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# The Predictability of High-Frequency Returns in the Cryptocurrency Markets and the Adaptive Market Hypothesis

**Abstract**
The objective of this study was to examine the level and behaviour of the weak-form efficiency of the 16 most capitalised cryptocurrencies using intraday data. The study employed martingale difference hypothesis tests utilising the rolling window method. The predictability of high frequency returns varied over time. For most of the time, the cryptocurrencies were unpredictable. Nevertheless, their weak-form efficiency appeared to decrease along with an increase in frequency. In general, most cryptocurrencies were marked by high levels of unpredictability. However, there were some significant differences between the most and least efficient ones. To exploit market inefficiencies, investors should focus on higher frequencies. Higher frequencies should also be a concern to regulators when it comes to ensuring market efficiency.

**Keywords**
cryptocurrency markets | adaptive market hypothesis | efficient market hypothesis [EMH] | predictability of returns | intraday returns

**JEL Codes**
G14

## 1. Introduction

The earliest studies on the predictability of returns in the cryptocurrency markets highlighted a possible presence of volatility in their weak-form efficiency (e.g., Nadarajah & Chu, 2017; Bariviera, 2017; Urquhart, 2016). This suggested a validity of the adaptive market hypothesis (AMH), which was first proposed by Lo (2004). According to the AMH (Lo, 2004; Lo, 2005), due to changes in market conditions, the predictability of returns and its closely related concept of weak-form efficiency may change over time. The theory of AMH makes an attempt to reconcile the bounded rationality of market participants and the efficient market hypothesis (EMH) proposed by Fama (1965) and Samuelson (1965). Based on the weak form of EMH, all past information, including historical quotations, are already reflected in the current prices. Thus, there is no possibility to systematically generate abnormal returns based on the historical timeseries of returns. Weak-form efficiency is often associated with the martingale difference hypothesis (MDH). According to the MDH, the returns of an asset follow the martingale difference sequence (MDS). Returns that can be considered to follow the MDS are not autocorrelated (Linton, 2019; Campbell et al., 1997). Informationally efficient markets ensure a convenient and fair environment for making investments.

The examination of the efficiency of cryptocurrency markets and their predictability plays an important role in providing indications to regulators pertaining to necessary actions that are required to ensure a smooth, functioning, informationally efficient, investing-convenient, and fair environment to market participants. Investors may use the results of such studies to decide, which cryptocurrency markets and frequencies of quotations are worth considering. In the case of some investors who aim to exploit market inefficiencies and gain systematically abnormal returns, some less efficient markets and some less efficient frequencies of quotations would be more preferred. Despite a significant interest of researchers that led to the publication of many studies pertaining to the weak-form efficiency of cryptocurrency markets, just a few of them focused on high-frequency data. Instead, the majority of the foregoing studies examined the predictability of daily returns. In addition, studies employing intraday data usually focused on a narrow

sample of cryptocurrencies, which did not allow any further generalisation of conclusions. Moreover, the conclusions of these studies devoted to the examination of the weak-form efficiency of cryptocurrency markets were not unambiguous when it came to the level of efficiency and its behaviour. The ambiguity of such conclusions from the foregoing studies and an insufficient examination of the cryptocurrency markets at the intraday level using narrow samples constitute a clear indication for further examination of the weak-form efficiency of cryptocurrency markets with the use of high-frequency data.

This study aims to examine the level and behaviour of the weak-form efficiency of the 16 most capitalised cryptocurrency markets (stablecoins are not considered) as of May 28, 2024, using intraday data. The first research hypothesis posed in this study states that the weak-form efficiency of cryptocurrency markets changes, and that due to this, the AMH should be considered valid. The second hypothesis states that cryptocurrency markets should be considered weak-form efficient for most of the time. The third hypothesis states that the cryptocurrency markets become less weak-form efficient at higher frequencies. Moreover, this study makes an attempt to check whether the examined cryptocurrencies were marked by different levels of weak-form efficiency and if any trends in the behaviour of weak-from efficiency can be recognised.

According to the results of this study, the weak-form efficiency of the examined cryptocurrencies used to vary over time—such results validated the AMH. The levels of weak-form efficiency suggested that for most of the time, the returns were unpredictable. However, despite the indication suggesting that in most cases the cryptocurrency markets were unpredictable, their weak-form efficiency appeared to decrease with the decrease of the time interval. The differences in the weak-form efficiency of the examined cryptocurrencies were not clear in the case of the 30-minute and 5-minute intervals. Nevertheless, in the case of the 1-minute interval, the predictability of the examined cryptocurrencies appeared to substantially increase. When it came to differences between individual cryptocurrencies, most cryptocurrencies were marked by high levels of unpredictability. Nevertheless, the range of the weak-form efficiency levels was high. A supplementary study showed some significant differences between the most and least efficient cryptocurrencies. According to the 30-minute interval, a medium-term trend in the weak-form efficiency of cryptocurrencies was upward. The opposite was valid when it came to a short-term trend in the 5-minute data. Moreover, according to the supplementary study, there was no consistency in cryptocurrency rankings when it came to efficiency across individual frequencies. Thus, it was difficult to indicate which cryptocurrencies were consistently the most and least efficient across all intervals.

Using a relatively broad sample of 16 cryptocurrencies, this study contributed to the body of knowledge pertaining to the examination of predictability in the cryptocurrency markets at the intraday levels, which have not attracted much attention compared to studies on lower time intervals so far. The sample applied in this study is one of the broadest ones among issue-related studies on high-frequency data (e.g., Aslan & Sensoy, 2020; Chu, et al., 2019; Mensi et al., 2019; Sensoy, 2019; Zargar & Kumar, 2019). As a contribution to a still poorly developed group of studies on high-frequency data, this paper may be of value to regulators, providing them with a guide when it comes to the results of their past regulatory actions and actions that need to be taken in the future. In this paper, investors may find some valuable indications when it comes to the cryptocurrency markets and the frequency of quotations that are worth consideration. To exploit market inefficiencies, investors should focus on higher frequencies. Higher frequencies should also be a concern for regulators when it comes to ensuring market efficiency.

Section 2 of this paper discusses the issue-related studies. Section 3 presents the research sample and the research methodology applied in this study. Section 4 presents the results and discusses them. Section 5 summarises the paper.

## 2. Literature review

Sensoy (2019) as well as Zargar and Kumar (2019), in the early studies on the forecasting features of cryptocurrencies at the level of intraday returns, pointed out that the weak-form efficiency of cryptocurrencies may be dependent on the frequency of returns examined. They also suggested that efficiency may decrease as the return frequency increases. These conclusions emphasise the necessity to pay more attention to intraday returns in the verification of predictability in cryptocurrency markets. Despite

that, the issue-related studies employing frequencies of data that are over one day are in a clear minority. A well-developing body of knowledge pertaining to the weak-form efficiency of cryptocurrency markets focuses mainly on daily returns (e.g., Kristjanpoller et al., 2024; Mokni et al., 2024; López-Martín, 2023). The reason for this may be the relatively difficult access to high quality high-frequency data as well as their large volume that causes additional problems with computations and analysis. Moreover, the collection of daily data appears to be relatively easy, for instance, due to the existence of coinmarketcap.com and crypto2 package in R, which are willingly used in issue-related studies (e.g., Palamalai et al., 2021; Noda, 2021; López-Martín et al., 2021). A daily frequency is the most the aforementioned sources can provide. Papers by Aslan and Sensoy (2020), Chu et al. (2019), Mensi et al. (2019), Sensoy (2019), and Zargar and Kumar (2019) are examples of studies considering high-frequency data in the examination of the weak-form efficiency of cryptocurrency markets. They all pointed out the importance of the frequency of data in terms of weak-form efficiency. Moreover, the foregoing studies focusing on intraday data rarely examined broader samples of cryptocurrencies. Aslan and Sensoy (2020) examined Bitcoin, Ethereum, Ripple, and Litecoin; Chu et al. (2019) and Mensi et al. (2019) focused on Bitcoin and Ethereum; and Zargar and Kumar (2019) as well as Sensoy (2019) analysed only Bitcoin.

Despite the relatively short history of cryptocurrency markets compared to more traditional markets like stock, bond, foreign exchange, or commodity markets, researchers managed to significantly develop a body of knowledge pertaining to the examination of the weak-form efficiency of cryptocurrencies. However, the conclusions coming from these studies are not unanimous. For instance, Zhang et al. (2023), Apopo and Phiri (2021), Hawaldar et al. (2019), and Zargar and Kumar (2019) proposed that the returns of the examined cryptocurrencies were unpredictable for most of the time. The opposite conclusions were proposed, for instance, by Fieberg et al. (2024), Meng and Khan (2023), Aslam et al. (2023), López-Martín (2023), Verma et al. (2022), and Kang et al. (2022).

The majority of studies on predictability in cryptocurrency markets appear to propose a non-constant nature of this phenomenon. However, only a part of them directly addresses the AMH. Papers by Okorie et al. (2024), Mokni et al. (2024), Aslam et al. (2023), Zhang et al. (2023), and Verma et al. (2022) are examples of such studies. The results indicating the variability of the forecasting features of cryptocurrencies, obtained in the aforementioned studies, allowed the validation of the AMH. According to Kristjanpoller et al. (2024), Yi et al. (2023), Khuntia and Pattanayak (2018), and Caporale et al. (2018), the trend of weak-form efficiency of the examined cryptocurrencies appeared to be increasing. On the other hand, such studies as the ones by Polyzos et al. (2024), Meng and Khan (2023), Kristoufek and Vosvrda (2019), and Bundi and Wildi (2019) suggested that the employed cryptocurrencies appeared to become more predictable over time. It is worth mentioning that the sample size in the foregoing issue-related studies varied much. The majority of studies employed, at most, several cryptocurrencies. Many of them focused on just a single cryptocurrency like Bitcoin (e.g., Urquhart, 2016; Nadarajah & Chu, 2017; Bariviera, 2017). Some of them aimed to employ possibly large samples for better generalisation of conclusions on cryptocurrency markets. For instance, Kang et al. (2022) employed a sample of 893 cryptocurrencies, Wei (2018) examined 456 cryptocurrencies, Hu et al. (2019) analysed 31 cryptocurrencies, and Kristoufek and Vosvrda (2019) focused on 14 cryptocurrencies. Nevertheless, such studies were in a clear minority.

## 3. Data and research methodology

The research sample for this study consists of 16 cryptocurrencies with the highest market cap as of May 28, 2024. The sample does not include stablecoins. A list of examined cryptocurrencies and their codes is as follows: Bitcoin (BTC), Ethereum (ETH), BNB (BNB), Solana (SOL), XRP (XRP), Dogecoin (DOGE), Toncoin (TON), Cardano (ADA), Shiba Inu (SHIB), Avalanche (AVAX), Chainlink (LINK), Polkadot (DOT), TRON (TRX), Bitcoin Cash (BCH), NEAR Protocol (NEAR), and Polygon (MATIC). The order of cryptocurrencies is descending, taking into account their market cap. Selecting the most capitalised cryptocurrencies to research samples of in the issue-related studies appears to be the most common approach. Due to an enormous number of cryptocurrencies and the fast pace of establishing new ones, the researchers decided to limit themselves only to the most important ones in terms of the entire crypto market and economy.

This study was focused on the examination of the predictability of intraday returns. The predictability of intraday returns of cryptocurrencies was examined with the use of two MDH tests, namely the automatic Portmanteau test for serial correlation proposed by Escanciano and Lobato (2009), and the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity proposed by Kim (2009). The tests were conducted for log returns of prices for three different time intervals, i.e., 1 minute, 5 minutes, and 30 minutes. The timeseries of prices were retrieved form the Thomson Reuters Eikon database on May 29, 2024. Due to a limited availability of intraday timeseries, 30-minute prices came from the period between May 31, 2023, and May 28, 2024; 5-minute prices came from the period between March 1, 2024, and May 28, 2024; 1-minute prices came from the period between April 30, 2024, and May 28, 2024. When a market had both ask and bid prices, their average price was calculated and then constituted as a basis for the calculation of log returns.

The applied MDH tests verify if the timeseries are the series of the martingale increments. The series of martingale increments can be assumed unpredictable and weak-form informationally efficient. Assuming a common non-normality, skewness, kurtosis, and other stylised facts of the distributions of returns of cryptocurrencies, MDH tests appear to be more suitable compared to testing the assumption of i.i.d. returns with a 0 expected value (Linton, 2019). According to Charles et al. (2011), the MDH tests of Escanciano and Lobato (2009) and Kim (2009) constituted a significant contribution to MDH testing. No size distortion in small samples, robustness to non-normality, and heteroscedasticity can be considered some of the most important features of the MDH tests applied in this study (Charles et al., 2012).

The MDH test of Escanciano and Lobato (2009) constitutes a modification of the Box–Pierce test. This modification employs an automatic choice of the autocorrelation order. The application of the bootstrap procedure to estimate the critical values is not needed. Their asymptotic null distribution is chi-square with one degree of freedom. The test is robust to conditional heteroskedasticity of an unknown form. The MDH test proposed by Kim (2009) constitutes a modification of the automatic variance ratio test of Choi (1999). In the wild bootstrapped automatic variance ratio test, no size distortion in small samples is present. According to Kim (2009), the wild bootstrapped automatic variance ratio test has more power compared to its competitors like the Chen–Deo test and the wild bootstrapped Chow–Denning test.

Both MDH tests used in this study were applied with the use of functions from the vrtest R package (v1.1; Kim, 2022). The function AutoBoot.test enabled the application of the automatic variance ratio test by Kim (2009). In the case of this test, 500 bootstrap iterations were applied. The automatic portmanteau test by Escansiano and Lobato (2009) was applied with the Auto.Q function. Both MDH tests applied assumed a significance level of $\alpha = 0.05$.

In order to verify the AMH, both MDH tests were applied with the use of the rolling window method. The application of this method enabled a dynamic verification of weak-form efficiency. The applied rolling window method had different parameters for each of the three time intervals. In the case of 30-minute log return timeseries, each window had 480 observations (returns) and was moved by 24 observations (24-rolling). It is worth mentioning that each day had 48 observations. When it came to the 5-minute log return timeseries, each window had 576 observations and was moved by 36 observations, and Each day consisted of 288 observations. In the case of the 1-minute log return timeseries, each window had a length of 720 returns and was moved by 72 returns, and each day consisted of 1440 returns. To run a test, a window had to contain at least 80% of returns.

In this study, main conclusions related to weak-form efficiency are drawn based on two measures, namely the percentage of efficient windows and the rate of efficiency changes. The percentage of efficient windows indicates a part of windows for which the MDH tests indicated weak-form efficiency. The rate of efficiency changes informs about a part of windows in which the MDH tests changed their indication from efficiency to inefficiency and from inefficiency to efficiency.

# 4. Results and discussion

## 4.1. General results of MDH tests

The main research objective of this study is to verify the return predictability of intraday returns of cryptocurrencies in the context of the AMH. This requires a dynamic approach to the analysis of the behaviour of weak-form efficiency over time. However, first, some general results pertaining to

**Table 1.** The summary of the results of the MDH tests

| Interval | 1 minute | | | 5 minutes | | | 30 minutes | | | All intervals | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Crypto-currency | Windows tested | Efficient windows | Efficiency change rate | Windows tested | Efficient windows | Efficiency change rate | Windows tested | Efficient windows | Efficiency change rate | Efficient windows | Efficiency change rate |
| Polygon | | | | | | | 709 | 97% | 2% | 97% | 2% |
| Avalanche | 571 | 90% | 7% | 697 | 94% | 3% | 709 | 95% | 2% | 94% | 4% |
| Chainlink | 571 | 83% | 8% | 697 | 96% | 4% | 709 | 90% | 5% | 90% | 6% |
| Bitcoin Cash | 571 | 83% | 8% | 697 | 91% | 5% | 709 | 95% | 3% | 90% | 5% |
| Solana | 571 | 72% | 12% | 697 | 95% | 3% | 709 | 97% | 3% | 89% | 6% |
| Cardano | 571 | 74% | 9% | 697 | 93% | 5% | 709 | 96% | 3% | 89% | 5% |
| BNB | 571 | 87% | 8% | 697 | 87% | 6% | 709 | 83% | 5% | 85% | 6% |
| Shiba Inu | 571 | 83% | 9% | 684 | 92% | 5% | 686 | 75% | 7% | 83% | 7% |
| Polkadot | | | | 51 | 96% | 4% | 687 | 82% | 7% | 83% | 7% |
| NEAR Protocol | 571 | 53% | 8% | 684 | 93% | 4% | 700 | 90% | 6% | 80% | 6% |
| Ethereum | 571 | 44% | 7% | 697 | 93% | 5% | 709 | 95% | 2% | 80% | 5% |
| Bitcoin | 571 | 39% | 9% | 697 | 89% | 5% | 709 | 99% | 1% | 78% | 5% |
| XRP | 571 | 23% | 4% | 685 | 82% | 6% | 709 | 91% | 5% | 68% | 5% |
| TRON | | | | 41 | 63% | 16% | 709 | 30% | 7% | 32% | 8% |
| Toncoin | 406 | 31% | 9% | 160 | 15% | 3% | 25 | 22% | 15% | 26% | 8% |
| Dogecoin | 380 | 3% | 2% | 697 | 24% | 5% | 709 | 24% | 3% | 20% | 3% |
| **Average** | **544** | **59%** | **8%** | **572** | **80%** | **5%** | **663** | **79%** | **5%** | **74%** | **5%** |

Note: The column 'Windows tested' refers to a number of windows for which the MDH tests were performed using the rolling window method. The column 'Efficient windows' indicates a part of windows for which the MDH tests indicated weak-form efficiency. The column 'Efficiency change rate' informs about a part of windows in which the MDH tests changed their indication from efficiency to inefficiency and from inefficiency to efficiency.

the entire research period will be discussed. Table 1 presents the number of windows tested, the percentage of efficient windows, and the efficiency change rate considering all MDH tests, individual intervals and all intervals together. The cryptocurrencies are ordered by the percentage of efficient windows in a descending manner considering all intervals examined. Taking into account, all intervals, the range of the percentage of efficient windows is high, i.e., between 20% in the case of Dogecoin and 97% in the case of Polygon. Nevertheless, a major part of cryptocurrencies had efficient windows rates of at least 80% in the case of 5-minute and 30-minute intervals, as well as all intervals. In the case of a 1-minute interval, the efficient windows rates were noticeably lower and more dispersed compared to the two other intervals. It is also indicated by the average results presented in the last row of Table 1. Both the average percentage of efficient windows and the average efficiency change rates for all cryptocurrencies examined are similar in the cases of 5-minute and 30-minute intervals. However, when it comes to a 1-minute interval, the average efficient windows rate is clearly lower, and the average efficiency change rate is higher. It may suggest that a lower percentage of efficient windows can be associated with a higher efficiency change rate. To verify this, Spearman's rho and Kendall's tau correlation coefficients were computed for the percentage of efficient windows and the efficiency change rate in individual intervals based on results presented in Table 1. The estimates of Spearman's rho and Kendall's tau correlation coefficients, as well as their p-values are presented in Table 2.

According to the estimates presented in Table 2, in the case of the 30-minute interval, a strong negative and significant correlation between efficient windows rate and efficiency change rate can be observed. In the case of the 5-minute interval, the strength of this correlation decreased. That time, it was moderate; however, it was still significant and negative. Surprisingly, when it came to the 1-minute interval, the correlation turned out to be low, positive, and insignificant. The results suggest that there are differences between the analysed intervals in terms of the connection between how often a cryptocurrency is efficient and how often its efficiency status changes.

Other differences between intervals examined can be noticed in the ranks of individual cryptocurrencies in terms of the efficient windows' percentage. It is not easy to indicate which cryptocurrencies were consistently marked by high or low efficiency in different intervals analysed. To check the consistency of efficiency rankings in different intervals, Spearman's rho and Kendall's tau correlation coefficients were calculated. The results of the estimations are presented in Table 3. According to estimated correlation coefficients, the correlation between ranks in 5-minute and 1-minute intervals, as well as 30-minute and 5-minute intervals, turned out to be low and statistically insignificant. However, the correlation between ranks in 30-minute and 1-minute intervals was negative, strong, and statistically significant. The results obtained suggest that there is no consistency of rankings when it comes to the percentage of efficient windows. Moreover, surprisingly, when comparing rankings in 30-minute and 1-minute intervals, they can even be opposites. Nevertheless, the results obtained should be approached with caution as it should be remembered that the research periods of individual intervals were different.

Figures 1 and 2 summarise data presented in Table 1 in the form of histograms. Figure 1 refers to the percentage of efficient windows while Figure 2 refers to the rate of changes. According to Figure 1, the distributions of the efficient windows' percentage were left-skewed for all intervals. In the case of 5-minute and 30-minute intervals, a noticeable majority of cryptocurrencies were efficient in at least 80% of windows. It did not apply to a 1-minute interval as the distribution was still left-skewed; however, clearly more cryptocurrencies were marked by low efficiency. According to Figure 2, in a 1-minute interval, the cryptocurrencies changed their efficiency status more often compared to the other two intervals.

**Table 2.** Correlation coefficients for the percentage of efficient windows and the efficiency change rate

| Test/result | Coefficient | | p-value | |
|---|---|---|---|---|
| **Interval** | **Spearman** | **Kendall** | **Spearman** | **Kendall** |
| **1 min** | 0.17 | 0.10 | 0.59 | 0.62 |
| **5 min** | -0.58 | -0.52 | 0.02 | 0.01 |
| **30 min** | -0.84 | -0.72 | 0.00 | 0.00 |

Note: Spearman's rho and Kendall's tau correlation coefficients, as well as their p-values, computed for the percentage of efficient windows and the efficiency change rate from Table 1 are presented for each interval.

**Table 3.** Correlation coefficients for the ranks of cryptocurrencies

| Test/result | Coefficient | | | | p-value | | | |
|---|---|---|---|---|---|---|---|---|
| **Spearman** | **Interval** | **1 min** | **5 min** | **30 min** | **Interval** | **1 min** | **5 min** | **30 min** |
| | **1 min** | 1.00 | | | **1 min** | 1.00 | | |
| | **5 min** | 0.21 | 1.00 | | **5 min** | 0.49 | 1.00 | |
| | **30 min** | -0.79 | -0.04 | 1.00 | **30 min** | 0.00 | 0.88 | 1.00 |
| **Kendall** | **Interval** | **1 min** | **5 min** | **30 min** | **Interval** | **1 min** | **5 min** | **30 min** |
| | **1 min** | 1.00 | | | **1 min** | 1.00 | | |
| | **5 min** | 0.10 | 1.00 | | **5 min** | 0.68 | 1.00 | |
| | **30 min** | -0.59 | 0.03 | 1.00 | **30 min** | 0.00 | 0.92 | 1.00 |

Note: Spearman's rho and Kendall's tau correlation coefficients calculated for the ranks of cryptocurrencies in terms of the percentage of efficient windows in different intervals.

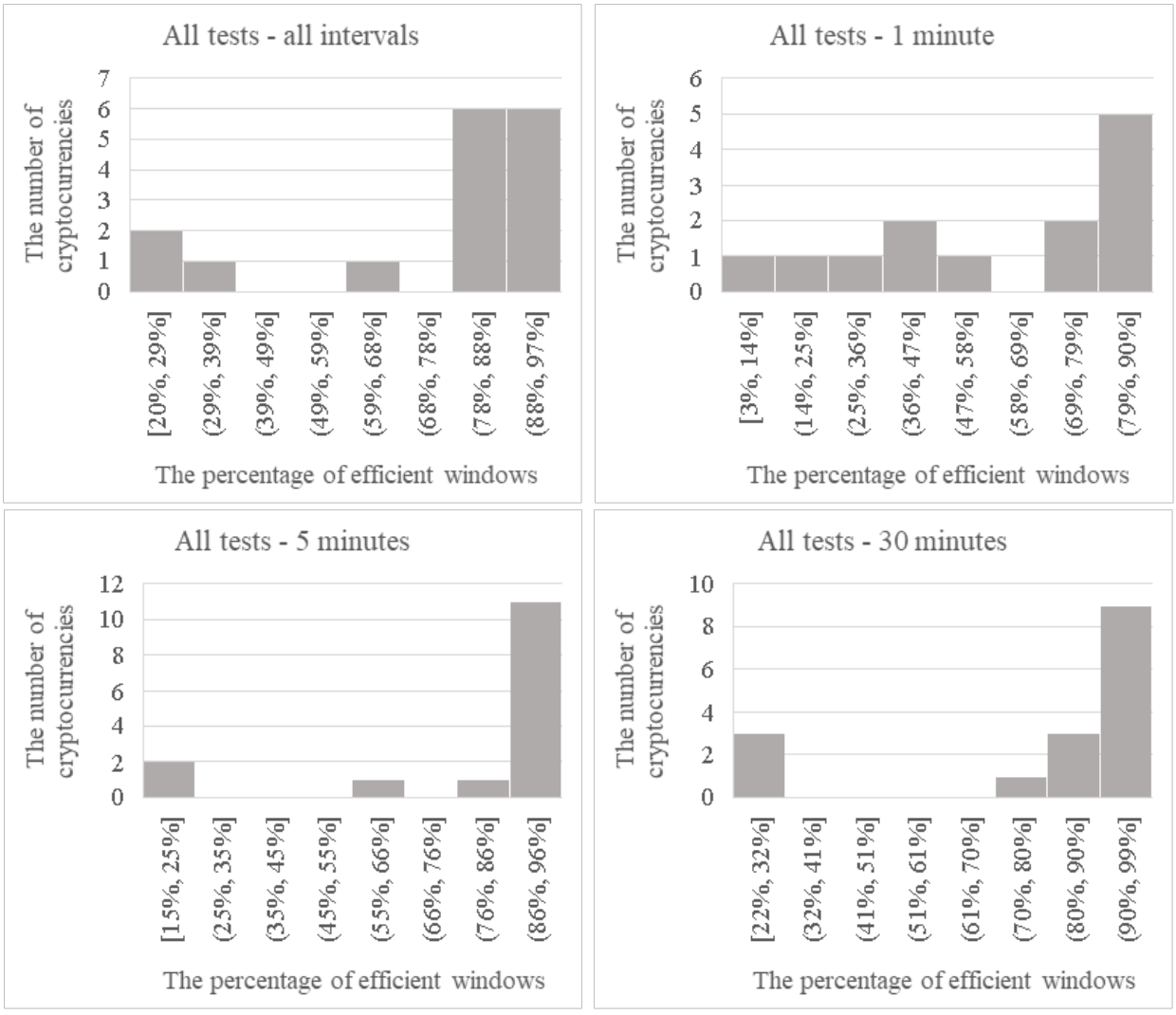


**Figure 1.** The histograms of the percentage of efficient windows
Note: The headers of distributions refer to the intervals considered.

## 4.2. Results of MDH tests over consecutive windows

The foregoing results were summarised for the entire research period and did not allow the drawing of any conclusions related to the behaviour of the predictability of returns over time. The following results will show how the percentage of efficient windows and the rate of changes behaved over months of the research period for all cryptocurrencies together, for each MDH test, separately, and for both MDH tests, together. 'Portmonteau' stands for the automatic Portmanteau test for serial correlation proposed by Escanciano and Lobato (2009). 'AVR' is an abbreviation for the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity proposed by Kim (2009). 'All tests' refers to both tests together. The results will be presented and discussed for 30-minute and 5-minute intervals. The results presented in Figure 3 refer to a 30-minute interval only. Each month refers to a month in which the rolling widow ended. Additionally, Figure 3 presents the number of windows tested. Such presentation of results allows the verification of returns predictability in the context of AMH.

Both MDH tests appeared to give similar indications when it comes to the level of efficiency and its changes. The behaviour of the percentage of efficient windows and the rate of changes over months confirms a clear negative correlation between these two variables. Considering all tests, the minimum and maximum percentage of efficient windows was approximately 71% and 93%, respectively. After reaching a minimum value in the window ending in September 2023, the percentage of efficient windows began a medium-term increasing trend with slight

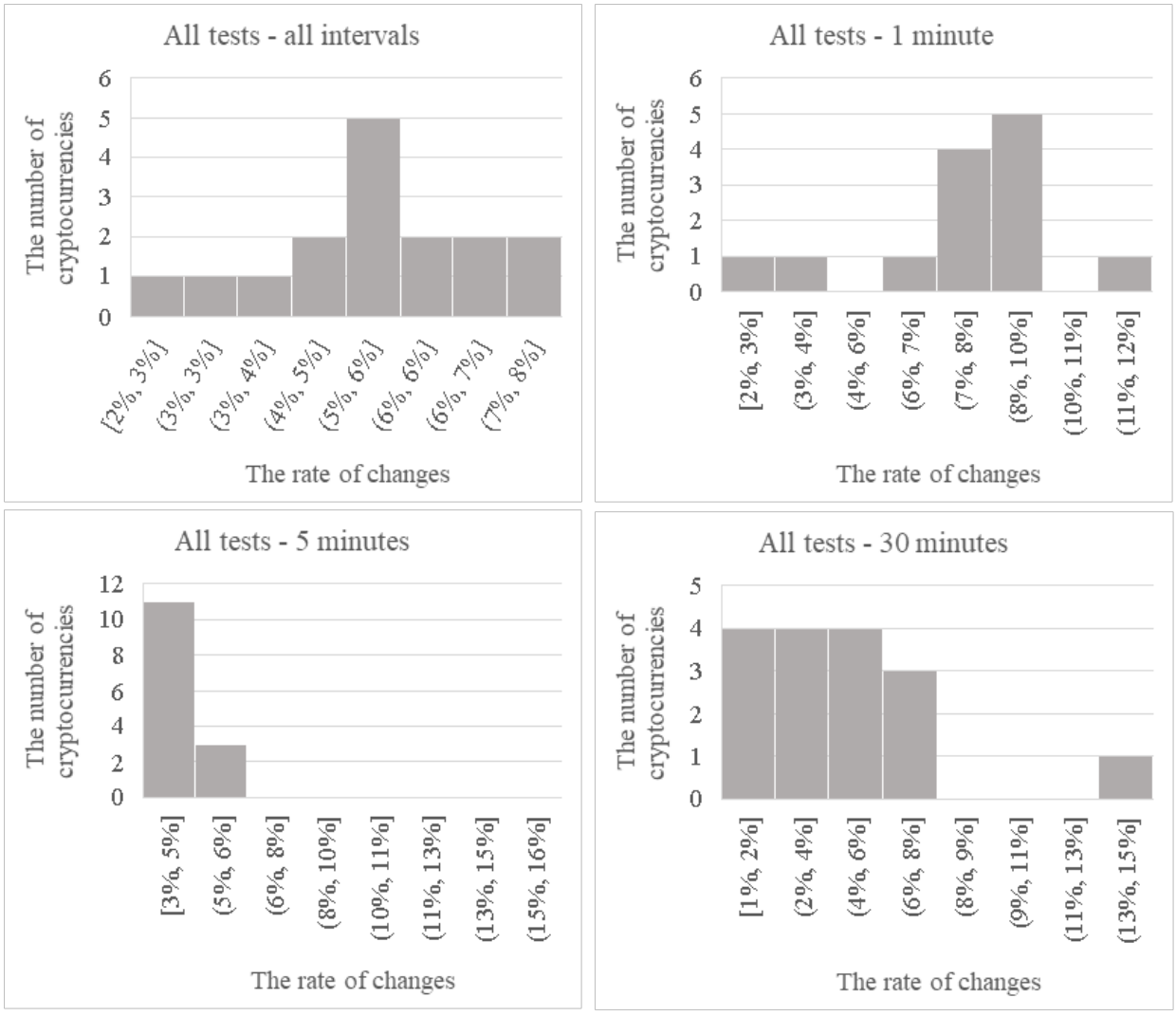


**Figure 2.** The histograms of the rate of changes
Note: The headers of distributions refer to the intervals considered.

short-term corrections. When it comes to the rate of changes, its minimum and maximum was about 1% and 7%, respectively. A rapid and significant increase of the rate of changes can be observed in the window ending in July 2023. Then, after a few months, a relatively stable level of changes decreased significantly in the window ending in January 2024. The next windows were marked by a relatively lower and stable rate of changes.

The analogous results pertaining to a 5-minute interval are presented in Figure 4. In the case of a 5-minute interval, the percentage of efficient windows and the rate of changes varied over the examined windows as well. The minimum and maximum percentages of efficient windows for all tests was approximately 80% and 89%, respectively. The results obtained indicate that the predictability of cryptocurrency returns tended to systematically increase in the short term. Surprisingly, in the case of a 5-minute interval, a negative correlation between the percentage of efficient windows and the rate of changes was not so clear. A minimum and maximum value of the rate of changes was about 4.4% and 4.9%, respectively.

## 4.3. Results of MDH tests for the most and the least efficient cryptocurrencies

To examine the behaviour of the predictability of returns in more detail, the results are also presented for the three most efficient (the top group) and three least efficient cryptocurrencies (the bottom group).

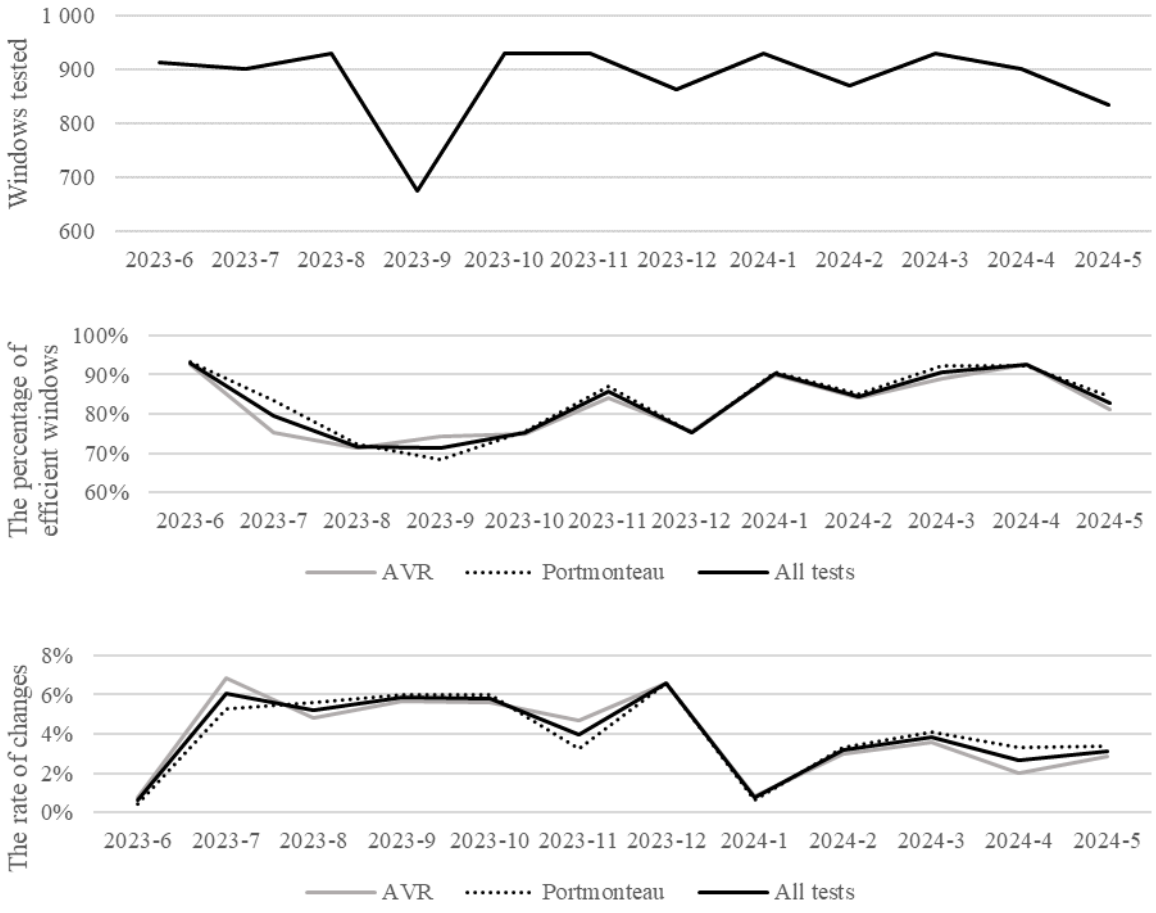


**Figure 3.** The results of the MDH tests over consecutive months for a 30-minute interval
Note: 'Portmonteau' stands for the automatic Portmanteau test for serial correlation proposed by Escanciano and Lobato (2009). 'AVR' is an abbreviation for the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity proposed by Kim (2009). 'All tests' refers to both tests together.

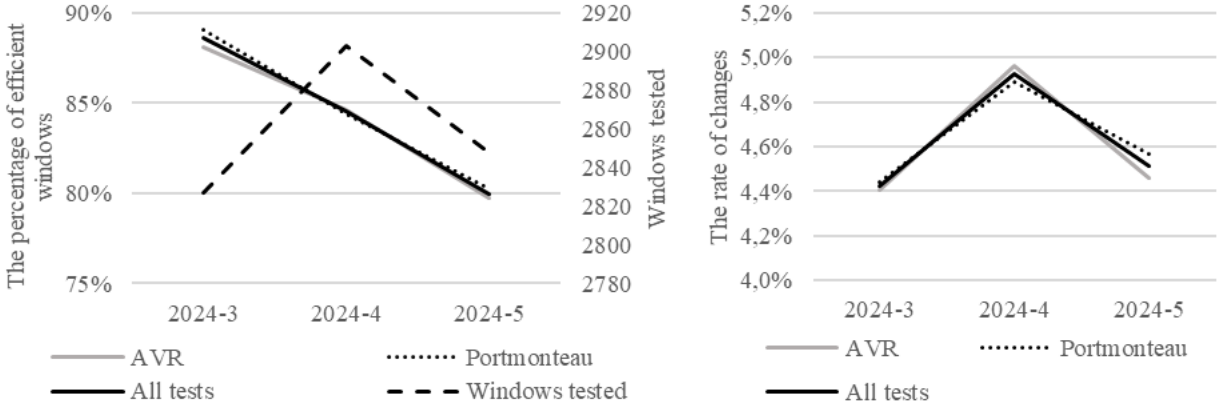


**Figure 4.** The results of the MDH tests over consecutive months for a 5-minute interval
Note: 'Portmonteau' stands for the automatic Portmanteau test for serial correlation proposed by Escanciano and Lobato (2009). 'AVR' is an abbreviation for the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity proposed by Kim (2009). 'All tests' refers to both tests together.

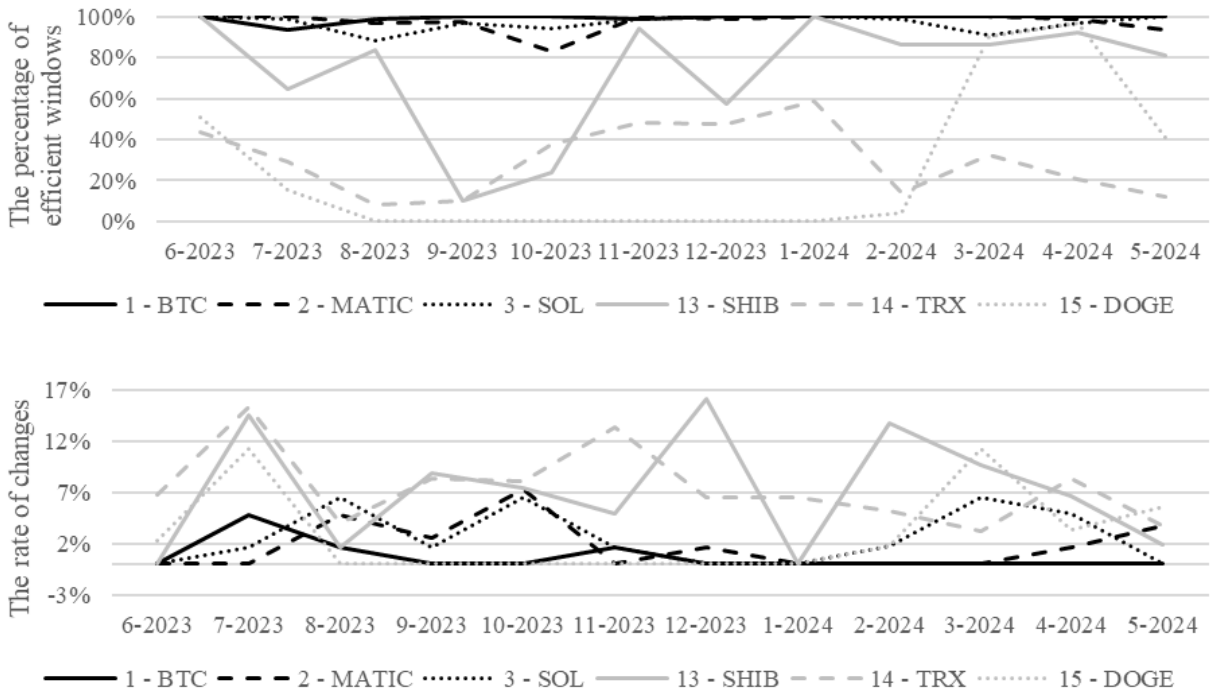


**Figure 5.** The results of the MDH tests for the three most efficient and three least efficient cryptocurrencies over consecutive months for a 30-minute interval
Note: The numbers refer to the ranking of efficiency based on the results presented in Table 1. Codes refer to cryptocurrencies in the efficiency ranking: Bitcoin (BTC), Polygon (MATIC), Solana (SOL), Shiba Inu (SHIB), TRON (TRX), and Dogecoin (DOGE).

The groups were distinguished by taking into account the average efficiency of cryptocurrencies in the entire research period. The ranking of efficiency was prepared based on the results presented in Table 1. Figure 5 pertains to a 30-minute interval and shows the percentage of efficient windows and the rate of changes for the 3 most efficient and 3 least efficient cryptocurrencies over consecutive windows. The research sample consists of 16 cryptocurrencies in the case of a 30-minute interval and 15 cryptocurrencies in the case of a 5-minute interval. However, due to a small number of tested windows, some cryptocurrencies were not taken into account in further considerations. Despite this, the original ranks are used in Figures 5 and 6.

Bitcoin, Polygon, and Solana were the most efficient cryptocurrencies in a 30-minute interval. On the other hand, Shiba Inu, TRON, and Dogecoin were considered the least efficient cryptocurrencies. The sixteenth cryptocurrency in the efficiency ranking, namely Toncoin, was not considered due to a small number of windows tested. A minimum percentage of efficient windows in the group of the most efficient cryptocurrencies was about 83%. When it came to a group of the least efficient cryptocurrencies, it was 0%. A significant difference between the groups is also visible in the average results. The average percentage of efficient windows in the top group was about 98%, while in the bottom group it was only 43%. A significantly lower dispersion of the percentage of efficient windows in the group of the most efficient cryptocurrencies appears to be in line with a significantly lower rate of changes compared to the bottom group. The average rate of changes in the top group was about 2%, while in the bottom group it was 6%.

In the case of a 5-minute interval, the most efficient cryptocurrencies were Chainlink, Solana, and Avalanche. The first cryptocurrency, i.e., Polkadot was not considered due to a small number of tested windows. On the other hand, BNB, XRP, and Dogecoin were considered the least efficient cryptocurrencies. The fifteenth cryptocurrency, i.e., Toncoin, was not considered due to a small number of tested windows as well. When it came to a 5-minute interval, the difference between the groups is not so large as in the case of a 30-minute interval. Nevertheless, it is still clear that the average percentage of efficient windows in the top group was about 95%, while in the bottom group it was only 64%. It should be noted that

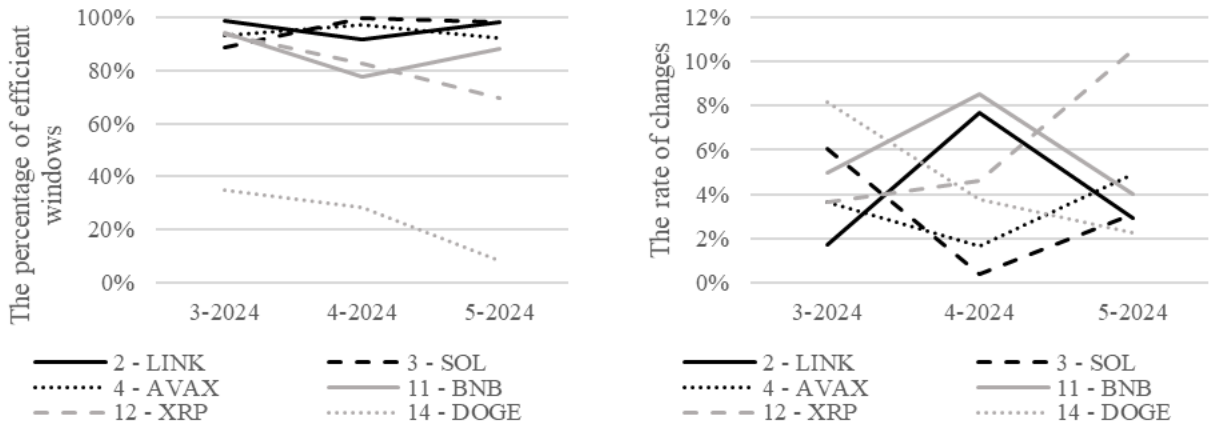


**Figure 6.** The results of the MDH tests for three most efficient and three least efficient cryptocurrencies over consecutive months for a 5-minute interval
Note: The numbers refer to the ranking of efficiency based on the results presented in Table 1. Codes refer to cryptocurrencies in the efficiency ranking: Chainlink (LINK), Solana (SOL), Avalanche (AVAX), BNB (BNB), XRP (XRP), and Dogecoin (DOGE).

especially Dogecoin is responsible for the decrease of the average result of the bottom group. Also, in the case of the average rate of changes, the difference between the examined groups is not as significant as in the case of the 30-minute interval. The average rate of changes in the top group was about 4%, while in the bottom group it was 6%. In the group of the most efficient cryptocurrencies, some surprisingly high rates of changes were observed for Chainlink.

## 4.4. Discussion

The changes in the weak-form efficiency that could be observed in the behaviour of the percentage of efficient windows and the rate of changes were much stronger in the case of the bottom group in both frequencies examined. However, in some periods, the most efficient cryptocurrencies still also suffered decreases in efficiency. The results obtained in this study appear to validate the AMH. They also appear to be in line with other studies, which validated this hypothesis, for instance, López-Martín et al. (2021), Noda (2021), Khursheed et al. (2020), Chu et al. (2019), Khuntia and Pattanayak (2018), and Caporale at al. (2018).

According to the distributions of the percentage of efficient windows, the range of the efficiency was broad. However, the distributions were left-skewed and indicated that most of cryptocurrencies were marked by high levels of efficiency. Only in the case of a 1-minute interval was the number of cryptocurrencies with higher efficiency lower. Such results appear to be in line with the studies of Hawaldar et al. (2019), Zargar and Kumar (2019), Tiwari et al. (2018), and Nadarajah and Chu (2017), which indicated that the examined cryptocurrencies were efficient most of the time. On the other hand, in this matter, the results of this study turn out to be inconsistent with the conclusions of the studies by Fieberg et al. (2024), Hu et al. (2019), Kristoufek and Vosvrda (2019), Kristoufek (2018), Yonghong et al. (2018), and Zhang et al. (2018).

The analysis of the behaviour of the percentage of efficient windows for all cryptocurrencies and a 30-minute interval indicated that a medium-term increasing trend in efficiency, with slight corrections, can be recognised. Thus, it is possible to find some similarities with the studies of Tran and Leirvik (2020), Sensoy (2019), Bariviera (2017), and Urquhart (2016). However, these observations are not in line with the studies by Meng and Khan (2023), Kristoufek and Vosvrda (2019), and Bundi and Wildi (2019). The situation was different when it comes to a 5-minute interval. The general efficiency of all cryptocurrencies tended to systematically fall in the short term.

The differences between the results obtained for three different time intervals pointed out the importance of the frequency of analysed returns. Overall, the results indicated that the predictability may increase as the data frequency increases. This conclusion appears to be in line with the outcomes of the studies by Aslan and Sensoy (2020), Chu, et al. (2019), Mensi et al. (2019), Sensoy (2019), Zargar and Kumar (2019). Investors looking for higher chances of

generating systematic and abnormal profits from the usage of informational inefficiencies should develop their investment strategies especially for higher frequencies of market data.

# 5. Conclusions

The changing weak-form efficiency of the cryptocurrency markets observed in the results of this study suggests that the predictability of high-frequency returns varied over time. According to the proxies of weak-form efficiency applied in this study, the predictability of returns is not constant, but reacts to changing institutional factors and market conditions. Such indications appear to validate the AMH and give no grounds for the rejection of the first research hypothesis. The weak-form efficiency of the examined cryptocurrencies used to vary over time. However, its levels suggested that for most of the time, returns were unpredictable, giving no grounds for the rejection of the second research hypothesis. Nevertheless, despite the indication suggesting that in most cases the cryptocurrency markets were unpredictable, their weak-form efficiency appeared to decrease with the decrease of the time interval. The difference in the forecasting features of the examined markets between the 30-minute and 5-minute intervals was not clear. However, in the 1-minute interval, the weak-form efficiency of the examined cryptocurrencies appeared to significantly decrease. Due to this, there are no grounds for the rejection of the third research hypothesis posed in the introduction.

When it came to differences between individual cryptocurrencies, the left-skewed distributions of the weak-form efficiency proxy generally showed that most of cryptocurrencies were marked by high levels of unpredictability. Nevertheless, it should be noted that the range of the weak-form efficiency proxy was high. A supplementary study showed some significant differences between the most and least efficient cryptocurrencies. Regarding trends in the forecasting features of cryptocurrencies, the 30-minute data appeared to indicate that in the medium term, the predictability used to decrease (weak-form efficiency increased). However, according to shorter 5-minute data, in a relatively short period the efficiency used to decrease.

This study aimed to constitute the answer to a need for further examination of the behaviour of forecasting features of cryptocurrency markets at high-frequency levels. Using a relatively broad sample of 16 cryptocurrencies, this study contributed to the body of knowledge pertaining to the examination of predictability in the cryptocurrency markets at the intraday levels, which have not attracted much attention compared to studies on lower time intervals so far. A sample applied in this study is one of the broadest ones among the issue-related studies on high-frequency data. This study may be especially valuable to regulators who want to control and ensure a smooth functioning, informationally efficient, investing-convenient, and fair environment to market participants.

Information pertaining to the levels of market efficiency, its behaviour, and trends may provide regulators with valuable guidance when it comes to the results of their past regulatory actions and actions that need to be taken in the future. The results of this study show that especially higher frequencies should become a primary interest of regulators who would have to focus on the increase of efficiency at lower time-intervals. Investors may find in this paper some valuable indications when it comes to the cryptocurrency markets and frequency of quotations that are worth considering. Some investors may even look for less efficient markets and higher frequencies of quotations when they aim to exploit market inefficiencies and gain systematically abnormal returns. According to the results of this study, such investors may be especially interested in higher frequencies.

Due to a relatively small part of studies covering the weak-form efficiency of cryptocurrency markets at high-frequency levels, a further examination of this issue is necessary, especially with the use of broader samples and longer timeseries that would allow the drawing of more general conclusions. Due to large sizes of high-frequency datasets, the computations of broad and long timeseries and their analyses are difficult. This study applied relatively short timeseries, especially when it came to the shortest intervals. This paper also does not focus on the specific reasons for efficiency changes and its factors, which also requires further studies.

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