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The weak-form efficiency of cryptocurrencies

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Abstract

This study aimed to examine the weak-form efficiency of some of the most capitalised cryptocurrencies. The sample consisted of 24 cryptocurrencies selected out of 30 cryptocurrencies with the highest market capitalisation as of October 19, 2022. Stablecoins were not considered. The study covered the period from January 1, 2018 to August 31, 2022. The results of robust martingale difference hypothesis tests suggest that the examined cryptocurrencies were efficient most of the time. However, their efficiency turned out to be time-varying, which validates the adaptive market hypothesis. No evidence was found for the impact of the coronavirus outbreak and the Russian invasion of Ukraine on the weak-form efficiency of the examined cryptocurrencies. The differences in efficiency between the most efficient cryptocurrencies and the least efficient ones were noticeable, but not large. The results also allowed to observe some slight differences in efficiency between the cryptocurrencies with the largest market cap and cryptocurrencies with the lowest market cap. However, the differences between the two groups were too small to draw any far-reaching conclusions about a positive relationship between the market cap and efficiency. The obtained results also did not allow us to detect any trends in efficiency.

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Keywords

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

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Introduction

Despite a relatively short history of cryptocurrencies, the issue of their weak-form efficiency in the sense of Fama (1970) attracted much interest from the academics. Researchers willingly verify the weak-form efficiency of cryptocurrencies that are considered speculative and high yield assets traded on online platforms, and (mostly) not in organised, law-abiding venues (Arouxet et. al., 2022). According to the weak form of the efficient market hypothesis (EMH), first proposed by Fama (1965) and Samuelson (1965), it is impossible to predict asset returns on a regular basis, as asset prices reflect all available and relevant information fully and instantaneously. A properly functioning market is believed to be informationally efficient, as under the conditions of informational efficiency market participants have equal chances (Mensi et al., 2019). Early studies devoted to the examination of the weak-form efficiency in cryptocurrency markets (e.g., Urquhart, 2016) proposed that the efficiency of different cryptocurrencies may vary and evolve over time. The inconsistent results obtained in those studies led to the adaptive market hypothesis (AMH) proposed by Lo (2004). According to Lo (2004, 2005), the efficiency of markets can change due to changing market conditions. Thus, efficiency should not be considered a stable feature of the market, as it can change over time. The foregoing studies directly addressing the AMH in cryptocurrency markets appeared to validate it (e.g. Khursheed et al., 2020; López-Martín et al., 2021; Noda, 2021).

This study aims to examine the weak-form efficiency of some of the most capitalised cryptocurrencies. Additionally, the study employs dynamic methods to weak-form efficiency testing in order to verify the AMH in cryptocurrency markets. Taking into account the occurrence of globally relevant crisis events in recent years, such as the coronavirus outbreak and the Russian invasion of Ukraine, this study also examines the impact of these events on the weak-form efficiency of cryptocurrencies. The possible change in the weak-form efficiency in the examined cryptocurrency markets directly relates to the AMH, which assumes that efficiency may change in response to such extreme events. Issue-related studies pertaining to the impact of the coronavirus outbreak on the weak-form efficiency of cryptocurrencies mostly suggest that the pandemic onset negatively affected the weak-form efficiency in cryptocurrency markets (e.g. Alvarez-Ramirez & Rodriguez, 2021; Kakinaka & Umeno, 2022; Mandaci & Cagali, 2022; Naeem et al., 2021; Usman & Nduka, 2022). Due to the recency of the Russian invasion of Ukraine, not many studies on the impact of this crisis event on the weak-form efficiency of different markets managed to be published. The existing literature suggests that the impact of the Russian invasion of Ukraine on the weak-form efficiency of markets was mostly negative; however, these studies do not pertain to cryptocurrency markets (e.g. Aslam et al., 2022; Gaio et al., 2022).

The first assumed research hypothesis states that the AMH is valid in relation to the weak-form efficiency of the examined cryptocurrencies. The second assumed research hypothesis states that most of the time the examined cryptocurrencies were efficient. The third research hypothesis states that the latest crisis events, such as the coronavirus outbreak and the Russian invasion of Ukraine, decreased the weak-form efficiency of the cryptocurrency markets examined. What is more, this study tries to find out whether there were any significant differences in efficiency between the examined cryptocurrencies, as well as whether there were any significant differences in efficiency between the cryptocurrencies featured by the largest and the lowest market caps.

In order to examine the behaviour of the weak-form efficiency of selected cryptocurrencies, the martingale difference hypothesis (MDH) was verified with the use of two robust 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). With the use of the rolling window method, these tests were conducted for 24 cryptocurrencies selected out of 30 cryptocurrencies with the highest market capitalisation as of October 19, 2022. The research sample did not include stablecoins. The MDH tests were conducted for daily returns in 2-month windows with 1-month rolling. Other studies related to this issue usually applied longer windows; however, in the case of this study, the application of longer windows could disenable the observation of a possible reaction of cryptocurrency markets on crisis events. This study covers the period from January 1, 2018 to August 31, 2022. This relatively short research period, which includes just several recent years, was selected in order to examine a broad sample of cryptocurrencies.

1. Literature review

In several studies raising the issue of the weak-form efficiency of cryptocurrencies, researchers pointed out that efficiency should be examined dynamically, as it can vary over time (e.g., Chu et al., 2019; Khuntia & Pattanayak, 2018; Khursheed et al., 2020; López-Martín et al., 2021; Noda, 2021; Sensoy, 2019; Tran & Leirvik, 2020). Some of the studies directly referred to the adaptive market hypothesis (e.g. Chu et al., 2019; Khuntia & Pattanayak, 2018; Khursheed et al., 2020; Noda, 2021). According to Khuntia and Pattanayak (2018), López-Martín et al. (2021), Sensoy (2019), Tran and Leirvik (2020) and Urquhart (2016), the efficiency of cryptocurrencies may increase over time. Bundi and Wildi (2019) proposed the opposite. Some of the studies indicated that the cryptocurrency markets were inefficient in the entire research period (e.g. Hu et al., 2019; Palamalai et al., 2021; Yonghong et al., 2018; Zhang et al., 2018). The studies proposing the opposite results seem to be in minority (e.g. Hawaldar et al., 2019; Nadarajah & Chu, 2017). Apopo and Phiri (2021) received inconsistent results dependent on the frequency of the examined returns.

Several papers on the reaction of the weak-form efficiency of cryptocurrency markets on the coronavirus outbreak have already been published. They all seem to suggest that the weak-form efficiency of cryptocurrency markets was affected by this crisis event (Alvarez-Ramirez & Rodriguez, 2021; Arouxet et. al., 2022; Assaf et al., 2022a, 2022b; Kakinaka & Umeno, 2022; Mandaci & Cagali, 2022; Naeem et al., 2021; Usman & Nduka, 2022). Most of them directly suggest a negative impact, namely, a decrease in efficiency after the onset of the coronavirus pandemic (Alvarez-Ramirez & Rodriguez, 2021; Kakinaka & Umeno, 2022; Mandaci & Cagali, 2022; Naeem et al., 2021; Usman & Nduka, 2022). Kakinaka and Umeno (2022) propose that the negative impact was limited just to a certain short term. In the long run, the impact was insignificant. Due to the recency of the Russian invasion of Ukraine, at this time, the body of knowledge is limited to the studies on the impact of this crisis event on the weak-form efficiency of other markets, such as equity markets or energy markets. The existing literature mostly suggests a negative impact of this crisis event (Aslam et al., 2022; Gaio et al., 2022).

Hawaldar et al. (2019) examined the weak-form efficiency of Bitcoin and Litecoin in the years 2013-2017 with the use of some popular stationarity tests such as the ADF test, PP tests and KPSS test. On the basis of the results obtained, the authors suggested that the daily returns of the examined cryptocurrencies followed a random walk and they were efficient in a weak form. A similar set of tests was applied by Apopo and Phiri (2021) in the study on the weak-form efficiency of Bitcoin, Ether, Bitcoin Cash, Litecoin and Ripple. However, the researchers supplemented their study with some more advanced stationarity tests such as the DF-GLS test, Ng-Perron test, KSS test and LM test with the flexible Fourier form. The tests were conducted for daily and weekly returns in the years 2009–2019. The tests conducted for daily returns suggested the weak-form efficiency of the examined cryptocurrencies. In the case of weekly returns, the opposite was true. Urquhart (2016) examined the weak-form efficiency of Bitcoin in the years 2010-2016 with the use of a battery of randomness tests. The obtained results suggested that, when considering the entire research period, the daily returns of Bitcoin did not appear to be random. The entire research period was also divided into two even subperiods. Some tests indicated that Bitcoin was efficient in the latter part of the period. The author suggested that Bitcoin might move towards efficiency. A study by Nadarajah and Chu (2017) constitutes the discussion with the aforementioned study by Urquhart (2016). The authors replicated it and proposed that a simple power transformation of daily returns was sufficient to satisfy the efficient market hypothesis. The authors also proposed that the transformation did not cause any loss of information.

Zhang et al. (2018) made an attempt to examine the efficiency of nine cryptocurrencies, i.e. Bitcoin, Ripple, Ether, NEM, Stellar, Litecoin, Dash, Monero and Verge, in the period between April 2013 and January 2018. The researchers applied many different tests to daily cryptocurrency returns, including the generalised multifractal detrended fluctuation analysis and multifractal detrended cross-correlation analysis. Based on the results obtained, the researchers proposed that all examined cryptocurrencies were inefficient. Yonghong et al. (2018) investigated a long-term memory in the time series of Bitcoin returns. They applied the generalised Hurst exponents to daily returns of Bitcoin in the period between December 2010 and November 2017. The researchers proposed that the long-term memory was observed and the Bitcoin market was featured by high inefficiency. Bitcoin did not become more and more efficient over time. Hu et al. (2019) examined daily returns of 31 cryptocurrencies between August 16, 2017 and January 16, 2019. The examined cryptocurrencies were selected from the top 50 cryptocurrencies considering the market cap. According to panel unit root/stationarity tests, the examined cryptocurrencies turned out to be inefficient. Palamalai et al. (2021) focused on the top ten cryptocurrencies in terms of market capitalisation as of August 5, 2019, which had been traded for more than 2 years. To examine the efficiency of the selected cryptocurrencies, the researchers applied several non-parametric tests such as the Runs test, Kolmogorov-Smirnov test and parametric tests such as unit root tests, a multiple variance ratio test and GARCH-type models. The examined research period varied across cryptocurrencies. The results of the study suggested that the examined cryptocurrencies were weak-form inefficient. In order to examine the weak-form efficiency of Bitcoin, Bundi and Wildi (2019) applied trading strategies based on moving average filters, classic time series models and non-linear neural nets. The study conducted for the period between April 2014 and January 2019 suggested that the trading performance of the applied strategies was significantly positive. The researchers proposed that Bitcoin was becoming less efficient.

Sensoy (2019) examined the weak-form efficiency of Bitcoin at the high-frequency level with the use of permutation entropy. The study was conducted in the period between January 2013 and March 2018. The results of the study suggested that Bitcoin became more efficient since the beginning of 2016. Moreover, the researcher proposed that the increase of frequency decreased efficiency. Additionally, it turned out that liquidity had a positive effect on the informational efficiency of Bitcoin. The opposite was true in the case of the effect of volatility. Tran and Leirvik (2019) proposed a method to quantify the level of the weak-form market efficiency, that is, Adjusted Market Inefficiency Magnitude. This measure was used in their study (Tran & Leirvik, 2020) on the efficiency of the top five cryptocurrencies in terms of market cap. The authors examined daily returns of Bitcoin, Ether, Ripple, Litecoin and EOS in the period between April 2013 and February 2019. The authors proposed that the level of efficiency was highly time-varying. The cryptocurrencies turned out to be mostly inefficient, especially before 2017. However, their efficiency increased over time in the period between 2017 and 2019. López-Martín et al. (2021) aimed to examine the weak-form efficiency of Bitcoin, Litecoin, Ether, Ripple, Stellar and Monero. Daily returns from the period between August 2015 and December 2019 were tested with the use of five different tests commonly applied in studies related to this issue, including the automatic variance test of Choi and the Hurst exponent. The tests were applied in a dynamic context as well. A clear increase in efficiency over time was observed in the case of Bitcoin, Litecoin and Ether. In the case of the remaining cryptocurrencies, the efficient periods alternated with inefficient periods.

Khuntia and Pattanayak (2018) made an attempt to verify the adaptive market hypothesis in relation to the weak-form efficiency of the Bitcoin market in the period between July 2010 and December 2017. The researchers examined daily returns using the MDH tests such as the Dominguez-Lobato test and Generalized Spectral test in rolling windows. The researchers proposed that the efficiency of Bitcoin tended to evolve over time. Chu et al. (2019) aimed to examine the adaptive market hypothesis with reference to the weak-form efficiency of Bitcoin and Ether in the period between July 2017 and September 2018. The martingale difference hypothesis was verified with the use of the Dominguez-Lobato test. The test was applied to high-frequency data. The researchers proposed that their results were consistent with the AMH, as the efficiency of both examined cryptocurrencies varied over time. Khursheed et al. (2020) aimed to verify the adaptive market hypothesis in relation to the time-varying market efficiency of such cryptocurrencies as Bitcoin, Monaro, Litecoin and Steller over the research period of 2014–2018. To examine the martingale difference hypothesis, they applied the Generalized Spectral test, Dominguez-Lobato test and automatic portmanteau test. The researchers proposed that the efficiency changes were noticeable and that Bitcoin, Monaro and Litecoin had the longest periods of efficiency. Steller turned out to have the longest inefficiency periods. Noda (2021) aimed to examine the adaptive market hypothesis with reference to the weak-form efficiency of Bitcoin and Ether in the period between April 2013 and September 2019. The researcher applied the GLS-based time-varying autoregressive model to daily returns. The results of the study suggested that the efficiency of both cryptocurrencies varied over time, and over most periods, Bitcoin was more efficient compared to Ether.

2. Data and research methodology

This study examines the weak-form efficiency of 24 cryptocurrencies selected out of 30 cryptocurrencies featured by the highest market capitalisation as of October 19, 2022, according to Yahoo Finance. The selected cryptocurrencies are as follows: Bitcoin, Ether, Binance Coin, XRP, Cardano, Solana, Dogecoin, Polygon, Polkadot, TRON, HEX, Shiba Inu, Uniswap, Wrapped Bitcoin, Avalanche, Lido Staked ETH, UNUS SED LEO, Litecoin, Cosmos, Chainlink, Ether Classic, FTX Token, Stellar and Cronos. They were listed in descending order in terms of market cap. The research sample does not include stablecoins. This study covers the period from January 1, 2018 to August 31, 2022. In order to examine the weak-form efficiency, this study verifies the martingale hypothesis, according to which, the returns of cryptocurrencies should constitute martingale increments. Taking into account the stylised facts of cryptocurrency returns, the assumption that cryptocurrency returns constitute martingale increments is much more general and better suited to their distribution compared to the strict assumption stating that returns are i.i.d. with a 0 expected value (Campbell et al., 1997; Linton, 2019).

This study employs two tests for the martingale difference hypothesis (MDH), 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). According to Charles et al. (2011), both tests constitute significant recent contributions to the group of the MDH tests. The tests were applied to daily logarithmic returns calculated for closing prices related to USD retrieved from Stooq.pl and Finance.yahoo.com.

Both MDH tests were performed for each cryptocurrency with the use of the rolling window method. This method allows to examine the behaviour of efficiency over time. The tests were conducted for two-month windows with one-month rolling, that is, the next window began one month after the beginning of the previous window. The calculations were made only if a given window had at least 80% of the maximum number of daily returns. Most studies related to this issue applied longer windows. However, the application of longer windows could disenable the observation of a possible impact of crisis events on the weak-form efficiency in cryptocurrency markets. Shorter windows should not constitute a problem, as the applied MDH tests show no size distortion in small samples. The first window stared on January 1, 2018. The last window ended on August 31, 2022. In the case of some cryptocurrencies, not all windows were examined. Markets for some cryptocurrencies were launched after January 1, 2018. In some cases, it was also due to the limitations of the applied databases.

The applied MDH tests were performed in R. The automatic Portmanteau test for serial correlation proposed by Escanciano and Lobato (2009) was applied with the use of the function Auto.Q from the package vrtest. The wild bootstrapped automatic variance ratio test under conditional heteroskedasticity proposed by Kim (2009) was applied with the use of the function AutoBoot.test from the package vrtest. 500 wild-bootstrap iterations using a standard normal distribution were applied. Both MDH tests used a significance level of $\alpha = 0.05$.

3. Results and discussion

Table 1 presents the summary results of the MDH tests for each cryptocurrency, taking into account all windows tested in the entire research period. The results of the MDH tests are presented as the percentage of efficient windows, i.e. the percentage of windows in which the wild bootstrapped automatic variance ratio test (AVR) and the automatic Portmanteau test for serial correlation (AP) indicated the efficiency of cryptocurrencies. The table also presents the number of windows tested and some descriptive statistics pertaining to daily returns, averaged across all windows tested. The order of cryptocurrencies is related to their market cap. The order is descending, that is, Bitcoin had the highest market cap, and Cronos the lowest.

Substantial differences between mean and median daily returns do not allow to unambiguously indicate the most profitable and the least profitable cryptocurrencies. Clear differences between the mean and median suggest that the distributions of cryptocurrency returns were mostly non-normal. Thus, the randomness tests assuming the i.i.d. returns with a 0 expected value are non-applicable in the case of this study. Regarding the obtained standard deviations, cryptocurrencies such as Polygon, Shiba Inu and Solana can be considered to be the most volatile ones. On the other hand, UNUS SED LEO, Bitcoin and FTX Token can be considered as the least volatile ones.

The percentages of the efficient windows (windows in which the MDH tests indicated the efficiency) in the majority of cases were high and exceeded 90%. This suggests that most of the time, the majority of the examined cryptocurrencies remained weak-form efficient. The differences between the results of both tests do not appear to be substantial.

Figure 1 presents the percentage of windows in which the MDH tests indicated the efficiency of cryptocurrencies. However, in order to further investigate the differences in efficiency between cryptocurrency markets, the figure shows only results for four most efficient and four least efficient cryptocurrencies, taking into account the results of both MDH tests in the entire research period. Only cryptocurrencies with data beginning at least in January 2020 were considered.

Table 1. Descriptive statistics of daily returns, percentage of efficient windows and number of windows tested

No.	Cryptocurrency	Mean (%)	Median (%)	Standard deviation (%)	AVR (%)	AP (%)	Windows tested
1	Bitcoin	0.04	0.15	3.74	98	96	55
2	Ether	0.04	0.12	4.82	100	98	55
3	Binance Coin	0.21	0.08	5.33	100	96	55
4	XRP	–0.09	–0.18	5.33	95	98	55
5	Cardano	–0.01	–0.24	5.67	98	98	55
6	Solana	0.45	0.20	7.64	100	96	28
7	Dogecoin	0.13	–0.40	6.14	89	93	55
8	Polygon	0.38	0.01	7.78	97	92	39
9	Polkadot	0.06	–0.07	6.49	100	96	23
10	TRON	0.02	0.07	5.62	98	96	55
11	HEX	–0.26	0.49	7.29	100	100	2
12	Shiba Inu	0.13	–0.54	7.68	92	92	13
13	Uniswap	0.13	0.13	6.92	100	95	22
14	Wrapped Bitcoin	0.08	0.06	5.68	76	74	34
15	Avalanche	0.25	0.03	7.52	95	82	22
16	Lido Staked ETH	0.25	–0.02	5.86	100	100	2
17	UNUS SED LEO	0.12	0.09	2.67	92	89	37
18	Litecoin	–0.07	–0.07	5.13	98	96	55
19	Cosmos	0.07	–0.05	6.32	100	97	39
20	Chainlink	0.15	–0.05	6.54	96	95	55
21	Ether Classic	0.02	–0.05	5.83	95	98	55
22	FTX Token	0.26	0.31	4.49	94	94	36
23	Stellar	–0.08	–0.24	5.44	98	95	55
24	Cronos	0.07	0.25	5.40	98	88	40

Source: author's own study.

Taking into account all windows tested, Ether, Cosmos, Solana and Binance Coin turned out to be most efficient. The differences between these cryptocurrencies are not substantial, the same as the differences between the results of the two MDH tests for particular cryptocurrencies. It looks a bit different in the case of the four least efficient cryptocurrencies, i.e. Dogecoin, UNUS SED LEO, Avalanche and Wrapped Bitcoin. The differences between these cryptocurrencies are more clear. In the case of Avalanche, the difference between the results of the two MDH tests is substantial. Regarding the differences in efficiency between the two compared groups, they are noticeable, but they are not large.

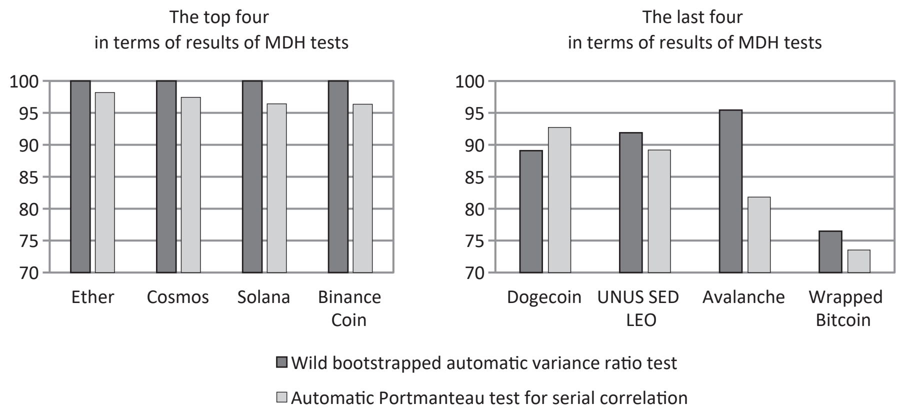

Figure 1. Percentage of efficient windows. Results only for four most efficient and four least efficient cryptocurrencies (in %)

Source: author's own study.

The presentation of data in Figure 2 is similar to the presentation of data in Figure 1. However, this time, in order to investigate possible differences in efficiency between the most and the least capitalised cryptocurrency markets, the data refer to four cryptocurrencies with the largest market capitalisation and four cryptocurrencies with the lowest market capitalisation. Some differences can be observed in the level of efficiency between the two groups. Cryptocurrencies with the largest market cap seem to be slightly more efficient compared to cryptocurrencies with the lowest market cap. However, it should be noticed that the differ-

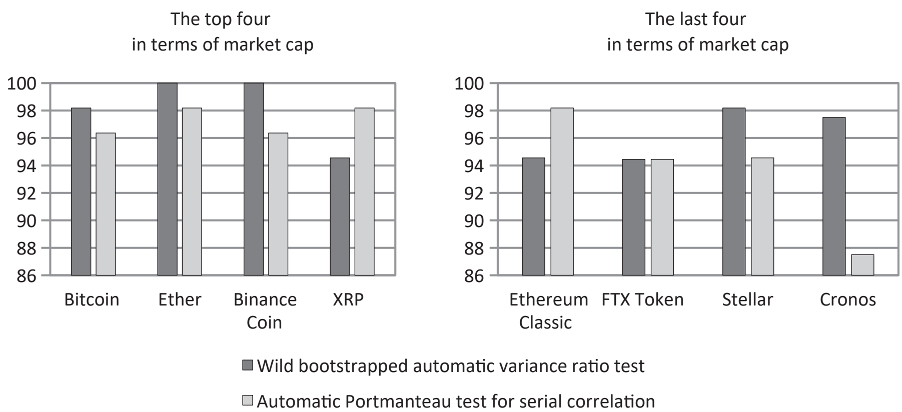

Figure 2. Percentage of efficient windows. Results only for four cryptocurrencies with largest market cap and four cryptocurrencies with lowest market cap (in %)

Source: author's own study.

ences between the two groups are too small to draw any far-reaching conclusions about the positive relation between market cap and efficiency.

Figure 3 allows us to observe the time-varying behaviour of the mean and median daily returns, as well as the standard deviation of daily returns of the examined cryptocurrencies. The statistics were averaged across all examined cryptocurrencies and windows ended in each quarter of the research period (for a clearer presentation of results). It is difficult to find any long-term trends in the performance of the cryptocurrency market. However, it is possible to distinguish several peaks and plunges. A very clear increase of risk-unadjusted returns can be observed in the 2nd quarter of 2019 and 1st quarter of 2021. Nevertheless, they were followed by severe plunges. Some of the largest decreases in risk-unadjusted returns can be observed from the 4th quarter of 2021 to 2nd quarter of 2022. This period was also related to the beginning of the Russian aggression against Ukraine. In the following quarter, the returns recovered rapidly. At the beginning of the research period, the volatility of the cryptocurrency market decreased substantially. It seemed to be at a stable level over the examined research period, except for the aforementioned 1st quarter of 2021 and the quarter that followed it, when the volatility clearly increased.

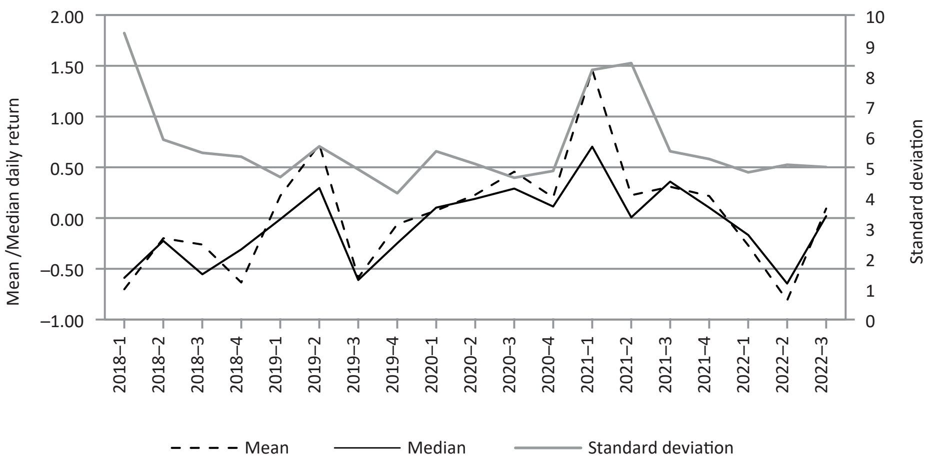

Figure 3. Descriptive statistics of daily returns averaged across all examined cryptocurrencies and windows tested in each quarter of research period (in %)

Source: author's own study.

Figure 4 shows how the efficiency of all examined cryptocurrencies behaved over particular quarters. In the majority of considered quarters, the differences between the results of both MDH tests were not substantial. However, some periods of clear divergence between the results of the MDH tests can also be observed.

For instance, the 1st quarter of 2019 and 4th quarter of 2021. The percentages of efficient windows, according to both tests, were in range between 85% and 100%. The results obtained allow us to state that the cryptocurrency markets were efficient in the great majority of cases. According to the results of this study, the efficiency was time-varying. However, it is very difficult to observe any long-term trends. In addition, no significant changes in the percentage of efficient windows could be observed in the periods related to the outbreak of the coronavirus pandemic and the Russian aggression against Ukraine.

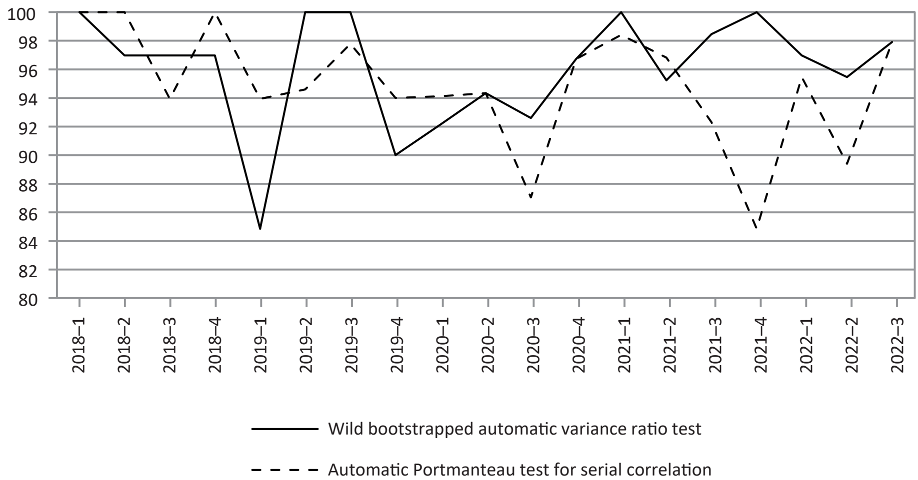

Figure 4. Percentage of efficient windows considering all examined cryptocurrencies (in %)

Source: author's own study.

In order to investigate possible differences in efficiency between the most and the least capitalised cryptocurrency markets, Figure 5 refers to the results of the MDH tests, but only for the top four and last four cryptocurrencies in terms of market cap. Cryptocurrencies with the lowest market cap suffered decreases in efficiency slightly more often. Again, the obtained results for both groups allow us to state that, in the great majority of cases, the cryptocurrency markets were efficient. In addition, the efficiency in both groups was time-varying. However, it is difficult to observe any long-term trends. In addition, no clear evidence can be found for the impact of the coronavirus pandemic and the Russian aggression against Ukraine on the weak-form efficiency of both groups.

The results of this study validate the adaptive market hypothesis, as the efficiency of the examined markets was time-varying, similarly as in the studies by Chu et al. (2019), Khuntia and Pattanayak (2018), Khursheed et al. (2020) and Noda

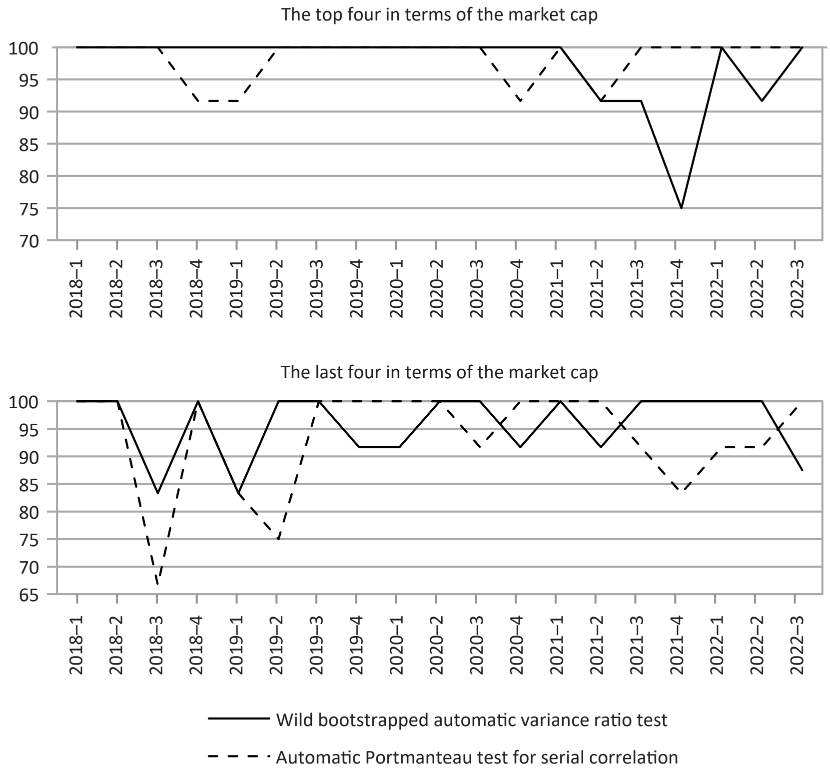

Figure 5. Percentage of efficient windows for top four and last four examined cryptocurrencies in terms of market capitalisation (in %)

Source: author's own study.

(2021). In line with the studies by Apopo and Phiri (2021), Hawaldar et al. (2019) and Nadarajah and Chu (2017), the examined cryptocurrencies turned out to be efficient most of the time. However, these results are not in line with the studies by such authors as Hu et al. (2019), Palamalai et al. (2021), Yonghong et al. (2018) and Zhang et al. (2018), according to whom, cryptocurrencies were inefficient.

The results received in this study may be associated with the results of the studies by Khuntia and Pattanayak (2018), López-Martín et al. (2021), Sensoy (2019), Tran and Leirvik (2020) and Urquhart (2016). According to these researchers, some cryptocurrencies tended to become more efficient over time. The end of their research periods was usually earlier compared to the beginning of the research period examined in this study. Thus, this study may examine the period of relatively high efficiency of cryptocurrencies. In addition, as opposed to the studies by Bundi and Wildi (2019), Khuntia and Pattanayak (2018), López-Martín et al.

(2021), Sensoy (2019) and Tran and Leirvik (2020), the obtained results did not allow to detect any trends in efficiency. However, this may result from the examination of different research periods.

Referring to the impact of the coronavirus outbreak on the weak-from efficiency of the cryptocurrency markets, this study provided no evidence of any clear reaction of the weak-from efficiency in the examined cryptocurrency markets. Thus, the results obtained in this study are not in line with most studies related to this topic (Alvarez-Ramirez & Rodriguez, 2021; Arouxet et. al., 2022; Assaf et al., 2022a, 2022b; Kakinaka & Umeno, 2022; Mandaci & Cagli, 2022; Naeem et al., 2021; Usman & Nduka, 2022). However, some similarities can be found in the study of Kakinaka and Umeno (2022) who examined hourly returns and found no significant impact of the coronavirus onset in the long run. It is also worth noting that many related studies focused on shorter intervals than daily (Arouxet et. al., 2022; Assaf et al., 2022a; Kakinaka & Umeno, 2022; Naeem et al., 2021). Thus, they could observe some short-term intra-day changes in efficiency. In addition, this study found no evidence for a clear impact of the recent Russian invasion of Ukraine on the weak-from efficiency in the examined cryptocurrency markets. These conclusions are not in line with a few other studies on other markets (Aslam et al., 2022; Gaio et al., 2022).

Conclusions

This study aimed to examine the weak-form efficiency of some of the most capitalised cryptocurrencies. The results of this study suggest that the examined cryptocurrencies were efficient most of the time. However, their efficiency turned out to be time-varying, which validates the AMH. The weak-form efficiency of the examined cryptocurrencies seemed to be immune to the latest crisis events, such as the coronavirus outbreak and the Russian invasion of Ukraine. The results obtained suggest that Ether, Cosmos, Solana and Binance Coin were the most frequently efficient cryptocurrencies. On the other hand, Dogecoin, UNUS SED LEO, Avalanche and Wrapped Bitcoin were the least frequently efficient ones. The differences in efficiency between the most efficient cryptocurrencies and the least efficient ones were noticeable, but not large. The results also allowed us to observe slight differences in efficiency between cryptocurrencies with the largest market cap and cryptocurrencies with the lowest market cap. However, the differences between the two groups were too small to draw any far-reaching conclusions about a positive relation between market cap and efficiency. The obtained results also did not allow us to detect any trends in efficiency.

The research period examined in this study covers just several recent years. It is caused by the intention to include a relatively large sample of cryptocurrencies. The selection of the research period could have affected the obtained results, as some related studies that covered earlier periods suggested the increase in efficiency of some cryptocurrencies. This may justify obtaining a relatively high rate of efficient windows. Future studies may implement other robust methods of efficiency evaluation. In addition, they may also examine data of higher frequencies. Further investigations related to the efficiency of cryptocurrencies should consider finding factors of efficiency and important variables which are correlated with it.

This study contributes to the development of a body of knowledge pertaining to the adaptive market hypothesis in relation to weak-form efficiency of the cryptocurrency market. It may be valuable to regulators and market participants who want to learn about the recent behaviour of efficiency on the cryptocurrency markets. The weak-form efficiency of a numerous sample of cryptocurrencies was examined with the use of robust MDH tests in several recent years, in which the efficiency could have been affected by some crisis events such as the coronavirus outbreak and the Russian aggression against Ukraine.

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