

Article

Impact of the COVID-19 Pandemic on Cryptocurrency Markets: A DCCA Analysis

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Abstract: Extraordinary events, regardless of their financial or non-financial nature, are a great challenge for financial stability. This study examines the impact of one such occurrence—the COVID-19 pandemic—on cryptocurrency markets. A detrended cross-correlation analysis was performed to evaluate how the links between 16 cryptocurrencies were changed by this event. Cross-correlation coefficients that were calculated before and after the onset of the pandemic were compared, and the statistical significance of their variation was assessed. The analysis results show that the markets of the assessed cryptocurrencies became more integrated. There is also evidence to suggest that the pandemic crisis promoted contagion, mainly across short timescales (with a few exceptions of non-contagion across long timescales). We conclude that, in spite of the distinct characteristics of cryptocurrencies, those in our sample offered no protection against the financial turbulence provoked by the COVID-19 pandemic, and thus, our study provided yet another example of ‘correlations breakdown’ in times of crisis.

Keywords: contagion; COVID-19; cryptocurrencies; detrended cross-correlation analysis; detrended cross-correlation analysis correlation coefficient; integration



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1. Introduction

The Bitcoin (BTC), created in 2008 by Satoshi Nakamoto, was the first cryptocurrency. Thousands have been launched since then, promoting the astonishing growth of cryptocurrency markets in terms of capitalization, negotiation volumes, and prices [1–3]. Cryptocurrencies are a relevant set of global financial assets [4], attracting investors’ interest due to their distinctive features (e.g., blockchain technology, decentralization, scarcity, high returns, low correlations with traditional assets, and susceptibility to speculative bubbles). Inter alia, the attention of academics and policymakers has also been attracted by these markets’ potential instability and contagion risks [5–7]. Several studies focusing on cryptocurrencies have assessed herding behavior [8], co-explosivity [9], contagions [10], interdependence [11], co-movements [12], information flows, and links with other financial assets [13–15].

Globalization has promoted the interdependence of financial markets and institutions [16], thus enhancing the probability of financial contagions, especially in periods of turmoil. Both financial and non-financial shocks may promote financial contagions, and the risks posed by episodes such as natural disasters and pandemics are an emerging line of research [17,18]. The COVID-19 pandemic is one such distressing phenomenon. It has impacted financial and real markets across the world, provoking a range of effects that often elicit comparison with the effects of the global financial crisis of 2008 [19,20]. The pandemic impacted daily market returns around the globe, froze economic activity,

spiked uncertainty, endangered global financial stability [21,22], reduced income, disrupted transportation, services, and manufacturing industries, raised unemployment, and affected other major economic variables [23,24]. However, such an extreme event provides an opportunity to study return spillovers among cryptocurrencies during highly uncertain and stressful periods. The links established in cryptocurrency markets during these phases are of special interest to investors and portfolio managers as they are directly related to return and volatility spillovers (i.e., contagions), and are relevant for risk management and portfolio diversification strategies [3].

The literature contains several different methodologies to assess financial contagions. Distinct crisis contexts have also been assessed (see [25]). To ensure conceptual and methodological coherence, various contagion definitions have been adopted (for example, [26–28]). In this study, we follow the precedent set by [26], which defines contagion as “a significant increase in cross-market linkages after a shock to one country (or group of countries)” [26] (p. 2223). In light of such a definition, a contagion would be considered a significant increase in correlation levels between cryptocurrencies due to the COVID-19 pandemic. On the contrary, if in a given cut-off moment, no significant increase in correlations is detected, there is no contagion (although there may be interdependence). In this study, we considered 31 December 2019 as the cut-off moment, based on the date when the World Health Organization was notified about the first cases of the disease, which made the information about COVID-19 publicly available for investors (see, for instance, [29–33]).

Several researchers have analyzed interdependence, dynamic linkages, comovements, and risk connectedness among major cryptocurrencies (e.g., [1,3,7,11,12], among others). Most of these studies are limited to a relatively small number of cryptocurrencies, usually the three or four with the highest market capitalization (where BTC is always included—see, for example, [34–38]). Evaluations are also often focused on the relationships between each cryptocurrency and BTC. Here, we try to improve knowledge of the behavior of cryptocurrency markets by using a larger set of 16 cryptocurrencies (doubling the number analyzed in [33]) in our evaluation of integration and contagions in cryptocurrency markets in the context of the COVID-19 pandemic.

To detect and measure cross-correlations, contagions, and efficiency in various stock markets, previous studies have used detrended cross-correlation analysis (DCCA) and DCCA, together with detrended fluctuation analysis (DFA) (e.g., [39–41]). We followed this methodological approach and estimated the DCCA correlation coefficient (ρ_{DCCA}) and its variation $\Delta\rho_{DCCA}$ (our measure of contagion) before and after 31 December 2019. The adopted approach allows the identification of possible non-linearities among variables, which are not accounted for when estimating simpler linear correlation coefficients. All possible pairs of cryptocurrencies in our sample were assessed, with the objective of providing more information about these markets’ complex dynamics.

Our study expands upon the existing literature in four ways. First, it focuses on a real shock that has severely affected financial markets [42] and that has challenged risk and management activities [20]. Second, as we analyzed both periods before and after the beginning of the COVID-19 pandemic, we provide new evidence concerning cryptocurrency markets’ behavior when the global financial system is disturbed by a real extreme shock. Third, it provides evidence of integration and contagions occurring between cryptocurrencies emanating from a health crisis rather than a financial one. Fourth, it employs a methodology that not only accounts for nonlinearities, but also allows for an assessment of a contagion across different timescales; thus, it produces information on its short- and long-run impacts, which is relevant because the effects across shorter and longer timescales may differ.

The remainder of the paper is organized as follows. Section 2 presents a brief literature review, and it provides recent empirical evidence of contagions in cryptocurrency markets. In Section 3, we present both the data and methodology, with results shown and discussed in Section 4, and Section 5 concludes.

2. Brief Literature Review

In this section, we briefly review the most relevant literature for our assessment (i.e., that examine co-movements between cryptocurrency markets, and between them and other financial markets).

The level of financial integration is of great relevance in international finance as it impacts, for example, diversification strategies, risk management, and the design of regulation. Integration has been enhanced by financial deregulation and liberalization, and also by technological progress [43]. One relevant sign of increasing market integration is the rising correlations across them (see, among others, [44]). Given its potential positive and negative real effects (for example, regarding positive effects, enhanced economic growth and welfare; conversely, regarding negative effects, increased risk of contagions), it is relevant to assess how individual financial markets relate to each other.

Cryptocurrencies have been considered a relevant part of the global financial market [4] and are increasingly included in investors' portfolios. It is thus important to analyze the co-movements between cryptocurrencies, as well as those between the cryptocurrency markets and other markets. One interesting feature that distinguishes the study of cryptocurrencies from those of other assets is that, given the former's short history, observing the structural organizational process of markets from their inception is possible.

A vast amount of the literature examines links between cryptocurrencies. Such studies include, for example, Granger causality tests, GARCH-based models, wavelets, and cointegration analyses. Before the outbreak of the COVID-19 pandemic, several features of the cryptocurrency markets' behavior were explored (e.g., interdependence, dynamic linkages, or co-movements). However, the analyses were performed using samples containing a small number of cryptocurrencies and using BTC as a benchmark. For example [10], using DCCA, based on a sample between July 2016 and May 2019, analyzed the evidence that a contagion from BTC had transferred to the other considered cryptocurrencies. Except for the USDT, the authors found evidence of a contagion being present in all the cryptocurrencies analyzed. Although Ref. [45] used a different approach by making use of copula functions, it found similar results. Using coherence and cross-wavelet transform techniques, Ref. [46] studied the connection between BTC and five other major cryptocurrencies, identifying co-movements in the time–frequency space, with the main relationships occurring between BTC and Dash, Monero (XMR), Ripple (XRP), a lagged relationship with Ethereum (ETH), and out-of-phase movements with Litecoin (LTC). Ref. [47] considered five leading and liquid cryptocurrencies, using a sample from 2016 to 2018, and it investigated the dynamics of their multiscale interdependence. The authors identified high levels of dependence on a daily frequency scale, and a contagion with its origins in XRP and ETH.

The spillovers of returns and/or volatilities between cryptocurrencies were evaluated *inter alia* by [7,48–53]. According to [45], BTC was the dominant contributor to return and volatility spillovers, contrary to [49], which found tight and time-varying volatility spillovers, but not with BTC as the leading contributor. Shared leadership between the BTC and LTC was also identified by [50], with ETH as the main net receiver. This evidence was corroborated by [51], which also highlighted the relevant links between these cryptocurrencies and various others. Conversely, Ref. [7] concluded that BTC, EHT, and LTC are the main net transmitters of volatility spillovers, with the short-term risk spillovers being stronger (in comparison to the medium- and long-term ones). These authors also found evidence of larger negative spillovers than positive ones, thus contradicting [52]. Although they identified ETH and XRP as the main receivers of negative-return shocks, it was also possible to make conclusions regarding very weak positive-return spillovers for Dash and ETH. Higher market capitalization cryptocurrencies exhibited leadership in terms of volatility spillover. Refs. [53,54] found evidence of frequent structural breaks, which were more relevant for larger cryptocurrencies, and small cryptocurrencies' exhibited volatility spillover leadership. The diversity of these results justifies the interest in further and deeper assessments.

As the COVID-19 pandemic spread, it affected stock markets worldwide, thus justifying the assessment of its contagion effects on other financial markets. The pandemic is a shock with no financial origin; this contrasts with, for example, the US subprime crisis of 2007/2008 or the Euro area sovereign debt crisis of 2010/2011. However, this non-financial disturbance caused turmoil in financial markets [55], increased uncertainty, and panicked investors [56], with significant price falls in several markets. Both financial and real markets have suffered the consequences of the pandemic [57,58], and for the first time in their short life, cryptocurrency markets were also impacted by the global shock [59].

Several studies assessed the effects of the COVID-19 pandemic on the cryptocurrency markets (see [60–66], among others). Results have identified significant changes in co-movement patterns and in correlations during the pandemic period. Moreover, they also showed the more influential role of altcoins during the crisis period compared with pre-pandemic times, changes in the structure of the cryptocurrency networks, and the intensification of the information flows between cryptocurrencies which simultaneously occurred with the abrupt fall in stock markets; this could warn of the possibility of contagions, and thus, increases in systematic risk.

The relationships between cryptocurrencies with several conventional assets, such as currencies, stock markets, or even commodities, were also analyzed during the pandemic (e.g., [20,61,67]), with mixed results. It is possible to find evidence of high symmetric dependence between cryptocurrencies during normal market conditions and an asymmetric one in bearish and bullish market conditions, negative dependence between cryptocurrencies and gold, thus indicating possible diversification opportunities for these assets during the pandemic, a low positive dependence between cryptocurrencies and gold under normal market conditions, low dynamic conditional correlations with other financial assets in stable periods, and weak or negative volatility dynamics before the pandemic, which became positive during the health crisis for the most assessed assets.

Evidence is also mixed regarding cryptocurrencies' hedge and safe haven properties. Although the results in [20] indicate that gold and cryptocurrencies can be used for hedge or diversification purposes across all timescales, Refs. [20,30,35,36], for example, concluded that BTC does not act as a hedge in periods of financial turmoil (such as the COVID-19 period). On the other hand, Ref. [37] suggests that BTC is a safe haven investment.

When analyzing the impact of the pandemic using multiscale cross-correlations among the cryptocurrency markets and several other assets, Refs. [68,69] estimated the generalized DCCA coefficient. Although they did not find significant cross-correlations in 2018 and 2019 between cryptocurrencies and other assets, this changed in 2020, when the cryptocurrency markets appeared to have become more connected with other financial markets. Ref. [69] also concluded that during the turbulent periods of the COVID-19 pandemic, cryptocurrencies were strongly cross-correlated, although the higher levels of cross-correlation were registered with other assets (the latter were, however, less independent among themselves). As the pandemic became a more normal feature of everyday life, cross-correlations between cryptocurrencies and other markets tended to decrease.

The effect of the pandemic on connectedness, returns, and volatility spillovers between cryptocurrencies was also analyzed (e.g., [21,68–73]). These studies provide evidence of several spillovers in both regimes, but also structural changes in spillovers in late 2018 and early 2020. There were also stronger cross-correlations between cryptocurrency markets during the COVID-19 pandemic. Results suggest that cryptocurrencies acted as net receivers and transmitters of shocks during the COVID-19 pandemic, and that this event enhanced the spillovers and increased the integration of cryptocurrency markets.

The dynamic properties of cryptocurrency markets are still not fully identified and understood [69]. One of the reasons for this is that most past research focused almost exclusively on BTC, or at most, on the four or five most important cryptocurrencies [74]. Samples of the main cryptocurrencies were used in most studies that focused on contagion, interdependence, or integration in cryptocurrency markets (e.g., [75]). Most of these studies evaluated the relationships between those cryptocurrencies and BTC. The other possible

links between the other cryptocurrencies have been explored less. To fill these gaps in the literature, we considered a sample of 16 cryptocurrencies and evaluated relationships between all possible pairs.

The COVID-19 pandemic is an interesting subject for an analysis of contagion. Its outbreak can be clearly identified, in contrast with other well-researched sources of financial contagion, for which there were various probable turmoil catalysts. For instance, there were various underlying causes for the 2007–08 subprime crisis, thus making it difficult to pinpoint exactly what provoked the crisis, and it created some noise in the assessment of contagion. Furthermore, most analyses evaluate financial contagions when the source of contagion is also of a financial nature; however, as cryptocurrencies' trading volumes attained record levels during the pandemic, an evaluation of possible variations in terms of integration levels and contagion, which were provoked by this real shock, is also of academic and practical interest.

When assessing these issues, and given that the variables of interest tend to exhibit non-linearities [76,77], this paper uses the DCCA and a variation of the ρ DCCA. This approach produces new insights into these markets' reactions to a global non-financial shock, and it allows analyses across different timescales, thus providing more detailed information on the structure of correlations. The obtained results are useful given that there are distinct preferences depending on the investment time horizon. Furthermore, the DCCA is robust in terms of evaluating power-law cross-correlations between two series regardless of their (non) stationarity (e.g., [78]).

3. Data and Methods

To perform the empirical analysis, we used the closing daily prices of 16 cryptocurrencies, with a market capitalization of more than a billion dollars, on 7 March 2020; on that date, 94% of the total market capitalization of all the cryptocurrencies were available in the used database (i.e., 263,364,575,633 USD). Furthermore, according to [66], the less well-known and less capitalized a cryptocurrency is, the less liquid and less reliable its related data are, thus justifying the use of cryptocurrencies with high market capitalization levels. We used an open-source database (<https://coinmarketcap.com>, accessed on 31 January 2021), which is considered to be an appropriate database with which to conduct research [79]. The sample selection considered various degrees of market capitalization and different underlying business models for cryptocurrencies. Due to data availability constraints, the time series of the different cryptocurrencies had distinct starting dates. Aiming to preserve all the possible information contained within each time series, all data available before the cut-off moment (31 December 2019) were considered. All time series ended by 30 January 2021 (details in Table 1). Cryptocurrencies' daily returns were calculated as $r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$, where $r_{i,t}$ is the return of cryptocurrency i at period t , and $P_{i,t}$ and $P_{i,t-1}$ are the prices at time t and $t - 1$, respectively.

Our main goal was to analyze how cryptocurrency markets behaved before and after the onset of the COVID-19 pandemic. More specifically, we evaluated the co-movements during the pre-crisis period (up to 31 December 2019) and during the crisis period (from this cut-off date until 30 January 2021), thus allowing us to make conclusions regarding integration, contagion, or independence, in accordance with the adopted definition of contagion (see [26]), as well as the studies of [41] or [80]. The non-linearity of data makes the use of classic linear approaches inappropriate; thus, the evaluation of a contagion between cryptocurrencies is based on the DCCA (commonly used in the finance literature, see for example [81–84]), the ρ DCCA, and variations thereof. DCCA does not require that the analyzed series are stationary, and it allows the establishment of cross-correlations (contagion effects) in both regimes by directly using the properties of the moments of the series (either linear or nonlinear relationships). Consequently, there is no sample reduction, and all original observations are used (an advantage, especially when the number of observations is not very high).

Table 1. Sample Description.

	Cryptocurrency		Start Date	Market Capitalization (USD)	
1	Bitcoin	BTC	29 April 2013	162,684,945,903	61.77%
2	Ethereum	ETH	7 August 2015	26,164,459,704	9.93%
3	Ripple	XRP	4 August 2013	26,164,459,704	9.93%
4	Bitcoin Cash	BCH	23 July 2017	6,059,789,428	2.30%
5	Bitcoin SV	BSV	9 November 2018	4,290,029,659	1.63%
6	Tether	USDT	25 February 2015	4,643,212,805	1.76%
7	Litecoin	LTC	29 April 2013	3,889,681,824	1.48%
8	EOS	EOS	1 July 2017	3,366,250,140	1.28%
9	BinanceCoin	BNB	25 July 2017	3,138,663,736	1.19%
10	Tezos	XTZ	2 October 2017	2,103,907,641	0.80%
11	ChainLink	LINK	20 September 2017	1,520,607,569	0.58%
12	Cardano	ADA	1 October 2017	1,268,987,677	0.48%
13	Stellar	XLM	5 August 2014	1,183,231,787	0.45%
14	TRON	TRX	13 September 2017	1,136,886,287	0.43%
15	Monero	XMR	21 May 2014	1,143,443,765	0.43%
16	Huobi Token	HT	3 February 2018	1,063,188,577	0.40%
Total				249,821,746,206	94.86%

Note: (i) Table shows basic information, such as each cryptocurrency’s starting date and market capitalization (in value and percentage) on 7 March 2020; (ii) The total market capitalization on 7 March 2020, of all the cryptocurrencies available on the database, was USD 263,64,575,633.

The DCCA approach was first proposed by [85] to evaluate long-term power-law cross-correlations between two time series of equal lengths N . It is a generalization of the DFA, proposed by [86], to a context where interest lies in the study of the joint behavior of two distinct time series of equal lengths N . DCCA produces results for different timescales through the detrended covariance function, $F_{DCCA}^2(n)$. In this study, the DFA is not applied directly, but the DFA exponent values are used to calculate the ρ_{DCCA} .

In accordance with DFA, if there is a long-range correlation between two time series, then $F_{DCCA} \sim n^\lambda$ with $\lambda = (\alpha_{DFA} + \alpha'_{DFA})/2$ [87]. Although the λ exponent allows quantification of the long-range power-law correlation and identification of seasonality, it does not quantify the level of identified cross-correlations [88]. To obtain such a quantification (with the DFA and DCCA approaches), it is thus necessary to use the ρ_{DCCA} , proposed by [87].

According to [89], the ρ_{DCCA} is obtained using two time series, x_k and y_k , with equal lengths N (k represents two equidistant observations), starting with the integration of those time series in order to obtain two new ones $x_t = \sum_{k=1}^t x_k$ and $y_t = \sum_{k=1}^t y_k$, with $t = 1, 2, \dots, N$. Then, both integrated time series are divided into $(N - n)$ overlapping boxes of equal lengths n , with $4 \leq n \leq N/4$. Subsequently, the local trend of each box, \tilde{x}_t and \tilde{y}_t , is calculated by a least-squares fit of each series. The detrended series are obtained by subtracting each trend from their original values. The detrended covariance of the residuals for a specific box is then calculated as:

$$f_{DCCA}^2(n) = \frac{1}{n-1} \sum_{k=i}^{i+n} (x_t - \tilde{x}_t)(y_t - \tilde{y}_t) \tag{1}$$

The next step is to obtain the new covariance function, which is given by the average of all $(N - n)$ overlapping boxes (i.e., $F_{DCCA}^2(n) = \frac{1}{N-n} \sum_{i=1}^{N-n} f_{DCCA}^2(n)$).

Finally, the ρ_{DCCA} is calculated as:

$$\rho_{DCCA}(n) = \frac{F_{DCCA}^2(n)}{F_{DFA\{x\}}(n)F_{DFA\{y\}}(n)} \tag{2}$$

This cross-correlation coefficient depends on the timescale (i.e., the box length, n) and on the size of the series, N . Based on Monte Carlo simulations, Ref. [90] tested this coefficient and compared it with the linear correlation coefficient. Regarding its efficiency, the study concluded that it displays the desirable properties of a correlation coefficient; indeed, it is composed of values between -1 and 1 ($-1 \leq \rho_{DCCA} \leq 1$, see [91] for a full description of the coefficient's properties). Thus, the interpretation is straightforward: if $\rho_{DCCA} = 0$, there is no cross-correlation; if $\rho_{DCCA} = 1$ or $\rho_{DCCA} = -1$, there is perfect cross-correlation, or perfect anti cross-correlation, respectively.

The ρ_{DCCA} values are an indicator of the presence of cross-correlations [92], and they capture the level of market integration [44]. To examine the statistical significance of ρ_{DCCA} (identifying the critical values), and to test the null hypothesis for ρ_{DCCA} (classical test), Ref. [92] proposed a set of procedures that we followed in order to empirically confirm the existence of cross-correlation between time series. However, as we wanted to assess the (non)existence of contagions in cryptocurrency markets during the pandemic, we considered two periods (before and after the onset of the pandemic), and thus, in accordance with [93], we calculated the $\Delta\rho_{DCCA}$ as:

$$\Delta\rho_{DCCA}(n) \equiv \rho_{DCCA}^{after}(n) - \rho_{DCCA}^{before}(n) \quad (3)$$

where, $\rho_{DCCA}^{after}(n)$ and $\rho_{DCCA}^{before}(n)$ represent the detrended cross-correlation coefficients, before and after the onset of the pandemic, respectively.

By considering the values displayed by the relevant coefficients before and after the cut-off moment, $\Delta\rho_{DCCA}(n)$ allows us to make conclusions based on the possible contagion effects of the pandemic on cryptocurrency markets. Thus, if $\Delta\rho_{DCCA}(n) > 0$, the correlation coefficients increased in the period after the cut-off moment and there are cross-correlation effects; thus, in accordance with [26], there is evidence of contagion. If $\Delta\rho_{DCCA}(n) < 0$, the correlation coefficients have decreased in the period after the cut-off moment, and dependence between markets declined.

The null and alternative hypotheses used to assess the significance of $\Delta\rho_{DCCA}(n)$ are:

$$\begin{aligned} H_0 : \Delta\rho_{DCCA}(n) &= 0, \text{ the differences are not significant} \\ H_1 : \Delta\rho_{DCCA}(n) &\neq 0, \text{ the differences are significant} \end{aligned} \quad (4)$$

The significance of $\Delta\rho_{DCCA}(n)$ is assessed using the critical values proposed by [89,94] for 90%, 95%, and 99%.

4. Results and Discussion

4.1. Descriptive Statistics

Table 2 presents the descriptive statistics of the cryptocurrencies' returns. To assess the stationarity of these series, a standard Augmented Dickey–Fuller (ADF) test was performed (using the StataSE 15[®] (64-bit) software, from StataCorp LLC, Lakeway Drive, College Station, TA, USA). The test's H_0 was rejected in all cases, thus suggesting that the examined series of returns are all stationary (results not shown, but available upon request).

As the volatility of the series of returns did not increase (and in fact, decreased) after 31 December 2019, we conclude that the onset of the COVID-19 pandemic did not significantly change the cryptocurrencies' behavior. As the number of observations is not constant across periods, such evidence should be considered carefully. For most cryptocurrencies, mean returns are positive and close to zero. With the exceptions of Bitcoin SV (BSV) and Binance Coin (BNB), mean returns increased after 31 December 2019.

BSV has shown the highest average return before the pandemic crisis, as well as the lowest average return and the highest volatility during the health crisis. Regarding skewness, it was positive in the pre-crisis period (except for BTC and USDT) and negative during the crisis period (except for BSV, USDT, and Stellar (XLM)); this is in accordance with [33,60], meaning that during the first period, there was a higher probability of large positive return variations than negative ones, which could be a sign of increased sensitivity

to the effects of the pandemic. In contrast, during the second period, negative returns were more frequent, thus reflecting the turmoil and uncertainty provoked by the pandemic. Regarding kurtosis, high values (i.e., leptokurtic distributions) were observed in both periods, thus suggesting that the returns do not follow a normal distribution; this is consistent with the existence of fat-tails, a well-known stylized fact in financial markets. This is also a justification for using nonlinear, rather than linear, techniques. Although the USDT is a stable cryptocurrency (pegged to the USD), it exhibited an extremely high kurtosis value before 31 December 2019. Shortly after it was launched in 2014, questions were raised concerning whether its issuer was setting aside enough collateral to maintain the dollar peg. The issuing company started reporting its reserves in 2017, due to mounting investors' doubts. This could be an explanation for the high kurtosis observed in this cryptocurrency during the first period that was assessed. According to a report examining June 2018 by Freeh Sporkin & Sullivan, LLP, after that date, all tethers in circulation were fully backed by USD reserves. This could be an explanation for the alignment of the kurtosis values of the USDT with those of the other cryptocurrencies in our sample during the second analyzed period.

Table 2. Descriptive Statistics of Cryptocurrencies' Returns.

Cryptocurrency	Before 31 December 2019				After 31 December 2019			
	Mean	Stdev.	Skewness	Kurtosis	Mean	Stdev.	Skewness	Kurtosis
BTC	0.0016	0.0427	−0.1527	10.7409	0.0039	0.0414	−3.4812	44.5290
ETH	0.0024	0.0714	−3.4274	74.6109	0.0060	0.0551	−2.5411	29.9171
XRP	0.0015	0.0727	2.0756	32.9133	0.0021	0.0660	−0.3960	26.4318
BCH	−0.0008	0.0794	0.6179	10.4098	0.0018	0.0603	−1.8145	24.2868
BSV	0.0008	0.0901	0.8643	19.9132	0.0015	0.0814	2.8755	46.5471
USDT	−0.0001	0.0211	−12.2749	829.3628	0.0000	0.0055	0.1522	37.9746
LTC	0.0009	0.0645	1.7163	28.5632	0.0030	0.0540	−1.5536	16.3358
EOS	0.0010	0.0827	2.2245	27.6377	0.0030	0.0545	−2.0790	22.8957
BNB	0.0055	0.0787	1.3888	15.1944	0.0003	0.0502	−3.3523	38.3843
XTZ	−0.0004	0.0751	0.1255	10.5396	0.0019	0.0634	−2.1090	24.3520
LINK	0.0027	0.0812	0.7048	7.1339	0.0065	0.0711	−1.4227	18.0953
ADA	0.0003	0.0792	2.9094	29.3140	0.0061	0.0623	−1.1089	14.6842
XLM	0.0015	0.0754	2.0089	19.6020	0.0050	0.0668	1.6195	21.9256
TRX	0.0023	0.0963	2.1343	19.3240	0.0022	0.0545	−2.2636	24.9947
XMR	0.0016	0.0703	0.6497	9.6001	0.0029	0.0509	−2.4056	26.4712
HT	0.0009	0.0518	0.6165	7.6063	0.0021	0.0431	−3.5911	49.8863

Notes: (i). Stdev represents the standard deviation; ii. Before the cut-off moment, there exists a different number of observations between series (as detailed in Table 1), but after the cut-off moment, all the series have a similar number of observations (396).

4.2. $\Delta\rho$ DCCA Analysis

Our goal is to analyze correlations in cryptocurrency markets before and after the COVID-19 pandemic crisis and to make conclusions on the types of observed relations. We thus compared the ρ DCCA before and after the cut-off moment, estimated the $\Delta\rho$ DCCA(n), and assessed whether there were significant correlation changes between the two periods.

As mentioned above, the statistical significance of $\Delta\rho$ DCCA(n) is tested using the critical values proposed by [89,94] for 90%, 95%, and 99%. Figure 1 depicts the lower (LL_99%) and upper (UL_99%) critical values (due to their proximity to zero, they are practically imperceptible). If the estimated $\Delta\rho$ DCCA(n) values are outside the referred limits (LL and UL), the correlation is statistically significant, and if positive, it can be interpreted, according to [10,26], as evidence of a contagion. Conversely, if the estimates lie within the critical values, the variation between correlations is not significant. In accordance with [44], a positive value for $\Delta\rho$ DCCA(n) can also be interpreted as an increase in integration between markets.

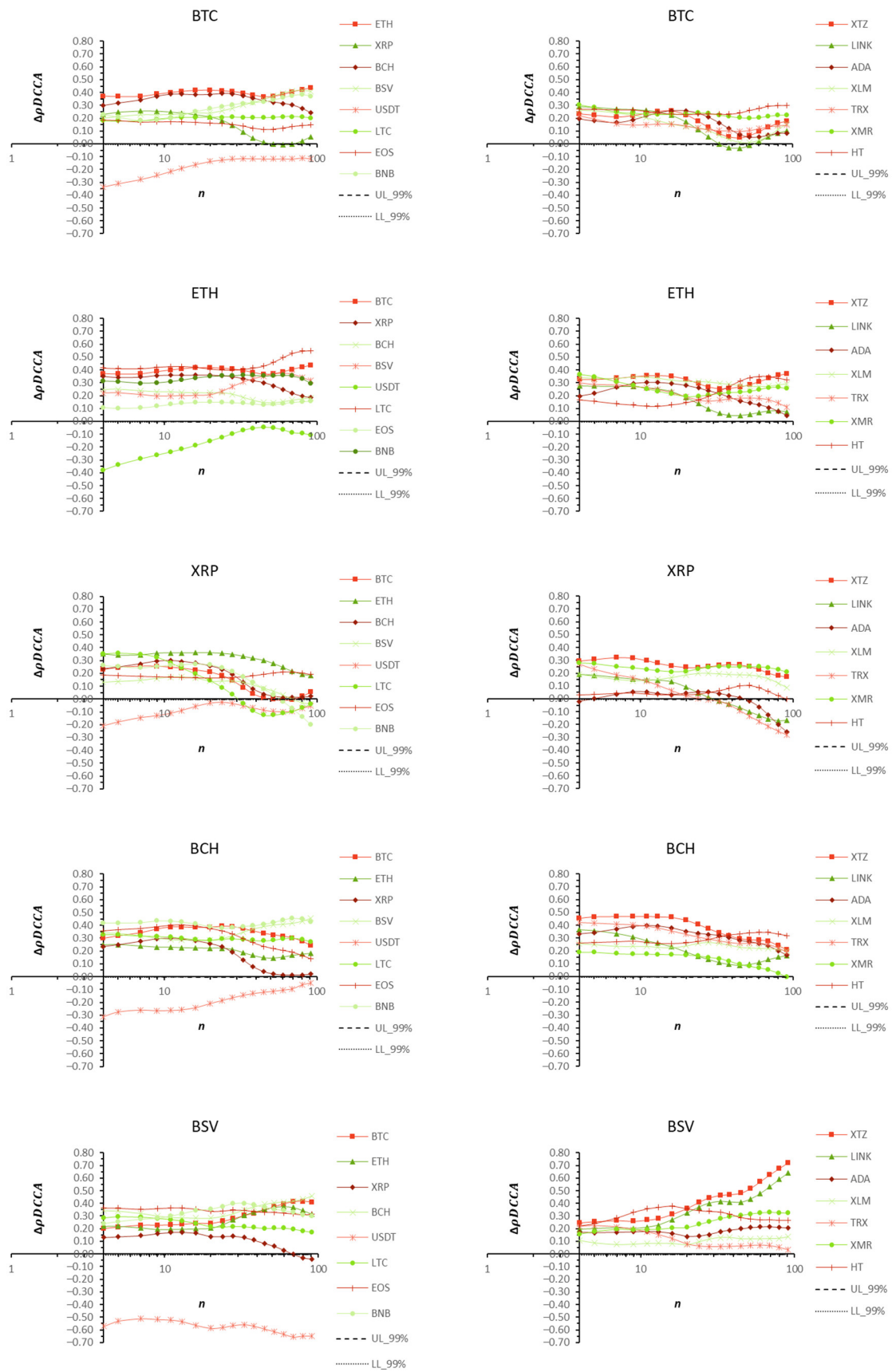


Figure 1. Cont.

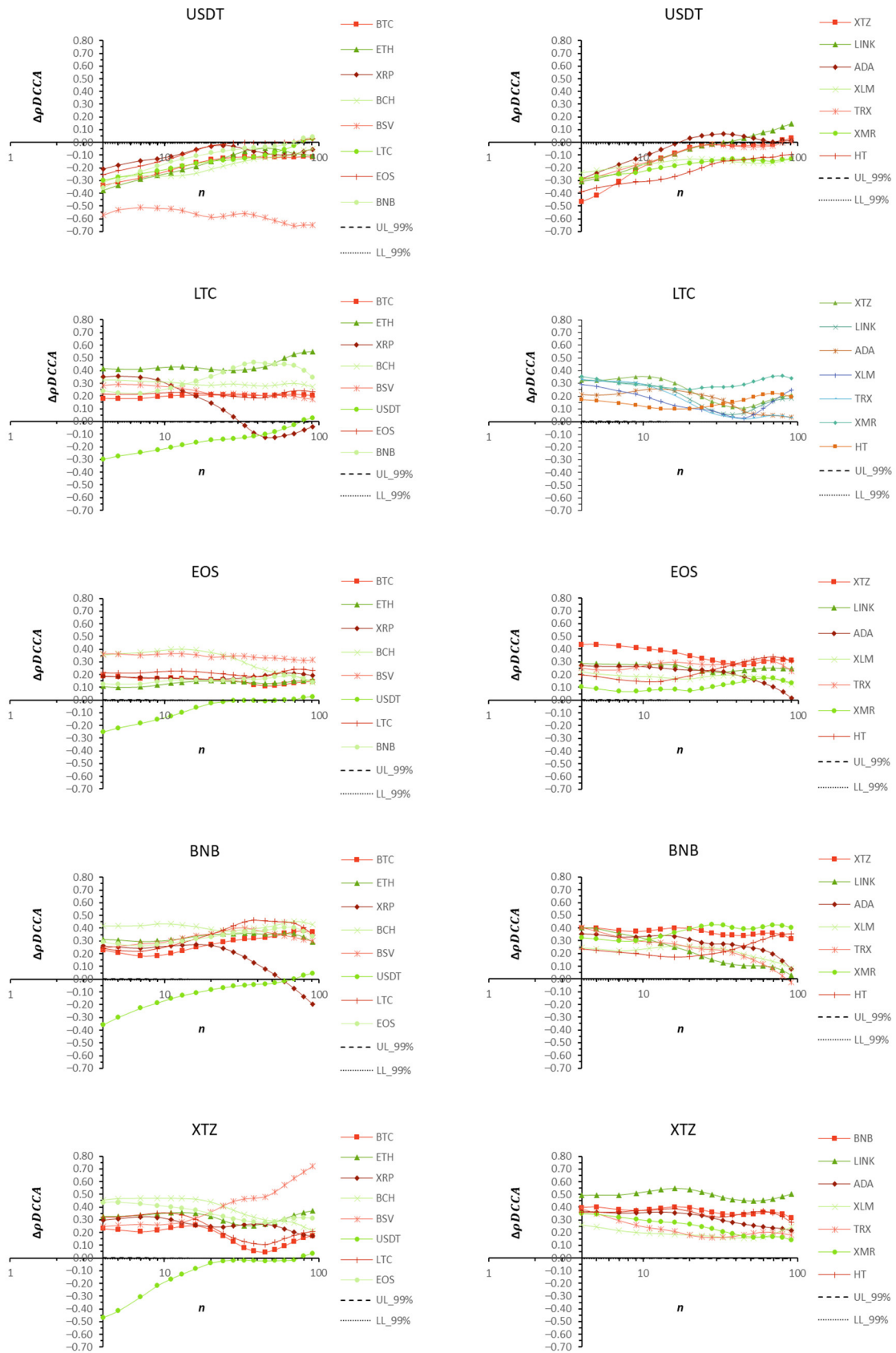


Figure 1. Cont.

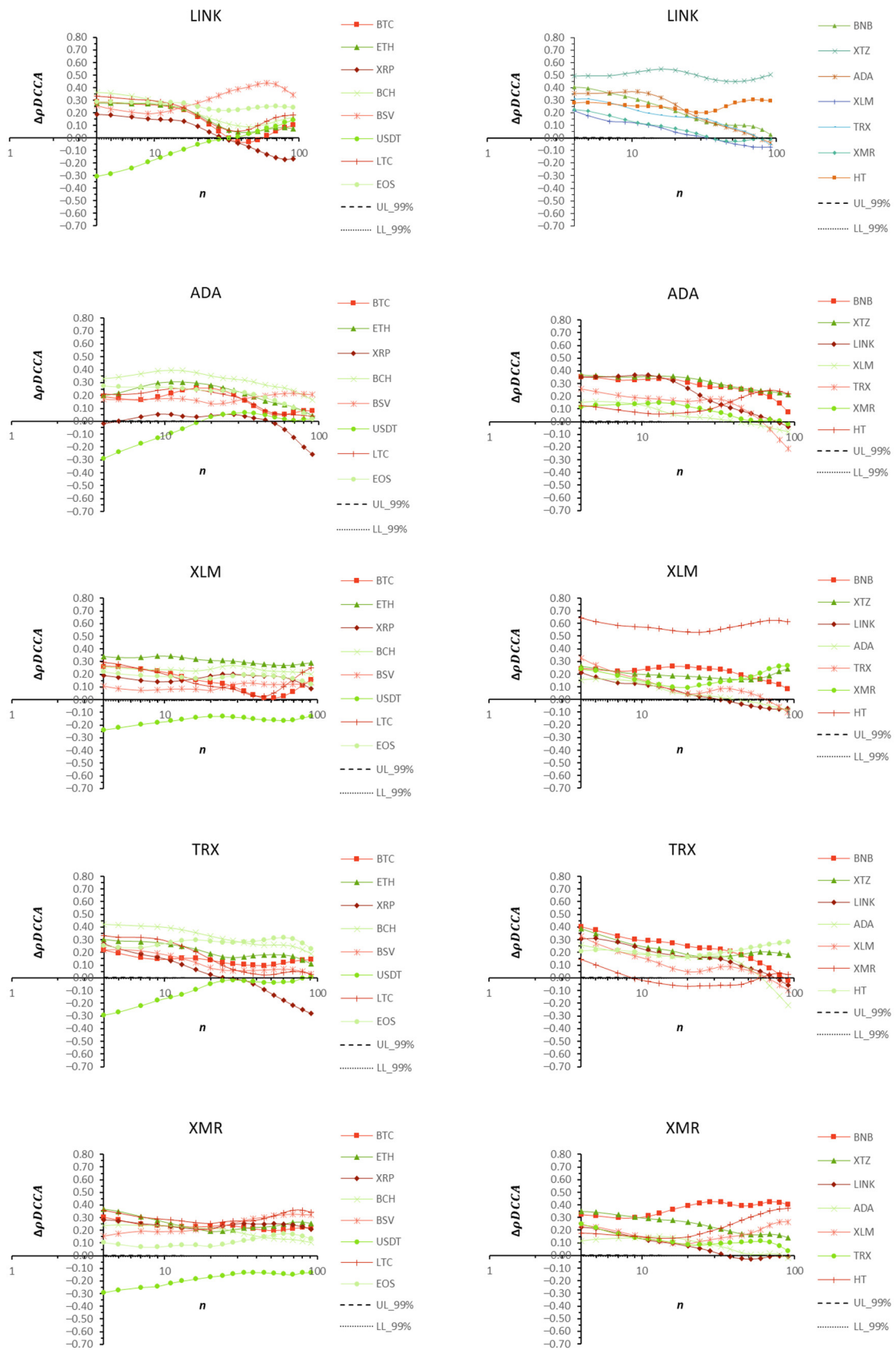


Figure 1. Cont.

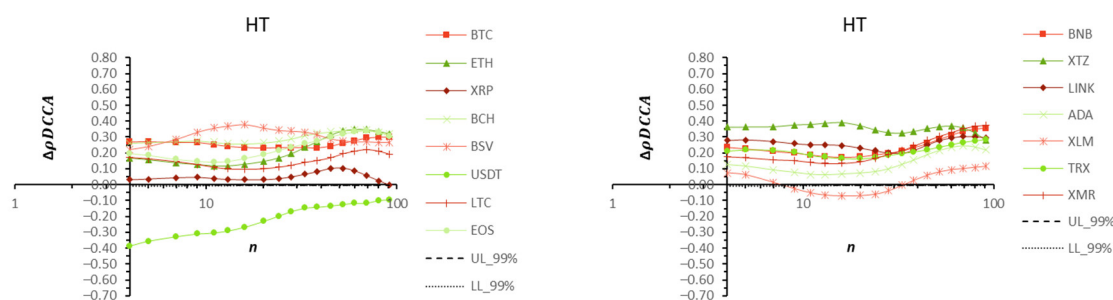


Figure 1. $\Delta\rho$ DCCA for each cryptocurrency in the title of each graph with the remaining cryptocurrency markets as a function of n (days). Note: UL and LL are the upper and lower critical values, respectively, and are used to assess the statistical significance of $\Delta\rho$ DCCA(n). If the estimated values are outside/inside both critical values, the variation in correlation is statistically significant/not significant, respectively. A statistically significant and positive variation in correlation may be interpreted as evidence of contagion and of increased market integration.

During the pandemic period, there was a statistically significant increase in the correlation coefficients (as can be seen by a $\Delta\rho$ DCCA(n) > 0) for most of the analyzed cryptocurrencies (the only exception was USDT); this contrasts, for example, with [20,95]. The statistically significant increase in the correlation coefficients between the majority of cryptocurrencies may indicate that the respective markets are integrated (contradicting, for example, [20]), and thus, that there was an increase in systemic risk. Stronger integration was found between the XTZ market and the remaining cryptocurrency markets, as well as between BSV and the other markets (as can be seen by the higher values of the $\Delta\rho$ DCCA(n)).

In accordance with [10], for short timescales, the null hypothesis of $\Delta\rho$ DCCA(n) = 0 was rejected in all cases and $\Delta\rho$ DCCA(n) > 0 (except for USDT), thus suggesting that there is evidence of contagion (corroborating the findings in [47]) and highlighting the contribution of this study. Thus, the crisis caused by the COVID-19 pandemic seems to have affected cryptocurrency markets, increasing integration (in accordance with [33,60,69], among others) and suggesting that movements in one cryptocurrency reflect movements in other cryptocurrencies.

For long timescales, although there continues to be evidence of a statistically significant absence of contagion between most cryptocurrencies and USDT (given $\Delta\rho$ DCCA(n) < 0 and statistically significant) there is statistically significant evidence of contagion between LTC, EOS, BNB, XTZ, LINK, ADA, TRX, and the USDT. Despite rejecting the null hypothesis for most cryptocurrencies, some contradictory evidence exists (with $\Delta\rho$ DCCA(n) < 0). For instance, there is a statistically significant absence of contagion between: i. XRP and LTC, BNB, BSV, TRX, LINK and ADA; ii. BNB and TRX; iii. LINK and the XLM, XMR, TRX, and ADA; iv. ADA and XLM, XMR and TRX; v. XLM and TRX; and vi. HT and XLM. These results contrast with those of [47].

The assessed cryptocurrencies thus appear to have mostly suffered short-term effects caused by the COVID-19 pandemic, possibly due to investor panic and as a reflex due to a lack of connection with the real economy (see [34]). The distinct behavioral patterns of both short and long timescales suggest that investors need to constantly update their positions (short vs. long) and consider the distinct preferences for different time horizons when building investment portfolios.

ETH, LTC, XTZ, and HT markets display the highest levels of integration with the other cryptocurrency markets in our sample.

5. Conclusions

Extraordinary events, regardless of their financial or non-financial nature, usually challenge the stability and alter the structure of financial markets. In this study, we assessed the impacts of a real shock—the COVID-19 pandemic—on cryptocurrency markets. We

used the DCCA approach to examine how relationships within a set of 16 cryptocurrencies were affected by this pandemic. More specifically, market integration and contagions were evaluated by comparing the cross-correlation coefficients (ρ DCCA) between all possible pairs of cryptocurrencies in our sample, before and after the onset of the COVID-19 crisis.

This analysis produced a multi-timescale perspective of the links established between the analyzed cryptocurrencies. We found out that correlation levels generally increased from the pre-crisis period to the crisis period, thus suggesting that there was a contagion during the pandemic that affected the cryptocurrency markets across both short and long timescales. This means that investors changed their behavior at the onset of the COVID-19 pandemic, leading to greater connectedness in the cryptocurrency markets (this does not corroborate the results of other studies, for example, [3]). Exceptions to this general conclusion are USDT (across short timescales) and XRP and USDT (across long timescales). This result hints that these cryptocurrencies could have safe-haven properties in periods of turmoil in the cryptocurrency markets.

Considering that a positive variation in ρ DCCA indicates that there was an increase in market integration, the analysis also shows, in accordance with [20,33,60,69], that cryptocurrency markets became more integrated after the onset of the pandemic. This means that, as a whole, they became more exposed to the effects of shocks, thus providing yet another example of the so-called correlations breakdown (i.e., that diversification becomes more difficult, precisely when it is more necessary). This evidence leads us to conclude that the analyzed cryptocurrency markets are neither immune to non-financial shocks affecting the global economy, nor independent from the global financial system.

Our results contribute to improving knowledge concerning the behavior of cryptocurrencies in times of stress, in this case, during the emergence of a pandemic. They are thus of use for investors, helping them to make more informed investment decisions that consider the time-varying nature of the structure of dependence between cryptocurrencies. The evidence for different levels of integration between cryptocurrencies across different timescales and periods has practical implications for investors during their decision-making processes, regarding portfolio diversification, risk management, and trading and hedging strategies.

The study is also useful for academics who are interested in how non-financial shocks impact financial integration, and how they provoke contagion in financial markets. Furthermore, this study may also assist policy makers and regulators who are in charge of anticipating potential triggers of cryptocurrency market instability, or who are attempting to reduce these markets' vulnerabilities and minimize the spread of risk and uncertainty across them. Our results point out a high risk of contagion during times of stress. Thus, policy makers involved in regulating the cryptocurrency markets should consider this empirical evidence when defining future policy measures. Furthermore, as cryptocurrency markets are interconnected and are also linked with other markets (e.g., [30]), this study highlights that regulatory oversight and monitoring are needed to prevent, for example, financial instability and systemic risk.

Overall, the study provides valuable information about the interconnectedness of cryptocurrencies and the role that real crises play in shaping such links, and thus, it should be considered by all agents interested in investing, studying, or regulating these markets.

In the last decade, as cryptocurrency markets have grown and gained relevance, regulators and environmentalists have intensified debates on the massive power consumption of the mining process and its adverse impact on ecosystems and climate change. Several studies found an increasing degree of interconnectedness between cryptocurrencies and other financial assets and also within cryptocurrencies. Our results corroborate the results of some previous studies that focus upon the interconnectedness between cryptocurrency markets. Considering this integration, and the Environmental, Social, and Governance (ESG) sustainability concerns that emerged from the Paris Agreement of 2015, cryptocurrency markets can play an important role in achieving ESG goals by promoting sustainable investments and via the integration of sustainable practices into their operating models.

As this is an innovative research area, where few studies have analyzed the ESG perspective, with regard to cryptocurrencies (see, for instance [96–98]), there is an urgent need to study cryptocurrency investments from the perspective of ESG investments. We intend to develop such a study as part of our future research (using, for example, the recently created cryptocurrency environmental attention (ICEA) index in [99]) in order to help the environmentally concerned investors who are willing to include crypto assets in their portfolio while contributing to the achievement of the ESG goals.

The different number of observations for each time series before 31 December 2019 could be a limitation of our study.

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