Empirical Paper

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Is the cryptocurrency market efficient? Evidence from an analysis of fundamental factors for Bitcoin and Ethereum

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Abstract: This article sheds new light on the informational efficiency of the cryptocurrency market by analyzing investment strategies based on structural factors related to on-chain data. The study aims to verify whether investors in the cryptocurrency market can outperform passive investment strategies by applying active strategies based on selected fundamental factors. The research uses daily data from 2015 to 2022 for the two major cryptocurrencies: Bitcoin (BTC) and Ethereum (ETH). The study applies statistical tests for differences. The findings indicate informational inefficiency of the BTC and ETH markets. They seem consistent over time and are confirmed during the COVID-19 pandemic. The research shows that the net unrealized profit/loss and percent of addresses in profit indicators are useful in designing active investment strategies in the cryptocurrency market. The factor-based strategies perform consistently better in terms of mean/median returns and Sharpe ratio than the passive "buy-and-hold" strategy. Moreover, the rate of success is close to 100%.

Keywords: active strategies, cryptocurrency, fundamental factors, informational efficiency, Ledoit and Wolf test
JEL Classification: F31, G11, G15

1 Introduction

In the literature, divergent views on the informational efficiency of the cryptocurrency market exist. Yonghong et al. [2018] have not found the Bitcoin (BTC) market informationally efficient. Some researchers have showed that with time, it may be heading toward efficiency, and there are periods when it was informationally efficient [see e.g. Urquhart, 2016; Vidal-Tomás and Ibañez, 2018; Sensoy, 2019]. Another strand of the literature suggests that periods in which it can be considered efficient are intertwined with periods in which it is not efficient [see e.g. Alvarez-Ramirez et al., 2018; Khuntia and Pattanayak, 2018]. There are also authors who examine a wider group of cryptocurrencies, and there are indications that most of them are not informationally efficient [see e.g. Caporale et al., 2018; Hu et al., 2019; Kristoufek and Vosvrda, 2019].

A deviation from the efficient market hypothesis (EMH) [Fama, 1970] implies that the path of the price development for cryptocurrencies contains long-lasting asset bubbles as they cannot be quickly

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eliminated by rational investors who are able to estimate the fundamental price of assets. However, for the cryptocurrency market, with BTC at its core, the measurement of intrinsic value is highly disputable. On the one hand, researchers indicate that BTC has no fundamental value [Cheah and Fry, 2015]. Moreover, Detzel et al. [2021] have noted that the fundamental source of intrinsic value of cryptocurrencies remains unclear. The authors also have added that the fundamentals of cryptocurrencies have few, if any, predictive signals that would be publicly available (e.g. analyst coverage and accounting statements). On the other hand, some researchers suggest that, in a sense, demand and supply in this market can be considered fundamental factors [Gbadebo et al., 2021], sometimes giving priority to demand indicators [Li and Wang, 2017] or supply indicators such as the cost of mining [Hayes, 2017]. Regardless of the view, the lack of informational efficiency of the market induces that there are investment strategies that generate extraordinary returns over a prolonged period.

The aim of this study is to verify whether investors in the cryptocurrency market can make excess returns by applying strategies based on fundamental factors. The study specifically investigates whether factor-based trading strategies generate higher returns than the passive "buy-and-hold" strategy, which is popular among investors known as "hodlers".[1] It should be noted that fundamental value and its indicators in the cryptocurrency market are highly debatable. The fundamental indicators analyzed in this study can be used to describe the structure of the cryptocurrency market. The examined set of indicators includes the net unrealized profit/loss (NUPL), the spent output profit ratio (SOPR), and the percent of addresses in profit (PAP). The study applies statistical tests for differences by Ledoit and Wolf [2008, 2018].

The analysis is based on daily data sourced from the Glassnode database for the period starting on 8 August 2015 and ending on 20 October 2022. The study calculates rates of returns and their volatility for several strategies based on fundamental (structural) factors for BTC and Ethereum (ETH). These cryptocurrencies have been selected based on two factors – their significant role in the ecosystem – taking account of volume as well as capitalization, and the availability of data.[2] The performance measurement for these strategies is based on mean/median returns and the Sharpe ratio. Furthermore, the study verifies whether there are any differences between the pre-pandemic and COVID-19 periods. The study investigates the consistency of conclusions drawn for the main sample period (2015–2019) in the out-of-sample period. The usefulness of fundamental factors in making investment decisions is verified in the COVID-19 period (2020–2022). This allows checking the consistency of the results across different economic and social environments.

To deepen the understanding of the cryptocurrency market and its efficiency, two research questions are formulated and discussed in the article:

- Do trading strategies based on fundamental factors in the BTC and ETH markets outperform the "buy-and-hold" strategy?
- Are the BTC and ETH markets informationally efficient based on the insight from the fundamental factor analysis?

The article aims to

- verify whether investors in the cryptocurrency market can outperform passive investment strategies and make excess returns by applying active strategies based on selected fundamental factors, and
- evaluate the efficiency of the BTC and ETH markets based on selected fundamental factors.

1 The so-called "hodl" can be defined as a buy and hold strategy in the cryptocurrency market. The name is derived from the misspelled word "hold" in one of the posts on the online forum – Bitcointalk, in 2013.This term is sometimes regarded as an acronym "hold on for dear life" [Kraken, n.a.]. The name "hodler" originates from the word "hodl".

2 According to CoinMarketCap.com as of the beginning of November 2022, Bitcoin and Ethereum ranked first and second, respectively, in terms of market capitalization. They also took the second and third position in the ranking based on the trade volume only with Tether ahead of them. Nevertheless, the trade volume should be considered with caution as it may be artificially inflated by some entities [for discussion see e.g. Alexander and Dakos, 2020].

The study formulates and tests a hypothesis describing the efficiency of the cryptocurrency market. The hypothesis states that investment strategies designed based on structural indicators may generate higher returns and outperform the "buy-and-hold" strategy (B&H), and consequently, the cryptocurrency market is not efficient.

The article contributes to the literature in several ways. First, it sheds new light on the efficiency of the cryptocurrency market by analyzing investment strategies based on fundamental (structural) factors and comparing their performance with that of the passive strategy. To the best of the authors' knowledge, such a topic has not been addressed in the literature, despite the fact that the analyzed indicators are used by cryptocurrency market practitioners. For this reason, the article aims to fill an important research gap. Second, the study identifies the best options for active investment strategies and assesses their effectiveness using selected statistical tests for the mean and the Sharpe ratio. Third, it considers recent trends in the efficiency of the cryptocurrency market by studying the COVID-19 pandemic alongside the pre-pandemic period. This approach also serves as a robustness check for the obtained results.

The rest of the article is structured as follows. Section 2 reviews the relevant literature, mainly related to the efficiency of the cryptocurrency market. Section 3 contains the description of the data used in the study. Section 4 describes the methodology. Section 5 depicts and discusses empirical results, and Section 6 concludes.

2 Literature review

According to Fama [1970], the market is informationally efficient from an economic point of view when stock prices reflect all information, and it is not possible to generate rates of returns higher than those with a passive strategy ("buy-and-hold"). In broader terms, the EMH applies to other markets in addition to stocks, including cryptocurrencies. From a theoretical point of view, on the one hand, the informational efficiency of the cryptocurrency market might be justified as the blockchain technology allows direct and quick access to information on all transactions. On the other hand, though, investors may lack the tools or technical skills to analyze blockchains and may not be able to make a proper use of the abundance of information that blockchains provide. Moreover, as mentioned in Introduction, there are divergent views on the fundamental value of cryptocurrencies. This makes it difficult for investors to establish whether a particular cryptocurrency is properly valued by the market, with all the information reflected in its prices, making this market informationally efficient.

There are many methods used by researchers to assess the efficiency of the cryptocurrency market. These methods test, among others, the properties of the cryptocurrency time series – whether they follow a random walk, whether they are characterized by long memory, self-similarity and scaling patterns, autocorrelation, or independence [e.g. Urquhart, 2016; Nadarajah and Chu, 2017; Brauneis and Mestel, 2018; Wei, 2018; López-Martín et al., 2021; Kakinaka and Umeno, 2022]. Moreover, researchers employ efficiency indices, which are synthetic measures that summarize either several statistical tests or results of one test in multiple sub-samples [e.g. Kristoufek, 2018; Yonghong et al., 2018; Kristoufek and Vosvrda, 2019; Tran and Leirvik, 2020]. They also detect pricing anomalies [e.g. Grobys and Sapkota, 2019; Cheng et al., 2019; Shen et al., 2020]. Another approach is to verify the profitability of investment strategies based on selected information, which is employed and expanded in this study.

The problems with the identification of fundamental factors in the cryptocurrency market, highlighted in Introduction, may induce investors to employ the technical analysis to build profitable investment strategies in the cryptocurrency market. One strand of the literature examines the performance of technical analysis in the BTC trading. In general, the results indicate that employing strategies based on technical indicators is justified. Gerritsen et al. [2020] investigated whether seven selected technical trading rules may outperform a "buy-and-hold" strategy in the BTC market using daily data. Their results indicate that specific trading rules, mainly trading range breakout, outperform the "buy-and-hold" strategy. Detzel et al. [2021] analyzed daily BTC data and found that trading strategies based on ratios of prices to their moving averages outperform the "buy-and-hold" strategy – they generate large alphas and result in higher Sharpe

ratios. Huang et al. [2019] built a classification tree-based model to predict BTC returns (specifically the range for the next day's return). Next, they checked its usefulness. To do that, they used daily BTC data and 124 technical indicators that they divided into five groups (viz., cycle indicators, momentum indicators, overlap studies indicators, pattern recognition indicators, and volatility indicators). They found that their model has out-of-sample predictive power and outperformed the "buy-and-hold" strategy as well as classic strategies that they have investigated. Resta et al. [2020] considered both daily and intraday (5-min interval) data. They built trend-following and mean-reverting strategies to evaluate the performance of technical trading rules. The authors also found that the strategies based on daily data are more profitable than the intraday approach. Moreover, they documented that simple moving averages yield best results when daily data are considered, whereas the "buy-and-hold" strategy outperforms the analyzed alternatives at the intraday frequency. Corbet et al. [2019] tested resistance and support levels and their performance using various technical trading rules based on high-frequency BTC returns. Their results support the choice of moving average strategies. The authors also indicated that the variable-length moving average rule yields the best results with buy signals compared to sell signals. Miller et al. [2019] searched for price patterns in the BTC 1-min price data with an algorithm using smoothing splines. They detected three patterns – head-and-shoulders, inverted head-and-shoulders, and triangle bottoms. Then, the authors constructed a trading strategy to assess the profitability of these patterns. The results indicate that the strategy yield returns that are significantly higher than the returns of unconditional/random strategies. Nakano et al. [2018] investigated trading strategies in the BTC market using artificial neural networks. They extracted trading signals from the technical indicators that are calculated based on intraday data (15-min intervals). The authors found that their approach helps obtain better results than those using the "buy-and-hold" strategy and primitive technical trading strategies.

The profitability of technical analysis is also investigated with regard to a wider group of cryptocurrencies. Grobys et al. [2020] analyzed a group of 11 cryptocurrencies with high market capitalization and found one of the moving average trading strategies profitable. Hudson and Urquhart [2021] used almost 15,000 rules from five main classes of technical trading rules and applied them to data from two BTC markets and ETH, Litecoin, and Ripple data. The results indicate that each class of technical trading rules yields profits. The authors also indicated that employing these rules generates higher risk-adjusted returns compared with the "buy-and-hold" strategy. Anghel [2021] investigated 861 cryptocurrencies using technical analysis and machine learning and found that statistically significant positive excess returns are rarely generated. The author controlled for risk, data snooping, and market frictions. The conclusion holds irrespective of the test significance level, the type of the trading position, and data sampling frequency (the author used daily data; however, for four cryptocurrencies, he additionally analyzed hourly data). The employed machine learning methods usually underperform simple alternatives based on the technical analysis, particularly after controlling for trading costs. The author notes, however, that applied machine learning solutions outperform the technical analysis on less liquid and small cryptoasset markets. Nevertheless, excess returns are not significant when they are controlled for data snooping. To sum up, the research conducted so far generally shows evidence that the cryptocurrency market is not informationally efficient as above-average profits can be achieved based on technical analysis.

Apart from the strategies based on the technical analysis presented earlier, Fang et al. [2021], in their extensive literature review on cryptocurrency trading, distinguished two other main types of systematic trading in this market – the usage of pairs trading [e.g. Lintilhac and Tourin, 2017] and informed trading [e.g. Feng et al., 2018]. This study extends this strand of literature further. To the best of our knowledge, this study is the first to use structural indicators derived from the on-chain data such as the NUPL or the SOPR to design investment strategies and test their performance. It is worth noting that data derived from blockchain were used in some previous studies, but in other contexts and to address other research problems [e.g. Maesa et al., 2017; Griffin and Shams, 2020; Mizerka et al., 2020].

Since the outbreak of the COVID-19 pandemic, researchers have started to analyze the cryptocurrency market developments under the new economic and social conditions. They examined the safe haven or hedging properties of selected cryptocurrencies [e.g. Demir et al., 2020; Ghorbel and Jeribi, 2021], volatility

of cryptocurrencies [e.g. Segnon and Bekiros, 2020; Ftiti et al., 2021; Özdemir, 2022], interrelationships between volatility and liquidity in this market [e.g. Corbet et al., 2022], and its efficiency. Mnif et al. [2020], using a multifractal analysis, discovered a positive impact of the pandemic on the efficiency of the cryptocurrency market. Naeem et al. [2021], however, applying asymmetric multifractal detrended fluctuation analysis, found that the outbreak of the COVID-19 pandemic has adversely affected the efficiency of the four cryptocurrencies analyzed: BTC, ETH, Litecoin, and Ripple. Kakinaka and Umeno [2022] examined the efficiency of BTC and ETH markets and concluded that during the COVID-19 period, they became more inefficient in the short term. This article sheds new light on this matter by applying another approach and taking a closer look at the cryptocurrency market efficiency before and during the pandemic.

3 Data and fundamental factors

The analysis is based on daily data for BTC and ETH sourced from the Glassnode database for the period from August 8, 2015 to October 20, 2022. The starting point of the analysis was based on the availability of the time series examined. The Glassnode database is a comprehensive library of the cryptocurrency data which provides different metrics as well as a wide range of indicators derived from cryptocurrency blockchains. It is used in scientific research [e.g. Hoang and Baur, 2022; Urquhart, 2022] and also by international financial institutions [e.g. Bank for International Settlements – Auer et al., 2022]. It is also among the top databases with on-chain data in Internet rankings [e.g. Oladotun, 2022].

The fundamental indicators analyzed in this study can be used to describe the structure of the cryptocurrency market. The factors studied include[3]

- net unrealized profit/loss (NUPL),
- spent output profit ratio (SOPR), and
- percent of addresses in profit (PAP).

The structural factors were selected based on two considerations. First, the study chooses from indicators calculated using the on-chain data. The on-chain analysis is a popular method among crypto community members for exploring information from a blockchain ledger to ascertain market sentiment. Second, only factors that generate enough transaction signals to evaluate investment strategies are used. This allows meeting assumptions of the statistical tests and drawing general conclusions. In other words, the study recognizes that indicators that generate rare signals are not practicable.

The NUPL indicator [Schultze-Kraft, 2019] considers the difference between relative unrealized profit and relative unrealized loss to determine whether the network as a whole is currently in a state of profit or loss (see Formula [1]). The relative unrealized profit represents the total profit accrued by the unspent coins (unspent transaction output, UTXO), which were created when the price of the asset was lower than the current price compared with the current market capitalization.[4] Consequently, the relative unrealized loss represents the total loss accrued by the unspent coins, which were created when the price of the asset was higher than the current price compared with the current market capitalization. The NUPL indicator can also

3 The description of the methodology for calculating structural indicators is based on the Glassnode database. All indicators for BTC and ETH are available at: https://studio.glassnode.com/metrics?a=BTC&category=&m=indicators.NetUnrealizedProfitLoss
https://studio.glassnode.com/metrics?a=ETH&category=&m=indicators.NetUnrealizedProfitLoss
https://studio.glassnode.com/metrics?a=BTC&category=&m=indicators.Sopr
https://studio.glassnode.com/metrics?a=ETH&category=&m=indicators.Sopr
https://studio.glassnode.com/metrics?a=BTC&category=&m=addresses.ProfitRelative
https://studio.glassnode.com/metrics?a=ETH&category=&m=addresses.ProfitRelative

4 The unspent transaction output (UTXO) refers to digital currency someone has left in his or her wallet after executing a cryptocurrency transaction.

be calculated by subtracting realized capitalization from market capitalization, and dividing the result by the market capitalization [Demeester et al., 2019; see Formula [4]]. The realized capitalization is a variation of market capitalization that values each unspent coin based on the price when it was last transferred (moved), as opposed to its current value. As such, the realized capitalization represents the realized value of all the coins in the network, as opposed to their current market value. The NUPL metric tries to answer the following question: if all units of a given cryptocurrency were sold today, how much would investors stand to gain or lose? If the NUPL indicator is positive (NUPL>0), the network is in a state of net profit. If the NUPL indicator is negative (NUPL<0), the network is in a state of net loss. In general, the further NUPL deviates from zero, the closer the market trends toward tops and bottoms. As such, NUPL can help investors identify when to take profit and when to re-enter the market. Figure 1 depicts the NUPL indicator for BTC and ETH, respectively, in the period investigated (August 8, 2015 – October 20, 2022).

$$NUPL = Relative\ \ Unrealised\ Profit - Relative\ \ Unrealised\ Loss \tag{1}$$

$$Relative\ Unrealised\ Profit = \frac{\sum_{UTXOs} value \cdot \max\left(0, price_{current} - price_{realised}\right)}{Market\ \ capitalisation} \tag{2}$$

$$Relative\ Unrealised\ Loss = \frac{\sum_{UTXOs} value \cdot \max\left(0, price_{realised} - price_{current}\right)}{Market\ \ capitalisation} \tag{3}$$

$$NUPL = \frac{Market\ \ capitalisation - Realised\ capitalisation}{Market\ \ capitalisation} \tag{4}$$

The SOPR indicator provides insights into macro-market sentiment, profits, and losses taken over a particular time frame [Shirakashi, 2019]. It captures the aggregate profit and loss realized on a particular day. Both the absolute value of the SOPR indicator and the prevailing trend provide insights into the market spending behavior. In general, the higher the SOPR value, the larger the profit realized on that day by investors. A SOPR value greater than 1 (SOPR > 1) implies that the coins transferred (moved) on that day are, on average, selling at a profit. A SOPR value less than 1 (SOPR < 1) implies that the coins transferred on that day are, on average, selling at a loss. A SOPR value amounting to 1 (SOPR = 1) implies that the coins transferred on that day are, on average, selling at break even. A SOPR value trending higher implies profits are being realized with potential for previously illiquid supply being returned to liquid circulation. A SOPR value trending lower implies losses are being realized, or profitable coins are not being spent. The SOPR

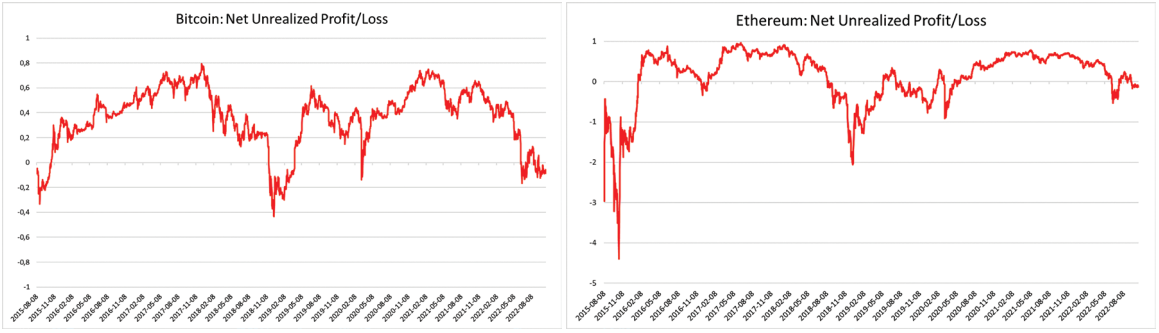


Figure 1. NUPL in the period from August 8, 2015 to October 20, 2022.

Source: own compilation based on the Glassnode data.

Notes: The left panel depicts NUPL for BTC. The right panel depicts NUPL for ETH. BTC, Bitcoin; ETH, Ethereum; NUPL, net unrealized profit/loss.

indicator is calculated by dividing the realized value of all spent outputs (in USD) by the value of these coins at creation (in USD) (see Formula) [5]. Figure 2 depicts the SOPR indicator for BTC and ETH, respectively, in the period investigated (August 8, 2015 – October 20, 2022).

$$\text{SOPR} = \frac{\text{Coin volume} \cdot \text{Price}_{\text{spent}}\left[\text{USD}\right]\left(\text{of all spent outputs}\right)}{\text{Coin volume} \cdot \text{Price}_{\text{created}}\left[\text{USD}\right]\left(\text{of all spent outputs}\right)} \tag{5}$$

The PAP refers to unique addresses whose funds have an average buy price, which is lower than the current price. The "buy price" is defined as the price at the time when coins were transferred into an address. The PAP indicator is calculated by dividing the number of addresses in profit by the total number of addresses in the network of a given cryptocurrency (see Formula) [6]. This metric represents an oscillator that describes the current state of the market for a given coin. In general, higher values may suggest market tops, while lower values may signal bottoms. Figure 3 depicts the PAP indicator for BTC and ETH, respectively, in the period investigated (August 8, 2015 – October 20, 2022).

$$\text{PAP} = \frac{\text{Number of addresses in profit}}{\text{Number of all addresses in the network}} \cdot 100\% \tag{6}$$

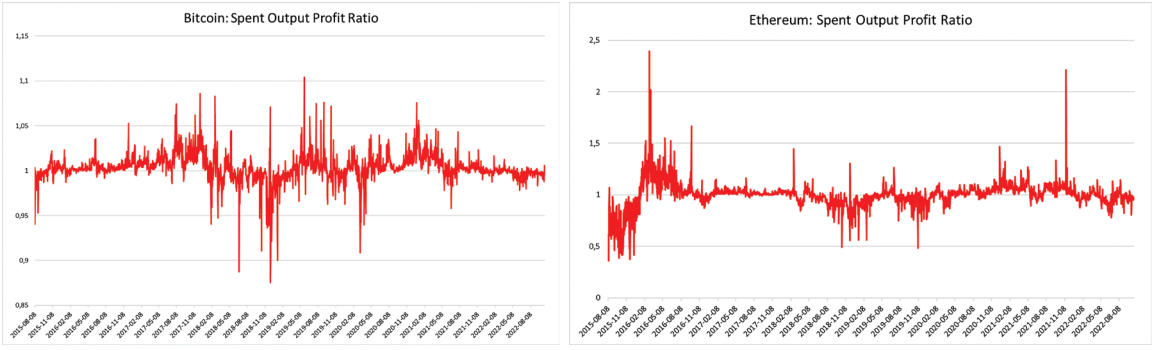


Figure 2. SOPR in the period from August 8, 2015 to October 20, 2022.

Source: own compilation based on the Glassnode data.

Notes: The left panel depicts SOPR for BTC. The right panel depicts SOPR for ETH. BTC, Bitcoin; ETH, Ethereum; SOPR, spent output profit ratio.

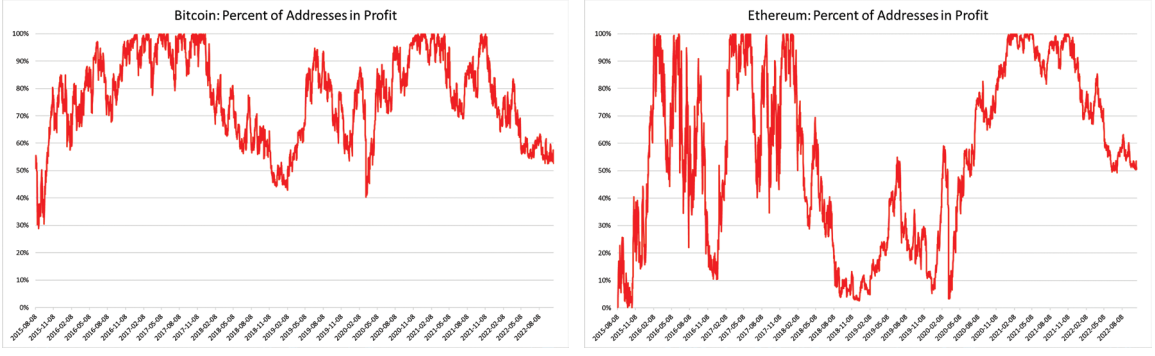


Figure 3. PAP in the period from August 8, 2015 to October 20, 2022.

Source: own compilation based on the Glassnode data.

Notes: The left panel depicts PAP for BTC. The right panel depicts PAP for ETH. BTC, Bitcoin; ETH, Ethereum; PAP, percent of addresses in profit.

4 Methodology

4.1 Active strategies

In general, there are two groups of investment strategies based on price dynamics: momentum strategies [e.g. Jagadeesh and Titman, 1993, 1995; Schiereck et al., 1999] and contrarian strategies [e.g. De Bondt and Thaler, 1985; Ball et al., 1995]. The study applies strategies belonging to the "contrarian category." The assumptions of these strategies are described in the following text.

The strategy based on the NUPL indicator uses the following assumptions:

- Open long position: whenever NUPL is in the capitulation phase. In the study, three levels of entry are considered (NUPL 1 < 0, NUPL 2 < 0.05, and NUPL 3 < 0.10).
- Close long position: when NUPL is in the belief–denial phase. Then, all long positions are closing. In the study, three levels of exit are considered (NUPL 1 > 0.5, NUPL 2 > 0.45, and NUPL 3 > 0.4).
- There are no short positions in the strategy – only long.

The strategy based on the SOPR indicator is realized under the following assumptions:

- Open long position: in the case of BTC, whenever SOPR is below 0.990 (SOPR 1), 0.992 (SOPR 2), and 0.995 (SOPR 3). In the case of ETH, the threshold values are 0.900, 0.920, and 0.950, respectively, and are selected based on the dynamics of the indicator.
- Close long position: in the case of BTC, when SOPR is above 1.010 (SOPR 1), 1.008 (SOPR 2), and 1.005 (SOPR 3). In the case of ETH, the threshold values are 1.100, 1.080, and 1.050, respectively, and are selected based on the dynamics of the indicator. Then, all long positions are closing.
- There are no short positions in the strategy – only long.

The strategy based on the PAP indicator consists of the following assumptions:

- Open long position: whenever PAP is below 50% (PAP 1), 52% (PAP 2), and 55% (PAP 3).
- Close long position: when PAP is above 95% (PAP 1), 93% (PAP 2), and 90% (PAP 3). Then, all long positions are closing.
- There are no short positions in the strategy – only long.

Strategies based on structural ratios (the so-called active strategies) are further compared with the passive "buy-and-hold" strategy for BTC and ETH. No transaction cost is considered in both active or passive strategies.

4.2 Performance measurement

Based on the analyzed time series, the annualized log returns for active strategies are calculated as follows:

$$R_i = \frac{1}{T} ln\left(\frac{P_{Sell}}{P_{Buy}}\right), \tag{7}$$

where T is the time of investment in years, and P_{Sell} and P_{Buy} relate to the prices of a cryptocurrency when an investor should close or open a position, according to rules for the strategies described in Section 4.1. The mean and volatility of returns are calculated as follows:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} R_i, \tag{8}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(R_i - \mu\right)^2}, \tag{9}$$

where N equals the number of returns calculated for the active strategy. The Sharpe ratio for a strategy is calculated using the following formula:

$$SR = \frac{\mu}{\sigma}. \tag{10}$$

For the passive strategy, the study applies specific assumptions. Since for the "buy-and-hold" strategy, there are no strict rules that unambiguously indicate the date on which the investment should start, the study assumes that a passive investor buys a cryptocurrency on a random day t and sells it on a day t+365. In this way, the random nature of the returns will imitate the actions of a "hodler" – an investor who starts the investment at some point and holds the position long term. Then, $P_{Buy} = P_t$, $P_{Sell} = P_{t+365}$, and the annual return equals to

$$R_i = ln\left(\frac{P_{t+365}}{P_t}\right). \tag{11}$$

The study randomly chooses N passive returns using uniform sampling without replacement and proceeds with a test for differences in the performance measures. It repeats this step 500 times and calculates the mean p-value. In the case of a large sample ($N \geq 200$), the research applies asymptotic HAC inference. Since this approach is not recommended by Ledoit and Wolf [2008, 2018] when samples sizes are small, the study uses a bootstrap inference method if $N < 200$.

4.3 Hypothesis testing for the performance of two strategies

The study applies tests for differences by Ledoit and Wolf [2008, 2018]. This approach is elaborated in the following text. Consider two alternative strategies A and B, whose raw returns[5] at the time t are $r_{t,A}$ and $r_{t,B}$, respectively. Let $\left(r_{t,A}, r_{t,B}\right)$ denote a strictly stationary time series with a mean vector $\boldsymbol{\mu} = (\mu_A, \mu_B)'$ and covariance matrix $\boldsymbol{\Sigma}$. If θ is a performance measure, for example, the mean return or the Sharpe ratio, the difference between θ_A and θ_B, that is,

$$\Delta = \theta_A - \theta_B \tag{12}$$

can be used to state the following null and alternative hypotheses:

$$H_0: \Delta = 0, \text{ vs. } H_1: \Delta > 0. \tag{13}$$

5 This study does not consider the excess return over a given benchmark. Since the main goal of the study is to compare two strategies and to indicate the one that performs better, using the excess return would lead to the same conclusions.

Ledoit and Wolf [2018] described the testing procedure using the popular delta method. To this end, they considered the mean return and the Sharpe ratio, which can be expressed as the smooth function of population moments $v^{(m)} = E\left(r_t^m\right)$. In general, one can express these performance measures as a function $h\left(v^{(1)},\ldots,v^{(M)}\right)$, where $M \geq 1$ denotes the maximum order of population moments needed to calculate the value of θ. Specifically, if a performance measure is the mean return, then $M=1$ and $\theta = h\left(v^{(1)}\right)$, where $h(a)=a$. However, in the case of the Sharpe ratio, $M=2$ and $\theta = h\left(v^{(1)},v^{(2)}\right)$, where $h(a,b)=\frac{a}{\sqrt{b-a^2}}$. Then, $\Delta = \theta_A - \theta_B = h\left(v_A\right) - h\left(v_B\right) = f\left(v\right)$, where $v_X' = \left(v_X^{(1)},\ldots,v_X^{(M)}\right), v' = \left(v_A', v_B'\right)$ and $f\colon \mathbb{R}^{2M} \to \mathbb{R}$ is also a smooth function.

The estimator of Δ is given as follows:

$$\hat{\Delta} = \hat{\theta}_A - \hat{\theta}_B = h\left(\hat{v}_A^{(1)},\ldots,\hat{v}_A^{(M)}\right) - h\left(\hat{v}_B^{(1)},\ldots,\hat{v}_B^{(M)}\right) = f\left(\hat{v}\right), \tag{14}$$

where $\hat{v}_X^{(m)}$ the mth sample moment of the observed returns from the strategy X:

$$\hat{v}_X^{(m)} = \frac{1}{T}\sum_{t=1}^{T} r_{t,X}^m. \tag{15}$$

If the following relation holds,

$$\sqrt{T}(v\text{-}\hat{v}) \xrightarrow{d} N\left(0,\Psi\right), \tag{16}$$

where Ψ is a symmetric positive definite matrix of dimension $2M \times 2M$ and $\xrightarrow{d}$ denotes the convergence in distribution, the delta method implies

$$\sqrt{T}(\Delta\text{-}\hat{\Delta}) \xrightarrow{d} N\left(0,\nabla'\ f\left(v\right)\Psi\nabla f\left(v\right)\right), \tag{17}$$

where $\nabla f\left(v\right)$ is a gradient of $f\left(v\right)$. An asymptotic standard error $s\left(\hat{\Delta}\right)$ for $\hat{\Delta}$ equals

$$s\left(\hat{\Delta}\right) = \sqrt{\frac{\nabla'\ f\left(\hat{v}\right)\widehat{\Psi}\nabla f\left(\hat{v}\right)}{T}}, \tag{18}$$

where $\hat{\Psi}$ is a consistent estimator of Ψ.

The method requires to use the following formulas for the gradient $\nabla h\left(v\right)$ since $\nabla' f\left(v\right) = \left(\nabla h'\left(v_A\right), -\nabla h'\left(v_B\right)\right)$:

1. $\nabla h\left(a\right) = 1$, if a performance measure θ is the mean return,
2. $\nabla' h\left(a,b\right) = \left(\frac{b}{\left(b-a^2\right)^{1.5}}, -\frac{1}{2}\frac{a}{\left(b-a^2\right)^{1.5}}\right)$, if a performance measure θ is the Sharpe ratio.

To properly test the hypothesis $H_0 : \Delta = 0$ using the methodology that is robust against fat tails or time series effects, Ledoit and Wolf [2008, 2018] proposed two alternate solutions: HAC inference and bootstrap inference. The first solution is similar to the method introduced by Jobson and Korkie [1981]. However, they

suggest using a delta method using heteroskedasticity and autocorrelation robust (HAC) kernel estimation. The second method is based on the construction of a studentized time series bootstrap confidence interval for the difference of the performance measures. Since the HAC inference is often liberal when samples sizes are small to moderate, Ledoit and Wolf [2008, 2018] suggested using a bootstrap inference method. See Ledoit and Wolf [2018] for a more detailed description of both methods.

5 Empirical results

5.1 Main sample period (2015–2019)

The results of the study for the main sample period (2015–2019) indicate that the use of the NUPL indicator is beneficial when making investment decisions in the BTC market (see Table A1 in Appendix). The rates of return on active investment strategies in all cases (for all thresholds analyzed) are higher than the average rate of return from the "buy-and-hold" strategy. Consequently, the rates of success – defined as the percentage of cases where the annualized return on an active strategy is greater than the mean passive return – amounts to 100%. Furthermore, there are no losses on active strategies, unlike the "buy-and-hold" strategy. The median and mean returns are more than twice as high as those on the passive investment. At the same time, the NUPL strategies are characterized by a high value of the Sharpe ratio, which is two or three times higher than that of the "buy-and-hold" strategy. To formally verify whether there is a statistically significant advantage of an active strategy over the passive strategy, the study conducts a test for differences in the performance measures. Due to the nature of the data (autocorrelation and non-normal distribution), and thus a violation of the assumptions of traditional tests, it is necessary to use a robust test instead. For large samples ($N >= 200$), heterogenous and autocorrelation consistent (HAC) tests are used, and for small samples, a bootstrap test under the methodology proposed by Ledoit and Wolf [2008, 2018]. The testing results $\left(H0: \mu_{B\&H} = \mu_{NUPL} \text{ vs. } H1: \mu_{B\&H} < \mu_{NUPL}\right)$ show that there is a statistically significant higher mean return on active strategies based on the NUPL 1 and NUPL 2 thresholds. A similar test is carried out for the Sharpe ratio $\left(H0: SR_{B\&H} = SR_{NUPL} \text{ vs. } H1: SR_{B\&H} < SR_{NUPL}\right)$, and it shows that the NUPL 1 strategy is significantly better than the "buy-and-hold" strategy.

The application of the NUPL indicator when making investment decisions in the ETH market is beneficial too (see Table A1 in Appendix). The rates of return on active strategies in all cases (for all thresholds analyzed) are higher than the average return on the B&H strategy; thus, the success rates amount to 100%. Similar to the BTC market, for ETH, there are no losses on active investment as opposed to the "buy-and-hold" strategy. The median returns on active strategies in the ETH market are over four times higher than those on the passive investment (the mean returns are six times higher). At the same time, active investments have a high value of the Sharpe ratio, which is more than twice as high as that for the "buy-and-hold" strategy. Statistical analysis for the active strategies' performance shows that the mean return and the Sharpe ratio of the NUPL-based investments are significantly higher than those of the passive strategy.

The study found that investment strategies in the BTC market based on the SOPR indicator can yield volatile returns (see Table A2 in Appendix). In only about half of the cases are the rates of return on active investments higher than the mean return on the "buy-and-hold" strategy. The median return on active strategies is close to that on the passive investment. The active strategies have relatively higher mean returns than the "buy-and-hold" strategy but, at the same time, are characterized by much higher volatility of returns. Consequently, the Sharpe ratio for active strategies is about two or three times lower than that for the "buy-and-hold" investment. Statistical analysis of the investment performance (mean returns) indicates the superiority of strategies based on the SOPR 1 and SOPR 3 thresholds over the passive strategy. However, a similar test conducted for the Sharpe ratio shows that the "buy-and-hold" strategy performs relatively worse than the SOPR 3 strategy.

In the case of the ETH market, the performance of the SOPR strategies is quite unsatisfactory too (see Table A2 in Appendix). The rates of return on active investments are higher than the mean returns on the

"buy-and-hold" strategy only in about 60% of cases. Although the average returns are greater than those of the passive investment, the differences are not statistically significant. At the same time, the SOPR-based strategies are characterized by low Sharpe ratios, which are significantly less than those for the "buy-and-hold" strategy. Nevertheless, test results show that the differences are not statistically significant.

The third structural factor analyzed in the study, the PAP indicator, clearly allows making profitable investment decisions in the BTC market. According to results presented in Table A3 in Appendix, rates of return on PAP-based active strategies in most cases are higher than the average return on the passive investment. It is worth noting that there are no losses on active strategies at all, unlike the "buy-and-hold" strategy. Both the median and mean returns for the PAP 2 and PAP 3 thresholds are more than twice as high as those for the passive investment. In the case of the PAP 1 strategy, the mean return is, however, only slightly higher than that for the "buy-and-hold" strategy. Simultaneously, PAP investments are characterized by a high value of the Sharpe ratio, which is approximately three times higher than that for the "buy-and-hold" strategy. Although statistical analysis of the investment performance indicates that mean returns are not significantly higher for active strategies, differences in Sharpe ratios are significantly greater than zero for the PAP 1 and PAP 2 thresholds.

The PAP ratio seems to be useful for investors in the ETH market (see Table A3 in Appendix). In the vast majority of cases (over 80%), the rates of return on PAP-based investments are higher than those for the passive strategy. There are no losses generated on such strategies (minimum returns are positive). The median returns are in this case about three times higher than those for the passive investment. The mean returns are almost four times higher, and tests indicate that the difference is statistically significant. Additionally, the PAP-based investments are characterized by a relatively high Sharpe ratio, which is more than twice as high as the ones for the "buy-and-hold" strategy. Hypothesis testing for the performance of two strategies indicates that the Sharpe ratio is significantly greater for the PAP 1 and PAP 3 thresholds than for the "buy-and-hold" strategy.

5.2 The COVID-19 period (2020–2022)

The study tests research findings, as presented in Section 5.1, in an out-of-sample period. The study investigates the consistency of conclusions drawn for the main sample period (2015–2019) in the out-of-sample period (2020–2022). In other words, the usefulness of fundamental factors in making investment decisions in the cryptocurrency market is verified in the COVID-19 period. Tables A4–A6 in Appendix contain the out-of-sample results, including mean returns, their standard deviations, Sharpe ratios, and success rates for the active investment strategies based on fundamental factors. Due to the low number of investment signals generated in the COVID-19 period (2020–2022), the statistical performance tests are not conducted. Instead, this study uses point estimates for measures of the strategies' performance.

The performance of investment strategies based on structural factors in the BTC market during the COVID-19 pandemic is consistent with the properties captured in the main sample period. Therefore, fundamental indicators seem to be useful for designing investment strategies that are superior to passive strategies. The strategies using the NUPL and PAP indicators are characterized by relatively higher mean and median returns than those for the passive investment (see Tables A4 and A6 in Appendix). Again, in the case of the SOPR index, the performance is unstable: risk measured by the standard deviation is very high, resulting in the relatively low Sharpe ratio, despite the relatively highest mean return (see Table A5 in Appendix).

In the case of ETH, the relationships detected in the main sample period (2015–2019) are, in turn, consistent with those observed during the COVID-19 pandemic. The NUPL-based strategies generate mean returns that are higher than those on the passive investment (see Table A4 in Appendix), which is in accordance with the general conclusions for the main sample period. For the PAP index (see Table A6 in Appendix), a relatively higher mean return is observed for all thresholds (PAP 1–PAP 3). Moreover, it is worth noting that the Sharpe ratio for the NUPL and PAP strategies is higher than that for the "buy-and-hold" strategy. Again, in the case of the SOPR index, returns are highly differentiated and volatile

(see Table A5 in Appendix). Therefore, despite the high mean return observed, the Sharpe ratio is lower than that for the passive investment.

6 Conclusions

This study aimed to verify whether investors in the cryptocurrency market can make excess returns by applying strategies based on fundamental factors and outperform the market participants characterized by the passive investment style. The fundamental on-chain indicators analyzed in the study can be used to describe the structure of the cryptocurrency market.

The research indicates several practical implications. It is confirmed that the NUPL and PAP indicators are useful in designing contrarian investment strategies in the BTC and ETH markets. Active strategies based on these indicators perform consistently better in terms of mean/median returns and the Sharpe ratio than the passive "buy-and-hold" strategy. Furthermore, the rate of success – defined as the percentage of cases where the annualized return on the active strategy is greater than the passive return – is close to 100%. Also, there are no losses on such active strategies as opposed to the "buy-and-hold" strategy. These observations are crucial for investors in the cryptocurrency market. The results are confirmed, to a large extent, by statistical tests for differences by Ledoit and Wolf [2008, 2018]. On the contrary, using the SOPR is not recommended since the relative investment performance is unstable. The conclusions drawn seem consistent over time. Findings for the main sample period (2015-2019) are confirmed in the out-of-sample period, that is, during the COVID-19 pandemic (2020–2022).

In general, the research findings indicate inefficiencies in the BTC and ETH markets as it is possible to consistently generate higher rates of returns and Sharpe ratios on active strategies based on fundamental factors than the passive strategy. Consequently, the results corroborate these obtained by other researchers [Huang et al., 2019; Gerritsen et al., 2020; Resta et al., 2020; Detzel et al., 2021; Hudson and Urquhart, 2021].

There are some limitations to the study conducted. First, it should be noted that due to the availability of data, the research considers only a limited period (2015–2022). During this period, an upward trend in the BTC and ETH markets prevailed. It cannot be ruled out that properties might change during a long market downturn. Second, the cryptocurrency market is not mature and, as such, is subject to constant development and changes; hence, careful observation and analysis in subsequent periods are recommended. Third, the study analyzes a limited number of active strategies based on fundamental indicators because the historical time series for such factors are relatively short. Fourth, a relatively short time series is examined in the COVID-19 period, which limits out-of-sample testing. Moreover, no transaction cost is considered in the analysis.

It should also be mentioned that there are aspects related to cryptocurrency investments and their profitability that have not been included in this study. Investors may be concerned about environmental issues. As Krause and Tolaymat [2018] noted, the process of adding blocks to blockchains is computationally intensive, and therefore, it needs large energy inputs. Mining BTC units and transacting with this cryptocurrency require the use of scarce energy resources for financial activities at a time when governments are supposed to reduce energy consumption (e.g. through the Paris Agreement commitments) to alleviate climate change implications for future [Truby, 2018]. This can apply to other cryptocurrencies as well. These problems are also noticed in the literature. Therefore, there are attempts to project such emissions [e.g. Mora et al., 2018; Masanet et al., 2019], determine the most sustainable countries for cryptocurrency mining [Náñez Alonso et al., 2021], or explore ways to encourage environmentally sustainable development of blockchain applications without jeopardizing this sector [Truby, 2018]. Legal issues may also concern cryptocurrency investors. Institutional investors see regulatory uncertainty as an obstacle to investment in cryptocurrencies [Fidelity, 2019]. The regulatory aspect of crypto assets is also considered in the literature, *inter alia*, by Hacker and Thomale [2018], Yadav et al. [2022], and Sanz-Bas et al. [2021]. Apart from that, investors must take account of the risk of a sudden closure of crypto exchanges [see e.g. Moore and Christin, 2013; Bhaskar and Lee, 2015; Moore et al., 2018] and price manipulations [see Hamrick et al., 2018].

All the aforementioned deficiencies are indications for further analysis and the setting of future research directions. The availability of relevant data will allow extending the sample, divide it into subperiods of downward/upward trends, perform out-of-sample tests, and add other structural factors. Last but not least, conducting a similar study for other cryptocurrencies, provided that the necessary fundamental indicators are available, would be of particular importance.

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Conflict of interest

None.

References

Alexander, C., Dakos, M. (2020), A critical investigation of cryptocurrency data and analysis, Quantitative Finance, Vol. 20, No. 2, pp. 173–188, https://doi.org/10.1080/14697688.2019.1641347.

Alvarez-Ramirez, J., Rodriguez, E., Ibarra-Valdez, C. (2018), Long-range correlations and asymmetry in the Bitcoin market, Physica A: Statistical Mechanics and its Applications, Vol. 492, pp. 948–955, https://doi.org/10.1016/j.physa.2017.11.025.

Anghel, D. (2021), A reality check on trading rule performance in the cryptocurrency market: machine learning vs. technical analysis, Finance Research Letters, Vol. 39, Article 101655, https://doi.org/10.1016/j.frl.2020.101655.

Auer, R., Farag, M., Lewrick, U., Orazem, L., Zoss, M. (2022), Banking in the shadow of Bitcoin? The institutional adoption of cryptocurrencies. Bank for International Settlement. BIS working papers No. 1013, retrieved from https://www.bis.org/publ/work1013.pdf [4th November 2022].

Ball, R., Kothari, S.P., Shanken, J. (1995), Problems in measuring portfolio performance an application to contrarian investment strategies, Journal of Financial Economics, Vol. 38, No. 1, pp. 79–107, https://doi.org/10.1016/0304-405X(94)00806-C.

Bhaskar, N.D., Lee, D.K.C. (2015), Bitcoin exchanges, in: D.K.C. Lee, (Ed), *Handbook of digital currency: Bitcoin, innovation, financial instruments and big data*, Elsevier, San Diego, pp. 559–573.

Brauneis, A., Mestel, R. (2018), Price discovery of cryptocurrencies: Bitcoin and beyond, Economics Letters, Vol. 165, pp. 58–61, https://doi.org/10.1016/j.econlet.2018.02.001.

Caporale, G.M., Gil-Alana, L., Plastun, A. (2018), Persistence in the cryptocurrency market, Research in International Business and Finance, Vol. 46, pp. 141–148, https://doi.org/10.1016/j.ribaf.2018.01.002.

Cheah, E., Fry, J. (2015), Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin, Economics Letters, Vol. 130, pp. 32–36, https://doi.org/10.1016/j.econlet.2015.02.029.

Cheng, Q., Liu, X., Zhu, X. (2019), Cryptocurrency momentum effect: DFA and MF-DFA analysis, Physica A: Statistical Mechanics and its Applications, Vol. 526, No. 80, Article 120847, https://doi.org/10.1016/j.physa.2019.04.083

Corbet, S., Eraslan, V., Lucey, B., Sensoy, A. (2019), The effectiveness of technical trading rules in cryptocurrency markets, Finance Research Letters, Vol. 31, pp. 32–37, https://doi.org/10.1016/j.frl.2019.04.027.

Corbet, S., Hou, Y., Hu, Y., Larkin, C., Lucey, B., Oxley, L. (2022), Cryptocurrency liquidity and volatility interrelationships during the COVID-19 pandemic, Finance Research Letters, Vol. 45, Article 102137, https://doi.org/10.1016/j.frl.2021.102137.

De Bondt, W.F.M., Thaler, R. (1985), Does the stock market overreact? The Journal of Finance, Vol. 40, No. 3, pp. 793–805, https://doi.org/10.2307/2327804.

Demeester, T., Blummer, T., Lescrauwaet, M. (2019), A primer on Bitcoin investor sentiment and changes in saving behavior, retrieved from https://medium.com/@adamant_capital/a-primer-on-bitcoin-investor-sentiment-and-changes-in-saving-behavior-a5fb70109d32 [5th November 2022].

Demir, E., Bilgin, M.H., Karabulut, G., Doker, A.C. (2020), The relationship between cryptocurrencies and COVID-19 pandemic, Eurasian Economic Review, Vol. 10, pp. 349–360, https://doi.org/10.1007/s40822-020-00154-1.

Detzel, A., Liu, H., Strauss, J., Zhou, G., Zhu, Y. (2021), Learning and predictability via technical analysis: evidence from Bitcoin and stocks with hard-to-value fundamentals, Financial Management, Vol. 50, pp. 107–137, https://doi.org/10.1111/fima.12310.

Fama, E.F. (1970), Efficient capital markets: a review of theory and empirical work, The Journal of Finance, Vol. 25, No. 2, pp. 383–417, https://doi.org/10.2307/2325486.
Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., Li, L. (2021), Cryptocurrency trading: a comprehensive survey, https://doi.org/10.48550/arXiv.2003.11352.
Feng, W., Wang, Y., Zhang, Z. (2018), Informed trading in the Bitcoin market, Finance Research Letters, Vol. 26, pp. 63–70, https://doi.org/10.1016/j.frl.2017.11.009.
Fidelity. (2019), Institutional investments in digital assets, retrieved from https://www.fidelity.com/bin-public/060_www_fidelity_com/documents/press-release/institutional-investments-in-digital-assets-050219.pdf [9th November 2022].
Ftiti, Z., Louhichi, W., Ameur, H.B. (2021), Cryptocurrency volatility forecasting: what can we learn from the first wave of the COVID-19 outbreak? Annals of Operations Research, https://doi.org/10.1007/s10479-021-04116-x.
Gbadebo, A.D., Adekunle, A.O., Adedokun, W., Lukman, A.-O.A., Akande, J. (2021), BTC price volatility: fundamentals versus information, Cogent Business & Management, Vol. 8, No. 1, pp. 1–21, https://doi.org/10.1080/23311975.2021.1984624.
Gerritsen, D.F., Bouri, E., Ramezanifar, E., Roubaud, D. (2020), The profitability of technical trading rules in the Bitcoin market, Finance Research Letters, Vol. 34, Article 101263, https://doi.org/10.1016/j.frl.2019.08.011.
Ghorbel, A., Jeribi, A. (2021), Volatility spillovers and contagion between energy sector and financial assets during COVID-19 crisis period, Eurasian Economic Review, Vol. 11, pp. 449–467, https://doi.org/10.1007/s40822-021-00181-6.
Griffin, J.M., Shams, A. (2020), Is Bitcoin really untethered? The Journal of Finance, Vol. 75, No. 4, pp. 1913–1964, https://doi.org/10.1111/jofi.12903
Grobys, K., Ahmet, S., Sapkota, N. (2020), Technical trading rules in the cryptocurrency market, Finance Research Letters, Vol. 32, Article 101396, https://doi.org/10.1016/j.frl.2019.101396.
Grobys, K., Sapkota, N. (2019), Cryptocurrencies and momentum, Economics Letters, Vol. 180, pp. 6–10, https://doi.org/10.1016/j.econlet.2019.03.028.
Hacker, P., Thomale, C. (2018), Crypto-securities regulation: ICOs, token sales and cryptocurrencies under EU financial law, European Company and Financial Law Review, Vol. 15, pp. 645–696, https://doi.org/10.1515/ecfr-2018-0021.
Hamrick, J.T., Rouhi, F., Mukherjee, A., Feder, A., Gandal, N., Moore, T., Vasek, M. (2018), The economics of cryptocurrency pump and dump schemes. Working paper, retrieved from https://www.tse-fr.eu/sites/default/files/TSE/documents/ChaireJJL/Digital-Economics-Conference/Conference/gandal_neil.pdf [5th November 2021].
Hayes, A. (2017), Cryptocurrency value formation: an empirical study leading to a cost of production model for valuing Bitcoin, Telematics and Informatics, Vol. 34, No. 7, pp. 1308–1321, https://doi.org/10.1016/j.tele.2016.05.005.
Hoang, L.T., Baur, D.G. (2022), Loaded for bear: Bitcoin private wallets, exchange reserves and prices, Journal of Banking and Finance, Vol. 144, Article 106622, https://doi.org/10.1016/j.jbankfin.2022.106622.
Hu, Y., Valera, H.G.A., Oxley, L. (2019), Market efficiency of the top market-cap cryptocurrencies: further evidence from a panel framework, Finance Research Letters, Vol. 31, pp. 138–145, https://doi.org/10.1016/j.frl.2019.04.012.
Huang, J.-Z., Huang, W., Ni, J. (2019), Predicting Bitcoin returns using high-dimensional technical indicators, The Journal of Finance and Data Science, Vol. 5, pp. 140–155, https://doi.org/10.1016/j.jfds.2018.10.001.
Hudson, R., Urquhart, A. (2021), Technical trading and cryptocurrencies, Annals of Operations Research, Vol. 297, pp. 191–220, https://doi.org/10.1007/s10479-019-03357-1.
Jegadeesh, N., Titman, S. (1993), Returns to buying winners and selling losers: implications for stock market efficiency, The Journal of Finance, Vol. 48, No. 1, pp. 65–91, https://doi.org/10.2307/2328882.
Jegadeesh, N., Titman, S. (1995), Overreaction, delayed reaction, and contrarian profits, The Review of Financial Studies, Vol. 8, No. 4, pp. 973–993, http://www.jstor.org/stable/2962296.
Jobson, J.D., Korkie, B.M. (1981), Performance hypothesis testing with the Sharpe and Treynor measures, Journal of Finance, Vol. 36, pp. 889–908, https://doi.org/10.2307/2327554.
Kakinaka, S., Umeno, K. (2022), Cryptocurrency market efficiency in short- and long-term horizons during COVID-19: an asymmetric multifractal analysis approach, Finance Research Letters, Vol. 46, Article 102319, https://doi.org/10.1016/j.frl.2021.102319.
Khuntia, S., Pattanayak, J.K. (2018), Adaptive market hypothesis and evolving predictability of Bitcoin, Economics Letters, Vol. 167, pp. 26–28, https://doi.org/10.1016/j.econlet.2018.03.005.
Kraken. (n.a.). Hodl meaning. What does HODL mean? retrieved from https://www.kraken.com/en-gb/learn/hodl [4th November 2022].
Krause, M.J., Tolaymat, T. (2018), Quantification of energy and carbon costs for mining cryptocurrencies, Nature Sustainability, Vol. 1, pp. 711–718, https://doi.org/10.1038/s41893-018-0152-7.
Kristoufek, L. (2018), On Bitcoin markets (in)efficiency and its evolution, Physica A: Statistical Mechanics and its Applications, Vol. 503, pp. 257–262, https://doi.org/10.1016/j.physa.2018.02.161.
Kristoufek, L., Vosvrda, M. (2019), Cryptocurrencies market efficiency ranking: not so straightforward, Physica A: Statistical Mechanics and its Applications, Vol. 531, pp. 2–8, https://doi.org/10.1016/j.physa.2019.04.089.
Ledoit, O., Wolf, M. (2008), Robust performance hypothesis testing with the Sharpe ratio, Journal of Empirical Finance, Vol. 15, pp. 850–859, https://doi.org/10.1016/j.jempfin.2008.03.002.
Ledoit, O., Wolf, M. (2018), Robust performance hypothesis testing with smooth functions of population moments. University of Zurich, Department of Economics. Working paper No. 305, http://dx.doi.org/10.2139/ssrn.3272196.

Li, X., Wang, C.A. (2017), The technology and economic determinants of cryptocurrency exchange rates: the case of Bitcoin, Decision Support Systems, Vol. 95, pp. 49–60, https://doi.org/10.1016/j.dss.2016.12.001.
Lintilhac, P.S., Tourin, A. (2017), Model-based pairs trading in the Bitcoin markets, Quantitative Finance, Vol. 17, No. 5, pp. 703–716, https://doi.org/10.1080/14697688.2016.1231928.
López-Martín, C., Benito Muela, S., Arguedas, R. (2021), Efficiency in cryptocurrency markets: new evidence, Eurasian Economic Review, Vol. 11, pp. 403–431, https://doi.org/10.1007/s40822-021-00182-5.
Maesa, D.D.F., Marino, A., Ricci, L. (2017), Detecting artificial behaviours in the Bitcoin users graph, Online Social Networks and Media, Vol. 3–4, pp. 63–74, https://doi.org/10.1016/j.osnem.2017.10.006.
Masanet, E., Shehabi, A., Lei, N., Vranken, H., Koomey, J., Malmodin, J. (2019), Implausible projections overestimate near term Bitcoin CO2 emissions. Lawrence Berkeley National Laboratory. retrieved from https://eta-publications.lbl.gov/sites/default/files/lbnl-2001235.pdf [5th November 2022].
Miller, N., Yang, Y., Sun, B., Zhang, G. (2019), Identification of technical analysis patterns with smoothing splines for Bitcoin prices, Journal of Applied Statistics, Vol. 46, No. 12, pp. 2289–2297, https://doi.org/10.1080/02664763.2019.1580251.
Mizerka, J., Stróżyńska-Szajek, A., Mizerka, P. (2020), The role of Bitcoin on developed and emerging markets – on the basis of a Bitcoin users graph analysis, Finance Research Letters, Vol. 35, Article 101489, https://doi.org/10.1016/j.frl.2020.101489.
Mnif, E., Jarboui, A., Mouakhar, K. (2020), How the cryptocurrency market has performed during COVID 19? A multifractal analysis, Finance Research Letters, Vol. 36, Article 101647, https://doi.org/10.1016/j.frl.2020.101647.
Moore, T., Christin, N. (2013), Beware the middleman: empirical analysis of Bitcoin-exchange risk, in: A. Sadeghi, (Ed), *Financial cryptography and data security*, Springer, Berlin, pp. 25–33, https://doi.org/10.1007/978-3-642-39884-1_3.
Moore, T., Christin, N., Szurdi, J. (2018), Revisiting the risks of Bitcoin currency exchange closure, ACM Transactions on Internet Technology, Vol. 18, No. 4, pp. 1–16, https://doi.org/10.1145/3155808.
Mora, C., Rollins, R.L., Taladay, K., Kantar, M.B., Chock, M.K., Shimada, M., Franklin, E.C. (2018), Bitcoin emissions alone could push global warming above 2°C, Nature Climate Change, Vol. 8, pp. 931–933, https://doi.org/10.1038/s41558-018-0321-8.
Nadarajah, S., Chu, J. (2017), On the inefficiency of Bitcoin, Economics Letters, Vol. 150, pp. 6–9, https://doi.org/10.1016/j.econlet.2016.10.033.
Naeem, M.A., Bouri, E., Peng, Z., Shahzad, S.J.H., Vo, X.V. (2021), Asymmetric efficiency of cryptocurrencies during COVID19, Physica A: Statistical Mechanics and its Applications, Vol. 565, Article 125562, https://doi.org/10.1016/j.physa.2020.125562.
Nakano, M., Takahashi, A., Takahashi, S. (2018), Bitcoin technical trading with artificial neural network, Physica A: Statistical Mechanics and its Applications, Vol. 510, pp. 587–609, https://doi.org/10.1016/j.physa.2018.07.017.
Náñez Alonso, S.L., Jorge-Vázquez, J., Echarte Fernández, M.Á., Reier Forradellas, R.F. (2021), Cryptocurrency mining from an economic and environmental perspective, analysis of the most and least sustainable countries, Energies, Vol. 14, Article 4254, pp. 1-22, https://doi.org/10.3390/en14144254.
Oladotun, A. (2022), 7 best on-chain analysis tools in 2022, retrieved from https://beincrypto.com/learn/on-chain-analysis-tools/ [2nd November 2022].
Özdemir, O. (2022), Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis, Financial Innovation, Vol. 8, No. 12, pp. 2–38, https://doi.org/10.1186/s40854-021-00319-0.
Resta, M., Pagnottoni, P., De Giuli, M.E. (2020), Technical analysis on the Bitcoin market: trading opportunities or investors' pitfall? Risks, Vol. 8, No. 2, Article 44, pp. 1-15, https://doi.org/10.3390/risks8020044.
Sanz-Bas, D., del Rosal, C., Náñez Alonso, S.L., Echarte Fernández, M.Á. (2021), Cryptocurrencies and fraudulent transactions: risks, practices, and legislation for their prevention in Europe and Spain, Laws, Vol. 10, No. 3, Article 57, pp. 1-20, https://doi.org/10.3390/laws10030057.
Schiereck, D., De Bondt, W., Weber, M. (1999), Contrarian and momentum strategies in Germany, Financial Analysts Journal, Vol. 55, No. 6, pp. 104–116, http://www.jstor.org/stable/4480212.
Schultze-Kraft, R. (2019), Dissecting Bitcoin's unrealised on–chain profit/loss, retrieved from https://medium.com/glassnode-insights/dissecting-bitcoins-unrealised-on-chain-profit-loss-73e735020c8d [5th November 2022].
Segnon, M., Bekiros, S. (2020), Forecasting volatility in Bitcoin market, Annals of Finance, Vol. 16, pp. 435–462, https://doi.org/10.1007/s10436-020-00368-y.
Sensoy, A. (2019), The inefficiency of Bitcoin revisited: a high-frequency analysis with alternative currencies, Finance Research Letters, Vol. 28, pp. 68–73, https://doi.org/10.1016/j.frl.2018.04.002.
Shen, D., Urquhart, A., Wang, P. (2020), A three-factor pricing model for cryptocurrencies, Finance Research Letters, Vol. 34, Article 101248, https://doi.org/10.1016/j.frl.2019.07.021.
Shirakashi, R. (2019), Introducing SOPR: spent outputs to predict Bitcoin lows and tops, retrieved from https://medium.com/unconfiscatable/introducing-sopr-spent-outputs-to-predict-bitcoin-lows-and-tops-ceb4536b3b9 [5th November 2022].
Tran, V.L., Leirvik, T. (2020), Efficiency in the markets of crypto-currencies, Finance Research Letters, Vol. 35, Article 101382, https://doi.org/10.1016/j.frl.2019.101382.

Truby, J. (2018), Decarbonizing Bitcoin: law and policy choices for reducing the energy consumption of blockchain technologies and digital currencies, Energy Research & Social Science, Vol. 44, pp. 399–410, https://doi.org/10.1016/j.erss.2018.06.009.

Urquhart, A. (2016), The inefficiency of Bitcoin, Economic Letters, Vol. 148, pp. 80–82, https://doi.org/10.1016/j.econlet.2016.09.019.

Urquhart, A. (2022), Under the hood of the Ethereum blockchain, Finance Research Letters, Vol. 47, Article 102628, https://doi.org/10.1016/j.frl.2021.102628.

Vidal-Tomás, D., Ibañez, A. (2018), Semi-strong efficiency of Bitcoin, Finance Research Letters, Vol. 27, pp. 259–265, https://doi.org/10.1016/j.frl.2018.03.013.

Wei, W.C. (2018), Liquidity and market efficiency in cryptocurrencies, Economics Letters, Vol. 168, pp. 21–24, https://doi.org/10.1016/j.econlet.2018.04.003.

Yadav, S.P., Agrawal, K.K., Bhati, B.S., Al-Turjman, F., Mostarda, L. (2020), Blockchain-based cryptocurrency regulation: an overview, Computational Economics, Vol. 59, pp. 1659–1675, https://doi.org/10.1007/s10614-020-10050-0.

Yonghong, J., He, N., Weihua, R. (2018), Time-varying long-term memory in Bitcoin market, Finance Research Letters, Vol. 25, pp. 280–284, https://doi.org/10.1016/j.frl.2017.12.009.

Appendix

Table A1. NUPL strategies: performance and testing results for the period 2015–2019

	BTC				ETH			
	B&H	**NUPL 1**	**NUPL 2**	**NUPL 3**	**B&H**	**NUPL 1**	**NUPL 2**	**NUPL 3**
Min	−1.79	1.13	0.96	0.91	−2.47	1.77	1.58	1.40
Max	3.22	4.02	4.88	5.48	4.93	20.72	27.44	27.44
Median	0.85	2.00	1.96	1.85	1.21	5.57	5.27	5.34
Mean	0.84	2.18	2.19	2.18	1.18	7.02	6.65	6.67
St. dev.	1.01	0.79	1.04	1.16	1.89	4.54	4.66	4.93
Sharpe ratio	0.83	2.76	2.10	1.88	0.62	1.54	1.43	1.35
N		210	214	217		205	213	227
Success rate		100%	100%	100%		100%	100%	100%
p-value (one-sided test for two means)		0.03**	0.06*	0.14		0.01**	<0.01***	<0.01***
p-value (one-sided test for two Sharpe ratios)		0.07*	0.15	0.24		0.07*	0.01**	0.03**

Source: own calculations based on the Glassnode data.

Notes: The success rate of an active strategy is defined as the percentage of cases where the annualized return on the active strategy is greater than the mean return on the passive strategy. Estimates significant at the significance levels of 0.01, 0.05, and 0.10 are denoted by three (***), two (**), and one (*) asterisk, respectively.

B&H, buy-and-hold; BTC, Bitcoin; ETH, Ethereum; NUPL, net unrealized profit/loss.

Table A2. SOPR strategies: performance and testing results for the period 2015–2019

	BTC				ETH			
	B&H	**SOPR 1**	**SOPR 2**	**SOPR 3**	**B&H**	**SOPR 1**	**SOPR 2**	**SOPR 3**
Min	−1.79	−22.33	−43.39	−43.39	−2.47	−11.18	−11.18	−33.09
Max	3.22	55.20	55.20	55.20	4.93	18.03	18.03	63.59
Median	0.85	1.13	0.80	0.90	1.21	2.18	2.15	1.29
Mean	0.84	2.96	2.13	2.06	1.18	1.93	1.77	1.55
St. dev.	1.01	7.73	8.74	8.51	1.89	4.18	4.36	7.28
Sharpe ratio	0.83	0.38	0.24	0.24	0.62	0.46	0.41	0.21
N		172	207	288		233	271	412
Success rate		54.65%	49.28%	50.69%		66.67%	64.58%	51.70%
p-value (one-sided test for two means)		0.03**	0.10	0.06*		0.25	0.27	0.39
p-value (one-sided test for two Sharpe ratios)		0.35	0.14	0.03**		0.27	0.28	0.35

Source: own calculations based on the Glassnode data.

Notes: The success rate of an active strategy is defined as the percentage of cases where the annualized return on the active strategy is greater than the mean return on the passive strategy. Estimates significant at the significance levels of 0.05 and 0.10 are denoted by two (**) and one (*) asterisk, respectively.

B&H, buy-and-hold; BTC, Bitcoin; ETH, Ethereum; SOPR, spent output profit ratio.

Table A3. PAP strategies: performance and testing results for the period 2015–2019

	BTC				ETH			
	B&H	**PAP 1**	**PAP 2**	**PAP 3**	**B&H**	**PAP 1**	**PAP 2**	**PAP 3**
Min	–1.79	0.52	1.00	0.69	–2.47	0.41	0.40	0.38
Max	3.22	1.50	3.69	3.91	4.93	14.18	26.56	26.56
Median	0.85	0.81	2.06	1.91	1.21	3.46	3.58	3.45
Mean	0.84	0.99	2.03	1.90	1.18	3.98	4.28	4.41
St. dev.	1.01	0.33	0.74	0.80	1.89	2.91	3.37	3.32
Sharpe ratio	0.83	2.97	2.74	2.38	0.62	1.37	1.27	1.33
N		125	150	181		326	337	363
Success rate		38.40%	100%	97.25%		82.82%	84.57%	90.64%
p-value (one-sided test for two means)		0.39	0.12	0.15		<0.01***	<0.01***	<0.01***
p-value (one-sided test for two Sharpe ratios)		0.04**	0.08*	0.14		0.05*	0.14	0.02**

Source: own calculations based on the Glassnode data.

Notes: The success rate of an active strategy is defined as the percentage of cases where the annualized return on the active strategy is greater than the mean return on the passive strategy. Estimates significant at the significance levels of 0.01, 0.05, and 0.10 are denoted by three (***), two (**), and one (*) asterisk, respectively.

B&H, buy-and-hold; BTC, Bitcoin; ETH, Ethereum; PAP, percent of addresses in profit.

Table A4. NUPL strategies: performance in the COVID-19 period (2020–2022)

	BTC				ETH			
	B&H	**NUPL 1**	**NUPL 2**	**NUPL 3**	**B&H**	**NUPL 1**	**NUPL 2**	**NUPL 3**
Min	1.24	1.38	1.83	3.90	–1.18	1.49	1.36	1.14
Max	2.47	1.59	2.18	4.87	3.11	3.21	5.10	14.84
Median	1.14	1.50	2.05	4.62	1.92	2.63	2.70	2.77
Mean	0.64	1.50	2.02	4.50	1.18	2.43	2.52	3.00
St. dev.	1.01	0.07	0.13	0.32	1.26	0.56	0.67	2.01
Sharpe ratio	0.63	20.91	15.18	13.95	0.94	4.34	3.75	1.49
N		7	8	9		103	121	158
Success rate		100%	100%	100%		100%	100%	98.10%

Source: own calculations based on the Glassnode data.

B&H, buy-and-hold; BTC, Bitcoin; ETH, Ethereum; NUPL, net unrealized profit/loss.

Table A5. SOPR strategies: performance in the COVID-19 period (2020–2022)

	BTC				ETH			
	B&H	**SOPR 1**	**SOPR 2**	**SOPR 3**	**B&H**	**SOPR 1**	**SOPR 2**	**SOPR 3**
Min	1.24	–4.77	–6.00	–6.00	–1.18	–4.14	–4.14	–21.67
Max	2.47	39.65	39.65	39.65	3.11	13.00	37.21	37.21
Median	1.14	4.40	2.99	–0.22	1.92	1.95	2.09	1.47
Mean	0.64	5.18	5.25	2.58	1.18	1.76	2.54	2.30
St. dev.	1.01	9.17	9.91	7.31	1.26	4.02	6.44	7.58
Sharpe ratio	0.63	0.57	0.53	0.35	0.94	0.44	0.39	0.30
N		28	39	114		48	49	98
Success rate		57.14%	62.16%	33.33%		52.08%	55.10%	50%

Source: own calculations based on the Glassnode data.

B&H, buy-and-hold; BTC, Bitcoin; ETH, Ethereum; SOPR, spent output profit ratio.

Table A6. PAP strategies: performance in the COVID-19 period (2020–2022)

	BTC				ETH			
	B&H	**PAP 1**	**PAP 2**	**PAP 3**	**B&H**	**PAP 1**	**PAP 2**	**PAP 3**
Min	1.24	1.74	1.59	1.44	–1.18	1.62	1.31	1.09
Max	2.47	2.27	2.19	2.18	3.11	2.93	2.58	2.43
Median	1.14	2.00	1.85	1.69	1.92	2.35	2.02	1.92
Mean	0.64	2.00	1.85	1.77	1.18	2.24	1.93	1.81
St. dev.	1.01	0.19	0.21	0.23	1.26	0.35	0.33	0.35
Sharpe ratio	0.63	10.56	9.01	7.74	0.94	6.42	5.87	5.18
N		13	17	22		136	151	174
Success rate		100%	100%	100%		100%	100%	94.83%

Source: own calculations based on the Glassnode data.

B&H, buy-and-hold; BTC, Bitcoin; ETH, Ethereum; PAP, percent of addresses in profit.