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High frequency market efficiency test for cryptocurrency

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Abstract
As the crypto currencies gained popularity, both investors and researchers became interested in understanding the economic and statistical properties of this new class of financial assets. In respect of these aspects, many studies have investigated the efficiency of the crypto currency market, which provides an understanding of the price dynamics. Moreover, the efficiency test can be used as an indicator of the market maturity. However, a large number of papers have focused on testing the Bitcoin market, concluding that is inefficient. Thus, the aim of this paper is to analyse the efficiency of the main crypto currencies, using prices with high frequency. The usage of intra-day frequency data is expected to provide a better insight over the dynamic of crypto currency market. It should also be noted that the properties of the virtual currencies are evaluated in the context of the late pandemic episode. Accordingly, a battery of tests is performed. Firstly, the autocorrelation of returns is examined using Ljung-Box test. Secondly, for assessing the independence of returns the runs test is performed. Thirdly, to analyse if the cryptocurrency prices follows a Random Walk the variance ratio test is applied. Considering that the cryptocurrency market is analysed both before and during the pandemic crisis, it is expected to obtain different levels of efficiency.

Keywords: Cryptocurrency market, Bitcoin, Market efficiency, High-frequency, Random walk

Introduction

In the recent years, the cryptocurrency market drew the attention of both investors and researchers, whose interest in studying the properties of this new class of assets have exponentially increased. Thus, a vast majority of papers concerning statistical and economic properties of the virtual currencies have appeared in the literature. One of them is the Efficient Market Hypothesis (EMH), which is considered a cornerstone of the modern finance. Although, the efficiency of cryptocurrency market was highly studied, many papers focused on a fixed time horizon. This motivates our research which proposes a dynamic approach for assessing the EMH property. Our analysis is applied on closing prices of the most important cryptocurrencies in terms of market liquidity, namely Bitcoin and Ethereum listed on two different exchanges (Bitfinex and Coinbase). In order to have an accurate insight of their behavior we used both daily and intraday data. For testing the efficiency, we applied a battery of tests proposed in the literature which were calculated dynamic using a rolling window.

Literature review

After over a decade since Bitcoin was introduced, the cryptocurrency market is still expanding, attracting the attention of researchers from various domains. However, the number of papers treating the subject from an economic perspective has significantly increased in the last years. Thus, several statistical and economic properties have been investigated in the literature. For example, (Cobert, Meegan, Larkin, Lucey, & Yarovya, 2018) analysed the relationship between the main three cryptocurrencies and a series of financial assets.

Their research showed that virtual currencies are relatively isolated from the market, but they tend to be connected with each other. (Bouri, Raubaud, & Shazad, 2020) analysed the safe-haven property of Bitcoin using the wavelet coherence approach. Their findings suggest that the Bitcoin has superior diversification properties compared to gold and commodities. Using a VAR model, (Zeng, Yang, & Shen, 2020) revealed that the connectedness between Bitcoin and conventional assets varies over time. The results are consistent with previous studies. For instance, (Ji, Bouri, Gupta, & Raubaud, 2018) concluded that the integration between bitcoin and other financial assets changes over time. (Bouri, Molnar, Azzi, Raubaud, & Hagfors, 2017) and (Shazad, Bouri, Raubaud, Kristoufek, & Lucey, 2019) also support these findings.

In addition to these properties the efficiency of cryptocurrency markets was extensively studied in the literature. Developed by (Fama, 1970) the Efficient Market Hypothesis (EMH) states that the prices already reflect all the available information. The EMH assumes that securities are always traded at their fair value, so it is impossible for investors to benefit from the price movements. The theory is presented in three main forms: i). weak which states that prices incorporate all the available information from the past, ii). semi-strong which implies that prices reflect all the public information, respectively iii). strong which asserts that prices contain all the available information. However, most of the studies have focused on testing the weak form efficiency on Bitcoin daily prices.

In order to analyse whether Bitcoin market is efficient, (Urquhart, 2016) has performed a series of tests: Ljung-box for analysing if the returns are correlated, runs and the Bartels for determining whether the returns are independent, variance ratio test for assessing if the prices follows a Random Walk, BDS for checking the serial dependencies of returns and Hurst exponent for evaluating the presence of long term memory. The results of the tests have suggested that the Bitcoin market was weakly inefficient over the whole analysed period (2010-2016). However, when the tests were performed on the sub-samples, the level of inefficiency has fluctuated. (Vidal, Ibanez, & Farinos, 2019) have extended the analysis by forming both equally weighted and cap-weighted portfolios over three different periods. For evaluating if the listing of a new cryptocurrency affects the efficiency of the market, the number of altcoins was changed for each period. The results indicated that the introduction of altcoins does not significantly affect the efficiency of the market. Overall, the tests implied that the cryptocurrency market was weakly inefficient.

Nevertheless, a large number of studies suggests that the level of efficiency fluctuates over time. (Bariviera 2017) has analysed the behaviour of long-term memory of returns on Bitcoin between 2011 and 2017 by calculating the Hurst exponent. The study indicated that returns have suffered from a regime switch. Moreover, the study suggest that volatility clustering is a key characteristic of the Bitcoin market, considering the fact that the presence of long-term memory is stronger in daily volatility than in daily returns. (Tran & Leirvik, 2020) have applied the Adjusted Market Inefficiency Magnitude (ANIM) for assessing the efficiency of the main five cryptocurrencies. Within this model the return at the moment t is expressed as the sum of its lagged versions weighted by a series of coefficients $(\beta_1, \beta_2, \beta_3, \beta_4, \dots., \beta_n)$ which are supposed to be closed to zero if the market is efficient. The results imply that the market was inefficient during the analysed period (2013-2019). However, in the last quarters there were signs of improvement.

(Sensoy, 2019) has investigated the weak efficiency of Bitcoin intra-day prices by applying permutation entropy. The Bitcoin intra-day prices were express in terms of US dollars (BTCUSD) and euro (BTCEUR). The results indicated an improvement in the level of efficiency after 2016. Withal, the efficiency improvement has a cyclical behaviour in the case of BTCUSD, while for BTCEUR the improvement was progressive. Furthermore, liquidity was identified as one of the factors that has a positive impact on efficiency. This finding is consistent with the work of (Wei, 2018) who examined 456 cryptocurrencies. In addition to the tests proposed by (Urquhart, 2016), Wei applied the methodology proposed by (Amihud, 2002) as a measure for liquidity. The results implied that the samples containing the most liquid cryptocurrencies tend to be more efficient.

(Kochling, Muller, & Posch, 2018) studied whether the introduction of Bitcoin futures has improved the efficiency. Following the methodology of (Urquhart, 2016) the authors have divided the data in two samples - pre and post Future – both for Bitcoin and Bitcoin Cash. The study concludes that the future introduction has enhanced the efficiency. (Zhang, Chan, Chu, & Sullieman, 2020) have analysed the efficiency of the most liquid five cryptocurrencies between 2017 and 2018 using hourly frequency prices. The authors used the methodology of (Bry & Boschan, 1971) and (Lunde & Timmerann, 2004) in order to identify the bear and bull periods. The results implied that the market is efficient during the bull period, prices following a random walk. Conversely, during the bear phase the market was inefficient, exhibiting positive autocorrelations.

Methodology

Most of the studies have investigated the efficiency of cryptocurrency market from a fixed time horizon perspective. Thus, the aim of this paper was to evaluate the EMH property in a dynamic manner. Accordingly, we used a rolling window for computing the p-values of various tests for randomness.

The analysis was applied on the historical prices of Bitcoin and Ethereum versus US Dollar (USD) listed on two different cryptocurrency exchanges, namely Coinbase and Bitfinex, which are among the most important exchanges regarding the trading volume. The data was downloaded from CoinApi. The cryptocurrencies were chosen according to their market capitalisation, Bitcoin and Ethereum being on the first two positions. To better understand their dynamic, we used data with both daily and intraday (per minute) frequency. The analysed period for daily data was between 24th May 2015 to 19th November 2020, respectively from 13th November 2020 to 20th November 2020 for intraday data. For both types of data, the logarithmic returns have been computed using the formula: $r_t = \ln(P_t/P_{t-1})$, where $\ln(P_t)$ represents the natural logarithm of Bitcoin or Ethereum closing price at time t.

In order to assess the efficiency of Bitcoin and Ethereum, we employed a battery of tests for both daily and intraday logarithmic returns, computed using various libraries from Python. Following the methodology proposed by (Urquhart, 2016) we firstly applied the Ljung-Box test (Ljung & Box, 1978) whose null hypothesis states that the returns are not autocorrelated. The statistics is computed using the formula:

$$Q_k = n(n+2)\sum_{j=1}^{k}\frac{c_j^2}{n-j} \quad (1)$$

where n represents the sample size, k represents the number of lags that are tested and c_j^2 is the sample autocorrelation at lag j.

Secondly, we applied both runs test (Wald & Wolfowitz, 1940) and Bartels test (Bartels, 1982) to evaluate the independence of

DOI: 10.2478/9788366675261-015

returns. The runs test, whose null hypothesis assumes that each element of a sequence is independent identical distributed (i.i.d.) is defined by the following formula:

$$Z = \frac{R - \mu_R}{\sigma_R} \quad (2)$$

where R represents the number of runs, μ_R designates the expected number of runs being defined by the formula: $\mu_R = \frac{2N_+N_-}{N} + 1$ and σ_R represents the standard deviations which is expressed as: $\sigma_R = \sqrt{\frac{2N_+N_-(2N_+N_- - N_+ - N_-)}{(N_+N_-)^2(N_+ + N_- - 1)}}$. N_+, N_- denotes the number of positive, respectively negative elements contained in a sequence. As previously mentioned, the independence property was also evaluated with Bartels test, which is computed using the formula:

$$RVN = \frac{\sum_{i=1}^{T-1}(R_i - R_{i+1})^2}{\sum_{i=1}^{T}\left(R_i - \overline{R}\right)^2} \quad (3)$$

where R_i represents the rank of the ith observation in a sequence of T observations. As the size of both our samples is larger than 100 ($T > 100$), the p-value was computed based on the approximation $\sim N\left(2, \frac{20}{5T+7}\right)$.

Thirdly, we analysed whether the returns follow a random walk by applying the Variance Ratio test (Lo & MacKinley, 1988). The statistics is defined by the formula:

$$Z^*(q) = \frac{\sqrt{nq}VR(q)}{\sqrt{\widehat{\Theta}(q)}} \sim N(0,1) \ (4)$$

where n represents the number of observations, q is the number of lags, VR represents the variance ratio and $\widehat{\theta(q)}$ designates the heteroscedasticity estimator of $\theta(q)$.

Finally, for analysing the long term memory of returns we applied the rescaled Hurst exponent (R/S Hurst), which is defined as follows:

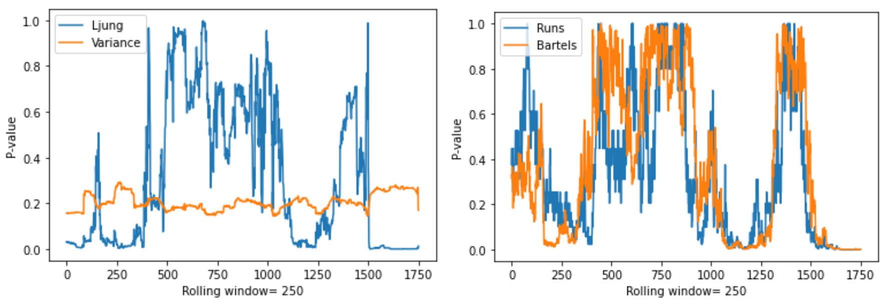
$$E\left[\frac{R(n)}{S(n)}\right] = Cn^H, as\ n \to \infty \quad (5)$$

where $R(n)$ represents the range of the first n cumulative standard deviations, $S(n)$ designated the standard deviation, C is a constant and n denotes the span.

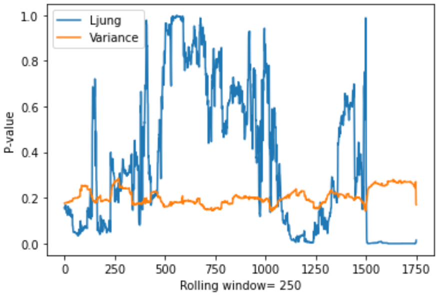
To investigate the behaviour of the cryptocurrency returns over time, we considered a dynamic approach which implies the usage of a rolling window of 250 observations (1 year) for daily data and 1440 observations (1 day) for intraday data. After each iteration we shifted forward one observation. Thus, the p-values of the above-mentioned tests, respectively the Hurst exponent were evaluated on each rolling window. The level of significance was set at 5%.

Results and discussions

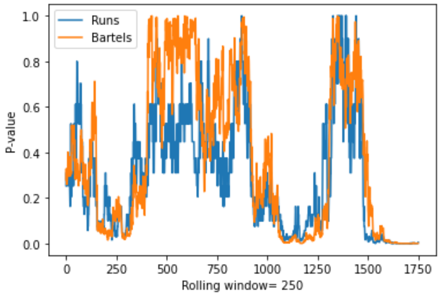
The p-values for each test applied to the data with daily frequency are depicted in the Figures 1 (Bitcoin) and 2 (Ethereum). In general, we find that over the analysed period the p-values corresponding to Ljung-Box test, Runs and Bartels have fluctuated, exhibiting periods of decreases and increases. However, for most of the periods, p-value is above the level of significance (> 0.05) which suggests that the returns are not autocorrelated and they satisfy the i.i.d. property. On the other hand, the p-values corresponding to Variance Ratio is quite stable in time for both cryptocurrencies and above >0.05, which implies a random behaviour of returns. It is important to point that the p-values did not significantly change between the two exchanges, Bitfinex, respectively Coinbase.



(a) Bitcoin (Bitfinex) (b) Bitcoin (Bitfinex)



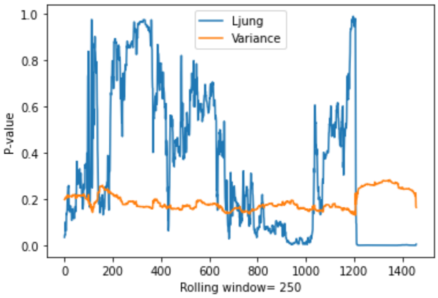
(c) Bitcoin (Coinbase)



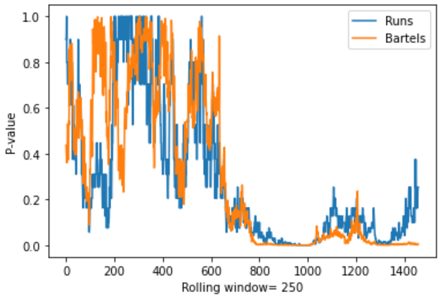
(d) Bitcoin (Coinbase)

Figure 1. Plot of the p-values computed using a rolling window of Bitcoin daily returns

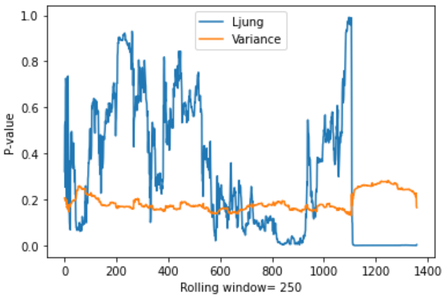
Source: Author's calculations



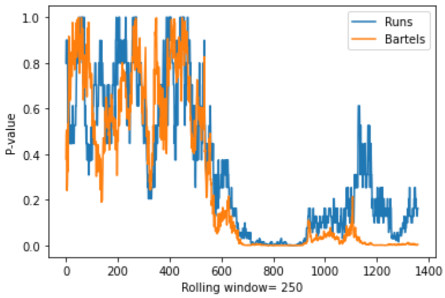
(a) Ethereum (Bitfinex)



(b) Ethereum (Bitfinex)



(c) Ethereum (Coinbase)

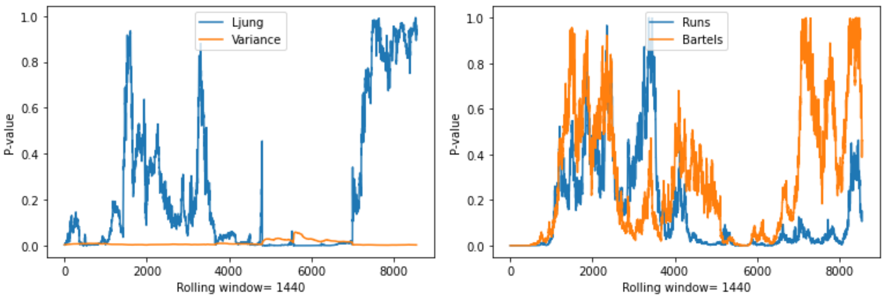


(d) Ethereum (Coinbase)

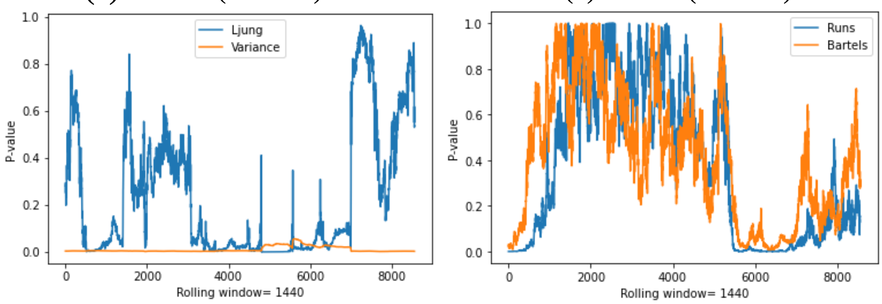
Figure 2. Plot of the p-values computed using a rolling window of Ethereum daily returns

Source: Author's calculations

The results of intraday returns are depicted in the figures 3 (Bitcoin) and 4 (Ethereum). Similarly, to the previous results (daily data), the p-values corresponding to Ljung-Box test, Runs test and Bartels have highly fluctuated, suggesting that the level of efficiency has changed during the analysed period. Moreover, the Bartels and Runs values tend to move in the same direction, but with a different pace. Oppositely, the Variance Ratio is stable in time. However, its p-values tend to be below the significance level (<0.05) which implies that the returns do not follow a random walk at intraday level. These results are applicable for both cryptocurrencies. It also should be noted that the p-value dynamic differs significantly between exchanges. This fluctuation can be explained by the fact that the trading volumes differs across Bitfinex and Coinbase, although there are among the largest exchanges.



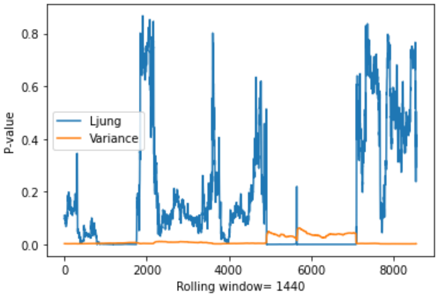
(a) Bitcoin (Bitfinex) (b) Bitcoin (Bitfinex)



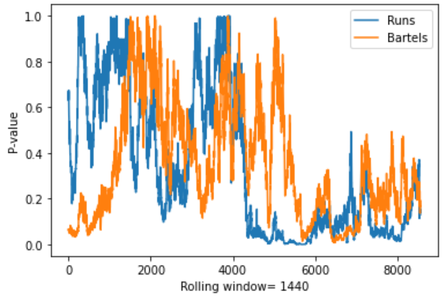
(c) Bitcoin (Coinbase) (d) Bitcoin (Coinbase)

Figure 3. Plot of the p-values computed using a rolling window of Bitcoin intraday returns

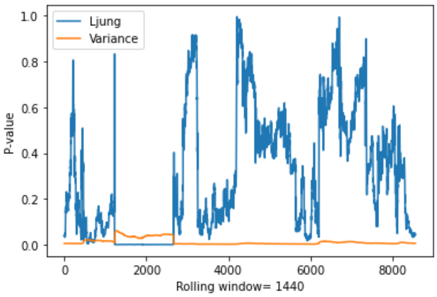
Source: Author's calculations



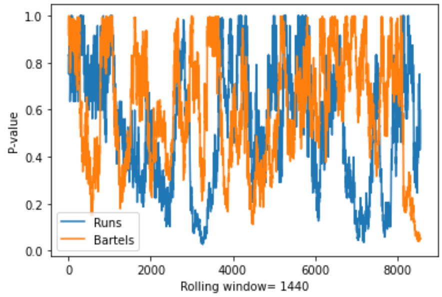
(a) Ethereum (Bitfinex)



(b) Ethereum (Bitfinex)



© Ethereum (Coinbase)

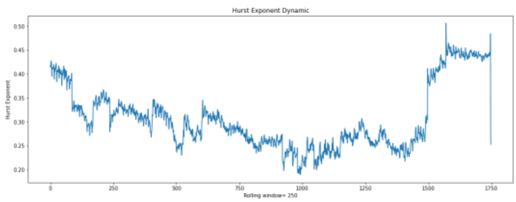


(d) Ethereum (Coinbase)

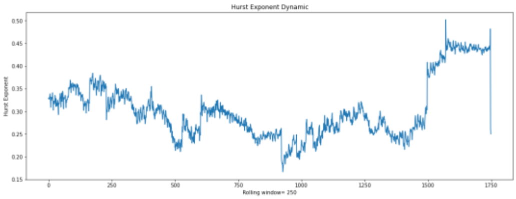
Figure 4. Plot of the p-values computed using a rolling window of Ethereum intraday returns

Source: Author's calculations

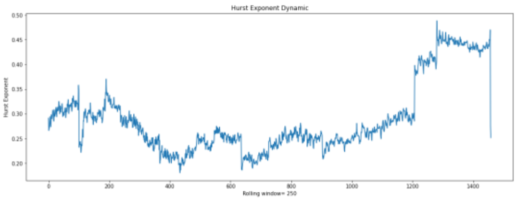
The dynamic of Hurst exponent is exhibit in the figure 5 for daily data, respectively in the figure 6 for intraday data. In both cases, R/S Hurst varies over time. However, the exponent did not exceed 0.5 in neither case, which is a strong evidence of an anti-persistent behaviour. Additionally, in the case of intraday data the Hurst exponent moved differently between the two exchanges.



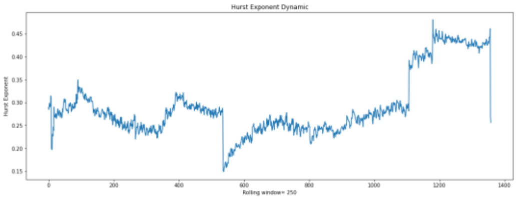
(a) Bitcoin (Bitfinex)



(b) Bitcoin (Coinbase)



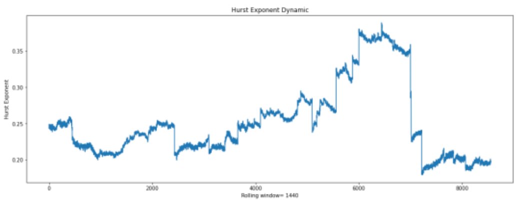
(c) Ethereum (Bitfinex)



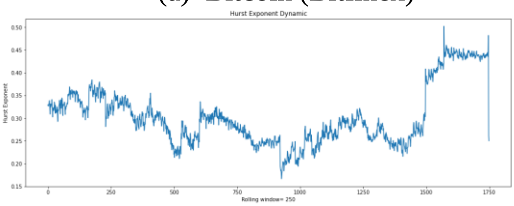
(d) Ethereum (Coinbase)

Figure 5. Plot of the Hurst exponent computed using a rolling window of daily returns

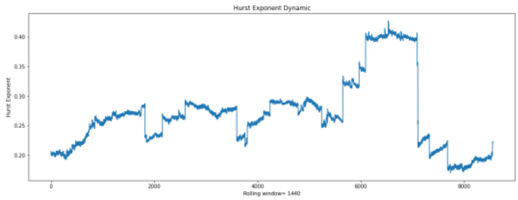
Source: Author's calculations



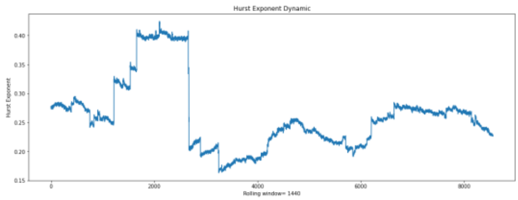
(a) Bitcoin (Bitfinex)



(b) Bitcoin (Coinbase)



(c) Ethereum (Bitfinex)



(d) Ethereum (Coinbase)

Figure 4. Plot of Hurst exponent computed using a rolling window of intraday returns

Source: Author's calculation

Conclusions

The aim of this paper was to investigate the efficiency of cryptocurrency market from a dynamic perspective. Consequently, we applied a battery of tests over the two most liquid virtual currencies, Bitcoin and Ethereum. The dynamic approach consisted in the usage of a rolling window for both daily and intraday data. After each iteration we shifted forward one observation. Thus, the p-values of the tests, were evaluated on each rolling window.

Our findings suggest that the p-values corresponding to Ljung-Box test, Runs and Bartels have fluctuated, exhibiting periods of decreases and increases. However, the Variance Ratio is stable in time. Yet, its p-values tend to be below the significance level (<0.05) which implies that the returns do not follow a random walk at intraday level. Moreover, we discovered that the p-value dynamic is different between the exchanges. One possible explanation can be motivated by the different trading volumes among Bitfinex and Coinbase.

The Hurst Exponent has indicated a strong evidence of anti-persistence behaviour for both cryptocurrencies (and markets) for intraday data. Although, we can conclude that at intraday level the market tends to be inefficient, we detected some periods of efficiency on the daily data. Further, the analysis can be applied to more cryptocurrencies and exchanges.

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