Quantifying the COVID-19 shock in cryptocurrencies

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Abstract

This paper sheds light on the changes suffered in cryptocurrencies due to the COVID-19 shock through a non-linear cross-correlations and similarity perspective. We have collected daily price and volume data for the seven largest cryptocurrencies considering trade volume and market capitalization. For both attributes (price and volume), we calculate their volatility and compute the Multifractal Detrended Cross-Correlations (MF-DCCA) to estimate the complexity parameters that describe the degree of multifractality of the underlying process. We detect (before and during COVID-19) a standard multifractal behaviour for these volatility time series pairs and an overall persistent long-term correlation. However, multifractality for price volatility time series pairs displays more persistent behaviour than the volume volatility time series pairs. From a financial perspective, it reveals that the volatility time series pairs for the price are marked by an increase in the non-linear cross-correlations excluding the pair Bitcoin vs Dogecoin ($\alpha_{xy}(0) = -1.14\%$). At the same time, all volatility time series pairs considering the volume attribute are marked by a decrease in the non-linear cross-correlations. The K-means technique indicates that these volatility time series for the price attribute were resilient to the shock of COVID-19. While for these volatility time series for the volume attribute, we find that the COVID-19 shock drove changes in cryptocurrency groups.

Keywords: COVID-19, Cryptocurencies, Volatility, Multifractality, Cross-correlation, Similarity

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1. Introduction

Even though the original proposal of [1] was to create a peer-to-peer transfer system, the market evolved in such way that cryptocurrencies [2] constitute a class of highly speculative financial assets. Until 2016 Bitcoin was the dominant player, encompassing more than 90% of the market. However, and specially since the end of 2017, investors' interest favored the entrance of new competitors into the market. As of February 2022, bitcoin accounts for 41% of total market capitalization, and the ten most important cryptocurrencies cover almost 80% of the capitalization [3]. It is undeniable that cryptocurrencies play an important role as an alternative financial market [4] and, consequently in the world economy.

The seminal paper by Mandelbrot [5] ignited a research line about the presence of long-term memory in the returns of different financial assets [6, 7]. In particular, there are several studies on the effect of economic and financial crises on the long-term memory of different financial assets such as stocks [8], sovereign bonds and corporate bonds [9].

Singular events such as large price swings or a situation of global health emergency, could reshape the stochastic structure behind returns and volatilities, and thus the long-term memory and correlation structrure. For example, [10] finds that Bitcoin volatility was asymmetric previous to the price crash of 2013, but the asymmetry vanished after the price crash. Cryptocurrency financial research is abundant, which prevents (due to space constraint) doing an appropriate literature review in this letter. Therefore, we refer to [11] and [12] for comprehensive surveys on the current state of cryptocurrency research.

Studies about the reaction of financial markets to the COVID-19 pandemic are more recent and has been gaining momentum [13, 14, 15]. Considering that cryptocurrencies seem to be detached from general economic variables [16], studying their reaction to the health crisis is worth of investigation. In a related research line close to our paper, [17] describes a suggestive increment in returns and trading volumes for large cryptocurrencies, and [18] finds that COVID-19 incidence levels caused a surge in Bitcoin prices.

The aim of this paper is twofold: (i) study the stochastic structure (in particular, the multifractality) and the non-linear cross-correlations between price/volume volatility pairs of five important cryptocurrencies; (ii) assess the effect of COVID-19 on the stochastic process of those cryptocurrencies. Given this, this paper contributed to the literature in several aspects:

(i) it draws new insights into the multifractal dynamics between price/volume volatility pairs of five relevant cryptocurrencies;

(ii) it exhibits that all price/volume volatility time series pairs are characterized for overall persistent long-term correlations for both periods (before and during the COVID-19);

(iii) it displays that all price/volume volatility time series pairs reveal an increase related to the informational efficiency level;

(iv) it reveals the usefulness of cryptocurrencies for investors in a liquidity risk diversification strategy.

The remainder of this paper is organized as follows. Section 2, describes the data and the methodology used in this letter. Section 3 presents our empirical results. Finally, Section 4 formalizes our concluding remarks.

2. Data and methodology

2.1. Data

We have collected the daily closing price and the daily trading volume time series for the seven largest cryptocurrencies considering trade volume and market capitalization. We consider two non-overlapping periods to investigate simultaneously the multifractal behaviour between price and volume changes and the similarity of these cryptocurrencies bearing in mind two cluster techniques. The first period goes from October 01, 2018, to December 31, 2019 (before the COVID-19) and contains 988 observations. The second period goes from January 01, 2020, until September 14, 2022 (during the COVID-19) and has 988 observations. These data were obtained from https://coinmarketcap.com/.

For both original time series (price and volume), we performed a systematic descriptive statistical analysis to obtain a global view of the variation of these values. Table 1 exhibits the values of the descriptive statistics for both original time series (price and volume) considering before COVID-19 pandemic.

Table 1: Describe statistic table of the cryptocurrencies price and volume before COVID-19 pandemic.

Price before COVID-19 Pandemic								
Cryptocurrencies	**n**	**mean**	**std**	**median**	**min**	**max**	**skew**	**kurtosis**
bitcoin	815	7739.07559	2905.332	7406.52002	3236.76165	19497.40039	0.9334	1.4819
ethereum	815	344.54518	257.22888	227.601	84.3083	1396.42004	1.52106	1.79064
tether	815	1.00288	0.00794	1.00224	0.96664	1.07788	1.15846	12.52635
bnb	815	14.28303	8.35256	13.0891	1.15257	38.81592	0.74156	0.06915
xrp	815	0.48322	0.38677	0.34412	0.1837	3.37781	3.70546	18.05867
cardano	815	0.13281	0.16182	0.07371	0.02048	1.11412	2.90143	9.82319
dogecoin	815	0.00338	0.00194	0.00276	0.00099	0.01709	2.58545	9.85948
Volume before COVID-19 Pandemic								
Cryptocurrencies	**n**	**mean**	**std**	**median**	**min**	**max**	**skew**	**kurtosis**
bitcoin	815	1.09E+10	7.72E+09	7.65E+09	1.22E+09	4.51E+10	1.11495	0.90177
ethereum	815	4.29E+09	3.15E+09	2.87E+09	2.57E+08	1.87E+10	0.93272	0.27077
tether	815	9.23E+09	9.38E+09	3.82E+09	8.54E+07	5.35E+10	1.15389	0.46759
bnb	815	1.34E+08	1.30E+08	8.84E+07	9.28E+03	7.42E+08	1.60897	2.96708
xrp	815	1.04E+09	1.09E+09	7.77E+08	2.69E+07	9.42E+09	3.47586	17.32199
cardano	815	1.13E+08	1.73E+08	6.23E+07	1.74E+06	1.71E+09	4.86218	31.25401
dogecoin	815	3.20E+07	3.28E+07	1.94E+07	1.07E+06	2.88E+08	2.74827	12.85244

Table 3 displays the values of the descriptive statistics for both original time series (price and volume) considering during COVID-19 pandemic.

Table 2: Describe statistic table of the cryptocurrencies price and volume during COVID-19 pandemic.

Price during COVID-19 Pandemic								
Cryptocurrencies	**n**	**mean**	**std**	**median**	**min**	**max**	**skew**	**kurtosis**
bitcoin	988	30064.38923	17636.94475	30924.30196	4970.7879	67566.83009	0.19224	-1.28769
ethereum	988	1731.5894	1332.61988	1691.34499	110.60588	4812.08761	0.37311	-1.08427
tether	988	1.00067	0.00278	1.00036	0.97425	1.05358	6.61456	150.59454
bnb	988	236.88479	199.04979	269.1468	9.38605	675.68408	0.234	-1.28634
xrp	988	0.56011	0.358	0.43121	0.13964	1.83924	0.90472	0.00996
cardano	988	0.78451	0.72969	0.52228	0.02396	2.96824	0.80953	-0.23703
dogecoin	988	0.10414	0.1176	0.06403	0.00154	0.68478	1.31406	1.88599
Volume during COVID-19 Pandemic								
Cryptocurrencies	**n**	**mean**	**std**	**median**	**min**	**max**	**skew**	**kurtosis**
bitcoin	988	3.73E+10	1.90E+10	3.35E+10	1.23E+10	3.51E+11	5.44395	75.70367
ethereum	988	1.98E+10	1.02E+10	1.74E+10	5.11E+09	8.45E+10	1.86275	5.15438
tether	988	6.60E+10	3.48E+10	5.73E+10	1.54E+10	2.79E+11	1.80715	4.60946
bnb	988	1.62E+09	1.70E+09	1.26E+09	1.37E+08	1.80E+10	2.85674	14.72671
xrp	988	3.94E+09	4.51E+09	2.36E+09	4.32E+08	3.70E+10	3.19637	12.85649
cardano	988	2.03E+09	2.50E+09	1.10E+09	2.08E+07	1.91E+10	2.47374	7.93242
dogecoin	988	1.79E+09	4.61E+09	5.14E+08	2.28E+07	6.94E+10	7.21433	72.02873

For these two attributes (price and volume), we note a substantial increase in all measures of central tendency (mean, median, minimum, and maximum) during the COVID-19. For the price, we observe a substantial decrease for standard deviation, skewness and kurtosis during the COVID-19. In contrast, for the volume, we note a substantial increase in the values for standard deviation, skewness and kurtosis during the COVID-19.

For each time series of daily closing price, we define absolute returns as a proxy for volatility:

$$V_i\left(t\right) \equiv |\ln P_i\left(t+\Delta t\right) - \ln P_i\left(t\right)| \tag{1}$$

where Δt represents one day, $P_i(t)$ is the daily price of cryptocurrency i at time t.

Similarly, for each time series of daily trading volume, we compute the volatility as the absolute logarithmic change in volume as:

$$V_i'\left(t\right) \equiv |\ln Q_i\left(t+\Delta t\right) - \ln Q_i\left(t\right)| \tag{2}$$

where Δt represents one day, $Q_i(t)$ is the daily trading volume of cryptocurrency i at time t.

2.2. Methodology

Our research encompasses a theoretical framework of a multifractal approach (Multifractal Detrended Cross-Correlation Analysis - MF-DCCA) and cluster technique (K-means). The mix of these methods allows us to investigate the non-linear cross-correlations and similarities in one of the most relevant components of the financial market, the cryptocurrencies for both attributes (price and volume), considering before and during COVID-19. It is essential to formalize that since Bitcoin is the cryptocurrency with the highest trading volume and market capitalization. We choose to verify the non-linear cross-correlations and the similarity between Bitcoin and the other cryptocurrencies (Ethereum, Tether, Bnb, Xrp, Cardano, and Dogecoin). This section is segregated into two subsections to facilitate the reading and understanding of specialists, academics and the general public.

2.2.1. Multifractal Detrended Cross-Correlation Analysis (MF-DCCA)

The MF-DCCA[19] is a mixed model between MF-DFA and DCCA originally proposed by [20]. It is designated to quantify long-term correlations between two simultaneously recorded non-stationary time series. The MF-DCCA method is implemented following these steps:

(i) Consider two time series denoted by $\{a_i, b_i, i = 1, 2, ..., N\}$, being N the length of time series. Determine the profile as:

$$A_t = \sum_{k=1}^{t} (a_k - \bar{a}), \; t = 1, 2, ..., N \tag{3}$$

$$B_t = \sum_{k=1}^{t} \left(b_k - \bar{b}\right), \; t = 1, 2, ..., N \tag{4}$$

where $\bar{a}$ and $\bar{b}$ denote the mean of the time series a_t and b_t.

(ii) Divide the time series A and B into $N_s \equiv [N/s]$ non-overlapping segments of equal length s, where s represents the time scale. Thus, $2N_s$ segments are obtained.

(iii) For each sub-segment v, apply least squares method to obtain the local trends with an k-th order polynomial fit.

$$a_v(i) = c_1 i^k + ... + c_2 i^{k-1} + ... + c_k i + c_{k-1}, i = 1, 2, ..., S; \; k = 1, 2, ... \tag{5}$$

$$b_v(i) = d_1 i^k + ... + d_2 i^{k-1} + ... + d_k i + d_{k-1}, i = 1, 2, ..., S; \; k = 1, 2, ... \tag{6}$$

(iv) Calculate the detrended covariance $F^2(s, v)$. When $v = 1, 2, ..., N_s$,

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{s} \{|X[(v-1)s + i]| \, |Y[(v-1)s + i] - y_v(i)|\} \tag{7}$$

When $v = N_s + 1, N_s + 2, ..., 2N_s$,

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{s} \{|A[N - (v - N_s)s + i] - x_v(i)| \, |B[N - (v - N_s)s + i] - y_v(i))|\} \tag{8}$$

(v) Average the detrended covariances to obtain the qth-order wave function as

$$F_q(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \left[F^2(s, v)\right]^{\frac{q}{2}} \right\}^{\frac{1}{q}} \tag{9}$$

(vi) When $q = 0$, it reads

$$F_q(s) = \exp\left(\frac{1}{2N_s} \sum_{v=1}^{2N_s} \ln\left[F^2(s, v)\right] \right) \tag{10}$$

If the scale behavior is verified, the Power-Law correlations must satisfy $F_q(s) \propto s^{h_{xy}(q)}$, where $h_{xy}(q)$ denote the Generalized Hurst exponent versus q. The extent of multifractality can be derived by calculating the range of $h_{xy}(q)$. A larger $\Delta H_{xy} = h_{xy}(q_{min}) - h_{xy}(q_{max})$ means stronger multifractal feature.

Thus, for $q = 2$, the MF-DCCA becomes the DCCA. In such case, if $h_{xy}(2) = 0.5$, the two time series exhibit no cross-correlations. However, when $h_{xy}(2) > 0.5$, the cross-correlations are positive (persistent), and when $h_{xy}(2) < 0.5$, the cross-correlations are anti-persistent.

The mass exponent spectrum is defined as,

$$\tau_{xy}(q) = qh_{xy}(q) - 1 \tag{11}$$

where $h_{xy}(q)$ is computed from MF-DCCA. The singularity strength α_{xy}, which displays the singular degree of each segment in a complex system; and the singularity spectrum $f_{xy}(\alpha)$, which reveals fractal dimension of α_{xy} are calculate by

$$\alpha = h_{xy}(q) + qh'_{xy}(q) \tag{12}$$

$$f_{xy}(\alpha) = q\left[\alpha_{xy} - h_{xy}(q)\right] + 1 \tag{13}$$

The range of the singularity strength $\Delta\alpha_{xy} = \alpha_{xy_{max}} - \alpha_{xy_{min}}$ specifies the strength of multifractality. Thus, the larger α_{xy} reveals a more intense fluctuation.

Also, to distinguish the multifractal spectrum $f(\alpha)$ quantitatively, it is also convenient to calculate the width of the spectrum $W(\alpha_{max} - \alpha_{min})$ obtained from equating the fitted curve to zero, and the skew parameter $r = (\alpha_{max} - \alpha_0)/(\alpha_{min} - \alpha_0)$, where α_0 represents the overall Hurst exponent, $r = 1$ for symmetric shapes, $r > 1$ for right-skewed shapes, and $r < 1$ for left-skewed shapes. The skew parameter r presents that the scaling behavior of small fluctuations dominates the multifractal behavior if the spectrum is right-skewed, and the scaling behavior of large fluctuations dominates if the spectrum is left-skewed.

2.3. K-means

Based on a statistical perspective, we note that these volatility time series display different standard deviation scales, making a comparative analysis unfeasible. Given this, to decrease the influence of different magnitudes of these data, we use a normalization procedure by

$$x^{'} = \frac{(x - x_{min})}{(x - x_{max})} \tag{14}$$

where x is one data point, x_{min} denotes the minimum and x_{max} represents the maximum value.

Thus, we use the K-means algorithm [21] to the dataset for clustering cryptocurrencies bearing in mind the similarity of their volatility. K-means is a partitioning-based clustering technique. Thus, for a dataset with n instances, it constructs k partitions of the data, where each partition depicts a group and $k \leq n$. K-means creates a partition and then uses an iterative reallocation technique to improve partitioning.

3. Empirical Results

Volatility is a usual approach to estimate risk in financial assets [22]. Figure 1 displays the volatility time series for both attributes (price and volume), considering the periods before COVID-19.

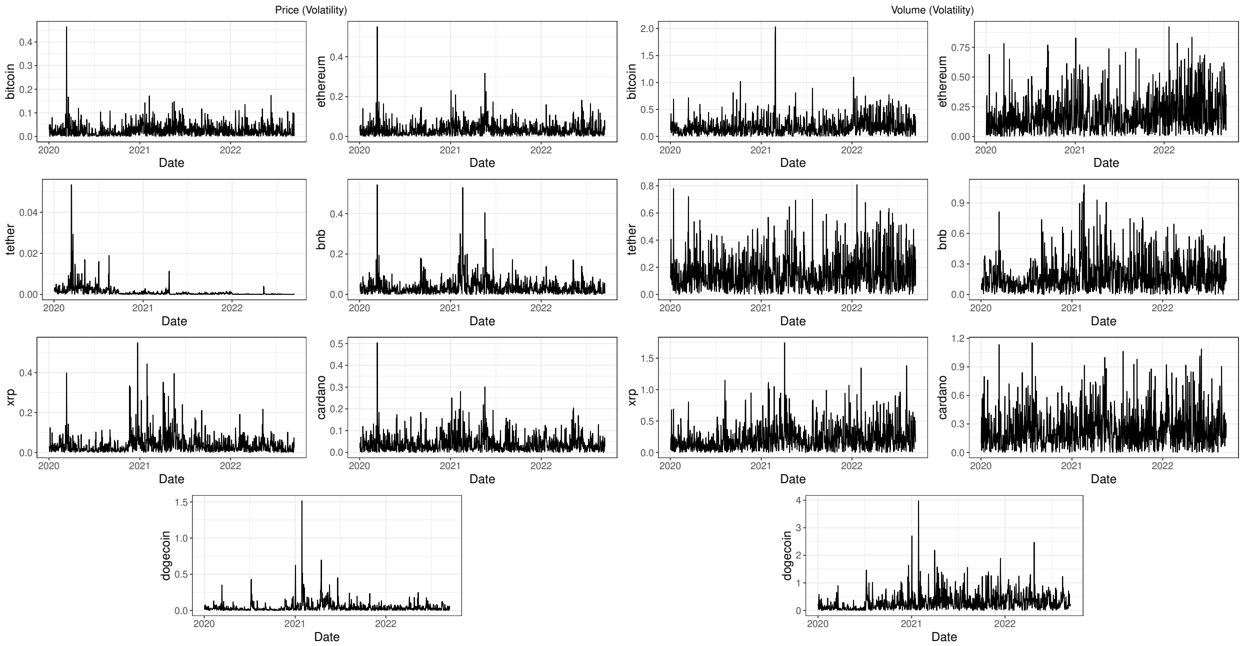

Figure 1: For both attributes, the volatility time series. These volatility time series cover the period from October 01, 2018, to December 31, 2019 (before COVID-19) and contains 988 observations.

The plot of the volatility time series for both attributes (price and volume), considering the periods during COVID-19, is shown in Figure 2.

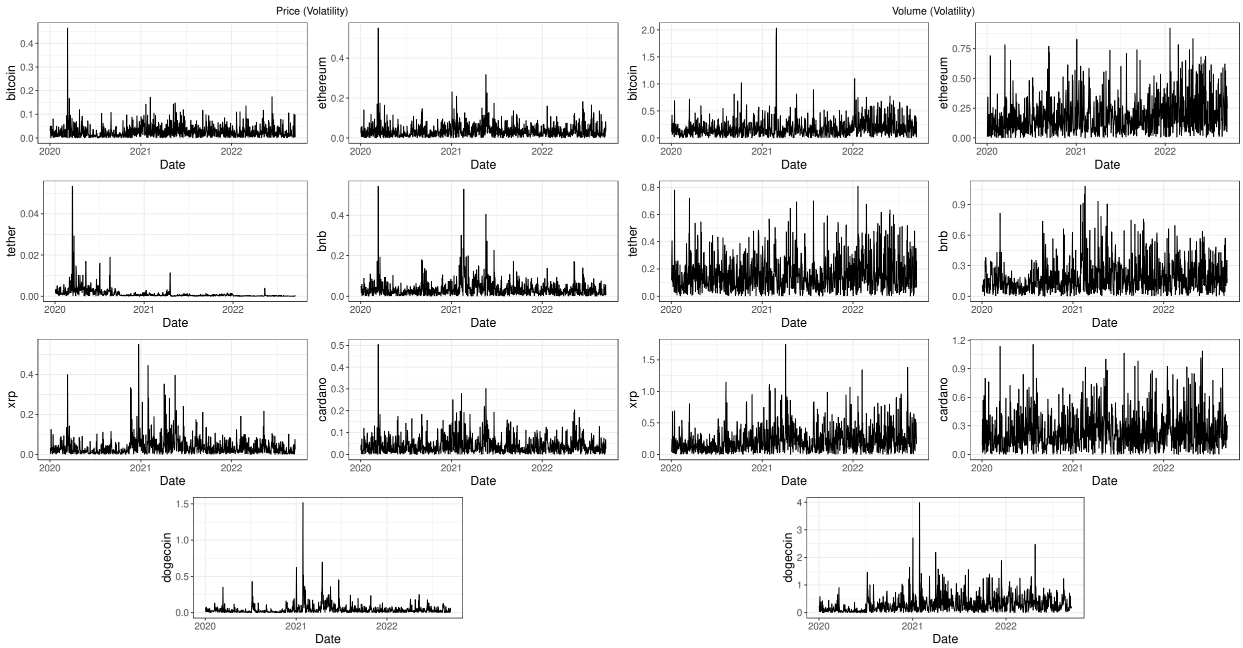

Figure 2: For both attributes, the volatility time series. These volatility time series cover the period from January 01, 2020, until September 14, 2022 (during COVID-19) and has 988 observations.

We apply the Box plot to investigate the extreme events bearing in mind the volatility time series for both attribute (price and volume) cover the period from October 01, 2018, to December 31, 2019 (before COVID-19) and contains 988 observations. Specifically, The Box plot is a non-parametric statistical method which allows us to explore the location by referring to 50% of the most probable values, the median and the extreme values for the investigated phenomenon.

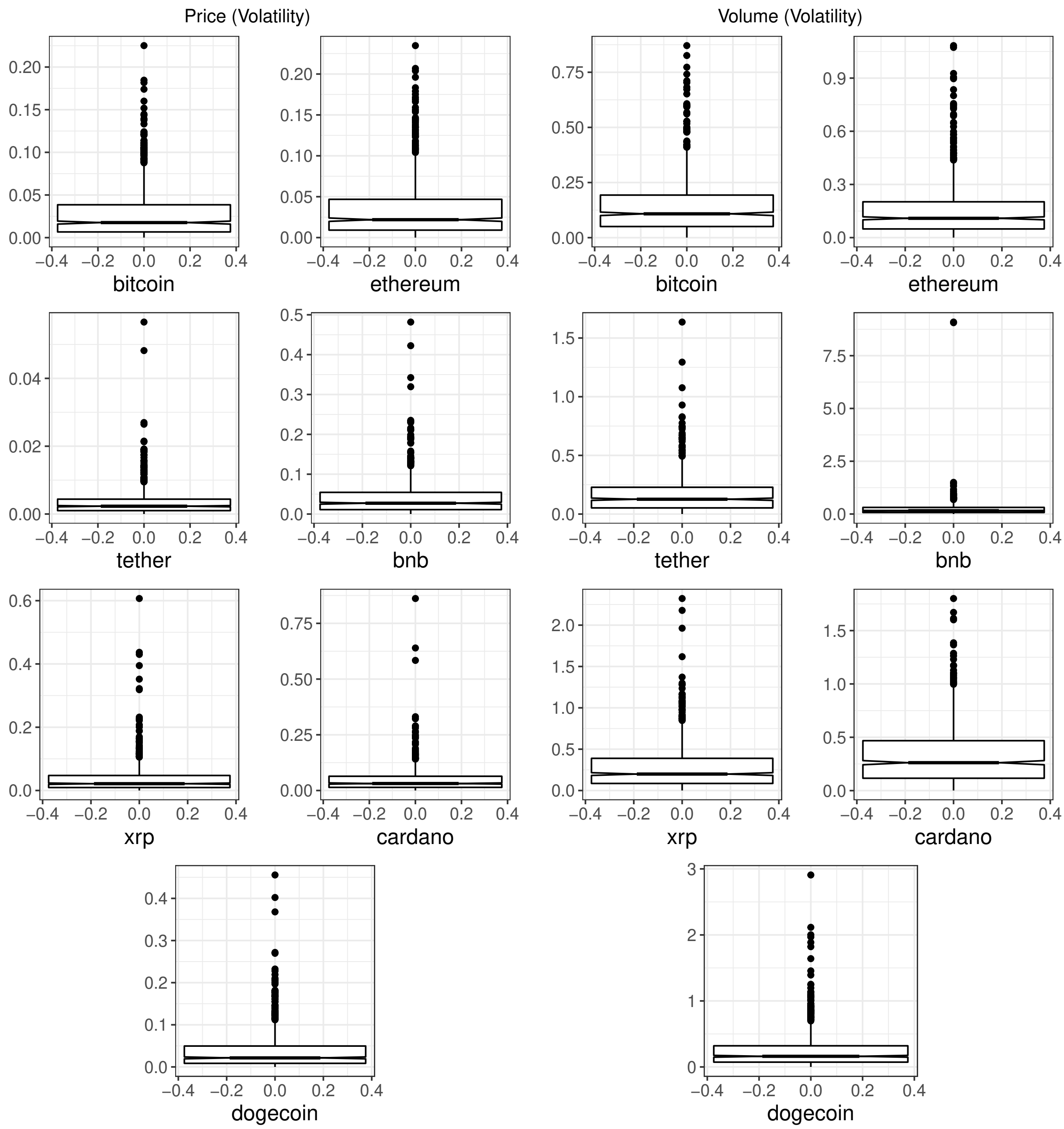

Figure 3: For both attributes, all cryptocurrencies are characterized by an extensive quantitative of extreme events. The black dots indicate the presence of outliers.

For both volatility time series, we observe a common characteristic of the cryptocurrencies inherent to the exacerbated presence of extreme events. Some past work studies the shocks related to extreme events in cryptocurrencies from the perspective of returns [23, 24, 25]. Also, we use the Box plot to study the extreme events considering these both attribute (price and volume) cover the period from January 01, 2020, until September 14, 2022 (during COVID-19) and has 988 observations.

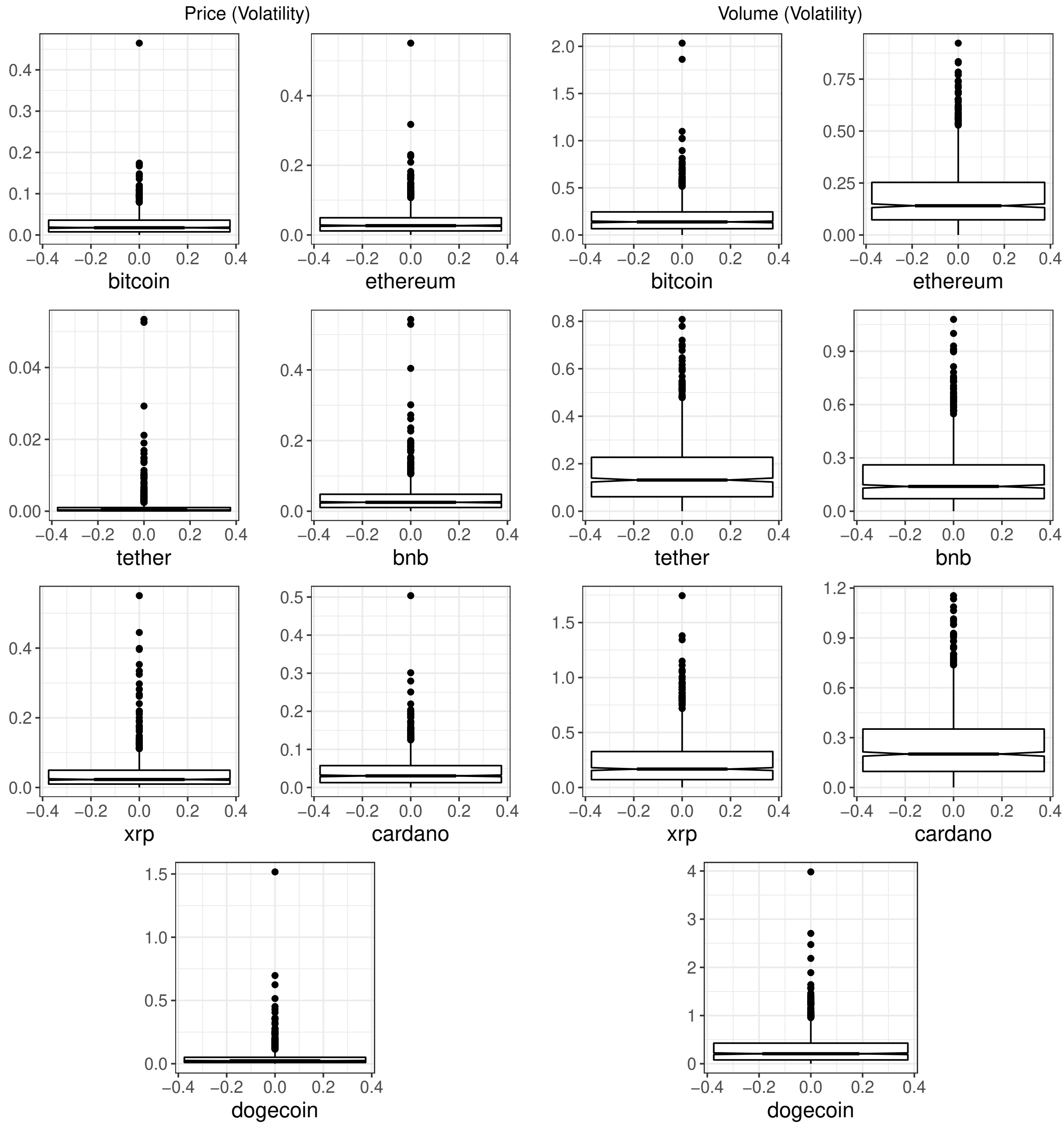

Figure 4: Looking into the difference between the third and first quartile (box size), we uncover a typical statistical pattern for these volatility time series. All the cryptocurrencies in our sample significantly increase the interquartile range during COVID-19. It means an increase in the dispersion of the data during COVID-19. Regarding the volume volatility time series, we find that almost all cryptocurrencies show a relevant decrease in the interquartile range during COVID-19 (exclude BNB, Cardano, and Tether).

Subsequently, we use the MF-DCCA analysis to explore the multifractal features in price and volume volatility for each cryptocurrency [26], considering two periods, i.e. before and during the COVID-19. In this way, we quantify the Generalized Hurst exponent $h_(q)$ and the Rényi exponent, which make it possible to investigate separately the contributing small scale (primarily via the negative moments q) and the large scale (via the positive moments q). Given this, we calculate $h_(q)$ with q ranging from -10 to 10 to obtain the multifractality quantitatively for these cryptocurrencies time series. We apply the shuffling procedure performed $1000 \times N$ transpositions on each series and was repeated 1000 times with different random number generator seeds.

We list the values inherent to the Generalized Hurst exponent for these volatility time series pairs for both attributes (price and volume) considering the period during COVID-19. Table. 3 presents the values inherent to the q order by $H\,(2)$ values (the Generalized Hurst exponent) for these volatility time series pairs for both attributes (price and volume) considering the period before COVID-19.

We display the values inherent to the Generalized Hurst exponent for these volatility time series pairs for both attributes (price and volume) considering the period during COVID-19. Table. 4 shows the values inherent to the q order by $H\,(2)$ values (the Generalized Hurst exponent) for these price/volume volatility time series pairs considering the period during COVID-19.

We use a fourth-order polynomial regression on the singularity spectrum $f\,(\alpha)$ to obtain the position of $\alpha_{xy}(0)$ and the zeros of the polynomial, $\alpha_{xy}max$ and $\alpha_{xy}min$, which are applied to calculate the complexity parameters, more specifically the width of spectrum W_{xy} and the asymmetry parameter r_{xy}. Fig. 5 shows the plots of the multifractal spectrum of these volatility time series pairs for both attributes (price and volume), bearing in mind the period before COVID-19.

Table 3: These values are inherent to the q order by $H\,(2)$ values (the Generalized Hurst exponent) for these volatility time series pairs for both attributes (price and volume) considering the period during COVID-19.

Price Before COVID-19 Pandemic						
q	**Bitcoin vs Ethereum**	**Tether**	**Bnb**	**Xrp**	**Cardano**	**Dogecoin**
-10	1.314177	1.223123	1.359201	1.342820	1.195066	1.460161
-9	1.302569	1.214305	1.346729	1.329871	1.184233	1.448842
-8	1.288153	1.203782	1.331164	1.313658	1.170864	1.434722
-7	1.269841	1.191019	1.311308	1.292932	1.154037	1.416674
-6	1.245972	1.175243	1.285348	1.265893	1.132400	1.392938
-5	1.213967	1.155290	1.250518	1.230102	1.104021	1.360676
-4	1.169783	1.129295	1.202552	1.182894	1.066417	1.315099
-3	1.107519	1.094032	1.134999	1.123176	1.017793	1.247653
-2	1.023985	1.044814	1.039580	1.053671	0.961093	1.144152
-1	0.934925	0.987348	0.924610	0.979171	0.904015	1.013455
0	0.861272	0.947106	0.847110	0.909372	0.850687	0.917999
1	0.808345	0.917923	0.808221	0.857165	0.805755	0.858101
2	0.772106	0.885779	0.782478	0.820679	0.768883	0.818828
3	0.746635	0.852857	0.759161	0.793163	0.734973	0.790222
4	0.727357	0.824306	0.737393	0.770904	0.703317	0.766818
5	0.711753	0.801517	0.718318	0.752507	0.675733	0.746673
6	0.698639	0.783646	0.702276	0.737327	0.653000	0.729274
7	0.687447	0.769469	0.688965	0.724810	0.634668	0.714372
8	0.677839	0.757991	0.677900	0.714438	0.619884	0.701678
9	0.669569	0.748501	0.668624	0.705767	0.607846	0.690867
10	0.662426	0.740510	0.660771	0.698439	0.597917	0.681627
Volume Before Covid-19 Pandemic						
q	**Bitcoin vs Ethereum**	**Tether**	**Bnb**	**Xrp**	**Cardano**	**Dogecoin**
-10	1.159860	1.284608	1.121035	1.160763	1.162086	1.229661
-9	1.147621	1.272897	1.110550	1.151183	1.150479	1.219369
-8	1.132521	1.258306	1.097781	1.139366	1.136032	1.206721
-7	1.113510	1.239698	1.081976	1.124430	1.117634	1.190808
-6	1.089044	1.215318	1.062068	1.105018	1.093576	1.170208
-5	1.056902	1.182414	1.036537	1.079025	1.061191	1.142663
-4	1.014115	1.136572	1.003210	1.043224	1.016485	1.104636
-3	0.957534	1.070357	0.959054	0.992757	0.954809	1.050869
-2	0.885585	0.972674	0.901313	0.920268	0.875067	0.974749
-1	0.801153	0.854183	0.838195	0.823414	0.786869	0.880514
0	0.714753	0.757157	0.793621	0.731877	0.710894	0.796768
1	0.638140	0.684948	0.768197	0.661243	0.653798	0.730527
2	0.573929	0.629037	0.737269	0.602922	0.609132	0.672776
3	0.520826	0.583099	0.685139	0.553993	0.572569	0.619248
4	0.477997	0.545187	0.630702	0.513810	0.542255	0.571945
5	0.444225	0.514528	0.587844	0.481532	0.517147	0.533454
6	0.417770	0.490011	0.556265	0.455903	0.496441	0.503599
7	0.396904	0.470386	0.532787	0.435545	0.479413	0.480719
8	0.380216	0.454548	0.514855	0.419235	0.465403	0.463057
9	0.366647	0.441622	0.500775	0.406004	0.453825	0.449216
10	0.355437	0.430944	0.489448	0.395123	0.444187	0.438184

Table 4: These values are inherent to the q order by $H\,(2)$ values (the Generalized Hurst exponent) for these volatility time series pairs for both attributes (price and volume) considering the period during COVID-19.

Price During COVID-19 Pandemic

q	bitcoin vs Ethereum	Tether	Bnb	Xrp	Cardano	Dogecoin
-10	1.160338	1.354225	1.095404	1.319841	1.168449	1.208903
-9	1.151282	1.344492	1.087345	1.309247	1.160214	1.198873
-8	1.140491	1.332584	1.077842	1.296213	1.150374	1.186618
-7	1.127429	1.317773	1.066525	1.279856	1.138417	1.171364
-6	1.111313	1.299021	1.052930	1.258841	1.123598	1.152022
-5	1.090948	1.274806	1.036548	1.231084	1.104771	1.127151
-4	1.064474	1.242836	1.016957	1.193262	1.080018	1.095065
-3	1.028939	1.199705	0.993816	1.140089	1.045850	1.054165
-2	0.979431	1.141742	0.965399	1.063740	0.996299	1.002812
-1	0.913235	1.074716	0.927033	0.963846	0.929446	0.939787
0	0.851814	1.028923	0.881388	0.876203	0.865658	0.873591
1	0.800891	0.984018	0.829244	0.807213	0.810607	0.812514
2	0.724047	0.837884	0.746582	0.729313	0.737388	0.745506
3	0.620548	0.698012	0.644375	0.638871	0.640724	0.674581
4	0.533965	0.615636	0.560872	0.560099	0.554904	0.614430
5	0.474622	0.565102	0.502422	0.502379	0.493446	0.569519
6	0.434480	0.531251	0.461906	0.461661	0.450849	0.536946
7	0.406248	0.507025	0.432929	0.432453	0.420451	0.512990
8	0.385502	0.488838	0.411430	0.410846	0.397897	0.494892
9	0.369672	0.474685	0.394940	0.394353	0.380567	0.480835
10	0.357215	0.463360	0.381928	0.381408	0.366857	0.469635

Volume During COVID-19 Pandemic

q	bitcoin vs Ethereum	Tether	Bnb	Xrp	Cardano	Dogecoin
-10	1.062787	1.076010	1.117835	1.072926	1.141759	1.152140
-9	1.051292	1.066940	1.107281	1.063509	1.133284	1.140384
-8	1.037397	1.055918	1.094429	1.051997	1.122892	1.126130
-7	1.020394	1.042275	1.078497	1.037647	1.109852	1.108565
-6	0.999316	1.025028	1.058310	1.019352	1.092993	1.086507
-5	0.972834	1.002674	1.032002	0.995372	1.070294	1.058223
-4	0.939114	0.972801	0.996447	0.962808	1.037843	1.021215
-3	0.895733	0.931209	0.946529	0.916534	0.986993	0.972291
-2	0.840413	0.870663	0.877244	0.848806	0.898133	0.909083
-1	0.774973	0.788250	0.799789	0.763438	0.777963	0.835544
0	0.709887	0.711726	0.740635	0.693675	0.711690	0.766076
1	0.654627	0.659009	0.700436	0.644859	0.669159	0.710850
2	0.609818	0.619817	0.670557	0.605659	0.632214	0.667751
3	0.573705	0.587556	0.646919	0.572709	0.598497	0.632295
4	0.544820	0.560322	0.628069	0.546099	0.568393	0.602117
5	0.521732	0.537609	0.613060	0.525424	0.542742	0.576462
6	0.503117	0.518913	0.601043	0.509463	0.521597	0.555019
7	0.487911	0.503567	0.591313	0.496939	0.504364	0.537352
8	0.475333	0.490902	0.583321	0.486867	0.490287	0.522874
9	0.464808	0.480352	0.576651	0.478567	0.478690	0.510975
10	0.455910	0.471468	0.570999	0.471577	0.469033	0.501122

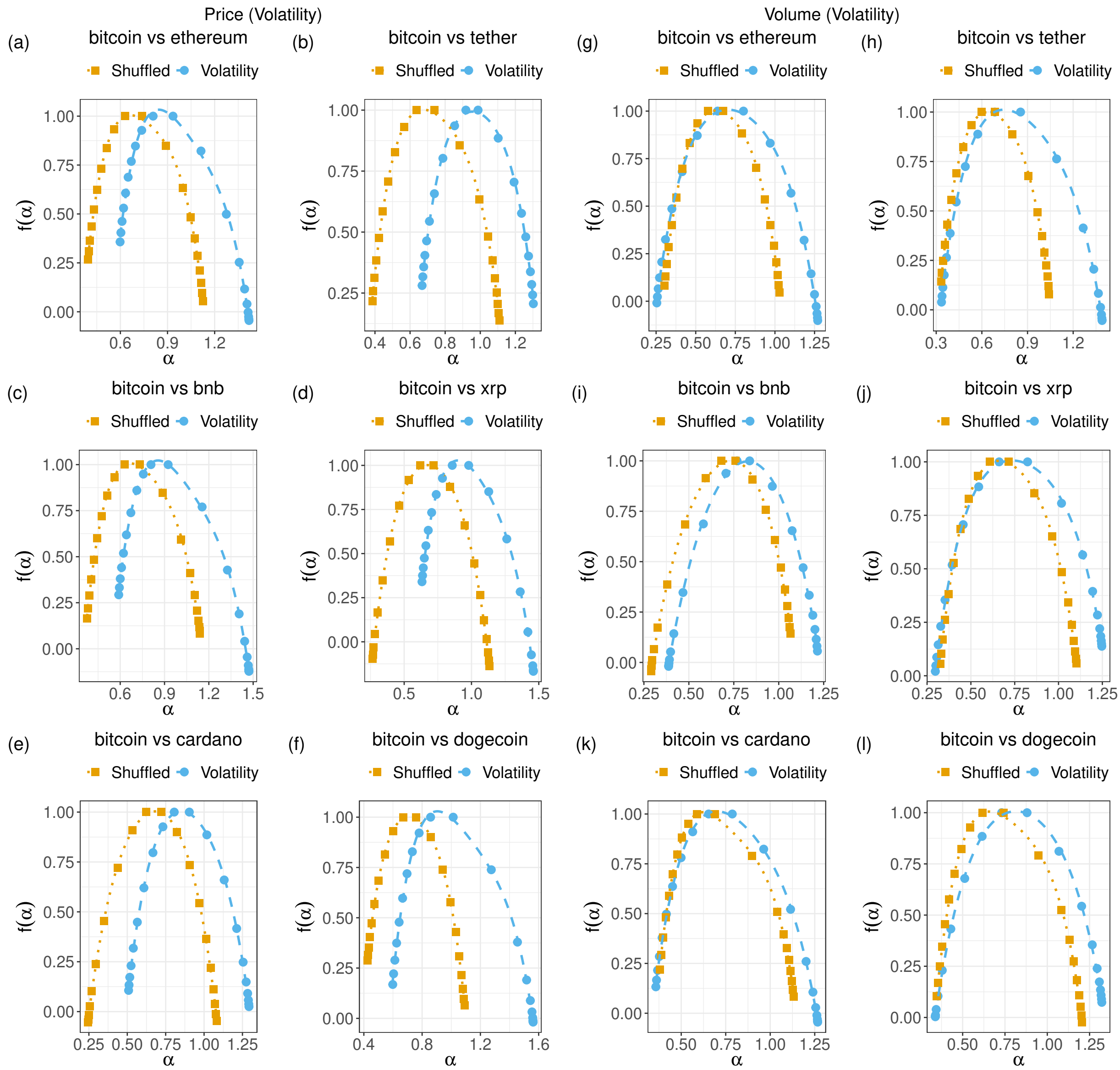

Figure 5: The plots of the multifractal spectrum of these volatility time series pairs for both attributes (price and volume) cover the period from October 01, 2018, to December 31, 2019 (before COVID-19) with 988 observations.

Based on the graphical analysis, we discover that these volatility time series pairs for both attributes (price and volume) considering the period before COVID-19 are characterized by long-term correlations or persistent process ($\alpha_{xy}(0) > 0.5$), a higher degree of multifractality, the dominance of low fractal exponents and both long-term correlations for small and large fluctuations and a broad probability density function as the source of multifractality.

Moreover, we observe that the multifractality for the price volatility time series show more persistent behaviour than the volume volatility time series. It is very plausible, given

Table 5: Multifractality table of the cryptocurrencies price and volume during COVID-19 pandemic.

Price before COVID-19 Pandemic												
Bitcoin	**Original**						**Shuffled**					
	$h(2)_{XY}$	ΔH_{xy}	$\alpha_{xy}(0)$	W_{xy}	r_{xy}	Γ	$h(2)_{XY}$	ΔH_{xy}	$\alpha_{xy}(0)$	W_{xy}	r_{xy}	Γ
Ethereum	0.772106	0.651750	0.844319	0.820501	2.333000	0.971791	0.585464	0.500397	0.642783	0.646852	2.860235	1.006329
Tether	0.885779	0.482613	0.955849	0.633895	1.206717	0.663174	0.585486	0.673175	0.715006	0.881413	0.872457	1.232735
Bnb	0.782478	0.698430	0.856298	0.881361	2.310768	1.029269	0.578640	0.504900	0.646000	0.650957	1.507540	1.007673
Xrp	0.820679	0.644381	0.898033	0.827091	2.114673	0.921003	0.575318	0.697257	0.724061	0.895356	0.750109	1.236576
Cardano	0.768883	0.597149	0.852377	0.784010	1.280290	0.919793	0.595703	0.599753	0.689913	0.810290	1.115544	1.174481
Dogecoin	0.818828	0.778535	0.904760	0.963577	2.145887	1.065009	0.576749	0.561878	0.657462	0.735637	1.348646	1.118903
Volume before COVID-19 Pandemic												
Bitcoin	**Original**						**Shuffled**					
	$h(2)_{XY}$	ΔH_{xy}	$\alpha_{xy}(0)$	W_{xy}	r_{xy}	Γ	$h(2)_{XY}$	ΔH_{xy}	$\alpha_{xy}(0)$	W_{xy}	r_{xy}	Γ
Ethereum	0.573929	0.804423	0.703825	1.015471	1.260194	1.442789	0.607178	0.493569	0.669433	0.672240	1.587917	1.004193
Tether	0.629037	0.853664	0.744870	1.055164	1.573419	1.416573	0.577224	0.537336	0.637830	0.682557	1.774158	1.070123
Bnb	0.737269	0.631587	0.827519	0.827896	0.881527	1.000456	0.647434	0.516341	0.711549	0.703958	0.946688	0.989331
Xrp	0.602922	0.765640	0.734675	0.949786	1.171029	1.292798	0.572466	0.552768	0.666730	0.727464	0.986938	1.091093
Cardano	0.609132	0.717899	0.699800	0.909102	1.655458	1.299088	0.634406	0.489688	0.683883	0.656072	2.060693	0.959334
Dogecoin	0.672776	0.791477	0.814778	0.983790	1.065561	1.207433	0.582336	0.623286	0.653723	0.811093	1.692312	1.240728

that the price volatility time series tends to show more fluctuations than the volume volatility time series. In addition Table 5 presents the values of complexity parameters considering the period before COVID-19.

Bearing in mind the period of before COVID-19, we discover a common behaviour for all these volatility time series pairs for both attributes (price and volume), considering $q = 2$, the values inherent to $h(2)$ are greater than 0.5. Also, we observe that for all these volatility time series pairs for both attributes (price and volume) the greater value of ΔH_{xy} leads in stronger multifractal features. An overview, our empirical results indicate that the volatility time series pairs for the volume attributes exhibit stronger multifractal features than the volatility time series pairs for the price attributes. In this way, the pairs of Bitcoin vs Tether ($\Delta H_{xy} = 0.853664$), Bitcoin vs Ethereum ($\Delta H_{xy} = 0.804423$), and Bitcoin vs Dogecoin ($\Delta H_{xy} = 0.791477$) for the volume attributes present stronger multifractal feature than other pairs.

We find that these volatility time series pairs for both attributes (price and volume) display values of $\alpha_{xy}(0) > 0.5$. It ratifies our graphical analysis. Thus, these volatility time series pairs for both attributes (price and volume) are characterized by overall persistent behaviour [27].

The study of the values of W_{xy} allows us to verify that the pairs of Bitcoin vs Ethereum ($W_{xy} = 1.015471$) and Bitcoin vs Tether ($W_{xy} = 1.055164$) Bitcoin vs Ethereum ($W_{xy} = 1.015471$) for the volume attribute display the greater value of W_{xy} than the other pairs (these pairs are more complexity than the other pairs).

The values of r_{xy} parameter reveal that the multifractality for these volatility time series pairs for both attributes (price and volume) equal dominance of small and large fluctuations ($r_{xy} > 1$), exclude the pair Bitcoin/Bnb for the volume attribute ($r_{xy} < 1$) dominance of large fluctuations.

The MRCC values indicate that the pairs Bitcoin vs Ethereum ($\Gamma_{xy} = 1.442789$), Bitcoin vs Tether ($\Gamma_{xy} = 1.416573$), and Bitcoin vs Cardano ($\Gamma_{xy} = 1.299088$) for the volume attribute is more complex and persistent than the other pairs. In contrast, Bitcoin vs

Tether ($\Gamma_{xy} = 0.663174$), Bitcoin vs Cardano ($\Gamma_{xy} = 0.919793$), and Bitcoin vs Xrp ($\Gamma_{xy} = 0.921003$) are less complex and persistent (values inherent to the price attribute.

Fig. 6 presents the plots of the multifractal spectrum of these volatility time series for both attributes (price and volume), considering the period during COVID-19.

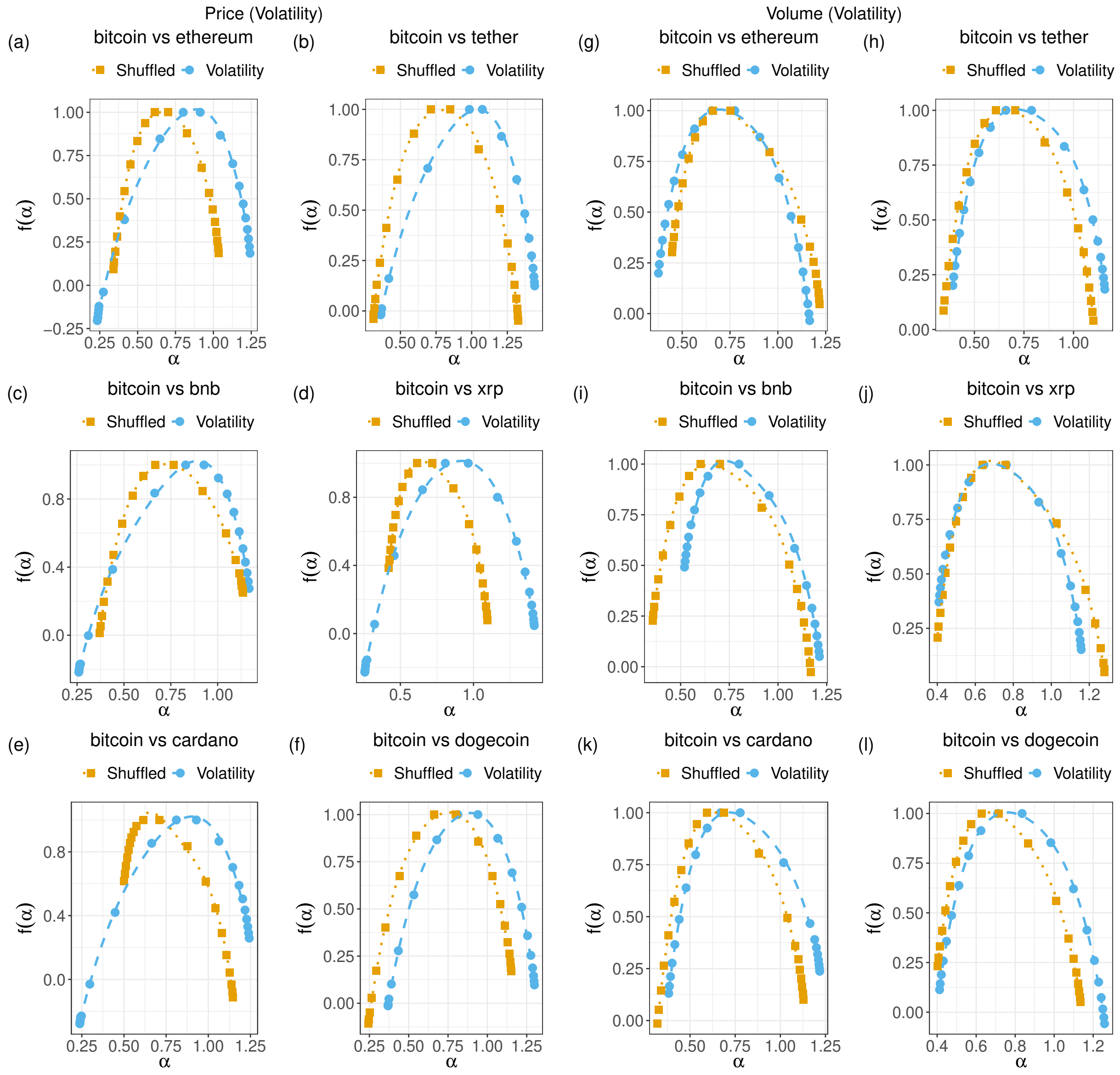

Figure 6: These multifractal spectrum cover the period from January 01, 2020, until September 14, 2022 (during COVID-19) with 988 observations.

Analogously to the period before COVID-19, we performed a graphical analysis and found that the period during COVID-19 is also characterized by a long-term correlations or persistent process ($\alpha_{xy}(0) > 0.5$), a higher degree of multifractality, the dominance of

Table 6: Multifractality table of the cryptocurrencies price and volume during COVID-19 pandemic.

Price during COVID-19 Pandemic												
Bitcoin	**Original**						**Shuffled**					
	$h(2)_{XY}$	ΔH_{xy}	$\alpha_{xy}(0)$	W_{xy}	r_{xy}	Γ	$h(2)_{XY}$	ΔH_{xy}	$\alpha_{xy}(0)$	W_{xy}	r_{xy}	Γ
Ethereum	0.724047	0.803123	0.889916	1.008069	0.536356	1.132769	0.646207	0.680337	0.779518	0.869072	0.960216	1.114885
Tether	0.837884	0.890865	1.044163	1.080388	0.582449	1.034693	0.664859	0.833411	0.826035	1.036541	1.032658	1.254839
Bnb	0.746582	0.713476	0.892649	0.908867	0.434500	1.018168	0.617280	0.542249	0.689259	0.711389	1.570872	1.032106
Xrp	0.729313	0.938433	0.918848	1.157977	0.750164	1.260249	0.683195	0.623413	0.763173	0.792516	1.693751	1.038448
Cardano	0.737388	0.801592	0.903778	1.004691	0.508749	1.111658	0.562763	0.591568	0.662894	0.793485	1.108424	1.197003
Dogecoin	0.745506	0.739268	0.894412	0.930965	0.769226	1.040869	0.589730	0.526397	0.694241	0.683712	0.843588	0.984834
Volume during COVID-19 Pandemic												
Bitcoin	**Original**						**Shuffled**					
	$h(2)_{XY}$	ΔH_{xy}	$\alpha_{xy}(0)$	W_{xy}	r_{xy}	Γ	$h(2)_{XY}$	ΔH_{xy}	$\alpha_{xy}(0)$	W_{xy}	r_{xy}	Γ
Ethereum	0.609818	0.606878	0.695070	0.790422	1.475924	1.137183	0.626847	0.645323	0.696425	0.838901	1.769522	1.204583
Tether	0.619817	0.604542	0.709730	0.766126	1.407577	1.079461	0.575267	0.580776	0.658380	0.781794	1.334332	1.187450
Bnb	0.670557	0.546836	0.729150	0.692692	2.314021	0.950000	0.594959	0.582384	0.697000	0.786554	1.008785	1.128485
Xrp	0.605659	0.601349	0.682100	0.749012	1.739305	1.098098	0.563818	0.667732	0.633412	0.852417	1.836942	1.345754
Cardano	0.632214	0.672726	0.718321	0.835912	1.486365	1.163703	0.604943	0.516284	0.689558	0.689979	1.083548	1.000611
Dogecoin	0.667751	0.651019	0.761463	0.845501	1.422511	1.110364	0.611633	0.726943	0.679359	0.921351	2.211767	1.356207

low fractal exponents and both long-term correlations for small and large fluctuations and a broad probability density function as the source of multifractality.

Again, we observe that the multifractality for the price volatility time series pairs display more persistent behaviour than the volume volatility time series pairs. Table 6 shows the values of complexity parameters considering the period during COVID-19.

Again, we find a common behaviour for all these volatility time series pairs for both attributes (price and volume), considering $q = 2$, the values inherent to $h(2)_{xy}$ are greater than 0.5. In an overview, we observe that during COVID-19, considering $q = 2$, the values inherent to $h(2)$, for both attributes price and volume) show a negative percentage variation in these values, excluding the pairs: Bitcoin vs Ethereum ($h(2)_{xy} = 0.57\%$), Bitcoin vs Xrp ($h(2)_{xy} = 0.45\%$), and Bitcoin vs Cardano ($h(2)_{xy} = 3.79\%$) for the volume attribute.

We note that COVID-19 has caused a shock to volatility time series pairs for the price attribute. In this sense, all pairs for this attribute showed a substantial positive percentage variation in the stronger multifractal features: Bitcoin vs Ethereum ($\Delta H_{xy} = 23.23\%$), Bitcoin vs Tether ($\Delta H_{xy} = 84.59\%$), Bitcoin vs Bnb ($\Delta H_{xy} = 2.15\%$), Bitcoin vs Xrp ($\Delta H_{xy} = 45.63\%$), Bitcoin vs Cardano ($\Delta H_{xy} = 34.24\%$). The only exception is the pair Bitcoin vs Dogecoin ($\Delta H_{xy} = -6.60\%$). For the volume attribute, we discover a common behaviour for the volatility time series pairs. Specifically, all the pairs display a negative percentage variation in these values: Bitcoin vs Ethereum ($\Delta H_{xy} = -24.56\%$), Bitcoin vs Tether ($\Delta H_{xy} = -29.18\%$), Bitcoin vs Bnb ($\Delta H_{xy} = -13.42\%$), Bitcoin vs Xrp ($\Delta H_{xy} = -21.49\%$), Bitcoin vs Cardano ($\Delta H_{xy} = -6.29\%$), and Bitcoin vs Dogecoin ($\Delta H_{xy} = -17.75\%$). It means that the COVID-19 shock has made stronger features in the volatility time series pairs for the price attribute than the volatility time series pairs for the volume attribute.

We observed that the COVID-19 shock hit the opposite way $\alpha_{xy}(0)$ for both attribute (price and volume). For the volatility time series pairs of the price attribute, we note that an overview the COVID-19 shock provide an increase in the persistence behaviour of these pairs: Bitcoin vs Ethereum ($\alpha_{xy}(0) = 5.4\%$), Bitcoin vs Tether ($\alpha_{xy}(0) = 9.24\%$), Bitcoin vs Bnb

($\alpha_{xy}(0) = 4.25\%$), Bitcoin vs Xrp ($\alpha_{xy}(0) = 2.32\%$), Bitcoin vs Cardano ($\alpha_{xy}(0) = 6.03\%$), and Bitcoin vs Dogecoin ($\alpha_{xy}(0) = -1.14\%$). For the volatility time series pairs of the volume attribute, the COVID-19 shock provide a decrease in the persistence behaviour (anti-persistence) of these all pairs: Bitcoin vs Ethereum ($\alpha_{xy}(0) = -1.24\%$), Bitcoin vs Tether ($\alpha_{xy}(0) = -4.72\%$), Bitcoin vs Bnb ($\alpha_{xy}(0) = -11.89\%$), Bitcoin vs Xrp ($\alpha_{xy}(0) = -7.16\%$), Bitcoin vs Cardano ($\alpha_{xy}(0) = -15.73\%$), and Bitcoin vs Dogecoin ($\alpha_{xy}(0) = -6.54\%$).

These findings reveal that the COVID-19 shock provides ambiguity effects in volatility time series pairs for both attributes (price and volume). An overview display that, in general, the volatility time series pairs for the price are characterized by an increase in the non-linear cross-correlations excluding the pair Bitcoin vs Dogecoin ($\alpha_{xy}(0) = -1.14\%$). In contrast, we discover that a decrease in the non-linear cross-correlations characterizes all volatility time series pairs considering the volume attribute.

Once again, we note that the COVID-19 shock hit the opposite way W_{xy} for both attributes (price and volume). For the volatility time series pairs of the price attribute, we verify that an overview the COVID-19 shock provides an increase in the W_{xy} of these pairs: Bitcoin vs Ethereum ($W_{xy} = 22.86\%$), Bitcoin vs Tether ($W_{xy} = 70.43\%$), Bitcoin vs Bnb ($W_{xy} = 3.12\%$), Bitcoin vs Xrp ($W_{xy} = 40.01\%$), Bitcoin vs Cardano ($W_{xy} = 28.15\%$), and Bitcoin vs Dogecoin ($\alpha_{xy}(0) = -3.38\%$). For the volatility time series pairs of the volume attribute, the COVID-19 shock provides a decrease in the W_{xy} of these all pairs: Bitcoin vs Ethereum ($W_{xy} = -22.16\%$), Bitcoin vs Tether ($W_{xy} = -27.39\%$), Bitcoin vs Bnb ($W_{xy} = 16.33\%$), Bitcoin vs Xrp ($W_{xy} = -21.14\%$), Bitcoin vs Cardano ($W_{xy} = -8.05\%$), and Bitcoin vs Dogecoin ($W_{xy} = -14.06\%$).

Our empirical results were inherent for the values of r_{xy} parameter reflects that the multifractality for all volatility time series pairs for price attribute is characterized by ($r_{xy} < 1$) dominance of large fluctuations. At the same time, all volatility time series pairs for the volume attribute are characterized by ($r_{xy} > 1$), which leads to equal dominance of small and large fluctuations. Moreover, all volatility time series pairs for the price display a notorious decrease in the values of r_{xy}: Bitcoin vs Ethereum ($r_{xy} = -77.01\%$), Bitcoin vs Tether ($r_{xy} = -51.73\%$), Bitcoin vs Bnb ($r_{xy} = -81.2\%$), Bitcoin vs Xrp ($r_{xy} = -64.53\%$), Bitcoin vs Cardano ($r_{xy} = -60.26\%$), and Bitcoin vs Dogecoin ($r_{xy} = -64.15\%$). However, the majority of the volatility time series pairs for the volume attribute present a relevant increase in the values of r_{xy}: Bitcoin vs Ethereum ($r_{xy} = -9.89\%$), Bitcoin vs Tether ($r_{xy} = -10.54\%$), Bitcoin vs Bnb ($r_{xy} = 0.14\%$), Bitcoin vs Xrp ($r_{xy} = 48.53\%$), Bitcoin vs Cardano ($r_{xy} = 16.1\%$), and Bitcoin vs Dogecoin ($r_{xy} = 33.5\%$).

An overview, for the volatility time series pairs for price attribute the MRCC values reveal an increase in the Γ_{xy} considering the majority of the pairs: Bitcoin vs Ethereum ($\Gamma_{xy} = 16.57\%$), Bitcoin vs Tether ($\Gamma_{xy} = 56.02\%$), Bitcoin vs Bnb ($\Gamma_{xy} = -1.08\%$), Bitcoin vs Xrp ($\Gamma_{xy} = 36.83\%$), Bitcoin vs Cardano ($\Gamma_{xy} = 20.86\%$), and Bitcoin vs Dogecoin ($\Gamma_{xy} = -2.27\%$). In contrast, for the volatility time series pairs for volume attribute the MRCC values reveal that the COVID-19 shock provides a decrease in values inherent to Γ_{xy} for all pairs: Bitcoin vs Ethereum ($\Gamma_{xy} = -21.18\%$), Bitcoin vs Tether ($\Gamma_{xy} = -23.8\%$), Bitcoin vs Bnb ($\Gamma_{xy} = -5.04\%$), Bitcoin vs Xrp ($\Gamma_{xy} = -15.06\%$), Bitcoin vs Cardano ($\Gamma_{xy} = -9.99\%$), and Bitcoin vs Dogecoin ($\Gamma_{xy} = -8.6\%$).

We performed an analysis based on two clustering techniques to investigate similar behaviours in the formation and amplitude of cryptocurrency clusters considering before and during COVID-19. Fig. 7 depicts the plots of the K-means of these volatility time series pairs for the price attribute, considering the period before COVID-19.

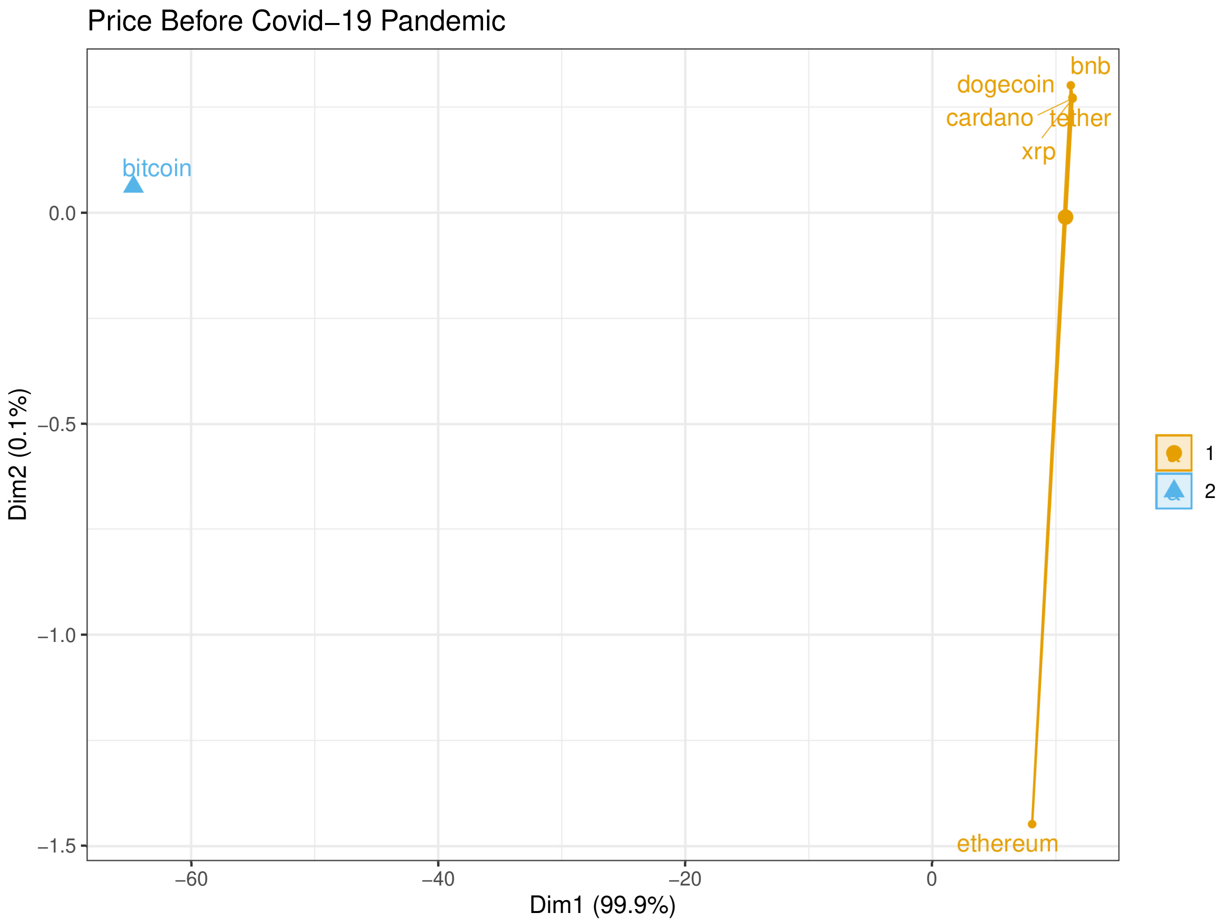

Figure 7: Before COVID-19, only 2 clusters are perceptible for these volatility time series pairs for the price attribute. The blue one encompasses only Bitcoin and the yellow one that includes the other cryptocurrencies. It indicates a high dissimilarity between the dynamics of the price volatility of Bitcoin and other cryptocurrencies price volatility.

Fig. 8 presents the plots of the K-means of these volatility time series pairs for the price attribute, considering the period during COVID-19.

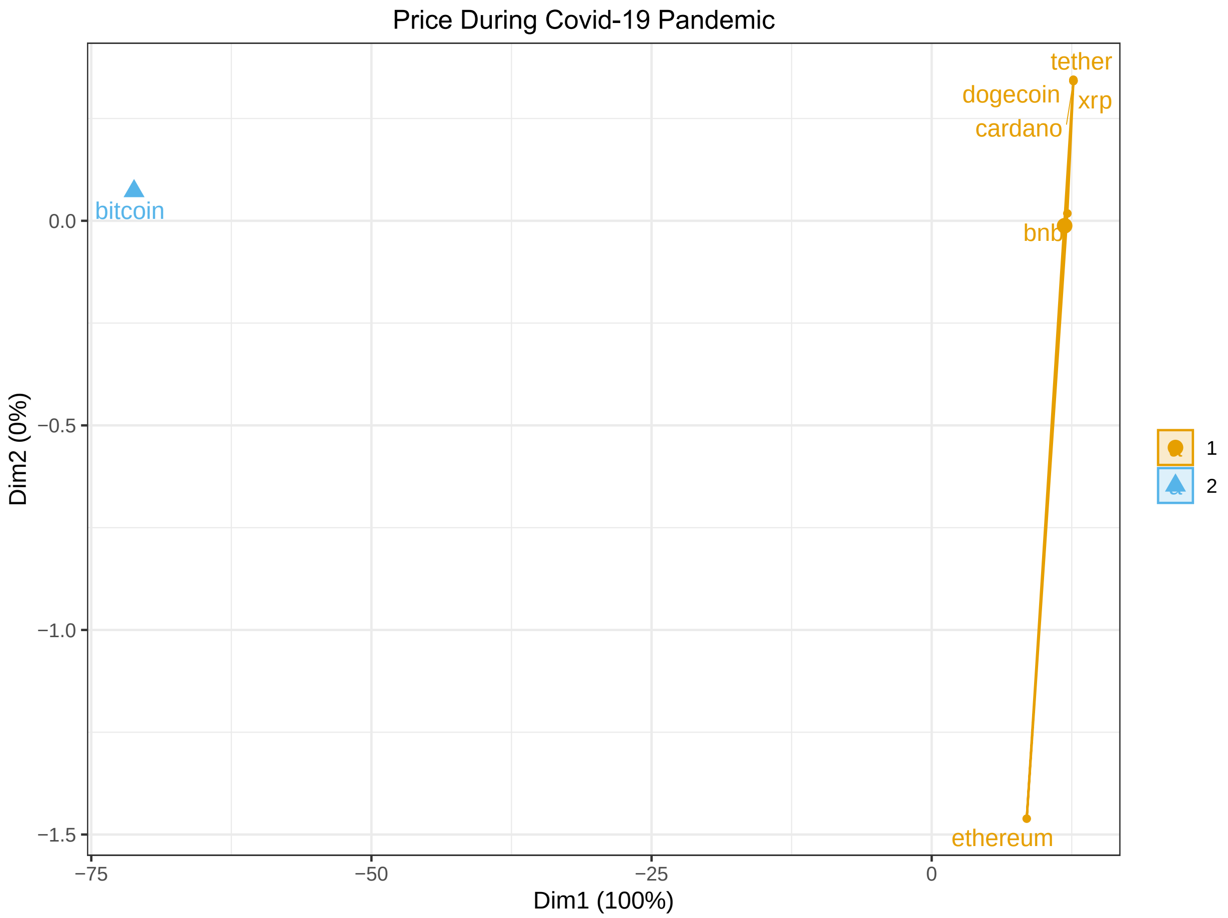

Figure 8: During COVID-19, there was no change in the clusters. It suggests that the COVID-19 shock was insufficient to drive a shift in cryptocurrency clusters.

Fernandes et al. (2022) [28] presented empirical evidence that cryptocurrencies were resilient to the shock of COVID-19. Our findings confirm that from a cluster perspective that these volatility time series for the price attribute were resilient to the shock of COVID-19.

Fig. 9 shows the plots of the K-means of these volatility time series for the volume attribute, considering the period before COVID-19.

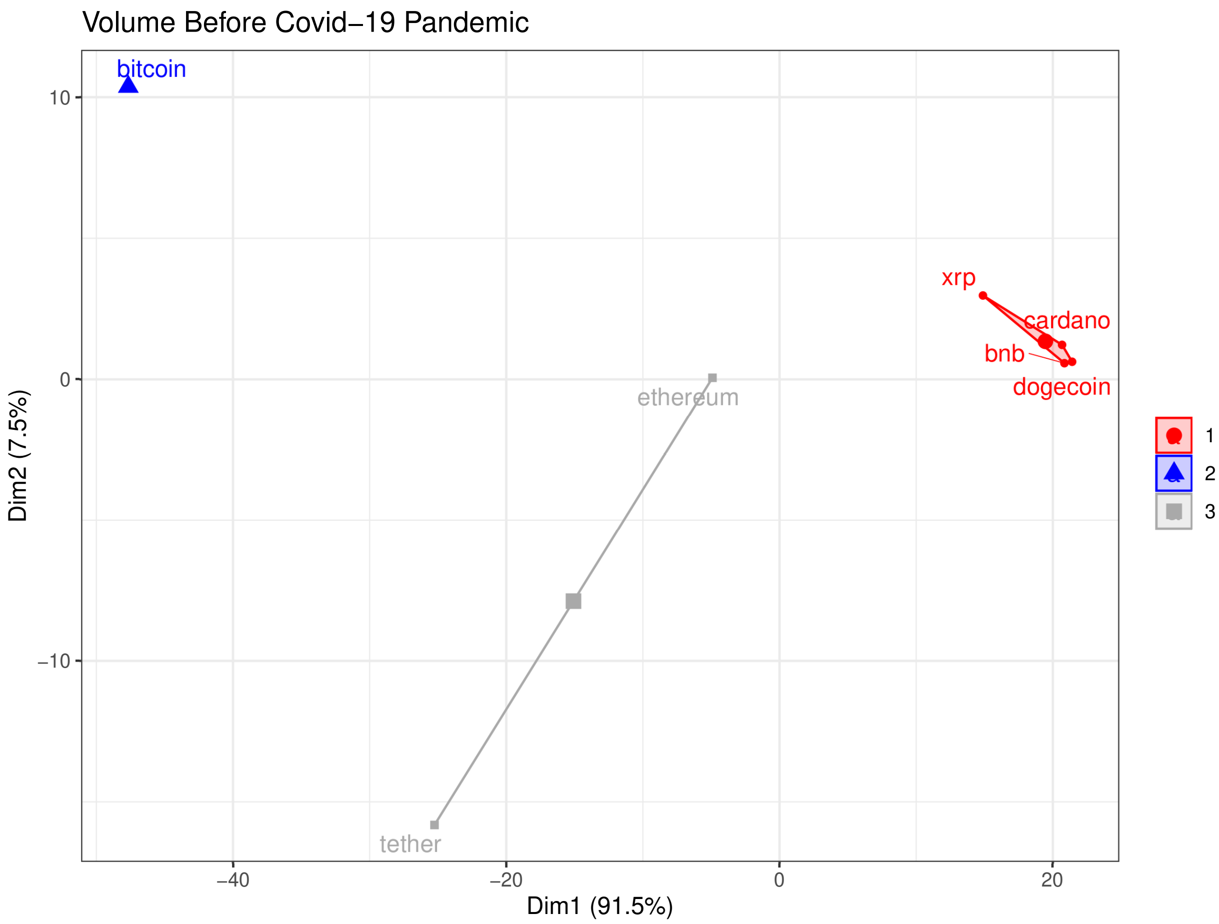

Figure 9: Before COVID-19, 3 clusters are perceptible for these volatility time series pairs for the volume attribute. The blue one encompasses only Bitcoin, the red one includes Tether and Ethereum, and the red one displays the other cryptocurrencies. It indicates the dynamics of the volume volatility of Bitcoin are singular, Tether and Ethereum are characterized by similar dynamics and Bnb, Cardano, Dogecoin, and Xrp are marked by similar dynamics.

Fig. 10 depicts the plots of the K-means of these volatility time series for the volume attribute, considering the period during COVID-19.

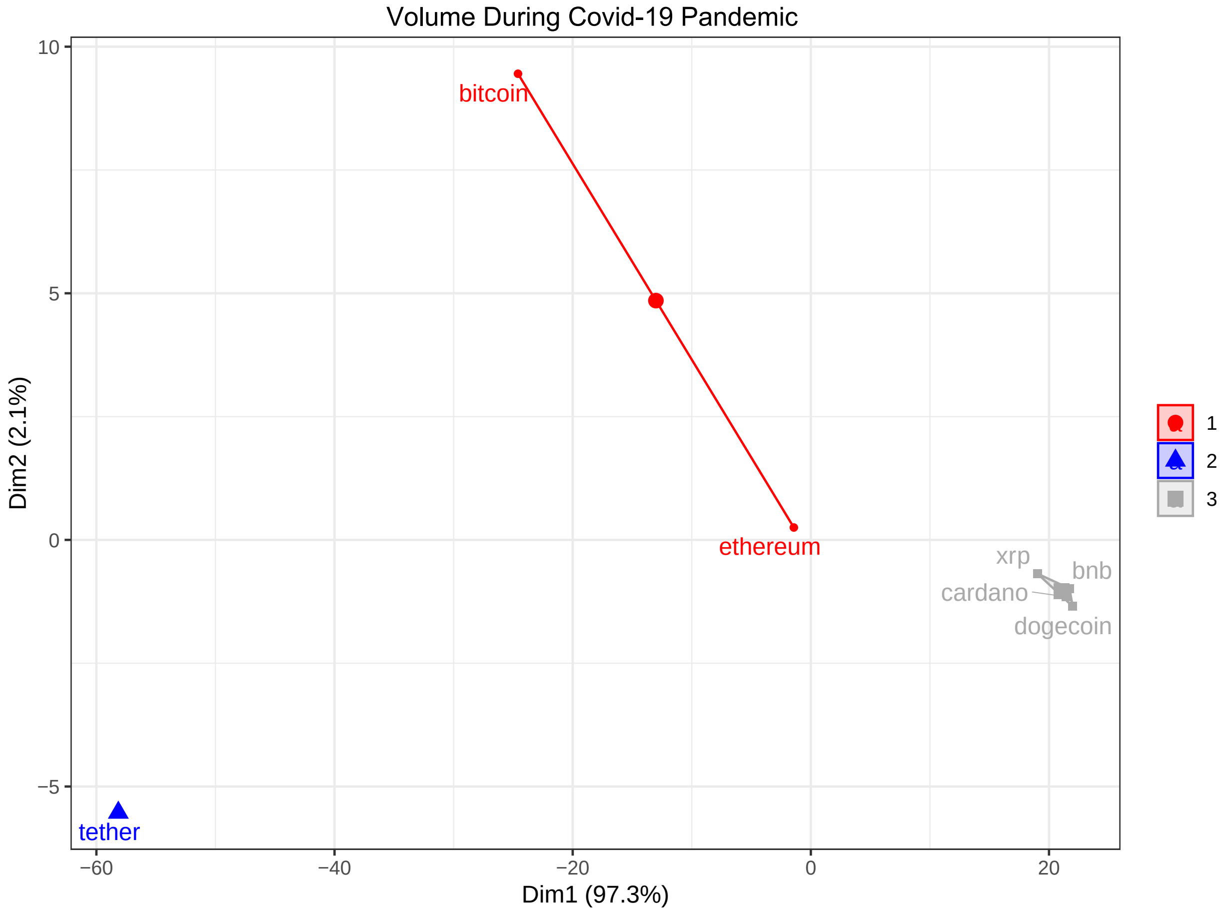

Figure 10: Before COVID-19, 3 clusters are perceptible for the volatility time series considering the volume attribute. The blue one encompasses only Tether, the red one includes Bitcoin and Ethereum, and the grey one displays the other cryptocurrencies. It indicates the dynamics of the volume volatility of Tether are unique, Bitcoin and Ethereum are characterized by similar dynamics and Bnb, Cardano, Dogecoin, and Xrp are marked by similar dynamics.

For these volatility time series for the volume attribute, we find that the COVID-19 shock drove changes in cryptocurrency groups. Specifically, before COVID-19, for the volume attribute, Bitcoin had a unique dynamic changed by COVID-19, as Bitcoin became similar to Ethereum. While before COVID-19, the Tether had a unique dynamic, which was altered by COVID-19, as Tether displays a unique dynamic.

4. Concluding remarks

We have presented empirical evidence related to the COVID-19 shock in one of the most intriguing components of the financial market, which is cryptocurrencies. Our research encompasses the daily closing price and the daily trading volume time series for the seven largest cryptocurrencies considering trade volume and market capitalization (Bitcoin, Ethereum, Tether, Bnb, Xrp, Cardano, and Dogecoin).

Effective quantification of the COVID-19 shock in these cryptocurrencies is closely associated with the consideration of two non-overlapping periods (before COVID-19, and during COVID-19) to examine the non-linear cross-correlations and the similarity between Bitcoin and the other cryptocurrencies.

For both time series, we calculate the volatility time series, defined as the absolute logarithmic difference between consecutive observations. Then, we employ the MF-DCCA with a fourth-degree polynomial regression fit, to estimate the complexity parameters that describe the degree of multifractality of the underlying process.

For both periods, our findings reveal a common multifractal dynamics behaviour for these volatility time series pairs for both attributes (price and volume). We find that all these volatility time series pairs for both attributes, considering both periods (before and during COVID-19) exhibit overall persistent long-term correlations ($\alpha_{xy}(0) > 0.5$), high degree of multifractality, the dominance of higher fractal exponents, and long-term correlations [29] for small and large fluctuations.

However, we conclude that the multifractality of the price volatility time series pairs displays more persistent behaviour than the volume volatility time series pairs. To complement our analysis, we performed a systematic analysis of the multifractal parameters and quantified the percentage variation for these parameters. It allowed us to diagnose that in an overview and excluding some singularities, the COVID-19 shock was completely distinct in price volatility time series pairs and volume volatility time series pairs.

Specifically, our findings indicate that the COVID-19 shock promotes ambiguity effects in volatility time series pairs for both attributes (price and volume). We discover that the volatility time series pairs for the price are marked by an increase in the non-linear cross-correlations excluding the pair Bitcoin vs Dogecoin ($\alpha_{xy}(0) = -1.14\%$). In contrast, all volatility time series pairs considering the volume attribute are marked by a decrease in the non-linear cross-correlations.

Also, we apply the classical K-means approach to investigate the similarity of the volatility dynamics for these cryptocurrencies for both attributes, considering both periods before and during COVID-19. Our results indicate that from a cluster perspective, these volatility time series for the price attribute were resilient to the shock of COVID-19. While for these volatility time series for the volume attribute, we find that the COVID-19 shock drove changes in cryptocurrency groups.

Our research provides a better understanding of the multifractal cross-correlations dynamics and the similarity in the cryptocurrency market, considering the periods before and during the COVID-19 crisis. Our results are relevant for investors to apply cryptocurrencies for liquidity risk diversification strategy.

Other articles by the authors, see:[30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54]

5. Declaration of Competing Interest

The authors declare that this work has no conflicting personal or financial influences.

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