	% difference
LTC	0.7872	0.8381	6.4660	0.7090	0.7731	9.0409
EOS	0.7737	0.7847	1.4217	0.6941	0.7082	2.0314
XRP	0.7186	0.6551	−8.8366	0.6536	0.7073	8.2160
BCH	0.7284	0.7974	9.4728	0.6597	0.7419	12.4602
ETC	0.6891	0.7235	4.9920	0.5958	0.6622	11.1447
TRX	0.6622	0.7436	12.2924	0.5941	0.6903	16.1926
BSV	0.5177	0.6479	25.1497	0.5079	0.6355	25.1231
NEO	0.7043	0.7591	7.7808	0.6205	0.6784	9.3312
DASH	0.7294	0.6786	−6.9646	0.6023	0.6784	12.6349
LINK	0.3202	0.7085	121.2680	0.3191	0.6009	88.3109
QTUM	0.6470	0.6969	7.7125	0.5550	0.6002	8.1441
BNB	0.5238	0.7607	45.2272	0.4663	0.6318	35.4922
XLM	0.6003	0.6710	11.7774	0.5169	0.5983	15.7477
ZEC	0.6718	0.7033	4.6889	0.5640	0.6190	9.7518
ADA	0.7369	0.7201	−2.2798	0.6320	0.6247	−1.1551
OMG	0.6800	0.5590	−17.7941	0.5524	0.5056	−8.4721
XMR	0.6934	0.7610	9.7491	0.5545	0.6170	11.2714
HT	0.4466	0.6557	46.8204	0.3904	0.5102	30.6865
ONT	0.6334	0.7469	17.9192	0.5549	0.6325	13.9845
VET	0.4750	0.5525	16.3158	0.4193	0.4698	12.0439
DOGE	0.3821	0.5333	39.5708	0.3562	0.5545	55.6710
BAT	0.4327	0.7019	62.2140	0.3766	0.5773	53.2926
WAVES	0.4568	0.5532	21.1033	0.4045	0.4683	15.7726
ABBC	0.1648	0.3829	132.3422	0.1954	0.3272	67.4514
XTZ	0.3444	0.6847	98.8095	0.2668	0.5599	109.8576
ZIL	0.5709	0.5879	2.9778	0.4684	0.4991	6.5542
ZRX	0.5319	0.5831	9.6259	0.4337	0.5033	16.0480
WETH	0.4363	0.6773	55.2372	0.5106	0.6795	33.0787
XEM	0.5416	0.4822	−10.9675	0.4439	0.3841	−13.4715
IOST	0.5470	0.6784	24.0219	0.4320	0.5614	29.9537

Table 11
T-test for the equality in the conditional correlations of Ether with altcoins in the two periods.

	pre-COVID period		COVID-19 period		t-statistic
	Mean	Variance	Mean	Variance	
LTC	0.7090	0.0048	0.7731	0.0057	−58.6420***
EOS	0.6941	0.0045	0.7082	0.0059	−12.9661***
XRP	0.6536	0.0062	0.7073	0.0109	−38.4072***
BCH	0.6597	0.0127	0.7419	0.0058	−56.5367***
ETC	0.5958	0.0105	0.6622	0.0084	−45.2770***
TRX	0.5941	0.0088	0.6903	0.0150	−58.3767***
BSV	0.5079	0.0140	0.6355	0.0105	−76.3744***
NEO	0.6205	0.0093	0.6784	0.0120	−37.1660***
DASH	0.6023	0.0090	0.6784	0.0109	−50.5390***
LINK	0.3191	0.0217	0.6009	0.0238	−123.7374***
QTUM	0.5550	0.0119	0.6002	0.0128	−26.9261***
BNB	0.4662	0.0174	0.6318	0.0146	−86.6088***
XLM	0.5169	0.0187	0.5983	0.0165	−40.6300***
ZEC	0.5640	0.0097	0.6190	0.0085	−38.2307***
ADA	0.6320	0.0091	0.6247	0.0147	4.3950***
OMG	0.5524	0.0090	0.5056	0.0276	22.9101***
XMR	0.5545	0.0121	0.6170	0.0131	−36.9333***
HT	0.3904	0.0129	0.5102	0.0185	−63.2128***
ONT	0.5549	0.0110	0.6325	0.0148	−45.2776***
VET	0.4193	0.0176	0.4698	0.0239	−23.1911***
DOGE	0.3562	0.0228	0.5545	0.0261	−83.9933***
BAT	0.3766	0.0159	0.5773	0.0163	−104.7918***
WAVES	0.4045	0.0201	0.4683	0.0294	−26.8373***
ABBC	0.1954	0.0192	0.3272	0.0252	−58.5734***
XTZ	0.2668	0.0140	0.5599	0.0193	−150.4914***
ZIL	0.4684	0.0178	0.4991	0.0270	−13.5873***
ZRX	0.4337	0.0193	0.5033	0.0222	−31.9971***
WETH	0.5106	0.0372	0.6795	0.0330	−59.6668***
XEM	0.4439	0.0153	0.3841	0.0194	30.0238***
IOST	0.4320	0.0162	0.5614	0.0185	−65.1079***

Notes: t-statistic for testing H_0: $\mu_{r_t}^{pre-COVIDperiod} - \mu_{r_t}^{COVID-19period} = 0$, against H_a: $\mu_{r_t}^{pre-COVIDperiod} - \mu_{r_t}^{COVID-19period} < 0$, assuming unequal variances. *** indicates statistical significance at the 1% level.

COVID and COVID-19 periods. We specifically examine the dominating role of Bitcoin in a rapidly evolving, dynamic, and highly integrated digital asset ecosystem. While our main results confirm the increased intraday linkages between the selected crypto assets during the COVID-19 period, this paper provides several novel results contributing to the rapidly growing cryptocurrency literature.

Using a very large sample of digital assets, accounting for 60% of the total cryptocurrency daily trading volume, we first categorised them based on their type, and then empirically demonstrated that, in contrast to the popular belief that Bitcoin is a single and dominant source of volatility in cryptocurrency markets, there is strong evidence suggesting that during the COVID-19 crisis period altcoins, and specifically Ether, became more influential in comparison to pre-pandemic times. In comparison to Bitcoin, Ethereum is a protocol that can be used as a foundation layer for creation of various decentralised applications, the purpose of which could exceed the money transfer. The Ethereum protocol has been used, for example, by recently popular Non-Fungible Tokens (NFTs) that attracted significant attention from investors. Thus, the more influential role of Ethereum after the COVID-19 outbreak can be explained by the 'DeFi boom' and the NFTs' popularity. Therefore, the inclusion of Ether in the investment portfolio after the COVID-19 outbreak can offer more long-term diversification benefits. Cryptocurrency investors should take into consideration the evolution of the digital asset ecosystem, specifically the versatility of the digital asset and scalability of the network to be more protected from unexpected crisis shocks and 'black swan' events in the future (e.g., Yarovaya et al., 2021).

Apart from high practical significance, these findings offer important theoretical contributions. While the majority of COVID-19 papers show financial contagion predominantly as a negative phenomenon that causes market crashes and financial distress (e.g., Davidovic, 2021; Iwanicz-Drozdowska et al., 2021), we provide important evidence of the '*positive contagion*' effect in cryptocurrency markets, i.e. from dApps to their underlying protocols and vice versa. Positive contagion in cryptocurrency markets enables investors to generate abnormal returns on crypto assets during periods of increased uncertainty, since increased returns in one category of digital assets will cause the increase in returns in other related categories. The findings reported in this paper suggest the importance of further theory development in the field of 'positive' financial contagion in cryptocurrency markets with strong emphasis on the heterogeneous characteristics of the various digital assets.

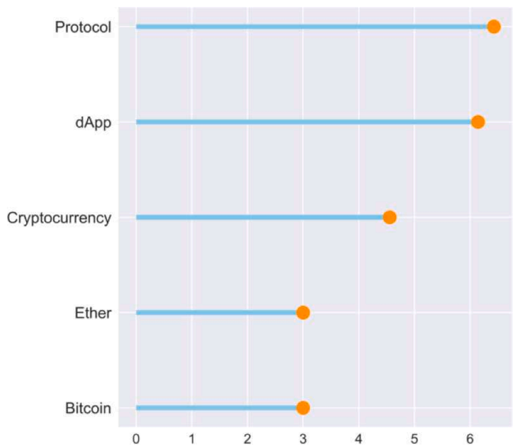
Our results further suggest that several new crypto assets (e.g., Iost and Wrapped Ether) became particularly popular during the COVID-19 pandemic period, a fact that can be explained not only by increased institutional interest in cryptocurrencies but also by improved accessibility of cryptocurrency markets among retail investors. Gamification of trading via online trading platforms, the impact of social distancing, as well as increased awareness of other crypto assets among retail investors might be the reasons why altcoins gained popularity specifically during the COVID-19 pandemic crisis.

Table 12
Average conditional covariances and conditional correlations in the two periods.

	Average conditional covariances			Average conditional correlations		
	pre-COVID period	COVID-19 period	% difference	pre-COVID period	COVID-19 period	% difference
BTC	1.1449	1.2910	12.7549%	0.4919	0.5588	13.6046%
ETH	0.2952	0.4953	67.7765%	0.4940	0.5810	17.6086%
LTC	0.3509	0.6097	73.7663%	0.4453	0.5572	25.1143%
EOS	0.3397	0.6183	81.9850%	0.4338	0.5186	19.5263%
XRP	0.3342	0.5767	72.5921%	0.4266	0.5227	22.5113%
BCH	0.2820	0.5939	110.6259%	0.4199	0.5415	28.9544%
ETC	0.3402	0.6191	81.9744%	0.3912	0.4995	27.6799%
TRX	0.3139	0.5975	90.3427%	0.3986	0.5249	31.7133%
BSV	0.3337	0.5886	76.3721%	0.3417	0.4645	35.9310%
NEO	0.3422	0.6074	77.5066%	0.4258	0.5241	23.1068%
DASH	0.3441	0.6167	79.2498%	0.4047	0.5220	28.9777%
LINK	0.3062	0.6210	102.8414%	0.2300	0.4592	99.6518%
QTUM	0.3676	0.6634	80.4382%	0.3846	0.4764	23.8429%
BNB	0.3392	0.6978	105.7142%	0.3237	0.4754	46.8888%
XLM	0.3348	0.6120	82.7820%	0.3607	0.4726	31.0111%
ZEC	0.3005	0.6122	103.7134%	0.3801	0.4774	25.6037%
ADA	0.3155	0.6324	100.4546%	0.4229	0.4891	15.6633%
OMG	0.3179	0.6276	97.4381%	0.3746	0.4031	7.6039%
XMR	0.3373	0.6728	99.4521%	0.3720	0.4681	25.8136%
HT	0.3280	0.6374	94.3117%	0.2713	0.3761	38.6199%
ONT	0.3217	0.6238	93.9162%	0.3874	0.5028	29.8062%
VET	0.3138	0.5987	90.8004%	0.3020	0.3819	26.4748%
DOGE	0.3117	0.6138	96.9250%	0.2501	0.4238	69.4496%
BAT	0.3374	0.6224	84.4745%	0.2663	0.4572	71.6868%
WAVES	0.3479	0.6181	77.6600%	0.2793	0.3616	29.4574%
ABBC	0.3291	0.6550	99.0163%	0.1288	0.2384	85.0426%
XTZ	0.5590	0.6396	14.4232%	0.1839	0.4372	137.7840%
ZIL	0.3292	0.6200	88.3555%	0.3359	0.3876	15.3740%
ZRX	0.3136	0.6521	107.9408%	0.3083	0.3908	26.7702%
WETH	0.3118	0.6277	101.2975%	0.2814	0.4153	47.5671%
XEM	0.3240	0.6027	86.0172%	0.3099	0.3023	−2.4385%
IOST	0.2984	0.6602	121.2360%	0.3119	0.4505	44.4333%

Notes: The average conditional covariances/correlations presented in this table were calculated as follows: For crypto asset $i, i = 1, \cdots, N$, the average conditional covariance ($h_{i,j,t}$) with all other crypto assets $j = 1, \cdots, N-1$, was calculated as $\frac{\sum_{j=1}^{N-1} \frac{\sum_{t=1}^{T} h_{i,j,t}}{T}}{N-1}$. The average conditional correlations ($r_{i,j,t}$) were calculated accordingly.

(a) PMFG - average degree, conditional correlation matrix, pre-COVID period



(b) PMFG - average degree, conditional correlation matrix, COVID-19 period

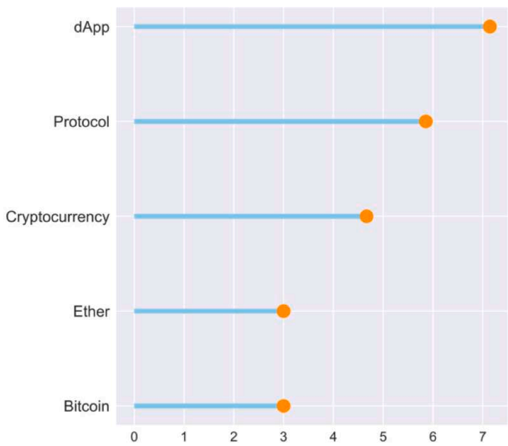


Fig. 15. Aggregated results of the PMFG analysis, with conditional correlation as distance matrices, in the pre-COVID and COVID-19 periods.

Table 13
The distribution of differences in the degree levels of crypto assets between the PMFG and TMFG.

Difference in degree level	pre-COVID period	COVID-19 period
−6	0	1
−5	1	0
−4	1	1
−3	0	1
−2	5	1
−1	4	6
0	10	13
1	4	4
2	4	2
3	1	0
4	2	2
5	0	1

Note: A negative difference implies a larger degree level of a node (crypto asset) in the TMFG, while a positive difference implies a larger degree level of a node (crypto asset) in the PMFG. For instance, there are five crypto assets in the first sub-period with a larger degree level in the TMFG than in the PMFG by 2.

Table 14
Average degree level of each crypto asset class category – comparison of results between the PMFG and TMFG.

Crypto asset category	pre-COVID period		COVID-19 period	
	PMFG	TMFG	PMFG	TMFG
Bitcoin	3	3	3	3
Ether	3	3	3	3
Cryptocurrency	4.56	4.56	4.67	4.11
Protocol	6.43	6.29	5.86	6.79
dApp	6.14	6.43	7.14	6.00

Our findings also imply that crypto assets which are categorised as dApps and protocols are becoming increasingly attractive to investors, while pure cryptocurrencies other than Bitcoin are becoming less impactful. One of the explanations is that protocols and dApps have always been predicted to take over the blockchain ecosystem, since they offer many more functionalities and business applications than pure cryptocurrencies, and less energy consumption in comparison to mineable cryptocurrencies. Therefore, their technological potential is one of the important factors influencing investors' decisions. We show that the COVID-19 pandemic became an important period in decentralised finance history, attracting more investors to this new market. Similar to the ICO-hype period in 2016–2017, increased interest in dApps during the COVID-19 period could become one of the additional causes of a new bubble-like behaviour that was observed at the beginning of 2021 in cryptocurrency markets. The increased interest around dApps and protocols might be also related to the introduction of the Polkadot and Cosmos blockchain platforms into the market during the 2019–2020 period. Specifically, Polkadot and Cosmos are platforms which enable a direct exchange of tokens between individual platforms, i.e., cross-blockchain transfers, attracting investors who would no longer need to use an intermediary cryptocurrency to trade such crypto assets between each other. Therefore, our research can be expanded by further including Polkadot and Cosmos into the sample and expanding the dataset to cover the most recent period of the cryptocurrency market's explosivity in 2021.

Finally, we conclude that it is too early to tell that Bitcoin lost its influential power. Our results also provide some evidence that when compared with other digital asset classes, such as protocols and dApps, Bitcoin still has strong power to influence the prices of other types of crypto assets. Therefore, while for investors and portfolio managers it is important to account for uncertainty beyond Bitcoin and keep an eye on the most recent developments in the digital asset ecosystem, our evidence from intraday data suggests that Bitcoin's volatility is still a strong indicator of cryptocurrency price movements.

From the policy makers' perspective, the evidence of the detected shifts of influential power in the interconnected digital assets' ecosystem also suggests that financial regulators need to assess the risk to financial stability imposed by other digital assets, such as Ether, Stellar, and Cardano protocols, and avoid using Bitcoin's volatility as a proxy of the risk of the entire cryptocurrency market in their risk modelling. Further research is needed in this area, in particular on the impact on systemic risks (e.g., So et al., 2021) and on alternative uncertainty measures for cryptocurrency markets (Lucey et al., 2022). New blockchains have become increasingly important and connected with other digital assets and they should therefore be taken into account in both academic and policy research.

CRediT authorship contribution statement

Paraskevi Katsiampa: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Larisa Yarovaya:** Conceptualization, Investigation, Validation, Writing – original draft, Writing – review & editing, Supervision. **Damian Zięba:** Conceptualization, Methodology, Software, Investigation, Data curation, Writing – original draft, Visualization.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intfin.2022.101578.

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