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Economics and Business Review
https://www.ebr.edu.pl
Vol. 9 (1), 2023: 94-118
https://doi.org/10.18559/ebr.2023.1.4

The adaptive market hypothesis and the return predictability in the cryptocurrency markets

Jacek Karasiński[1]

Abstract

This study employs robust martingale difference hypothesis tests to examine return predictability in a broad sample of the 40 most capitalized cryptocurrency markets in the context of the adaptive market hypothesis. The tests were applied to daily returns using the rolling window method in the research period from May 1, 2013 to September 30, 2022. The results of this study suggest that the returns of the majority of the examined cryptocurrencies were unpredictable most of the time. However, a great part of them also suffered some short periods of weak-form inefficiency. The results obtained validate the adaptive market hypothesis. Additionally, this study allowed the observation of some differences in return predictability between the examined cryptocurrencies. Also some historical trends in weak-form efficiency were identified. The results suggest that the predictability of cryptocurrency returns might have decreased in recent years also no significant relationship between market cap and predictability was observed.

Keywords

- cryptocurrency markets
- adaptive market hypothesis
- efficient market hypothesis
- cryptocurrency return predictability
- weak-form efficiency of cryptocurrency markets
- martingale difference hypothesis

JEL codes: G14

Article received 12 December 2022, accepted 7 April 2023.

Suggested citation: Karasiński, J. (2023). The adaptive market hypothesis and the return predictability in the cryptocurrency markets. *Economics and Business Review*, *9*(1), 94–118. https://doi.org/10.18559/ebr.2023.1.4

[1] Faculty of Management, University of Warsaw, ul. Szturmowa 1/3, 02-678 Warszawa, Poland, jkarasinski@wz.uw.edu.pl, https://orcid.org/0000-0003-4326-5044.

Introduction

The issue of return predictability can be directly related with the efficient market hypothesis (EMH) of Fama (1965) and Samuelson (1965) who proposed that when the market is efficient all relevant and available information is instantaneously and fully reflected in asset prices. According to EMH an accurate and instantaneous adjustment of asset price to new information disables the predictability of asset returns (Fama, 1970). Based on past returns the future returns are purely unpredictable and the asset returns follow a martingale difference sequence (MDS). This assumption is especially related to the weak form of EMH (Charles et al., 2012).

The issue of return predictability in the cryptocurrency markets has already drawn the attention of many researchers. This resulted in the publication of many issue-related papers, despite the short history of cryptocurrency markets compared to other frequently examined markets such as stock or foreign exchange markets. However, researchers who examined the weak-form efficiency of cryptocurrency markets came to ambiguous conclusions. Already at an early stage of studies researchers proposed that results were time-varying (e.g., Bariviera, 2017; Nadarajah & Chu, 2017; Urquhart, 2016). The lack of unambiguity encouraged them to apply a dynamic approach to weak-form efficiency testing and led them to the adaptive market hypothesis (AMH) of Lo (2004). The theory proposed by Lo (2004, 2005) reconciles the EMH with the notion of a bounded rationality of market participants. According to AMH, weak-form efficiency may change over time as a result of changing market conditions and institutional factors. The relationship between expected return and risk can also vary over time. Thus a consistent level of expected returns can be achieved by adapting to evolving market conditions. It contradicts the EMH according to which the degree of risk taken determines the level of expected returns that can be achieved (Chu et al., 2019).

Only a part of the studies devoted to the examination of the weak-form efficiency of cryptocurrencies explicitly addressed the AMH. The AMH does not provide any formal test procedure. However, the evidence of time-varying levels of weak-form efficiency was sufficient for the authors of the issue-related studies to validate the AMH. According to the knowledge of the author of this study, most studies testing AMH in the cryptocurrency markets validated this hypothesis (Caporale et al., 2018; Chu et al., 2019; Khuntia & Pattanayak, 2018; Khursheed et al., 2020; López-Martín et al., 2021; Noda, 2021).

This study aims to examine the return predictability in a broad sample of cryptocurrency markets in the context of the adaptive market hypothesis. The first research hypothesis assumes that the degree of predictability of cryptocurrency daily returns varied over time in line with the AMH. The second research hypothesis assumes that the daily returns of the examined cryptocurrencies were unpredictable most of the time. In addition, this study aims to answer a question as to whether: there were any substantial differences in return predictability between the examined cryptocurrencies; there were any trends in the weak-form efficiency of the examined cryptocurrencies over time; there were any significant differences in return predictability between cryptocurrencies marked by the highest and the lowest market cap.

A great part of the issue-related studies focused on a very limited number of cryptocurrencies. In many cases they focused only on Bitcoin (e.g., Bariviera, 2017; Bundi & Wildi, 2019; Khuntia & Pattanayak, 2018; Nadarajah & Chu, 2017; Sensoy, 2019; Tiwari et al., 2018; Urquhart, 2016; Yonghong et al., 2018; Zargar & Kumar, 2019). There were also studies that covered much larger samples. However, they were a minority. For instance, a study by Wei (2018) examined one of the largest samples of cryptocurrencies among studies devoted to weak-form efficiency testing. The sample used in this study included 456 cryptocurrencies. Hu et al. (2019) examined 31 top market-cap cryptocurrencies. Palamalai et al. (2021) examined 10 top market-cap cryptocurrencies, while Zhang et al. (2018) examined 9 cryptocurrencies. These studies can be considered the other ones with the outstanding number of cryptocurrencies included in the research sample. This study includes 40 cryptocurrencies with the highest market capitalization as of November 15, 2022 according to coinmarketcap.com. Stablecoins were not included in the research sample. According to the knowledge of this author the sample covered here may be one of the largest among studies devoted to the testing of return predictability in the cryptocurrency markets. The application of such a broad sample also allowed the comparison of return predictability between different cryptocurrencies. This issue was not commonly addressed in the issue-related literature.

This study examines the return predictability in the cryptocurrency markets with the use of tests for the martingale difference hypothesis (MDH), which are able to detect linear and non-linear dependence. Under the MDH the cryptocurrency returns follow the aforementioned martingale difference sequence (MDS) where the returns are uncorrelated with the historical values. The return predictability was tested with the use of three MDH tests that are frequently used in the literature namely the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity proposed by Kim (2009), the automatic Portmanteau test for serial correlation proposed by Escanciano and Lobato (2009) and the generalized spectral test for the martingale difference hypothesis by Escanciano and Velasco (2006). The verification of the AMH requires the application of a dynamic approach to MDH testing. Thus the MDH tests were applied using the rolling window method. This study covers the period from May 1, 2013 to September 30, 2022. Such a long research period permits a comprehensive insight over a relatively long time period (compared to other issue-related studies) and a current state of daily return predictability in a broad sample of cryptocurrency markets. This relatively long research period included covers a turbulent history of the cryptocurrency markets which experienced spectaculars ups and downs. In 2022 a great part of cryptocurrency markets experienced severe crashes that led to discounts of even several dozen percent. These events are also included in this research period.

1. Literature review

The issue of the weak-form efficiency of the cryptocurrency markets has drawn the attention of many researchers in the last years. However, their findings were not unambiguous. Additionally, the majority of studies focused on at most several cryptocurrency markets. Results suggesting that for most of the time cryptocurrency markets were weak-form efficient can be found for instance in the studies by Nadarajah and Chu (2017), Tiwari et al. (2018), Zargar and Kumar (2019), Hawaldar et al. (2019), Apopo and Phiri (2021). On the other hand results which suggest that for most of the time cryptocurrencies were weak-form inefficient can be found e.g. in the studies by Zhang et al. (2018), Yonghong et al. (2018), Kristoufek (2018), Kristoufek and Vosvrda (2019), Hu et al. (2019), Bundi and Wildi (2019), Mensi, Lee et al. (2019), Palamalai et al. (2021), Łęt et al. (2022). Some studies focussed on a dynamic examination of the weak-form efficiency of the cryptocurrency markets. For instance, studies by Urquhart (2016), Bariviera (2017), Sensoy (2019), Tran and Leirvik (2020), Caporale et al. (2018), Khuntia and Pattanayak (2018) suggested that the examined cryptocurrency markets became more efficient over time. The opposite conclusions were proposed by Bundi and Wildi (2019). Some studies directly referred to the adaptive market hypothesis as for example the studies by Caporale et al. (2018), Khuntia and Pattanayak (2018), Chu et al. (2019), Khursheed et al. (2020), Noda (2021), López-Martín et al. (2021). The results of all of these studies suggested that efficiency was time-varying. The results of these studies also validated the adaptive market hypothesis. A greater part of the studies which test the weak-form efficiency of cryptocurrency markets considered daily data or data of even lower frequency. Zargar and Kumar (2019) and Sensoy (2019) examined intraday data and suggested that at higher intraday frequencies the cryptocurrency markets might not be efficient. Thus it is important to emphasize the frequency of data for which efficiency was tested.

The identification of events which could affect the weak-form efficiency in the cryptocurrency markets within the meaning of AMH fell in most cases outside the scope of issue-related studies. Only a small part of them made an attempt to identify events that could have a significant impact on market conditions and on the predictability of cryptocurrency returns (e.g., Chu et al., 2019; Khuntia & Pattanayak, 2018; Tran & Leirvik, 2020). However, such studies usually pertained only to a small number of markets.

Urquhart (2016) applied a set of random walk and MDH tests to daily returns of Bitcoin in the period August 2010–July 2016 to examine the weak--from efficiency of this cryptocurrency. The results of this study suggested that Bitcoin was inefficient when considering the entire research period. However, when the research period was divided into two even subperiods, in the latter some tests indicated efficiency. Due to such results the author suggested that Bitcoin might become more efficient over time. The aforementioned study by Urquhart (2016) was directly discussed and replicated by Nadarajah and Chu (2017) who proposed that Bitcoin turned out to be efficient in the entire research period after a simple power transformation of daily returns. According to the results obtained, Bitcoin was efficient even in two subperiods. The authors proposed that the transformation of returns did not cause any loss of information. A set of efficiency measures applied by Urquhart (2016) was also used by Wei (2018) who aimed to examine the liquidity and weak-form efficiency of a large sample of 456 cryptocurrencies. The results of the study indicated a strong relationship between liquidity and efficiency. While the most liquid cryptocurrencies exhibited efficiency cryptocurrencies marked by a low liquidity appeared to be inefficient. Sensoy (2019) made an attempt to investigate the weak-form efficiency of Bitcoin in relation to USD and EUR at the intra-day level in the period January 2013–March 2018. The researcher applied the permutation entropy. Based on the results obtained the researcher proposed several main conclusions. Since 2016 Bitcoin has become more efficient. In relation to the USD Bitcoin was slightly more efficient compared to Bitcoin in relation to the EUR. Efficiency decreased with higher data frequencies. Volatility had a negative effect on the efficiency of Bitcoin. The opposite was true in the case of liquidity. Tran and Leirvik (2020) examined the weak-form efficiency of Bitcoin, Ethereum, Ripple, Litecoin and EOS in the period April 2013–February 2019. They aimed to select some of the most capitalized cryptocurrencies. The researchers applied their own weak-form efficiency measure (Tran & Leirvik, 2019), i.e., Adjusted Market Inefficiency Magnitude to daily data. The results of the study suggested that the efficiency of the examined cryptocurrencies varied over time. Before 2017 the cryptocurrencies were mostly inefficient. However, in the next periods their efficiency tended to increase over time.

Zhang et al. (2018) applied a battery of randomness, random walk and MDH tests to examine the weak-form efficiency of nine cryptocurrencies namely Bitcoin, Ripple, Ethereum, NEM, Stellar, Litecoin, Dash, Monero and Verge. The tests were applied with the use of rolling window method in the period April 2013–January 2018. The results suggested that the examined currencies were inefficient. Yonghong et al. (2018) focused on Bitcoin and the investigation of long-term memory in its daily returns in the period December 2010–November 2017. The researchers employed the generalized Hurst exponents and the rolling window method. The results suggested that Bitcoin was inefficient and did not tend to become more efficient over time. Kristoufek (2018) examined the efficiency of two Bitcoin markets with the use of the Efficiency Index of Kristoufek and Vosvrda (2013). The results of the study suggested that both Bitcoin markets remained mostly inefficient between 2010 and 2017. Kristoufek and Vosvrda (2019) applied the Efficiency Index that comprised the long-range dependence, entropy components and fractal dimension to examine the efficiency of a set of cryptocurrencies including Bitcoin, Litecoin, DASH, Monero, Stellar and Ripple. The examined cryptocurrencies appeared to be mostly inefficient except for the period between July 2017 and June 2018 when most cryptocurrencies were efficient. Hu et al. (2019) applied panel unit root tests to examine the efficiency of 31 of the top market-cap cryptocurrencies in the period August 2017–January 2019. Based on the results obtained the researchers proposed that the examined cryptocurrencies were inefficient. Bundi and Wildi (2019) chose an approach to weak-form efficiency testing that is much different from methods applied in other studies reviewed in this section. Namely to test the weak-form efficiency of Bitcoin the researchers used trading strategies based on classic time series models, on moving average filters and on non-linear neural nets. The study was conducted for daily data in the period April 2014–January 2019. The results of the study suggested that the applied trading strategies generated a significantly positive performance. Thus Bitcoin turned out to be weak-form inefficient. In addition, the researchers proposed that the efficiency of Bitcoin tended to decrease. Mensi, Lee et al. (2019) examined the weak-form efficiency of Bitcoin and Ethereum using the asymmetric multifractal detrended fluctuation analysis. The study covered the period June 2013–June 2018 and considered three different data frequencies, i.e., 5, 10 and 15 min. The researchers proposed that both cryptocurrencies were inefficient and that their inefficiency varied over time. Additionally, there were differences in inefficiency between the upward and downward-trending markets. The inefficiency was lower during the upward market. Palamalai et al. (2021) made an attempt to examine the weak-form efficiency of the top ten currencies in terms of the market cap as of August 5, 2019. The research period varied across cryptocurrencies. However, it ended on August 5, 2019 in the case of all cryptocurrencies. The cryptocurrencies had to be traded for at least two years. The researchers applied several non-parametric and parametric random walk tests to daily returns. The results suggested that the examined cryptocurrencies were inefficient. Similar results were obtained for two subperiods which were distinguished in the case of each cryptocurrency. Łęt et al. (2022) tested the weak-form efficiency of Bitcoin and Ethereum in years 2015–2022 by applying active strategies based on selected fundamental factors to verify whether they can outperform passive investment strategies. The study used daily data. Both cryptocurrencies tested appeared to be consistently inefficient over time.

Caporale et al. (2018) aimed to examine persistence in four cryptocurrency markets namely Bitcoin, Litecoin, Ripple and Dash. The study covered the period 2013–2017 and employed R/S analysis and fractional integration to examine daily returns of the examined cryptocurrencies. The authors proposed that the results obtained validated the adaptive market hypothesis as the weak-form efficiency in the cryptocurrency markets changed over time. The examined cryptocurrencies turned out to be mostly inefficient. However, their efficiency tended to increase over time. Khuntia and Pattanayak (2018) examined the adaptive market hypothesis with reference to the weak-form efficiency of Bitcoin in the period July 2010–December 2017. The authors employed some MDH tests to daily returns using rolling windows. The results obtained allowed them to state that the efficiency of Bitcoin evolved over time. Thus the results validated the adaptive market hypothesis. Chu et al. (2019) made an attempt to examine the weak-form efficiency of Bitcoin and Ethereum versus both the USD and the EUR. The study covered the period July 2017–September 2018 and employed one MDH tests, i.e., the Dominguez-Lobato test to intraday returns in rolling windows. Based on the results obtained the researchers proposed that the adaptive market hypothesis was valid due to the time-varying efficiency of Bitcoin and Ethereum. Khursheed et al. (2020) investigated the weak-form efficiency of Bitcoin, Monaro, Litecoin and Steller in the period 2014–2018. The researchers applied a set of MDH tests to daily returns of the aforementioned cryptocurrencies. The general conclusions from this study were that the changes in efficiency were significant. Bitcoin, Monaro and Litecoin were marked by the longest efficiency periods. The opposite was true for Steller. Noda (2021) tried to verify the adaptive market hypothesis with reference to the weak-form efficiency of two most capitalized cryptocurrencies, i.e., Bitcoin and Ethereum. The study employed the GLS-based time-varying autoregressive model to daily returns of the aforementioned cryptocurrencies in the period April 2013–September 2019. The results of the study validated the adaptive market hypothesis as the efficiency of both examined cryptocurrencies varied over time. Furthermore, Bitcoin seemed to be more efficient compared to Ethereum for most of the time. López-Martín et al. (2021) focused on the investigation of the weak--form efficiency of Bitcoin, Litecoin, Ethereum, Ripple, Stellar and Monero in the period August 2015–December 2019. They applied a set of tests (mostly MDH tests) to daily returns using rolling windows. The authors proposed that Bitcoin, Litecoin, and Ethereum were marked by an increase in efficiency over the examined research period. As far as other cryptocurrencies are concerned the periods of efficiency of Ripple, Stellar, and Monero alternated with the periods of inefficiency. The authors suggested that the results obtained validated the adaptive market hypothesis.

2. Data and research methodology

This study aims to examine the return predictability in a broad sample of cryptocurrency markets in the context of the adaptive market hypothesis. For this reason, the research sample consists of the 40 most capitalized cryptocurrencies according to coinmarketcap.com as of November 15, 2022. Stablecoins were not considered in this study. Taking into account descending order in terms of market cap a list of cryptocurrencies included in the research sample can be presented as follows: Bitcoin, Ethereum, BNB, XRP, Cardano, Dogecoin, Polygon, Polkadot, Solana, Shiba Inu, Uniswap, TRON, Litecoin, Avalanche, Wrapped Bitcoin, UNUS SED LEO, Chainlink, Cosmos, Ethereum Classic, Stellar, Monero, Toncoin, Bitcoin Cash, Algorand, Cronos, NEAR Protocol, Quant, VeChain, Filecoin, Chiliz, Flow, Hedera, OKB, Terra Classic, Internet Computer, MultiversX (Elrond), Chain, EOS, Tezos, ApeCoin.

The martingale difference hypothesis (MDH) tests were used to examine the weak-form efficiency of selected cryptocurrencies. The MDH tests applied in this study were conducted for daily log returns of cryptocurrencies included in the research sample in the period from May 1, 2013 to September 30, 2022. The aforementioned daily log returns were calculated based on daily closing prices retrieved from coinmarketcap.com using *crypto2* package in R. The same website constituted a primary source of time series data in the issue-related studies by Caporale et al. (2018), Zhang et al. (2018), Hu et al. (2019), Tran and Leirvik (2020), López-Martín et al. (2021), Noda (2021), and Palamalai et al. (2021).

This study employs three MDH tests, the wild bootstrapped automatic variance ratio test under conditional heteroskedasticity proposed by Kim (2009), the automatic Portmanteau test for serial correlation proposed by Escanciano and Lobato (2009) and the generalized spectral test for the martingale difference hypothesis by Escanciano and Velasco (2006). The examples of the applications of the aforementioned tests can be found in other issue-related studies such as Urquhart (2016), Nadarajah and Chu (2017), Khuntia and Pattanayak (2018), Khursheed et al. (2020), and López-Martín et al. (2021).

Referring to the martingale hypothesis it can be assumed that the returns of cryptocurrencies constitute the martingale increments. Considering the stylized facts of cryptocurrency returns this assumption seems to be more correct compared to the often tested assumption which states that returns are i.i.d. with a 0 expected value (Campbell et al., 1997; Linton, 2019). The aforementioned tests by Kim (2009) and Escanciano and Lobato (2009) were considered by Charles et al. (2011) to be a substantial contribution to the area of MDH testing. The applied tests are able to detect any linear and non-linear dependence. They are robust to heteroscedasticity and non-normality as well as they show no size distortion in small samples (Charles et al., 2012; Escanciano & Lobato, 2009; Kim, 2009). All tests were applied with the use of functions included in *vrtest* package in R (v1.1; Kim, 2022). The test of Kim (2009) was applied using a function AutoBoot.test. For the test of Escanciano and Lobato (2009), a function Auto.Q was applied. A function Gen.Spec.Test was used to perform the test of Escanciano and Velasco (2006). In the case of the tests of Kim (2009) and Escanciano and Velasco (2006), 500 bootstrap iterations were applied. In the case of all tests, a significance level of $\alpha = 0.05$ was used.

The verification of the adaptive market hypothesis required the application of a dynamic approach to weak-form efficiency testing. Therefore, all selected tests for MDH were performed using the rolling window method. This approach was also frequently used in other issue-related studies (e.g., Bariviera, 2017; Caporale et al., 2018; Chu et al., 2019; Khuntia & Pattanayak, 2018; López-Martín et al., 2021; Tiwari et al., 2018; Tran & Leirvik, 2020; Yonghong et al., 2018; Zargar & Kumar, 2019; Zhang et al., 2018). Each window had a fixed length of 250 days and a 5-day rolling, i.e., windows were moved by 5 days. A test was performed only when a window contained at least 75% of a maximum number of daily observations. It is worth mentioning that in the case of some cryptocurrencies not all windows could be tested due to the limitations of the applied database and some missing data as well as due to the launch date of some cryptocurrency markets after the first day of the research period.

3. Results and discussion

The rolling window method was applied to examine the behaviour of return predictability in the cryptocurrency markets over time. The nature of the problem addressed in this study requires a look at the results obtained in different time periods. However, a summary of the results obtained in all windows will be discussed first. Table 1 presents some general results obtained for each cryptocurrency in all windows. The descriptive statistics of daily returns presented in Table 1 were calculated as the average of the mean, median and standard deviation obtained in all windows. Taking into account the aim of this study the most important results are presented in two columns on the right. The percentage of efficient windows refers to the percentage of examined windows in which all applied MDH tests indicated weak-form efficiency, i.e., in which MDH could not be rejected. The rate of changes in the column on the right refers to the percentage of windows in which the change in the efficiency status occurred. In other words this measure provides information about the frequency of changes from efficiency to inefficiency and from inefficiency to efficiency. In addition, Table 1 presents information on the number of windows tested in the entire research period. Cryptocurrencies were sorted in descending order in terms of market cap.

The differences between the mean and median daily returns do not allow an unambiguous distinction of the best and the worst performing cryptocurrencies in terms of raw returns. Instead the differences between the mean and median daily returns say a lot about the non-normality of cryptocurrency returns and the validity of the application of the MDH tests which perform well in such conditions. Taking into account the standard deviation of daily returns Shiba Inu, Terra Classic, ApeCoin and Filecoin can be considered some of the most volatile cryptocurrencies in the sample. On the other hand UNUS SED LEO, Bitcoin, Wrapped Bitcoin and Ethereum can be considered the least volatile.

When it comes to the percentage of efficient windows the results range from about 46% to 100%. Litecoin, NEAR Protocol, Flow, Chain and ApeCoin can be considered the most frequently efficient. However, in the case of Chain and ApeCoin the number of windows tested was the least considering the entire research sample. Filecoin, Hedera, Toncoin, Shiba Inu and Internet Computer were the least frequently efficient. Some cryptocurrencies with the highest percentage of efficient windows also turned out to have the lowest rate of changes. Analogically, some cryptocurrencies with the lowest percentage of efficient windows also turned out to have the highest rate of changes. The rate of changes varied between 0% and about 8%. Among the cryptocurrencies with the lowest rate of changes were NEAR Protocol, Flow, Chain, ApeCoin and Solana. On the other hand, Toncoin, Hedera, Wrapped Bitcoin, Internet Computer, and UNUS SED LEO were marked by the highest rate of changes. Again due to a small number of windows tested the results of Chain and ApeCoin should be approached with caution.

It is also worth taking a look at the distribution of results presented in Table 1. Figure 1 shows the histograms of the percentage of efficient windows over the entire research period considering the results of each MDH test separately and all of them together. Analogically, Figure 2 presents the histograms of the rate of changes. The histograms of the percentage of efficient windows obtained using the results of different MDH tests can be considered similar. They are highly left-skewed which suggests that the majority of cryptocurrencies had a higher share of efficient windows compared to the average. Indeed according to all applied MDH tests more than 85% of the examined cryptocurrencies were efficient in more than 85% of windows.

Table 1. The number of windows tested, the descriptive statistics of daily returns, the percentage of efficient windows and the rate of changes considering all MDH tests

Market cap rank	Cryptocurrency	The number of windows tested	Mean (%)	Median (%)	Standard deviation (%)	The % of efficient windows (%)	The rate of changes (%)
1	Bitcoin	639	0.16	0.21	4.01	97.29	1.99
2	Ethereum	485	0.32	0.12	5.71	96.22	2.75
3	BNB	341	0.35	0.19	6.02	95.11	1.96
4	XRP	632	0.12	–0.17	6.43	96.36	2.32
5	Cardano	328	0.12	0.00	6.29	98.27	1.33
6	Dogecoin	605	0.17	–0.22	6.80	96.86	1.60
7	Polygon	213	0.43	0.15	8.33	97.03	1.57
8	Polkadot	117	0.13	0.13	6.96	99.43	0.57
9	Solana	144	0.54	0.20	8.00	96.99	0.47
10	Shiba Inu	121	1.86	–0.24	22.42	78.24	2.22
11	Uniswap	112	0.06	0.11	7.15	89.29	3.60
12	TRON	332	0.14	0.07	6.52	94.98	2.32
13	Litecoin	639	0.09	–0.05	5.87	99.53	0.68
14	Avalanche	111	0.31	0.19	8.13	95.80	3.03
15	Wrapped Bitcoin	231	0.15	0.15	4.09	86.15	6.23
16	UNUS SED LEO	209	0.14	0.07	3.12	86.12	5.13
17	Chainlink	330	0.21	–0.02	7.13	97.37	2.23
18	Cosmos	222	0.10	–0.01	7.07	97.60	1.81
19	Ethereum Classic	415	0.15	–0.02	6.58	97.91	2.09
20	Stellar	559	0.14	–0.15	6.63	91.71	1.19
21	Monero	573	0.16	0.06	6.25	90.23	3.50
22	Toncoin	43	0.10	–0.30	7.88	77.52	7.94
23	Bitcoin Cash	342	–0.07	–0.11	6.50	88.79	3.62
24	Algorand	202	–0.03	0.05	6.94	97.52	1.00
25	Cronos	240	0.17	0.17	6.22	93.47	3.07
26	NEAR Protocol	106	0.25	0.07	8.27	100.00	0.00
27	Quant	265	0.36	–0.30	7.82	95.09	2.78
28	VeChain	267	0.10	0.10	6.62	85.64	3.76
29	Filecoin	313	–0.02	–0.20	9.45	46.11	2.56
30	Chiliz	200	0.27	0.15	7.96	98.00	1.68

Market cap rank	Cryptocurrency	The number of win-dows tested	Mean (%)	Median (%)	Stan-dard devia-tion (%)	The % of efficient win-dows (%)	The rate of changes (%)
31	Flow	85	–0.36	–0.49	6.94	100.00	0.00
32	Hedera	185	0.12	0.10	7.30	72.61	6.52
33	OKB	213	0.20	0.06	5.99	99.06	0.63
34	Terra Classic	195	–0.31	0.00	13.87	94.70	0.86
35	Internet Computer	64	–0.71	–0.57	7.05	79.17	5.82
36	MultiversX (Elrond)	114	0.28	0.04	6.94	98.83	2.36
37	Chain	3	0.13	–0.12	6.56	100.00	0.00
38	EOS	346	–0.01	–0.01	6.59	98.27	2.32
39	Tezos	273	0.02	0.10	6.45	98.78	1.23
40	ApeCoin	2	–0.22	–0.30	9.49	100.00	0.00

Source: Own work.

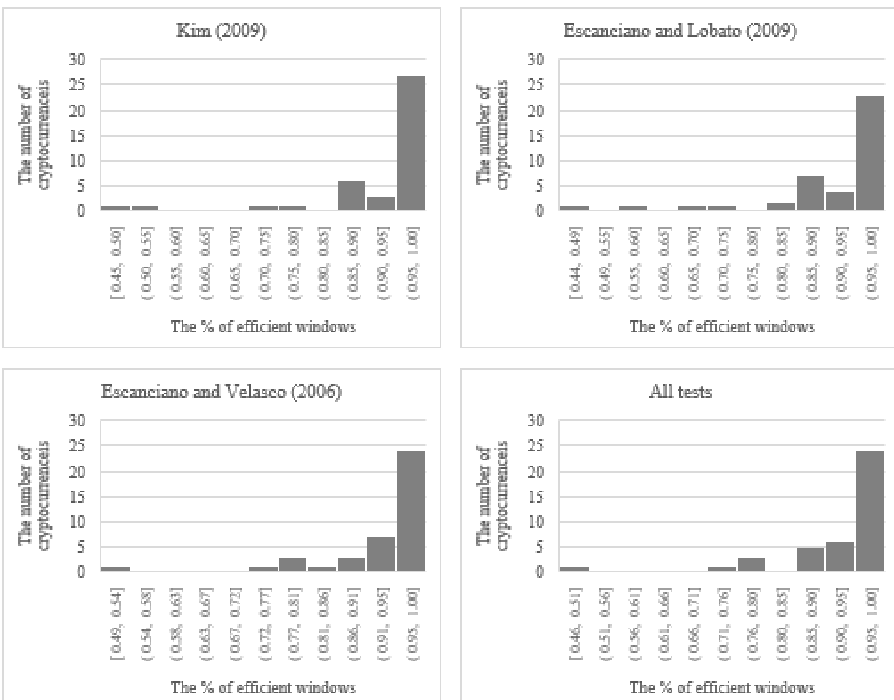

Figure 1. The histograms of the percentage of efficient windows in the entire research period considering the results of each MDH test separately and all of them together

Source: Own work.

Surprisingly the histograms of the rate of changes across the applied tests do not look as similar as in the case of the percentage of efficient windows. According to the results of the Escanciano and Lobato (2009) test the efficiency status (efficient/inefficient) of cryptocurrencies changed more frequently compared to other MDH tests. However, the results of the applied tests share some common features such as the right skewness. Taking into account the results of all MDH tests in more than 85% of cryptocurrencies the rate of changes was equal to or less than 4%.

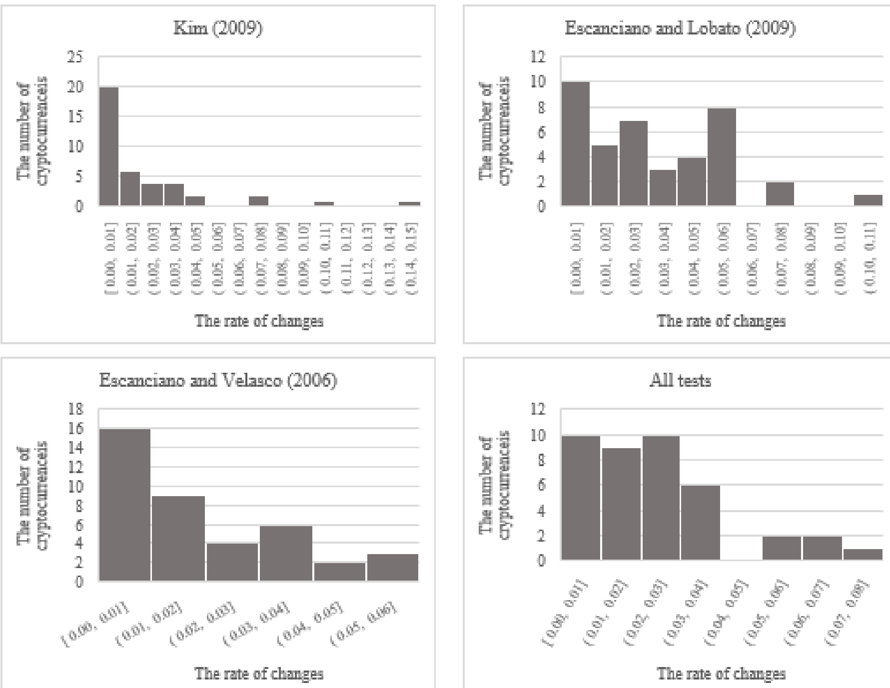

Figure 2. The histograms of the rate of changes in the entire research period considering the results of each MDH test separately and all of them together

Source: Own work.

Spearman's rho and Kendall's tau rank correlation coefficients calculated for the average standard deviation and the percentage of efficient windows presented in Table 1 indicated a very low and insignificant negative correlation. The same pertained to the relationship between the average standard deviation and the rate of changes. However, the rank correlation between the percentage of efficient windows and the rate of changes turned out to be strongly negative and significant. It suggests that more frequently efficient cryptocurrencies usually tended to change their efficiency status less often. The results of the aforementioned rank correlations are presented in Table 2.

Table 2. Spearman's rho and Kendall's tau rank correlation coefficients for pairs of summary statistics presented in Table 1

Variables		Spearman's rho		Kendall's tau	
variable 1	variable 2	coefficient	*p*-value	coefficient	*p*-value
Standard deviation	The % of efficient windows	–0.07	0.68	–0.05	0.67
Standard deviation	The rate of changes	–0.16	0.32	–0.11	0.32
The % of efficient windows	The rate of changes	–0.79	0.00	–0.64	0.00

Source: Own work.

Moving on to the discussion on the behaviour of the weak-form efficiency in the cryptocurrency markets over time Figure 3 presents the number of cryptocurrencies and windows tested over the research period. The *x*-axis refers to the quarters in which the windows ended. The number of cryptocurrencies and windows tested gradually increased over time. It was related to later launch dates of some markets. The research period began on May 1, 2013 but due to the application of a 250-day window the first windows ended only in the 1st quarter of 2014. The number of cryptocurrencies for which the calculations were completed in the 1st quarter of 2014 was only four. In the same quarter the calculations for 47 windows were finished. In the last quarter of the research period, i.e., in the 3rd quarter of 2022, the calculations were ended for 40 cryptocurrencies in 727 windows.

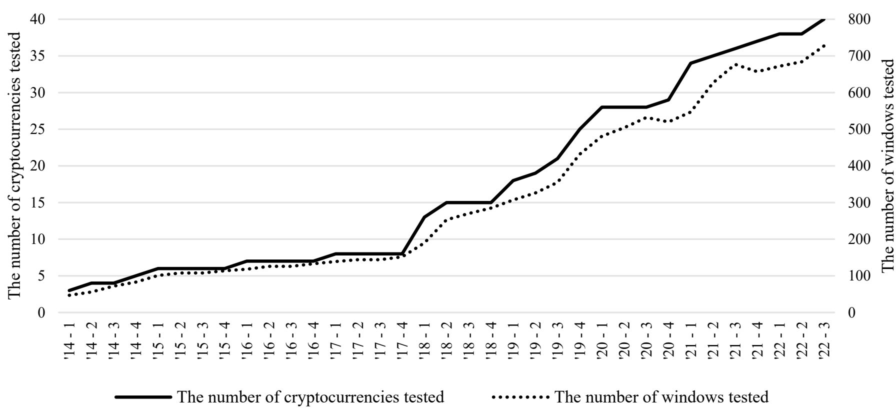

Figure 3. The number of cryptocurrencies and windows tested over the consecutive quarters of the research period

Source: Own work.

Figure 4 presents the percentage of efficient windows and the rate of changes over the consecutive quarters of the research period. The results consider all cryptocurrencies and all applied MDH tests. Similarly as in the case of Figure 3, the x-axis refers to the quarters in which the windows ended. The percentage of efficient windows varied between about 80% and 100%. Two plunges (falls) in efficiency can be observed. However, they were followed by a rapid recovery. The bottom of the first plunge can be observed in the 1st quarter of 2016. The percentage of the efficient windows decreased in this quarter to the aforementioned 80%. The bottom of the second plunge can be observed in the 3rd quarter of 2019. The level of efficient cases reached then about 85%. Also some trends were observable. There was a downtrend in the percentage of efficient windows from the first quarter presented up to the 1st quarter of 2016. Then up to the 4th quarter of 2017 a clear recovery took place. After that efficiency decreased up to the 3rd quarter of 2019. In the subsequent periods the percentage of efficient cases was in a moderate uptrend. The rate of changes varied between 0% and about 5%. It is difficult to indicate any long-term trend in the behaviour of this measure. However, it should be noted that the highest rates of changes occurred in the periods related with the lowest levels of the percentage of efficient windows.

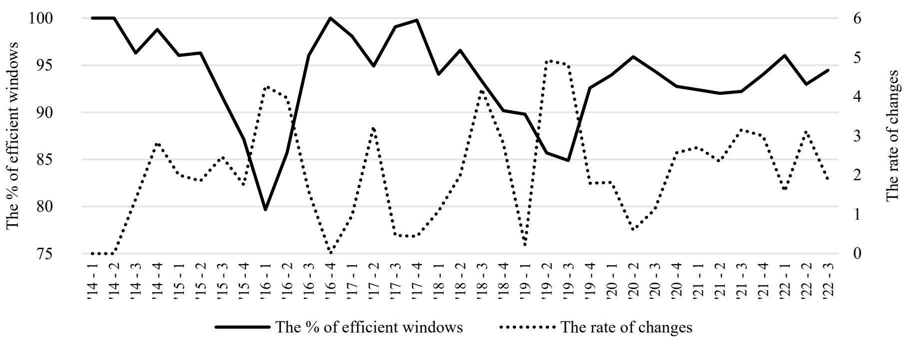

Figure 4. The percentage of efficient windows and the rate of changes over the quarters considering all cryptocurrencies all applied MDH tests

Source: Own work.

Referring to Figure 5 the trends in the percentage of efficient windows and especially its plunges observed in Figure 4, are difficult to explain with the behaviour of the average mean/median daily returns and the average standard deviation of daily returns. The foregoing studies raising the issue of the impact of market shocks and bear market on the weak-form efficiency of equity markets (e.g., Anagnostidis et al., 2016; Aslam et al., 2020; Cheong et al., 2007; Horta et al., 2014; Kian-Ping et al., 2007; Mensi, Sensoy et al., 2020; Mensi, Tiwari et al., 2017; Sensoy & Tabak, 2015) would suggest that

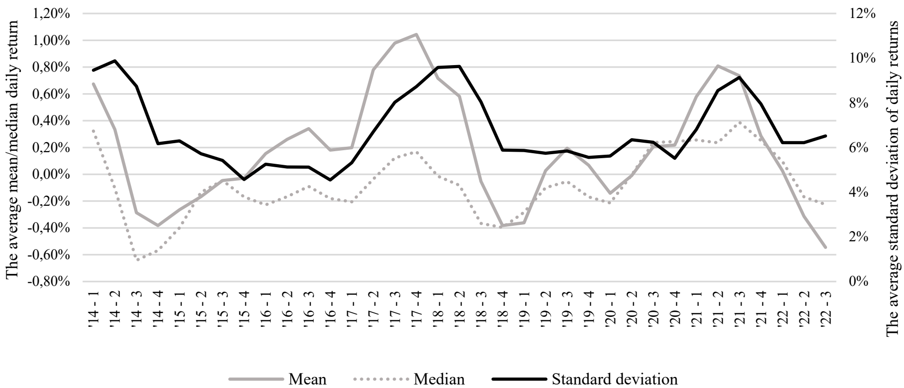

Figure 5. The average mean/median daily returns and the average standard deviation of daily returns over the quarters considering all cryptocurrencies and MDH tests

Source: Own work.

the decrease in efficiency could be most likely observed in the periods of low returns and high volatility. However, in the case of this study the decrease of efficiency cannot be associated with the decrease of returns and the increase of volatility.

In order to investigate the behaviour of cryptocurrency return predictability more deeply the top eight, middle eight and bottom eight cryptocurrencies in terms of the percentage of efficient windows were distinguished. Figure 6 presents the average percentage of efficient windows and the average rate of changes of the top, middle and bottom eight cryptocurrencies in terms of the percentage of efficient windows. The results presented in Figure 6 take into account all MDH tests applied and the entire research period. The results seem to confirm the right skewness of the percentage of efficient windows, as the bottom group is marked by a clearly lower percentage compared to the top and middle group. A highly negative rank correlation between the percentage of efficient windows and the rate of changes seems to be confirmed as well.

The results presented in Figure 7 show clear differences especially between the bottom group and two other groups, i.e., the top and middle groups. The percentage of efficient windows in the case of the top group oscillated between about 94% and 100%. In the case of the middle group the range was between about 87% and 100%. Starting from the windows that ended in the last quarter of 2019 the amplitude of the percentage of efficient windows for the middle and top groups has decreased. The stabilization of efficiency level in these groups can also be observed in the part of Figure 7 that pertains to the rate of changes. The percentage of efficient windows in these two groups has stabilised at a relatively high level. In the case of the bottom group

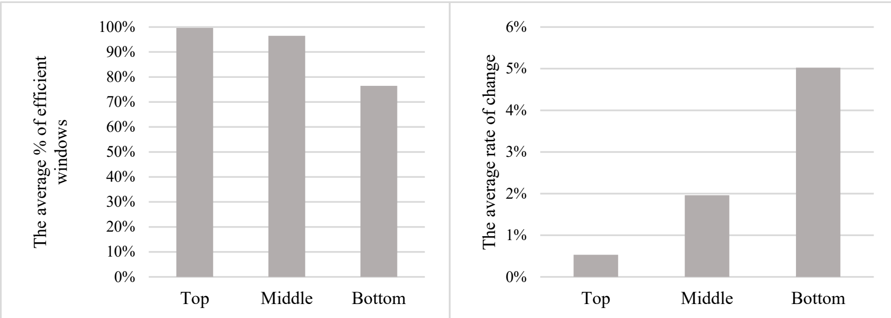

Figure 6. The average percentage of efficient windows and the average rate of changes of the top, middle and bottom eight cryptocurrencies in terms of the percentage of efficient windows

Source: Own work.

the percentage of efficient windows oscillated between about 2% and 100%. However, over the examined period, the percentage of efficient windows in this group seemed to gradually increase. Surprisingly in some periods the top group had even higher rate of changes compared to the middle group. The top group also had a higher rate of changes compared to the bottom group once (the 2nd quarter of 2019). It was also the second highest observation.

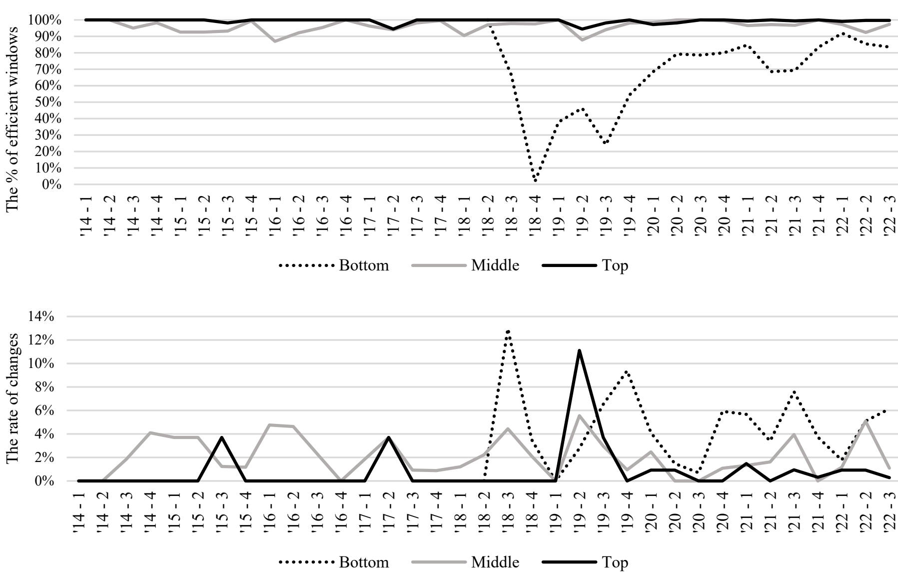

Figure 7. The percentage of efficient windows and the rate of changes of the top, middle, and bottom eight cryptocurrencies in terms of the percentage of efficient windows

Source: Own work.

In order to check whether there were any significant differences in return predictability between cryptocurrencies marked by the highest and the lowest market cap two groups of cryptocurrencies were distinguished. Each group consisted of ten cryptocurrencies. The first group comprised cryptocurrencies with the highest market cap. The second group comprised cryptocurrencies with the lowest market cap. Referring to Figure 8 the differences in the average percentage of efficient windows and the average rate of changes between the top ten and bottom ten cryptocurrencies do not appear to be substantial. The top group was efficient slightly more frequently and its efficiency status changed slightly less often.

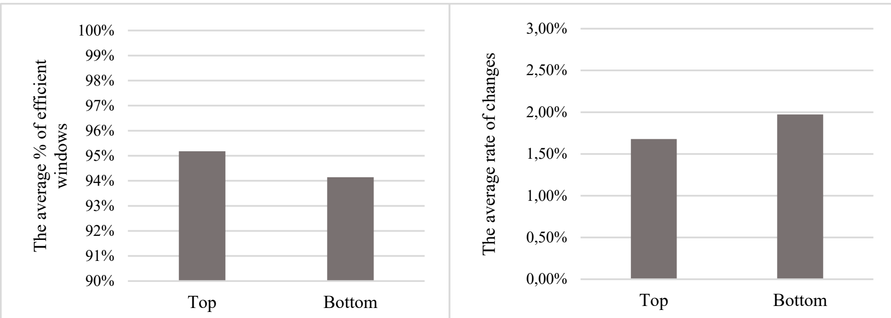

Figure 8. The average percentage of efficient windows and the average rate of change of the top and bottom ten cryptocurrencies in terms of market capitalization

Source: Own work.

The average results presented in Figure 8 suggesting just slight differences between the groups seem to be in line with the results presented in Figure 9 as both groups behaved quite similarly over the examined research period. Clearer differences started to appear since the 3rd quarter of 2021 when it comes to the percentage of efficient windows. However, a small number of divergent observations does not allow the drawing of any far-reaching conclusions regarding significant differences between the groups.

According to the results of this study the majority of examined cryptocurrencies turned out to be weak-form efficient in the majority of examined windows. According to all applied MDH tests, more than 85% of the examined cryptocurrencies were efficient in more than 85% of windows. Such results strongly contradict the results of the studies by Zhang et al. (2018), Yonghong et al. (2018), Hu et al. (2019), Bundi and Wildi (2019), Mensi, Lee et al. (2019) and Palamalai et al. (2021). According to these studies, the examined cryptocurrencies were inefficient in the entire examined research period. On the other hand the obtained results are in line with the studies by Nadarajah and Chu (2017), Tiwari et al. (2018), Zargar and Kumar (2019),

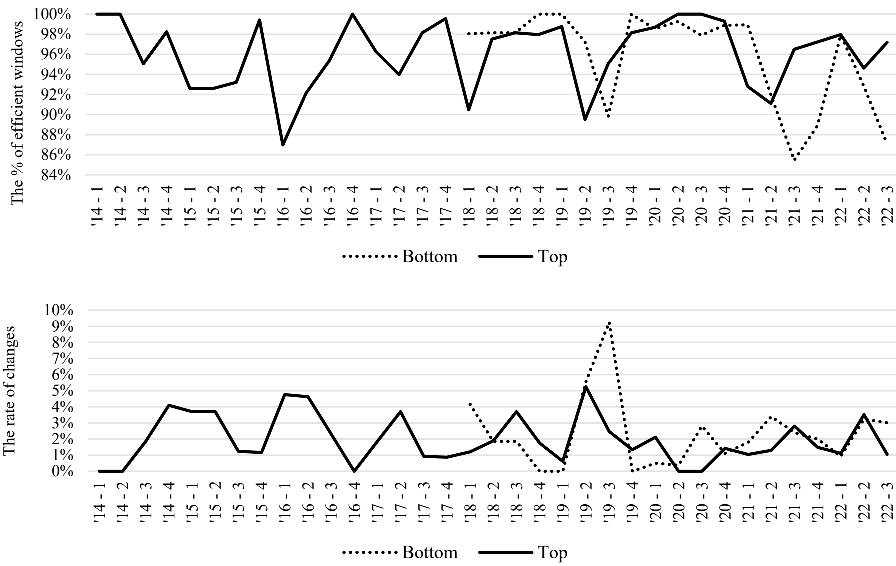

Figure 9. The percentage of efficient windows and the rate of changes of the top and bottom ten cryptocurrencies in terms of market capitalization

Source: Own work.

Hawaldar et al. (2019), and Apopo and Phiri (2021) who proposed that cryptocurrencies included in their samples were efficient for most of the time.

According to results obtained here, only four cryptocurrencies did not change their efficiency status. However, two of them had a marginal number of windows tested (Chain and ApeCoin). Considering all MDH tests applied 75% of cryptocurrencies changed their efficiency status in more than 1% of windows. About 53% of cryptocurrencies changed their efficiency status in more than 2% of windows. Results obtained in this study appear to validate AMH which was also validated in the studies by Caporale et al. (2018), Khuntia and Pattanayak (2018), Chu et al. (2019), Khursheed et al. (2020), Noda (2021) and López-Martín et al. (2021).

The results of this study also allowed the distinction of a moderate long-term trend in the percentage of efficient windows considering all examined cryptocurrencies which continued up to the end of the research period. This trend began in the windows that ended in the last quarters of 2019. The increase in the percentage of efficient windows which began in this period could also be observed in the group of cryptocurrencies marked by the lowest percentage of efficient windows. In the same period the efficiency of the group of most efficient cryptocurrencies started to stabilise as well. These observations suggest that in recent years the predictability in the cryptocurrency markets might decrease. Such conclusions would be in line with the conclusions of Urquhart (2016), Bariviera (2017), Sensoy (2019), Tran and Leirvik

(2020), Caporale et al. (2018), Khuntia and Pattanayak (2018), López-Martín et al. (2021) who proposed that cryptocurrencies may become more weak-form efficient over time. The opposite conclusions were proposed by Bundi and Wildi (2019).

Conclusions

The results of this study suggest that the majority of the examined cryptocurrencies were weak-form efficient for most of the time. However, a large part of them also suffered short periods of inefficiency. The results obtained indicate that the cryptocurrencies which were more frequently efficient tended to change their efficiency status (a change from efficiency to inefficiency and vice versa) less frequently. However, this rule did not apply to all cases. The time-varying predictability of daily returns in the cryptocurrency markets observed does not allow the rejection of the first research hypothesis which stated that the degree of predictability of cryptocurrency daily returns varied over time in line the AMH. Additionally, the observed high fraction of weak-form efficient windows across the majority of examined cryptocurrencies provides no grounds for rejecting the second research hypothesis stating that daily returns of the examined cryptocurrencies were unpredictable for most of the time.

The first supplementary research question referred to the significance of differences in return predictability between the examined cryptocurrencies. As mentioned above the majority of the examined cryptocurrencies were weak-form efficient for most of the time. However, a small fraction of the examined cryptocurrencies clearly had worse results in this matter. In addition, such cryptocurrencies usually changed their efficiency status more frequently compared to other currencies. However, this fraction of cryptocurrencies tended to clearly increase their efficiency over time. Filecoin, Hedera, Toncoin, Shiba Inu and Internet Computer can be considered the least frequently efficient. On the other hand Litecoin, NEAR Protocol, Flow, Chain and ApeCoin were the most frequently efficient. However, the results of Chain and ApeCoin should be approached with caution as their number of windows tested was very limited. Referring to the second supplementary research question which pertained to the existence of trends in the weak-form efficiency of the examined cryptocurrencies over time some of them could be distinguished. However, they could not be associated with the behaviour of market returns and volatility. The latest trend suggests that weak-form efficiency in the cryptocurrency markets may increase. This observation may be in line with the suggestions of many issue-related studies.

The third supplementary research question pertained to the significance of differences in return predictability between cryptocurrencies marked by the highest and the lowest market cap. The results obtained in this study suggest that the group of the most capitalized cryptocurrencies was more frequently efficient and changed its efficiency status less often, but these differences were only slight.

This study contributes to the body of knowledge pertaining to weak-form efficiency in cryptocurrency markets by providing a comprehensive insight on a relatively long history (compared to other issue-related studies) and a current state of daily return predictability in a broad sample of cryptocurrency markets. A broad sample of the 40 most capitalised cryptocurrencies examined seems to be one of the largest samples included in the issue-related studies. The application of such a broad sample allowed the examination of the issue, which is raised rarely, namely, the issue of differences in the behaviour of predictability in various cryptocurrency markets. Furthermore, this study investigated trends in predictability in cryptocurrency markets and possible differences in return predictability between cryptocurrencies with the highest and the lowest market cap. Such a comprehensive study may constitute a value to regulators and other market participants who want to learn about and control one of the most important features of properly operating markets, namely, weak-form efficiency. This study may also be helpful to investors who want to get to know if the market which they invest on constitutes a convenient investing environment which provides equal opportunities to all market participants and is immune to unprecedented shocks. However, the comprehensiveness of this study required some compromises. Due to a broad sample this study did not make an attempt to identify events that could be related with changes in the weak-form efficiency of cryptocurrencies. There are a few studies which made an attempt to do that, and they focused just on a few cryptocurrencies as such studies require an in depth analysis at the level of particular cryptocurrencies. Additionally, this study focused on the examination of the predictability of just daily returns. Some researchers proposed that for higher frequencies of data the predictability may also be higher. Thus future studies may also examine a broad sample of cryptocurrencies with the use of high-frequency data. Further considerations may also employ other predictability measures and make an attempt to determine factors affecting predictability in cryptocurrency markets.

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