Physica A 531 (2019) 120853

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Cryptocurrencies market efficiency ranking: Not so straightforward

Ladislav Kristoufek *, Miloslav Vosvrda

Institute of Information and Automation, Czech Academy of Sciences, Pod Vodarenskou vezi 4, Prague, Czech Republic

HIGHLIGHTS

- Set of top cryptocurrencies is examined for market efficiency.
- Persistence, fractal dimension and entropy are studied.
- Historical cryptocurrencies are found inefficient.
- Between July 2017 and June 2018, most coins and tokens were efficient.
- Ethereum and Litecoin are the least efficient, DASH is the most efficient.

ARTICLE INFO

Article history:
Received 7 December 2018
Available online 3 June 2019

Keywords:
Cryptocurrency
Efficient market hypothesis
Efficiency index
Long-range dependence
Fractal dimension
Approximate entropy

ABSTRACT

We study the cryptocurrency market with respect to the efficient market hypothesis. Specifically, we are interested in testing whether the examined coins and tokens are efficient or not but we also compare the levels of efficiency within the cryptomarket. To do so, we utilize the Efficiency Index comprising the long-range dependence, fractal dimension and entropy components. Focusing on a set of historical currencies – Bitcoin, DASH, Litecoin, Monero, Ripple, and Stellar – as well as popular currencies and tokens of the last year (with market capitalization above $0.5 billion), we uncover some surprising results. First, the historical currencies are unanimously inefficient over the analyzed period. Second, efficiency itself and ranking as well are dependent on the denomination (the US dollar or Bitcoin). Third, most of the coins and tokens were efficient between July 2017 and June 2018. And fourth, the least efficient coins turn out to be Ethereum and Litecoin whereas DASH is the winner as the most efficient cryptocurrency.

1. Introduction

Cryptocurrencies have attracted considerable public attention since 2017. It has not been only Bitcoin [1] but many other cryptocurrencies (altcoins) and tokens that experienced astronomical growth mainly in the second half of 2017. Bitcoin itself as a leader of this market segment started year 2017 at the level of $1,000[1] per a bitcoin and finished it at around $14,000 per a coin, i.e. increasing its value 14-fold. Crazily enough, this can considered as a quite mild increase as year 2017 was mainly the year of altcoins. The runner-up to Bitcoin with respect to the market capitalization – Ethereum – started year 2017 at $8 per an ether and ending the year at $750 per a coin, i.e. around 94-fold the starting price. It

* Corresponding author.
E-mail addresses: kristouf@utia.cas.cz (L. Kristoufek), vosvrda@utia.cas.cz (M. Vosvrda).

1 Prices used in here and elsewhere in this study are based on https://coinmarketcap.com which reports volume-weighted prices over active exchanges.

https://doi.org/10.1016/j.physa.2019.04.089
0378-4371/

had seemed that the price increases would never end and the FOMO (fear of missing out) effect dragged in many people that would have never thought about cryptocurrencies, many started investing into crypto-mining equipment causing shortages of GPUs (graphical cards) that would normally be used for gaming computers. Gamers were even able to sell their used GPUs for prices higher than the original purchasing prices, something unseen in the informatics industry. Mining equipment producers flourished. One would say a typical bubble. The stop sign came at the end of January 2018 when most cryptocurrencies and tokens reached their all-time highs. Since then, the whole market has slipped into the bear mode with some short-term episodes of increasing prices but overall, the total crypto-market capitalization dropped from above $800 billion in January 2018 down to slightly above $200 billion in August 2018. This is certainly a huge dropdown but one needs to keep in mind that the market started year 2017 with total capitalization of just around $18 billion.

A natural question comes whether the price dynamics of cryptocurrencies could have been predicted which in turn gets us to the efficient market hypothesis [2–5]. Even though the historical research on Bitcoin and cryptocurrencies is quite sparse and not finance related [6–9], there are several quantitative studies that cover Bitcoin dynamics before the craze of 2017 [10–14]. Predictability and efficiency has been analyzed in various studies. Urquhart [15] studies efficiency of the Bitcoin market between 2010 and 2016 using a palette of tests and argues that the market is mostly inefficient but reports that it can be seen as efficient in the later periods. Nadarajah & Chu [16] oppose these results and argue that the market is in fact efficient (using different set of tests). Bariviera et al. [17,18] study persistence of Bitcoin returns series and argue that the market moves towards efficiency in time. Alvarez-Ramirez et al. [19] study the issue at high frequencies and find that the market can be characterized by switching periods of efficiency and inefficiency. Vidal-Tomas & Ibanez [20] study effects of Bitcoin events and monetary policy news on Bitcoin price and summarize that Bitcoin has become more efficient in time and it does not react to monetary news. Kristoufek [21] examines efficiency evolution of two Bitcoin markets (US dollar and Chinese yuan) finding the markets to be mostly inefficient. Al-Yahyaee et al. [22] compare Bitcoin efficiency with gold, stocks and foreign exchange rates and finds that Bitcoin is the least efficient in the set. Zargar & Kumar [23] study efficiency of high-frequency Bitcoin returns using various variance ratio tests, showing mostly inefficiency of the markets. And Begusic et al. [24] show that Bitcoin returns have a finite second moment for different scales making the efficiency discussion reasonable.

All the above-mentioned studies focus on Bitcoin as a sole cryptocurrency in their examinations with respect to the market efficiency. Proper comparison of different cryptocurrencies is thus missing. In our study, we not only enlarge the dataset to more than just Bitcoin, we also utilize the Efficiency Index [25] that can be used both for efficiency testing and for ranking with respect to efficiency, and in addition, it is based on more than a single measure of efficiency. In the next section, we describe the Efficiency Index together with its components. The following section includes a detailed description of the dataset together with caveats during its construction. Results and discussion close the study. We show that studying a wider dataset of cryptocurrencies comes at cost of quite limited data availability in the sense that many of the most successful currencies (or more generally projects represented by Ethereum or EOS-based tokens) are very new, hence with a short data history. Nevertheless, when we consider only the big cryptocurrencies that have been around at least since 2015, they have all been clearly inefficient while DASH is closest to efficiency. When we look at the dynamics of the last year, there are many currencies and tokens that can be considered efficient. The least efficient ones turn out to be Ethereum and Litecoin. For the others, the results are very dependent on the currency of denomination, i.e. whether we look at prices in the US dollar or Bitcoin. Overall, we show that the results are not straightforward and simple such as "all cryptocurrencies are inefficient" but one needs to go deeper into the dynamics of specific coins and tokens.

2. Methods

Ranking various financial assets with respect to their efficiency in the logic of the efficient market hypothesis (EMH) is not a new thing [26–34]. Most of these rankings are based on a single measure of efficiency. However, the efficiency definitions [2,3] are rather loose and one can imagine various methods of its testing. To incorporate more measures or tests of an efficient market, Kristoufek & Vosvrda [25] introduce the Efficiency Index that can comprise many measures of efficiency as long as their range is known and as long as their value for an efficient market is known. As the historical definitions of market efficiency come to the martingale or random walk dynamics of the price process, it is not difficult to find theoretical values for many measures. In our application, we construct the index with a use of long-range dependence, fractal dimension, and approximate entropy.

2.1. Capital market efficiency measure

Kristoufek & Vosvrda introduced their Efficiency Index in 2013 [25] and since then, it has been extended and adjusted in the follow-up studies [35–37]. The definition itself has not changed and the Efficiency Index is defined as

$$EI = \sqrt{\sum_{i=1}^{n} \left(\frac{\widehat{M}_i - M_i^*}{R_i} \right)^2}, \tag{1}$$

where M_i is the ith measure of efficiency, $\widehat{M}_i$ is an estimate of the ith measure, M_i^* is an expected value of the ith measure for the efficient market and R_i is a range of the ith measure. A natural interpretation of the index is as a distance from an efficient state of the market. An inclusion of the range variable R_i limits potential market measures that can be used in the index. Here, we approach the issue in the same way as in the original articles [25,35–37] and we include long-range dependence, fractal dimension and entropy in the index construction. As for the expected values of these measures with respected to market efficiency, these are well defined — long-range dependence parameter Hurst exponent H with an expected value of 0.5 ($M_H^* = 0.5$), fractal dimension D with an expected value of 1.5 ($M_D^* = 1.5$), and the approximate entropy with an expected value of 1 ($M_{AE}^* = 1$). The range of the parameters is not the same as the approximate entropy has twice the range of long-range dependence and fractal dimension (for weakly stationary processes) so that we rescale the measure and set $R_{AE} = 2$ and $R_D = R_H = 1$.

Long-range dependence

Processes are long-range dependent if their auto-correlation function decays slowly [38], typically hyperbolically. In the time domain, this is characterized as the autocorrelation function $\rho(k)$ with time lag k decaying as $\rho(k) \propto k^{2H-2}$ for $k \to +\infty$. In the frequency domain, this translates to the spectrum $f(\lambda)$ with frequency λ scaling according to $f(\lambda) \propto \lambda^{1-2H}$ for $\lambda \to 0+$ [39,40]. Hurst exponent H is a measure of long-range dependence and it ranges between 0 and 1 for stationary processes. The separation point is $H = 0.5$ which means no long-range dependence. Above this value, the processes are persistent and they remind of locally trending series which, however, remain stationary and mean-reverting. The much less frequent case of processes with Hurst exponent below the separation point are characterized by frequently switching signs. The separation point of $H = 0.5$ is also the value of an efficient market. We use two estimators of H that have been shown to work well for short time series — the local Whittle estimator and the GPH estimator [39–43].

Fractal dimension

Fractal dimension D is a measure of local correlation structure in the time series [25] and it ranges between $1 < D \leq 2$ for univariate series with the central point of $D = 1.5$ for serially uncorrelated processes and thus also the efficient ones. Low fractal dimension means lower roughness of the analyzed series and hence local positive serial correlation dynamics. High fractal dimension suggests rougher series with locally negative serial correlations. For the estimation, we utilize the Hall–Wood and Genton methods [44,45] which are suitable for short time series.

Approximate entropy

We use entropy as a complexity measure of time series dynamics. High entropy of time series suggests little or no information in the system connected to high uncertainty and thus unpredictability. From the other end, low entropy series are understood as deterministic and thus predictable [46]. In the efficient market hypothesis environment, maximum entropy means efficiency as maximum entropy series are serially uncorrelated while the lower the entropy is the less efficient the market is as well. As the entropy use can be limited by its unboundedness, we use the approximate entropy which is bounded [47].

2.2. Statistical inference

Most methodological developments in the Efficiency Index since the original article have been connected to its statistical inference. As the index is defined quite generally (Eq. (1)), statistical properties and limiting distribution under the null hypothesis of market efficiency do change depending on the utilized efficiency measures. The distributional properties and statistical significance should be thus studied for each specific case. We propose the following bootstrap-based procedure:

1. Estimate efficiency index EI for the original series (according to Eq. (1)).
2. Generate bootstrapped series from the original returns series with the same number of observations (i.e. with replacement).
3. Estimate efficiency index EI for the bootstrapped series from the previous step.
4. Repeat the previous two steps 1000 times.
5. Based on the estimates from the previous step, construct any statistics needed for significance testing. Specifically, we find the 5th and 95th quantiles as critical values for testing the null hypothesis of an efficient market at 90% significance level. In addition, we also find p-value for the same null hypothesis as $1 - 2 \times |r/1001 - 0.5|$ where r is a rank of the original EI in the set of all estimated EIs (original and bootstrapped).
6. Based on the previous step, assess significance of the original EI. If the null hypothesis is rejected, take it as evidence against market efficiency.

This way, we control for distributional properties and number of observations of the original series. In other words, we are simulating the distribution of EI for an efficient market with the same distributional properties and length as the analyzed series.

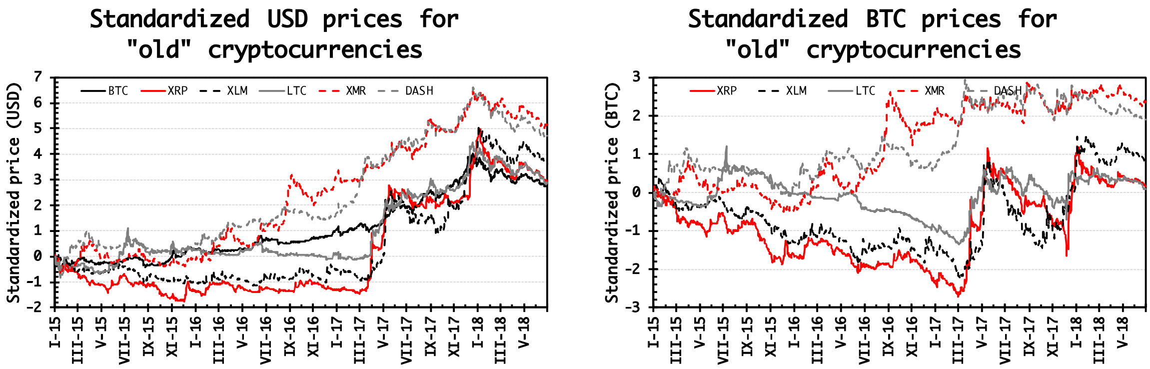

Fig. 1. Price evolution of "old" cryptocurrencies. Chart shows normalized logarithmic prices of "old" cryptocurrencies. The starting point is zero for better comparison between currencies. Cryptocurrencies denominated in USD (*left*) and in BTC (*right*) are shown.

Table 1
Descriptive statistics for "old" cryptocurrencies (since 01/2015).

ticker	mean	SD	min	max	skewness	ex. kurtosis
in USD						
BTC	0.0022	0.0402	−0.2288	0.2269	−0.4033	5.6144
XRP	0.0023	0.0733	−0.6020	1.0253	3.1831	42.4951
XLM	0.0028	0.0825	−0.3611	0.7198	2.1145	16.3119
LTC	0.0023	0.0620	−0.5126	0.5127	0.7120	14.1445
XMR	0.0041	0.0724	−0.2956	0.5846	0.8942	6.7800
DASH	0.0037	0.0605	−0.2426	0.4388	0.9596	5.7785
in BTC						
XRP	0.0001	0.0732	−0.6384	1.0055	3.0925	40.9034
XLM	0.0006	0.0789	−0.3792	0.7089	2.3294	18.6882
LTC	0.0001	0.0515	−0.5694	0.5280	1.2059	28.1217
XMR	0.0019	0.0642	−0.2822	0.5775	1.5438	10.1302
DASH	0.0015	0.0555	−0.2705	0.4952	1.3030	9.5984

Notes: Cryptocurrencies are sorted with respect to their market capitalization as of 31.8.2018.

3. Data

Most studies analyze only Bitcoin or a small set of cryptocurrencies due to, in a sense, limited data availability. Even though the breadth of the available data is unprecedented for most cryptocurrencies (prices, traded volume, number of transactions, difficulty, and several others, not to mention that each and every transaction can be tracked on the blockchain), the length is by definition limited. Even though Bitcoin goes back to 2009, many nowadays popular cryptocurrencies came to existence only in 2016 or 2017. Therefore, there needs to be a compromise between how many cryptocurrencies we cover and how long the analyzed series can actually be.

We opt to work only with cryptocurrencies that have high market capitalization and necessary liquidity can be thus assumed. Specifically, our original dataset covers all cryptocurrencies and tokens with market capitalization of at least $0.5 billion as of 31.8.2018 (based on https://coinmarketcap.com[2]). This gives us 23 candidates starting from Bitcoin with the highest capitalization going down to Lisk. Out of these, we do not work with Tether (*USDT*) which is a digital substitute of the US dollar (*USD*) used on many cryptoexchanges. Now when we limit our dataset only to the cryptocurrencies and tokens that have existed (have been listed on https://coinmarketcap.com) at least since 1 July 2017, we are down to 14 time series. This is our base dataset.[3] As an additional dataset, we also consider the cryptocurrencies that have been in circulations at least since 1 January 2015 which contains only 6 series out of the base dataset – *BTC*, *DASH*, *LTC*, *XLM*, *XMR*, and *XRP*. We thus have two dataset – "old cryptocurrencies" (between 01.01.2015 and 30.06.2018) and "new cryptocurrencies" (between 01.07.2017 and 30.06.2018) – with a daily frequency.

Dynamics of prices for the historical cryptocurrencies are shown in Fig. 1. As USD is the most widely used fiat currency in the trading pairs with cryptocurrencies and tokens, we will consider prices denominated in USD. However, most trading

2 https://coinmarketcap.com is the most popular website that summarizes price dynamics of cryptocurrencies and tokens. There are other alternatives but the selection is independent of the used source as all websites work with very similar inputs.

3 This set contains Bitcoin (ticker *BTC*), DASH (*DASH*), EOS (*EOS*), Ethereum (*ETH*), Ethereum Classic (*ETC*), Iota (*MIOTA*), Lisk (*LSK*), Litecoin (*LTC*), Monero (*XMR*), NEM (*XEM*), NEO (*NEO*), Ripple (*XRP*), Stellar (*XLM*), and Zcash (*ZEC*).

Table 2
Descriptive statistics for cryptocurrencies between 07/2017 and 06/2018.

ticker	mean	SD	min	max	skewness	ex. kurtosis
in USD						
BTC	0.0025	0.0542	−0.2057	0.2269	0.1019	2.2739
ETH	0.0008	0.0622	−0.2570	0.2209	−0.1713	1.9044
XRP	0.0015	0.0853	−0.3500	0.6100	1.6974	11.6947
EOS	0.0013	0.0983	−0.3900	0.3500	0.3711	2.1978
XLM	0.0051	0.1052	−0.3300	0.6700	1.0567	5.7885
LTC	0.0016	0.0735	−0.3900	0.4000	0.6757	6.4233
MIOTA	0.0027	0.0984	−0.3900	0.3800	0.2609	2.4027
XMR	0.0028	0.0774	−0.2900	0.3500	0.2062	2.0876
DASH	0.0007	0.0709	−0.2400	0.4400	0.8677	5.3682
ETC	−0.0005	0.0826	−0.4300	0.3100	−0.3887	4.6758
NEO	0.0029	0.0943	−0.3300	0.5100	0.8435	3.7908
XEM	−0.0009	0.1019	−0.4300	1.0000	2.6111	26.8706
ZEC	−0.0021	0.0746	−0.2400	0.2600	0.0674	1.0244
LSK	0.0019	0.0917	−0.4100	0.3500	0.1410	1.9209
in BTC						
ETH	−0.0017	0.0492	−0.2576	0.1920	0.0327	4.1674
XRP	−0.0010	0.0800	−0.2669	0.5991	2.4415	15.5558
EOS	−0.0012	0.0846	−0.3469	0.3844	0.8394	4.1671
XLM	0.0027	0.0947	−0.3669	0.6633	1.4603	9.2166
LTC	−0.0009	0.0578	−0.2469	0.3711	1.7445	10.8169
MIOTA	0.0002	0.0816	−0.3069	0.3502	0.6112	3.8651
XMR	0.0004	0.0629	−0.2169	0.3719	1.3088	5.8608
DASH	−0.0018	0.0610	−0.2695	0.4964	1.7998	17.0998
ETC	−0.0030	0.0695	−0.2712	0.3202	0.5261	4.5131
NEO	0.0004	0.0825	−0.2812	0.4983	1.3176	6.3114
XEM	−0.0034	0.0920	−0.3669	1.0718	4.4581	52.7622
ZEC	−0.0045	0.0649	−0.3269	0.2563	0.3797	3.3745
LSK	−0.0005	0.0772	−0.3769	0.3366	0.4152	4.4041

Notes: Cryptocurrencies and tokens are sorted with respect to their market capitalization as of 31.8.2018.

activity takes place for trading pairs against Bitcoin, which thus needs to be included in the analysis as well. Many cryptotraders are actually trying to maximize their BTC holdings rather that their USD holdings as the cryptocommunity belief is that BTC will continue its long-term growing trend so that it makes sense to maximize the BTC holdings rather than fiat holdings. For better comparison, the logarithmic prices are shown for the same starting point. We can see that out of these six currencies, three (Litecoin, Stellar, and Ripple) had been in a quite stable bear market between 01/2015 and 03/2017 and only then they started the 2017 rally. Bitcoin had been in a quite stable but retrospectively slow growing trend until the beginnings of 2017, and it was only DASH and Monero that had experienced quite stable exponential growth throughout the period between 01/2015 and 01/2018. Significant correction and a bear market of the first half of 2018 has come for all of them. Interestingly, all other cryptocurrencies ended above Bitcoin as of 30 June 2018 when 1 January 2015 is taken as a starting point. This is supported by the descriptive statistics presented in Table 1 where we see that the return mean values are the lowest for BTC even though the differences are not huge when compared to LTC, XRP and XLM while DASH and XMR outperform it markedly. As for the other statistics, we observe that apart from Bitcoin, which is close to symmetrically distributed, all other cryptocurrencies have positive skewness, i.e. a longer right tail. This is reflected in their minima and maxima which are quite symmetric for Bitcoin but clearly asymmetric for the others. Compared to values we know from standard financial instruments, these are quite extreme for daily returns. Returns are clearly leptokurtic, i.e. heavy-tailed, yet not as extremely as one might expect. The most extreme values are observed for Ripple with a daily maximum gain of more than 100%, maximum daily loss of 60% and excess kurtosis above 40.

Table 2 presents the descriptive statistics for the larger dataset of the "new" cryptocurrencies and tokens.[4] Coincidentally, our data range covers both the huge boom of (mainly the second half of) 2017 but also the corrections and following bear market of the first half of 2018. Therefore, we do not see extremely high mean returns. We even see negative mean returns for some, specifically Ethereum Classic, NEM and Zcash. Compared to Bitcoin, most coins underperformed and only Iota, NEO, Ripple, and Stellar outperformed Bitcoin. The altcoin fever was apparently followed by the altcoin bust. As for other statistics, we again see that vast majority is positively skewed, many actually close to symmetry. All coins are leptokurtic with NEM and Ripple leading the way. Maximum gains and losses remain quite extreme compared to standard financial instruments.

[4] We do not show charts as these would be quite confusing with so many time series.

Table 3
Efficiency ranking for "old" cryptocurrencies (since 01/2015).

ticker	EI	EI_{null}	↑distance↑	SD	$q_{0.05}$	$q_{0.95}$	p-value
in USD							
DASH	0.4577	0.5215	2.1749	0.0293	0.4819	0.5732	<0.01
XMR	0.3944	0.5233	4.7828	0.0269	0.4853	0.5712	<0.01
BTC	0.3741	0.5709	5.4532	0.0361	0.5191	0.6300	<0.01
XLM	0.3233	0.5226	6.0949	0.0327	0.4752	0.5781	<0.01
XRP	0.2971	0.5516	6.9375	0.0367	0.4936	0.6130	<0.01
LTC	0.3215	0.6104	7.5031	0.0385	0.5476	0.6738	<0.01
in BTC							
XMR	0.4149	0.5191	3.6421	0.0286	0.4821	0.5739	<0.01
XRP	0.3469	0.5090	4.4527	0.0364	0.4544	0.5706	<0.01
DASH	0.3708	0.5154	5.0308	0.0287	0.4780	0.5699	<0.01
XLM	0.3221	0.5110	6.0220	0.0314	0.4663	0.5670	<0.01
LTC	0.1635	0.5593	10.1541	0.0390	0.5001	0.6252	<0.01

Notes: *EI* is the Efficiency Index according to Eq. (1). EI_{null} is the mean value of Efficiency Index calculated for the null hypothesis of an efficient market based on steps in *Statistical inference*. Connected to the mean value are also 5% and 95% quantiles ($q_{0.05}$ and $q_{0.95}$, respectively), the standard deviation *SD* and the p-value testing the null hypothesis of an efficient market. *Distance* is measured as a number of standard deviations *SD* of *EI* from EI_{null} and is an alternative measure to p-value. The table is sorted with respect to *distance*.

4. Results and discussion

Our main aim is to test the efficient market hypothesis in the most popular cryptocurrencies (and tokens) and rank them with respect to their efficiency. We are interested in two samples — the "old" cryptocurrencies, which have been around since 2015 and still belong to the most popular ones (their total market capitalization was at least \$0.5 billion as of the end of August 2018), and the "new" popular cryptocurrencies and tokens. The former sample comprises only 6 coins – Bitcoin, DASH, Litecoin, Monero, Ripple, and Stellar – and the latter one has 14 coins and tokens, which are listed in the previous section.

We start with the sample of historical currencies that go back to 2015 and are still successfully around in 2018. The results are summarized in Table 3. For each currency, we find the Efficiency Index (EI), the average Efficiency Index for the null hypothesis based on the bootstrapping procedure detailed in the previous section (EI_{null}), its standard deviation (SD), critical values for the 90% significance level ($q_{0.05}$ and $q_{0.95}$), and p-value for the null hypothesis of market efficiency. We test efficiency for cryptocurrencies denominated both in USD and in BTC. We can see that for all six pairs with USD and all five pairs with BTC, the efficiency is strongly rejected. Even though such result is not completely surprising and the rejection holds for all coins, we can see that both EI and EI_{null} vary quite strongly. To be able to rank the coins with respect to their efficiency, we cannot realistically use p-value as these are the same for all of them. However, we can see that EI, EI_{null} and SD are not. Therefore, we construct an alternative sorting measure that we call "distance" in the table and it is defined as the number of standard deviations (SD) between the original index (EI) and the bootstrapped mean index (EI_{null}). The further away the EI is from its null hypothesis counterpart, the less efficient the cryptocurrency is. In such ranking, the least efficient of the group is Litecoin (LTC) and that is true for both trading pairs. For other currencies, the ranking is quite dependent on the denomination currency. Overall, Monero (XMR) seems to be the most efficient of the group, even though in absolute terms, it is clearly inefficient.

Results for the wider but shorter dataset are summarized in Table 4. We observe that the results are much more heterogeneous than for the case of the traditional cryptocurrencies. For the USD pairs, we see that only 5 out of 14 coins and tokens are marked as inefficient. In addition, the 9 cases that are identified as efficient are not close calls but have p-value at around 0.5 and higher, i.e. the non-rejection of efficiency is confident. Among the inefficient ones are Litecoin (LTC), Ethereum Classic (ETC), Ethereum (ETH), Monero (XMR), and Zcash (ZEC), listed from the most efficient to the least efficient. Interestingly, this covers two anonymous coins (XMR and ZEC), and Ethereum and its fork (ETC). Looking at the BTC pairs, we again find Litecoin and Ethereum among the least efficient coins. If we look at 95% significance level, the only additional inefficient coin is NEO. If we enlarge the set to the 90% significance level, we also have Lisk (LSK), Iota (MIOTA), Stellar (XLM), and NEM (XEM), sorted from the most efficient to the least efficient. On the other side of the spectrum, we have DASH, Ripple (XRP) and EOS being efficient for both denominations. Overall, DASH seems to be the most efficient in this dataset.

Coming back to the least efficient of the group, Litecoin and Ethereum are not complete surprises. As mentioned already in the Introduction, Ethereum experienced unprecedented price surge in 2017 which was mostly driven by its utility function as a smart contract carrier and a leading currency in initial coin offerings (ICOs), which are digital counterparts to initial public offerings (IPOs) in standard finance, as well as due to an extreme demand connected to some relatively obscure phenomena such as Crypto-Kitties (modern blockchain-based version of the old school Tamagotchi games built

Table 4
Efficiency ranking for cryptocurrencies between 07/2017 and 06/2018.

ticker	EI	EI_{null}	↑distance↑	SD	$q_{0.05}$	$q_{0.95}$	p-value
in USD							
LSK	0.2941	0.2967	0.0228	0.1148	0.1412	0.5426	0.8591
XEM	0.3538	0.3630	0.1135	0.0813	0.2670	0.5301	0.9810
DASH	0.3435	0.3777	0.2144	0.1593	0.2003	0.6223	0.8492
NEO	0.2692	0.2951	0.2742	0.0944	0.1615	0.4787	0.7812
XLM	0.2760	0.3055	0.2762	0.1066	0.1615	0.5554	0.9151
MIOTA	0.2317	0.2598	0.2855	0.0986	0.1259	0.4371	0.8352
EOS	0.3984	0.3369	0.4652	0.1323	0.1614	0.5831	0.5075
BTC	0.3229	0.2775	0.5468	0.0829	0.1729	0.4372	0.4655
XRP	0.2820	0.4061	0.7831	0.1584	0.2034	0.6220	0.6434
LTC	0.1754	0.3359	1.1630	0.1380	0.1953	0.5916	0.0340
ETC	0.1351	0.3536	1.5495	0.1410	0.1837	0.5968	<0.01
ETH	0.1533	0.2938	1.5953	0.0881	0.1796	0.4556	0.0140
XMR	0.1478	0.3226	1.7906	0.0976	0.1897	0.5021	<0.01
ZEC	0.1223	0.3082	2.1121	0.0880	0.1795	0.4550	<0.01
in BTC							
XMR	0.3331	0.3320	0.0137	0.0789	0.2217	0.4758	0.9051
DASH	0.3147	0.3407	0.3383	0.0770	0.2331	0.4803	0.7972
ZEC	0.3968	0.3535	0.5275	0.0820	0.2379	0.4957	0.5195
XRP	0.3865	0.4320	0.5396	0.0844	0.3092	0.5705	0.6314
ETC	0.2697	0.3648	1.2077	0.0788	0.2410	0.5037	0.2258
EOS	0.3921	0.2759	1.3160	0.0883	0.1675	0.4531	0.1918
LSK	0.2420	0.3583	1.3452	0.0864	0.2442	0.5121	0.0979
MIOTA	0.1956	0.3146	1.4745	0.0808	0.2052	0.4634	0.0619
XLM	0.2254	0.3583	1.5702	0.0846	0.2350	0.5048	0.0719
XEM	0.2363	0.3733	1.6715	0.0819	0.2555	0.5221	0.0659
NEO	0.1739	0.3598	2.1735	0.0855	0.2353	0.5039	<0.01
ETH	0.1420	0.3428	2.4325	0.0826	0.2267	0.4928	<0.01
LTC	0.1608	0.3668	2.6107	0.0789	0.2593	0.5136	<0.01

Notes: *EI* is the Efficiency Index according to Eq. (1). EI_{null} is the mean value of Efficiency Index calculated for the null hypothesis of an efficient market based on steps in *Statistical inference*. Connected to the mean value are also 5% and 95% quantiles ($q_{0.05}$ and $q_{0.95}$, respectively), the standard deviation *SD* and the *p*-value testing the null hypothesis of an efficient market. *Distance* is measured as a number of standard deviations *SD* of *EI* from EI_{null} and is an alternative measure to *p*-value. The table is sorted with respect to *distance*.

on Ethereum platform). We do not delve into these topics here, we merely mention them to make it clear that the price hikes are not out of nowhere. Similar claim can be made for Litecoin as well, even though from a different perspective. In the crypto-world, Litecoin has been to Bitcoin what silver is to gold, even though such connection has been diluted by an explosion of new coins and tokens from 2016 onwards. Nevertheless, Litecoin has kept most of its appeal and in the first half of 2017, it was the first one of the top cryptocurrencies that had adopted the Segregated Witness (SegWit) transaction format, which has been repeatedly postponed for Bitcoin itself, so that the hype around the coin is not unfounded.

Overall, the results are very interesting. Apart from the fact that the historical coins are all found to be inefficient, which is not too surprising, other results are non-trivial. First, the efficiency itself, i.e. whether the underlying coin or token is or is not efficient, as well as the efficiency ranking itself vary strongly when USD and BTC pairs are compared. This shows that for these two classes of investors, the efficiency perception can be quite different. Note that the proportion of investors that are maximizing their BTC holdings rather than USD holdings is not negligible and even though the exact number is not available, the feel from the community and across various discussion boards and chats gives the impression that the proportion might be considerable. Monero (XMR) is a nice example here as it is one of the least efficient coins in the USD pair but the most efficient in the BTC pair. This might be connected to the Monero reputation as a coin that does not care about Bitcoin movements as it is not a Bitcoin fork but a Bytecoin fork that has been developed separately from Bitcoin. In addition, Monero takes anonymity to a higher level compared to Bitcoin and similar coins. Second, most of the coins and tokens were efficient between July 2017 and June 2018, which might be unexpected. However, keep in mind that this period covers not only the boom of 2017 but also the bust of 2018. Strategies that might have worked during the bull market do not necessarily work during bear markets and vice versa. It thus seems that if the markets had been predictable during 2017, it was offset by the 2018 developments. The "long-term returns" part of EMH has thus come forward. Third, if we wanted to pick winners and losers, the least efficient of the group seems to be the LTC-ETH pair and the most efficient coin would be DASH. And fourth, even though the overall feel could be that even if just few of the coins or tokens are inefficient and thus well predictable, it would be enough to make overall huge profits, it needs to be kept in mind that even though the sample selection is mostly driven by data availability and liquidity, the results suffer from the survivor bias. There have been hundreds and thousands of projects (and thus coins and tokens) that have been unsuccessful or even straight frauds when the founders "ran away" with the money. The discussion about predictability, profitability and viability of cryptocurrencies and tokens is still in its infancy and only time will tell what the outcome is.

Acknowledgments

Miloslav Vosvrda acknowledges support from the Czech Science Foundation under project No. P402/12/G097 "DYME – Dynamic Models in Economics". Ladislav Kristoufek gratefully acknowledges financial support of the Czech Science Foundation under project 17-12386Y "Multifractal analysis in finance: Extreme events, portfolio and risk management, and market complexity".

References

[1] S. Nakamoto, Bitcoin: A peer-to-peer electronic cash system, http://bitcoin.org/bitcoin.pdf.
[2] E. Fama, Random walks in stock market prices, Financ. Anal. J. 21 (5) (1965) 55–59.
[3] P. Samuelson, Proof that properly anticipated prices fluctuate randomly, Ind. Manag. Rev. 6 (1965) 41–49.
[4] E. Fama, Efficient Capital markets: A review of theory and empirical work, J. Financ. 25 (2) (1970) 383–417.
[5] E. Fama, Efficient Capital markets: II, J. Financ. 46 (5) (1991) 1575–1617.
[6] S. Barber, X. Bayen, E. Shi, E. Uzun, Financial cryptography and data security, in: Bitter to Better–How to Make Bitcoin a Better Currency, Springer; Berlin Heidelberg, Germany, 2012, pp. 399–414, (chapter).
[7] J. Clark, A. Essex, Financial cryptography and data security, in: CommitCoin: Carbon Dating Commitments with Bitcoin, Springer; Berlin Heidelberg, Germany, 2012, pp. 390–398, (chapter).
[8] F. Reid, M. Harrigan, Security and privacy in social networks, in: An Analysis of Anonymity in the Bitcoin System, Springer; New York, NY, 2013, pp. 197–223, (chapter).
[9] F.R. Velde, Bitcoin: A primer, Chicago Fed Lett. 317 (2013) 1–4.
[10] L. Kristoufek, BitCoin Meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era, Sci. Rep. 3 (2013) 3415.
[11] S. Bornholdt, K. Sneppen, Do Bitcoins make the world go around? On the dynamics of competing crypto-currencies, arXiv:1403.6378, 2014, pp. 1–5.
[12] D. Kondor, M. Posfai, I. Csabai, G. Vattay, Do the rich get richer? An empirical analysis of the Bitcoin transaction network, PLoS One 9(2) (2014) e86197.
[13] D. Garcia, C. Tessone, P. Mavrodiev, N. Perony, The digital traces of bubbles: feedback cycles between socio-economic signals in the bitcoin economy, J. R. Soc. Interface 11 (2014) 2014623.
[14] L. Kristoufek, What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis, PLoS One 10 (2015) e0123923.
[15] A. Urquhart, The inefficiency of Bitcoin, Econom. Lett. 148 (2016) 80–82.
[16] S. Nadarajah, J. Chu, On the inefficiency of Bitcoin, Econom. Lett. 150 (2017) 6–9.
[17] A. Bariviera, M. Basgall, W. Hasperué, Some stylized facts of the Bitcoin market, Physica A 484 (2017) 82–90.
[18] A. Bariviera, The inefficiency of Bitcoin revisited: A dynamic approach, Econom. Lett. 161 (2017) 1–4.
[19] J. Alvarez-Ramirez, E. Rodriguez, C. Ibarra-Valdez, Long-range correlations and asymmetry in the Bitcoin market, Physica A 492 (2018) 948–955.
[20] D. Vidal-Tomas, A. Ibanez, Long-range correlations and asymmetry in the Bitcoin market, Finance Res. Lett. 492 (2018) 948–955.
[21] L. Kristoufek, On Bitcoin markets (in)efficiency and its evolution, Physica A 503 (2018) 257–262.
[22] K. Al-Yahyaee, W. Mensi, S.-M. Yoon, Efficiency, multifractality, and the long-memory property of the Bitcoin market: A comparative analysis with stock, currency, and gold markets, Finance Res. Lett. 27 (2018) 228–234.
[23] F. Zargar, D. Kumar, Informational inefficiency of Bitcoin: A study based on high-frequency data, Res. Int. Bus. Finance 47 (2019) 344–353.
[24] S. Begusic, Z. Kostanjcar, H. Stanley, B. Podobnik, Scaling properties of extreme price fluctuations in Bitcoin markets, Physica A 510 (2018) 400–406.
[25] L. Kristoufek, M. Vosvrda, Measuring capital market efficiency: Global and local correlations structure, Physica A 392 (2013) 184–193.
[26] T. Di Matteo, T. Aste, M. Dacorogna, Scaling behaviors in differently developed markets, Physica A 324 (2003) 183–188.
[27] T. Di Matteo, T. Aste, M. Dacorogna, Long-term memories of developed and emerging markets: Using the scaling analysis to characterize their stage of development, J. Bank. Financ. 29 (2005) 827–851.
[28] T. Di Matteo, Multi-scaling in finance, Quant. Finance 7(1) (2007) 21–36.
[29] D. Cajueiro, B. Tabak, The Hurst exponent over time: testing the assertion that emerging markets are becoming more efficient, Physica A 336 (2004) 521–537.
[30] D. Cajueiro, B. Tabak, Ranking efficiency for emerging markets, Chaos Solitons Fractals 22 (2004) 349–352.
[31] D. Cajueiro, B. Tabak, Evidence of long range dependence in Asian equity markets: the role of liquidity and market restrictions, Physica A 342 (2004) 656–664.
[32] D. Cajueiro, B. Tabak, Ranking efficiency for emerging equity markets II, Chaos Solitons Fractals 23 (2005) 671–675.
[33] K.-P. Lim, Ranking market efficiency for stock markets: A nonlinear perspective, Physica A 376 (2007) 445–454.
[34] L. Zunino, M. Zanin, B. Tabak, D. Pérez, O. Rosso, Complexity-entropy causality plane: A useful approach to quantify the stock market inefficiency, Physica A 389 (2010) 1891–1901.
[35] L. Kristoufek, M. Vosvrda, Commodity futures and market efficiency, Energy Econ. 42 (March) (2014) 50–57.
[36] L. Kristoufek, M. Vosvrda, Measuring capital market efficiency: long-term memory, fractal dimension and approximate entropy, European Physical Journal B 87 (2014) 162.
[37] L. Kristoufek, M. Vosvrda, Gold, currencies and market efficiency, Physica A 449 (2016) 27–34.
[38] J. Beran, Statistics for Long-Memory Processes, in: Monographs on Statistics and Applied Probability, vol. 61, Chapman and Hall, New York, 1994.
[39] J. Geweke, S. Porter-Hudak, The estimation and application of long memory time series models, J. Time Series Anal. 4(4) (1983) 221–238.
[40] P. Robinson, Gaussian semiparametric estimation of long range dependence, Ann. Statist. 23(5) (1995) 1630–1661.
[41] M. Taqqu, W. Teverosky, W. Willinger, Estimators for long-range dependence: an empirical study, Fractals 3 (4) (1995) 785–798.
[42] M. Taqqu, V. Teverovsky, On estimating the intensity of long-range dependence in finite and infinite variance time series, in: A Practical Guide To Heavy Tails: Statistical Techniques and Applications, 1996.
[43] P.C.B. Phillips, K. Shimotsu, Local whittle estimation in nonstationary and unit root cases, Ann. Statist. 32(2) (2004) 659–692.
[44] T. Gneiting, M. Schlather, Stochastic models that separate fractal dimension and the hurst effect, SIAM Rev. 46(2) (2004) 269–282.
[45] T. Gneiting, H. Sevcikova, D. Percival, Estimators of Fractal Dimension: Assessing the Roughness of Time Series and Spatial Data, Technical Report, Department of Statistics, University of Washington, 2010.
[46] S. Pincus, R. Kalman, Irregularity, volatility, risk, and financial market time series, Proc. Natl. Acad. Sci. USA 101(38) (2004) 13709–13714.
[47] S. Pincus, Approximate entropy as a measure of system complexity, Proc. Natl. Acad. Sci. USA 88 (1991) 2297–2301.