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COVID-19, cryptocurrencies bubbles and digital market efficiency: sensitivity and similarity analysis

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ABSTRACT

This paper compares the degree of cryptocurrency market efficiency during the pre- and post COVID-19 pandemic with the bubble and non-bubble periods of cryptocurrency markets. Furthermore, it examines and clusters eighteen cryptocurrencies by exploring their market efficiency similarity. Comparing the cryptocurrency bubble periods with the COVID-19 pandemic, the results indicate that this pandemic has the highest impact on cryptocurrency market efficiency. Interestingly, using the dynamic time warping clustering approach, we found evidence on the presence of three clusters that essentially represent mining coins, non-mining coins and token categorizations .

1. Introduction

The COVID-19 pandemic has re-opened interest in re-examining several important finance research questions (Baker et al., 2020; Corbet et al., 2020; Okorie and Lin, 2020). While most of the recently published papers have focused on evaluating the financial impact of the COVID-19 pandemic at both the global and sectional levels, only a few studies have examined how the pandemic has affected the dynamic of financial markets, in particular the market efficiency hypothesis (MEH) (Wang and Wang, 2021). This study tries to fill the above-mentioned gap by exploring the evolving behavior of the market efficiency of the major traded digital cryptocurrencies during periods of extreme events. In particular, this study extends the recent work of Le Tran and Leirvik (2020) by comparing the degree of digital market efficiency during the pre- and post-pandemic announcement periods of COVID-19 to market efficiency during periods of cryptocurrency price bubbles and price stability[1]. Furthermore, it extends the analysis of Le Tran and Leirvik (2020) by exploring possible similarities between the market efficiency of 18 cryptocurrency time series.

Recently, the market efficiency of crypto-currency markets has received increasing attention and seen the use of a range of empirical methods (Urquhart, 2016; Vidal-Tomás and Ibañez, 2018; Charfeddine and Maouchi, 2019; Le Tran and Leirvik, 2020). This was mainly motivated by its important implications for portfolio managers, investors, and regulators. However, empirically the literature provides mixed results and distinguishes two dominant research strands. In the first strand, the MEH has been largely rejected (Urquhart, 2016; Vidal-Tomás and Ibañez, 2018; Jiang et al., 2018; Wei, 2018). Some authors have found an exception of a particular cryptocurrency market that may be efficient, among the studied larger set of cryptocurrencies (see Charfeddine and

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[1] We use the Phillips and Shi (2020) approach to data-stamping the bubbles (see also Enoksen et al., 2020).

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Maouchi, 2019). However, the second strand recognizes the time-varying aspect of crypto-currencies and considers market efficiency by period. In this vein, Bariviera (2017) found that Bitcoin returns are inefficient before 2014, while the market has become more efficient since 2014. Le Tran and Leirvik (2020) studied five cryptocurrencies, namely Bitcoin, Ethereum, Ripple, Litecoin, and EOS, and found that before 2017, crypto-currency markets are mostly inefficient. However, the authors claimed these markets become more efficient during the 2017–2019 period. The only study that has assessed the effects of the COVID-19 pandemic on the efficiency of financial markets is the paper of Wang and Wang (2021). Using the refined composite multi-scale fuzzy entropy at all scales, the authors have indeed found that the efficiency of the S&P 500 Index, gold, Bitcoin, and the US Dollar Index markets sharply and persistently decreased during February-March 2020.

The contribution of this paper is threefold. First, it examines how market efficiency degree of the top eighteen cryptocurrencies have evolved during the periods of pre- and post-announcements of the COVID-19 pandemic, and the bubble and stable periods of cryptocurrency market. Second, it uses the dynamic time warping [DTW] paths to examine the lead-lag relationship between the different cryptocurrencies. Consequently, it will help to predict the timing of extreme event disturbances transmission from one market to another. Finally, using the DTW-based clustering technique, we examine the similarities between the efficiency of the studied different cryptocurrencies. The results of this clustering show that to construct their portfolios, investors may opt for diversification between the studied cryptocurrencies.

The rest of the paper proceeds as follows. Section 2 describes and provides a preliminary analysis of the studied cryptocurrencies, along with a description of the methodology used. Section 3 interprets and discusses the empirical results. Finally, Section 4 concludes the paper.

2. Data and methodology

2.1. Data and variables description

Daily closing prices of major eighteen crypto-currencies, selected based on their market capitalization, types (coins and tokens) and data availability, are collected from https://coinmarketcap.com/. Only cryptocurrencies issued and traded before the 2017–2018 cryptocurrency bubble are considered in our sample. The selected 18 cryptocurrencies are: Bitcoin [BTC], Ethereum [ETH], Ripple [XRP], Cardano [ADA], Litecoin [LTC], Bitcoin Cash [BCH], Chainlink [Link], Stellar [XLM], Binance [BNB], TRON [TRX], Tezos [XTZ], Maker [MKR], OMG Network [OMG], Loopring [LRC], 0X [0X], Monero [XMR], EOS [EOS], NEM [XEM]. The data cover the period stretching from October 02, 2017 until January 15, 2021. The return series are calculated using the compound return formula $r_t = 100*(\log(p_t) - \log(p_{t-1}))$.

2.2. Market efficiency tests

Suppose that the dynamics of returns is described by an $AR(q)$:

$$r_t = \mu + \beta_1 r_{t-1} + \beta_2 r_{t-2} + \ldots + \beta_q r_{t-q} + \varepsilon_t. \quad (1)$$

The coefficients ($\beta_1, \beta_2, \ldots, \beta_q$) must be close to zero or at least insignificantly different from zero for the efficient market hypothesis (EMH) to hold. Denote by $\widehat{\beta}$ the column vector of the OLS estimated coefficients $(\widehat{\beta}_1, \widehat{\beta}_2, \ldots, \widehat{\beta}_q)'$. The asymptotic variance of $\widehat{\beta}$, denoted by V, admits Cholesky decomposition as: $V = LL'$. In this way, we get the vector of the standardized estimated coefficients designed by $\widehat{\beta}^s = (\widehat{\beta}_1^{\,s}, \widehat{\beta}_2^{\,s}, \ldots, \widehat{\beta}_q^{\,s})' = L^{-1}\widehat{\beta}$. In a first step, Le Tran and Leirvik (2019) constructed a first measure of market inefficiency and called it magnitude market inefficiency (*MIM*). Such a measure is defined by :

$$MIM_t = \frac{\left|\sum_{j=1}^{q} \widehat{\beta}_{j,t}^{s}\right|}{1 + \left|\sum_{j=1}^{q} \widehat{\beta}_{j,t}^{s}\right|}. \quad (2)$$

By construction, MIM_t is between 0 (very efficient market) and 1 (inefficient market).Le Tran and Leirvik (2019) have shown that this measure is more powerful than those in the literature. Using Monte Carlo simulations, the authors determined the range R_{CI} between 0 and the 95% quantile of *MIM* under the null hypothesis of efficiency for several values of the lag q of the autoregressive process in (1). In a second step, Le Tran and Leirvik (2019) have introduced the adjusted magnitude of market inefficiency (*AMIM*) defined by:

$$AMIM_t = \frac{MIM_t - R_{CI}}{1 - R_{CI}}. \quad (3)$$

The market is inefficient if $AMIM > 0$ and it will be efficient if $AMIM \leq 0$. $AMIM_t$ can be calculated at the annual frequency for each crypto-currency market or at daily frequency using rolling windows.

2.3. Dynamic time warping distance- based clustering

Next, we focus on clustering the obtained efficiency series based on the dynamic time warping *(DTW)* distance which is a

Table 1
Descriptive statistics and static market efficiency tests.

Cryptocurrencies Symbol	Rank	Descriptive statistics Mean	Max	Min	St. Dev	Skw.	Kurt.	Market efficiency tests Q-stat	VR	Runs	R/S	GPH	ELW
Mineable coins													
BTC	1	0.18	22.51	−46.47	4.17	−1.05	18.21	14.81	1.04	1.59	1.83	0.09	0.06
ETH	2	0.11	23.47	−55.07	5.15	−1.12	15.80	16.55	1.07	2.05	1.77	0.14	0.09
LTC	6	0.08	38.93	−44.90	5.58	0.34	11.85	15.31	1.07	2.90	1.51	0.09	0.12
ADA	7	0.20	86.12	−50.37	7.41	2.20	28.23	38.33	1.23	1.64	1.85	0.11	0.12
BCH	8	0.01	43.16	−56.14	6.87	0.09	13.02	9.45	1.10	3.20	1.54	0.07	0.10
XMR	15	0.05	24.82	−49.42	5.47	−0.73	10.54	34.56	0.86	4.53	1.67	0.08	0.06
Non-Mineable coins													
XRP	4	0.03	60.68	−55.04	6.39	1.01	23.08	38.85	1.17	3.55	1.30	0.18	0.11
XLM	10	0.26	66.67	−41.00	7.09	1.69	17.56	12.71	1.10	1.32	1.99	0.12	0.13
BNB	11	0.25	48.24	−54.28	5.93	0.08	16.98	25.97	1.07	1.69	1.38	−0.01	0.04
EOS	16	0.12	34.73	−50.32	6.68	0.16	10.09	19.19	1.04	4.55	1.46	0.13	0.16
TRX	17	0.20	78.68	−52.35	7.93	2.12	26.17	80.36	1.33	1.53	1.39	0.14	0.16
XTZ	19	0.03	56.87	−60.55	7.15	−0.39	13.62	46.56	0.32	0.59	1.13	−0.01	0.01
XEM	22	−0.01	99.54	−36.13	6.85	2.73	43.09	62.22	0.80	3.26	1.78	0.11	0.13
Tokens													
LINK	9	0.34	48.42	−61.75	7.60	0.07	10.00	6.67	1.01	0.83	1.11	0.06	0.10
MKR	28	0.15	45.85	−81.82	6.48	−0.89	29.98	12.31	1.05	0.86	1.17	0.01	0.03
OMG	56	−0.08	53.50	−56.24	6.82	0.03	11.80	18.01	1.02	1.01	1.40	0.03	0.01
LRC	58	0.08	44.99	−57.78	7.98	0.25	8.67	8.81	1.00	3.26	1.81	0.06	0.03
0X	63	0.08	33.96	−41.05	6.77	0.22	6.83	30.23	0.98	3.65	1.42	0.07	0.03

Notes : These statistics are applied to the cryptocurrency returns. VR stands for the variance ratio statistic. R/S, GPH, and ELW are the three long memory test statistics.

nonparametric tool highlighting similarities between time series (see Franses, 2020). More explicitly, let $DTW(i, j)$ be the optimal distance between the first i and first j elements of the two market efficiency series x et z, respectively. Then, $DTW(i, j)$ can be defined as:

$$DTW(i,j) = d(x_i, z_j) + \min[DTW(i,j-1), DTW(i-1,j),\ DTW(i,j-1)], \tag{4}$$

where $d(x_i,z_j)$is a distance measure. Specifically, clustering of market efficiency series is ensured by the k-medoids algorithm with the DTW distance. More precisely, we use the Partitioning Around Medoids (PAM) algorithm to determine local minima involved in this problem (Kaufman and Rousseeuw, 1987, 1990; and Giordani et al., 2020). The k-medoids algorithm is solved iteratively and can be formulated as follows,

$$\begin{aligned}
&\min_{W,B} \sum_{i=1}^{N}\sum_{h=1}^{k} w_{ih} dtw^2(m_i, b_h), \\
&s.t.\ \ w_{ih} \in [0,1], \quad i = 1,\ldots,N, \quad h = 1,\ldots.,k, \\
&\quad \sum_{h=1}^{k} w_{ih} = 1, \quad i = 1,\ldots,N, \\
&(c_1,\ldots,c_k) \subseteqq (m_1,\ldots,m_N)
\end{aligned} \tag{5}$$

The variables defining the above constrained minimization problem are the following : DTW denotes DTW distance and $m_i, i = 1, \ldots N$, stands for the AMIM measure for the efficiency of the cryptocurrency (unit) i market, and where N is the total number of cryptocurrencies studied in this paper. Moreover, $b_h, h = 1, \ldots k$, designates a candidate medoid among the k ones, while w_{ih} is a function describing the membership degree of the i th unit to the h-cluster; $w_{ih} = 1$ if the i th unit belongs to the h-cluster and $w_{ih} = 0$ otherwise. w_{ih} is the generic term of the allocation matrix W while B is the medoid matrix of order $(k \times p)$ containing, as rows, the medoids $b_h, h = 1, \ldots, k$, and p is the number of observations of each unit.

Unlike the k-means algorithm, the medoids are data points in the k-medoids algorithm. Comparative studies between k-medoids and k-means algorithms for clustering have pointed to the superiority of the first over the second (Arbin, 2015).

3. Empirical results

3.1. Descriptive statistics and static market efficiency

Table 1 reports the descriptive statistics of the cryptocurrencies return series along with some static market efficiency tests. Table 1 shows that the average daily return is quite high for most of the coins and tokens, e.g. it varies between −0.08% and 0.34%. The highest means are found for ChainLink (0.34%), Stellar (0.26%), and Binance coin (0.25%). Only two cryptocurrencies have a negative mean, e.g. OMG (−0.08%) and XEM (−0.01%). In terms of volatility, the results show that the lowest (4.17%) and the highest volatility (7.98%) are obtained for Bitcoin and Tezos, respectively. Finally, the normality hypothesis is rejected by the Jarque-Bera test for all the return series.

Table 2
Market Efficiency Ranking of Cryptocurrencies (over the whole period, bubbles versus non- bubbles periods, and Pre- and post COVID-19 announcement periods).

	Whole period			Bubble Period			Non Bubble Period			Pandemic Period			Pre – Pandemic Period		
Symbol	% ME	Rank	Median	%ME	Rank	Median	%ME	Rank	Median	%ME	Rank	Median	%ME	Rank	Median
BTC	45.808	13	0.0209	32.061	14	0.0349	48.456	15	0.001	4.193	17	0.214	65.912	11	−0.056
ETH	45.509	14	0.0258	16.867	16	0.1494	49.325	14	0.003	7.742	13	0.219	64.706	13	−0.070
LTC	53.493	8	−0.0167	34.722	12	0.0247	54.938	10	−0.023	7.419	14	0.173	74.962	7	−0.102
ADA	46.108	12	0.0204	39.743	10	0.2625	50.838	12	−0.006	19.032	8	0.219	64.404	14	−0.029
BCH	53.094	9	−0.0434	62.857	2	−0.0870	56.716	9	−0.106	39.032	2	0.109	65.309	12	−0.185
XMR	37.824	16	0.0638	38.636	11	0.0998	43.703	16	0.035	0.000	18	0.163	63.80	16	−0.064
XRP	52.495	10	−0.0157	11.428	17	0.1568	57.889	8	−0.046	21.290	7	0.185	72.549	8	−0.131
XLM	48.403	11	0.0108	55.000	5	−0.032	53.846	11	−0.2684	23.871	6	0.106	69.532	10	−0.095
BNB	57.685	5	−0.0518	59.091	3	−0.072	91.240	2	−0.2835	4.516	16	0.163	91.252	1	−0.191
EOS	54.491	7	−0.0322	45.454	8	0.0799	61.935	6	−0.050	26.774	5	0.147	77.828	6	−0.098
TRX	62.075	3	−0.0791	33.333	13	0.1527	65.244	4	−0.099	17.742	9	0.119	86.878	2	−0.207
XTZ	36.627	18	0.0902	55.128	4	−0.1485	39.776	18	0.092	14.516	10	0.153	53.394	18	−0.023
XEM	37.824	17	0.0618	4.8197	18	0.2257	42.921	17	0.024	6.129	15	0.093	55.354	17	−0.016
LINK	58.582	4	−0.0477	46.575	7	0.0773	64.449	5	−0.058	10.968	11	0.102	85.520	3	−0.158
MKR	68.563	2	−0.1761	50.000	6	0.1584	70.262	3	−0.236	37.742	3	0.069	84.917	4	−0.278
OMG	57.584	6	−0.0364	40.000	9	0.1003	60.236	7	−0.031	33.871	4	0.094	71.342	9	−0.068
LRC	44.611	15	0.0191	18.293	15	0.2321	49.607	13	0.002	10.323	12	0.228	64.103	15	−0.042
0X	70.758	1	−0.1245	71.088	1	−0.1270	100.00	1	−0.3432	65.301	1	−0.120	84.193	5	−0.189
Average	51.752			39.728			58.966			19.470			71.998		

Notes:% ME denotes how often the cryptocurrency markets are efficient throughout the considered period. The ranks of the different cryptocurrencies are then determined according to% ME. Median is the median of the different market efficiency series.

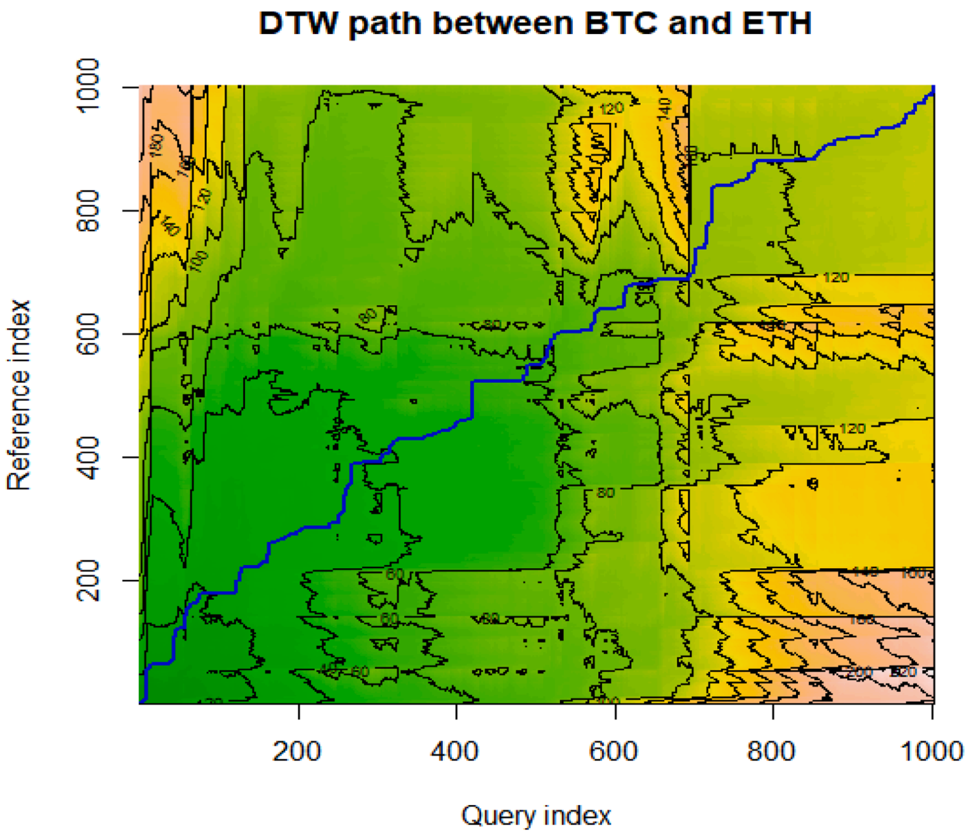

Fig. 1. The DTW path between BTC (Reference) and ETH (Query) for the whole sample
Notes: Fig. 1 presents the dynamic time warping (DTW) path between Bitcoin and Ethereum for the whole studied sample.

Table 1 reports also the results of several static market efficiency tests including the Ljung-Box Q-statistic, the Variance Ratio (VR), the Runs tests and three long-memory test statistics. The results indicate that, using a conventional significance level, the null hypothesis of market efficiency is rejected for seven CCs (XMR, Ripple, Binance coin, TRON, Tezos, XEM and 0x) using Ljung and Box's (1978) Q-Stat, it is rejected for only the TRON coin when using the Variance ratio test, and for nine return series using the Runs test (Ethereum, Litcoin, Bitcoin cash, XMR, Ripple, EOS, XEM, Loopring and 0x).

Using the long memory tests, the results indicate that the market efficiency hypothesis is rejected in only one case (Stellar) using the R/S test, seven cases (Ethereum, Ripple, Cardano, Stellar, XEM, EOS and TRON) using the GPH technique and eight cases (Ethereum, Bitcoin Cash, Litecoin, Cardano, Ripple, Stellar, EOS, TRON, XEM, and ChainLink) using the ELW method.

3.2. Analysis of market efficiency

Table 2 reports the ranking results of the 18 cryptocurrencies based on percentage and median of the AMIM market efficiency criteria. It should be noted in this respect that compared to Le Tran and Leirvik (2020), we have reduced the rolling window to 200 observations to have a larger surveyed part of the year 2018. The results are analyzed by comparing the whole period results to the bubble versus non-bubble periods results, and to the pre- and post- COVID-19 pandemic announcement results.

The findings reported in Table 2 columns 2–4 for the entire sample period show that 10 out of the 18 cryptocurrencies are efficient in more than half of the sample period points. In particular, we found that most of the top cryptocurrencies in terms of market capitalization (such as BTC, ETH, XRP, ADA, LTC, LTC) are not well ranked (between rank 8 for LTC and 14 for ETH). Using the median criterion, we found that the tokens category is more efficient (4 out of the 5 medians are negative) than non-mining coins (4 out of the 7 medians are negative). For the mining coins, we found that they are the least efficient with only two medians negative out of the six mining coins.

However, much clearer and interesting patterns emerge when analyzing the percentages and medians of the CCs market efficiency time series over the bubble periods versus the non-bubble periods and between the pre- COVID-19 pandemic announcement period versus the post- COVID-19 pandemic announcement period. We summarize the main results drawn from Table 2 in the following points:

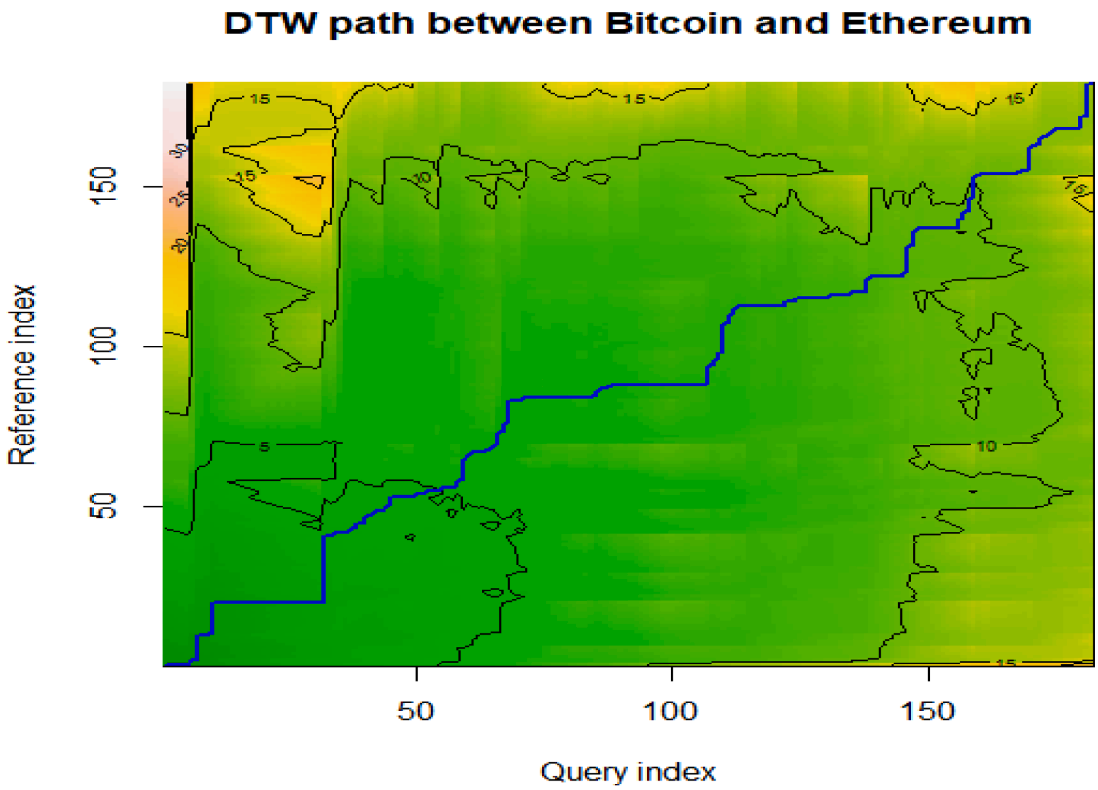

Fig. 2. The DTW path between BTC (Reference) and ETH (Query) from July 18, 2020, until January 15, 2021
Notes: Fig. 2 presents the dynamic time warping [DTW] path between BTC (Reference) and ETH (Query) from July 18, 2020, until January 15, 2021. We chose this subsample to highlight where Ethereum begins to lead Bitcoin.

- All CCs are less efficient during bubble periods when compared to non-bubble periods, e.g. 4 negative medians for bubble periods compared to 12 negative medians for bubble periods (see columns 7 and 10 of Table 2).
- All CCs are less efficient during the post-pandemic announcement period compared to the pre-pandemic announcement period, e.g. all CCs have a positive median in the post- announcement period except for 0x and all CCs have a negative median in the pre-announcement period (see columns 13 and 16 of Table 2).
- By cryptocurrency category, we found that generally, mining coins are not well efficient when compared to the two other categories (non-mining and tokens). The only exception is Bitcoin cash, which is ranked second during the bubble and post-pandemic announcement periods. However, we found mixed results for the non-mining coins and tokens categories (see columns 4, 7, 10, 13 and 16 of Table 2).

Overall, the results show that the highest rates of rejection of the CC market efficiency hypothesis were obtained during the post-pandemic announcement period followed by the bubble sub-periods including the bubble sub-periods, the non-bubble sub-periods, and finally the pre- COVID-19 announcement period. These results point to the huge impact of the announcement by the WHO that the COVID-19 is considered as a health pandemic in March 11, 2020. The impact of this announcement on cryptocurrency market efficiency seems to persist over time since all the studied cryptocurrencies have a rate of market inefficiency that exceeds the 50% (negative medians) only during the post-pandemic announcement period.

3.3. Clustering of the studied cryptocurrencies according to the efficiency of their markets

Despite the significant results obtained on the impact of extreme events on the market efficiency degree of the studied cryptocurrencies, an interesting question that can help market participants and investors to optimize their portfolio diversification is to analyze market efficiency similarity across all the studied cryptocurrencies.

As pointed above, the key element in the AMIM series clustering is DTW distance. Figs. 1 and 2 present the DTW path between Bitcoin and Ethereum during the entire sample and during the last six months, more specifically from July 18, 2020, until January 15, 2021, respectively. In the two Figures, we see that Bitcoin leads Ethereum in approximately the first three-quarters of the sample. However, Ethereum takes over from October 10, 2020.

Next, we will apply the DTW distance-based k-medoids algorithm to examine the similarities between the market efficiency measures for the different cryptocurrencies. We set three clusters for our data with the Silhouette index (see Kaufman and Rousseeuw,

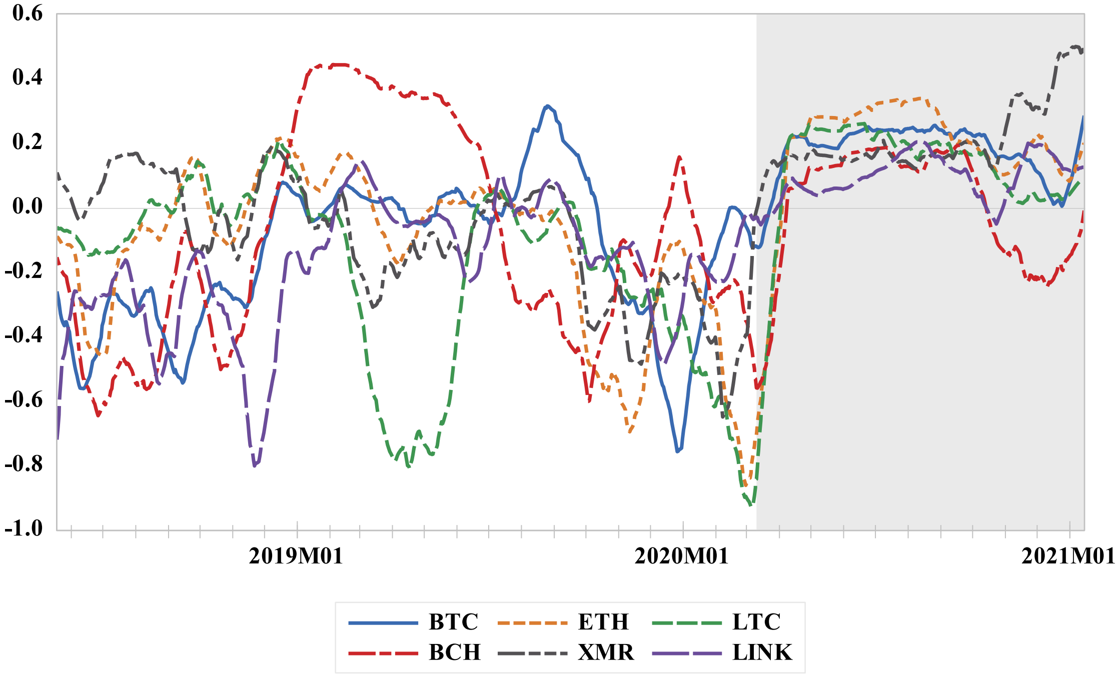

Fig. 3. Moving-Average 30 days of AMIM for the cryptocurrencies in cluster 1, shaded area refers to the COVID-19 period.
Notes: Fig. 3 shows the Moving-Average 30 days evolution of AMIM for the cryptocurrencies in cluster 1 in the periods before COVID-19 and after COVID-19 (shaded area).

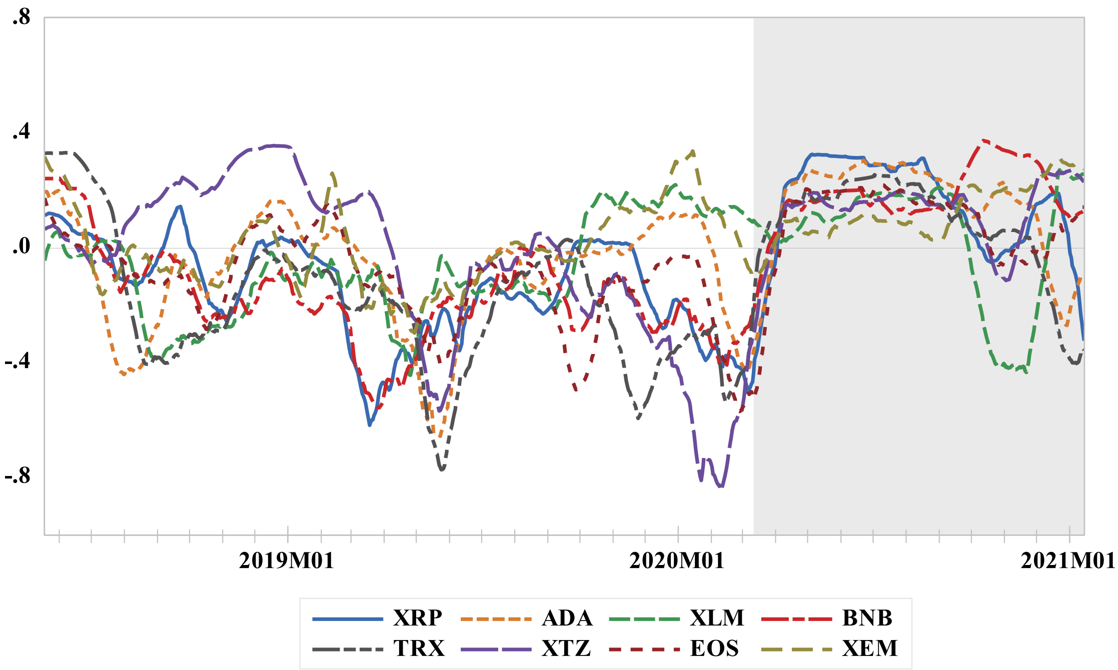

Fig. 4. Moving-Average 30 days of AMIM for the cryptocurrencies in cluster 2, shaded area refers to the COVID-19 period.
Notes: Fig. 4 shows the Moving-Average 30 days evolution of AMIM for the cryptocurrencies in cluster 2 in the periods before COVID-19 and after COVID-19 (shaded area).

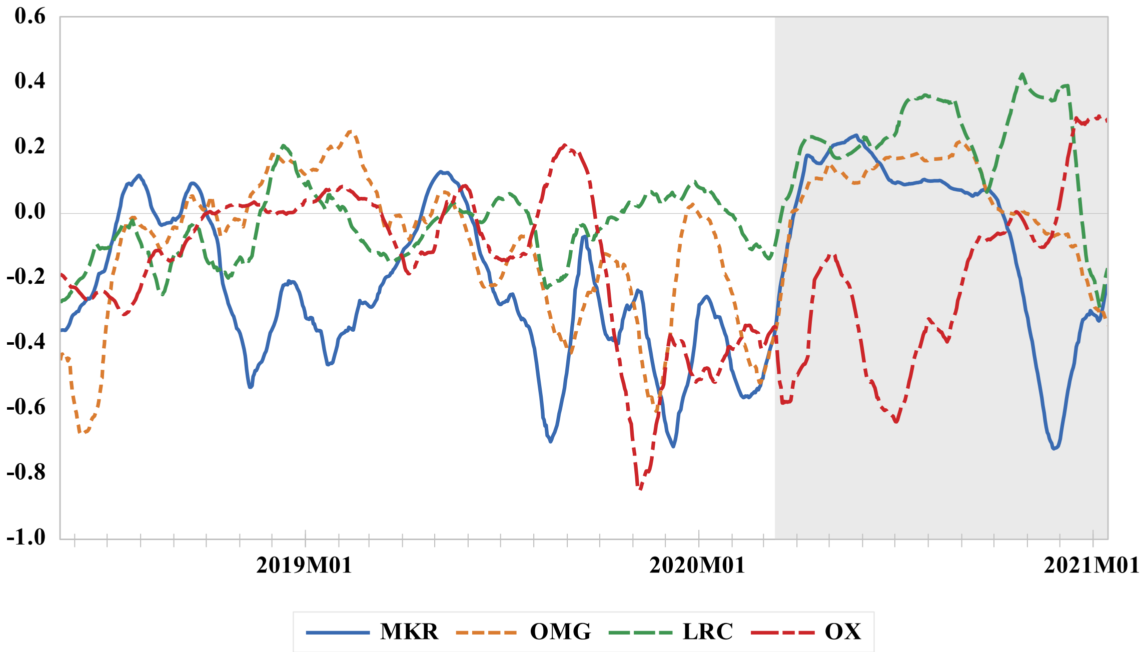

Fig. 5. Moving-Average 30 days of AMIM for the cryptocurrencies in cluster 3, shaded area refers to the COVID-19 period (March 12, 2020 – January 15, 2021).
Notes: Fig. 5 shows the Moving-Average 30 days evolution of AMIM for the cryptocurrencies in cluster 3 in the periods before COVID-19 and after COVID-19 (shaded area).

1990). Figs. 3, 4 and 5 display the results of our clustering. We distinguish three groups. The first contains BTC, ETH, LTC, BCH, LINK, and XMR where LINK, XMR, and LTC are the most efficient cryptocurrencies. The second group consists of XRP, ADA, XLM, BNB, TRX, XTZ, EOS, and XEM. Within this group, XTZ and ADA markets are the most efficient. The last group includes MKR, OMG, LRC, and 0X, where OMG and 0X markets are the most efficient. Our clustering sounds interesting about the composition of the different groups. Type of the different cryptocurrencies seems to be a major factor in the analysis of similarities of their market efficiency. In this regard, we notice that the first group essentially consists of the mineable crypto-currencies, except LINK. On the other hand, the third group includes four tokens while the second consists of non-mineable coins, except for Cardano and XEM.

4. Conclusion

In this paper, we have examined efficiency of cryptocurrency markets by exploring how cryptocurrency bubbles and the COVID-19 pandemic have affected time-varying market efficiency. Our results show that market efficiency behavior of the major traded cryptocurrencies have strongly changed in the aftermath of the COVID-19 pandemic announcement. However, the results identified three cryptocurrency bubbles; end of 2017, beginning of 2018 and during July 2020. These decentralized finance bubbles have a lower impact on cryptocurrency market efficiency. In a second stage, we performed a clustering analysis of the different efficiency series to determine the similarities between the studied cryptocurrencies. However, the obtained clusters deserve a timely note of caution.

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