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ORIGINAL PAPER

Efficiency in cryptocurrency markets: new evidence

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Abstract

In this paper we carried out a comprehensive study of the efficiency in the cryptocurrency markets. The markets under study are: Bitcoin, Litecoin, Ethereum, Ripple, Stellar and Monero. To study the efficiency of these markets, we use a set of five test which are applied in both a static context and dynamic context. The results obtained depend on both the analysis period and the methodology used to test the predictability of the return. However, some conclusions can be drawn: first, we observe that overall, the efficiency degree tends to increase with the time. Second, although the efficiency market seems to change along the period, the changes in the Bitcoin, Litecoin and Ethereum market show a clear tendency that evolves from less to more efficiency. In the case of Ripple, Stellar and Monero, periods of efficiency alternate with periods of inefficient, which is consistent with the adaptive market hypothesis.

Keywords Market efficiency · Adaptive market hypothesis · Cryptocurrencies · Random walk · Hurst exponent · Variance ratio test

JEL Classification G1 · G11 · G14 · G15

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1 Introduction

Efficient market hypothesis (EMH) is one of the main paradigms in corporate finance and one of the most widely used theories to study the behavior of prices in financial markets. This hypothesis is of paramount importance in the area of finance as many theories like Markowitz's portfolio theory (Markowitz, 1952, 1959), the Capital Asset Pricing Model (Lintner, 1965; Mossin, 1966; Sharpe, 1964), the Arbitrage Pricing Theory (Ross, 1976) and the Black–Scholes–Merton option pricing model (Black & Scholes, 1973; Merton, 1973) have directly and indirectly originated from it.

Efficient Market Theory is based on the original contributions from Samuelson (1965), Mandelbrot (1963a, 1963b, 1966), Malkiel (1992) and above of them Fama (1965, 1970, 1991, 1998). These authors propose that a market is efficient if the agents are rational and there is enough liquidity so any type of relevant information is included in the prices instantly, making systematic prediction impossible. More specifically, according to Fama (1970), a market is efficient if the current price of an asset fully reflects all available information. In an informationally efficient market, price changes must be unpredictable if they fully incorporate the information and expectations of all market participants. Depending on the available information included in the prices, three types of efficiency stand out (Fama, 1970): (i) *Weak efficiency*: asset prices reflect all historical information; (ii) *Semi-strong efficiency*: in this case, prices reflect both the historical and public information available on the assets and (iii) *Strong efficiency*: asset prices reflect all existing information (historical, public and private). If any investor had access to inside information, the price would adjust quickly, and would not allow them to benefit from that information.

The financial academic literature has focused mainly on testing the weak-form efficiency which implies that the future price changes are purely unpredictable based on the asset's price history. This is equivalent to say that the assets price follows a martingale model and/or a random walk. So that to test weak-form efficiency implies testing these models (LeRoy, 1989; Malkiel & McCue, 1985; Mills & Patterson, 2009).[1]

Recently, the efficiency of the cryptocurrency markets has received increasing attention, especially the Bitcoin market,[2] see for instance, Urquhart (2016), Nadarajah and Chu (2017), Bariviera et al. (2017), Bariviera (2017), Tiwari et al. (2018), Wei (2018), Vidal-Tomás and Ibáñez (2018), Aggarwal (2019), and Köchling et al. (2019). The literature approach to this market is quite conclusive

[1] As pointed by Vidal-Tomás et al. (2019), the latter is more restrictive since the martingale rejects any dependence of the conditional expectation of price increments while the random walk rejects also dependence involving the higher conditional moments of price (Charles et al., 2011a, b; LeRoy, 1989; Lim and Brooks, 2011).

[2] A cryptocurrency is a digital asset designed to work as a medium of exchange using cryptography to secure the transactions (Katsiampa et al., 2018). The first and largest cryptocurrency in the world by market capitalization is the Bitcoin followed by Ethereum, Ripple, Litecoin, Stellar and Monero. All of them represent over 80% of the total market of cryptocurrencies.

in terms of showing Bitcoin as an inefficient behavior in the beginning but evolving to greater efficiency over the time.

For the other cryptocurrencies, the existing literature is somewhat reduced. See for instance, Caporale et al. (2018), Kristoufek and Vosvrda (2019), Charfeddine and Maouchi (2019), Zhang et al. (2018) and Hu et al. (2019) among others. All these papers conclude that the cryptocurrency markets are clearly inefficient although some of them point out that the inefficiency tends to decrease with the time. This is in line with the studies made by Brauneis and Mestel (2018) and Wei (2018). These authors analyze efficiency and liquidity of a large number of cryptocurrencies and, although there is a heterogeneous pattern of behavior, they find markets become less inefficient as liquidity increases. As the depth and liquidity of these markets increases their efficiency will tend to increase as well.

As the behavioral economics point out, the market efficiency can be influenced by change in market conditions, the number of competitors, composition of investors, profit opportunities, and the risk–reward relationship. According to this, Lo (2004) proposed a new concept called adaptive market hypothesis (AMH); this author argues that financial markets are not static, but they change over time. As a consequence, the degree of efficiency may also change over time. Thus, the AMH entails the efficiency not only can adopt two states (efficient or inefficient) but even the level of efficiency varies over the time.

Support in favor of the AMH can be found in Alvarez-Ramirez et al. (2018), Sensoy (2019), Zargar and Kumar (2019), Khuntia and Pattanayak (2018), Mensi et al. (2019), Chu et al. (2019) and Tran and Leirvik (2020). In line with this group of studies, this paper assesses the efficiency of the cryptocurrencies market from a dynamic perspective.

The study improves and complements previous literature in several aspects: first, it is a new contribution in the incipient study of cryptocurrency analysis; secondly, unlike most of the papers focused on the study of Bitcoin, this study covers six of the most important cryptocurrencies by capitalization; and thirdly, unlike the most above-cited papers which analyze the efficiency in a static context, we analyze the efficiency in both a static and a dynamic context. The aim is to know whether the degree of efficiency of the cryptocurrency markets changes over time suggesting that the AMH is fulfilled. Unlike the papers aforementioned, we assess the robustness of the results obtained by considering four subsamples. In the static analysis and different size rolling windows in the dynamic analysis which notably contributes to enrich the study. To last, the paper ranks the markets analyzed in terms of efficiency.

Our findings indicate that, in line with a literature trend, the efficiency of the cryptocurrencies markets tends to increase over the time. Second, although the efficiency market seems to change with the time, the changes in the Bitcoin, Litecoin and Ethereum market show a clear tendency that has evolved from less to more being currently efficient. In the case of Ripple, Stellar and Monero periods of efficiency alternate with periods of inefficient, being consistent with the AMH. This result opens the door to the possibility that, trend trading strategies may be used in certain periods to generate abnormal profits in the Ripple, Stellar and Monero markets.

The rest of the paper is organized as follows. Section 2 presents a brief recent literature review on efficiency in cryptomarkets. Section 3 describes the methodology used in this paper; in this section we summarize the statistical test used to evaluate the market efficiency. Section 4 presents the data and empirical results and Sect. 5 ends with the main conclusions.

2 Literature review

Price efficiency focused on cryptocurrency markets have received increasing attention in the literature, especially the Bitcoin market. The literature is quite conclusive indicating that Bitcoin market was clearly inefficient in the early years but it has become more efficient in time (Aggarwal, 2019; Bariviera, 2017; Bariviera et al., 2017; Köchling et al., 2019; Nadarajah & Chu, 2017; Tiwari et al., 2018; Urquhart, 2016; Vidal-Tomás & Ibáñez, 2018; Wei, 2018, among others).

Urquhart (2016) is the first to investigate the market efficiency of the Bitcoin market using a battery of five robust tests. The findings of the study highlight the inefficient characteristics of the Bitcoin market over the full sample period. However, based on the non-overlapping window analysis, Urquhart (2016) argues that the Bitcoin market may become more efficient as it matures. Nadarajah and Chu (2017) investigate the efficient market hypothesis dealing with power transformation of Bitcoin return. The study is carried out in two samples. They conclude that Bitcoin market is clearly efficient in the second sample but no in the first sample. Aggarwal (2019) finds strong evidence that the Bitcoin market is inefficient by examining the unit root test and volatility persistence. Wei (2018) studies the relationship between the liquidity and efficiency in the Bitcoin market. He finds that the more liquid the market is, the more efficient it becomes. He also observes that the Bitcoin inefficiency is decreasing with time. Vidal-Tomás and Ibáñez (2018) study the effects that monetary policy news and any other event may produce over Bitcoin price, reaching the conclusion that Bitcoin has evolved to a more efficient behavior, not reacting to monetary news. Köchling et al. (2019) analyze the weak-form efficient market hypothesis before and after the launch of Bitcoin futures, finding that the pricing of Bitcoin before the launch of futures is partially predictable; whereas after the launch of Bitcoin futures the weak-form informational efficiency of Bitcoin cannot be rejected. Bariviera (2017) studies the long memory of the Bitcoin market using the Hurst exponent, through two alternative methods. He advocates for the use of the Detrended Fluctuation Analysis (DFA) method because it is more robust and less sensitive to departures from stationarity conditions. They find that daily returns suffered a regime switch. From 2011 until 2014 the returns time series was essentially persistent ($H > 0.5$), whereas after that year, the behavior seems to be compatible with a white noise. Bariviera et al. (2017) test the presence of long memory in Bitcoin returns from 2011 to 2017. They compute the Hurst exponent by means of the DFA method, using a sliding window in order to measure long range dependence. They detect that Hurst exponents changes significantly during the first years of existence of Bitcoin, tending to stabilize in recent times. Tiwari et al. (2018) address the issue of informational efficiency of Bitcoin using a battery of computationally efficient long-range dependence estimators for a period spanning over 2010 to 2017. They found that market is informational efficient with some exception to the period of April–August, 2013 and August–November, 2016. Corbet et al. (2019) asses the efficiency in an indirect way by analyzing different technical trading rules and evaluating which of them provides the best results. The Bitcoin market study uses intraday data. For some trend trading strategies abnormal returns are captured, which confirms that the Bitcoin market is inefficient.

Recently the study of the efficiency market has been expanded to other cryptocurrencies such as the Ethereum, Litecoin, Ripple, Dash, Monero, etc. Some studies related to this issue can be found in Caporale et al. (2018), Kristoufek and Vosvrda (2019), Charfeddine and Maouchi (2019), Zhang et al. (2018) and Hu et al. (2019) among others.[3] For a comprehensive review of the efficiency in the cryptocurrency markets, see Kyriazis (2019).

Caporale et al. (2018) use R/S analysis and Hurst exponent to examine persistence for the daily returns of four cryptocurrencies (Bitcoin, Litecoin; Dash and Ripple); they found these markets remain inefficient, but this inefficiency tends to decrease. Kristoufek and Vosvrda (2019) examine the efficiency of large set of cryptocurrencies (Bitcoin, Dash, Litecoin, Monero, Ripple, and Stellar) and compare the levels of efficiency of those markets in the period 2015–2018. They find that the hypothesis of efficiency is strongly rejected. Besides, they find that the least efficient coins turn out to be Ethereum and Litecoin whereas Dash is the winner as the most efficient cryptocurrency. Caporale and Plastun (2019) examine the day of the week effect in the cryptocurrency market focusing on Bitcoin, Litecoin, Ripple and Dash. Applying both parametric and non-parametric methods, they find evidence of an anomaly (abnormal positive returns on Mondays) only in the case of Bitcoin. Charfeddine and Maouchi (2019) analyze the long-range dependence in both returns and volatility series of four cryptocurrencies (Bitcoin, Litecoin, Ethereum and Ripple). Using a robust approach, they find evidence of long dependence in the returns and volatility series of the Bitcoin, Litecoin, and Ripple. As for Ethereum, the results show that the long dependence is only supported for the volatility series. Their results confirm the inefficiency of all the considered markets, except for Ethereum. Zhang et al. (2018) use a battery of test for assessing the efficiency of the cryptocurrency

[3] Aslan and Sensoy (2020) use intraday sampling frequency for investigating the weak-form efficiency of the four highest capitalized cryptocurrencies. Applying a battery of long memory tests, they provide evidence of major discrepancies on the predictability of cryptocurrency returns for alternative high frequency intervals. Accordingly, efficiency demonstrates a U-shaped pattern with respect to alternative sampling frequencies, hence they conclude that there exists an optimal intraday sampling frequency that maximizes the market efficiency. Akyildirim et al. (2020) use returns obtained at various intraday frequencies for the most liquid twelve cryptocurrencies in order to test their return predictability via machine learning. The authors refer to the state of the art methodologies used in decision sciences that provide them the potential patterns to be exploited and the resulting gains if the selected strategy is implemented. Also, they use different timescales for prediction that can be easily verified in their ability to generalize in different timescales for different cryptocurrencies. The results find that the direction of returns in cryptocurrency markets can be predicted for the daily or minute level time scales in a consistent manner with classification accuracies reaching as high as 70% success ratio. Their results also indicate the possibility to design trading rules based on the classification algorithms.

markets for Bitcoin, Ripple, Ethereum, NEM, Stellar, Litecoin, Dash, Monero and Verge. Their empirical results indicate that the markets of all these cryptocurrencies are inefficient. Hu et al. (2019) re-visit the Efficient Market Hypothesis for 31 of the top market-cap cryptocurrencies using various panel tests. The panel evidence suggests that there is no empirical support for the EMH, indicating market inefficiency in cryptocurrencies. Summarizing, all of these papers conclude that the cryptocurrency markets are clearly inefficient although some of them point out that the inefficiency tends to decrease with the time.

Overall, most paper aforementioned, assess the issue of the efficiency from a static point of view, but as Lo (2004) remarks the efficiency of the market may change over the time, it is to say, may be dynamic. Support in favor, this hypothesis can be found in Alvarez-Ramirez et al. (2018), Khuntia and Pattanayak (2018), Sensoy (2019), Zargar and Kumar (2019), Mensi et al. (2019), Chu et al. (2019), Noda (2020), Khursheed et al. (2020) and Tran and Leirvik (2020) between others.

Alvarez-Ramirez et al. (2018) study the issue at high frequencies and find that the market can be characterized by switching periods of efficiency and inefficiency. Khuntia and Pattanayak (2018) examine the AMH for Bitcoin and show that market efficiency changes over time as this theory predicts. Sensoy (2019) compares the time-varying weak-form efficiency of Bitcoin prices in terms of US Dollars (BTCUSD) and Euro (BTCEUR). The author finds that BTCUSD and BTCEUR markets have become more informationally efficient since the beginning of 2016. Zargar and Kumar (2019) examine the evolution of informational efficiency of Bitcoin across different periods using non-overlapping and overlapping moving window analysis which allows testing of the AMH in the Bitcoin market. The results about the higher frequencies of Bitcoin prices indicate a consistent departure from the random behavior. Mensi et al. (2019) examine asymmetric multifractality, long-range memory, and the efficiency of the two largest cryptocurrencies (i.e. BTC and ETH). The study is carried out in different subsamples. Their results show that efficiency changes over time but does not change symmetrically. Chu et al. (2019) investigate the AMH with respect to the high frequency markets of the two largest cryptocurrencies—Bitcoin and Ethereum. The findings are consistent with the AMH and show that the efficiency of the markets varies over time.

Noda (2020) measures the degree of market efficiency of Bitcoin (data from April 2013 to September 2019) and Ethereum (data from August 2015 to September 2019) using a generalized least squares (GLS)-based time-varying model that does not depend on sample size, unlike previous studies that used conventional methods.[4]

[4] Noda (2016) also employs a GSL-based time-varying model to test AMH using Japanese stock market data (TOPIX and TSE2) and also concludes that the degree of market efficiency varies with time. Tran and Leirvik (2019), following Noda's (2016) study, pointed out that sometimes markets work oddly and the time-varying degree of market efficiency measure show that a market is more efficient when the autocorrelation level is high than the autocorrelation is low. To solve this problem, these authors introduced a measure to quantify the level of market inefficiency (MIM) which varies smoothly from zero (very efficient market) to 1 (inefficient market). Their empirical results (based on the same dataset that Noda (2016) and US stock market data) show that in many periods of major economic events, financial markets becomes less efficient. They conclude that markets are often efficient but can be very inefficient over longer periods.

The empirical results show that (i) the Bitcoin's market efficiency level is higher than that of Ethereum over most periods and (ii) the degree of market efficiency varies along the time. The study concludes that the results support the AMH for the most established cryptocurrency market. Khursheed et al. (2020) examine the AMH in relation to time-varying market efficiency by using three tests, Generalized Spectral, Dominguez–Lobato and the automatic portmanteau test- on four-digital currencies (Bitcoin, Monaro, Litecoin, and Steller) over the sample period of 2014–2018. The results indicate that price movements with linear and nonlinear dependences varies over time. The tests also reveal that Bitcoin, Monero and Litecoin have the longest efficiency periods, while Stellar shows the longest inefficient market period. Tran and Leirvik (2020) study the market-efficiency in the five largest cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, and EOS); they find that the efficiency degree is highly time varying. Specifically, before 2017, cryptocurrency-markets are mostly inefficient. However, the cryptocurrency-markets become more efficient over time in the period 2017–2019.

3 Methodology

A market is efficient if the prices "fully reflect" available information (Fama, 1970). As Fama (1970) points, this definition is so general that it has no empirically testable implications. For testing such hypothesis, it is necessary to specify what we understand by available information. This author calls "weak efficient" when the information subset of interest is just historical prices or return sequences. When the available information set includes historical price and publicly information (e.g. announcements of annual earnings, stock splits, etc.) it is called "semi-strong efficient". To last, "strong efficient" implies that no investor has access to any information relevant for price formation, it is to say, no individual has higher expected trading profits than others because he has monopolistic access to some information.

In this study, we test the "weak efficient" in the cryptocurrencies market. As we have just indicated above, under the weak-form efficiency, where the information set consists of past prices and returns, the prices and return are unpredictable. For testing the return predictability, we use a battery of test. Firstly, we examine the autocorrelation of returns via Ljung–Box (LB) and Box–Pierce (BP) test. These tests have the null hypothesis of no autocorrelation.

$$Q_{LB}(k) = T(T+2)\sum_{k=1}^{m}\frac{1}{T-k}\hat{\rho}^2(k) \quad \sim \quad \chi_m^2 \tag{1}$$

$$Q_{BP}(k) = T\sum_{k=1}^{m}\hat{\rho}^2(k) \quad \sim \quad \chi_m^2 \tag{2}$$

where T is the size sample, k is the number of lags and $\hat{\rho}(k)$ is the correlation of order k.

Second, Dominguez-and Lobato test (DL) is employed to detect non-linear dependence in the returns. This test examines the no directional predictability in the returns. This test is robust to non-normality and conditional heteroscedasticity that are typical features of the financial returns. Dominguez-and Lobato test (DL) is based on Cramer–von Mises (CvM) and Kolmogorov–Smirnov (KS) statistics, and we can be written as:

$$CvM_{n,p} = \frac{1}{\hat{\sigma}^2 n^2} \sum_{j=1}^{n} \left[\sum_{t=1}^{n} \left(Y_t - \tilde{Y} \right) \mathbf{1} \left(\tilde{Y}_{t,p} - \tilde{Y}_{j,p} \right) \right]^2 \tag{3}$$

$$KS_{n,p} = \max_{1 \le i \le n} \left| \frac{1}{\hat{\sigma} \sqrt{n}} \sum_{t=1}^{n} \left(Y_t - \tilde{Y} \right) \mathbf{1} \left(\tilde{Y}_{t,p} - \tilde{Y}_{j,p} \right) \right| \tag{4}$$

being $\hat{\sigma}^2 = \frac{1}{n} \sum_{t=1}^{n} (Y_t - \bar{Y})^2$, p is a positive integer and $1(\tilde{Y}_{t,p} - \tilde{Y}_{j,p})$ the indicator function. The p-value for $C_v M_{n,p}$ and $KS_{n,p}$ tests are obtained by bootstrapping. A p-value smaller than 5% (10%) shows there is evidence to reject the null hypothesis of no directional predictability and there is significant inefficiency in the financial market. A p-value close to one indicates efficiency in the market.

Thirdly, we employ a variance ratio test based on the proposed of Lo and MacKinlay (1988). Under the null hypothesis, the price process is a random walk or martingale, the returns are serially uncorrelated, and the variance of those returns should increase linearly in the sampling intervals. That means that, the variance of $r_t - r_{t-2}$ is twice the variance of $r_t - r_{t-1}$. Overall, $\text{var}(r_t - r_{t-k}) = k * \text{var}\,(r_t - r_{t-1})$. Hence, the variance ratio $VR(k)$ is defined as the ratio of $1/k$ times the variance of k-period return to that of one-period return, for all k. An issue with this test is the choice of parameters k. To avoid an arbitrary choice of k Choi (1999) proposes the automatic variance test (AVR) where k determined automatically using a data-dependent procedure (see Charles & Darné, 2009 for additional details). The VR estimator is defined as:

$$\hat{VR}(l) = 1 + 2 \sum_{i=1}^{T-1} k(i/l) \hat{\rho}(i), \quad \hat{\rho}(i) = \sum_{t=1}^{T-i} \Delta r_i \Delta r_{t+i} / \sum_{t=1}^{T} r_t^2 \tag{5}$$

where $\hat{\rho}(i)$ is the autocorrelation function and h(x) is the quadratic spectral kernel defined as follows:

$$h(x) = \frac{25}{12\pi^2 x^2} \left[\frac{\sin\left(\frac{6\pi x}{5}\right)}{\frac{6\pi x}{5}} - \cos\left(\frac{6\pi x}{5}\right) \right] \tag{6}$$

To implement this test, one should test for the null hypothesis that the RV is equal to one for a set of k. The standardized statistic is:

$$VR_f = \frac{VR(k) - 1}{\sqrt{\frac{2k}{T}}} \tag{7}$$

AVR test is an asymptotic test which may show deficient small sample properties. In order to overcome this limitation, we utilize the wild-bootstrapped AVR test of Kim (2009) which greatly improves the small sample properties of the AVR test.

Finally, we analyze the existence of long memory of cryptocurrencies returns to which we use the rescaled Hurst exponent (Hurst, 1951). This exponent is a classical test to check long memory in the data. The procedure to obtain Hurst exponent (H) is the follow:

(i) To divide the time series $\{Y_i, \quad i = 1, \ldots N\}$ in M subinterval with length n.
(ii) For each subinterval ($j = 1, \ldots, M$), the sample mean (E_j), sample standard deviation (S_j), accumulated dispersion (D_j) and extreme difference of dispersion (R_j) are obtained as follows:

$$\begin{aligned} E_j &= \frac{\sum_{i=1}^{n} Y_{n,j}}{n}; \quad S_j = \sqrt{\frac{\sum_{i=1}^{n} \left(Y_{n,j} - E_j\right)^2}{n}}; \\ D_j &= \sum_{k=1}^{n} \left(Y_{n,j} - E_j\right); \quad R_j = \max\left(D_j\right) - \min\left(D_j\right) \end{aligned} \tag{8}$$

The rescaled range for each subinterval is obtained as:

$$(R/S)_n = \frac{\sum_{j=1}^{M}(R_j/S_j)}{M} \tag{9}$$

The Hurst exponent is the slope of the least square linear regression of equation:

$$\log(R/S)_n = \log(c) + H \cdot \log(n) \tag{10}$$

The Hurst exponent lies in the interval [0, 1]. Depending on the H values, we can identify three types of different process. If $H = 0.5$, the process will be a random walk; if $0.5 < H < 1$, the series has long-term memory and if $0 < H < 0.5$ will be anti-persistent. It is admitted that if Hurst exponent falls into the interval [0.45, 0.55], then returns will be a random walk.

4 Data and empirical findings

4.1 Data

For our empirical analysis, we use data from six cryptocurrencies: Bitcoin Monero, Ripple, Litecoin, Ethereum and Stellar, representing over 81% of the total market of cryptocurrencies. The data consists of the closing daily price extracted

Table 1 Descriptive statistics of discrete daily returns for the six cryptocurrencies

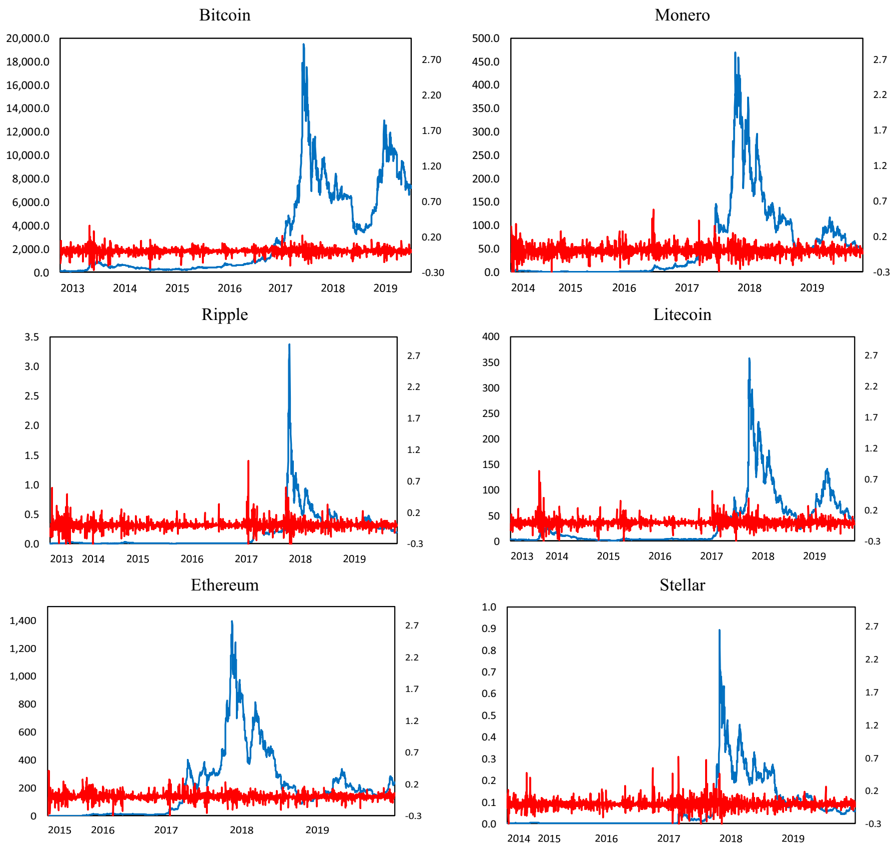
	Bitcoin	Monero	Ripple	Litecoin	Ethereum	Stellar
Mean (%)	0.16	0.16	0.15	0.09	0.24	0.15
Median (%)	0.18	−0.12	−0.28	−0.07	−0.09	−0.35
Max	0.36	0.59	1.03	0.83	0.41	0.72
Min	−0.27	−0.38	−0.62	−0.51	−1.30	−0.37
Std. Dev.	0.04	0.07	0.07	0.06	0.07	0.08
Skewness	−0.15*	0.65*	2.08*	1.72*	−3.43*	2.01*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Kurtosis	7.73*	9.61*	32.98*	28.62*	74.84*	19.65*
	(0.10)	(0.11)	(0.10)	(0.10)	(0.12)	(0.11)
Jarque-Bera	6094	3858	88927	67553	346513	23998
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	2437	2049	2340	2437	1607	1974
Correlations						
Bitcoin	1					
Monero	0.527	1				
Ripple	0.342	0.324	1			
Litecoin	0.634	0.466	0.394	1		
Ethereum	0.423	0.390	0.262	0.410	1	
Stellar	0.389	0.408	0.566	0.413	0.283	1
Sample period	Apr 29, 2013 Dec 31, 2019	Aug 05, 2013 Dec 31, 2019	Aug 05, 2013 Dec 31, 2019	Apr 30, 2013 Dec 31, 2019	Aug 08, 2015 Dec 28, 2019	Aug 06, 2014 Dec 31, 2019

Note: This table presents the descriptive statistics of the daily returns. Standard errors of the skewness and excess kurtosis, in brackets, are calculated as $\sqrt{6/n}$ and $\sqrt{24/n}$ respectively. The JB (Jarque Bera) statistic is distributed as the Chi-square with two degrees of freedom. (*) denotes significance at the 5% level. The correlations report Pearson's linear unconditional sample correlation between the daily returns from August 8th, 2015 to December 31st, 2019. The efficiency analysis periods are presented in the last row

from CoinMarketCap. All currencies are expressed in terms of US dollar. The data periods are showed in Table 1 for all assets.

The prices are transformed into returns by taking logarithmic differences of the closing daily price. Figure 1 illustrates the daily price and returns of the data set.

As we can see in Fig. 1, along the period analysis Bitcoin price has shown a spectacular growth going from $68.43 in July 2nd, 2013 to around $7194 at the end of 2019. This growth was especially strong between 2014 and 2017, which was almost exponential. In these three years, the price increased by 2429%, from $771 at the beginning of 2014 to $19,497 at the end of 2017. At the end of 2017 the Bitcoin's price collapsed producing important drops in price. Since then, the Bitcoin has shown a sawtooth profile, alternating up and down movements. The other cryptocurrencies show a similar behavior although in the case



Note: This figure illustrates the daily evolution of returns (in red) and price (in blue) of six cryptocurrencies. The sample periods are presented in Table 1.

Fig. 1 Prices and return for all cryptocurrencies. Note: This figure illustrates the daily evolution of returns (in red) and price (in blue) of six cryptocurrencies. The sample periods are presented in Table 1 Source: CoinMarketCap (http://coinmarketcap.com)

of Monero, Ripple, Ethereum and Stellar, after the collapse of 2017 prices have barely recovered.

Referring to the returns, we observe that their range fluctuation is not constant, which means that the return's variance changes over time. The volatility of all cryptocurrencies was particularly high from 2017 to 2018, particularly Stellar and Ripple. In 2019, a more stable period is observed.

The basic descriptive statistics are provided in Table 1. The unconditional mean for all daily return is positive and moves between 0.24% (Ethereum) and 0.09% (Litecoin). Ethereum shows the highest range (1.7) being three times greater than Bitcoin range (0.63). Besides, Bitcoin has the minor standard deviation. The skewness statistic is negative for Bitcoin and for Ethereum, implying that the distribution of daily returns is skewed to the left; for the rest of currency this statistic is positive. The kurtosis coefficients show that the distributions have much thicker tails than the normal distribution. In all cases, the Jarque–Bera test is statistically significant, rejecting the hypothesis of normality. All this evidence shows that a normal distribution cannot fit the empirical distributions of daily returns, as it exhibits a significant excess of kurtosis and asymmetry (fat tails and peakness). The correlation coefficient figures are all positive for each pair of the currency return series. The Stellar–Ripple (0.57) and Bitcoin–Litecoin (0.63) have the highest correlation and the Ethereum–Ripple has the lowest (0.26).

4.2 Empirical findings

4.2.1 Evaluating return predictability

This section begins with results for our proposed tests of price predictability for the six cryptocurrencies under consideration. These tests are: Ljung–Box (LB) test, Box–Pierce (BP) test, Dominguez–Lobato (DL) test, wild-bootstrapped automatic variance ratio (AVR) test (Kim, 2009) and Hurst exponent.

We examine these test over full sample period and four subsamples period of equal length.[5] The aim is to evaluate whether the level of efficient of these market has varied over time. Table 2 reports the results for Ljung–Box (LB) and Box–Pierce (BP) test, at different lags: 5, 10 and 15.

When we consider full sample, we find that for all considered lags, the Ljung–Box (LB) and Box–Pierce (BP) test are rejected at standard level of confidence indicating significant inefficiency of all cryptocurrencies; only Bitcoin and Litecoin are efficient when we considered five lags. However, the subsample analysis reveals something different. For Bitcoin, the null hypothesis of no correlation is rejected in the first and second subsample but no in the rest. This indicate that this market had initially an inefficient behavior but it has evolved to greater efficiency over the time. This result is in line with these obtained by Bariviera et al. (2017), Bariviera (2017), Tiwari et al. (2018), Wei (2018), Vidal-Tomás and Ibáñez (2018), Aggarwal (2019), and Köchling et al. (2019) between others. Ethereum market shows a behavior inefficient in the first sample but is efficient in the second, third and fourth sample analyzed. Litecoin market shows a behavior efficient along the whole sample, except the second sample. In the case of Ripple, Stellar and Monero, which are coins with less capitalization, periods of efficiency alternate with periods of inefficiency are observed. For instance, for Ripple the null hypothesis of no correlation is rejected in the first and third sample while in the second and fourth sample this hypothesis cannot be rejected. In the case of Stellar, the returns seem to be unpredictable in the first and fourth sample but they can be predictable in the second and third sample. Similar results are found for Monero. Table 3 reports the p-value of the

[5] For instance, in the case of the Bitcoin the first sub-sample runs from April 29th, 2013 to December 28th, 2014. The second sub-sample runs from December 29th, 2014 to August 29th, 2016. The third sample goes from August 30th, 2016 to May 1st, 2018 and the fourth sample runs from May 2nd, 2018 to December 31th, 2019.

Dominguez–Lobato (DL) test and the wild-bootstrapped automatic variance ratio (AVR) test (see column 3 to 5).

According to Dominguez–Lobato (DL) test, which analyzes the existence of non-lineal relationship between returns, Bitcoin returns were predictable during and after his launch becoming unpredictable since December 29th, 2014 which is the beginning of the second sample. These results are in line with these obtained by the correlation test. Again, we find that the Bitcoin has a behavior inefficient initially becoming efficient with the time.

By contract, according to this test Litecoin and Ethereum are always efficient as in the full sample as in the four subsamples analyzed. surprisingly Stellar also shows a mostly efficient behavior. In the case of Ripple, the Dominguez–Lobato (DL) test suggests the returns are predictable from its launch until August 4th, 2018. Since then the null hypothesis of unpredictability of the returns cannot be rejected. To last, Monero market show periods of efficiency alternating with periods of inefficiency, in line with the results obtained in the previous analysis.

In column (6) of Table 3 we report the Hurst exponent. When this exponent falls within the interval [0.45, 0.55] asset price is said to follow a random walk (Liu et al., 2019). When we analyze the full sample, we find that for all assets the Hurst exponent falls out of the mentioned interval, showing these markets are inefficient. The subsample analysis corroborates this result for Bitcoin, Litecoin and Ethereum. These cryptocurrencies show an inefficient behavior mostly throughout the entire sample. However, in the case of Ripple, Stellar and Monero we observed again periods of efficiency alternating with periods of inefficiency, in line with the results obtained in the correlation analysis.

To last, AVR test suggest that all cryptocurrency markets are efficient over the long period.

Table 4 summarizes the results reported in Tables 2 and 3. As we can see, the results obtained depend on the statistical use to test the weak efficient hypothesis, so that it is necessary to define the criteria used to consider that a market is efficient. In this study we say that a market is efficient if it passes most of the tests, that is, five out of six (5/6). Using this criterion, we can conclude that Bitcoin and Ethereum market were not efficient in the first and second sample, but it was efficient in the rest. This shows that these markets had initially an inefficient behavior, but they have evolved to greater efficiency over the time. In the case of the Bitcoin, which is the most studied cryptocurrency, this result is line with these obtained by Bariviera et al. (2017), Bariviera (2017), Tiwari et al. (2018), Wei (2018), Vidal-Tomás and Ibáñez (2018), Aggarwal (2019), and Köchling et al. (2019). Litecoin shows a behavior mostly efficient with the only exception of the second sample. Stellar market alternates periods of efficiency (first and fourth) with periods of inefficiency (second and third) which is consistent with the AMH. To last, Monero and Ripple behave inefficiently in the first, second, and third sample. Just only in the fourth sample the return of these currencies was unpredictable.

Using as a criterion the Hurst exponent, the results of the study are somewhat different. According to this measure Bitcoin, Ethereum and Litecoin markets are clearly inefficient as just only in one subsample the Hurst exponent indicate efficiency. In

Table 2 Ljung–Box and Box–Pierce tests (p-valor)

	Bitcoin	Monero	Ripple	Litecoin	Ethereum	Stellar
Full sample						
LB						
5 lags	0.22	**0.05**	**0.00**	0.12	**0.01**	**0.00**
10 lags	**0.01**	**0.00**	**0.00**	**0.00**	**0.01**	**0.00**
15 lags	**0.03**	**0.00**	**0.00**	**0.00**	**0.03**	**0.01**
BP						
5 lags	0.23	**0.05**	**0.00**	0.12	**0.01**	**0.00**
10 lags	**0.01**	**0.00**	**0.00**	**0.00**	**0.01**	**0.00**
15 lags	**0.00**	**0.00**	**0.00**	**0.00**	**0.04**	**0.01**
1st subsample						
LB						
5 lags	**0.02**	0.35	**0.00**	0.27	**0.00**	0.24
10 lags	**0.00**	0.17	**0.00**	0.10	**0.00**	0.35
15 lags	**0.00**	0.05	**0.00**	0.18	**0.01**	0.62
BP						
5 lags	**0.02**	0.36	**0.00**	0.27	**0.00**	0.24
10 lags	**0.00**	0.18	**0.00**	0.10	**0.00**	0.36
15 lags	**0.00**	0.05	**0.00**	0.20	**0.01**	0.63
2nd subsample						
LB						
5 lags	**0.01**	**0.01**	**0.03**	**0.01**	0.74	**0.00**
10 lags	**0.01**	**0.00**	0.11	**0.00**	0.82	**0.00**
15 lags	**0.00**	**0.01**	0.28	**0.01**	0.72	**0.00**
BP						
5 lags	**0.01**	**0.01**	0.30	**0.01**	0.75	**0.00**
10 lags	**0.01**	**0.00**	0.12	**0.00**	0.83	**0.00**
15 lags	**0.00**	**0.01**	0.30	**0.01**	0.74	**0.01**
3rd subsample						
LB						
5 lags	0.51	**0.04**	**0.00**	0.91	0.22	**0.00**
10 lags	0.47	**0.01**	**0.00**	0.06	0.13	**0.00**
15 lags	0.70	**0.05**	**0.00**	0.08	0.30	**0.02**
BP						
5 lags	0.52	**0.04**	**0.00**	0.91	0.23	**0.00**
10 lags	0.48	**0.01**	**0.00**	0.07	0.15	**0.00**
15 lags	0.72	**0.05**	**0.00**	0.09	0.33	**0.02**
4th subsample						
LB						
5 lags	0.72	0.74	0.63	0.98	0.21	0.95
10 lags	0.10	0.47	0.84	0.40	0.20	0.61
15 lags	0.22	0.66	0.81	0.62	0.49	0.87
BP						
5 lags	0.73	0.75	0.64	0.98	0.22	0.95
10 lags	0.10	0.48	0.84	0.42	0.21	0.62
15 lags	0.73	0.68	0.83	0.64	0.52	0.88

Note: The four subsamples for each cryptocurrency are of equal length. We bold the cases in which the null hypothesis of no correlation is rejected at standard confidence level the case of Ripple, Stellar and Monero, periods of efficiency are alternated with periods of inefficiency which is consistent with the AMH.

4.2.2 Evaluating time-varying return predictability

In the previous analysis, we have seen that returns of some cryptocurrencies have gone through periods of independence and dependence. This finding suggests that the degree of market efficiency may vary over time, which is consistent with AMH. To asses this hypothesis we use a rolling window since this approach is capable of measuring time-varying return predictability. For this propose, we select initially a rolling window of 350 observations of daily returns and compute the p-value of the different tests applied (LB, BP, DL, AVR tests) and Hurst exponent. The study is carried out in two subsamples of equal length. The first subsample includes the first and second subsample of the static analysis and the second subsample includes the third and fourth.

In the Appendix of this paper, we include Figs. 2, 3, 4, and 5. Figure 2 shows the p-value of Ljung–Box for 5 lags.[6] Figures 3 and 4 plot the p-value for Dominguez–Lobato test and AVR test respectively. Figure 5 illustrates how Hurst exponent evolves over the time. The horizontal line parallel to the x-axis at points 0.05 in Figs. 2, 3 and 4 denote level of significance at 5%. If the p-values reported in these figures fall under these lines the market will not be efficient. The two horizontal line parallel to the x-axis in Fig. 5, mark off the interval within the market has approximated the state of random walk.

A visual inspecion of thes Figures suggests that efficiency of these market is not static. Even in periods in which a market behaves efficiently most time, there is some days in which it is not efficient. In addition, we observed that, the null hypothesis of unpredictability of the returns tends to be rejected in the first part of the sample, but tends to be accepted in the second, thus indicating that the degree of efficiency of cryptocurrency markets tends to increase.

Table 5 reports the percentage of days in which a market behaviour is efficient according to each one of the tests considered. In this table we also include the percentage of days in which Bitcoin market and others cryptocurrency were efficient. As in the earlier section we say that a market is efficient if it passes mostly test, it is to say, 5 out of 6 (5/6).

The dynamic analysis of the predictability returns reveals some interesting things. First, we observe that for all cryptocurrencies the degree of efficient of these markets increase in the second subsample. This was already observed in the subsample analysis for some currencies, but not all. For instance, in the case of the Bitcoin market we find that this market was efficient the 42% of the days in the first subsample. This percentage increase to 100% in the second subsample. In the case of Litecoin the market was efficient the 57% of the days in the first subsample and the

[6] In order to save space, only the graphs of the estimation of the p-value for Ljung–Box test for five lags have been presented. The plots corresponding to the p-values of 10 and 15 delays as well as for Box–Pierce have also been obtained. They are available for any interested reader upon request to the authors.

Table 3 Test results for random walk for daily cryptocurrencies returns

	DL		AVR	Hurst
	CvM	KS		
Bitcoin				
Full	**0.023**	**0.003**	0.924	**0.552**
1st subsample	**0.040**	0.087	0.982	**0.610**
2nd subsample	0.913	0.947	0.856	0.527
3rd subsample	0.297	0.097	0.662	**0.570**
4th subsample	0.580	0.637	0.447	**0.584**
Monero				
Full	0.517	0.537	0.928	**0.581**
1st subsample	0.050	**0.033**	0.177	**0.551**
2nd subsample	0.527	0.690	0.384	0.541
3rd subsample	**0.037**	0.097	0.108	0.548
4th subsample	0.367	0.497	0.226	**0.552**
Ripple				
Full	**0.000**	**0.000**	0.262	**0.568**
1st subsample	**0.007**	**0.003**	0.326	**0.567**
2nd subsample	**0.003**	**0.010**	0.278	0.507
3rd subsample	**0.040**	**0.007**	0.649	**0.583**
4th subsample	0.627	0.510	0.968	0.511
Litecoin				
Full	0.630	0.567	0.657	**0.551**
1st subsample	0.530	0.287	0.644	**0.578**
2nd subsample	0.680	0.867	0.857	0.548
3rd subsample	0.560	0.703	0.652	**0.576**
4th subsample	0.830	0.763	0.928	**0.600**
Ethereum				
Full	0.120	0.103	0.052	**0.603**
1st subsample	0.690	0.873	0.063	**0.558**
2nd subsample	0.060	**0.040**	0.707	**0.616**
3rd subsample	0.293	0.277	0.623	**0.576**
4th subsample	0.313	0.217	0.228	**0.564**
Stellar				
Full	0.140	0.010	0.311	**0.573**
1st subsample	0.313	0.437	0.824	0.507
2nd subsample	0.140	0.077	0.031	**0.424**
3rd subsample	**0.033**	**0.010**	0.114	**0.560**
4th subsample	0.493	0.503	0.395	0.503

Note: Columns 3 to 5 report the corresponding p-value of considered tests. Column 6 reports the Hurst statistic. Bolded cells denote the cases in which the null hypothesis has been rejected

100% in the second. Another example, the Ripple market was efficient just only the 11% of the days in the first sample and the 59% of the days in the second. By other hand, although the efficiency of the cryptocurrency markets tends to increase over the time, we observed that even in the second sample there is a considerable percentage of days in which the returns could be predictable with past information for some currencies which is consistent with the AMH. This result is in line with those obtained by Chu et al. (2019) and Khuntia and Pattanayak (2018).[7]

To last, considering the number of days in which those markets have behaved efficiently, we could say that the most efficient market is the Bitcoin and Litecoin market, closely followed by the Ethereum. The markets less efficient are Ripple, Stellar and Monero.

To analyze the robustness of the results we repeat the dynamic analysis for two additional sizes of rolling window: 250 and 500. Table 6 reports the results for theses sizes rolling window.

For a size rolling window of 250 days we obtain similar results. We observe again that for all cryptocurrencies the degree of efficient of these markets increase in the second subsample. For instance, in the case of the Bitcoin market we find that this market was efficient the 53% of the days in the first subsample. This percentage increases to 99% in the second subsample. In the case of Ripple, the percentage of days that this market had an efficiency behavior was of 23% in the first sample and 74% in the second. We find again that the most efficient market is the Bitcoin and Litecoin market, closely followed by the Ethereum. The markets less efficient are Ripple, Stellar and Monero.

For these currencies the percentage of days in which the market behave inefficiently is still high so that the ability of the speculators to beat these markets and generate abnormal returns is more evident that in the case of Bitcoin, Litecoin and Ethereum market.

For a size rolling window of 500 the results are qualitative similar. The degree of efficiency increases in the second sample for all cryptocurrencies except the Ethereum and Monero. The percentage of days that this last currency shows an efficient behavior is similar in both samples. For the rest we appreciate an important increase. Again, the most efficient markets are Litecoin, Bitcoin and Ethereum, followed by far by Stellar, Monero and Ripple.

[7] Chu et al. (2019) investigated the AMH for Bitcoin and Ethereum to high frequency data, applied Dominguez and Lobato test in a rolling window, and the results were consistent with the AMH. Khuntia and Pattanayak (2018) examine the AMH for Bitcoin and show that market efficiency changes over time and prove presence of AMH.

Table 4 Summary of the results

	Bitcoin	Monero	Ripple	Litecoin	Ethereum	Stellar
Panel (a) Full sample						
Ljung–Box	No efficiency	No efficiency	No efficiency	No efficiency	No efficiency	No efficiency
Box Pierce	No efficiency	No efficiency	No efficiency	No efficiency	No efficiency	No efficiency
DL (CvM)	No efficiency	No efficiency	No efficiency	Efficiency	Efficiency	Efficiency
DL (KS)	No efficiency	Efficiency	No efficiency	Efficiency	Efficiency	Efficiency
AVR	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency
Hurst exponent	No efficiency	No efficiency	No efficiency	No efficiency	No efficiency	No efficiency
Panel (a) First subsample						
Ljung–Box	No efficiency	No efficiency	No efficiency	**Efficiency**	No efficiency	**Efficiency**
Box Pierce	No efficiency	No efficiency	No efficiency	**Efficiency**	No efficiency	**Efficiency**
DL (CvM)	No efficiency	Efficiency	No efficiency	**Efficiency**	Efficiency	**Efficiency**
DL (KS)	Efficiency	No efficiency	No efficiency	**Efficiency**	Efficiency	**Efficiency**
AVR	Efficiency	Efficiency	Efficiency	**Efficiency**	Efficiency	**Efficiency**
Hurst exponent	No efficiency	No efficiency	No efficiency	**No efficiency**	No efficiency	**Efficiency**
Panel (b) Second subsample						
Ljung–Box	No efficiency	No efficiency	Efficiency	No efficiency	Efficiency	No efficiency
Box Pierce	No efficiency	No efficiency	Efficiency	No efficiency	Efficiency	No efficiency
DL (CvM)	Efficiency	Efficiency	No efficiency	Efficiency	Efficiency	Efficiency
DL (KS)	Efficiency	Efficiency	No efficiency	Efficiency	No efficiency	Efficiency
AVR	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency	Efficiency
Hurst exponent	Efficiency	Efficiency	Efficiency	Efficiency	No efficiency	No efficiency
Panel (c) Third subsample						
Ljung–Box	**Efficiency**	No efficiency	No efficiency	**Efficiency**	**Efficiency**	No efficiency
Box Pierce	**Efficiency**	No efficiency	No efficiency	**Efficiency**	**Efficiency**	No efficiency
DL (CvM)	**Efficiency**	No efficiency	No efficiency	**Efficiency**	**Efficiency**	No efficiency
DL (KS)	**Efficiency**	Efficiency	No efficiency	**Efficiency**	**Efficiency**	No efficiency
AVR	**Efficiency**	Efficiency	Efficiency	**Efficiency**	**Efficiency**	Efficiency
Hurst exponent	**No efficiency**	Efficiency	No efficiency	**No efficiency**	**No efficiency**	No efficiency
Panel (d) Fourth sample						
Ljung–Box	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**
Box Pierce	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**
DL (CvM)	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**
DL (KS)	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**
AVR	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**	**Efficiency**
Hurst exponent	**No efficiency**	**No efficiency**	**Efficiency**	**No efficiency**	**No efficiency**	**Efficiency**

Note: We bolded the cases in which at least 5 tests have been passed

Table 5 Proportion of days in which the efficiency market hypothesis has been accepted and/or rejected

	Bitcoin	Monero	Ripple	Litecoin	Ethereum	Stellar
Panel (a) First sample						
Ljung–Box	No effic(*) (51%)	**Efficien (61%)**	No effic (79%)	**Efficien (58%)**	**Efficien (93%)**	No effic (73%)
Box Pierce	No effic (51%)	**Efficien (61%)**	No effic (79%)	**Efficien (60%)**	**Efficien (93%)**	No effic (73%)
DL (CvM)	**Efficien(+) (95%)**	**Efficien (96%)**	No effic (69%)	**Efficien (98%)**	**Efficien (89%)**	**Efficien (66%)**
DL (KS)	**Efficien (93%)**	**Efficien (98%)**	No effic (66%)	**Efficien (98%)**	**Efficien (77%)**	**Efficien (68%)**
AVR	**Efficien (100%)**	**Efficien (100%)**	**Efficien (92%)**	**Efficien (100%)**	**Efficien (99%)**	**Efficien (57%)**
Hurst exponent	**Efficien (74%)**	**Efficien (56%)**	No effic (54%)	**No effic (55%)**	**No effic (92%)**	No effic (55%)
Efficiency	42% days(**)	**61% days**	11% days	**57% days**	**69% days**	26% days
Panel (b) Second sample						
Ljung–Box	**Efficien (93%)**	**Efficien (96%)**	**Efficien (61%)**	**Efficien (100%)**	**Efficien (71%)**	No effi (83%)
Box Pierce	**Efficien (93%)**	**Efficien (96%)**	**Efficien (62%)**	**Efficien (100%)**	**Efficien (79%)**	No effi (68%)
DL (CvM)	**Efficien (100%)**	**Efficien (58%)**	**Efficien (97%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (94%)**
DL (KS)	**Efficien (100%)**	**Efficien (69%)**	**Efficien (72%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (75%)**
AVR	**Efficien (100%)**	**Efficien (99%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (100%)**
Hurst exponent	**Efficien (86%)**	**Efficien (65%)**	No effic (60%)	No effic (66%)	No effic (79%)	No effic (56%)
Efficiency	**100% days**	**68% days**	**59% days**	**100% days**	**71% days**	61% days

Note: (*) Percentage of days in which the null hypothesis of Lung-Box test at 5 lags is rejected. (+) Percentage of days in which the null hypothesis of DL test is accepted. (**) Percentage of days in which Bitcoin market was efficienct. We consider that a market is efficient when it passes most all of tests, it is to say, 5 of 6 test. In bold the tests where the number of days in which the market was efficient exceeds the rest. Size of rolling window: 350 days

Table 6 Proportion of days in which the efficiency market hypothesis has been accepted and/or rejected

	Bitcoin	Monero	Ripple	Litecoin	Ethereum	Stellar
Panel A: window size = 250						
Panel (a.1) First subsample						
Ljung–Box	**Efficien$^{(+)}$ (61%)**	**Efficien (64%)**	No effic$^{(*)}$ (72%)	**Efficien (76%)**	**Efficien (86%)**	No effic (64%)
Box Pierce	**Efficien (63%)**	**Efficien (65%)**	No effic (72%)	**Efficien (77%)**	**Efficien (87%)**	No effic (64%)
DL (CvM)	**Efficien (98%)**	**Efficien (99%)**	No effic (57%)	**Efficien (99%)**	**Efficien (93%)**	**Efficien (65%)**
DL (KS)	**Efficien (96%)**	**Efficien (100%)**	**Efficien (58%)**	**Efficien (99%)**	**Efficien (83%)**	**Efficien (64%)**
AVR	**Efficien (100%)**	**Efficien (97%)**	**Efficien (88%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (62%)**
Hurst exponent	**Efficien (72%)**	No effic (52%)	No effic (55%)	**Efficien (51%)**	No effic (77%)	**Efficien (68%)**
Efficiency	**53% days**	**64% days**	23% days	**75% days**	**74% days**	36% days
Panel (a.2) Second subsample						
Ljung–Box	**Efficien (93%)**	**Efficien (98%)**	**Efficien (75%)**	**Efficien (97%)**	**Efficien (94%)**	**Efficien (77%)**
Box Pierce	**Efficien (93%)**	**Efficien (99%)**	**Efficien (75%)**	**Efficien (97%)**	**Efficien (95%)**	**Efficien (78%)**
DL (CvM)	**Efficien (100%)**	**Efficien (74%)**	**Efficien (99%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (95%)**
DL (KS)	**Efficien (100%)**	**Efficien (81%)**	**Efficien (87%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (88%)**
AVR	**Efficien (100%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (100%)**
Hurst exponent	**Efficien (89%)**	**Efficien (77%)**	**Efficien (50%)**	No effic (55%)	**Efficien (50%)**	No effic (64%)
Efficiency	**99% days**	**80% days**	**74% days**	**97% days**	**95% days**	**73% days**
Panel B: size window = 500						
Panel (b.1) First subsample						
Ljung–Box	**Efficien (59%)**	No effic (54%)	No effic (79%)	**Efficien (59%)**	**Efficien (99%)**	No effic (84%)
Box Pierce	**Efficien (59%)**	No effic (53%)	No effic (79%)	**Efficien (60%)**	**Efficien (99%)**	No effic (84%)
DL (CvM)	**Efficien (87%)**	**Efficien (100%)**	No effic (96%)	**Efficien (100%)**	**Efficien (79%)**	**Efficien (61%)**
DL (KS)	**Efficien (88%)**	**Efficien (99%)**	No effic (80%)	**Efficien (100%)**	**Efficien (71%)**	**Efficien (61%)**
AVR	**Efficien (100%)**	**Efficien (100%)**	**Efficien (91%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (52%)**
Hurst exponent	**Efficien (70%)**	**Efficien (72%)**	No effic (64%)	No effic (69%)	No effic (100%)	No effic (62%)

Table 6 (continued)

	Bitcoin	Monero	Ripple	Litecoin	Ethereum	Stellar
Efficiency	**46% days**(**)	46% days	13% days	**59% days**	**67% days**	14% days
Panel (b.1) Second subsample						
Ljung–Box	**Efficien (100%)**	**Efficien (76%)**	No effic (60%)	**Efficien (100%)**	**Efficien (63%)**	**Efficien (54%)**
Box Pierce	**Efficien (100%)**	**Efficien (82%)**	No effic (56%)	**Efficien (100%)**	**Efficien (66%)**	**Efficien (54%)**
DL (CvM)	**Efficien (100%)**	**Efficien (62%)**	**Efficien (91%)**	**Efficien (100%)**	**Efficien (99%)**	**Efficien (92%)**
DL (KS)	**Efficien (93%)**	**Efficien (71%)**	**Efficien (61%)**	**Efficien (100%)**	**Efficien (97%)**	**Efficien (58%)**
AVR	**Efficien (100%)**	**Efficien (99%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (100%)**	**Efficien (100%)**
Hurst exponent	No effic (73%)	**Efficien (58%)**	No effic (70%)	No effic (98%)	No effic (100%)	**Efficien (53%)**
Efficiency	**95% days**	**47% days**	40% days	**100% days**	**59% days**	**47% days**

Note: (*) Percentage of days in which the null hypothesis of Ljung–Box test at 5 lags is rejected. (+) Percentage of days in which the null hypothesis of DL test is accepted. (**) Percentage of days in which Bitcoin market was efficienct. We consider that a market is efficient when it passes most of tests, it is to say, 5 of 6 test. In bold the tests where the number of days in which the market was efficient exceeds the rest

5 Conclusion

The study of efficiency in financial markets has been an essential theme in finance. Most of these studies asses this subject in traditional financial markets. The aim of this paper is to analyze the degree of efficiency of the new markets that have emerged with the appearance of what are called cryptocurrencies. To that, six of the top market-cap cryptocurrencies have been chosen and six tests have been used to check the weak Efficient Market Hypothesis (Ljung–Box test, Box–Pierce test, Dominguez–Lobato test, wild-bootstrapped automatic variance ratio (AVR) test and Hurst exponent).

The analysis has been carried out from various perspectives. First, a static analysis of the behavior of the markets has been carried out, studying full and splitting the samples into four subsamples of equal size. The results reaped in this first analysis, corroborate the obtained in the literature, showing that some cryptocurrencies, such as Bitcoin and Ethereum, while not efficient in their early years, tend to be efficienct over the time. However, Litecoin seems to show an efficient behavior in most sample. Other cryptocurrencies such as Ripple, Monero and Stellar alternate periods of efficiency and inefficiency, which is consistent with the AMH.

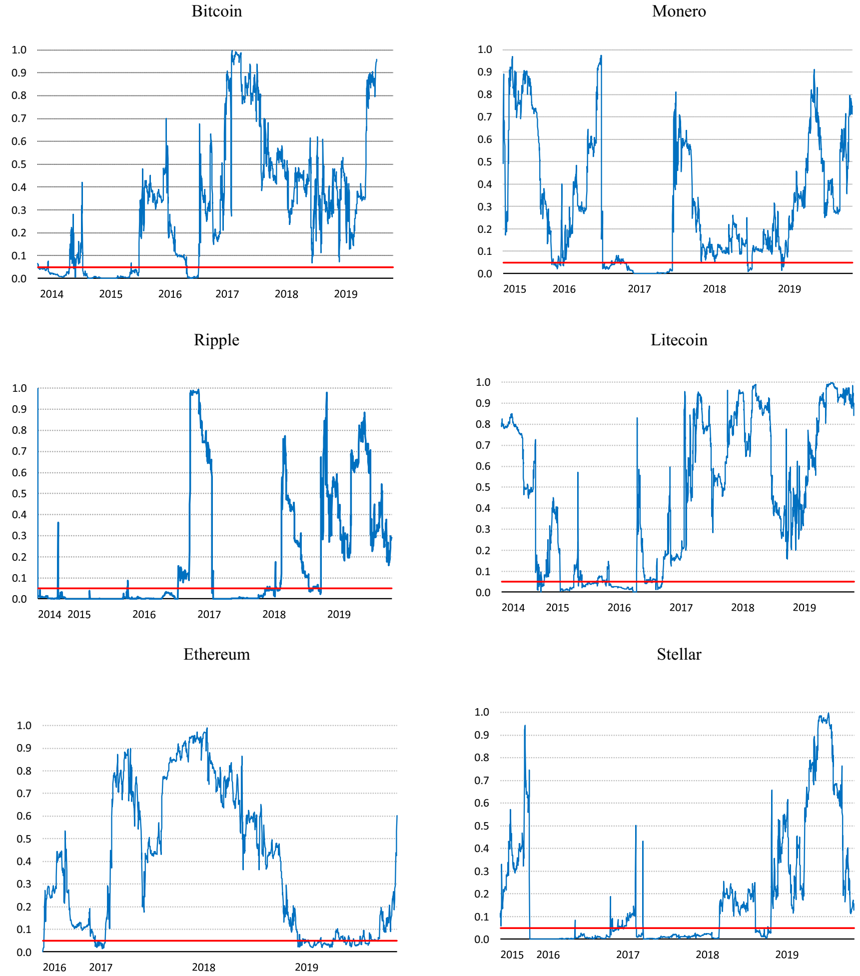
In second place, we evaluate the time-varying return predictability through a dynamic analysis of the evolution of the six tests already mentioned. For this purpose, we select several rolling window sizes: 250, 350 and 500 observations of daily returns and compute the p-value of the different tests applied (LB, BP, DL, AVR tests) and Hurst exponent.

Overall, for all size rolling window we observe that, for all cryptocurrencies, the degree of efficiency of these markets increases in the second subsample. On the other hand, although the efficiency of the cryptocurrency markets tends to increase over the time, we observed that even in the second sample there is a considerable percentage of days in which the returns could be predictable with past information for some currencies (Ripple, Monero and Stellar) which is consistent with the AMH. This result is in line with those obtained by Chu et al. (2019) and Khuntia and Pattanayak (2018).

Finally, considering the number of days in which those markets have efficiently behaved, we could say that the most efficient market is the Bitcoin and Litecoin market, closely followed by the Ethereum. The less efficient markets are Ripple, Stellar and Monero.

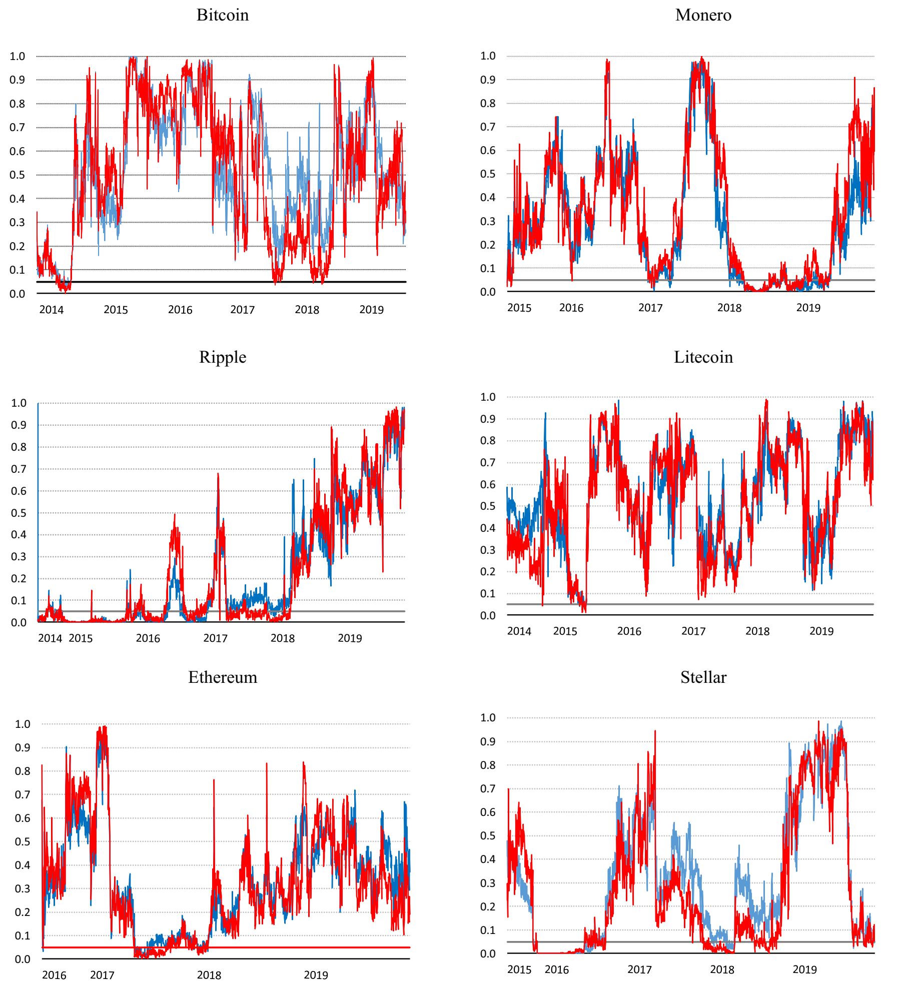
Appendix

See Figs. 2, 3, 4 and 5.



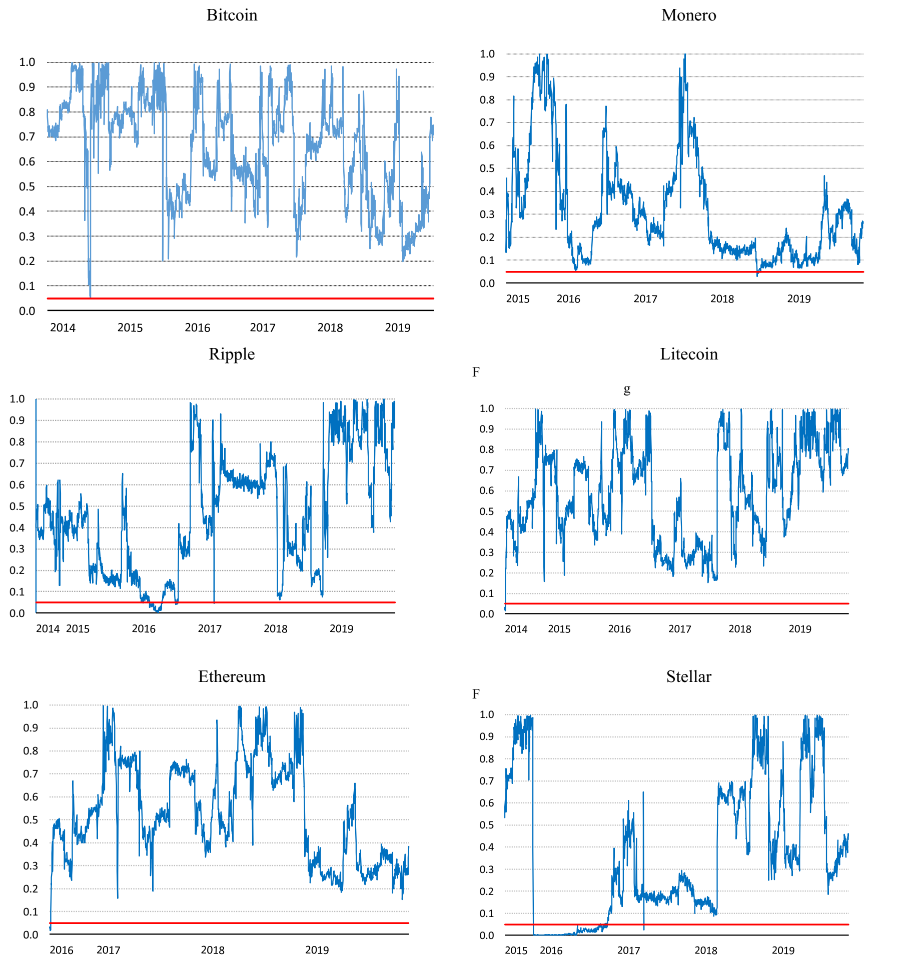
Note: Figures show Ljung-Box p-values for five lags. The horizontal lines correspond 5% level of confidence. The results haven been obtained on rolling window with a size of 350 observations.

Fig. 2 Evolution of p-value of LB with 5 lags



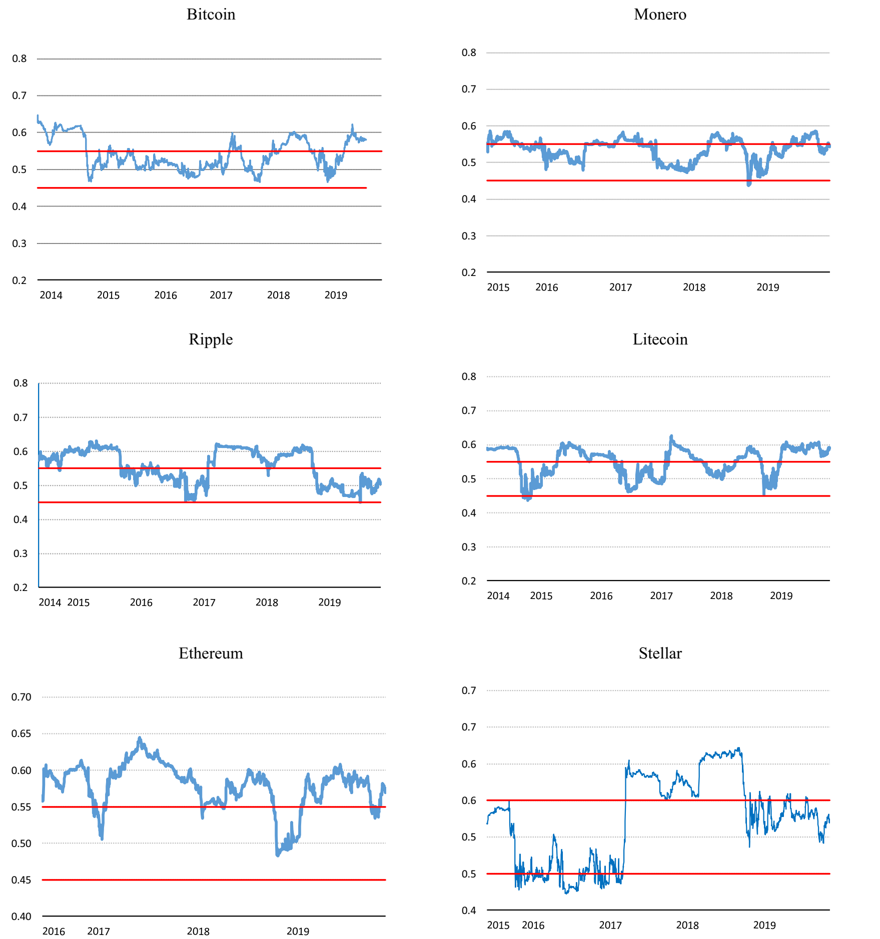
Note: Figures show the p-value of CvM (in red) and KS (in blue) of the DL test. The black horizontal line corresponds 5% level of confidence. The results haven been obtained on rolling window with a size of 350 observations.

Fig. 3 Evolution of p-value of Dominguez–Lobato test



Note: Black horizontal correspond to 5% level of confidence. The results haven been obtained on rolling window with a size of 350 observations.

Fig. 4 Evolution of p-value of Automatic Variance Ratio test



Note: Figure shows the evolution of Hurst exponent estimate obtained with a rolling window. The length of window is 350 observations. Horizontal lines in red show the upper (0.55) and lower (0.45) limit of the interval where the market can be approached to random walk.

Fig. 5 Evolution of Hurst exponent

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