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Transitions in the cryptocurrency market during the COVID-19 pandemic: A network analysis

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Abstract

In this letter, we identify the transitions of the cryptocurrency market during the pandemic by means of a network analysis. This method allows us to observe that COVID-19 significantly affected cryptocurrencies during a short period of financial panic, from 12 March 2020 to 1 April 2020, giving rise to a remarkable increase of market synchronisation. However, since April 2020, the cryptocurrency market progressively recovered its initial state, since the strong synchronisation, observed as a consequence of COVID-19, continuously disappeared. Therefore, our analysis highlights different market phases, which can be related to some of the phenomena reported in the existing literature.

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1. Introduction

On 31 December 2019, China reported a cluster of what was thought to be viral pneumonia in Wuhan, Hubei Province. This isolated virus, called coronavirus disease 2019 (COVID-19), spread quickly around the world due to social interactions during close contact. As a consequence, the World Health Organization (WHO) declared the outbreak a Public Health Emergency of International Concern on 30 January 2020 and a pandemic on 11 March. Due to this unprecedented situation, scholars have analysed the COVID-19 pandemic from different perspectives, even though most of the studies have focused on its effects on human health (Bai et al., 2020; Zheng et al., 2020) and its impact on the economy (McKibbin and Fernando, 2020). In relation to the latter, Goodell (2020) stated that the pandemic caused enormous economic costs by affecting banking, governments and financial markets. In this context, economic studies assessed how financial assets behave when faced with the current pandemic and possible future resurgences of the virus (see Yarovaya et al. (2020a) for a recent review). For instance, Al-Awadhi et al. (2020) observed that both the daily growth in total confirmed cases and in total cases of death, caused by COVID-19, had significant negative effects on stock returns in the Hang Seng Index and Shanghai Stock Exchange Composite Index. Baker et al. (2020) reported that the U.S. stock market reacted much more forcefully to COVID-19 than to previous pandemics, due to the government measures. In the same line, Zaremba et al. (2020) also contended that non-pharmaceutical interventions significantly increased equity market volatility during the COVID-19 pandemic. However, interestingly enough, Mazur et al. (2020) demonstrated that healthcare, food, natural gas, and software sectors in U.S. performed abnormally well, generating high returns, while those firms connected with crude petroleum, real estate, entertainment and hospitality sectors suffered from the negative effects falling significantly.

In addition to the international stock markets, academics also examined the effects of COVID-19 on the cryptocurrency market. In particular, scholars have analysed the performance of digital currencies during the pandemic (i) to understand the financial effects of the COVID-19 pandemic on different financial theories, like efficiency or herding, and (ii) to shed some light on the hedge properties of cryptocurrencies.¹

In relation to the former point, Yarovaya et al. (2020b) analysed herding behaviour with the four highest-traded cryptocurrencies (Bitcoin, Ethereum, Litecoin and Ripple) contending that COVID-19 does not significantly amplify herding in the cryptocurrency markets. In a similar vein, Susana et al. (2020) did not find herding when analysing the market upswing and downswing during the pandemic. Connected with the efficiency literature, Lahmiri and Bekiros (2020) explored the evolution of the informational efficiency in 45 cryptocurrency markets and 16 international stock markets before and during the COVID-19 pandemic. They stated that, from an informational efficiency perspective, cryptocurrencies are found to be more affected by the pandemic than international stock markets. This result is supported by Naeem et al. (2021), who observed that the COVID-19 outbreak adversely affects the efficiency of the

¹These topics have been widely analysed in the existing literature (see, e.g. Corbet et al., 2019 and Kalyvas et al., 2020).

largest four cryptocurrencies.

In relation to the latter point, which is related to the hedge properties of cryptocurrencies, authors found different results. On the one hand, [Conlon and McGee \(2020a\)](#) observed that Bitcoin is not a safe haven, since it substantially increases portfolio downside risk when held alongside the S&P 500. [Corbet et al. \(2020b\)](#) reported that Bitcoin does not act as a hedge given that it amplifies the financial contagion. [Goodell and Goutte \(2020\)](#) found a strong negative co-movement between Bitcoin prices and COVID-19 deaths by means of the coherence wavelet approach. [Conlon et al. \(2020\)](#) showed that Bitcoin and Ethereum does not act as a safe haven for different international equity markets. On the other hand, [Iqbal et al. \(2020\)](#) contended that most of the 10 largest cryptocurrencies are able to absorb the small shocks of COVID-19; and specifically, Bitcoin, ADA, CRO and Ethereum also resist against extreme market-turbulence conditions, acting as a hedge. [Caferra and Vidal-Tomás \(2020\)](#) stated that both cryptocurrency and stock prices fell steeply in March 2020. However, unlike stock markets, cryptocurrencies promptly rebounded. Finally, [Corbet et al. \(2020a\)](#) reported that the 22 largest digital currencies could be used as a safe-haven, even though cryptocurrency returns are found to be significantly affected by negative sentiment connected with COVID-19.

As can be observed, most of the literature connected with cryptocurrencies has focused on (i) Bitcoin or a small group of cryptocurrencies and (ii) have analysed different cryptocurrency properties, in relation to other markets, without considering the internal dynamical evolution of the cryptocurrency market as a whole.² Compared to the existing studies, in this paper we contribute to the cryptocurrency literature by examining the market transitions, with a network approach, and considering 69 long-lived cryptocurrencies. This analysis allows us to examine the evolution of the cryptocurrency system when faced with the COVID-19 pandemic. Interestingly, we observe that the cryptocurrency market was significantly affected by COVID-19 during a short period of financial panic from 12 March 2020 to 1 April 2020. Afterwards, the market progressively recovered to its initial state. Indeed, we observe that the effect of COVID-19 disappeared completely after July. We consider that this study is relevant for investors and scholars since it underlines the transitions of the cryptocurrency market as a system during the pandemic, highlighting the periods in which the market is more/less affected by COVID-19. These market transitions could be related to some of the existing findings observed in the literature, regarding efficiency, herding and diversification. In other words, the results observed by scholars could be connected with the market phase in which the cryptocurrency market is analysed.

2. Data

For the purpose of this letter, we use cryptocurrency prices from the Brave New Coin database ([BNC, 2020](#)) in daily frequency. More specifically, we analyse 69 long-lived cryptocurrencies³ between 1 August 2019 and 1

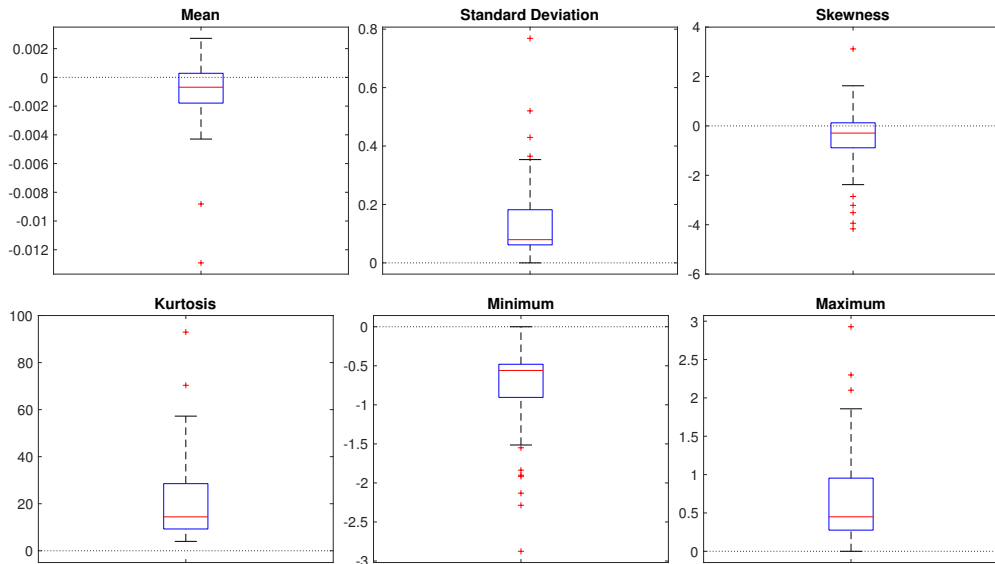
²Despite the fact that [Lahmiri and Bekiros \(2020\)](#) analysed 45 cryptocurrencies, they used a “static” approach, exclusively considering two periods (before and during the COVID-19 pandemic) in their analysis.

³These cryptocurrencies were trading each day from 1 January 2016 to 1 August 2020.

August 2020. Thus, it is possible to analyse how the COVID-19 pandemic affected the network topology of relevant cryptocurrencies before and after 31 December 2019, when China confirmed the existence of the COVID-19 outbreak. Moreover, for the empirical analysis, we compute returns for each cryptocurrency as the log price difference.⁴

In Fig. (1), we show the descriptive statistics of all the cryptocurrencies by means of box plots. As expected, we observe a volatile market with a high standard deviation and kurtosis (Corbet et al., 2019). Interestingly, the average return and skewness are negative, with minima and maxima whose values are three orders of magnitude higher than the average, as a consequence of the COVID-19 pandemic. Indeed, we find on 12 March 2020 the minimum return for 37 cryptocurrencies (i.e. 54% out of our sample). On this day, all the financial markets suffered from a negative shock, probably due to the insufficient measures taken by the European Central Bank (ECB) in response to COVID-19, which was officially declared a pandemic by the WHO on 11 March 2020 (Inman, 2020).

Figure. 1: Descriptive statistics of the 69 cryptocurrencies at our disposal.



⁴The list of the different cryptocurrencies is provided as supplementary material.

3. Methodology

As stated in the introduction, we use a network analysis to study the dynamical evolution of the cryptocurrency market as a whole.

3.1. Network analysis

A network is defined as a group of nodes connected by links or edges. In the cryptocurrency market, we consider a network in which the nodes are individual cryptocurrencies and a link between the two nodes denotes that some similarity between them exists. In particular, this similarity is reflected by the weight of each link, indicating the strength of a given relationship. This weight is traditionally represented by the Pearson’s correlation coefficient (ρ_{ij}) between the returns of every possible pair of cryptocurrencies i and j .

In order to compute a suitable network, we use the winner-takes-all approach following [Chi et al. \(2010\)](#), [Heiberger \(2014\)](#) and [Moghadam et al. \(2019\)](#); i.e. we only consider those cryptocurrencies with a return correlation higher than a given connection criterion, z . The rest of the connections are not taken into account, thus they do not appear in the network. More specifically, we define the threshold between two cryptocurrencies as $\rho_{ij} > z$, in which $z = 0.5$. With this choice, we implement a reasonable threshold that allows us to properly observe the dynamics without losing relevant information. In fact, as contended by [Heiberger \(2014\)](#), the winner-takes-all approach is not worse than other reduction techniques (like the multiple spanning tree (MST) ([Mantegna, 1999](#)) and the planar maximally filtered graph (PMFG) ([Tumminello et al., 2005](#))) given that “no essential information about the networks is lost” ([Heiberger, 2014](#)).⁵ Moreover, we use $z = 0.5$ in order to include strong cryptocurrency correlations, excluding only those correlations $\rho_{ij} < 0.5$.⁶ Therefore, the network includes the relevant connections of the cryptocurrency market taking into account that, graphically, the higher the correlation the shorter the distance between two digital currencies. Consequently, following the network literature (see e.g. [Zieba et al., 2019](#)), the network reports the distance between two nodes as a function of the correlation, which is defined as $d(i, j) = \sqrt{2(1 - \rho_{ij})}$. Within this framework, two close cryptocurrencies are two correlated cryptocurrencies.

Finally, to capture the dynamics of the network, we use a dynamic correlation network, which includes a rolling time window of 15 days; i.e. the network is computed for each 15 days of our sample. Hence, we calculate the network, Pearson’s correlation coefficients and distances for the first 15 observations (returns), then we delete the first return and add the following return of the time series. This procedure continues until the end of data.

⁵The MST ([Mantegna, 1999](#)) and PMFG ([Tumminello et al., 2005](#)) are strong reduction techniques that only represent *the most* relevant links of a given network. For instance, the MST decreases the complexity of financial market relationships by only selecting the sub-network that connects all the nodes (cryptocurrencies) with the *minimum* possible total edge weight (i.e. the *minimum* distance or the highest correlation among cryptocurrencies). Consequently, it removes connections, even with high correlation, if the cryptocurrencies are already within the reduced graph. This procedure, then, reduces drastically the network, which does not allow us to analyse all the dynamics of the cryptocurrency market. In contrast, the winner-takes-all approach is not a powerful reduction technique since it does not remove so many connections, thus it provides us with more information.

⁶For robustness purposes, we show in the Appendix, Sec. (6), the results with $z = 0.1$, $z = 0.3$ and $z = 0.7$.

3.1.1. Network measures

In order to examine the network topology, we use validated measures that allow us to systematically characterise the network and the nodes within them. In particular, we analyse the degree centrality and betweenness centrality.⁷ These measures provide us with information regarding the centrality of the network, which is a broad concept employed to detect and determine the most relevant nodes in a given network. (Golbeck, 2013; Gómez et al., 2013; Moghadam et al., 2019). On the one hand, the degree centrality is the simplest measure, since it is based on the number of edges connecting to each node; thus, the higher the degree, the more central the node is. This measure is calculated as follows:

$$C_D(i) = \sum_{j=1}^n \alpha(j, i) \quad (1)$$

where n is the number of cryptocurrencies in the network, and $\alpha(j, i)$ is equal to 1 if the two nodes (j, i) are connected to each other, and 0 otherwise. On the other hand, the betweenness centrality type measures how often each node i appears on the shortest path between two nodes (s, j) in the graph. It is used to quantify the control of an asset on information flow in the network. Hence, in our case, the cryptocurrency with the highest score is considered as a relevant cryptocurrency in terms of its role in transmitting the information among cryptocurrencies. In other words, this cryptocurrency acts as a “bridge” that connects different parts of the network. Mathematically, the betweenness centrality for the node i is calculated as follows:

$$C_B(i) = \sum_{s, j \neq i} \frac{n_{sj}(i)}{N_{sj}}, \quad (2)$$

where $n_{sj}(i)$ is the number of shortest paths from s to j that pass through node i , and N_{sj} is the total number of shortest paths from s to j .

3.1.2. Financial context

From the financial perspective, the network analysis allows us to identify the market transitions over time, underlining those periods in which there is a remarkable synchronisation of all the cryptocurrencies. To do so, we analyse the centrality scores, given that high/low values of the degree/betweenness centrality are related to periods characterised by a remarkable co-movement of the cryptocurrencies.⁸ Indeed, the existence of a highly interconnected environment is traditionally related to financial crises (Nobi et al., 2014; Kenett et al., 2012), given that investors’ response in the presence of losses and down markets is more extreme than their reaction to gain and up markets (Tversky and Kahneman, 1986).⁹ In this economic situation, the market is described by a fully-

⁷For the sake of space, we focus on these two measures. However, we observe the same results with closeness and eigenvector centrality (material upon request).

⁸High values of degree centrality are related to periods in which most of the cryptocurrencies are connected. During these periods, the betweenness centrality is low, given that there are not relevant cryptocurrencies acting as “bridges”, i.e. if all the market is interconnected, the presence or absence of a given asset is not relevant for the network.

⁹This investor’s response is also observed in the cryptocurrency market (see Feng et al., 2017 and Vidal-Tomás and Ibañez, 2018).

connected network, in which most of the assets are interconnected, since during down-turns, the number of links (degree centrality) is higher than the historical (or more recent) average (Raddant and Kenett, 2017). Nevertheless, once the co-movement and financial panic start to decrease, the market dynamics will move towards a new state in which the centrality values are similar to the historical ones, consequently the fully-connected network will disappear in favour of a core-periphery¹⁰ network. Therefore, within this framework and in the context of the pandemic, the centrality scores can be used to identify the particular periods in which the market is more/less affected by COVID-19, given the cryptocurrency correlations. Interestingly, an strong asset synchronisation can be related to different theories such as herding (Christie and Huang, 1995), efficiency (Fama, 1965) and diversification (Abanomey and Mathur, 1999), which could shed some light on the recent findings regarding COVID-19 and cryptocurrencies. First, a high interconnectedness of the network is considered as a sign of herding in the market, since during these periods all the cryptocurrencies co-move towards the market consensus (Christie and Huang, 1995; Chang et al., 2000).¹¹ As highlighted by Christie and Huang (1995), “herds are characterised by individuals who suppress their own beliefs and base their investment decisions solely on the collective actions of the market”. Second, the existence of this kind of co-movement could give rise to relevant implications for asset pricing models since the synchronisation of the market is in disagreement with the Efficient Market Hypothesis (Fama, 1965), i.e. the market is not efficient if investors ignore their own beliefs in order to imitate other investors’ actions (Banerjee, 1992). Finally, the analysis of the correlation among different asset returns has traditionally been used to define different investment diversification strategies due to the benefits of using uncorrelated financial instruments (Abanomey and Mathur, 1999). Thus, traders focused on cryptocurrency portfolios could not take advantage of any diversification strategy during periods in which there is a high correlation in the market, i.e. high/low values of the degree/betweenness centrality.

4. Empirical results

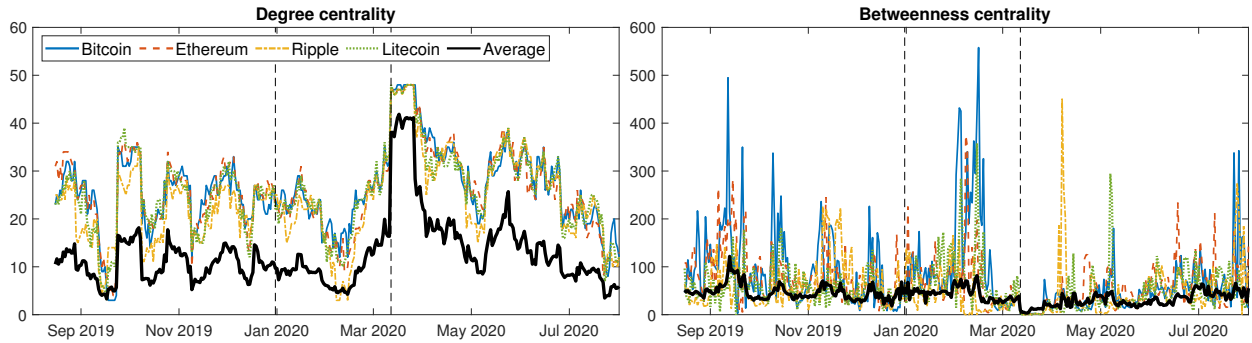
We report the main results of this study in Fig. (2), Fig. (3), Fig. (4) and Fig. (5). On the one hand, in Fig. (2), we report the average degree and betweenness centrality along with the centrality scores of the largest cryptocurrencies in the market: Bitcoin, Ethereum, Ripple and Litecoin. In particular, the average centrality is computed as the mean of the individual degree and betweenness centrality scores of all the cryptocurrencies at each time, t . Moreover, we underline with dashed lines two relevant dates in the COVID-19 timeline: 31 December 2019, when China confirmed the existence of the COVID-19 outbreak, and 12 March 2020, when the market suffered from a negative shock, giving rise to the most negative day of the sample. On the other hand, in Fig. (4) and Fig. (5), we show the network of the cryptocurrency market represented by the degree and betweenness centrality,

¹⁰A core-periphery network is characterised by a core of central cryptocurrencies that are connected to some isolated cryptocurrencies. This is the most common network observed in the financial markets.

¹¹More specifically, the cross-sectional standard deviation (CSSD) approach, proposed by Christie and Huang (1995), and the cross-sectional absolute deviation (CSAD) method, proposed by Chang et al. (2000), are based on the synchronisation of the assets towards the market consensus. Some studies in the cryptocurrency market using this methodology are da Gama Silva et al. (2019) and Vidal-Tomás et al. (2019).

respectively. In these figures, the bigger the node, the higher its centrality. Moreover, we also show a shadowed area that indicates the particular period in which the network and average centrality are calculated. As previously mentioned, these areas include 15 days. For the sake of space, we report four particular periods, even though a complete video of the evolution of the network is provided as supplementary material. More specifically, we report significant periods in the COVID-19 timeline: from 17 December 2019 to 31 December 2019, from 26 February 2020 to 11 March 2020 and from 27 February 2020 to 12 March 2020. The first period includes the day on which China announced the existence of the COVID-19 outbreak (31 December 2020), the second period includes the day on which the WHO officially declared the COVID-19 outbreak a pandemic (11 March 2020) and the third period includes the day on which the ECB announced measures to tackle the COVID-19 pandemic, giving rise to a relevant down-market (12 March 2020). Finally, we report the last window of the sample (from 18 July 2020 to 1 August 2020) in which we show the current state of the market.

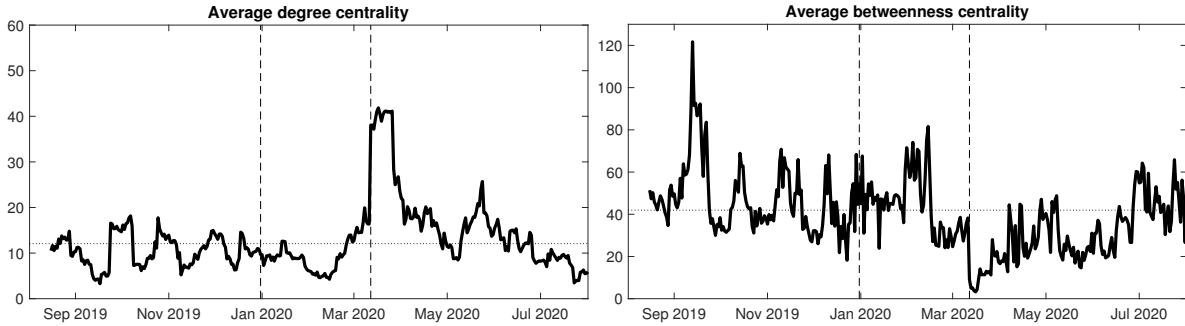
Figure. 2: Degree and betweenness centrality of Bitcoin, Ethereum, Ripple and Litecoin, along with the average centrality of the market. Vertical dashed lines refer to 31 December, when China confirmed the existence of the COVID-19 outbreak, and 12 March, when the market suffered from a negative shock, giving rise to the most negative day of the sample.



As can be observed in Fig. (2), the cryptocurrency network did not change as a consequence of the first cases of the COVID-19 outbreak on 31 December. Indeed, the average degree and betweenness centrality, as long as the centrality of the largest cryptocurrencies, showed similar behaviour compared to the last months of 2019. We only observe a remarkable change on 12 March 2020 when most of the cryptocurrencies were interconnected. In fact, the average degree centrality computed from 27 February 2020 to 12 March 2020 was around 40; i.e. each cryptocurrency was connected on average to 40 different cryptocurrencies. On the other hand, the average betweenness centrality obtained its minimum value during this period given that there were not relevant cryptocurrencies acting as “bridges”. In other words, all the cryptocurrencies were irrelevant since most of them were connected, thus there were multiple “bridges” in the network. For instance, Bitcoin, Ethereum, Litecoin and Ripple were not relevant for the network given their low betweenness scores. Afterwards, we observe that the market progressively recovered to its initial state, even though it was more interconnected, as can be observed with the lower betweenness centrality and higher degree centrality. Finally, we identify a new market phase after July 2020, given the low values of the centrality scores, in which the effect of COVID-19 completely disappeared. For robustness purposes, we report in

Fig. (3) the average centrality measures including a horizontal dotted line to show the average centrality calculated before 12 March 2020. With this dotted line, we can observe that, indeed, the market completely recovered its initial state, since the average centrality measures are more similar to those observed before 12 March.

Figure. 3: Average degree and betweenness centrality of the cryptocurrency market. Vertical dashed lines refer to 31 December, when China confirmed the existence of the COVID-19 outbreak, and 12 March, when the market suffered from a negative shock giving rise to the most negative day of the sample. Horizontal dotted lines refer to the average centrality computed before 12 March 2020.



To support these results, we observe in Fig. (4) and Fig. (5) that the cryptocurrency network is characterised by a core-periphery network over time. In fact, this topology is observed even on 31 December 2019, when China confirmed the COVID-19 outbreak, and on 11 March 2020, when the WHO announced that the COVID-19 outbreak was a pandemic. As stated before, the network only changed on 12 March 2020, giving rise to a fully-connected network when most of the cryptocurrencies were interconnected. Since then, the network has again tended towards a core-periphery network, with the effect of COVID-19 disappearing continuously. Therefore, we can confirm that the cryptocurrency market was significantly affected by the COVID-19 pandemic during a short period of financial panic in the market, although it recovered relatively quickly to its initial state. Given this analysis, we distinguish four different scenarios: (i) from 1 August 2019 to 11 March 2020, the market was characterised by a core-periphery network; (ii) from 12 March 2020 to 1 April 2020, the financial panic was spread among cryptocurrencies; (iii) from 2 April 2020 to 30 June 2020, the market progressively recovered the initial state of the network even though it was more interconnected; and (iv) since 1 July 2020, we can state that the effect of COVID-19 completely disappeared; i.e. the centrality was similar to that reported before the negative shock on 12 March.^{12,13}

From the financial perspective, the market transitions observed with the network analysis allow us to explain and support different results of the existing literature. First, as previously mentioned, we observe that the strongest effect of COVID-19 on the cryptocurrency market is only found from 12 March 2020 to 1 April 2020, given the extreme co-movement of the market. This fact could explain that Yarovaya et al. (2020b) and Susana et al. (2020)

¹²The last day is approximate for the second and third period; i.e. 1 April 2020 and 30 June 2020.

¹³There are not significant differences even when selecting alternative thresholds (see Sec. (6)). With $z = 0.1$ and $z = 0.3$, the dynamics of the centrality measures is almost identical. With $z = 0.7$, the centrality measures fluctuate more since the network only includes the strongest correlations. Indeed, the average centrality measures returns faster to the average centrality computed before 12 March. However, we must take care with this threshold since many connections are deleted from the network.

did not detect herding phenomenon during the down-market, given that the former only analysed this phenomenon from 1 January 2019 to 13 March 2020 while the latter used a static methodology by means of the cross-sectional standard deviation approach. Second, in terms of efficiency, our study supports the results observed by [Naeem et al. \(2021\)](#) since they contended that, despite the initial increase of inefficiency in the cryptocurrency market, the largest cryptocurrencies became more efficient at the end of March 2020, which is in line with the decrease of market synchronization in our study since 1 April 2020. Third, the down-market in the cryptocurrency market seems to finish sooner than in the traditional stock markets. Indeed, we observe that the synchronisation generated by the COVID-19 crash decreases on 1 April 2020, which is in line with [Caferra and Vidal-Tomás \(2020\)](#). Compared to the permanent bear phase of the stock markets, they only detected a bear phase in the Bitcoin market from 9 March to 19 March, with the subsequent bull market since the end of March.¹⁴ Moreover, the market transition since April 2020 could explain that the initial papers focused on COVID-19 ([Conlon and McGee, 2020a](#), [Corbet et al., 2020b](#), [Goodell and Goutte, 2020](#) and [Conlon et al., 2020](#)), which used sample periods generally until March 2020, found that cryptocurrencies could not be used as a safe haven. In contrast, recent papers ([Iqbal et al., 2020](#); [Caferra and Vidal-Tomás, 2020](#)), which employed longer sample periods, observed that cryptocurrencies could be use, indeed, as a hedge. Finally, in terms of investment strategies, our study also allows traders, who focused on cryptocurrency portfolios, to identify those periods in which diversification strategies can be used due to the absence of correlations. Indeed, our results are in line with [Omanović et al. \(2020\)](#), who observed a poor performance of cryptocurrency portfolios in March 2020, but a fast recovery with positive results since April 2020.

Given all the results reported in this paper, on the one hand, we underline the use of dynamical methodologies since they allow scholars to examine the dynamical evolution of the market, identifying phenomena that may last a short period of time. Indeed, the presence of a strong market synchronisation from 12 March 2020 to 1 April 2020 could give rise to biased results if scholars (i) employ static methodologies to analyse different cryptocurrencies features or (ii) employ too short/long sample periods. On the other hand, we state that the cryptocurrency market is becoming more mature given its fast recovery after the initial shock generated by COVID-19 in March 2020. This fact is in line with other scholars, who observed the decrease of gamblers transacting Bitcoin ([Conlon and McGee, 2020b](#)) and the decrease of illegal activity, as a percentage of total Bitcoin activity, ([Foley et al., 2019](#)). In other words, there are more investors than noise traders, who provide more liquidity to the cryptocurrency market guaranteeing fast market transitions.

¹⁴According to [Caferra and Vidal-Tomás \(2020\)](#), the main bear phase started, indeed, on 12 March 2020.

Figure. 4: Network of the cryptocurrency market, in terms of degree centrality, along with the average degree centrality during four particular periods: (i) from 17 December 2019 to 31 December 2019, (ii) from 26 February 2020 to 11 March 2020, (iii) from 27 February 2020 to 12 March 2020 and (iv) from 18 July 2020 to 1 August 2020. Vertical dashed lines refer to 31 December 2019 and 12 March 2020.

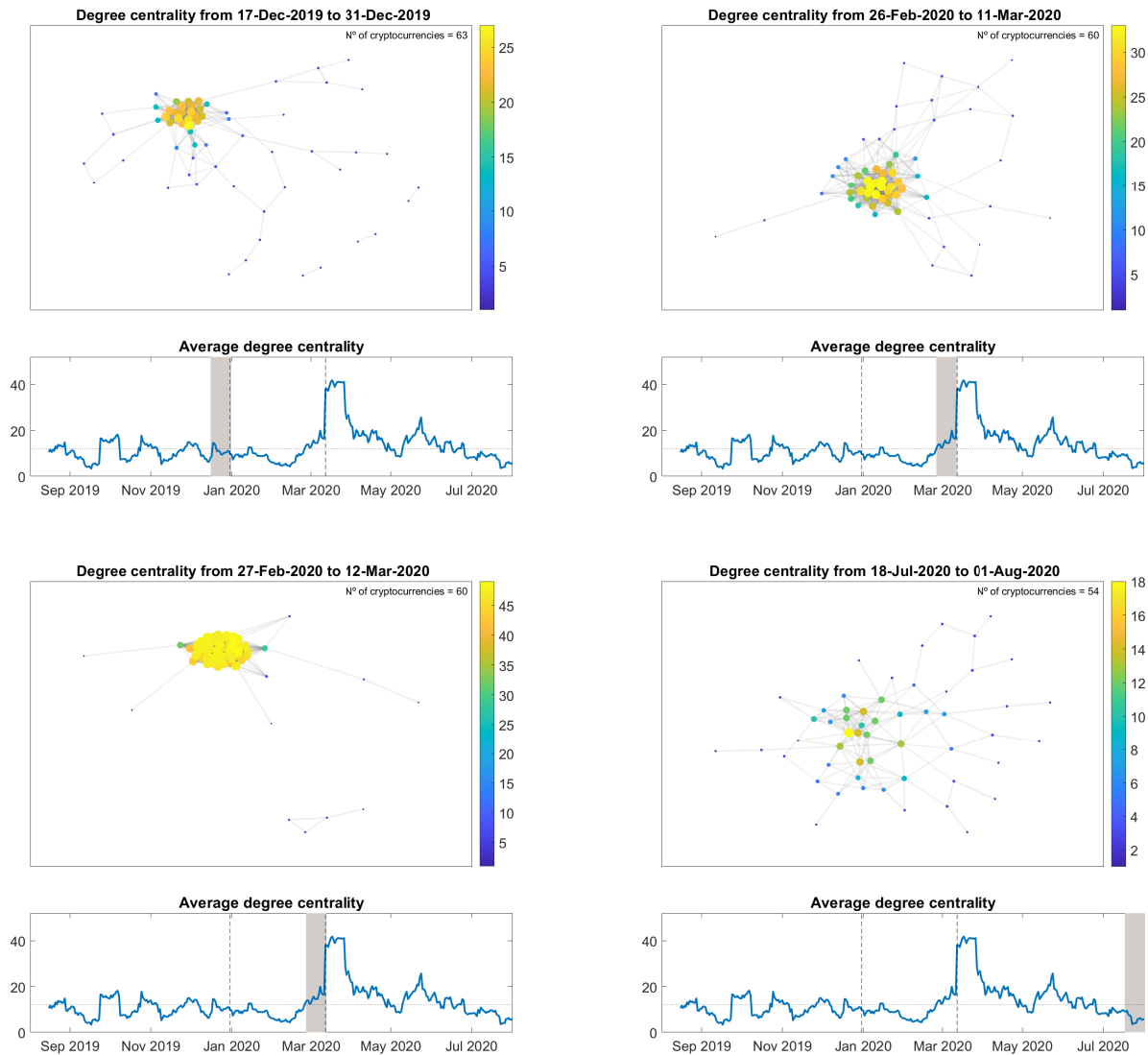
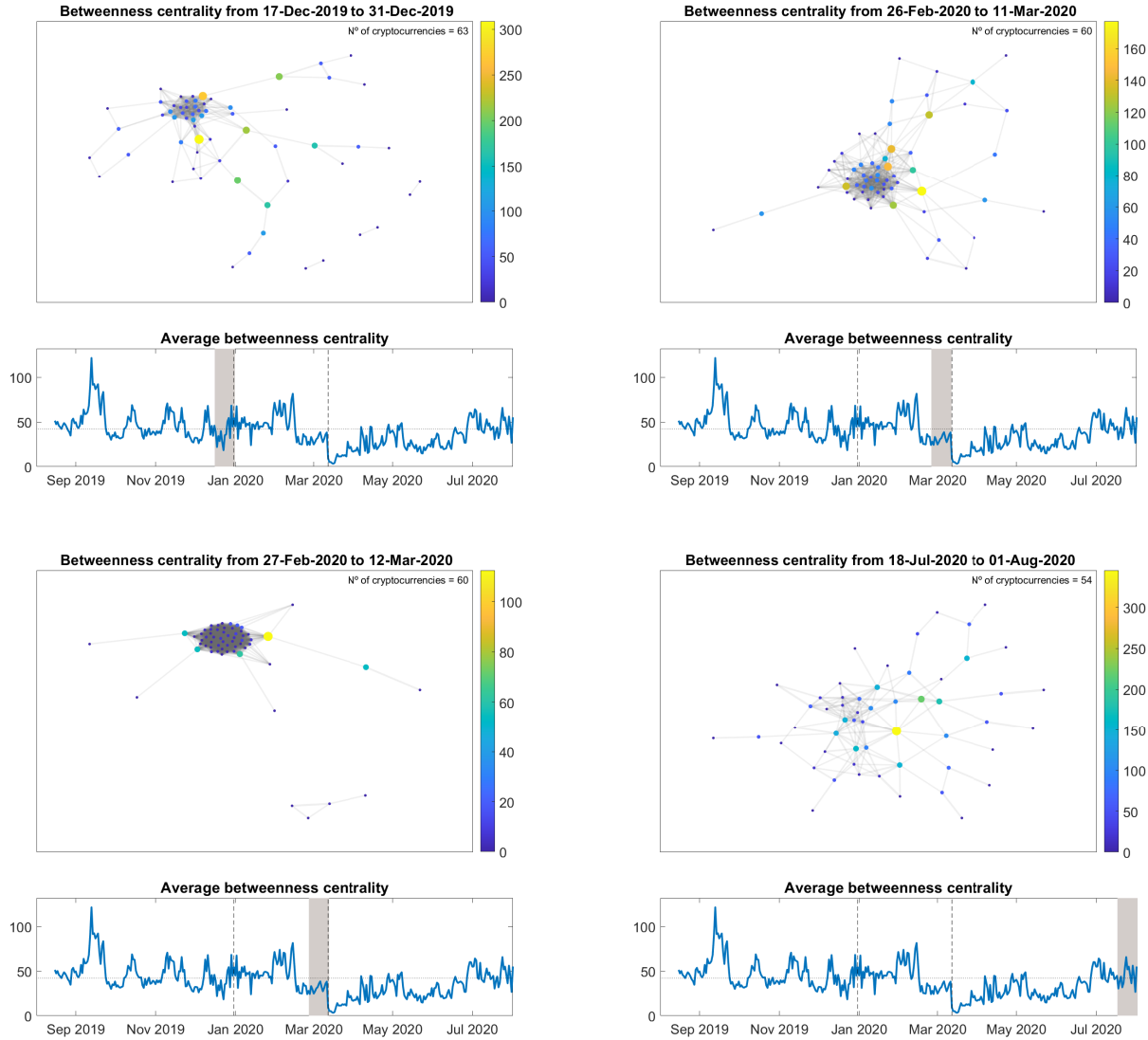


Figure 5: Network of the cryptocurrency market, in terms of betweenness centrality, along with the average betweenness centrality during four particular periods: (i) from 17 December 2019 to 31 December 2019, (ii) from 26 February 2020 to 11 March 2020, (iii) from 27 February 2020 to 12 March 2020 and (iv) from 18 July 2020 to 1 August 2020. Vertical dashed lines refer to 31 December 2020 and 12 March 2020.



5. Conclusion

In this letter, we analyse the evolution of the cryptocurrency network during the COVID-19 pandemic. Our results show that the cryptocurrency network did not change significantly due to (i) the emergence of the COVID-19 outbreak on 31 December 2019, or (ii) the declaration by the WHO that the COVID-19 outbreak was a pandemic. However, the topology of the network changed on 12 March 2020, possibly due to the financial panic spread among all the markets as a consequence of the insufficient measures taken by the ECB to reduce the impact of COVID-19. Since then, the market progressively recovered its initial state. This result is relevant for scholars and investors, given that some of the existing findings in the literature, such as the existence of herding, efficiency and diversification

benefits, could be related to particular market phases. Therefore, in the future research, scholars should consider dynamical methodologies instead of the static ones in order to analyse the effects of the pandemic.

6. Appendix

Figure. 6: Degree and betweenness centrality of Bitcoin, Ethereum, Ripple and Litecoin, along with the average centrality of the market. Vertical dashed lines refer to 31 December, when China confirmed the existence of the COVID-19 outbreak, and 12 March, when the market suffered from a negative shock giving rise to the most negative day of the sample. Horizontal dotted lines refer to the average centrality computed before 12 March 2020. Centrality measures are computed with $z = 0.1$.

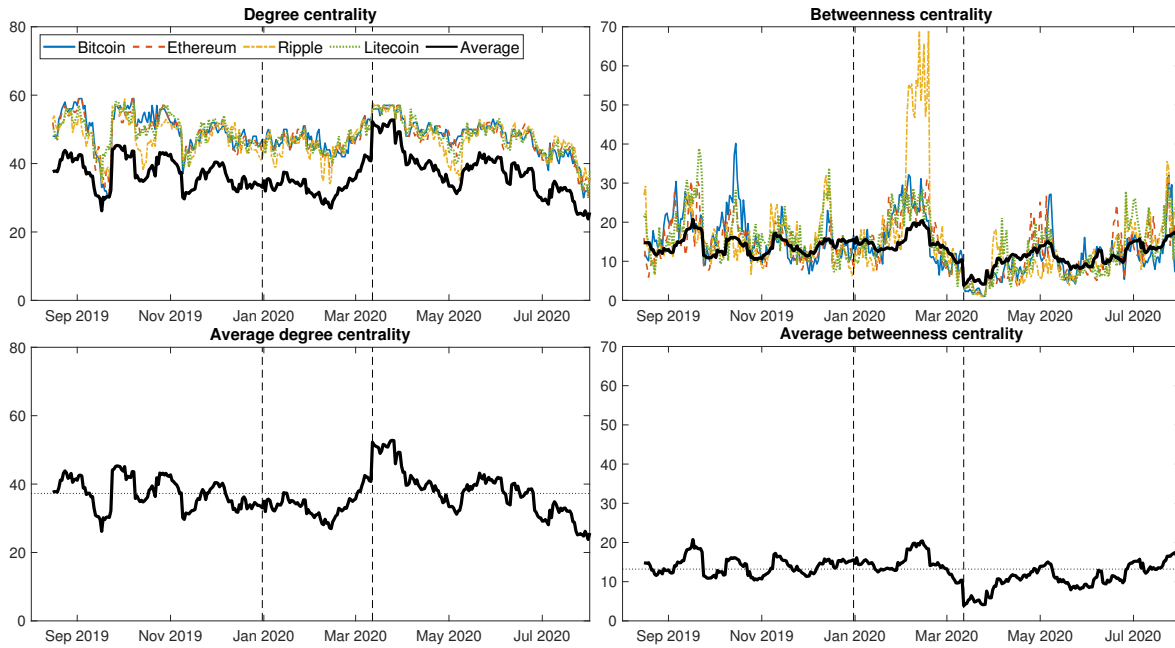


Figure. 7: Degree and betweenness centrality of Bitcoin, Ethereum, Ripple and Litecoin, along with the average centrality of the market. Vertical dashed lines refer to 31 December, when China confirmed the existence of the COVID-19 outbreak, and 12 March, when the market suffered from a negative shock giving rise to the most negative day of the sample. Horizontal dotted lines refer to the average centrality computed before 12 March 2020. Centrality measures are computed with $z = 0.3$.

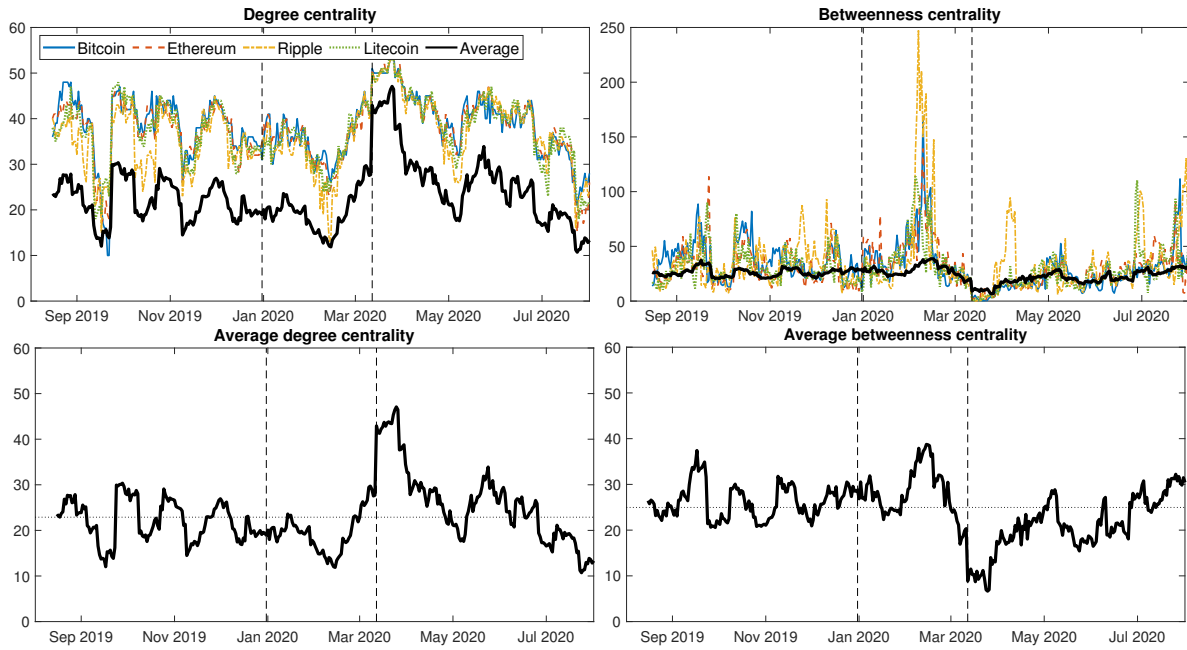
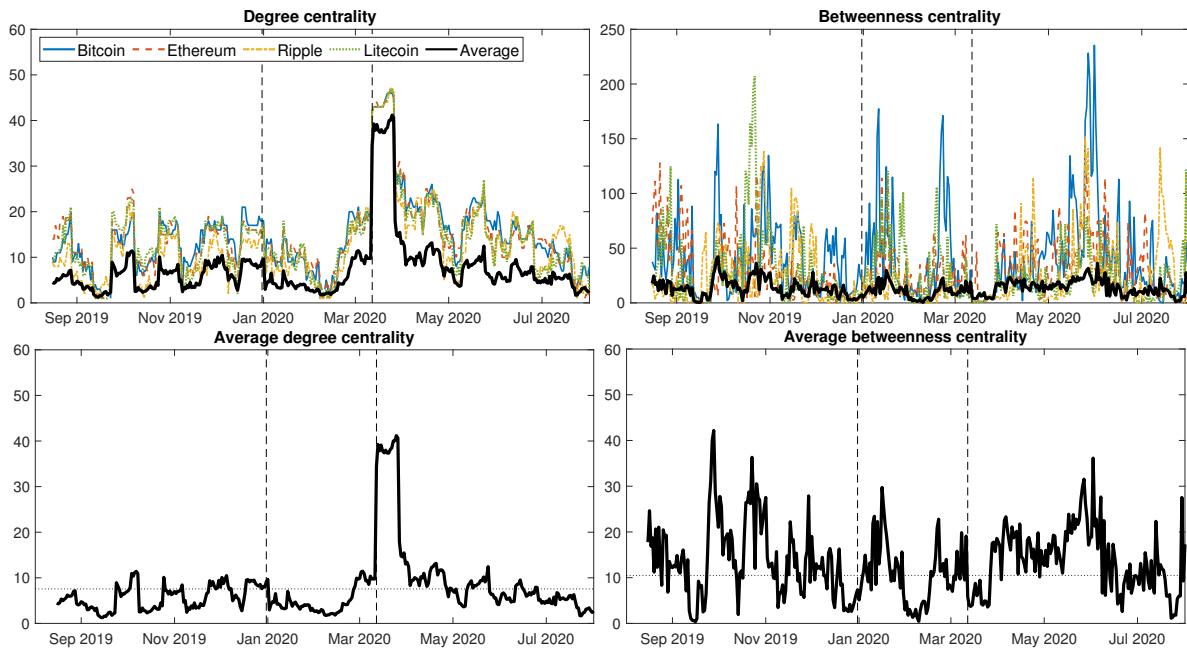


Figure. 8: Degree and betweenness centrality of Bitcoin, Ethereum, Ripple and Litecoin, along with the average centrality of the market. Vertical dashed lines refer to 31 December, when China confirmed the existence of the COVID-19 outbreak, and 12 March, when the market suffered from a negative shock giving rise to the most negative day of the sample. Horizontal dotted lines refer to the average centrality computed before 12 March 2020. Centrality measures are computed with $z = 0.7$.



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