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DCCA and DMCA correlations of cryptocurrency markets

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ABSTRACT

We examine the serial correlation structure of six liquid cryptocurrencies with a long data record – Bitcoin, DASH, Stellar, Litecoin, Monero, and Ripple – with a use of the detrended cross-correlation (DCCA) and detrending moving-average cross-correlation (DMCA) correlation coefficients. We find that these cryptocurrencies behave differently from the stock markets which are much closer to the random walk (efficient) dynamics. We further discuss issues connected to strong statements about cryptocurrency markets practical inefficiency.

1. Introduction

Cryptocurrencies correspond to digital currencies based on the blockchain technology and cryptography for validation of new transactions either via specialized exchange, over the counter, or direct retail purchases. Thus, unlike the vast majority of other available financial assets, they have no association with any centralized institutional authority, have no physical representation, and are infinitely divisible. Additionally, and again unlike traditional financial assets, the intrinsic value of encrypted currencies has been controversial since the beginnings as it cannot be derived from any tangible assets [1]. Often, the whole cryptocurrencies market is interchanged with Bitcoin which is the most popular one and also the original one introduced in the whitepaper under (most likely) a pseudonym of Satoshi Nakamoto and launched in 2009 with the first and now legendary Bitcoin purchase of a pizza for 10,000 BTC in May 2010. Since then, the worldwide capitalization of the cryptocurrencies market has been increasing and reaching a total of 260 billion USD as of May 2019, with Bitcoin itself with a capitalization of almost 150 billion USD, equivalent to approximately 55% of the entire value of cryptocurrencies market. In 2016, about 62.5 million transactions were carried out of 109 million accounts. In contrast to traditional currencies, Bitcoin transactions are not dependent on central banks, but rather on a decentralized computer network to validate transactions and increase the money supply [1].

The evolution and development of cryptocurrencies called the attention of researchers. A quick search using the word "cryptocurrencies" in Google Scholar shows the exponential increasing trend of documents, year by year, starting with a total of 15 works in 2009 to about 7650 works in 2018. If we use Bitcoin, the most known cryptocurrency, the trend is similar, starting with 363 works in 2009 and 16,800 in 2018 (both results are present in Fig. 1).

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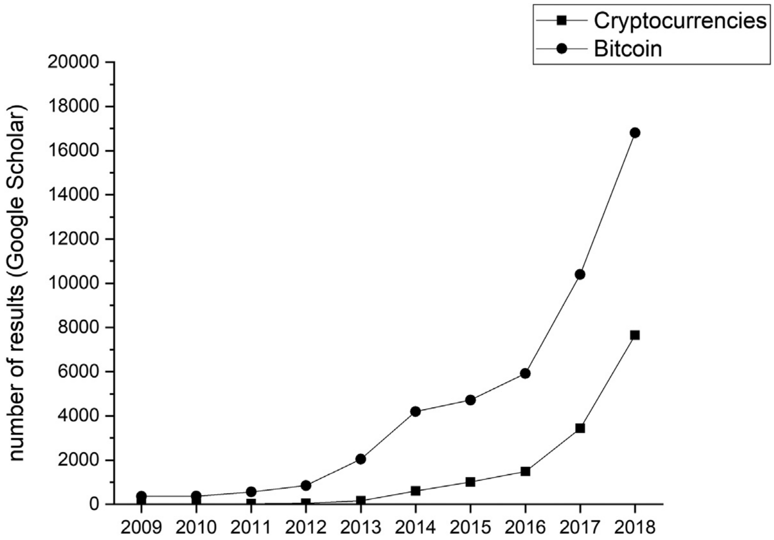

Fig. 1. Evolution of works using the words "Cryptocurrencies" or "Bitcoin", according to Google Scholar.

One of the hot research topics is the analysis of the evolution of the cryptocurrencies value. In the literature review, we will explore firstly the studies which center on the analysis of cryptocurrencies' efficiency and secondly in studies which analyze, in some sense, the comovements among and involving them. This is the starting point for our study, which proposes to extend the existent studies about cryptocurrencies, using Detrended Cross-Correlation Analysis (DCCA) and Detrended Moving Average Cross-Correlation Analysis (DMCA) identifying the extent that the main cryptocurrencies returns correlate with the respective lagged returns, following the rationality of the works of Ferreira and Dionísio [2,3], which analyze how long the correlation memory of several stock indices is (for the US stock market in the first case and for the G7 stock markets in the other study), finding that the correlations last between the 140th or 210th lag (depending on the index).

Our main results point to the existence of long-range cross-correlations between the cryptocurrencies' returns and the respective lags for about 30 days. Although it means that the correlations do not disappear quickly, the velocity of vanish of correlation between lags is higher than the one observed in stock indices, as identified in previous studies. It could be caused by the fact that cryptocurrencies are more distant to the efficient market, when compared with stock markets.

The remainder of the paper is organized as follow: Section 2 presents a literature review on papers which study cryptocurrencies, namely those which analyze its efficiency and which study the comovements among cryptocurrencies or between them and other financial assets; Section 3 presents the used data and methodology; Section 4 shows the results; and Section 5 concludes.

2. Literature review

We focus the literature review on two different topics in the discussion about the of cryptocurrencies' value: efficiency and comovements.

The efficiency analysis of the cryptocurrencies price series, especially Bitcoin, has generated several results, without unanimity of the results. Some works find evidence against the efficiency, like Jiang et al. [4], which used the Generalized Hurst Exponent to analyze the market of Bitcoin and states that it is inefficient and that the return of the series presents a strong persistence. Another study that found persistence in the price of Bitcoin was the one Alvarez-Ramirez et al. [5], which analyzed Bitcoin between 30th June, 2013 to 3rd June, 2017. These authors detected asymmetry and anti-persistence and a cyclic behavior of the Hurst exponent.

On the opposite side, there are studies that conclude in favor of the efficiency of Bitcoin's market or at least for the largest part of the samples under analysis. Tiwari et al. [6] show that the Bitcoin market is efficient, except for the period from April to August 2013 and August to November 2016. Nadarajah and Chu [7] which analyze the efficiency of Bitcoin between 1st August, 2010 and 31st July, 2016, with eight different statistical tests, demonstrating that it follows the efficiency hypothesis. Sigaki et al. [8] analyzed the cryptocurrencies market using the permutation entropy and statistical complexity to quantify the dynamic efficiency of more than four hundred encrypted currencies, finding that 37% of them remain efficient in more than 80% of the time, while 20% are efficient in terms of informational efficiency in less than 20% of the time. According to these authors, the cryptocurrency market shows remarkable adherence to the efficiency hypothesis, although this does not happen with all the currencies analyzed.

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It is also possible to find several studies identifying that although inefficiency appears at first, the market tends to a more efficient behavior. Urquhart [9] analyzed the market efficiency of Bitcoin in USD (dollar) between 1st August, 2010 to 31st July, 2016 using the R/S analysis and found strong evidence of anti-persistence, concluding that the Bitcoin market is inefficient throughout the sampling period, but with the decreasing inefficiency in a second period. In this line, Bariviera [10] analyzed the efficiency of the daily returns of Bitcoin between 2011 and 2017, and found inefficiency at the beginning of the series, but since 2014 the trend for the Hurst exponent was to be around 0.5. Bariviera et al. [11] analyzed the persistence of the Hurst exponent of the daily returns of the Bitcoin market in a dynamic process using the R/S and DFA methods with a sliding window between 18/08/2011 to 05/02/2017 and despite of having found a persistent behavior between 2011 and the end of 2014, the market becomes more efficient between 2014 and 2017. In another study that found that the price of Bitcoin became more efficient over time, Sensoy [12] concludes for: (i) The BTC/USD and BTC/EUR markets have become more efficient in terms of intraday information since the beginning of 2016; (ii) BTC/USD market is slightly more efficient than the BTC/EUR market in the sample period; (iii) Regardless of the choice of currency, the higher the frequency, the lower the price efficiency.

Testing the Adaptive Market Hypothesis of Lo [13] and Khuntia and Pattanayak [14] analyzed the prices of Bitcoin from 18th July, 2010 to 21st December, 2017 and detected high efficiency in the period between mid-2012 and November 2013 and, from 2015, while results point to inefficiency from August 2011 to August 2012 and from December 2013 to December 2014. Another contribution of these authors was to associate the period of efficiency of the returns in the prices of Bitcoin to certain economic events. At the same time, Kurihara and Fukushima [15] find evidence against efficiency in its weak form in Bitcoin market, however, this market tends to be more efficient over the time. In a recent analysis, Kristoufek [16] analyzed Bitcoin in the US dollar and the Chinese Yuan terms, and using the efficiency index of Kristoufek and Vosvrda [17] between 2010 and 2017, found moments of inefficiency of Bitcoin prices intertwined with moments of efficiency (since middle 2011 to the middle of 2012 and between March and November of 2014).

In this paper, we propose to extend the existent studies about cryptocurrencies using the Detrended Cross-Correlation Analysis (DCCA) and the Detrended Moving Average Cross-Correlation Analysis (DMCA) identifying the extent up to which the main cryptocurrencies returns correlate with their respective lagged returns.

The literature about cryptocurrencies is also enriched with studies analyzing the comovements involving cryptocurrencies. One of the first studies involving correlations was the one of Kristoufek [18], which studied how search queries on Google and Wikipedia pages visits with respect to the term Bitcoin relate with its price. Using the vector autoregression (VAR) and vector error-correction model (VECM), a positive bidirectional correlation between those variables has been found.

It is possible to find several studies devoted to the analysis of comovements between different cryptocurrencies. For example, Cagli [19], Huynh et al. [20], Huyngm [21], Mensi et al. [22], Antonakakis et al. [23], or Omane-Adjepong and Alagidede [24] all study the comovements between two or more cryptocurrencies. They identify significant comovements and call for the attention of investors when deciding for their portfolio diversification. Katsiampa [25] also identifies evidence of interdependency among cryptocurrencies, but also finds that this particular market is somehow responsive to major news. Ji et al. [26] uncover that Litecoin and Bitcoin were most important in a network of several cryptocurrencies, and also find that the connections are larger when returns are negative than when they are positive. They also use the network analysis between several cryptocurrencies finding that although Bitcoin is important in the network, it is not the dominant cryptocurrency in the market. In the follow-up study, Ji et al. [27] find that cryptocurrencies within a broadly defined network of commodities.

Although most of the studies that employ comovement analysis study them between different cryptocurrencies, it is also possible to find studies analyzing the comovements with other assets. For example, Baumöhl [28] analyzes the correlation between cryptocurrencies and the Forex market, finding weaker correlations than the expected. Al-Yahyaee et al. [29] and Conrad et al. [30] make the comparison with stock market indices, finding evidence of significant comovements. Kurka [31] analyzes the comovements with several assets (commodities, exchange rates, stocks and other financial assets) finding that the connectedness between them is negligible. Rehman and Apergis [32] study the comovements with several commodities and conclude for a significant causality running from cryptocurrencies to commodity market. Shahzad et al. [33,34] study the safe-haven characteristics of Bitcoin when compared to gold with respect to commodity and stock markets showing that the characteristics are quite dynamic in time and Bitcoin is a weaker instrument in such cases.

In our analysis, we focus on the most liquid cryptocurrencies and study their serial correlation with the use of the DCCA and DMCA methods that will provide deeper insights into their correlation structure. Studying and understanding serial correlations of non-standard series, which cryptocurrencies certainly are, is a necessary pre-emptive step towards further studies of cross-correlations as much of the serial dynamics gets translated into the cross-dynamics.

3. Methodology

In this study, we employ the correlation coefficients of the detrended cross-correlation analysis (DCCA) and the detrended moving-average cross-correlation analysis (DMCA) with the objective of understanding how long the memory of selected cryptocurrencies is.

DCCA was created by Podobnik and Stanley [35] and is calculated based on two different datasets x_k and y_k with k referring to equidistant observations. The first step consists of calculating $x(t) = \sum_{k=1}^{t} x_k$ and $y(t) = \sum_{k=1}^{t} y_k$, i.e., integration both time series. Then, both samples are divided into boxes of equal length n and divided into $N-n$ overlapping boxes. For each box, local trends $\tilde{x}_k$ and $\tilde{y}_k$ are fit using an ordinary least square regression and used to detrend the series. The detrended covariance of the residuals for a specific box is then calculated as $f^2_{DCCA} = \frac{1}{n-1}\sum_{k=i}^{i+n}(x_k - \tilde{x}_k)(y_k - \tilde{y}_k)$ and finally the detrended covariance function for a given scale n is given by $F^2_{DCCA}(n) = \frac{1}{N-n}\sum_{i=1}^{N-n} f^2_{DCCA}$. With this information is possible to obtain the DCCA exponent, which according to Podobnik et al. [36] could be tested in order to quantify the long-range cross-correlations between two time series. Zebende [37] proposed the scale-specific correlation coefficient based on DCCA given as $\rho_{DCCA} = \frac{F^2_{DCCA}}{F_{DFA\{x\}}F_{DFA\{y\}}}$, where DFA refers to the Detrended Fluctuation Analysis of Peng et al. [38]. The correlation coefficient ρ_{DCCA} is considered efficient and has the same desirable properties of a correlation coefficient, namely $-1 \le \rho_{DCCA} \le 1$ (see [39]). In this paper, the procedure of Podobnik et al. [40] is used to test the significance of the correlation coefficient.

DCCA and the respective correlation coefficient are commonly used in finance. Works like the ones of Bashir et al. [41,42] or Zebende et al. [43], evolving stock markets and exchange rates are just some examples. Although, these methods are also used in other research fields such as criminology [44], car accidents [45] or car traffic [46]. Recently, Zebende and Filho [47] developed a multiple coefficient based on the DCCA, which could be used in future research related with this subject.

The correlation coefficient based on DMCA was created by Kristoufek [48] and has some similarities to the previously identified methodology. It starts from the same integrated series, and calculates the fluctuation functions $F^2_{\mathrm{DMA\{xi\}}} = \frac{1}{T-\delta+1}\sum_{k=[\delta-\theta(\delta-1)]}^{[T-\theta(\delta-1)]}\left(\mathrm{x_k} - \widetilde{\mathrm{x}}_{\mathrm{k},\delta}\right)^2$ and $F^2_{DMA\{yi\}} = \frac{1}{T-\delta+1}\sum_{k=[\delta-\theta(\delta-1)]}^{[T-\theta(\delta-1)]}\left(y_k - \widetilde{y}_{k,\delta}\right)^2$, where δ refers to the moving average window length and θ to the type of moving average ($\theta = 0$ for forward moving average, $\theta = 0.5$ for centered and $\theta = 1$ for backward). The expressions $\widetilde{x}_{k,\delta}$ and $\widetilde{y}_{k,\delta}$ correspond to the moving averages with window size δ. We use the centered moving average as it has been repeatedly shown to overperform the other options [48]. With the DMA fluctuation functions, it is possible to calculate the bivariate fluctuation of DMCA, which is a covariance measure, and is given by $F^2_{DMCA} = \frac{1}{T-\delta+1}\sum_{k=[\delta-\theta(\delta-1)]}^{[T-\theta(\delta-1)]}\left(x_k - \widetilde{x}_{k,\delta}\right)\left(y_k - \widetilde{y}_{k,\delta}\right)$. With the previous expressions, it is possible to calculate the correlation coefficient given by $\rho_{DMCA}(\delta) = \frac{F^2_{DMCA}(\delta)}{F_{\mathrm{DFA\{xi\}}}(\delta)F_{\mathrm{DFA\{yi\}}}(\delta)}$, which has also the desirable properties of a correlation coefficient ($-1 \le \rho_{DMCA}(\delta) \le 1$). In this case, we use the procedure of Kristoufek [48] to perform the test of significance of the coefficient.

4. Dataset

We analyze the correlation properties of the most important cryptocurrencies with the DCCA and DMCA correlation coefficient. One of the limiting factors of the cryptocurrency markets and connected research is its relative youth, i.e. there is only a restricted set of cryptocurrencies that have a long data history. Combining the limiting factors of short time span, many illiquid cryptoassets and low survivor rates, we focus only on the most important cryptocurrencies that have reliable data at least down to 1 Jan 2015 and have been in the Top 20 with respect to their market capitalization as of the mid-2018. Our dataset thus covers six cryptocurrencies between 1 Jan 2015 and 30 Jun 2018, specifically Bitcoin (BTC), DASH (DASH), Litecoin (LTC), Stellar (XLM), Monero (XMR), and Ripple (XRP), giving us 1277 observations for each. The dataset has been obtained from the CoinMarketCap.com website.

5. Results and discussion

Before estimating DCCA and DMCA, we present the descriptive statistics of the return rates of the six cryptocurrencies used in this study in Table 1.[1] There, we can see that all the cryptocurrencies have positive average returns, which means that all of them increased their values over the analyzed period. Standard deviations suggest that Bitcoin is the least risky of the set while Stellar the most. Stellar, however, also gives the highest average return. The extreme values show that the indices experienced several extreme variations, which is confirmed by the kurtosis levels, with all indices over the limits of normal distribution. This is consistent with the regular stylized fact of fat tails. Again, Bitcoin seems to be the more standard asset as it has the lowest excess kurtosis and the lowest skewness. Either way, all analyzed cryptocurrencies show extreme movements in tens of percent per day. The most extreme of the lot is Ripple with its maximum daily loss of 60% and maximum daily gain of more than 100%. Excepting Bitcoin, all cryptocurrencies have a positive skewness, meaning that occurred more extremely positive values than negative ones. The continuous increase of value of cryptocurrencies could explain this result.

We now proceed with the DCCA and DMCA correlation coefficients between the return rates and the respective lags for each cryptocurrency up to the 30th lag. Results are presented in Figs. 2 and 3. In those figures, where we can compare the correlation coefficients with the critical values in order to evaluate the significance of those coefficients, we can see that at the 30th lag almost all the coefficients are under the critical values and, when not, they are near. It means that the correlations between lags vanish almost all during the first 30 days.

[1] Both skewness and kurtosis are calculated using the Excel functions.

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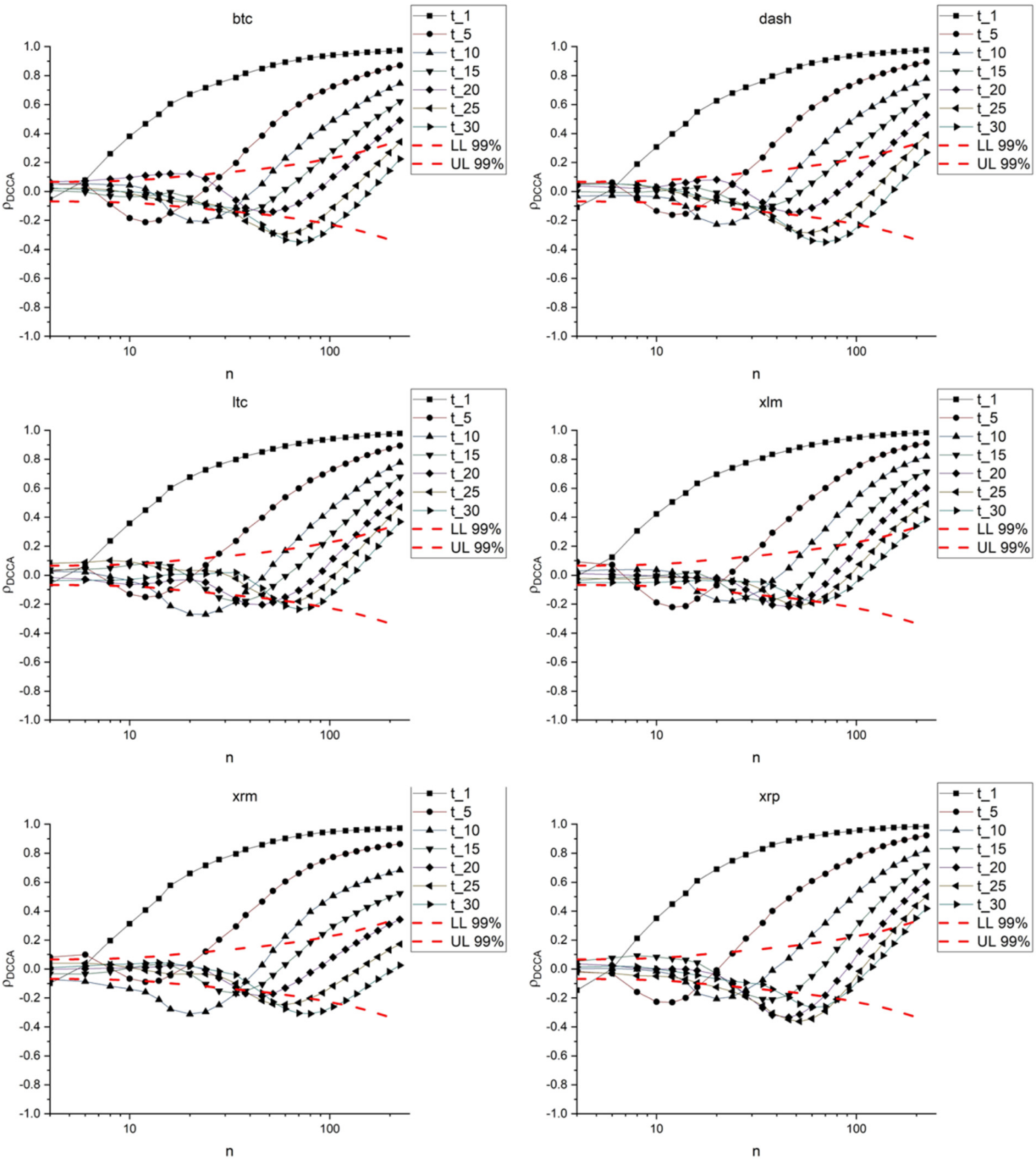

Fig. 2. DCCA cross-correlation coefficient returns of each cryptocurrency and their own lags – n (days) is the time scale. The dashed lines correspond to the 99% critical value for the test of absence of correlation.

These are interesting results, mainly when we compare to the findings of Ferreira and Dionísio [2,3] which use similar approaches but for stock indices, in the first case for the US market and in the other one for the G7 countries. In those studies, the complete absence of correlation was found in longer lags, with at least 140 lags with significant correlations. The faster decay of the DCCA and DMCA based correlations can be interpreted as a possible sign of inefficiency of these markets. When a series is close to the random walk dynamics, which is characteristic for an efficient market, its correlation structure would decay very slowly as observed for the stock markets in Ferreira and Dionísio [2,3]. However, when the dynamics deviates from the random walk patterns, we will observe deviations from such dynamics of the DCCA and DMCA

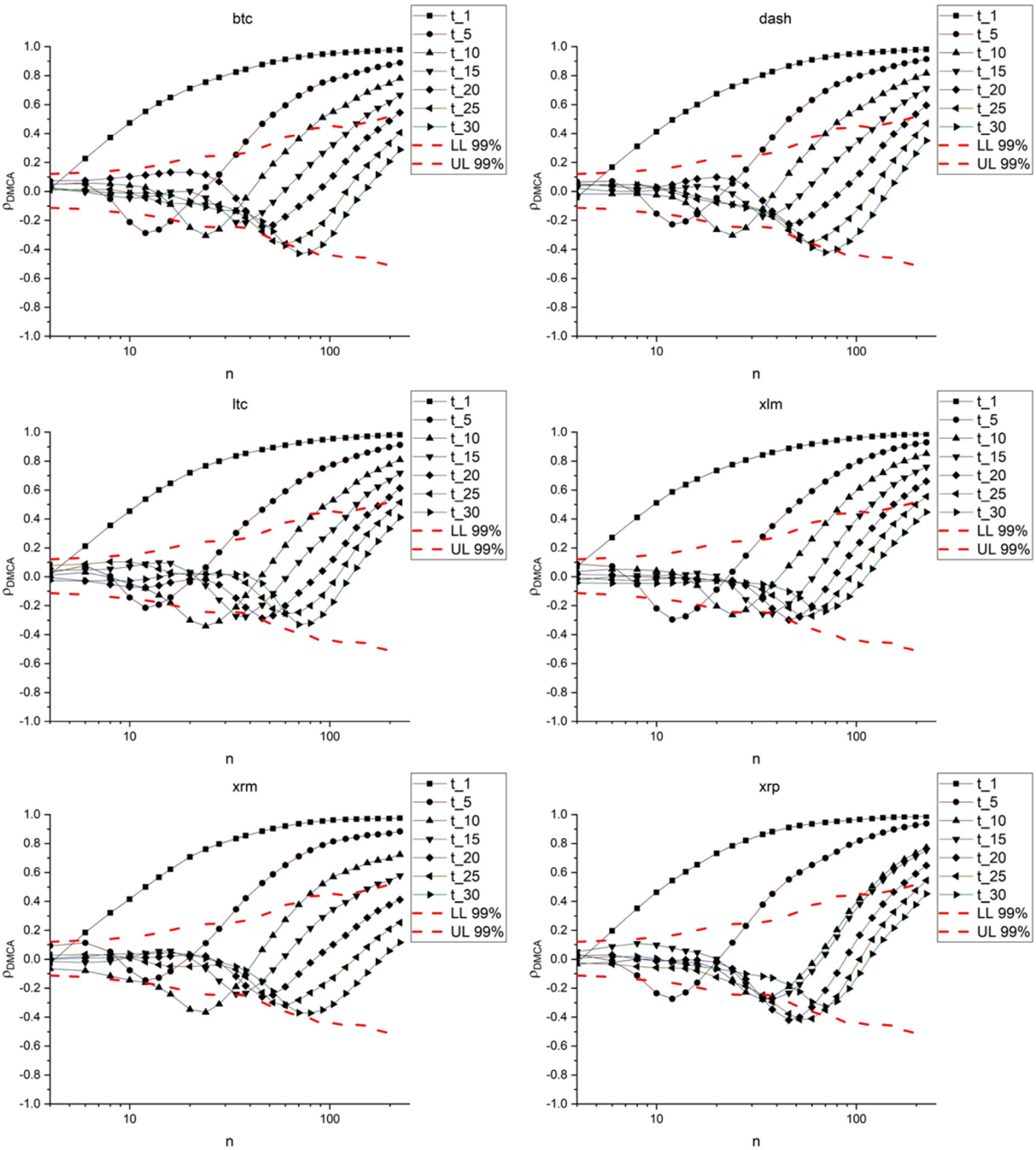

Fig. 3. DMCA cross-correlation coefficient returns of each cryptocurrency and their own lags – n (days) is the window length. The dashed lines correspond to the 99% critical value for the test of absence of correlation.

correlations as well. And that is exactly what we find for all analyzed cryptocurrencies. In a previous study, Begušić et al. [49] also find differences between the behavior of Bitcoin returns and stock markets, identifying that cryptocurrency as more volatile and exhibiting heavier tails than stocks.

Even though the results seem to be quite straightforward, we need to keep in mind that finding market inefficiency in the statistical manner, i.e. deviations from the random walk dynamics, does not automatically imply economic inefficiency in the sense of profit-making. The crypto-markets are very specific with their low liquidity, market manipulation, withdrawal fees, hacking risks, and similar troubles that increase uncertainty in the given markets. It is then only natural

Table 1
Descriptive statistics for the return rates of the cryptocurrencies.

	BTC	DASH	LTC	XLM	XRM	XRP
Mean	0.0030	0.0047	0.0028	0.0054	0.0056	0.0047
Std. Dev.	0.0416	0.0619	0.0607	0.0918	0.0750	0.0804
Minimum	−0.2057	−0.2426	−0.3937	−0.3611	−0.2928	−0.6020
Maximum	0.2269	0.4388	0.5127	0.7198	0.5846	1.0253
Skewness	−0.1678	0.9615	1.3558	2.0381	1.0708	3.0842
Kurtosis	4.3413	5.7893	12.7265	13.8344	7.07791	37.5529

that participating in such market will be connected with a risk premium represented by higher expected returns than for much less risky, standardized and regulated stock markets. A detailed study into practical (in)efficiency of the crypto-markets would need to be built on a detailed transaction and order book data that would control for the market depth. Our results thus provide further evidence about potential for profitable trading strategies but the results do not guarantee their existence.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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