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# Theoretical and Practical Market Efficiency of Leading Cryptocurrencies

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# Chapter 1

## Introduction

"It might make sense just to get some in case it catches on", Satoshi Nakamoto, the pseudonymous individual or group of individuals behind the Bitcoin whitepaper, wrote in "The Cryptography Mailing List" about two weeks after the blockchain's initial launch in January 2009. Two years would go by until individual Bitcoins became worth one US dollar in 2011, before the first significant all-time high of more than 16,000\$ in late 2017. Considering this rapid growth, it does not surprise that, in hindsight, virtually every portfolio would have benefited from even the smallest capital allocation to Bitcoin. Contrarily, the extensive price volatility, hype, and arguable lack of established fundamental valuations mobilize critics to proclaim that cryptocurrencies are a scam and should not be invested in at all. With no reliable investment outlook being available, this dissertation investigates the market efficiency of leading cryptocurrencies, with emphasis on (1) the degree of randomness in the price changes of Bitcoin and Ethereum compared with the S&P 500, (2) the profitability of popular technical trading strategies for the two largest cryptocurrencies, and (3) the profitability of trend trading for a range of different cryptocurrency types.

Firstly, I revisit the efficient market hypothesis in chapter 2. Previous research predominantly focuses on testing the degree of randomness of Bitcoin returns for comparably short time intervals and without providing a benchmark of more established financial instruments. In doing so, the literature points to low efficiency and randomness in Bitcoin's early years, with increasing return randomness and, thus, efficiency over time. By utilizing the entire price history available at the time of the analysis, I will show that the markets of Bitcoin and

Ethereum were inefficient during their early days. However, I will be able to demonstrate that the notion of slowly but surely increasing market efficiency is not well supported but that this efficiency varies over time. Further, Ethereum and Bitcoin returns predominantly exhibit long-range dependence when diverting from randomness. Lastly, by employing a benchmark of the S&P 500 index, I will show that Bitcoin and Ethereum are substantially less market efficient than the globally dominant equity index.

Secondly, in chapter 3, I will apply long-established technical trading strategies at different implementations for Bitcoin and Ethereum. In doing so, I will be able to show that some trend-following strategies yield superior absolute returns compared to the buy-and-hold portfolio. Cryptocurrency markets are less developed than equity markets, so that shorting, for example, Bitcoin, was and still is not possible across many exchanges. I thus apply trading strategies in their literal sense where shorting is possible and in a long or out manner. As will be shown, long or out strategies offer larger risk-adjusted return improvements versus buy-and-hold due to reduced volatility when going out of the market, while fully implemented strategies offer higher absolute returns. Conducting the analyses for hourly and daily return data, I also will be able to show that absolute returns are more substantial for hourly trading, while Sharpe ratio differences versus buy-and-hold are larger when trading on daily data.

Lastly, I will analyze the performance of modified trend-following trading strategies for several cryptocurrencies in chapter 4. In doing so, I will be able to show that shorter than usually considered signal periods are beneficial when trading cryptocurrencies. As before, it will be shown that long or out strategies offer risk-adjusted return improvements versus buy-and-hold with higher statistical significance than long or short strategies. Within the considered sample, the buy-and-hold performance of the considered cryptocurrencies is not indicative of strategy performance.

Overall, this dissertation highlights that the markets of cryptocurrencies lack the level of efficiency present in equity markets. However, the degree to which these inefficiencies can be exploited via technical trading strategies varies strongly across cryptocurrencies. Detecting mostly long-range dependence and finding that the most attractive

strategies are trend-followers, my results offer an avenue for future research on herd behavior in cryptocurrency markets.



# Chapter 2

## Time-Varying Informational Efficiency of Bitcoin and Ethereum<sup>1</sup>

### 2.1 Introduction

In the past decade, cryptocurrencies have attracted immense attention from investors, traders, academics, and policy markets. An evident reason for this is that since their inception as known today in early 2009, when a Bitcoin was worth only a fraction of a U.S. dollar, the total market capitalization of cryptocurrencies developed to about \$2.5tn in November 2021 (Coinmarketcap, 2022). The largest and most well-known cryptocurrencies today are Bitcoin and Ethereum, which consistently rank at the very top of all cryptocurrencies as measured by market capitalization.

While the umbrella term "cryptocurrencies" suggests a certain similarity, Bitcoin and Ethereum differ drastically in the way they work and thus also in their investment hypothesis. The Bitcoin whitepaper (Nakamoto, 2008) was published in October 2008, with the first Bitcoin block being mined in early January 2009. The publication and subsequent global propagation of the Bitcoin network is the success of decades of cryptographic research and development efforts to create a decentralized electronic currency.<sup>2</sup>

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<sup>1</sup>This chapter is based on Becker, M. (2022c). Time Varying Informational Efficiency in the High Frequency Markets of Bitcoin and Ethereum *Unpublished working paper*.

<sup>2</sup>Chaum (1983) is credited for the first electronic, anonymous cryptographic money, an invention today honored as being the first cryptocurrency.

From an academic standpoint, Bitcoin is an emerging financial technology with no apparent precedents in recent times. It, therefore, lends itself to studies of exotic financial technologies differing from existing asset and exchange systems (Alvarez-Ramirez et al., 2018). Whereas Bitcoin and Ethereum are both cryptocurrencies, their respective investment hypotheses divert considerably. While Bitcoin’s blockchain is intended to make it digital money, it is only granted the store of value property, as its price volatility denies it the status as a medium of exchange and unit of account (cf. Baur & Dimpfl, 2021). The Ethereum protocol is intended to create and run decentralized web applications, as it allows for anonymous transactions and the execution of Turing-complete code attached to these transactions (Buterin, 2013).

Pointing out that neither Bitcoin nor Ethereum has yet reached their envisioned potential, Shiller (2020) proposes that cryptocurrencies and Bitcoin especially are a prime example of what he calls economic narrative; Bitcoin is valuable only if investors think it is valuable, and this value depends on what investors think Bitcoin represents. With no common consensus on the true value of the cryptocurrencies and acknowledging their tremendous rise in market capitalization in the past decade, it is interesting to investigate the efficiency of the markets in which they are traded. Famously, Fama (1970) proposed that capital markets are efficient, as investors are rational profit maximizers utilizing all available information to collect the highest returns possible. This competition leads to prices fully reflecting all available information, making price developments unpredictable as they depend on the equally unpredictable emergence of new information in the world.

Distinguishing types of information, Fama (1970) segments the efficient market hypothesis (EMH) into three classes, weak form, semi-strong, and strong form efficiency. In a weakly efficient market, historical price data cannot be utilized to predict future returns. In a semi-strong efficient market, all public information does not help predict future returns. If the strong form is present, all public and private information (insider trading) cannot be used to determine how prices will develop in the future.

It is common to test market efficiency by scrutinizing its weak form, as it is both the easiest to validate (since it is non-trivial to consider

all public information and rather of theoretical nature to account for all public and private information) and because in its absence, there is no reason to assume semi-strong or strong form efficiency. Regarding the historical origin of his seminal work, Fama (1970) states: "[...] the impetus for the development of a theory came from the accumulation of evidence in the middle 1950's and early 1960's that the behavior of common stock and other speculative prices could be well approximated by a random walk. Faced with the evidence, economists felt compelled to offer some rationalization. What resulted was a theory of efficient markets stated in terms of random walks [...]." As this statement implies that the proposition of a random walk and its subsequent rationalization derived directly from the observation of randomness in price data, it follows that without this randomness, there is no basis for assuming efficient capital markets. Considering that the herewith presumed efficiency of markets presents the foundation of essential financial theories and models,<sup>3</sup> it is evident that deviations from the strong assumptions of the EMH have far-reaching implications.

A more lenient alternative to the EMH was presented by Lo (2004) is the adaptive market hypothesis (AMH). According to the AMH, efficiency is not a fixed but an evolving property of markets that varies over time. Important factors driving the degree of efficiency are the number of market participants, overall market conditions, the type and distribution of investors, opportunities for profit, and the associated risk-return profile. Further, instead of assuming humans to be rational, the AMH proposes that market participants are biased individuals driven by fear and greed. Under the AMH, humans are not utility maximizers but adapt to changing environments via a satisficing process, meaning they aim not to make the best but good enough decisions for their objectives. Therefore, market efficiency is assumed to be an evolving property based on competition, adaptation, and natural selection (Lo, 2004).

Behavioralists often cite the work of Kahneman and Tversky (1979) on prospect theory, and hence, loss aversion, to criticize the idea of rationality and market efficiency. However, behavioral biases are com-

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<sup>3</sup>The idea that asset prices accurately reflect all currently available information is fundamental for theories such as (in alphabetical order) the arbitrage pricing theory by Ross (1976), Black-Scholes option pricing model by Black and Scholes (1973) and Merton (1973), capital asset pricing model by Sharpe (1964), Lintner (1965), and Mossin (1966), and the portfolio theory of Markowitz (1952, 1959).

monly considered consistent with a market efficiency model based on evolutionary properties, where individuals interact with and adapt to changing environments based on heuristics (Lo, 2005).

Research on the market efficiency of cryptocurrencies, and most prominently Bitcoin, has increased in recent years, beginning with the study of Urquhart (2016). By employing daily data from 1. August 2010 to 31. July 2016, the study rejects the EMH for the entire sample but found increasing efficiency over time when splitting the sample data (Urquhart, 2016). These findings were further supported by later studies, as summarized by Kyriazis (2019), who finds in his meta-study that most research on the efficiency of the Bitcoin (and those of other cryptocurrencies, such as Ethereum) market finds inefficiency (especially long-range dependence) during the first years, with increasing efficiency over time.

Notably, most previous studies employ data only until the end of 2019 (cf. López-Martín et al., 2021), before the significant bull market in 2021 (Coinmarketcap, 2022). Further, few studies on the market efficiency of cryptocurrencies utilize high-frequency data, and if, only for comparably short time frames (cf. Chu et al., 2019 and Zhang et al., 2019). Another fact is that previous studies have looked at cryptocurrencies in isolation and do not present comparative analyses of traditional assets.

We, therefore, employ a high-frequency data set of hourly resolution for Bitcoin and Ethereum to test the AMH and do the same for the S&P 500 in this study. Thus, to the best of our knowledge, we contribute to literature by utilizing the most comprehensive time series of Bitcoin and Ethereum to date and by providing an easily comprehensible benchmark analysis by employing the same methodology for the S&P 500 index.

Doing so, we find strong support for the AMH for all three assets under consideration, with higher degrees of inefficiency for Bitcoin and Ethereum compared with the S&P 500. Thus, our findings imply that Bitcoin and Ethereum exhibit (especially compared with the S&P 500) prolonged and recurring periods of comparably low market efficiency. Ultimately, evidence for the AMH provides reason to believe that it may be possible to trend trade even the largest cryptocurrencies profitably. The remainder of this paper is divided into five sections. First, we provide descriptive statistics on our employed dataset in section

2.2. Next, we explain and rationalize our methodology in section 2.3. Next, we present our results in section 2.4 and afterward discuss them in section 2.5. In section 2.6 we conclude our study.

## 2.2 Data

The hourly price data of Bitcoin and Ethereum (versus the U.S. Dollar) used for the primary analysis of this paper was obtained from Glassnode (2021), a leading data and analytics provider in the cryptocurrency space. For the benchmark analysis, hourly price data of the S&P 500 index was used, which we obtained from BacktestMarket (2022). As this paper aims to provide an extensive analysis of the market efficiency of Bitcoin and Ethereum, we include their entire price history available at the time of this analysis. For Bitcoin, this means hourly data from 17.07.2010 till 27.11.2021, and for Ethereum from 08.08.2015 till 27.11.2021.

With cryptocurrencies being tradable around the clock, regardless of the weekend or holidays, this sample starts and ends during times when the S&P 500 was not traded, as both the 17.07.2010 and the 27.11.2021 are Saturdays. Hence, the benchmark price data of the S&P 500 spans from 19.07.2010 to 26.11.2021. For our analyses, we transform the price data into logarithmic returns via

$$r_t = \ln \left( \frac{X_t}{X_{t-1}} \right) \quad (2.1)$$

Table 2.1 presents descriptive statistics of the thus computed Bitcoin, Ethereum, and S&P 500 returns. The mean for all hourly returns is positive, with the mean of Bitcoin and Ethereum being very similar and significantly larger than the average hourly S&P 500 return in the sample period. The returns of the crypto assets also exhibit a higher standard deviation and range than those of the S&P 500. All time series under investigation have a negative skewness statistic; thus, all hourly return distributions are skewed to the left. With all kurtosis statistics highlighting that the return distributions are fat-tailed compared with the normal distribution and the Jarque-Bera test for normality being significant at the 1% level, it is shown that the returns do not fit a normal distribution.

Table 2.1: Descriptive statistics of Bitcoin, Ethereum, and S&P 500 log returns

	Bitcoin	Ethereum	S&P 500
Minimum (%)	-68.9716	-26.7479	-4.7151
Mean (%)	0.0141	0.0142	0.0021
Maximum (%)	55.6482	25.5594	5.6067
Median (%)	0.0002	0	0
Standard Deviation	0.0145	0.014	0.0022
Skewness	-0.6599	-0.0889	-0.2475
Kurtosis	190.0852	31.0433	53.8674
Jarque-Bera	148,798,852*	2,211,577*	8,248,046*
Sample period	Jul 17, 2010 - Nov 27, 2021	Aug 08, 2015 - Nov 27, 2021	Jul 19, 2010 - Nov 26, 2021

Note: \* denotes statistical significance at the 1% level

## 2.3 Methodology

Price movements in markets adhering to weak form efficiency, as put forward by Fama (1970), are unpredictable given past prices of the respective asset. Testing the weak form efficiency is predominantly done by examining the martingale difference hypothesis (MDH) and the random walk hypothesis (RWH) (cf. Khuntia & Pattanayak, 2018), as outlined below in this chapter. Following the argumentation of Lo (2004) that market efficiency is an evolutionary, non-static property, we test the MDH and the RWH based on a rolling window of the time series at hand. Specifically, all statistics described hereafter are computed based on a 1000-hour window, continuously incremented by one hour.

When a market exhibits weak form efficiency, prices do not follow their past trend and are mean-independent. Hence, they follow a martingale sequence. What follows is

$$E [Y_t | Y_{t-1}, Y_{t-2}, \dots] = \mu \quad (2.2)$$

$$Y_t = X_t - X_{t-1}, \text{ and} \quad (2.3)$$

$$E [X_t | X_{t-1}, X_{t-2}, \dots] = X_{t-1} \quad (2.4)$$

where  $X_t$  is the natural logarithm of an asset's price at time  $t$  and  $Y_t$  is the change in log price between  $t$  and  $t - 1$ . Examining the

MDH can be done by testing the null hypothesis that a time series process, given an information set  $\Phi_t$ , consisting of the process past, has constant conditional expectation

$$H_0 : E(Y_t|\Phi_t) = \mu \quad (2.5)$$

The alternative hypothesis is that the process adheres to a function of the said information set

$$H_1 : E(Y_t|\Phi_t) = \mu(\Phi_t) \quad (2.6)$$

Dominguez and Lobato (2003) developed a consistent test capable of detecting dependencies, even for processes that are uncorrelated and have non-linear dependencies. It is also robust to common features of financial return data, such as heteroscedasticity and non-normality. Because the underlying distribution and function of the examined time series are unknown, their test is computed by employing two test statistics ('Cramer von Mises' [CvM] and 'Kolmogorov Smirnov' [KS]) with similar results yet slightly different empirical power for different processes. With  $Y_t$  being the logarithmic return of period  $t$ , they are written as

$$CvM_{n,P} = \frac{1}{\hat{\sigma}^2 n^2} \left[ \sum_{t=1}^n (Y_t - \tilde{Y}) 1(\tilde{Y}_{t,P} - \tilde{Y}_{j,P}) \right]^2 \quad (2.7)$$

$$KS_{n,P} = \max_{1 \leq i \leq n} \left| \frac{1}{\hat{\sigma} \sqrt{n}} \sum_{t=1}^n (Y_t - \tilde{Y}) 1(\tilde{Y}_{t,P} - \tilde{Y}_{j,P}) \right| \quad (2.8)$$

where  $\sigma^2 = \frac{1}{n} \sum_{t=1}^n (Y_t - \bar{Y})^2$ ,  $P$  is a positive integer, and  $\tilde{Y}_{t,P} = (Y_{t-1}, \dots, Y_{t-P})$  is the indicator function. Note that the  $CvM$  and  $KS$  statistics serve as inputs for the test developed by Dominguez and Lobato (2003) and do not immediately yield indicative  $p$ -values. Refer to Dominguez and Lobato (2003) for a detailed description of the testing procedure. As Escanciano and Lobato (2009) show, the critical values and test statistics cannot be computed directly but can be obtained via bootstrapping. The null hypothesis of constant conditional expectation is confirmed if the resulting  $p$ -values are close to one, implying market efficiency, and rejected for  $p$ -values of less than 5%.

After considering whether past prices contain an informational value for predicting future prices, it is interesting to determine if a time series exhibits anti-persistence (mean-reversion) or long-range dependence (persistence). In this regard, the RWH can be investigated as it is directly consistent with the efficient market hypothesis because it assumes that price changes occur randomly and can thus not be predicted. Hence

$$f(r_{j,t+1}|\Phi_t) = f(r_{j,t+1}) \quad (2.9)$$

where the information set, denoted  $\Phi_t$ , includes only past returns. The equation implies that the conditional and marginal probability distribution of an independent random variable are identical. While the RWH asserts that the past helps assess an asset's return distribution, it precludes predictive power over the sequence of future returns.

The RWH is closely related to the Wiener process (WP), the Brownian motion (BM) mathematical model. The application of the BM for stocks by Bachelier (1900) famously constitutes the first use of higher mathematics in finance. A stochastic process  $\{W(t), t \geq 0\}$  is a WP if it satisfies all of the following

- i  $W_0 = 0$
- ii For any points in time  $t_1 \leq t_2 \leq t_3 \leq t_4$ , the increments  $W(t_2) - W(t_1)$  and  $W(t_4) - W(t_3)$  are independent
- iii Increments of  $W$  are Gaussian increments with variance equal to their difference in time:  $W(t) - W(s) \sim N(0, t - s)$
- iv  $W_t$  is continuous in  $t$

Mandelbrot and Van Ness (1968) introduced fractional Brownian motion (FBM), a generalization of the BM. In contrast to the BM, the FBM increments do not need to be independent, making it an ideal candidate for describing processes where the conditional and marginal probability distribution are not equal. Thus, the FBM is a stochastic process  $\{W(t), t \geq 0\}$  starting at zero, zero-mean for all  $t$ , and autocovariance function



$$\text{Cov}[FBM_H(t), FBM_H(t + \Delta t)] = \frac{1}{2}(|t|^{2H} + |t + \Delta t|^{2H} - |\Delta t|^{2H}) \quad (2.10)$$

with  $H \in (0, 1)$  and  $H$  denoting the Hurst exponent, which was first described in the seminal work by Hurst (1951). When  $H = 0.5$ , it follows

$$\text{Cov}[FBM_H(t + \Delta t) - FBM_H(t), FBM_H(t)] = 0 \quad (2.11)$$

so that the FBM increments are independent. In this case, the FBM is equal to the BM. When  $H \in (0, 0.5)$ , it follows

$$\text{Cov}[FBM_H(t + \Delta t) - FBM_H(t), FBM_H(t)] < 0 \quad (2.12)$$

and when  $H \in (0.5, 1)$ , it follows

$$\text{Cov}[FBM_H(t + \Delta t) - FBM_H(t), FBM_H(t)] > 0 \quad (2.13)$$

Therefore,  $H$  is equal to 0.5 for random processes, while values smaller than 0.5 describe processes with anti-persistence, and values greater than 0.5 belong to processes with long-range dependence. The level of anti-persistence or long-range dependence is stronger the further away  $H$  is from 0.5. As pointed out by Liu et al. (2019), values of  $H$  between 0.45 and 0.55 describe processes reasonably close to the random walk.

The RWH can thus be examined by considering the time-varying dependence of a time series by estimating  $H$ . We do so by utilizing the detrended fluctuation analysis (DFA) as developed by Peng et al. (1994) and employed in previous studies on the RWH in the Bitcoin market (cf. Alvarez-Ramirez et al., 2018; Bariviera, 2017; Tiwari et al., 2018; Zhang et al. 2019).

To obtain the Hurst exponent for a time series  $x_k, k = 1, \dots, M$ , the DFA first calculates the mean  $\bar{x}_k$  of the time series as

$$\bar{x}_k = \frac{1}{M} \sum_{j=1}^M x_j \quad (2.14)$$

Then, an integrated sequence  $Y_k$  is calculated by summing up the difference between each value of  $x_k$  and  $\bar{x}_k$

$$Y_k = \frac{1}{M} \sum_{j=1}^M x_j - \bar{x}_k \quad (2.15)$$

Afterward, the integrated sequence  $Y_k$  is divided into  $N$  non-overlapping sequences of equal length  $m$ . A least-squares line is then computed for each sub-sequence to identify the present trend  $Y_{m,k}$ . The integrated sequence is detrended by subtracting  $Y_{m,k}$  from  $Y_k$  in each sub-sequence. The fluctuation of the integrated and detrended sequence is computed by

$$F(m) = \sqrt{\frac{1}{M} \sum_{k=1}^M [Y_k - Y_{m,k}]^2} \quad (2.16)$$

This computation is repeated for all sub-sequences for different subseries sizes  $m$ , to determine how  $F(m)$  relates to  $m$ .  $F(m)$  acts as a power-law of  $m$ ,  $F(m) \approx m^H$ , where  $H$  denotes the Hurst exponent. Lastly, by regressing  $\ln(F(m))$  on  $\ln(m)$ ,  $H$  is obtained (Peng et al., 1995). To improve our results, we follow Hardstone et al. (2012) recommendations regarding the setting of  $m$ . We use a 50% overlap for the sequences to obtain more windows and hence, improved test statistics. Furthermore, values of  $m < 4$  makes polynomial least squares fitting prone to error, while  $m$  should not be set so high that later less than ten windows are available to calculate the average fluctuation (Hardstone et al., 2012). Considering this, we chose window sizes of  $m = \{4, 5, 6, 8, 9, 11, 14, 17, 20, 24, 29, 35, 42, 51, 61, 73, 88\}$ .

## 2.4 Results

Figure 2.1 presents the estimated  $p$ -values of the Dominguez-Lobato test for Bitcoin, and Figure 2.2 provides the S&P 500 benchmark analysis for the respective time frame. The horizontal line presents the 5% threshold. Values of the CvM and KS test statistic falling under this line hence mark where the DL test rejects the null hypothesis of constant conditional expectation and thus deviation from weak form market efficiency (at the 5% significance level).

Figure 2.1: DL results Bitcoin

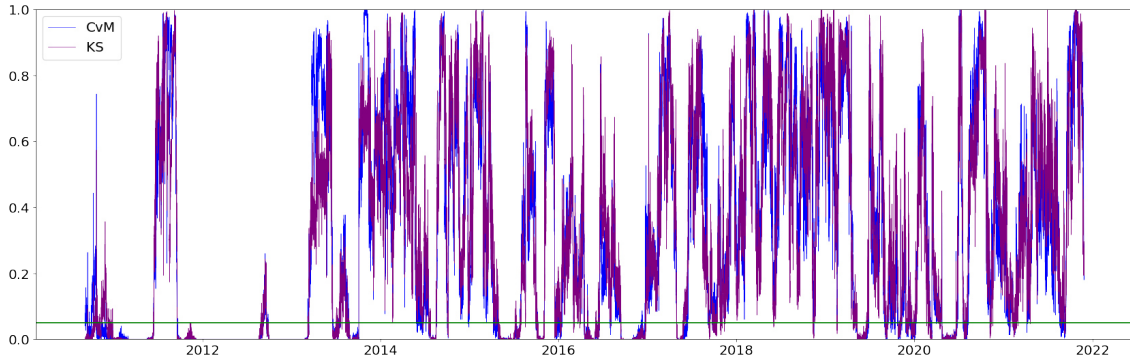
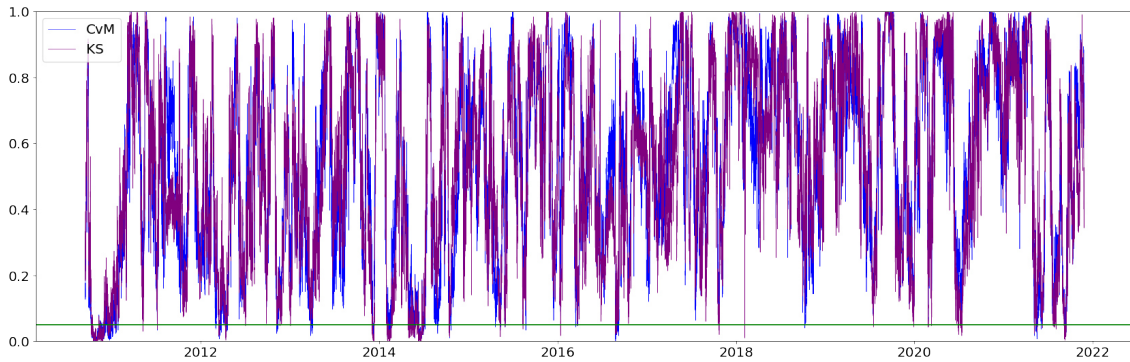


Figure 2.2: DL results S&P 500 benchmark to Bitcoin



We find ample evidence for the AMH in the Bitcoin market in the results presented in Figure 2.1. In the timeframe from 05.09.2012 to 27.11.2021, the CvM statistic estimates inefficiency during 35.3% of the time (1,441 days), and the KS statistic 33.6% of the time (1,372 days). While the most prolonged periods are during the first three years of the sample, there is no apparent improvement in market efficiency over time visible in the data. Instead, and in line with evolving nature of market efficiency as proposed by the AMH,  $p$ -values swing considerably, with extensive periods of market inefficiency scattered across the entire sample period.

In this regard, Figure 2.2 also seems to confirm the AMH for the S&P 500, with the respective  $p$ -values moving to an extent similar to those associated with the prices of Bitcoin. However, the CvM statistic estimates inefficiency only 3.4% of the time (94 days), and the KS statistic 3.6% of the time (100 days). Comparing the respective percentage inefficiencies thus shows that Bitcoin was 10.4 (9.3) times as inefficient as the S&P 500 during the period under review, according to the CvM (KS) statistics.

Figure 2.3: DL results Ethereum

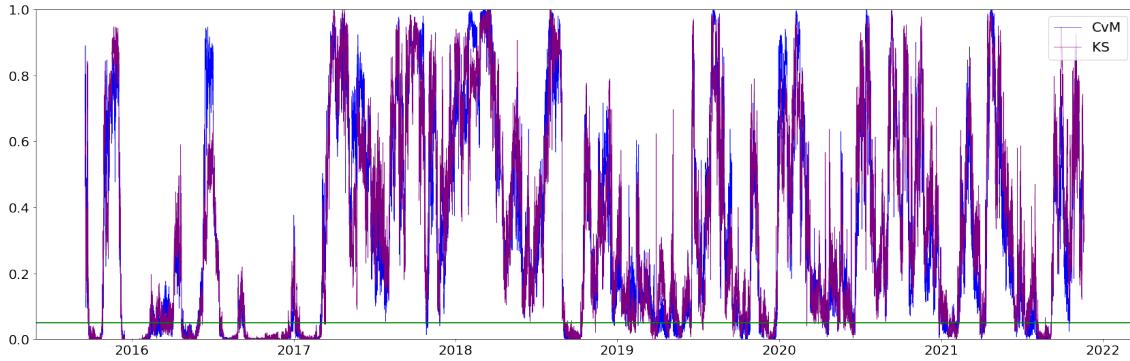


Figure 2.4: DL results S&P 500 benchmark to Ethereum

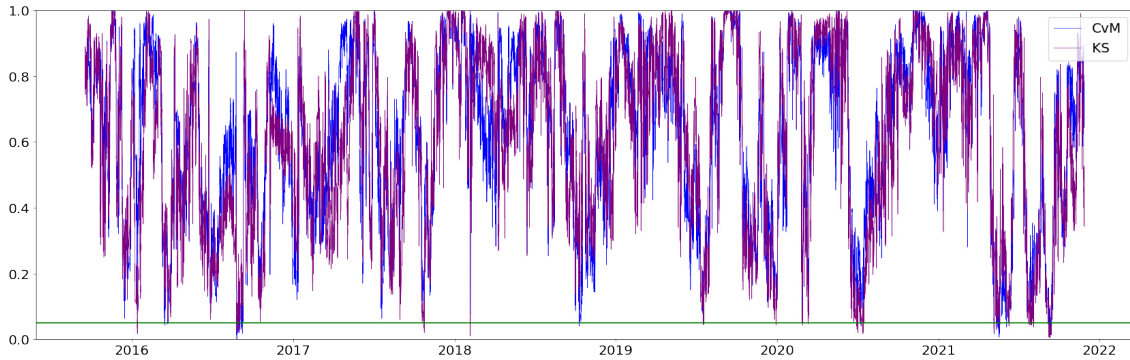
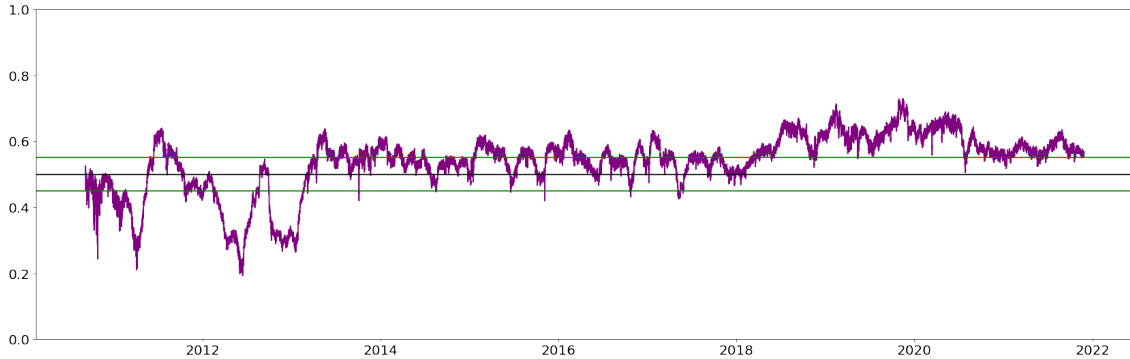


Figure 2.3 presents the estimated  $p$ -values of the Dominguez-Lobato test for Ethereum, and Figure 2.4 provides the S&P 500 benchmark analysis for the respective time frame. Again, the horizontal line presents the 5% threshold.

As in the case of Bitcoin, we find ample evidence for the AMH in the Ethereum market, as presented in Figure 2.3. In the timeframe from 18.09.2015 to 27.11.2021, the CvM statistic estimates inefficiency 27.7% of the time (623 days), and the KS statistic 24.4% of the time (549 days). Interestingly, the most prolonged inefficiencies are located at the beginning of the analyzed period, just like in the case of Bitcoin. Afterward, inefficiency occurs dispersed across the entire considered period.

While the values presented in Figure 2.4, displaying a subset of those contained in Figure 2.2, again confirm the AMH for the S&P 500, periods of inefficiency are relatively rare and short-lived. The CvM statistic estimates inefficiency 0.6% of the time (8 days), and the KS statistic 0.8% of the time (12 days).

Figure 2.5: DFA test results Bitcoin



Consequentially, while Ethereum exhibits proportionally less inefficiency than Bitcoin, it is, in comparison, significantly more inefficient than its benchmark, being 46.2 (30.5) times as inefficient as the S&P 500 during the sample period, according to the CvM (KS) statistic. As seen in Figure 2.2, this is because the S&P 500 is particularly inefficient in the period before September 2015, when the analysis of Ethereum begins.

Figure 2.5 presents the Hurst exponent estimated by the DFA for Bitcoin, and Figure 2.6 displays the S&P 500 benchmark during the same period. The black horizontal line is set at 0.5, representing points at which the DFA estimates the fractional Brownian motion to be a Brownian motion, and thus, price changes to be independent. Points above the line indicate long-range dependence, while points below the line signify anti-persistence. The green horizontal lines enclose the corridor between 0.45 and 0.55, where the fractional Brownian motion resembles the Brownian motion reasonably closely.

In line with the results of the Dominguez-Lobato test, the DFA rarely predicts Bitcoin prices to develop perfectly randomly. We again find evidence for the AMH, with the Hurst exponent varying significantly over time. During most of the considered period, Bitcoin prices exhibit long-range dependence (78% of the time), with longer intervals of anti-persistence, lasting several months, only being present during the first three years (with a minimum value of 0.192). After that and until 2018, anti-persistence exists only minutely. From 2018 onwards, only long-range dependence is present, with the highest Hurst exponent values (with a maximum of 0.729) occurring at the end of 2019. On average, the DFA predicts a Hurst exponent of 0.538 for the returns of Bitcoin.

Figure 2.6: DFA test results S&P 500 benchmark to Bitcoin

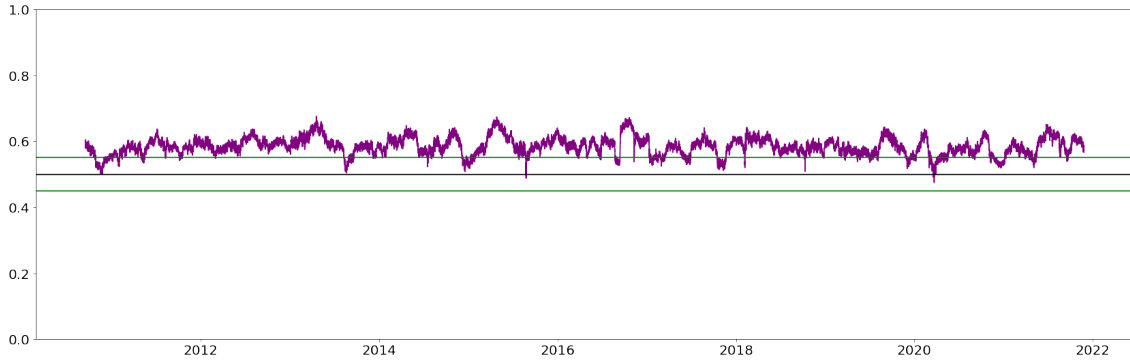
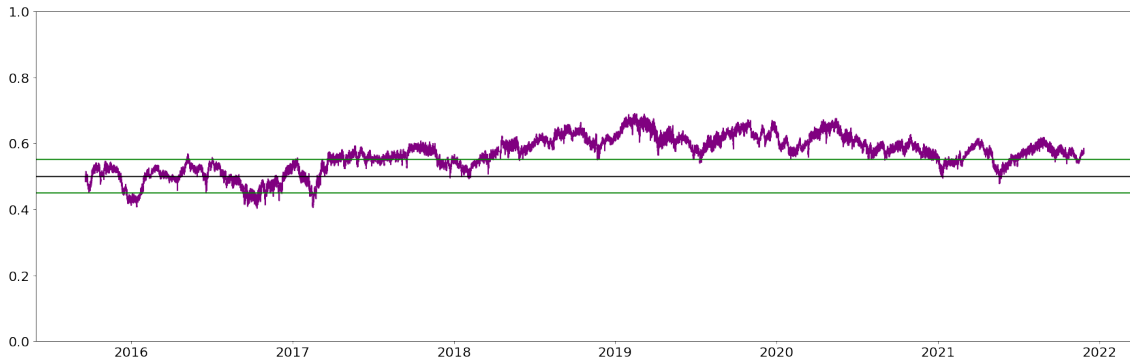


Figure 2.7: DFA test results Ethereum

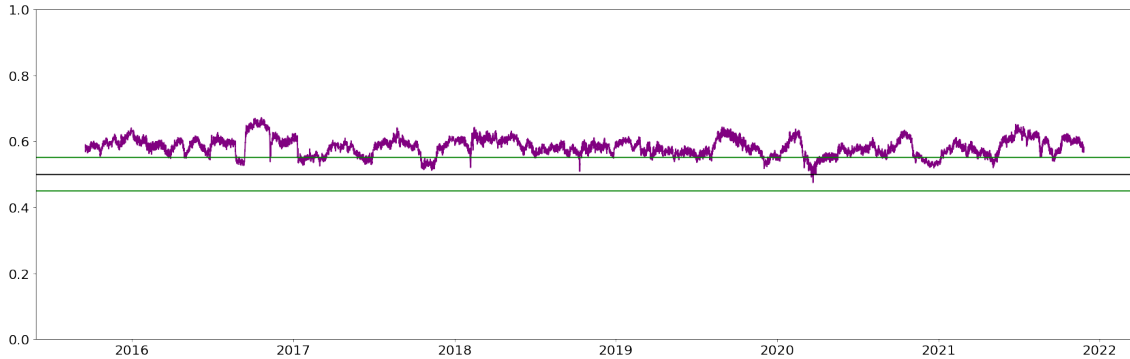


Contrasting the results for Bitcoin, the S&P 500 benchmark analysis yields virtually no indication for the presence of anti-persistence but consistently finds the presence of long-range dependence. The DFA, on average, finds a Hurst exponent of 0.566, with a maximum value of 0.676 and a minimum value of 0.475. As depicted in Figure 2.6, the estimates for the S&P 500 are considerably more evenly distributed around their mean value than those for Bitcoin. However, these changing values are above 0.5, which points to a persistent deviation from the RWH and supports the AMH.

Figure 2.7 presents the Hurst exponent estimated by the DFA for Ethereum, and Figure 2.8 displays the S&P 500 benchmark during the same period. As before, the black horizontal line is set to 0.5, indicating the level at which price changes are independent, and the green horizontal lines indicate the corridor where the fractional Brownian motion resembles the Brownian motion reasonably closely.

Just as for Bitcoin, the DFA confirms the notion of varying efficiency and hence, the AMH for Ethereum. On average, we find a Hurst exponent of 0.566, and Ethereum returns to be long-range de-

Figure 2.8: DFA test results S&P 500 benchmark to Ethereum



pendent 87% of the time. Strikingly, the only noticeable phases that show anti-persistence are also at the beginning of the observed period, with a low of 0.403 in late 2016. After crossing the horizontal line briefly in early 2018, values stay consistently above 0.5 until 2021, with a maximum of 0.690 in early 2019.

As the benchmark analysis for Ethereum consists of a subset of the benchmark analysis for Bitcoin, it is unsurprising that S&P 500 returns are again found to develop almost exclusively with long-range dependence. The DFA, on average, finds a Hurst exponent of 0.583, with a maximum value of 0.672 and a minimum value of 0.475. Thus, the higher average value compared with Ethereum is not due to exceptionally high values but because of the absence of comparably low values.

## 2.5 Discussion

Previous research studying the EMH by means of the MDH for Bitcoin and Ethereum has focussed chiefly on data of lower resolution and, in general, shorter timeframes. The first famous study utilizing the DL test for a cryptocurrency was conducted by Khuntia and Pattanayak (2018). Utilizing daily Bitcoin return data from 18. July 2010 to 21. December 2017 and employing a rolling window of 400 days, they find ample evidence for the AMH. They show that periods of heightened efficiency and inefficiency repeatedly alternate. Although they demonstrate mostly efficient periods from 2015 until the end of their data, they argue for the AMH, rather than general increasing market

efficiency, given the observed variance in the computed test statistics (Khuntia & Pattanayak, 2018).

López-Martín et al. (2021) also employ the DL test for Bitcoin and Ethereum, considering data from 29. April 2013 to 31. December 2019 and from 9. August 2015 to 28. December 2019, respectively. They utilize rolling windows of different sizes (250, 350, and 500 days) to examine weak form efficiency over time. In line with the study by Khuntia and Pattanayak, they find Bitcoin returns to be predominantly efficient from 2015 until the end of their data set. For Ethereum, they also find, besides a period of inefficiency during 2017, a high degree of market efficiency. In contrast to the study by Khuntia and Pattanayak, López-Martín et al. (2021), while also finding varying degrees of efficiency over time, conclude that the overall trend of the returns of Bitcoin and Ethereum trend towards efficiency, ultimately not supporting the AMH for Bitcoin and Ethereum.

Finally, Chu et al. (2019) consider the DL test for hourly Bitcoin and Ethereum return data from 1. July 2017 to 1. September 2018, calculating the test statistics for a comparably short rolling window of 168 hours, corresponding to 7 days. They find for both assets that the level of return predictability varies enormously over time and interpret their findings as solid support for the AMH.

As for the AMH, previous research concerned with the RWH for crypto assets considered return data of lower resolution and, in general, shorter timeframes compared to the present study. The first study to examine the RWH for Bitcoin by estimating the Hurst exponent via the DFA was conducted by Bariviera (2017). Utilizing a rolling window of size 500 for daily price data from 18. August 2011 to 15. February 2017, the study finds long-range dependence in the first half of the investigated period up until 2014. Afterward, the market is found to behave more informational efficient. After observing this steadily increasing efficiency, the study argues for the disappearance of inefficiency in the Bitcoin market.

Alvarez-Ramirez et al. (2018) employ a slightly smaller data set of Bitcoin returns, spanning from 30. June 2013 to 3. June 2017. Employing a rolling window of 250 days, they find alternating periods of efficiency and anti-persistence, computing mostly Hurst exponents of below 0.45. Their findings lead them to reject the EMH, and their observations are in line with the propositions of the AMH.



Employing a range of test statistics, Tiwari et al. (2018) studied daily Bitcoin returns from 18. July 2010 to 16. June 2017. While they argue for informational efficiency overall, by employing a rolling window of 300 days, they exclusively compute Hurst exponents of less than 0.5, with many falling below 0.45. As a consequence, also their findings are in line with the AMH.

Later, Zhang et al. (2019) utilized the DFA for a high-frequency data set of hourly Bitcoin and Ethereum returns from 25. February 2017 to 17. August 2017. While they do not test for the AMH directly, their employed rolling window of 1,000 hours yields strongly varying Hurst exponents, with many values above or below 0.55 and 0.45, respectively, for both crypto assets.

The results of the meta-study on efficiency in cryptocurrency markets by Kyriazis (2019) are in line with these studies. The survey concludes that most studies find evidence for some inefficiency in the markets of cryptocurrencies, which, however, diminishes over time. In contrast, we find constant deviations from the EMH and thus ample support for the AMH. Bitcoin and Ethereum returns exhibit recurring periods where the MDH does not hold throughout the considered sample. Further, the DFA predicts  $H$  to be greater than 0.55 at the end of the period, indicating strong long-range dependence.

Comparing our results to previous studies utilizing the same methods, it seems that inefficiencies are more clearly detectable at higher data resolution. The findings presented in the studies of Chu et al. (2019) and Zhang et al. (2019), which also employed hourly returns, correspond to our endorsement of the AMH, while the studies that use daily returns do not find a consistent conclusion on efficiency, with some arguing for the AMH and others for the EMH.

Finally, by conducting a benchmark analysis, we show that Bitcoin and Ethereum divert significantly more substantially from the MDH than the S&P 500. Our test results for the RWH reveal that Bitcoin and Ethereum exhibit more extreme values and hence a greater range for  $H$  (between 0.192 and 0.729 for Bitcoin and between 0.403 and 0.690 for Ethereum) than the S&P 500 during the examined periods. While the average  $H$  for the S&P 500 is higher than for Bitcoin and Ethereum, the more significant swings in the cryptocurrency markets further support the notion of the AMH. Cryptocurrencies are an exotic new financial instrument of great interest to various stakeholders,

not only because of the underlying technology and its implications, but also because of the sharp rise in their prices over the last decade. Previous studies on the efficiency of the Bitcoin and Ethereum market utilizing daily data find initial periods of inefficiency but at large argue for an increase in efficiency over time. By employing an extensive dataset covering the earlier trading days of the two cryptocurrencies until the price rally in 2021 of hourly resolution, we show that efficiency is not steadily increasing over time and hence find support for the AMH as proposed by Lo (2004).

Testing the MDH, we find extensive reoccurring periods where Bitcoin and Ethereum returns are not developing randomly, with significant periods of inefficiency after 2019, the end of the datasets in many previous studies. Further, after some anti-persistence in their respective first years of trading, we detect strong long-range dependence for the cryptocurrencies, with the DFA predicting values of above 0.55 at the end of our sample, further adding against the case of steadily increasing efficiency.

Computing our test statistics for an established equity index, we also show that the Bitcoin and Ethereum markets are less efficient than the one of the S&P 500. With the hourly returns of the cryptocurrencies exhibiting a significantly higher mean than the benchmark and accounting for the persistent detection of long-range dependence, the high-frequency market of Bitcoin and Ethereum seems attractive for speculation.

Considering the contrast between our findings and those of studies employing hourly data, future research should focus on the impact of the resolution of the price data. While the lenient propositions of the AMH are considerably easier met than the idea of constantly high market efficiency, it is certainly interesting how efficient Bitcoin and Ethereum returns develop when examining even smaller intervals between prices.

# Chapter 3

## Performance of Technical Trading in the Markets of Bitcoin and Ethereum<sup>1</sup>

### 3.1 Introduction

Bitcoin and Ethereum are two of the most popular cryptocurrencies in the world today. Bitcoin was invented in 2008 by an unknown person or group of people under the name Satoshi Nakamoto to create fully functional digital money (Nakamoto, 2008). Ethereum, a distributed computing platform featuring smart contract functionality, was envisioned by Vitalik Buterin in 2013 (Buterin, 2013). It provides a decentralized Turing-complete virtual machine that can execute scripts using an international network of public nodes without any chance of fraud, censorship, or third-party interference (Buterin, 2013). As the most popular cryptocurrencies, Bitcoin and Ethereum prices have skyrocketed tremendously since their inception, making them unique subjects of financial studies (cf. Alvarez-Ramirez et al., 2018).

According to the seminal work of Fama (1970) on market efficiency, asset prices accurately reflect all available information at any given time, making it impossible for investors to beat the market systematically. In its weak form, the efficient market hypothesis (EMH) postulates that prices develop like a random walk<sup>2</sup> or martingale dif-

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<sup>1</sup>This chapter is based on Becker, M. (2022a). Data-Resolution Dependent Performance of Technical Trading Strategies in the Markets of Bitcoin and Ethereum *Unpublished working paper*.

<sup>2</sup>A random walk is a process where the probability distribution conditional on past data of the process is equal to the marginal probability distribution. This implies that knowledge of past prices does not improve the prediction of future prices.

ference sequence<sup>3</sup>, rendering an information set including historical prices of a given asset useless for predicting its future price (Fama, 1970).

An extensive research body testing the weak form efficiency is thus concerned with whether the random walk hypothesis (RWH) and the martingale difference hypothesis (MDH) hold up (cf. Kyriazis, 2019). Barriviera (2017), Alvarez-Ramirez et al. (2018), and Zhang et al. (2019) notably tested the RWH and MDH for Bitcoin and Khuntia and Pattanayak (2018), López-Martín et al. (2021), and Chu et al. (2019) for Ethereum.

Barriviera (2017) and Alvarez-Ramirez et al. (2018) find evidence against the RWH and, hence, market inefficiency in the early parts of their investigated sample by employing a rolling window of daily data but increasing efficiency over time. Zhang et al. (2019), who utilize a rolling window of hourly data, observe constant deviations from the RWH and consequentially argue for the absence of efficiency. Similarly, Khuntia and Pattanayak (2018) and López-Martín et al. (2021), investigating the MDH using a rolling window of daily data, find evidence against the weak form efficiency at the beginning of their respective samples but decreasing return predictability at later stages. However, Chu et al. (2019), examining a rolling window of hourly returns, find persisting evidence against the MDH, implying market inefficiency. Summarizing their findings, the markets of Bitcoin and Ethereum seem to deviate stronger from weak form efficiency at higher data resolution.

The study by Noda (2021) further supports these findings by directly comparing the efficiency of Bitcoin and Ethereum. Building upon the adaptive market hypothesis proposed by Lo (2004), which proposes that the efficiency of financial markets varies over time, the study supports the notion of time-varying efficiency for Bitcoin and Ethereum. It concludes that the market of Ethereum is significantly less efficient than the market of Bitcoin (Noda, 2021).

Besides these statistical properties of price developments, Fama (1970) formulates: "By contrast, the stock market trader has a much more practical criterion for judging what constitutes important de-

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<sup>3</sup>A martingale difference sequence is a process that does not follow its trend and is mean independent. Thus, if a price develops like a martingale difference sequence, the best predictor of the next price is the current price.

pendence in successive price changes. For his purposes the random walk model is valid as long as knowledge of the past behaviour of the series of price cannot be used to increase expected gains.” Therefore, weak form efficiency can also be investigated through technical trading strategies, which, in direct contrast to the EMH, generate trading decisions based on asset price movements.

By considering price movements directly, rather than basing trading decisions on an intrinsic valuation of the asset, the central idea of technical analysis is the identification and following of the trend. Regardless of their origin and validity, this following of trends tends to turn even randomly initiated ones into self-fulfilling prophecies. This effect is more pronounced in markets where many agents employ such strategies, propelling the emergence of speculative bubbles (Froot et al., 1992).

Gerritsen et al. (2020) conducted a comprehensive study on the profitability of commonly used technical trading strategies for daily Bitcoin returns. While they intentionally utilize methods that were popular before the emergence of Bitcoin to minimize the risk of data mining, they still find a range of strategies to outperform the buy-and-hold approach. Hence, their results favor technical strategies for Bitcoin traders, conflicting with the propositions of Fama (1970).

This study adds to the literature by examining the practical market efficiency of Bitcoin and Ethereum in general, the notion of higher inefficiency at higher data resolution, and findings of previous studies arguing for a lesser efficiency of the Ethereum market compared with the Bitcoin market. We do so by employing 19 technical trading rules from Gerritsen (2016) and Gerritsen et al. (2020) for daily and hourly data.

We find that popular technical trading strategies achieve significantly higher absolute returns than the buy-and-hold approach. From a risk-adjusted perspective, many strategies yield higher Sharpe ratios than buy-and-hold, albeit statistical significance is mostly present for partially implemented strategies for daily data. The rest of this study is structured in five sections. First, we present our data and descriptive statistics in section 3.2. Second, we rationalize and explain our methodology in section 3.3. We then present our results in section 3.4. Afterward, we discuss our findings and compare them to results from

Table 3.1: Descriptive statistics of hourly (h) and daily (d) cryptocurrency log returns

	Bitcoin (h)	Ethereum (h)	Bitcoin (d)	Ethereum (d)
Minimum (%)	-68.9716	-26.7479	-67.8734	-56.0618
Mean (%)	0.0139	0.0142	0.3220	0.3728
Maximum (%)	55.6482	25.5594	42.3719	44.0341
Median (%)	0.0002	0.0000	0.1996	0.1049
Standard Deviation	1.4474	1.3952	5.3182	6.1627
Skewness	-0.6813	-0.0889	-0.8981	-0.0242
Kurtosis	190.4485	31.0439	18.6860	7.8407
Jarque-Bera	149,367,011*	2,211,612*	60,935*	5,899*
Sample period	Jul 17, 2010 - Nov 27, 2021	Aug 08, 2015 - Nov 27, 2021	Jul 18, 2010 - Nov 27, 2021	Aug 09, 2015 - Nov 27, 2021

*Note:* \* denotes statistical significance at the 1% level

previous research in section 3.5 before concluding our study in section 3.6.

## 3.2 Data

We obtained hourly and daily price data of Bitcoin and Ethereum (in terms of US Dollars) from Glassnode (2021), a cryptocurrency analytics and data provider. With our study aiming to provide a comprehensive analysis of the validity of technical trading strategies, we utilize all historic prices available at the time of this writing. In the case of Bitcoin, this includes hourly prices from 17.07.2010 and daily prices from 18.07.2010 to 27.11.2021. In the case of Ethereum, this includes hourly prices from 08.08.2015 and daily prices from 09.08.2015 to 27.11.2021. We compute logarithmic returns from the price data using:

$$r_t = \ln \left( \frac{X_t}{X_{t-1}} \right) * 100 \quad (3.1)$$

Where  $X_t$  is the price at time  $t$ . Table 3.1 presents descriptive statistics of the thus computed Bitcoin and Ethereum hourly and daily returns.

The mean hourly return of Bitcoin and Ethereum is positive, while Bitcoin exhibits a slightly larger median and mean. Hourly Bitcoin returns exhibit a significantly more extensive range (124.6197 compared

with 52.3073 for Ethereum), while the associated standard deviations are very similar (1.4474 for Bitcoin and 1.3952 for Ethereum). Both distributions are skewed to the left and are fat-tailed. The Jarque-Bera test rejects normality at the 1% significance level.

In line with this, the mean daily return of both cryptocurrencies is also positive. Ethereum has a slightly higher mean (0.3728 compared with 0.3220 for Bitcoin), but Bitcoin has a nearly twice as large median (0.1996 compared with 0.1049 for Ethereum). Both exhibit a comparable range, while Ethereum returns have a higher standard deviation. Daily Bitcoin returns are skewed to the left and Ethereum returns have a near zero skew, while both distributions exhibit fat tails. The Jarque-Bera test again rejects normality at the 1% significance level.

### 3.3 Methodology

In line with the literature focusing on the validity of the random walk hypothesis (by investigating the presence of long-range dependence or anti-persistency in return data), technical trading approaches mostly belong to one of two categories, countertrend or trend follower strategies (Wong et al., 2003).

#### Moving Average

The moving average (MA) strategy is one of the oldest, most straightforward, and most popular trend-following strategy (Brock et al. 1992). The strategy considers the average historical price of an asset during a predefined time window and compares it to recent price data.  $MA(X)_{t,n}$  is the simple  $n$ -day moving average for a given asset  $X$  at day  $t$ , and  $X_i$  is the asset's closing price on day  $i$ , defined as:

$$MA(X)_{t,n} = \frac{1}{n} \sum_{i=t-n+1}^t X_i \quad (3.2)$$

To generate trading signals, a long-term (MAL) and short-term (MAS) moving average is created, where  $s$  is the number of MAS and  $l$  is the number of MAL periods ( $n$ ). Popular windows ( $s-l$ ) are 1-50,

1-150, 5-150, 1-200, and 2-200, with 1-200 being the most common (Brock et al. 1992).

The strategy signals a buying decision when the MAS rises above the MAL and a sell decision when the MAS falls below the MAL. The rationale is to smooth out volatile time series via the MAL and to detect deviations from it utilizing the MAS. The strategy filters out noise signals to determine real up or downward trends. The strategy works well if a clear trend is present, while excess volatility diminishes its profitability (Wong et al. 2003). In formal terms, the moving average trading rule is defined as:

$$\textit{Buy} : MAS(X)_{t,s} > MAL(X)_{t,l}$$

$$\textit{Sell} : MAS(X)_{t,s} < MAL(X)_{t,l}$$

## Trading Range Breakout

The trading range breakout strategy is another popular trend following investing strategy (Brock et al. 1992). Based on the belief that investors are willing to sell their positions at price peaks and buy positions at price lows, the strategy creates trading signals based on local price maxima (called resistance level) and minima (called support level). Support and resistance levels for an asset X are defined as:

$$\textit{Support}(X)_t = \textit{Min}(X_{t-1}, X_{t-2}, \dots, X_{t-n-1}) \quad (3.3)$$

$$\textit{Resistance}(X)_t = \textit{Max}(X_{t-1}, X_{t-2}, \dots, X_{t-n-1}) \quad (3.4)$$

For  $n$ , we utilize the most popular window sizes of 50, 150, and 200 days (Brock et al. 1992). The strategy issues a buy signal when the price rises above the current resistance level. Following the rationale that investors are willing to sell at local maxima, the current price only exceeds its resistance level when the selling pressure is too weak to compensate for the upwards trend, indicating a price rally. Investors are assumed to be willing to buy at the previous minimum, so it is difficult for the price to fall below its support level. A new local minimum price is assumed to initiate a downward trend (Brock et al. 1992). Hence, the trading rule is defined as:



*Buy* :  $X_t > Resistance(X)_t$   
*Sell* :  $X_t < Support(X)_t$

## Moving Average Convergence Divergence

The moving average convergence divergence (MACD) strategy is trend following and based on the difference between two exponential moving averages (EMA). The EMA gives more weight to the most recent closing price than the previously introduced moving average. The weighting factor is defined as  $\frac{2}{n+1}$ , where  $n$  is the EMA period. The most commonly used timeframes are the 12-day and 26-day EMA (Murphy, 1999). The EMA for an asset  $X$  is calculated as:

$$EMA(X)_{t,n} = [X_t - EMA(X)_{t-1,n}] \times \frac{2}{n+1} + EMA(X)_{t-1,n} \quad (3.5)$$

As the formula contains the EMA of the previous period, the first-day EMA period,  $EMA(X)_{t-1,n}$ , is defined as the simple  $MA(X)_{t,n}$ . The MACD can then be calculated as:

$$MACD(X)_t = EMA(X)_{t,12} - EMA(X)_{t,26} \quad (3.6)$$

The MACD strategy follows the same rationale as the moving average strategy. It issues a buy signal when the short-term EMA is larger than the longer-term EMA and a sell signal when the short-term EMA is smaller than the longer-term EMA (Murphy, 1999). The trading rule is thus defined as:

*Buy* :  $MACD(X)_t > 0$   
*Sell* :  $MACD(X)_t < 0$

## Moving Average Convergence Divergence Signal Line

A method related to the MACD is the MACD signal line strategy, which aims to smooth out the sensitivities of the MACD. For this purpose, a 9-day EMA of the MACD is constructed as:

$$\begin{aligned}
MACDSignal(X)_t = [MACD_{i,t} - EMA(MACD_i)_{t-1,9}] \\
\times \frac{2}{n+1} + EMA(MACD_i)_{t-1,9} \quad (3.7)
\end{aligned}$$

As for the MACD, the MACD signal line strategy employs the simple MA for the first EMA, and hence,  $MA(MACD(X))_{t-1,9}$  is used as the starting value (Gerritsen, 2016). The trading rule is accordingly defined as:

$$\begin{aligned}
Buy : MACDSignal(X)_t > 0 \\
Sell : MACDSignal(X)_t < 0
\end{aligned}$$

## Moving Average Convergence Divergence Histogram

Combining the MACD and the MACD signal line methods, the MACD histogram strategy considers the difference between the two:

$$MACDHistogram(X)_t = MACD(X)_t - MACDSignal(X)_t \quad (3.8)$$

With the MACD signal line smoothing out sensitivities of the MACD, it results in a comparably slower moving average than the MACD. The MACD histogram gets larger during a "MACD divergence" when the faster moving MACD moves away from the MACD signal line, and vice versa, smaller during a "MACD convergence", when the MACD and MACD signal line move towards each other. At the initiation of a new trend, the faster MACD reacts before the MACD signal line and will cross it before diverging further; the MACD histogram's purpose is to detect such a crossover early on (Murphy, 1999). Consequentially, positive values again indicate an uptrend and negative a downtrend, resulting in the trading rule formulation as:

$$\begin{aligned}
Buy : MACDHistogram(X)_t > 0 \\
Sell : MACDHistogram(X)_t < 0
\end{aligned}$$

## Rate of Change

The rate of change is a simple trend following strategy that derives trading signals from the difference between the price today and the price  $n$  days ago (Gerritsen, 2016). The rate of change is calculated as:

$$ROC(X)_t = X_t - X_{t-n-1} \quad (3.9)$$

For  $n$ , we use 10 trading days, the most common timeframe for this strategy (Gerritsen, 2016). The strategy aims to capitalize on persisting price trends, expecting that price increases are followed by more increases and price decreases are succeeded by further price decreases. Accordingly, the rule issues trading signals as:

$$\begin{aligned} Buy &: ROC(X)_t > 0 \\ Sell &: ROC(X)_t < 0 \end{aligned}$$

## On-Balance Volume

The on-balance volume (OBV) indicator is trend following and one of the best-known technical trading strategies utilizing volume data (Gerritsen, 2016). The indicator is set to 0 in the beginning before adding the respective trading volume (denoted  $V$ ) of days with price increases and subtracting the trading volume of days with price decreases. The trading volume of days without a price change is excluded:

$$OBV(X)_t = OBV(X)_{t-1} + \left\{ \begin{array}{l} V \text{ if } X_t > X_{t-1} \\ 0 \text{ if } X_t = X_{t-1} \\ -V \text{ if } X_t < X_{t-1} \end{array} \right\} \quad (3.10)$$

To generate trading signals, as for the MA strategy, a MAS and MAL of the OBV are created (with the same time windows of 1-50, 1-150, 5-150, 1-200, and 2-200). The OBV strategy's rationale is that volume changes occur before prices change. When the MAS rises above the MAL, the increasing volume pressure is assumed to lead to rising prices (Gerritsen, 2016). Thus, the strategy issues signals as:

$$\begin{aligned} Buy &: MAS(OBV_i)_{t,k} > MAL(OBV_i)_{t,l} \\ Sell &: MAS(OBV_i)_{t,k} < MAL(OBV_i)_{t,l} \end{aligned}$$

## Relative Strength Index

The relative strength index is the most frequently used counter trend indicator and considers the share of up- to down-closes over a prespecified period of usually 14 trading days (Wong et al., 2003). Up-closes (U) and down-closes (C) are defined as:

$$U_{i,t} \left\{ \begin{array}{l} X_t - X_{t-1} \text{ if } X_t > X_{t-1} \\ 0 \text{ otherwise} \end{array} \right\} \text{ and } D_{i,t} \left\{ \begin{array}{l} X_{t-1} - X_t \text{ if } X_{t-1} > X_t \\ 0 \text{ otherwise} \end{array} \right\} \quad (3.11)$$

Afterward, the averages of these closes are determined by:

$$\bar{U}_{i,t} = \frac{1}{14} \sum_{t-13}^t U(X)_t \text{ and } \bar{D}_{i,t} = \frac{1}{14} \sum_{t-13}^t D(X)_t \quad (3.12)$$

Then, the relative strength (RS) is calculated as the ratio between the average up- and down-closes:

$$RS(X)_t = \frac{\bar{U}(X)_t}{\bar{D}(X)_t} \quad (3.13)$$

Last, the relative strength index at time t is computed as:

$$RSI(X)_t = 100 - \frac{100}{1 + RS(X)_t} \quad (3.14)$$

The resulting RSI ranges between values of 0 and 100, where 0 represents exclusive downward movement and 100 exclusive price increases. Therefore, as a countertrend indicator, an RSI closer to 0 indicates an asset is oversold, while an RSI closer to 100 indicates an asset is overbought. For the standard 14-day horizon, an RSI of 30 or below denotes a buy signal, and an RSI of 70 or above a sell signal, while the number of trading signals is negatively correlated with the duration of the considered time period (Wong et al., 2003). Formally, the trading rule is defined as:

*Buy* :  $RSI(X)_t < 30$

*Sell* :  $RSI(X)_t > 70$

## Bollinger Bands

Bollinger bands are another countertrend indicator that J. Bollinger initially proposed in the 1980s (Lento et al. 2007). The strategy creates and utilizes two bands, which are created based on the moving average of an asset's price and the respective standard deviation of the price during the considered timeframe. The two bands are created by adding (subtracting) the associated standard deviation to (from) the moving average. Traditionally, a 20-day MA and a corridor of two standard deviations between the bands are utilized (Lento et al. 2007). What results are an upper and a lower band:

$$BBUPPER(X)_t = MA(B)_{t,20} + \sigma_{B,20} \quad (3.15)$$

$$BBLOWER(X)_t = MA(B)_{t,20} - \sigma_{B,20} \quad (3.16)$$

Where  $\sigma_{B,20}$  is the standard deviation of the price during the last 20-day period. As a countertrend indicator, the strategy assumes that the price will return to its moving average; when the price exceeds the upper band, a sell signal is issued, and when it falls below the lower band, a buy signal is rendered:

*Buy* :  $X < BBLOWER(X)_t$

*Sell* :  $X > BBUPPER(X)_t$

## Summary and Application

In line with the scope of our research, we apply all trading rules to daily and hourly data and generate trading signals for daily and hourly increments, respectively. Table 2.2 summarizes all previously elaborated trading strategies.

Accounting for the fact that shorting cryptocurrencies was impossible in the early years after their inception and is still not possible across many exchanges today, we implement the trading signals in two ways. First, we consider this circumstance and go long in case of a buy signal and out of the market (into the risk-free asset) in case of no signal or a sell signal (partial implementation). Second, we take the trading signals literally and go long in case of a buy signal, out of the market (into the risk-free asset) for no signal, and short for a sell signal (full implementation). We obtained the risk-free rates used

Table 3.2: Technical trading strategies summary

Strategy name	Trend	Buy signal	Sell signal
Moving average	Follower	Short MA > Long MA	Short MA < Long MA
Trading range breakout	Follower	Price > Resistance	Price < Support
MACD	Follower	MACD > 0	MACD < 0
MACD Signal	Follower	MACD Signal > 0	MACD Signal < 0
MACD Histogram	Follower	MACD Histogram > 0	MACD Histogram < 0
Rate of change	Follower	ROC > 0	ROC < 0
On balance volume	Follower	Short MA > Long MA	Short MA < Long MA
Relative strength index	Counter	RSI < 30	RSI > 70
Bollinger bands	Counter	Price < Lower band	Price > Upper band

for this purpose from Kenneth R. French’s online data suppository (French, 2022).

To judge the performance of the strategies, we follow Sharpe (1966) and calculate the Sharpe ratio for every strategy  $i$ , at partial or full implementation  $j$ , and for daily or hourly data  $k$  as:

$$S_{i,j,k} = \frac{R_{i,j,k} - rf_k}{\sigma_{i,j,k}} \quad (3.17)$$

where  $R_{i,j,k}$  is the return and  $\sigma_{i,j,k}$  the standard deviation of the returns of strategy  $i$ , at implementation  $j$ , for data resolution  $k$ , and where  $rf_k$  is the risk-free rate at data resolution  $k$ .

In the last step of our analysis, we test if the Sharpe ratios achieved by the technical trading strategies are statistically significantly different from the Sharpe ratio associated with the buy-and-hold portfolio. This can be done via statistical inference and bootstrapping, and we follow the thus developed approach of Ledoit and Wolf (2008). Their method is based on a  $t$ -test examining whether the Sharpe ratio of two portfolios is equal. The null hypothesis is therefore formulated as:

$$H_0 = \frac{R_{i,j,k} - rf_k}{\sigma_{i,j,k}} = \frac{R_{BH,k} - rf_k}{\sigma_{BH,k}} \quad (3.18)$$

where  $R_{BH,k}$  is the return and  $\sigma_{BH,k}$  the standard deviation of the returns of the buy-and-hold portfolio at data resolution  $k$ . We use 1,000 (20,000) bootstrap resamples for daily (hourly) data and generate  $p$ -values in accordance with Ledoit and Wolf (2008).

## 3.4 Results

Below we report Sharpe ratios at the resolution of the analyzed data, meaning in daily and hourly terms, respectively. Table 3.3 presents the Sharpe ratios of the technical trading strategies for hourly Bitcoin returns. Of the 38 applied strategies, 10 strategies yield higher returns than the buy-and-hold approach. Of those 10 strategies, three exhibit statistically significant higher Sharpe ratios than the buy-and-hold portfolio. Appendix A displays the associated return developments.

The MA 1-50 strategy is the only moving average strategy yielding higher absolute returns than the buy-and-hold approach during our investigated period. The return of the MA 1-50 strategy is slightly higher at full than at partial implementation. All Sharpe ratios achieved by moving average strategies are lower at full than at partial implementation, without a single being statistically different from the Sharpe ratio associated with the buy-and-hold approach.

All trading range breakout strategies are associated with lower absolute returns than buy-and-hold. The Sharpe ratio of the SUP/RES50 strategy is statistically significant at the 5% level for both implementations, and all trading range breakout strategies yield lower Sharpe ratios at full implementation.

All on-balance volume strategies underperform buy-and-hold in absolute terms, with none of the strategies achieving higher absolute returns. At full implementation, all on-balance volume strategies yield lower Sharpe ratios than buy-and-hold. The higher Sharpe ratios at partial implementation exist due to lowered volatility from being out of the market for extensive time periods. The associated Sharpe ratios are statistically not different from buy-and-hold, and all strategies perform worse at full implementation while simultaneously achieving lower  $p$ -values. Bollinger bands achieve lower absolute returns than buy-and-hold at partial and full implementation. At the same time, the reduction in the Sharpe ratio is statistically significant at the 10% level for partial implementation.

The worst performing strategy is the relative strength index, with a Sharpe ratio difference to buy-and-hold of -5.73 basis points at partial and -8.96 basis points at full implementation. We find both of these differences statistically significant at the 1% level. As shown in Table

3.3, this is the most considerable basis point difference achieved of all considered strategies.

The best performing strategy is MACD, achieving the highest absolute return at partial and full implementation and the most substantial Sharpe ratio increase at full implementation. While absolute returns are higher at full implementation, all Sharpe ratios are lower, and all  $p$ -values are higher at full implementation compared with partial implementation (where MACD and MACD Hist are statistically significant at the 5% level). The second-best performing strategy is rate of change, achieving the highest Sharpe ratio increase of all partially implemented strategies (statistically significant at the 5% level) and the second highest absolute return increase. As for the MACD strategies, the absolute rate of change return is higher at full implementation (consider Appendix A7 and A8).

Table 3.3: Sharpe ratios of technical trading strategies for hourly Bitcoin returns

	Long or out				Long, out, and short			
	Profitable vs B&H	Sharpe Ratio	Difference to B&H in basis points	$p$ -value	Profitable vs B&H	Sharpe Ratio	Difference to B&H in basis points	$p$ -value
<b>Moving Average</b>								
MA 1-50	Yes	0.012	0.27	0.19	Yes	0.011	0.09	0.80
MA 1-150	No	0.012	0.20	0.38	No	0.010	0.07	0.81
MA 5-150	No	0.012	0.20	0.37	No	0.011	0.10	0.76
MA 1-200	No	0.011	0.12	0.61	No	0.009	-0.02	0.94
MA 2-200	No	0.011	0.10	0.66	No	0.009	-0.05	0.88
<b>Trading range breakout</b>								
SUP/RES50	No	0.001	-0.81**	0.05	No	0.000	-0.99**	0.02
SUP/RES150	No	0.010	0.02	0.95	No	0.008	-0.19	0.66
SUP/RES200	No	0.012	0.24	0.55	No	0.011	0.15	0.71
<b>MACD</b>								
MACD	Yes	0.013	0.36*	0.07	Yes	0.012	0.24	0.50
MACD Signal	Yes	0.013	0.30	0.10	Yes	0.012	0.22	0.49
MACD Hist	Yes	0.014	0.40*	0.08	Yes	0.011	0.12	0.77
<b>Rate of Change</b>	Yes	0.014	0.41*	0.07	Yes	0.011	0.16	0.70
<b>On balance volume</b>								
OBV MA 1-50	No	0.013	0.29	0.20	No	0.010	-0.00	0.98
OBV MA 1-150	No	0.011	0.15	0.52	No	0.009	-0.09	0.79
OBV MA 5-150	No	0.012	0.20	0.41	No	0.009	-0.02	0.96
OBV MA 1-200	No	0.011	0.13	0.60	No	0.009	-0.08	0.82
OBV MA 2-200	No	0.011	0.13	0.59	No	0.009	-0.08	0.83
<b>Relative strength index</b>	No	-0.048	-5.73***	0.00	No	-0.080	-8.96***	0.00
<b>Bollinger bands</b>	No	0.003	-0.61*	0.08	No	0.002	-0.73	0.12
<b>Buy and hold</b>		0.010						

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 3.4 presents the Sharpe ratios of the technical trading strategies for hourly Ethereum returns. Of the 38 applied strategies, 17 strategies yield higher returns than the buy-and-hold approach. Appendix B displays the associated return developments.

The MA 5-150 strategy offers the highest increase in Sharpe ratio and absolute return of the moving average strategies, with MA 1-50 and MA 1-150 also improving absolute returns. None of the Sharpe



ratios associated with the moving average strategies is statistically significantly different from buy-and-hold. However, while the Sharpe ratio of all moving average strategies is lower at full implementation, MA 1-50, MA 1-150, and MA 5-150 achieve higher absolute returns when allowed to go short.

The on-balance volume strategies behave similarly, with the in absolute terms profitable OBV MA 1-150 and OBV MA 5-150 strategies achieving higher returns at full implementation. All on-balance volume strategies achieve lower Sharpe ratios at full implementation, while none is statistically significantly different from buy-and-hold. As for hourly Bitcoin returns, none of the trading range breakout strategies offer an improvement to buy-and-hold in absolute terms.

Relative strength index and Bollinger bands are the worst performing strategies. Statistically significantly different from buy-and-hold at the 1% level, the relative strength index strategy yields a negative Sharpe ratio at both partial and full implementation. Bollinger bands are associated with a negative Sharpe ratio at both implementations, statistically insignificant for partial and significant at the 1% level at full implementation.

The best performing strategies are rate of change (achieving the highest Sharpe ratio increase at partial implementation, statistically significant at the 5% level) and MACD (yielding a statistically significant Sharpe ratio increase for partial and the highest Sharpe ratio increase at full implementation). MACD, MACD Signal, and the rate of change strategy yield lower Sharpe ratios but higher absolute returns at full implementation. In contrast, the MACD Histogram strategy resembles buy-and-hold at partial and underperforms buy-and-hold at full implementation.

Table 3.5 presents the Sharpe ratios of the technical trading strategies for daily Bitcoin returns. Of the 38 applied strategies, 14 strategies yield higher returns than the buy-and-hold approach. Appendix C displays the associated return developments.

Of all moving average strategies, the MA 1-50 is the only strategy more profitable than buy-and-hold. At partial implementation, MA 1-50, MA 1-150, and MA 5-150 yield better risk-adjusted returns than buy-and-hold, while only the MA 1-50 strategy returns are statistically significantly different from the buy-and-hold returns (at the 5% level). All moving average strategies perform worse at full implementation,

Table 3.4: Sharpe ratios of technical trading strategies for hourly Ethereum returns

	Long or out				Long, out, and short			
	Profitable vs B&H	Sharpe Ratio	Difference to B&H in basis points	<i>p</i> -value	Profitable vs B&H	Sharpe Ratio	Difference to B&H in basis points	<i>p</i> -value
<b>Moving Average</b>								
MA 1-50	Yes	0.014	0.41	0.17	Yes	0.011	0.06	0.89
MA 1-150	Yes	0.014	0.41	0.13	Yes	0.013	0.28	0.50
MA 5-150	Yes	0.015	0.43	0.11	Yes	0.014	0.34	0.40
MA 1-200	No	0.012	0.18	0.52	No	0.011	0.12	0.77
MA 2-200	No	0.012	0.20	0.49	No	0.012	0.14	0.72
<b>Trading range breakout</b>								
SUP/RES50	No	0.010	0.02	0.97	No	0.006	-0.37	0.53
SUP/RES150	No	0.010	-0.03	0.95	No	0.012	0.15	0.79
SUP/RES200	No	0.010	-0.04	0.93	No	0.012	0.14	0.80
<b>MACD</b>								
MACD	Yes	0.016	0.54*	0.06	Yes	0.014	0.38	0.45
MACD Signal	Yes	0.014	0.39	0.17	Yes	0.012	0.17	0.73
MACD Hist	Yes	0.014	0.40	0.21	No	0.010	0.02	0.97
<b>Rate of Change</b>	Yes	0.016	0.60*	0.05	Yes	0.014	0.35	0.52
<b>On balance volume</b>								
OBV MA 1-50	No	0.013	0.28	0.36	No	0.009	-0.16	0.76
OBV MA 1-150	Yes	0.014	0.35	0.21	Yes	0.012	0.14	0.74
OBV MA 5-150	Yes	0.013	0.29	0.29	Yes	0.011	0.04	0.92
OBV MA 1-200	No	0.013	0.24	0.42	No	0.012	0.17	0.69
OBV MA 2-200	No	0.013	0.24	0.41	No	0.012	0.18	0.67
<b>Relative strength index</b>	No	-0.068	-7.83***	0.00	No	-0.111	-12.10***	0.00
<b>Bollinger bands</b>	No	0.004	-0.59	0.22	No	-0.006	-1.66***	0.01
<b>Buy and hold</b>		0.010						

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

and only the MA 1-50 and MA 5-150 strategy achieves a positive difference in Sharpe ratio compared with the buy-and-hold strategy.

None of the trading range breakout strategies is more profitable than the buy-and-hold approach. The SUP/RES50 and SUP/RES150 yield statistically significant improved Sharpe ratios. Further, all trading range breakout strategies suffer at full implementation. Of the on-balance volume strategies, OBV MA 1-50 and OBV MA 5-150 achieve higher absolute returns than buy-and-hold at both partial and full implementation. However, as for the moving average strategies, all on-balance volume strategies perform worse at full implementation. Only the resulting Sharpe ratio difference compared to buy-and-hold of the OBV MA 1-50 is statistically significant at the 10% level.

While not achieving any noteworthy absolute returns and underperforming buy-and-hold heavily (see Appendix C13 and Appendix C14), Bollinger bands offer the highest increase in Sharpe ratio of all fully implemented strategies, statistically significant at the 5% level. The Sharpe ratio increase at partial implementation of the Bollinger bands is found to be statistically insignificant.

The most salient results are achieved by the MACD, rate of change, and relative strength index implementations. The highest absolute returns of all considered strategies are achieved by the MACD strategies,

whereas absolute returns are higher at full implementation. At partial implementation, all MACD strategies offer an increased Sharpe ratio significant at the 5% level. While absolute returns are improved at full implementation, all thus achieved Sharpe ratios are lower than at partial implementation and lose their statistical significance compared with the buy-and-hold approach.

The highest Sharpe ratio increase at partial implementation is achieved by the rate of change strategy, with an increase of 3.05 basis points, significant at the 1% level. The increase is lowered to 1.34 basis points at full implementation and loses statistical significance. In absolute terms, however, rate of change is the second most profitable strategy, with a strong increase in profitability at full implementation.

Last, the worst performing strategy is the relative strength index, being the only strategy to yield a negative Sharpe ratio. Significant at the 1% level in both cases, the strategy yields a -16.26 basis point difference at partial and a -28.89 basis point difference at full implementation. The relative strength index strategy hence exhibits the most striking and most negative results of all strategies employed for daily Bitcoin returns.

Table 3.5: Sharpe ratios of technical trading strategies for daily Bitcoin returns

	Long or out				Long, out, and short			
	Profitable vs B&H	Sharpe Ratio	Difference to B&H in basis points	p-value	Profitable vs B&H	Sharpe Ratio	Difference to B&H in basis points	p-value
<b>Moving Average</b>								
MA 1-50	Yes	0.085	2.43**	0.02	Yes	0.072	1.14	0.54
MA 1-150	No	0.070	0.95	0.35	No	0.060	-0.09	0.96
MA 5-150	No	0.072	1.13	0.26	No	0.064	0.31	0.85
MA 1-200	No	0.058	-0.24	0.81	No	0.044	-1.64	0.32
MA 2-200	No	0.062	0.11	0.91	No	0.051	-0.98	0.55
<b>Trading range breakout</b>								
SUP/RES50	No	0.100	3.91**	0.02	No	0.078	1.78	0.36
SUP/RES150	No	0.091	3.05*	0.08	No	0.085	2.42	0.20
SUP/RES200	No	0.085	2.49	0.16	No	0.079	1.81	0.33
<b>MACD</b>								
MACD	Yes	0.086	2.51**	0.02	Yes	0.075	1.44	0.44
MACD Signal	Yes	0.085	2.46**	0.02	Yes	0.076	1.53	0.40
MACD Hist	Yes	0.090	2.89**	0.01	Yes	0.071	1.07	0.60
<b>Rate of Change</b>	Yes	0.091	3.05***	0.01	Yes	0.074	1.34	0.51
<b>On balance volume</b>								
OBV MA 1-50	Yes	0.079	1.87*	0.05	Yes	0.069	0.87	0.61
OBV MA 1-150	No	0.072	1.17	0.20	No	0.069	0.85	0.57
OBV MA 5-150	Yes	0.073	1.23	0.17	Yes	0.071	1.02	0.48
OBV MA 1-200	No	0.068	0.72	0.44	No	0.066	0.57	0.69
OBV MA 2-200	No	0.068	0.79	0.39	No	0.068	0.69	0.63
<b>Relative strength index</b>	No	-0.102	-16.26***	0.00	No	-0.228	-28.89***	0.00
<b>Bollinger bands</b>	No	0.079	1.80	0.30	No	0.114	5.36**	0.01
<b>Buy and hold</b>		0.061						

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Table 3.6 presents the Sharpe ratios of the technical trading strategies for daily Ethereum returns. Of the 38 applied strategies, nine

strategies yield higher returns than the buy-and-hold approach. Appendix D displays the associated return developments.

Of the moving average strategies, MA 1-50 and MA 1-150 yield higher absolute returns than buy-and-hold at partial implementation. MA 1-150 is the only moving average strategy achieving higher absolute returns at full implementation. While the return increase is more pronounced at full implementation, all Sharpe ratios are statistically insignificant.

As for daily Bitcoin returns, not one of the trading range breakout strategies is more profitable than the buy-and-hold approach or yields a statistically significant improved Sharpe ratio, while performance worsens at full implementation. The same holds for all on-balance volume strategies. Similarly to the moving average strategies, the performance of the on-balance volume seems to deteriorate when considering older data, with the OBV MA 1-50 strategy resulting in the lowest and the OBV MA 2-200 strategy resulting in the highest reduction in Sharpe ratio compared with buy-and-hold.

Mirroring the results for daily Bitcoin returns again, Bollinger bands achieve the highest Sharpe ratio increase of all fully implemented strategies (statistically significant at the 10% level) while heavily underperforming buy-and-hold in absolute terms (see Appendix D13 and Appendix D14). The rate of change strategy achieves the highest absolute returns of our tested strategies, where gains are more substantial for full than for partial implementation. At partial implementation, the strategy offers the second highest Sharpe ratio increase (statistically significant at the 5% level) and the third highest increase at full implementation.

The second highest absolute returns are associated with the MACD strategies. As for rate of change, absolute returns are higher at full implementation, while Sharpe ratio increases (statistically significantly different from buy-and-hold for partial implementation at the 10% level) are higher at partial than at full implementation of the strategies.

The only strategy to achieve Sharpe ratios statistically different from buy-and-hold at the 1% level is the relative strength index, with a -15.31 basis point difference at partial and a -29.29 basis point difference at full implementation. The relative strength index is the only strategy with an overall negative Sharpe ratio.

Table 3.6: Sharpe ratios of technical trading strategies for daily Ethereum returns

	Long or out				Long, out, and short			
	Profitable vs B&H	Sharpe Ratio	Difference to B&H in basis points	<i>p</i> -value	Profitable vs B&H	Sharpe Ratio	Difference to B&H in basis points	<i>p</i> -value
<b>Moving Average</b>								
MA 1-50	Yes	0.082	2.10	0.16	No	0.062	0.18	0.94
MA 1-150	No	0.070	0.94	0.45	No	0.058	-0.20	0.92
MA 5-150	Yes	0.078	1.72	0.16	Yes	0.073	1.27	0.53
MA 1-200	No	0.059	-0.16	0.90	No	0.052	-0.80	0.69
MA 2-200	No	0.059	-0.13	0.92	No	0.053	-0.74	0.72
<b>Trading range breakout</b>								
SUP/RES50	No	0.089	2.80	0.21	No	0.068	0.79	0.76
SUP/RES150	No	0.089	2.80	0.21	No	0.087	2.61	0.28
SUP/RES200	No	0.078	1.74	0.45	No	0.076	1.56	0.53
<b>MACD</b>								
MACD	Yes	0.086	2.50*	0.09	Yes	0.075	1.41	0.58
MACD Signal	Yes	0.079	1.88	0.19	Yes	0.066	0.54	0.83
MACD Hist	No	0.075	1.49	0.36	No	0.050	-1.08	0.71
<b>Rate of Change</b>	Yes	0.092	3.17**	0.04	Yes	0.080	1.90	0.48
<b>On balance volume</b>								
OBV MA 1-50	No	0.066	0.59	0.69	No	0.039	-2.12	0.42
OBV MA 1-150	No	0.064	0.33	0.81	No	0.042	-1.82	0.44
OBV MA 5-150	No	0.061	0.00	1.00	No	0.038	-2.23	0.33
OBV MA 1-200	No	0.058	-0.28	0.85	No	0.045	-1.53	0.51
OBV MA 2-200	No	0.057	-0.34	0.82	No	0.044	-1.60	0.48
<b>Relative strength index</b>	No	-0.093	-15.31***	0.00	No	-0.232	-29.29***	0.00
<b>Bollinger bands</b>	No	0.110	4.97**	0.04	No	0.111	5.00*	0.09
<b>BuYes and hold</b>		0.061						

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

In summary, we find trend-following strategies to outperform countertrend strategies for Bitcoin and Ethereum, regardless of the data resolution. Moreover, strategies utilizing comparably recent information perform better than strategies relying on older information. The best and most reliably performing strategies across all data sets are MA 1-50 (utilizing the last 50 days), MACD and MACD signal (drawing from the last 26 days), and rate of change (generating trading signals from the last 10 days). All these strategies are also found to yield higher absolute returns at full implementation, indicating that they are well suited for detecting downward trends. The two considered countertrend strategies, relative strength index and Bollinger bands, underperform buy-and-hold considerably. Equally, the trading range breakout strategy underperforms buy-and-hold regardless of the chosen time frame.

## 3.5 Discussion

Previously, Kyriazis (2019), who considered thirty-eight studies on the efficient market hypothesis, concluded that most research detects the presence of, with time, fading long-range dependence in the markets of Bitcoin and other cryptocurrencies. Notably, Khuntia and Pattanayak

(2018) consider the MDH for daily Bitcoin returns from July 2010 to December 2017. Their results point to time-varying degrees of market efficiency, with a trend towards increased efficiency at the end of their sample.

Studying the MDH for daily Bitcoin and Ethereum returns from April 2013 and August 2015 until December 2019, respectively, López-Martín et al. (2021) argue for periods of market inefficiency during the earlier trading years of the cryptocurrencies. However, they also find that the markets tend towards efficiency in later parts of their sample (López-Martín et al., 2021). Contrasting this, Chu et al. (2019) find that, by employing hourly Bitcoin and Ethereum data from July 2017 to September 2018, the return predictability of both cryptocurrencies, according to the MDH, varies enormously over time and conclude by arguing against market efficiency.

Researching weak form market efficiency by considering the RWH, Barriviera (2017) utilizes daily Bitcoin data from August 2011 to February 2017, finding that inefficiency is diminishing over time. These findings were later confirmed by Alvarez-Ramirez et al. (2018), who considered the RWH for daily Bitcoin from June 2013 to June 2017. Like the study of Chu et al. (2019) employing hourly data contrasts with the findings of studies using daily data for tests of the MDH, the results of Zhang et al. (2019) deviate from the aforementioned studies on the RWH. By employing hourly data Bitcoin and Ethereum data from February 2017 to August 2017, Zhang et al. (2019) find significant deviations from efficiency in both cryptocurrency markets.

We examine the market efficiency of Bitcoin and Ethereum at hourly and daily data resolution by means of popular technical trading strategies as previously mentioned by Gerritsen et al. (2020) in their study on Bitcoin and by Gerritsen (2016) for Dutch listed firms and the major indices in the Netherlands. In our sample, the best performing strategies are the MACD and rate of change. The worst performing strategy is the countertrend strategy relative strength index. In terms of the Sharpe ratio, we find our strategies to produce more considerable differences to buy-and-hold for both Bitcoin and Ethereum when considering daily data. Further, we find higher absolute returns when employing the strategies for hourly than for daily data.

Corbet et al. (2019), Gerritsen et al. (2020), Grobys et al. (2020), and Svogun and Bazán-Palomino (2022) previously conducted extensive studies on technical trading strategies for Bitcoin and Ethereum. Corbet et al. (2019) investigate moving average and trading range breakout strategies for 1-minute Bitcoin data from 01.01.2014 to 25.06.2018. They find that a multitude of moving average strategies yield excess returns. However, the best performing strategies do not utilize the most common timeframes as described by Brock et al. (1992) of 1-50, 1-150, 5-150, 1-200, and 2-200 days, but significantly shorter durations of 1-5, 2-5, and 1-10 minutes. Considering that they calculate returns for 24 different moving average timeframes, their study does not focus on confirming popular strategies before the emergence of Bitcoin but on researching the profitability of many possible moving average strategies.

The study of Grobys et al. (2020) on moving average strategies draws a similar conclusion. They consider daily data of several cryptocurrencies from 01.01.2016 to 31.12.2018 and find that a 1-20 days moving average strategy is more profitable than both moving average strategies with longer timeframes as proposed by Brock et al. (1992) and the buy-and-hold strategy for Bitcoin and Ethereum.

Our findings are in line with the findings of the study of Gerritsen et al. (2020), who found the MACD strategies and the rate of change strategy to be the best performing and the relative strength index and Bollinger band strategy to be the worst performing in terms of Sharpe ratio improvement relative to the buy-and-hold portfolio. As in our study, they find these strategies to yield more substantial results at full implementation.

In a more recent study, Svogun and Bazán-Palomino (2022) examine moving average and trading range breakout strategies for daily and 1-minute returns of multiple cryptocurrencies from 01.01.2016 to 10.11.2021. As in our study, they find that many technical strategies yield higher Sharpe ratios than the buy-and-hold strategy. Additionally, their results are stronger for Ethereum than for Bitcoin, while for daily data, more Ethereum than Bitcoin, and for 1-minute data, more Bitcoin than Ethereum strategies outperformed their respective buy-and-hold benchmark.

In summary, the studies of Corbet et al. (2019), Gerritsen et al. (2020), Grobys et al. (2020), and Svogun and Bazán-Palomino (2022)

all find evidence for the profitability of some technical trading strategies in the markets of Bitcoin and Ethereum. Similarly to the other studies, which all highlight the profitability of strategies using shorter than traditionally usual timeframes, we find strategies utilizing comparably recent information to yield better results than those that employ older price data.

While the literature on the MDH and RWH finds at least periods of deviations from weak form efficiency in the markets of Bitcoin and Ethereum (cf. Alvarez-Ramirez et al., 2018; Bariviera, 2017; Chu et al., 2019; Khuntia & Pattanayak, 2018; Kyriazis, 2019; López-Martín et al., 2021; Zhang et al., 2019), our study shows that these inefficiencies are significant enough for technical trading strategies (even those which emerged before cryptocurrencies as known today) to achieve higher absolute returns than the buy-and-hold strategy. While the MA 1-50, the three MACD, and the rate of change strategy only achieve Sharpe ratios statistically significantly different from buy-and-hold for daily Bitcoin data at partial implementation, they yield impressive absolute returns for both Bitcoin and Ethereum. Hence, the random walk model, as put by Fama (1970), is, in the eyes of a stock market trader capitalizing on their knowledge of past prices, questionable for Bitcoin and Ethereum.

## 3.6 Conclusion

Technical trading strategies aim to capitalize on persisting trends in asset price changes and have been around for centuries. We consider the claim of Fama (1970) that from a trader’s perspective, a market is inefficient so long as knowledge of past prices offers them opportunities to outperform the market. To mitigate the risk of data mining, we investigate this hypothesis for Bitcoin and Ethereum by employing several of the most popular technical approaches that have been popularized before the emergence of Bitcoin, the first cryptocurrency as they are known today.

Utilizing daily and hourly returns, we show that typical implementations of some technical trading strategies yield significantly higher absolute returns for Bitcoin and Ethereum than buy-and-hold. For daily and hourly returns, the trend following MACD, MACD signal, and rate of change strategy offer strongly increased absolute returns



for both cryptocurrencies. In contrast, the relative strength index strategy yields a negative Sharpe ratio. Our results also show that different data resolutions favor different strategies and that there exists a clear counterplay between momentum and contrarian approaches; with trend following strategies achieving the best results, it is not surprising that countertrend approaches perform considerably worse.

We find some statistically significant different Sharpe ratios from buy-and-hold, especially at partial implementation of the strategies for daily data. However, this significance is always lost at full implementation, making our findings ambivalent regarding the weak form market efficiency. Some widely popular technical strategies offer significantly higher returns to traders, while others heavily underperform buy-and-hold. Comparing hourly and daily data reveals that absolute returns are more significant when the technical strategies are employed at higher data resolution (e.g., Appendix A8 and C8 for Bitcoin and Appendix B8 and D8 for Ethereum). In this regard, we align with existing literature finding that the markets of Bitcoin and Ethereum deviate stronger from weak form market efficiency at higher data resolution.

With other studies finding that technical methods building on shorter than previously standard timeframes offer better results than traditional ones, future research should focus on further analyses of technical strategies utilizing short timeframes. Since Ethereum is an even more novel asset than Bitcoin, these strategies should also be tested on newer cryptocurrencies to investigate the relationship between the novelty of an asset and the associated market efficiency.

# Chapter 4

## Performance of Trend Trading in Cryptocurrency Markets<sup>1</sup>

### 4.1 Introduction

As Fama (1970) hypothesized, asset prices change like a random walk in the weakest form of efficient capital markets, making it impossible for investors to trade profitably by relying on past price data. For cryptocurrencies and predominantly bitcoin, this hypothesis has been extensively tested. Summarizing thirty-eight studies concerned with the efficient market hypothesis, Kyriazis (2019) infers that while some research finds prevailing trends in cryptocurrency prices, most works find increasing randomness and, thus, efficiency over time.

Other research has directly focused on the viability of trend trading in cryptocurrency markets. Gerritsen et al. (2020) studied the profitability of technical trading strategies commonly employed for equities for Bitcoin data, finding that some strategies outperform buy-and-hold. Other studies analyzed variations of popular strategies such as moving average trading, finding that the utilization of shorter than commonly used timeframes for signal generation is advantageous (cf. Corbet et al., 2019; Grobys et al. (2020); Svogun & Bazán-Palomino, 2022).

While most previous research has focused on the market efficiency and profitability of technical trading strategies for Bitcoin and Ethereum, our study adds to the literature by considering a range of popular cryptocurrencies. Lo (2004) hypothesized that market efficiency is a time-varying property of markets following an evolutionary process

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<sup>1</sup>This chapter is based on Becker, M. (2022b). Timeframe Dependent Performance of Trend Trading in Cryptocurrency Markets *Unpublished working paper*.

deriving from the behavior of its participants. With smaller and newer cryptocurrencies being traded by less individuals than e.g. Bitcoin, we hypothesize that the market efficiency of more novel cryptocurrencies should be respectively lower. This assumption is in line with previous research, finding that Ethereum is less efficient than Bitcoin (cf. Kyriazis, 2019). Therefore, we expect technical trading strategies to be profitable for the cryptocurrencies included in this study. We build on previous findings to validate this hypothesis and utilize comparably short timeframes to generate trading signals.

## Asset Description

While the seminal work of Nakamoto (2009) introduced the public to the first generation of blockchains in the form of Bitcoin, there are nowadays more than 8,000 new blockchain project uploads to GitHub annually (Connors & Sarkar, 2022). First-generation blockchains are distributed digital ledgers resistant to manipulation, providing the foundation for cryptocurrencies like Bitcoin (Yaga et al., 2018). In the second generation of blockchains, smart contracts were added to this foundation, effectively allowing entire computer programs to run on a blockchain. Computer programs running on blockchains are called decentralized applications (dApps) and stand at the core of the next iteration of the internet (Web3.0), envisioned to function without centralized parties managing data (Zou et al., 2021).

The vast technological progress underscores the apparent confusion when Bitcoin gets equated with blockchain or cryptocurrencies at large. Relating the total market capitalization of cryptocurrencies, standing at about \$1.0tn (Coinmarketcap, 2022), to the companies included in the Wilshire 5000 Index tracking all actively traded equities in the United States, reemphasizes the relevance of cryptocurrencies as financial assets, with the median (average) market capitalization of said companies being \$1.2bn (\$13.2bn) (Sure Dividend, 2022). With current Bitcoin dominance levels (the percentage share of Bitcoin's market capitalization relative to the entire cryptocurrency market) of merely 40% (Coinmarketcap, 2022), many blockchain projects have valuations on par with US companies. Below we provide a brief introduction to the cryptocurrencies included in this study.

## Cardano

Envisioned by Ethereum co-founder Charles Hoskinson in 2015, Cardano is a cryptocurrency project launched in 2017. Setting exceptionally high standards for itself, the team behind Cardano is developing the protocol based on peer-reviewed research (Hoskinson, 2017). Cardano aims to provide an energy-efficient blockchain capable of executing smart contracts and dApps.

For this objective, a Proof-of-Stake (PoS) consensus protocol is employed, where the verification of transactions does not depend on solving an arbitrary hash puzzle, as is the case for Proof-of-Work (PoW) networks such as Bitcoin. Instead, PoS randomly selects validators to agree on the accuracy of a transaction, while every such validator vouches with their stake of ADA, the native currency of Cardano. Confirming fraudulent transactions is penalized with the destruction of the staked ADA, and confirming correct transactions is rewarded with credited ADA, aligning the validators' and Cardano project's incentives (Hoskinson, 2017). Besides verifying transactions, ADA is intended to serve as a secure global exchange of value and can also be used to pay for dApps or transaction fees. As of early November 2022, ADA had a market capitalization of \$12.3bn (Coinmarketcap, 2022).

## Decentraland

The initial whitepaper for Decentraland was published in 2017 (cf. Ordano et al., 2017), and the platform was subsequently released in 2020. Running on top of the Ethereum blockchain, Decentraland is a platform for a virtual reality metaverse. Decentraland enables users to build applications and create content that other users of the metaverse can experience. Land within the platform is ownable by users, and the digital real estate owner controls which (user) generated content is associated with the virtual Land. While Land is a non-fungible token (NFT), MANA, the asset considered in this study, is the currency with which users of Decentraland can pay for both Land and make purchases within the metaverse (Ordano et al., 2017). In early November 2022, MANA had a market capitalization of \$1.0bn (Coinmarketcap, 2022).

## **Ethereum**

Vitalik Buterin publicized the idea of Ethereum in a white paper in 2013. Building on the ideas of Bitcoin, Ethereum does not only provide for decentralized, tamper-proof transactions but also for the hosting of a Turing-complete virtual machine (Buterin, 2013). The so-called Ethereum Virtual Machine (EVM) can run smart contracts, laying the foundation for smart contracts on the distributed computing platform. While initially launched with a Bitcoin-like PoW consensus mechanism heavily dependent on high energy consumption, the "Merge" upgrade executed in September 2022 changed Ethereum's consensus mechanism to PoS, effectively reducing its energy consumption by more than 99.9% (Ethereum, 2022). As the second largest cryptocurrency, the total market capitalization of ETH, the native token of the Ethereum blockchain, stood at \$148.5bn in early November 2022 (Coinmarketcap, 2022).

## **Ripple**

Founded in 2012, the digital currency often referred to as Ripple is XRP, a digital currency running on RippleNet, a digital platform for payments. RippleNet, in turn, runs on top of the XRP ledger, a distributed database (Arslanian, 2022). Being released shortly after Bitcoin's original inception, Ripple's main objective is to facilitate transactions in very short time at low costs, qualities that Bitcoin does not have due to its PoW consensus mechanism. Accordingly, Ripple and XRP cater to large institutions engaged in cross-border transactions (Schwartz et al., 2014). Consistently ranking among the largest cryptocurrencies, XRP had a market capitalization of \$18.9bn in November 2022 (Coinmarketcap, 2022).

## **Sandbox**

Like Decentraland, the Sandbox is a decentralized virtual gaming world on top of the Ethereum blockchain. Like MANA in Decentraland, SAND (the native token of the Sandbox) can be used to buy ASSET and LAND NFTs in the Sandbox. ASSET NFTs correspond to user-generated content, while LAND represents digital real estate in the metaverse; the first sale of LAND NFTs took place in late 2019

(The Sandbox, 2020). The market capitalization of SAND in early November 2022 was \$1.0bn, on par with the market capitalization of Decentraland (Coinmarketcap, 2022).

## **Shiba Inu**

Shiba Inu is a blockchain project based on an anonymously published white paper from August 2020 (Pagariya et al., 2022). Mentioning the GameStop and AMC short squeeze of 2021 directly, the project’s self-declared goal is to build a decentralized community-based cryptocurrency, returning power to its users (Ryoshi, 2021). Shiba Inu runs on top of the Ethereum blockchain and was initially intended to become a ”dogecoin killer”, meaning it was meant to replace the previously launched cryptocurrency themed around the same Shiba Inu dog breed (Arslanian, 2022). The project actively supports dog shelters and while arguably being a less serious venture than standalone blockchains, SHIB, the native token of the Shiba Inu, had a market capitalization of \$5.4bn in November 2022 (Coinmarketcap, 2022).

## **Solana**

Based on the white paper of Yakovenko (2017), Solana is an open-source blockchain project utilizing a Proof of History (PoH) published in 2020. Based on the PoH, the Solana blockchain can link specific events with distinct points in time. Combining the PoH with a PoS consensus mechanism, Solana is a highly scalable and fast blockchain, theoretically able to handle up to 710,000 transactions per second (Yakovenko, 2017). Combining its low transaction costs and speed with the ability to execute smart contracts, Solana is inherently designed to facilitate dApps. SOL, the native token of Solana used to pay for the hosting of on-chain programs or transaction validation, had a market capitalization of \$6.8bn in early November 2022 (Coinmarketcap, 2022).

## **Contribution**

We add to the literature by applying previous insights on the profitability of technical strategies using short-term signals to a wide range of cryptocurrencies. Further, we incorporate data spanning until the

end of September 2022, thus examining trading performance during the latest price peaks in late 2021 and the following troughs in the first three quarters of 2022.

In line with previous research, we find that cryptocurrency price trends are short-lived and that more recent information is significantly more helpful for trading strategies across assets. Some technical trading strategies make investors in absolute and risk-adjusted terms better off than the buy-and-hold portfolio. Statistical significance of the Sharpe ratio improvements associated with our implemented strategies almost exclusively drops away when allowing shorting the asset. Last, neither novelty, size, nor the associated buy-and-hold return of our investigated cryptocurrencies are reliable indicators for the profitability of technical trading strategies (and hence, market efficiency).

The remaining sections are structured as follows. First, our data and descriptive statistics are presented in section 4.2. Second, we present and explain our methodology in section 4.3. Third, we present our results in section 4.4. Fourth, we discuss our findings in section 4.5 before coming to a conclusion in section 4.6.

## 4.2 Data

We obtained hourly price data of Cardano, Decentraland, Ethereum, Ripple, Sandbox, Shiba Inu, and Solana in terms of US Dollars from Kraken (2022), a leading cryptocurrency exchange. While the availability of the first price point depends on the date when the respective cryptocurrency got listed on the exchange, price data for all assets is available until 30.09.2022. We compute logarithmic returns from the price data using:

$$r_t = \ln \left( \frac{X_t}{X_{t-1}} \right) * 100 \quad (4.1)$$

Where  $X_t$  is the price at time  $t$ . Table 4.1 presents descriptive statistics of the thus computed hourly cryptocurrency log returns.

Ethereum returns constitute the longest available time series of about seven years, whereas Shiba Inu returns are the shortest time series of slightly less than a year. The mean hourly return of all assets besides Shiba Inu and Solana is positive, with Decentraland exhibiting the largest median and mean return. Ripple has the lowest mean re-

Table 4.1: Descriptive statistics of hourly cryptocurrency log returns

	Cardano	Decentraland	Ethereum	Ripple	Sandbox	Shiba Inu	Solana
Minimum	-25.9254	-39.4544	-191.6923	-25.7402	-23.9489	-9.4616	-21.9849
Mean	0.0043	0.0130	0.0103	0.0007	0.0097	-0.0194	-0.0015
Maximum	17.0188	33.5789	207.9433	26.5020	24.0961	11.7783	15.9177
Median	0.0000	0.0039	0.0029	0.0000	0.0000	0.0000	-0.0158
Standard deviation	1.2694	1.9044	2.0895	1.4626	1.8764	1.2923	1.3951
Skewness	-0.4099	0.5487	3.5659	0.3920	0.8074	0.4654	-0.0201
Kurtosis	17.8853	31.1880	3204.9899	36.0991	16.0858	8.8996	13.5968
Jarque-Bera	464,832*	634,940*	25,337,200,213*	2,550,541*	122,981*	24,364*	86,683*
Sample period	Sep 28, 2018 - Sep 30, 2022	Dec 15, 2020 - Sep 30, 2022	Aug 11, 2015 - Sep 30, 2022	May 18, 2017 - Sep 30, 2022	May 20, 2021 - Sep 30, 2022	Nov 30, 2021 - Sep 30, 2022	May 17, 2021 - Sep 30, 2022

Note: \* denotes statistical significance at the 1% level

turn, and all cryptocurrency returns have comparable standard deviations, ranging from 1.2923 (Shiba Inu) to 2.0895 (Ethereum). Ethereum returns exhibit the strongest positive skew, followed by Sandbox, Decentraland, Shiba Inu, and Ripple. Solana returns have a negative, near zero skew, and Cardano returns are skewed to the left the most with a value of -0.4099. All logarithmic return distributions are fat-tailed and the Jarque-Bera test rejects normality at the 1% significance level for all assets.

### 4.3 Methodology

Following previous studies on the profitability of technical trading strategies in cryptocurrency markets (cf. Corbet et al., 2019; Gerritsen et al., 2020; Svogun & Bazán-Palomino, 2022), we examine the performance of the trend-following moving average and rate of change strategy. Trend-following strategies have historically been identified to be more worthwhile than counter-trend strategies for the trading of Bitcoin (Gerritsen et al., 2020). Further, Corbet et al. (2019) and Svogun & Bazán-Palomino (2022) show that these strategies perform better when they are employed utilizing shorter timeframes than commonly used for equities. The strategies and timeframes employed in this study are explained below.

#### Moving Average

Considering historical average prices of an asset during a predefined time window and relating them to more recent price levels, the moving average (MA) is among the oldest and most popular technical trading



strategies (Brock et al. 1992). The strategy considers the average historical price of an asset during a predefined time window and compares it to recent price data.  $MA(X)_{t,n}$  is the  $n$ -day moving average of an asset  $X$  at time  $t$ , denoted as:

$$MA(X)_{t,n} = \frac{1}{n} \sum_{i=t-n+1}^t X_i \quad (4.2)$$

Trading signals are generated by firstly computing a short-term moving average (MAS) and a long-term moving average (MAL), with  $s$  corresponding to the number of days considered for the MAS and  $l$  corresponding to the number of MAL days. The most common time window ( $s - l$ ) traditionally used for equities trading is 1-200, with other popular windows being 1-50, 1-150, 2-200, and 5-150 (Brock et al. 1992).

After the computation of MAS and MAL values, the moving average strategy issues a sell signal when the MAS drops below the MAL and a buy signal when the MAS increases above the MAL. The basic principle is to smooth volatile time series using the MAL and to detect deviations from them using the MAS. The strategy filters out spurious signals to identify true uptrends or downtrends. The strategy works well when there is a clear trend, while excessive volatility reduces its usefulness (Wong et al. 2003). Formally, the moving average trading rule is defined as follows:

$$\begin{aligned} \text{Buy} : MAS(X)_{t,s} &> MAL(X)_{t,l} \\ \text{Sell} : MAS(X)_{t,s} &< MAL(X)_{t,l} \end{aligned}$$

For Bitcoin, Corbet et al. (2019) conducted a comprehensive study of a wider range of MAS and MAL combinations, adding 10 as an additional MAS period and using values as low as 5 for the MAL. Following their approach, we utilize a similar yet slightly more extensive range of possible timeframes for our analysis.

## Rate of Change

The rate of change (ROC) is a simple trend-following strategy that derives trading signals from the difference between today's and the price  $n$  days ago (Gerritsen, 2016). As such, the strategy seeks to ex-

exploit continuing price trends with the expectation that price increases will be followed by further price increases and that price reductions will be followed by further price reductions. The rate of change is thus computed as follows:

$$ROC(X)_t = X_t - X_{t-n-1} \quad (4.3)$$

The most common timeframe employed for traditional rate of change trading is 10 days (Gerritsen, 2016), and the strategy generates trading signals as:

*Buy* :  $ROC(X)_t > 0$

*Sell* :  $ROC(X)_t < 0$

As for moving average trading, we employ a more extensive range for  $n$  to determine whether cryptocurrency price trends persist for shorter or longer than commonly assumed for equities. Accordingly, we compare current prices with price levels from 2 through 15 days ago.

## Application

As we employ high-frequency data at hourly resolution while utilizing trading strategies that use daily timeframes, we incrementally roll forward both strategies by one hour. Correspondingly, we determine the current day's price by computing a moving average of the last 24 hours. In the same way, a MAL of 200 days corresponds to the moving average of the last 4,800 hours.

While the Kraken exchange, the source of the data employed in this study, today offers futures with hourly settlement (Kraken, 2022b), taking short positions in cryptocurrencies was not possible during the early years after their creation. Therefore, we compute strategy returns for two different implementations. In the first, we take the constraint into account and hence go long in an asset when a strategy issues a buy decision and out of the market when a sell signal is issued (partial implementation). In the second, we fully implement the trading strategy with a long position for buy signals and short for sell signals (full implementation).

To evaluate the performance of the strategies, we follow Sharpe (1966) and calculate the Sharpe ratio ( $S_{i,j}$ ) for every strategy  $i$ , at partial or full implementation  $j$  as:

$$S_{i,j} = \frac{R_{i,j} - rf}{\sigma_{i,j}} \quad (4.4)$$

where  $R_{i,j}$  is the return and  $\sigma_{i,j}$  the associated standard deviation of of strategy  $i$  at implementation  $j$  and  $rf$  denotes the risk-free rate. Considering the interest rate environment during our sample period and the impracticality of investing at the risk-free rate for only hours, we assume the risk-free rate to be zero. Last, we test whether the Sharpe ratios achieved by the technical strategies differ from the Sharpe ratio associated with the buy-and-hold portfolio to a statistically significant degree. We do so by statistical inference and bootstrapping, following the approach developed by Ledoit and Wolf (2008). Their method utilizes a  $t$ -test investigating whether the Sharpe ratio of two portfolios is equal. The respective null hypothesis is formulated as:

$$H_0 = \frac{R_{i,j} - rf}{\sigma_{i,j}} = \frac{R_{BH} - rf}{\sigma_{BH}} \quad (4.5)$$

$R_{BH}$  denotes the return and  $\sigma_{BH}$  the standard deviation of the returns of the buy-and-hold portfolio. We use 20,000 bootstrap re-samples and generate  $p$ -values following Ledoit and Wolf (2008).

## 4.4 Results

Below we report profitability and Sharpe ratios of the previously introduced moving average and rate of change strategies. Timeframes are referenced by the numbers in the respective strategy name. For example, MA 2-20 refers to a moving average strategy with a MAS of 2 and a MAL of 20. In the same way, ROC 10 corresponds to the traditional application of the rate of change strategy, comparing the current day's price to the price 10 days ago, and ROC 15 compares the current day's price to the price 15 days ago.

Table 4.2 presents the strategy performances for Cardano, and Appendix A visualizes the associated return developments. Of the 50 moving average strategies, 12 exhibit a statistically significant Sharpe

ratio increase over buy-and-hold. Of the 28 rate of change strategies, only one results in a statistically significant Sharpe ratio increase.

At partial implementation, all moving average strategies using a 20-day window for the MAL achieve a statistically significant Sharpe ratio different from buy and hold. Absolute returns and Sharpe ratios are mostly higher at full implementation; however, these strategies lose statistical significance due to a substantial increase in volatility (consider Appendix A).

The best-performing rate of change strategy for partial and full implementation considers the last 11 days. While the strategy achieves a statistically significant improved Sharpe ratio at partial implementation (being the only rate of change strategy to do so for Cardano), this statistical significance is lost at full implementation due to a substantial increase in volatility. However, the fully implemented version of ROC 11 achieves a more than fivefold absolute return compared with the partially implemented version.

Table 4.3 presents the strategy performances for Decentraland, and Appendix B visualizes the associated return developments. None of the 50 moving average and 28 rate of change strategies achieves a statistically significantly increased Sharpe ratio. At partial implementation and the corresponding going out of the market, the forgone returns are too substantial for the thus equally reduced volatility to affect the Sharpe ratio favorably. With full implementation, return volatility increases too much to improve the Sharpe ratio statistically significantly despite increased absolute returns.

Table 4.4 presents the strategy performances for Ethereum, and Appendix C visualizes the associated return developments. Of the 50 moving average strategies, 9 exhibit a statistically significant Sharpe ratio increase over buy-and-hold. Of the 28 rate of change strategies, seven result in a statistically significant Sharpe ratio increase.

At partial implementation, all moving average strategies employing a 20-day MAL window yield improved Sharpe ratios significant at the 5% level. The basis point increase is higher for all of them at full implementation. However, the statistical significance drops to the 10% level in all cases, while the MA 5-20 strategy loses its statistical significance completely. In general, moving average strategies utilizing a 100-day MAL or longer perform worse than strategies with shorter timeframes.

Table 4.2: Sharpe ratios of technical trading strategies for Cardano

	Long or out				Long or short			
	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value
<b>Moving Average</b>								
MA 1-5	Yes	0.010	0.62	0.14	Yes	0.010	0.62	0.42
MA 1-10	Yes	0.011	0.76*	0.06	Yes	0.012	0.87	0.25
MA 1-20	Yes	0.011	0.76*	0.05	Yes	0.012	0.86	0.24
MA 1-50	Yes	0.009	0.55*	0.16	Yes	0.008	0.45	0.52
MA 1-100	Yes	0.011	0.71	0.07	Yes	0.011	0.76	0.26
MA 1-150	Yes	0.010	0.65*	0.09	Yes	0.010	0.66	0.31
MA 1-200	Yes	0.009	0.57	0.13	Yes	0.011	0.72	0.26
MA 2-5	Yes	0.006	0.26	0.52	Yes	0.005	0.12	0.87
MA 2-10	Yes	0.009	0.55	0.16	Yes	0.009	0.59	0.42
MA 2-20	Yes	0.012	0.85**	0.03	Yes	0.013	0.99	0.17
MA 2-50	Yes	0.009	0.55	0.16	Yes	0.008	0.46	0.52
MA 2-100	Yes	0.011	0.73*	0.06	Yes	0.011	0.79	0.24
MA 2-150	Yes	0.010	0.63*	0.10	Yes	0.010	0.64	0.32
MA 2-200	Yes	0.009	0.54	0.15	Yes	0.010	0.67	0.29
MA 5-10	Yes	0.005	0.19	0.63	Yes	0.004	0.07	0.92
MA 5-20	Yes	0.012	0.87**	0.02	Yes	0.014	1.06	0.14
MA 5-50	Yes	0.011	0.74*	0.06	Yes	0.011	0.75	0.28
MA 5-100	Yes	0.010	0.69*	0.08	Yes	0.011	0.73	0.28
MA 5-150	Yes	0.009	0.60	0.11	Yes	0.009	0.59	0.36
MA 5-200	Yes	0.009	0.56	0.14	Yes	0.010	0.70	0.27
MA 10-20	Yes	0.011	0.71*	0.06	Yes	0.012	0.85	0.23
MA 10-50	Yes	0.012	0.81**	0.04	Yes	0.012	0.85	0.23
MA 10-100	Yes	0.008	0.47	0.22	Yes	0.007	0.39	0.55
MA 10-150	Yes	0.008	0.42	0.25	Yes	0.007	0.33	0.60
MA 10-200	Yes	0.007	0.40	0.26	Yes	0.008	0.48	0.42
<b>Rate of Change</b>								
ROC 2	No	0.002	-0.18	0.66	No	-0.002	-0.49	0.53
ROC 3	Yes	0.007	0.37	0.36	Yes	0.006	0.29	0.71
ROC 4	Yes	0.008	0.41	0.33	Yes	0.007	0.32	0.67
ROC 5	Yes	0.006	0.20	0.62	Yes	0.004	0.04	0.96
ROC 6	Yes	0.005	0.18	0.65	Yes	0.004	0.02	0.97
ROC 7	Yes	0.008	0.49	0.21	Yes	0.008	0.50	0.49
ROC 8	Yes	0.009	0.57	0.15	Yes	0.009	0.60	0.41
ROC 9	Yes	0.007	0.34	0.38	Yes	0.006	0.28	0.70
ROC 10	Yes	0.009	0.51	0.20	Yes	0.009	0.52	0.47
ROC 11	Yes	0.011	0.71*	0.07	Yes	0.012	0.82	0.26
ROC 12	Yes	0.009	0.56	0.15	Yes	0.009	0.58	0.42
ROC 13	Yes	0.008	0.44	0.26	Yes	0.008	0.41	0.57
ROC 14	Yes	0.008	0.42	0.28	Yes	0.007	0.37	0.60
ROC 15	Yes	0.010	0.63	0.11	Yes	0.010	0.68	0.35
<b>Buy and hold</b>		0.003						

\**p* < 0.10, \*\**p* < 0.05, \*\*\**p* < 0.01

No rate of change strategy yields statistically significant results at full implementation. Interestingly, the best-performing strategy (which also exhibits the lowest *p*-value) is the ROC 3 strategy, while the traditional ROC 10 strategy does not yield significant results. Besides the short-term ROC 3 strategy, the best results are derived from strategies considering slightly older than traditional data, with ROC 12, ROC 13, and ROC 15 yielding improved Sharpe ratios significant at the 5% level.

Table 4.5 presents the strategy performances for Ripple, and Appendix D visualizes the associated return developments. Of the 50 moving average strategies, seven achieve a statistically significant Sharpe ratio increase over buy-and-hold. Of the 28 rate of change strategies, 14 result in a statistically significantly increased Sharpe ratio..

Table 4.3: Sharpe ratios of technical trading strategies for Decentraland

	Long or out				Long or short			
	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value
<b>Moving Average</b>								
MA 1-5	Yes	0.010	0.36	0.54	Yes	0.009	0.16	0.88
MA 1-10	Yes	0.010	0.28	0.62	Yes	0.007	0.04	0.97
MA 1-20	Yes	0.015	0.81	0.14	Yes	0.016	0.91	0.37
MA 1-50	Yes	0.011	0.39	0.53	Yes	0.011	0.44	0.67
MA 1-100	No	0.000	-0.68	0.34	No	0.001	-0.59	0.59
MA 1-150	No	-0.002	-0.83	0.26	No	0.000	-0.65	0.55
MA 1-200	No	0.001	-0.58	0.45	No	0.000	-0.66	0.54
MA 2-5	No	0.007	-0.00	1.00	No	0.003	-0.35	0.74
MA 2-10	Yes	0.012	0.53	0.35	Yes	0.011	0.41	0.69
MA 2-20	Yes	0.014	0.68	0.21	Yes	0.014	0.72	0.47
MA 2-50	No	0.010	0.29	0.63	Yes	0.010	0.30	0.77
MA 2-100	No	0.003	-0.38	0.59	No	0.005	-0.15	0.88
MA 2-150	No	0.001	-0.55	0.46	No	0.004	-0.23	0.83
MA 2-200	No	0.003	-0.42	0.59	No	0.003	-0.41	0.70
MA 5-10	Yes	0.012	0.49	0.39	Yes	0.010	0.34	0.74
MA 5-20	Yes	0.013	0.56	0.29	Yes	0.012	0.55	0.58
MA 5-50	Yes	0.012	0.54	0.38	Yes	0.014	0.67	0.52
MA 5-100	No	0.004	-0.27	0.69	No	0.007	0.00	1.00
MA 5-150	No	0.001	-0.58	0.43	No	0.004	-0.28	0.79
MA 5-200	No	0.004	-0.31	0.69	No	0.004	-0.26	0.81
MA 10-20	Yes	0.014	0.69	0.21	Yes	0.014	0.71	0.48
MA 10-50	Yes	0.011	0.41	0.48	Yes	0.012	0.56	0.57
MA 10-100	No	0.003	-0.39	0.58	No	0.005	-0.16	0.88
MA 10-150	No	0.002	-0.48	0.50	No	0.005	-0.13	0.90
MA 10-200	No	0.002	-0.45	0.57	No	0.002	-0.47	0.66
<b>Rate of Change</b>								
ROC 2	No	0.003	-0.35	0.56	No	-0.002	-0.90	0.42
ROC 3	Yes	0.010	0.29	0.63	Yes	0.007	0.01	0.99
ROC 4	No	0.006	-0.09	0.87	No	0.002	-0.49	0.65
ROC 5	No	0.008	0.10	0.85	No	0.005	-0.19	0.85
ROC 6	No	0.009	0.20	0.72	No	0.006	-0.06	0.95
ROC 7	Yes	0.012	0.47	0.40	Yes	0.010	0.34	0.74
ROC 8	Yes	0.013	0.61	0.27	Yes	0.012	0.53	0.61
ROC 9	Yes	0.012	0.54	0.34	Yes	0.011	0.44	0.67
ROC 10	Yes	0.013	0.64	0.25	Yes	0.013	0.58	0.58
ROC 11	Yes	0.012	0.53	0.35	Yes	0.011	0.43	0.68
ROC 12	Yes	0.013	0.58	0.30	Yes	0.012	0.51	0.62
ROC 13	Yes	0.012	0.54	0.32	Yes	0.012	0.47	0.64
ROC 14	Yes	0.012	0.47	0.39	Yes	0.010	0.33	0.75
ROC 15	Yes	0.014	0.69	0.20	Yes	0.014	0.73	0.47
<b>Buy and hold</b>		0.007						

\**p* < 0.10, \*\**p* < 0.05, \*\*\**p* < 0.01

The best-performing moving average strategy is MA 2-10, which at partial implementation achieves a Sharpe ratio increase of 0.92 basis points (significant at the 5% level) and 1.20 basis points at full implementation (significant at the 10% level). At partial implementation, all strategies utilizing a MAS of 1 or 2 and a MAL from 5 up to 20 yield Sharpe ratio improvements at least statistically significant at the 10% level.

Of the exclusively profitable rate of change strategies, ROC4 and ROC 6 up to ROC 15 yield statistically significant Sharpe ratio improvements at partial implementation. Further, the Sharpe ratio improvements associated with the ROC 7, ROC 11, and ROC 12 strategies are also statistically significant at the 10% level at full implementation. Despite this high level of the overall significance of the

Table 4.4: Sharpe ratios of technical trading strategies for Ethereum

	Long or out				Long or short			
	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value
<b>Moving Average</b>								
MA 1-5	Yes	0.012	0.73*	0.06	Yes	0.011	0.63	0.25
MA 1-10	Yes	0.011	0.57	0.13	Yes	0.009	0.41	0.43
MA 1-20	Yes	0.013	0.85**	0.03	Yes	0.014	0.91*	0.08
MA 1-50	Yes	0.011	0.56	0.15	Yes	0.010	0.52	0.30
MA 1-100	No	0.007	0.25	0.53	No	0.007	0.16	0.74
MA 1-150	No	0.009	0.36	0.36	Yes	0.009	0.39	0.42
MA 1-200	Yes	0.010	0.46	0.26	Yes	0.010	0.51	0.29
MA 2-5	Yes	0.012	0.66*	0.09	Yes	0.010	0.52	0.34
MA 2-10	Yes	0.010	0.55	0.14	Yes	0.009	0.39	0.44
MA 2-20	Yes	0.014	0.88**	0.02	Yes	0.015	0.98*	0.06
MA 2-50	Yes	0.011	0.64	0.10	Yes	0.012	0.65	0.19
MA 2-100	No	0.007	0.21	0.60	No	0.006	0.09	0.84
MA 2-150	No	0.009	0.41	0.30	Yes	0.010	0.47	0.33
MA 2-200	Yes	0.009	0.44	0.28	Yes	0.010	0.48	0.32
MA 5-10	Yes	0.011	0.56	0.13	Yes	0.009	0.40	0.45
MA 5-20	Yes	0.013	0.76**	0.05	Yes	0.013	0.79	0.12
MA 5-50	Yes	0.011	0.62	0.11	Yes	0.011	0.63	0.20
MA 5-100	No	0.009	0.36	0.36	Yes	0.009	0.37	0.44
MA 5-150	No	0.009	0.40	0.31	Yes	0.010	0.48	0.32
MA 5-200	No	0.009	0.38	0.34	Yes	0.009	0.40	0.40
MA 10-20	Yes	0.013	0.80**	0.03	Yes	0.014	0.90*	0.07
MA 10-50	Yes	0.011	0.56	0.15	Yes	0.010	0.55	0.26
MA 10-100	No	0.008	0.29	0.46	No	0.008	0.26	0.58
MA 10-150	Yes	0.009	0.44	0.26	Yes	0.010	0.55	0.25
MA 10-200	No	0.009	0.39	0.32	Yes	0.009	0.42	0.37
<b>Rate of Change</b>								
ROC 2	No	0.007	0.20	0.59	No	0.003	-0.14	0.80
ROC 3	Yes	0.016	1.10**	0.01	Yes	0.013	0.81	0.19
ROC 4	Yes	0.012	0.70*	0.07	Yes	0.011	0.57	0.30
ROC 5	Yes	0.009	0.45	0.24	Yes	0.007	0.22	0.68
ROC 6	Yes	0.010	0.55	0.14	Yes	0.009	0.39	0.46
ROC 7	Yes	0.011	0.63*	0.09	Yes	0.011	0.58	0.27
ROC 8	Yes	0.011	0.56	0.14	Yes	0.009	0.43	0.41
ROC 9	Yes	0.009	0.43	0.24	Yes	0.007	0.24	0.63
ROC 10	Yes	0.011	0.58	0.12	Yes	0.009	0.42	0.41
ROC 11	Yes	0.010	0.55	0.14	Yes	0.009	0.39	0.45
ROC 12	Yes	0.013	0.81**	0.04	Yes	0.012	0.74	0.17
ROC 13	Yes	0.013	0.78**	0.04	Yes	0.012	0.70	0.18
ROC 14	Yes	0.012	0.73*	0.06	Yes	0.011	0.63	0.22
ROC 15	Yes	0.013	0.82**	0.03	Yes	0.012	0.75	0.15
<b>Buy and hold</b>		0.005						

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

rate of change strategies, it should be noted that the Sharpe ratio improvement associated with the best-performing rate of change strategy (ROC 7) is slightly smaller than the one associated with the best moving average strategy (MA 2-10).

Table 4.6 presents the strategy performances for Sandbox, and Appendix E visualizes the associated return developments. Of the 50 moving average and 28 rate of change strategies none achieves a statistically significant Sharpe ratio increase. While most strategies yield higher absolute returns than buy-and-hold, Sandbox is the only asset associated with any (and only) statistically significant deteriorated Sharpe ratios.

As for the other currencies, moving average strategies tend to perform worse the longer the timeframe of the MAL gets. The negative, statistically significant results are all associated with MA strategies

Table 4.5: Sharpe ratios of technical trading strategies for Ripple

	Long or out				Long or short			
	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value
<b>Moving Average</b>								
MA 1-5	Yes	0.008	0.75**	0.04	Yes	0.011	1.01	0.12
MA 1-10	Yes	0.008	0.73**	0.04	Yes	0.010	0.93	0.15
MA 1-20	Yes	0.007	0.63*	0.08	Yes	0.009	0.85	0.18
MA 1-50	Yes	0.004	0.31	0.37	Yes	0.004	0.37	0.54
MA 1-100	No	0.000	-0.07	0.83	No	-0.002	-0.21	0.71
MA 1-150	No	0.000	-0.07	0.83	No	-0.001	-0.18	0.75
MA 1-200	No	0.000	-0.02	0.95	No	-0.001	-0.11	0.84
MA 2-5	Yes	0.007	0.63*	0.08	Yes	0.009	0.85	0.19
MA 2-10	Yes	0.010	0.92**	0.01	Yes	0.012	1.20*	0.07
MA 2-20	Yes	0.008	0.75**	0.03	Yes	0.011	1.03	0.10
MA 2-50	Yes	0.005	0.48	0.16	Yes	0.007	0.64	0.29
MA 2-100	No	-0.002	-0.28	0.41	No	-0.005	-0.54	0.36
MA 2-150	Yes	0.001	0.02	0.94	No	0.000	-0.02	0.96
MA 2-200	No	0.000	-0.01	0.97	No	-0.001	-0.10	0.86
MA 5-10	Yes	0.006	0.50	0.16	Yes	0.007	0.61	0.35
MA 5-20	Yes	0.006	0.53	0.14	Yes	0.007	0.70	0.28
MA 5-50	Yes	0.002	0.11	0.75	Yes	0.001	0.07	0.90
MA 5-100	No	-0.001	-0.12	0.71	No	-0.003	-0.30	0.61
MA 5-150	No	0.001	0.01	0.97	No	0.000	-0.05	0.93
MA 5-200	No	-0.001	-0.13	0.71	No	-0.002	-0.28	0.62
MA 10-20	Yes	0.004	0.36	0.31	Yes	0.005	0.46	0.46
MA 10-50	Yes	0.002	0.17	0.61	Yes	0.002	0.17	0.78
MA 10-100	No	-0.001	-0.13	0.70	No	-0.003	-0.30	0.60
MA 10-150	No	-0.001	-0.10	0.76	No	-0.002	-0.23	0.68
MA 10-200	No	-0.001	-0.12	0.71	No	-0.002	-0.28	0.62
<b>Rate of Change</b>								
ROC 2	Yes	0.003	0.28	0.42	Yes	0.004	0.37	0.57
ROC 3	Yes	0.006	0.51	0.15	Yes	0.007	0.69	0.29
ROC 4	Yes	0.007	0.61*	0.09	Yes	0.009	0.80	0.22
ROC 5	Yes	0.006	0.55	0.12	Yes	0.008	0.74	0.26
ROC 6	Yes	0.007	0.69**	0.05	Yes	0.010	0.95	0.14
ROC 7	Yes	0.009	0.88**	0.01	Yes	0.012	1.17*	0.07
ROC 8	Yes	0.008	0.76**	0.03	Yes	0.011	1.02	0.12
ROC 9	Yes	0.007	0.66*	0.07	Yes	0.009	0.83	0.20
ROC 10	Yes	0.008	0.73**	0.04	Yes	0.010	0.94	0.15
ROC 11	Yes	0.009	0.85**	0.02	Yes	0.012	1.12*	0.08
ROC 12	Yes	0.009	0.84**	0.02	Yes	0.011	1.10*	0.09
ROC 13	Yes	0.008	0.77**	0.03	Yes	0.011	1.02	0.11
ROC 14	Yes	0.007	0.61*	0.09	Yes	0.009	0.83	0.19
ROC 15	Yes	0.007	0.60*	0.08	Yes	0.009	0.83	0.18
<b>Buy and hold</b>		0.000						

\**p* < 0.10, \*\**p* < 0.05, \*\*\**p* < 0.01

utilizing the last 200 days as MAL at partial implementation. No rate of change strategy does achieve statistically significant results. ROC 2 is the only strategy yielding a reduced Sharpe ratio compared to buy-and-hold, while ROC 2 and ROC 11 lead to a decreased absolute return.

Table 4.7 presents the strategy performances for Shiba Inu, and Appendix F visualizes the associated return developments. All 78 strategies achieve higher absolute returns than the buy-and-hold benchmark. Shiba Inu exhibits the lowest buy-and-hold ratio of all assets in our sample (-0.015) and the shortest time series. Therefore, Sharpe ratios of partially implemented moving average strategies with high MAL values are partially incomputable because these strategies are simply out of the market (nearly) all the time.



Table 4.6: Sharpe ratios of technical trading strategies for Sandbox

	Long or out				Long or short			
	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value
<b>Moving Average</b>								
MA 1-5	Yes	0.008	0.23	0.75	Yes	0.006	0.04	0.97
MA 1-10	Yes	0.012	0.70	0.34	Yes	0.013	0.80	0.53
MA 1-20	Yes	0.011	0.60	0.41	Yes	0.011	0.56	0.65
MA 1-50	Yes	0.012	0.72	0.38	Yes	0.017	1.17	0.36
MA 1-100	Yes	0.013	0.76	0.39	Yes	0.017	1.17	0.38
MA 1-150	No	0.000	-0.49	0.63	No	0.009	0.41	0.77
MA 1-200	No	-0.017	-2.23**	0.05	No	-0.001	-0.61	0.69
MA 2-5	No	0.007	0.14	0.84	No	0.004	-0.07	0.95
MA 2-10	Yes	0.014	0.85	0.25	Yes	0.015	1.00	0.44
MA 2-20	Yes	0.013	0.82	0.26	Yes	0.014	0.89	0.47
MA 2-50	Yes	0.012	0.66	0.42	Yes	0.016	1.07	0.40
MA 2-100	Yes	0.012	0.72	0.42	Yes	0.016	1.11	0.40
MA 2-150	No	0.000	-0.50	0.62	Yes	0.009	0.40	0.78
MA 2-200	No	-0.014	-1.87*	0.10	No	0.002	-0.26	0.86
MA 5-10	Yes	0.011	0.59	0.43	Yes	0.011	0.61	0.64
MA 5-20	Yes	0.014	0.90	0.21	Yes	0.016	1.03	0.39
MA 5-50	Yes	0.009	0.36	0.66	Yes	0.012	0.63	0.62
MA 5-100	Yes	0.010	0.52	0.56	Yes	0.014	0.84	0.52
MA 5-150	No	0.001	-0.44	0.66	Yes	0.010	0.46	0.74
MA 5-200	No	-0.014	-1.91*	0.09	No	0.002	-0.31	0.83
MA 10-20	Yes	0.011	0.54	0.46	Yes	0.010	0.44	0.72
MA 10-50	Yes	0.011	0.57	0.48	Yes	0.015	0.95	0.45
MA 10-100	Yes	0.010	0.49	0.58	Yes	0.013	0.81	0.54
MA 10-150	No	0.000	-0.46	0.64	Yes	0.010	0.44	0.75
MA 10-200	No	-0.014	-1.92*	0.09	No	0.002	-0.31	0.84
<b>Rate of Change</b>								
ROC 2	No	-0.001	-0.66	0.36	No	-0.005	-1.05	0.42
ROC 3	Yes	0.011	0.61	0.41	Yes	0.011	0.58	0.66
ROC 4	Yes	0.009	0.39	0.59	Yes	0.008	0.29	0.82
ROC 5	Yes	0.009	0.43	0.55	Yes	0.009	0.37	0.77
ROC 6	Yes	0.013	0.81	0.27	Yes	0.015	0.96	0.45
ROC 7	Yes	0.013	0.75	0.30	Yes	0.014	0.91	0.48
ROC 8	Yes	0.014	0.88	0.23	Yes	0.015	1.03	0.42
ROC 9	Yes	0.014	0.83	0.25	Yes	0.015	0.98	0.44
ROC 10	Yes	0.009	0.39	0.59	Yes	0.009	0.35	0.78
ROC 11	No	0.007	0.17	0.81	No	0.005	0.02	0.99
ROC 12	Yes	0.010	0.46	0.52	Yes	0.010	0.52	0.68
ROC 13	Yes	0.009	0.43	0.55	Yes	0.009	0.42	0.73
ROC 14	Yes	0.010	0.45	0.53	Yes	0.009	0.37	0.76
ROC 15	Yes	0.012	0.63	0.37	Yes	0.012	0.68	0.58
<b>Buy and hold</b>		0.005						

\**p* < 0.10, \*\**p* < 0.05, \*\*\**p* < 0.01

While all strategies outperform buy-and-hold, many are associated with an overall negative Sharpe ratio. No moving average strategy achieves statistically significant Sharpe ratio improvements. Only MA 1-5 and MA 2-5 achieve a non-negative Sharpe ratio at partial implementation. Rate of change strategies behave similarly, with only a few strategies achieving a positive Sharpe ratio at partial implementation. However, ROC 13 is associated with a 1.85 basis point increase compared to buy-and-hold significant at the 10% level and the highest increase of all strategies and all assets at full implementation (3.12 basis point increase, also significant at the 10% level).

Table 4.8 presents the strategy performances for Solana, and Appendix G visualizes the associated return developments. Of the 50 moving average strategies, seven achieve a statistically significantly increased Sharpe ratio compared with the buy-and-hold benchmark.

Table 4.7: Sharpe ratios of technical trading strategies for Shiba Inu

	Long or out				Long or short			
	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value
<b>Moving Average</b>								
MA 1-5	Yes	0.000	1.46	0.15	Yes	0.012	2.67	0.14
MA 1-10	Yes	-0.007	0.77	0.46	Yes	0.003	1.84	0.32
MA 1-20	Yes	-0.004	1.06	0.33	Yes	0.005	2.01	0.29
MA 1-50	Yes	-0.016	-0.09	0.94	Yes	-0.007	0.80	0.68
MA 1-100	Yes	-0.012	0.32	0.81	Yes	-0.002	1.33	0.51
MA 1-150	Yes	-0.013	0.23	0.88	Yes	0.006	2.07	0.34
MA 1-200	Yes	NaN	NaN	NaN	Yes	-0.007	0.77	0.70
MA 2-5	Yes	0.001	1.65	0.11	Yes	0.014	2.90	0.11
MA 2-10	Yes	-0.005	1.04	0.34	Yes	0.007	2.18	0.25
MA 2-20	Yes	-0.003	1.20	0.28	Yes	0.007	2.17	0.25
MA 2-50	Yes	-0.020	-0.46	0.69	Yes	-0.011	0.42	0.83
MA 2-100	Yes	-0.011	0.36	0.78	Yes	-0.001	1.39	0.49
MA 2-150	Yes	-0.005	1.02	0.50	Yes	0.009	2.37	0.27
MA 2-200	Yes	NaN	NaN	NaN	Yes	-0.007	0.77	0.70
MA 5-10	Yes	-0.005	1.03	0.35	Yes	0.007	2.17	0.25
MA 5-20	Yes	-0.006	0.93	0.41	Yes	0.004	1.89	0.33
MA 5-50	Yes	-0.014	0.11	0.92	Yes	-0.004	1.06	0.59
MA 5-100	Yes	-0.006	0.87	0.51	Yes	0.004	1.86	0.35
MA 5-150	Yes	-0.015	-0.04	0.98	Yes	0.007	2.23	0.30
MA 5-200	Yes	NaN	NaN	NaN	Yes	-0.007	0.77	0.70
MA 10-20	Yes	-0.014	0.08	0.94	Yes	-0.006	0.93	0.63
MA 10-50	Yes	-0.005	1.04	0.38	Yes	0.005	2.03	0.30
MA 10-100	Yes	-0.008	0.68	0.61	Yes	0.002	1.69	0.40
MA 10-150	Yes	NaN	NaN	NaN	Yes	0.010	2.48	0.25
MA 10-200	Yes	NaN	NaN	NaN	Yes	-0.007	0.77	0.70
<b>Rate of Change</b>								
ROC 2	Yes	-0.014	0.12	0.89	Yes	-0.005	1.04	0.54
ROC 3	Yes	0.001	1.59	0.11	Yes	0.015	3.02*	0.09
ROC 4	Yes	-0.002	1.31	0.20	Yes	0.011	2.57	0.16
ROC 5	Yes	0.000	1.54	0.14	Yes	0.013	2.77	0.13
ROC 6	Yes	-0.008	0.68	0.52	Yes	0.003	1.75	0.34
ROC 7	Yes	0.000	1.48	0.15	Yes	0.013	2.78	0.12
ROC 8	Yes	-0.001	1.40	0.18	Yes	0.012	2.67	0.14
ROC 9	Yes	-0.006	0.85	0.43	Yes	0.005	1.99	0.29
ROC 10	Yes	-0.008	0.69	0.52	Yes	0.003	1.79	0.35
ROC 11	Yes	-0.005	1.04	0.33	Yes	0.007	2.16	0.25
ROC 12	Yes	-0.001	1.35	0.21	Yes	0.010	2.54	0.17
ROC 13	Yes	0.004	1.85*	0.09	Yes	0.016	3.12*	0.10
ROC 14	Yes	-0.004	1.07	0.32	Yes	0.007	2.17	0.25
ROC 15	Yes	-0.002	1.28	0.24	Yes	0.009	2.40	0.21
<b>Buy and hold</b>		-0.015						

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Of the 28 rate of change strategies, five result in a statistically significant Sharpe ratio increase.

Solana's buy-and-hold performance is associated with a negative Sharpe ratio, yet the only strategies that strictly result in a negative Sharpe ratio are partially implemented moving average strategies utilizing a 100-day MAL or older data. Despite the poor buy-and-hold performance of Solana, the associated moving average strategy performances are the best out of all examined assets. The MA 2-10 strategy (significant at the 5% level for partial and the 10% level for full implementation) achieves both the highest Sharpe ratio of all partially implemented (0.019) and fully implemented (0.026) strategies.

Of the rate of change strategies, at partial implementation, ROC 4 to ROC 8 yield Sharpe ratio improvements above one basis point compared to buy-and-hold (significant at the 10% level). While losing

Table 4.8: Sharpe ratios of technical trading strategies for Solana

	Long or out				Long or short			
	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value	Profitable vs B&H	Sharpe ratio	Difference to B&H in basis points	<i>p</i> -value
<b>Moving Average</b>								
MA 1-5	Yes	0.009	1.04	0.18	Yes	0.011	1.24	0.37
MA 1-10	Yes	0.015	1.60**	0.05	Yes	0.020	2.10	0.14
MA 1-20	Yes	0.004	0.54	0.51	Yes	0.006	0.67	0.64
MA 1-50	Yes	0.013	1.42*	0.08	Yes	0.019	1.96	0.16
MA 1-100	No	-0.005	-0.44	0.67	Yes	0.006	0.72	0.65
MA 1-150	No	-0.010	-0.85	0.46	Yes	0.009	1.04	0.53
MA 1-200	No	-0.010	-0.92	0.45	Yes	0.011	1.17	0.50
MA 2-5	Yes	0.014	1.50*	0.05	Yes	0.018	1.89	0.17
MA 2-10	Yes	0.019	2.03**	0.01	Yes	0.026	2.66*	0.06
MA 2-20	Yes	0.007	0.84	0.31	Yes	0.009	1.05	0.46
MA 2-50	Yes	0.015	1.59*	0.05	Yes	0.021	2.20	0.11
MA 2-100	No	-0.007	-0.58	0.58	Yes	0.005	0.59	0.71
MA 2-150	No	-0.010	-0.90	0.43	Yes	0.009	1.00	0.55
MA 2-200	No	-0.011	-0.97	0.43	Yes	0.010	1.14	0.51
MA 5-10	Yes	0.011	1.21	0.13	Yes	0.015	1.60	0.25
MA 5-20	Yes	0.004	0.51	0.53	Yes	0.005	0.63	0.66
MA 5-50	Yes	0.012	1.31	0.11	Yes	0.017	1.83	0.19
MA 5-100	No	-0.010	-0.84	0.42	Yes	0.002	0.34	0.83
MA 5-150	No	-0.012	-1.04	0.36	Yes	0.008	0.89	0.59
MA 5-200	No	-0.013	-1.14	0.35	Yes	0.009	1.02	0.55
MA 10-20	Yes	0.008	0.86	0.29	Yes	0.010	1.10	0.44
MA 10-50	Yes	0.015	1.65**	0.04	Yes	0.022	2.28	0.10
MA 10-100	No	-0.010	-0.87	0.40	Yes	0.002	0.30	0.85
MA 10-150	No	-0.011	-1.03	0.36	Yes	0.008	0.89	0.59
MA 10-200	No	-0.020	-1.84	0.13	Yes	0.005	0.63	0.71
<b>Rate of Change</b>								
ROC 2	Yes	0.002	0.29	0.70	Yes	0.003	0.41	0.77
ROC 3	Yes	0.005	0.56	0.46	Yes	0.006	0.72	0.60
ROC 4	Yes	0.012	1.28*	0.10	Yes	0.015	1.57	0.26
ROC 5	Yes	0.014	1.48*	0.06	Yes	0.017	1.85	0.18
ROC 6	Yes	0.013	1.43*	0.07	Yes	0.017	1.81	0.19
ROC 7	Yes	0.013	1.40*	0.08	Yes	0.017	1.81	0.20
ROC 8	Yes	0.013	1.41*	0.08	Yes	0.016	1.73	0.22
ROC 9	Yes	0.009	1.04	0.19	Yes	0.012	1.28	0.36
ROC 10	Yes	0.012	1.26	0.12	Yes	0.015	1.65	0.24
ROC 11	Yes	0.009	0.98	0.23	Yes	0.012	1.28	0.36
ROC 12	Yes	0.010	1.11	0.17	Yes	0.013	1.45	0.31
ROC 13	Yes	0.012	1.27	0.12	Yes	0.015	1.64	0.25
ROC 14	Yes	0.006	0.72	0.37	Yes	0.008	0.91	0.52
ROC 15	Yes	0.007	0.81	0.32	Yes	0.010	1.06	0.45
<b>Buy and hold</b>		-0.001						

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

their statistical significance at full implementation, ROC 5 to ROC 8 achieve the highest Sharpe ratio (0.017) of all rate of change strategies in this study.

Summarizing our findings, we first of all find that our examined strategies perform to vastly different degrees across cryptocurrencies. This underscores that the returns of our sample assets do neither develop synchronously nor follow the same patterns. Our strategies yield the most statistically significantly increased Sharpe ratios for (in descending order) Ripple, Ethereum, Cardano, and Solana. In the case of Ripple, 27% of all strategies achieve significant Sharpe ratio increases, while 15% do so for Solana. Only three strategies result in significantly increased Sharpe ratios when applied for Shiba Inu, zero for Decentraland, and Sandbox is associated with four significantly decreased Sharpe ratios. Thus, we find our examined strategies to

perform better for more serious cryptocurrencies and worse for gaming and meme cryptocurrencies.

Statistical significance is nearly uniformly higher for partially implemented strategies, whereas actual absolute returns are larger at full implementation. Partially implemented strategies exhibit higher statistical significance due to the inherently lower volatility of strategies that can go out of the market. Conversely, fully implemented strategies that also short the asset are associated with large volatility increases. Hence, the increased absolute returns are counterbalanced by increased volatility, rendering most Sharpe ratio increases of fully implemented strategies statistically insignificant.

Last, the profitability of the strategies is not conditional on the general profitability of the assets. Whereas Shiba Inu buy-and-hold has a negative Sharpe ratio, it is the only currency for which all strategies outperform buy-and-hold. A buy-and-hold investment in Solana is also associated with a negative Sharpe ratio, yet it is the asset where our examined strategies perform the best.

## 4.5 Discussion

Previously, many studies considered the market efficiency of cryptocurrencies from various angles. Whereas Kyriazis (2019) provides a good overview of the research focused on the statistical properties of cryptocurrency price developments, other studies investigated the performance of trend trading directly (cf. Corbet et al., 2019; Gerritsen et al., 2020; Grobys et al., 2020; Svogun & Bazán -Palomino, 2022). Where the former concludes by arguing for increasing randomness and thus efficiency over time, the latter all find at least small opportunities for profitable technical trading.

We examine the profitability and risk-adjusted returns of trend-following technical trading strategies for seven cryptocurrencies. More precisely, we employ moving average strategies as described by Brock et al. (1992) and use similar MAS and MAL timeframes as applied by Corbet et al. (2019). Additionally, we analyze momentum by utilizing the rate of change strategy (cf. Gerritsen, 2016) with a corridor of 2 to 15 days as the benchmark for the current price. To increase the practical relevance of our work, we apply these trading strategies to hourly data corresponding to the futures settlement rhythm traded on

the Kraken exchange. Last, our study examines time series spanning until the end of September 2022, covering the market correction following the price peaks in late 2021, thus analyzing the performance of trend trading during both recent boom and bust periods.

Across all our sampled cryptocurrencies, using 10 or 20 days as the MAL period improves Sharpe ratios at both full and partial implementation of the trading strategies. Conversely, all strategies that rely on a 200-day MAL yield, on average, a reduction in Sharpe ratio across cryptocurrencies and implementations. With commonly used MAL periods being at least 50 days long (cf. Brock et al., 1992), our findings are in line with the studies of Corbet et al. (2019) and Grobys et al. (2020), who previously identified the profitability of short timeframes for moving average cryptocurrency trading.

Similarly, we only find the ROC 2 strategy to, on average, yield a negative Sharpe ratio across all assets and implementations. For the full sample, ROC 7 to ROC 15 strictly lead to an improved Sharpe ratio, and upon exclusion of Decentraland (MANA), all rate of change strategies but ROC 2 lead to an increased Sharpe ratio. The best-performing rate of change strategy, yielding not only a Sharpe ratio increase but also achieving higher absolute returns for every asset, is ROC 7. The only cryptocurrencies in our sample where no rate of change strategy produced a statistically significant Sharpe ratio difference are the two metaverse tokens of Decentraland and Sandbox, which are also the assets with the lowest market capitalization in our study. In contrast to this stand the results for Ripple, the oldest considered cryptocurrency, for which seven rate of change strategies achieve improved Sharpe ratios significant at the 5% level and another seven at the 10% level.

Our results show that trend trading is no reliable strategy in cryptocurrency markets. As highlighted before, the performance and associated statistical significance of our examined strategies varies widely across assets. However, as demonstrated by the performance of the MA 2-20 strategy, we find some generality for the previous finding of the relatively higher profitability of shorter-term signals for Bitcoin and Ethereum (cf. Corbet et al., 2019; Grobys et al., 2020; Svogun & Bazán-Palomino, 2022).

The initially hypothesized relationship between the market efficiency of a cryptocurrency and its novelty and size could not be con-

firmed. For the two smallest assets, Decentraland and Sandbox, no strategy yields a statistically significant improved Sharpe ratio, while many do so for the three largest assets (Ethereum, Ripple, and Cardano). This dynamic is noteworthy since the market capitalization of these cryptocurrencies is comparable to or larger than the average market capitalization of the companies included in the Wilshire 5000 index. The market thus seems to successfully differentiate between different cryptocurrencies, with their returns neither developing synchronously nor follow the same patterns. With our trend following strategies performing better for currencies with large market capitalizations, it seems that more popular cryptocurrencies are experiencing more market inefficiencies. Whether these exist due to herding and hype or due to entirely different phenomena remains a topic for future research.

Finally, we find that the performance of our strategies did not explicitly suffer during the market downturn. On the contrary, we find the most considerable improvements for the two assets with a negative buy-and-hold Sharpe ratio. Trend trading in Solana (Sharpe ratio of -0.001) is associated with this study's most considerable Sharpe ratio improvements, and all strategies generate higher absolute returns for Shiba Inu (Sharpe ratio of -0.015).

## 4.6 Conclusion

The term cryptocurrency today entails a broad universe of vastly different assets. While Bitcoin pioneered the space intending to become a decentralized global currency, more recent projects aim to create the next version of the internet with WEB3.0. Next to those initiatives, even community ventures without an apparent purpose, such as Shiba Inu, attract enough interest to amass valuation levels of multiple billion US dollars.

Trend trading, the attempt to trade profitably on past price data, has been around for centuries. This fact is in direct contrast to the efficient market hypothesis popularized by Fama (1970), who argues that this is a futile approach with asset prices developing unpredictably. Previous research has identified that technical trading strategies that were widely known before the emergence of Bitcoin can outperform the buy-and-hold approach. Later studies found that utilizing shorter

than previously standard timeframes for generating trading signals leads to even more significant gains when trading cryptocurrencies.

We build upon these previous findings and employ an extensive range of moving average and rate of change strategies for the native tokens of the Cardano, Decentraland, Ethereum, Ripple, Sandbox, Shiba Inu, and Solana blockchains. Utilizing hourly data from the Kraken exchange, we find trend trading to make investors better off in many cases. Across our entire sample, moving average strategies using shorter than standard MAL timeframes is associated with higher, and using the longest commonly used MAL timeframes is associated with lower Sharpe ratios. Statistical significance of the thus achieved Sharpe ratios varies strongly across cryptocurrencies and implementation of the strategies. For larger cryptocurrencies, some Sharpe ratio improvements of partially implemented moving average strategies are statistically relevant. At full implementation this significance drops away due to increased volatility. For Decentraland, Sandbox, and Shiba Inu, none of the moving average strategies offers statistically significant Sharpe ratio increases.

While some of our employed rate of change strategies offer increased absolute returns, only few yield statistically significantly increased Sharpe ratios compared to buy-and-hold. As for moving average strategies, we find absolute returns to be greater at full implementation, while partially implemented strategies achieve Sharpe ratio improvements with higher statistical significance. Again, this is due to more substantial increases in volatility than returns when allowing the strategies to short the underlying asset.

Arguing for market inefficiency regardless of the overall market development, we find technical trading strategies to outperform buy-and-hold also after extending our time series to incorporate recent price downward trends. However, our initial hypothesis of more novel cryptocurrencies being less efficient than older ones could not be verified. While Ripple and Ethereum are the oldest assets considered in this study, they are also those where the most trading strategies achieve statistically significant results. With the largest cryptocurrencies increasingly possessing market capitalizations greater than many publicly traded companies, future research should focus on fundamental valuation drivers of blockchain projects and the underlying reasons for trend trading apparently working better for large cryptocurrencies.

# Chapter 5

## Conclusion

Over the past decade, cryptocurrencies and blockchain technology attracted vast interest and capital. Starting with Bitcoin as envisioned by Satoshi Nakamoto, the crypto space rapidly developed and is still creating innovative technologies, be it smart contracts or metaverses. With high price volatility, no definite investment hypotheses, and short price histories, investing in cryptocurrencies remains a risky endeavor. Previous research attested cryptocurrencies, and Bitcoin in particular, diminishing market inefficiencies. Within this dissertation, I am analyzing the market efficiency of Bitcoin and Ethereum with the, to the best of my knowledge, most extensive high-frequency dataset to date. I do this by focusing on theoretical and practical market efficiency aspects. With the practical aspect of market efficiency being easier to grasp, I also examine the risk-adjusted profitability of simple technical trading strategies for a broader range of different types of cryptocurrencies.

Overall, I find that a strict interpretation of the efficient market hypothesis, be it in a theoretical sense focusing on the patterns present in price data or the practical sense relating to the profitability of trend trading, does not withstand rigorous analysis. This finding can not be attributed to the respective size of a cryptocurrency, going against the notion that less popular projects are subject to fewer profit-seeking investors, driving up market efficiency.

First, in chapter 2, I show that the adaptive market hypothesis better describes the price development of Bitcoin and Ethereum than the efficient market hypothesis does. Both cryptocurrencies exhibit apparent deviations from a truly random process, where the degree of efficiency constantly varies over time. Further, by conducting the same



analysis for the S&P 500, I find that Bitcoin and Ethereum exhibit significantly more extended periods of inefficiency than the world's dominant equity index. Bitcoin, Ethereum, and the S&P 500 exhibited mostly long-range dependence during the investigated period.

Second, I investigate the practical market efficiency of Bitcoin and Ethereum in chapter 3. By employing only popular technical trading strategies that existed before Bitcoin was invented, I ensure that data mining is not a concern. In doing so, I still show that some basic trend-following strategies yield superior absolute returns compared to the buy-and-hold approach. In line with this, countertrend strategies perform poorly. In general, absolute returns are higher when considering hourly data, indicating that exploitable patterns are short-lived.

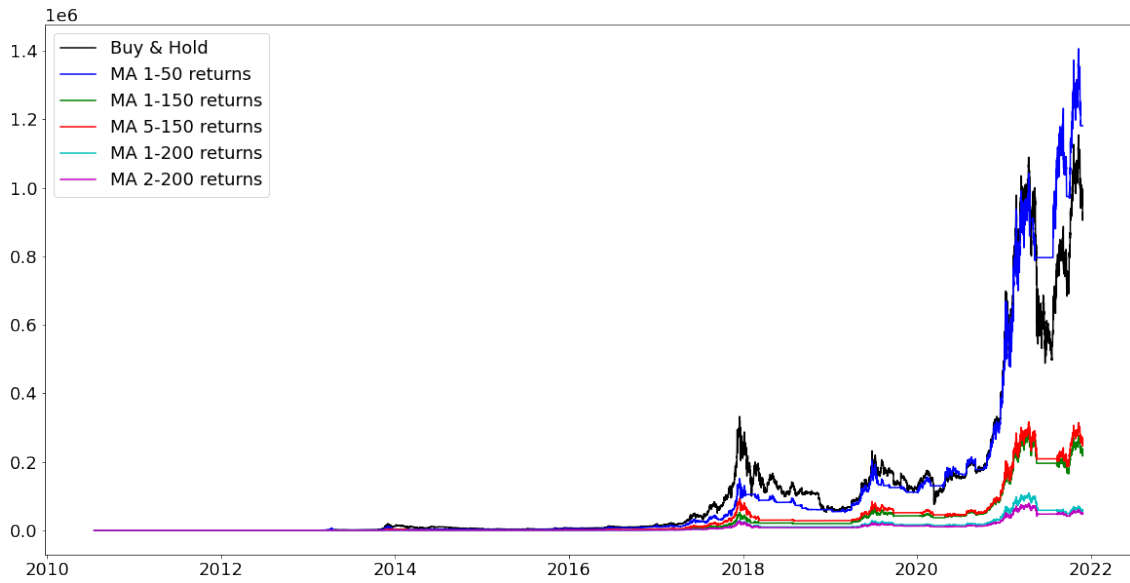
Third, I consider a more comprehensive range of cryptocurrencies for the performance of modified trend-following strategies in chapter 4. I find that exploitable price patterns across cryptocurrencies are short-lived compared with the commonly assumed duration of equity price patterns. The best-performing strategies utilize input data significantly shorter than usually considered in trend trading. I can also show that market inefficiencies can be substantial, with the most significant Sharpe ratio gain being achieved by an asset with negative buy-and-hold performance.

To conclude, I find ample, sometimes minor, deviations from one of the most fundamental theories in financial literature. While the deviations from the efficient market hypothesis might appear minuscule, it is essential to highlight that, for example, the neoclassical capital asset pricing model is just the best model existing in practice. Considering all the evidence from behavioral finance, a model incorporating individual preferences would be more appropriate. While this remains a significant challenge, this dissertation highlights that even the best available models in finance are based on theories with rather stark assumptions which only partially hold up when rigorously scrutinized. I show that simple technical trading strategies can make investors better off, something categorically ruled out by the efficient market hypothesis. However, with cryptocurrencies remaining a novel asset class, only time will tell how the efficiency will develop in the forthcoming years.

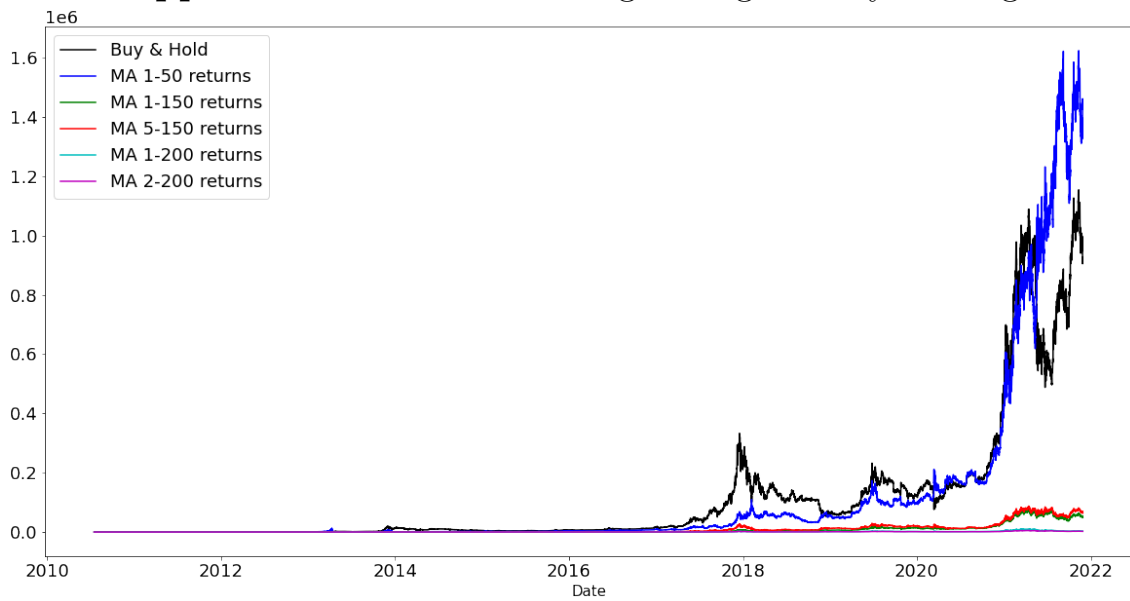
# Appendix A

## Appendix to Chapter 3

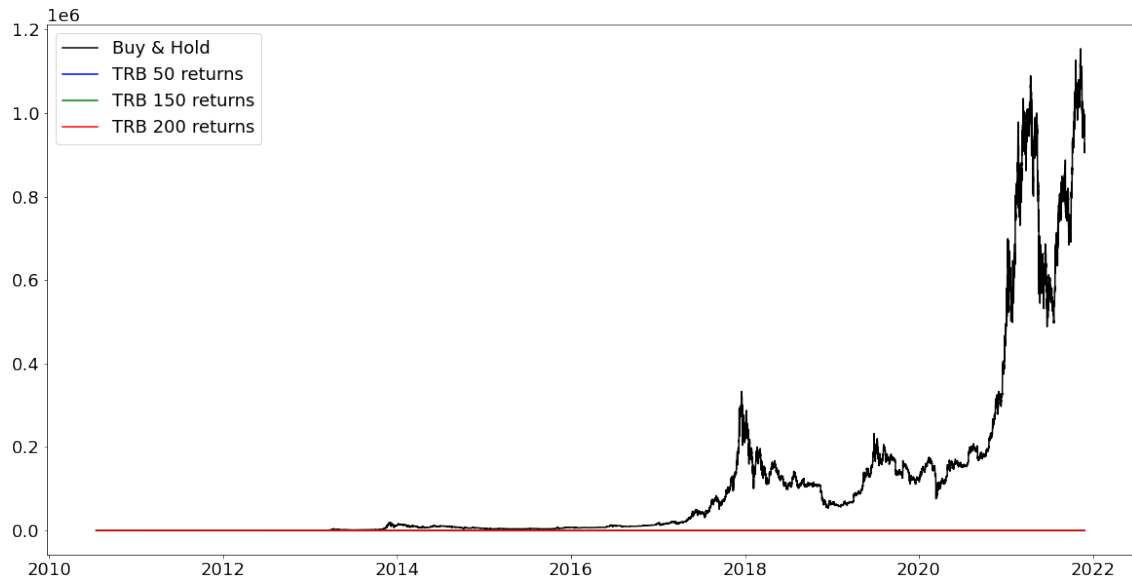
## Appendix A1 Bitcoin moving average hourly trading (long or out)



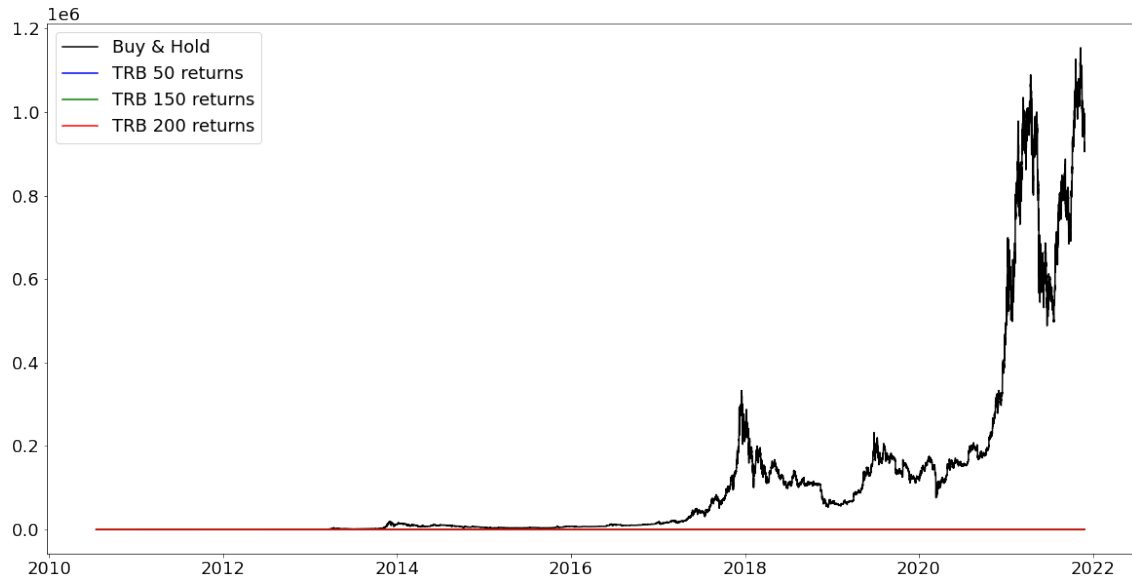
## Appendix A2 Bitcoin moving average hourly trading



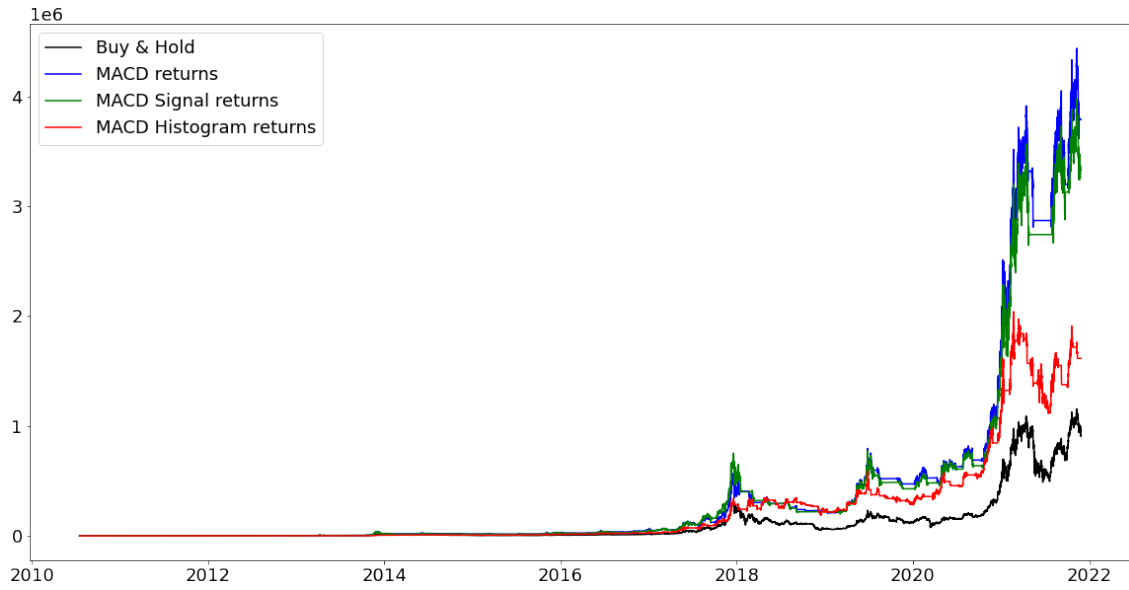
### Appendix A3 Bitcoin trading range breakout hourly trading (long or out)



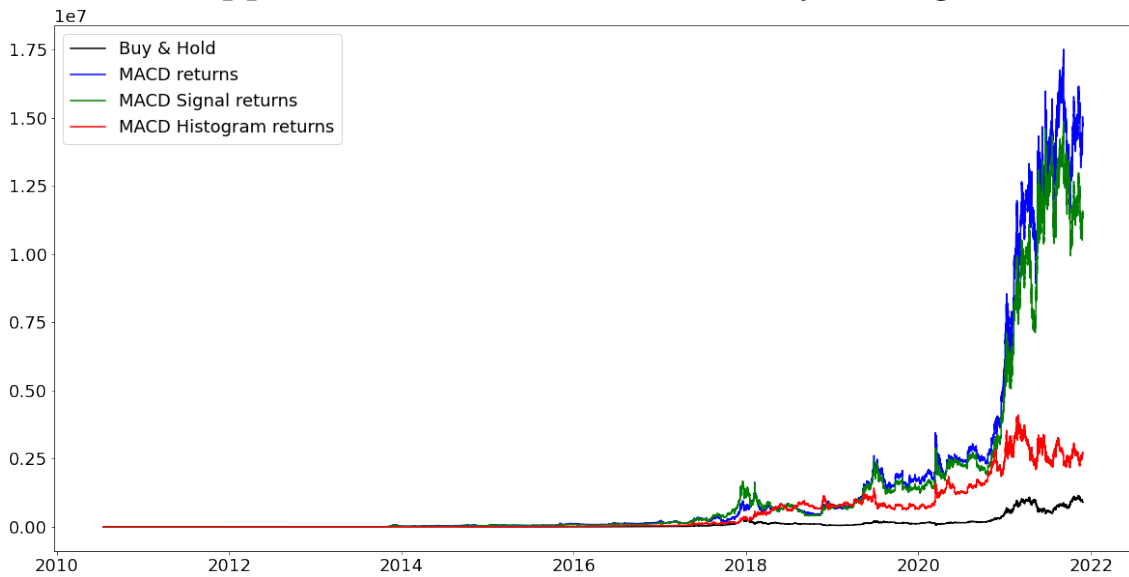
### Appendix A4 Bitcoin trading range breakout hourly trading



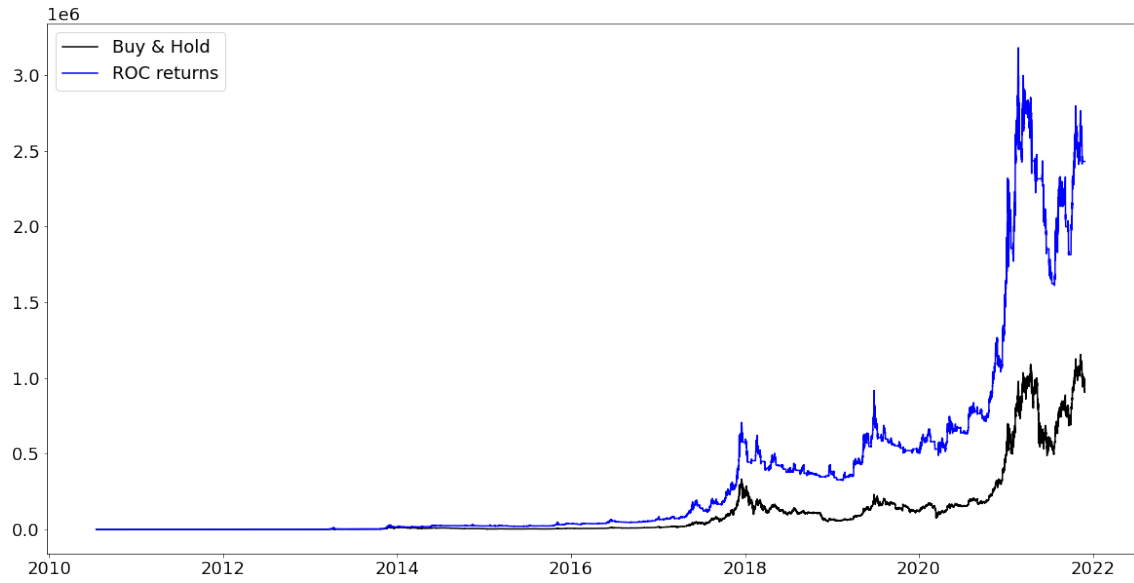
## Appendix A5 Bitcoin MACD hourly trading (long or out)



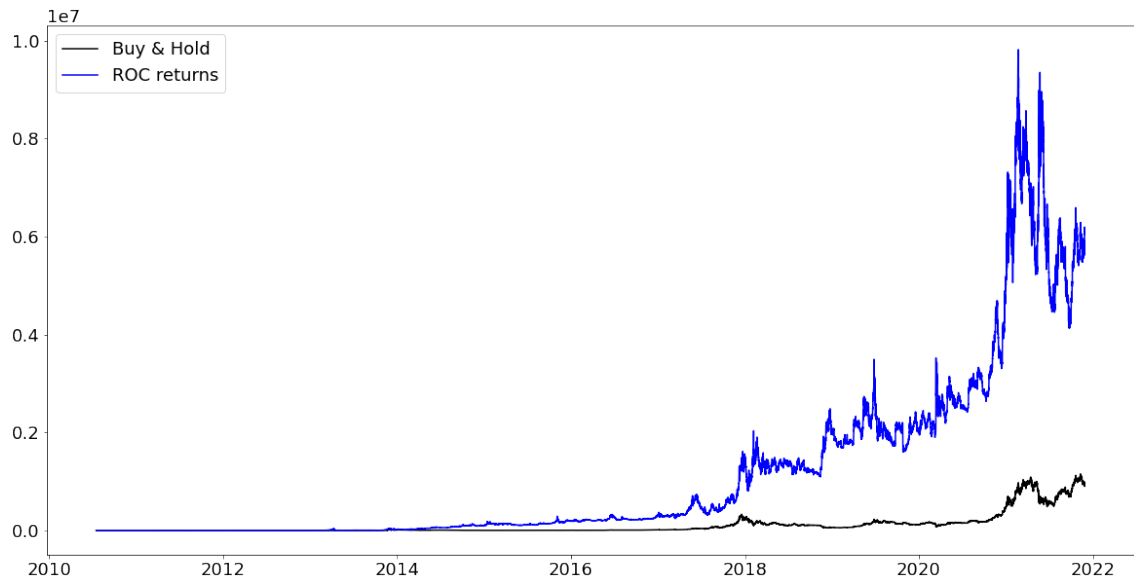
## Appendix A6 Bitcoin MACD hourly trading



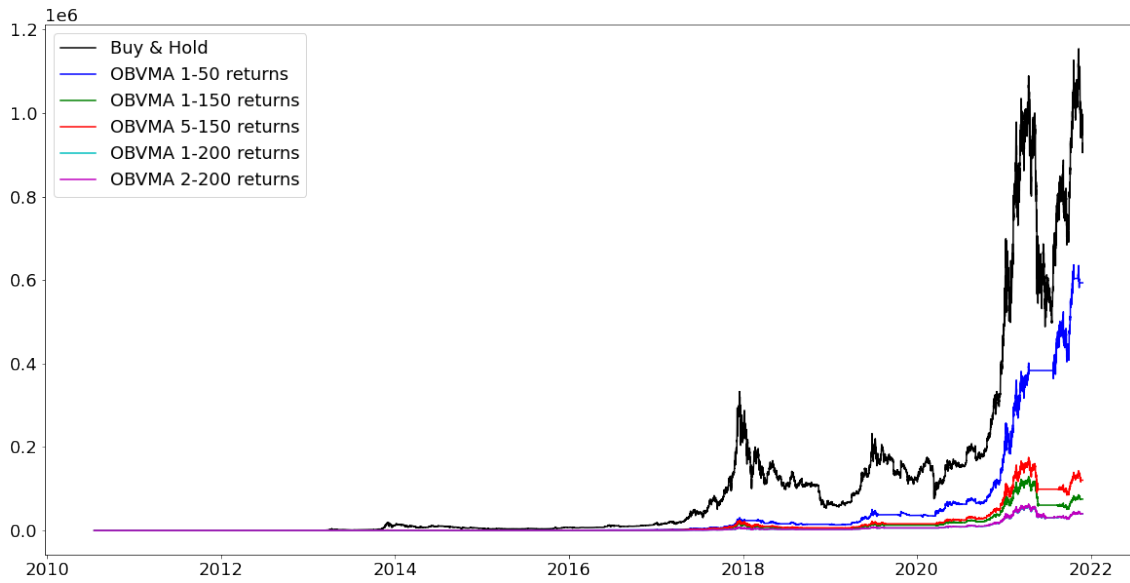
### Appendix A7 Bitcoin rate of change hourly trading (long or out)



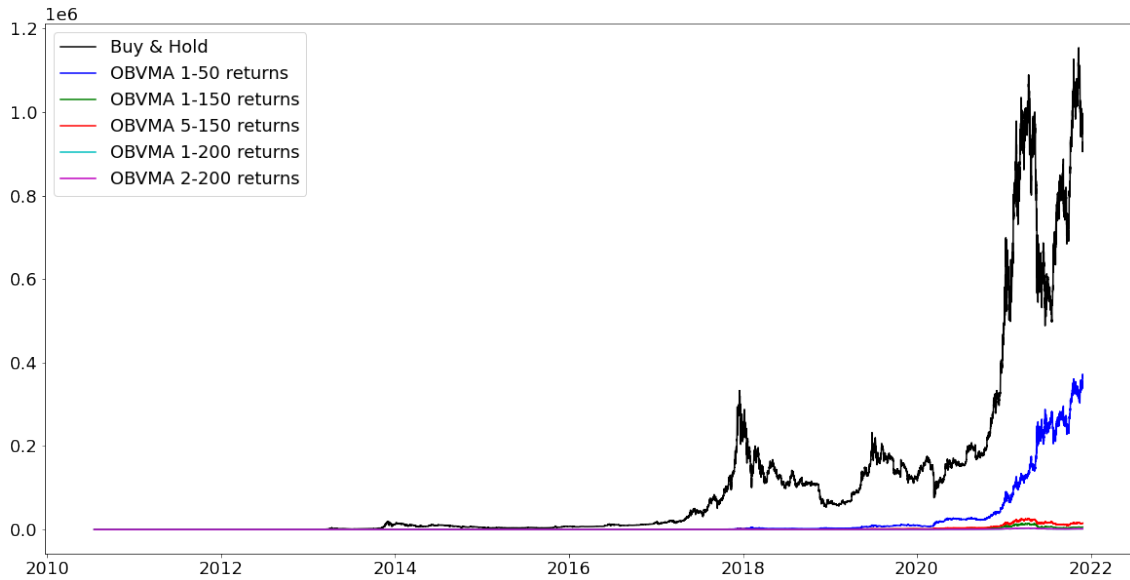
### Appendix A8 Bitcoin rate of change hourly trading



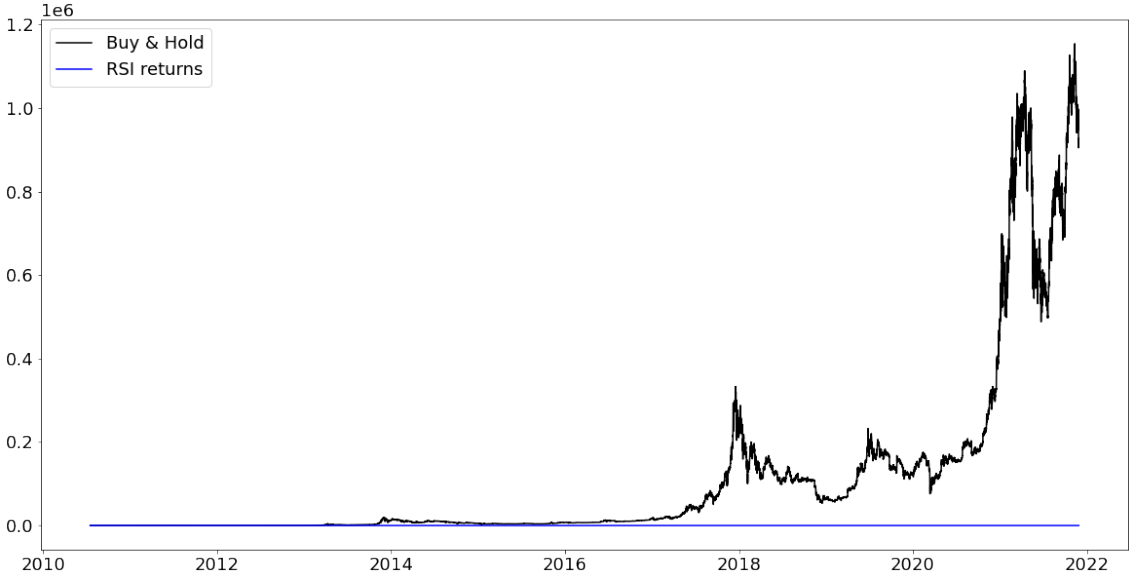
## Appendix A9 Bitcoin on-balance volume hourly trading (long or out)



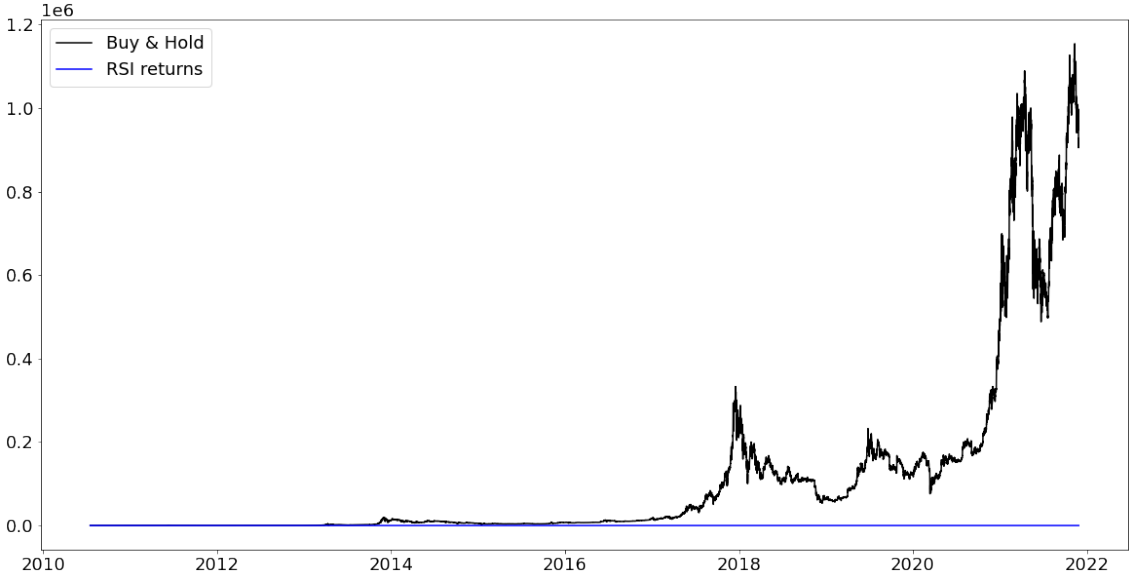
## Appendix A10 Bitcoin on-balance volume hourly trading



### Appendix A11 Bitcoin relative strength index hourly trading (long or out)

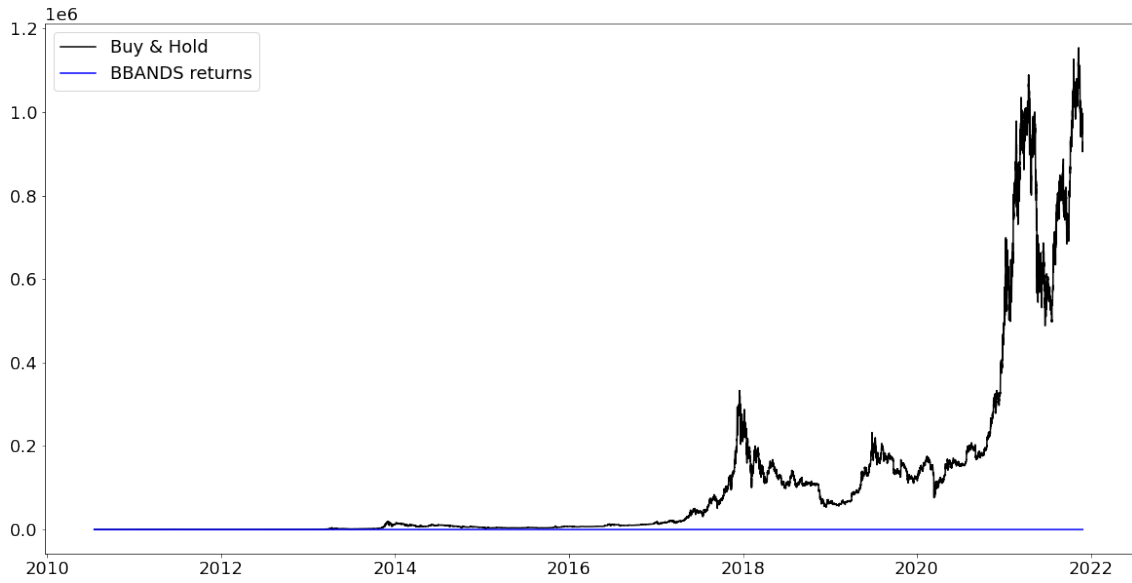


### Appendix A12 Bitcoin relative strength index hourly trading

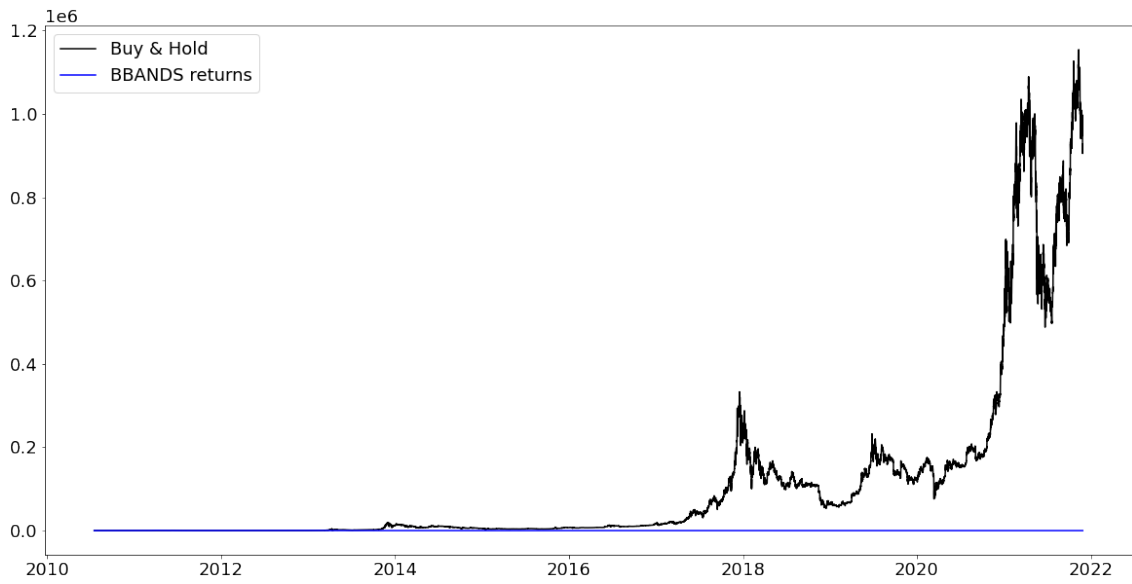




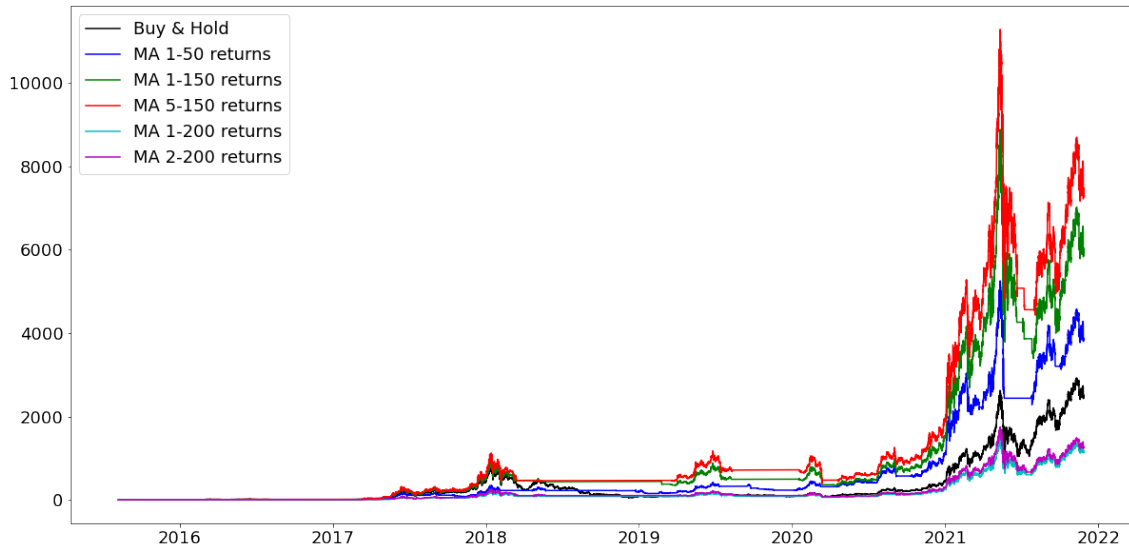
### Appendix A13 Bitcoin Bollinger bands hourly trading (long or out)



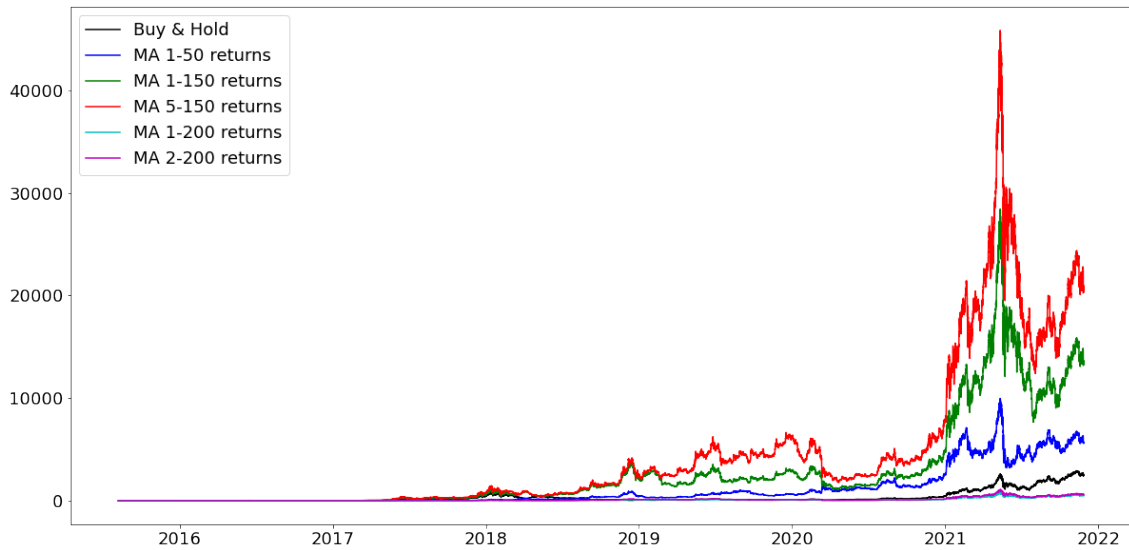
### Appendix A14 Bitcoin Bollinger bands hourly trading



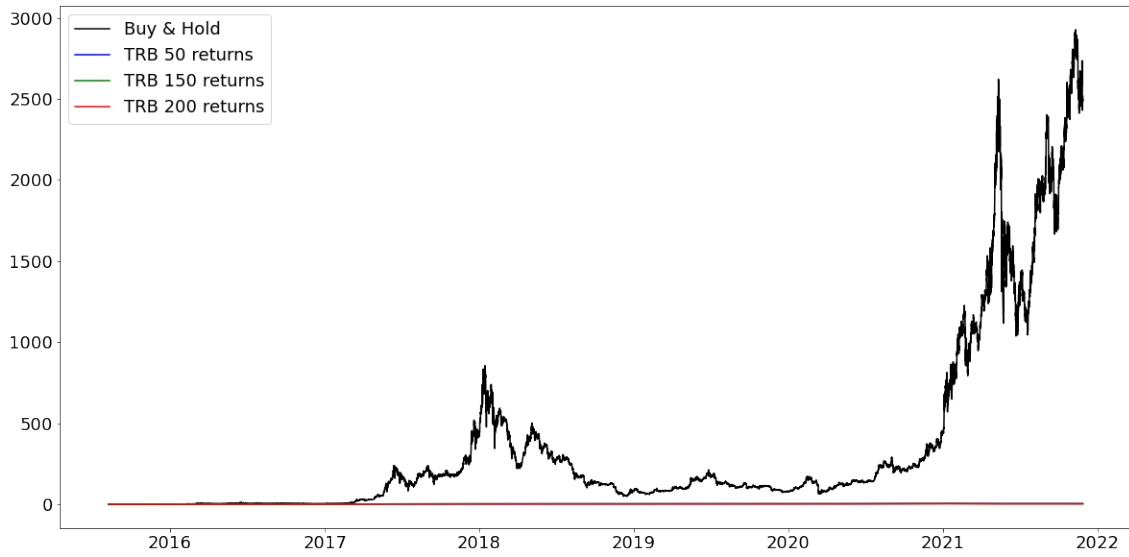
## Appendix B1 Ethereum moving average hourly trading (long or out)



## Appendix B2 Ethereum moving average hourly trading



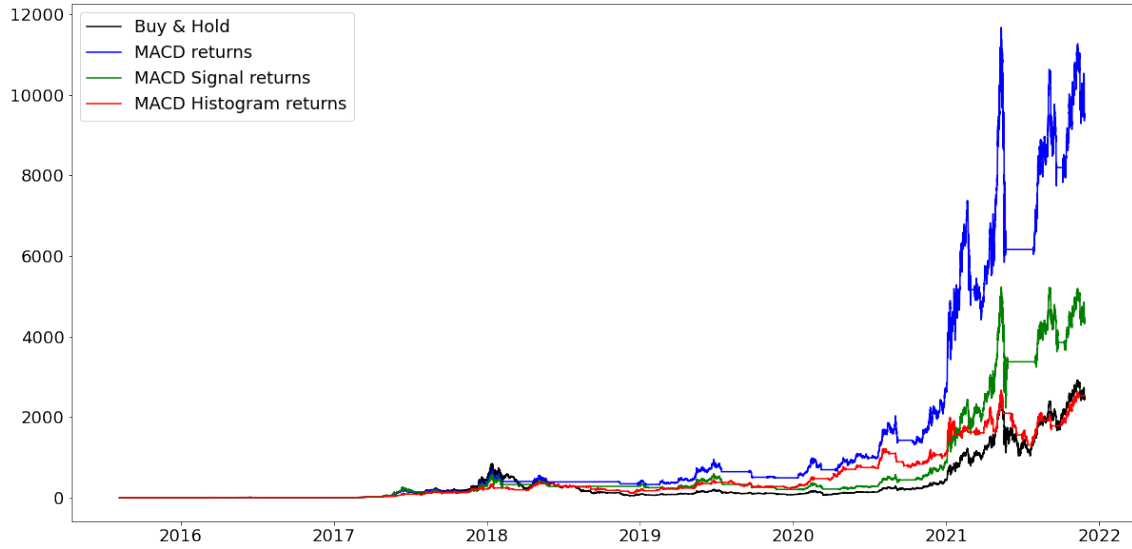
### Appendix B3 Ethereum trading range breakout hourly trading (long or out)



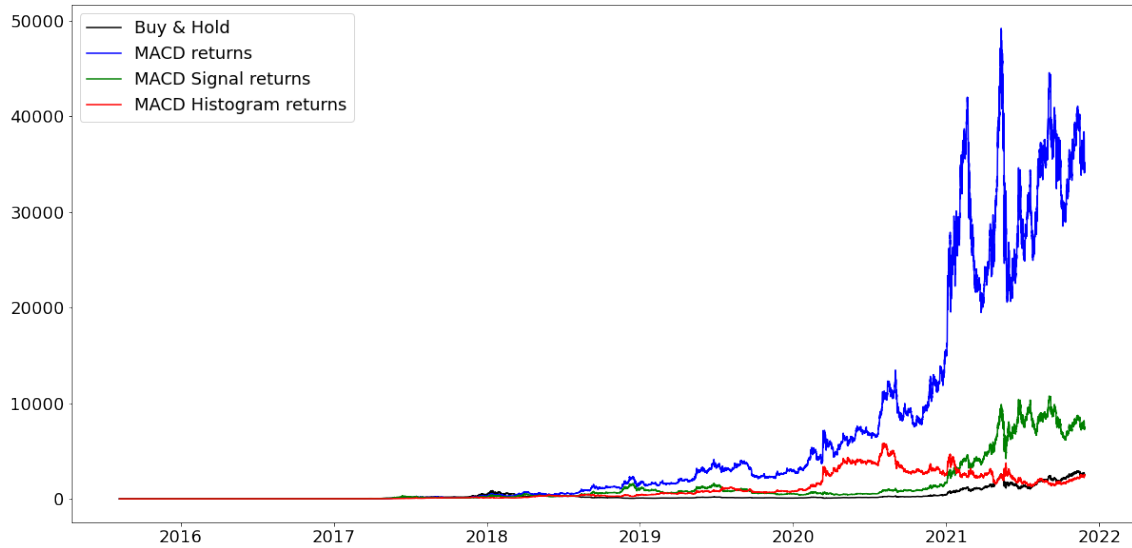
### Appendix B4 Ethereum trading range breakout hourly trading



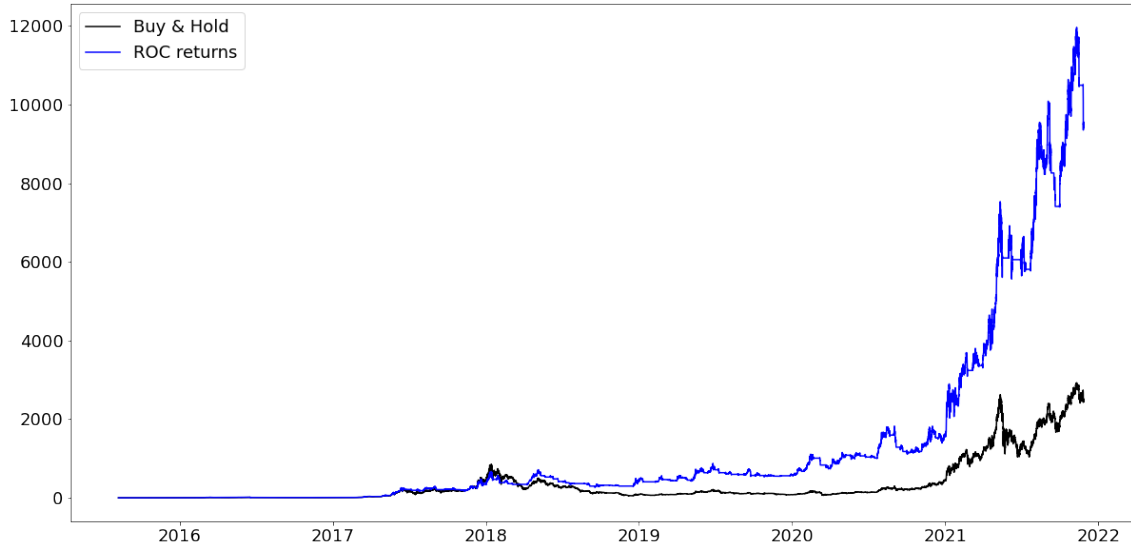
### Appendix B5 Ethereum MACD hourly trading (long or out)



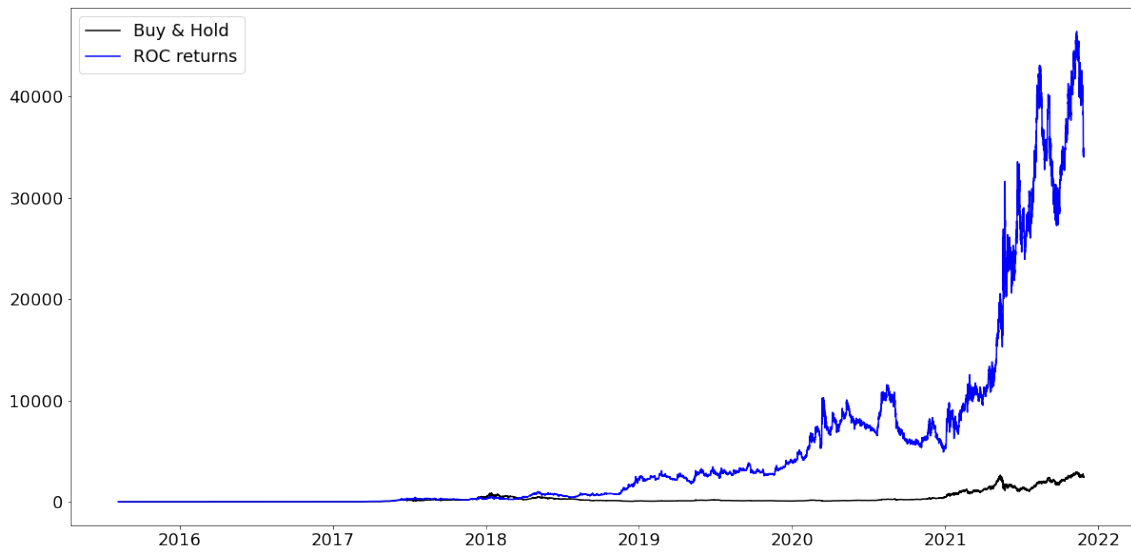
### Appendix B6 Ethereum MACD hourly trading



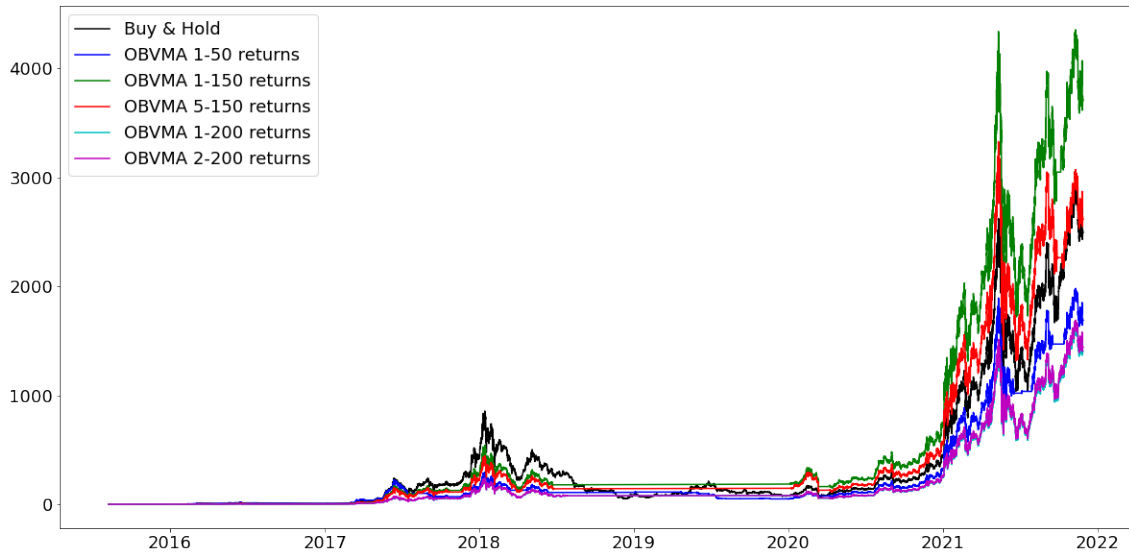
### Appendix B7 Ethereum rate of change hourly trading (long or out)



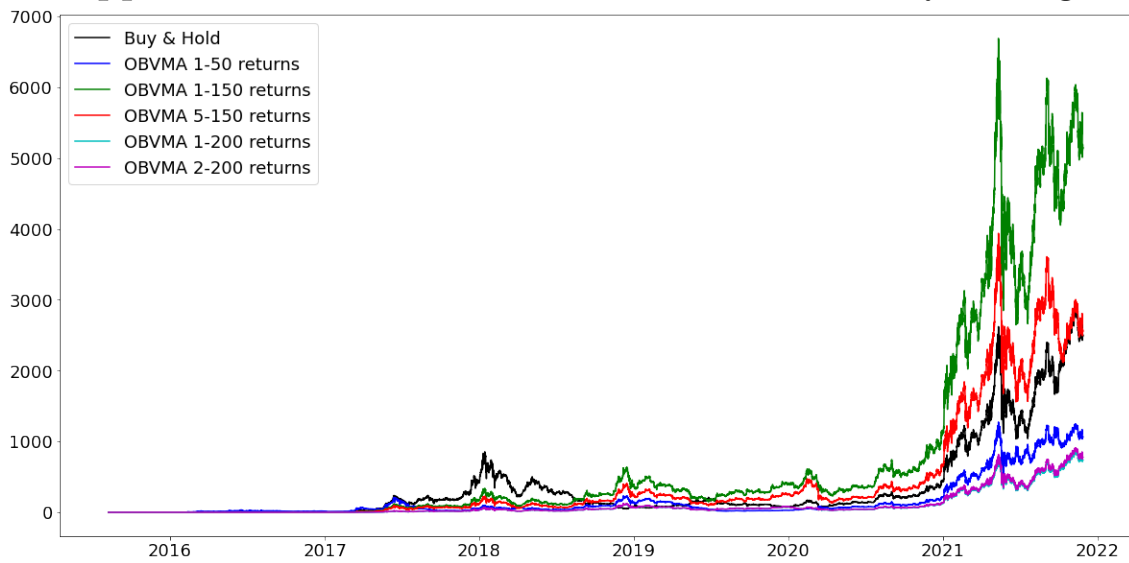
### Appendix B8 Ethereum rate of change hourly trading



## Appendix B9 Ethereum on-balance volume hourly trading (long or out)



## Appendix B10 Ethereum on-balance volume hourly trading



### Appendix B11 Ethereum relative strength index hourly trading (long or out)



### Appendix B12 Ethereum relative strength index hourly trading



### Appendix B13 Ethereum Bollinger bands hourly trading (long or out)

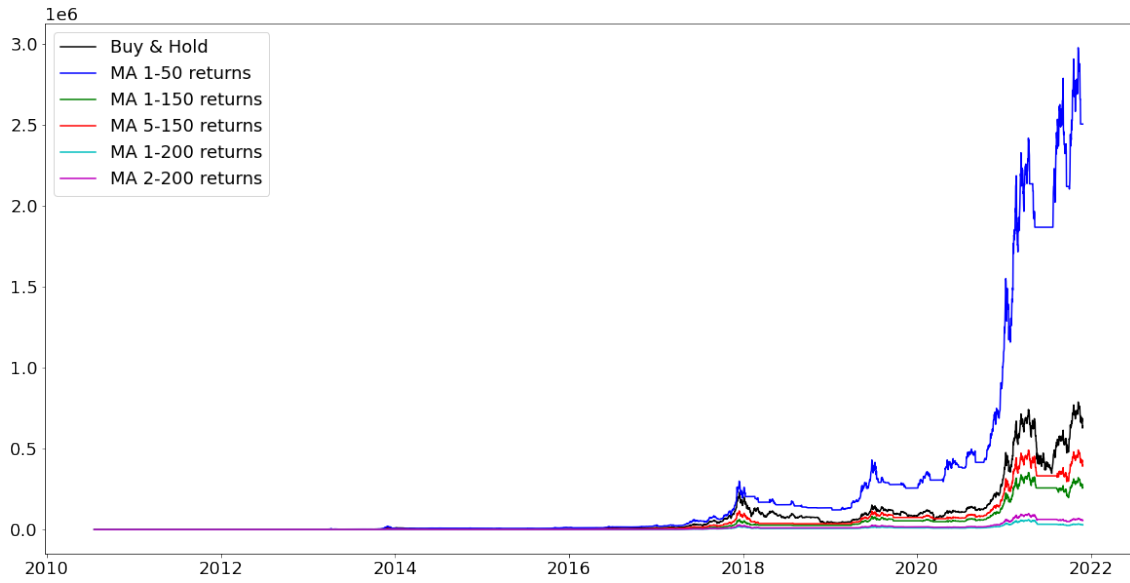


### Appendix B14 Ethereum Bollinger bands hourly trading

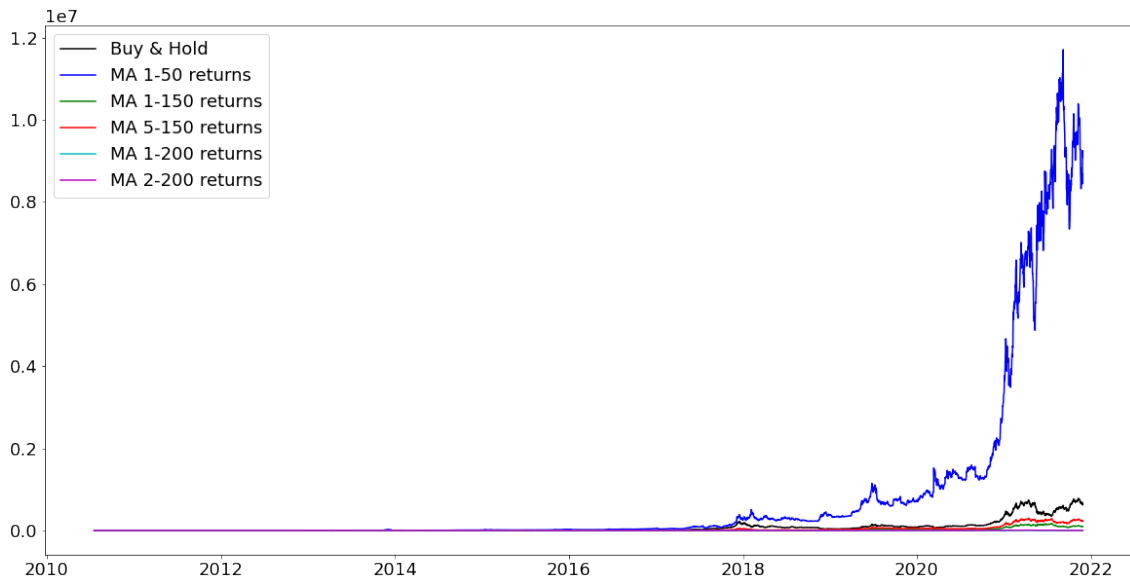




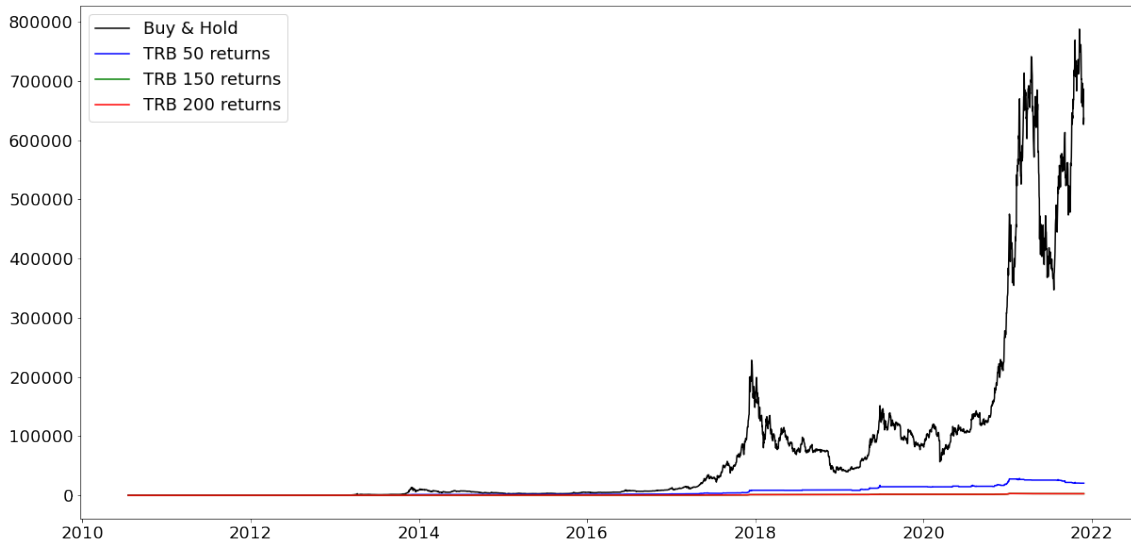
## Appendix C1 Bitcoin moving average daily trading (long or out)



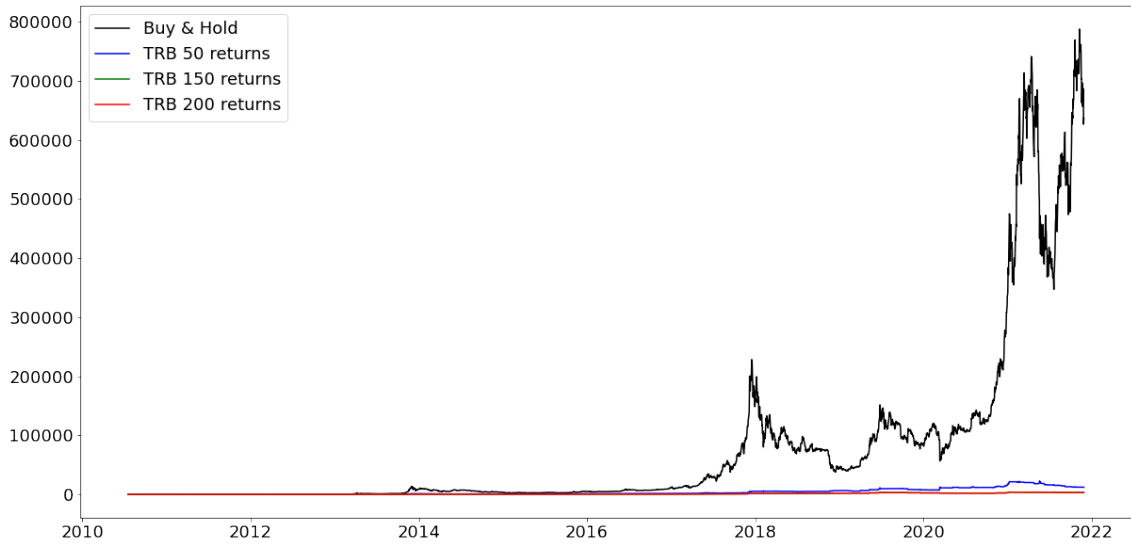
## Appendix C2 Bitcoin moving average daily trading



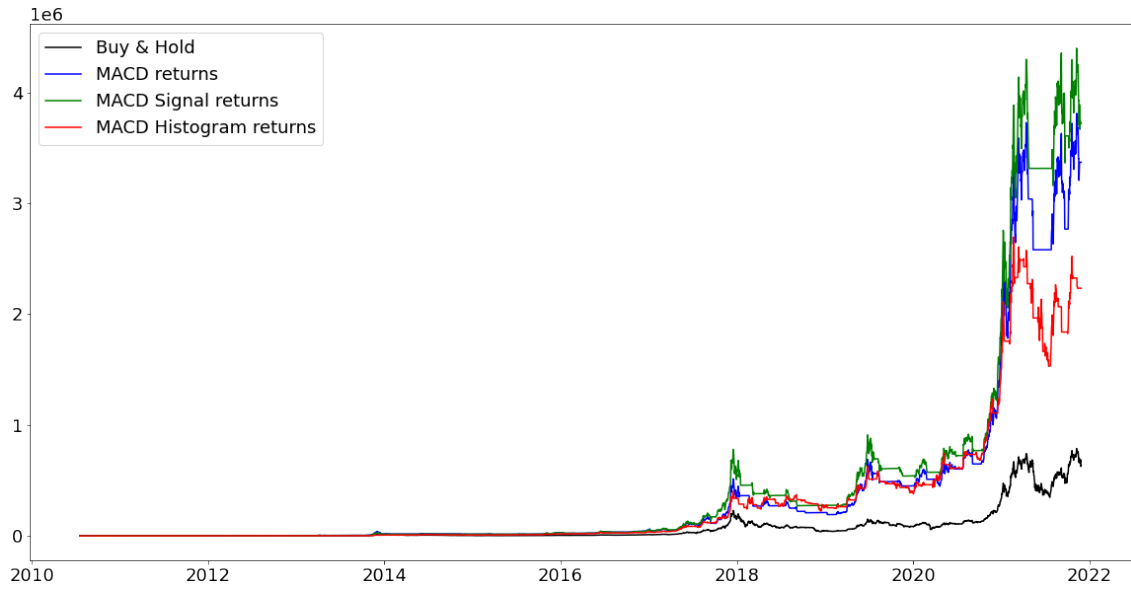
### Appendix C3 Bitcoin trading range breakout daily trading (long or out)



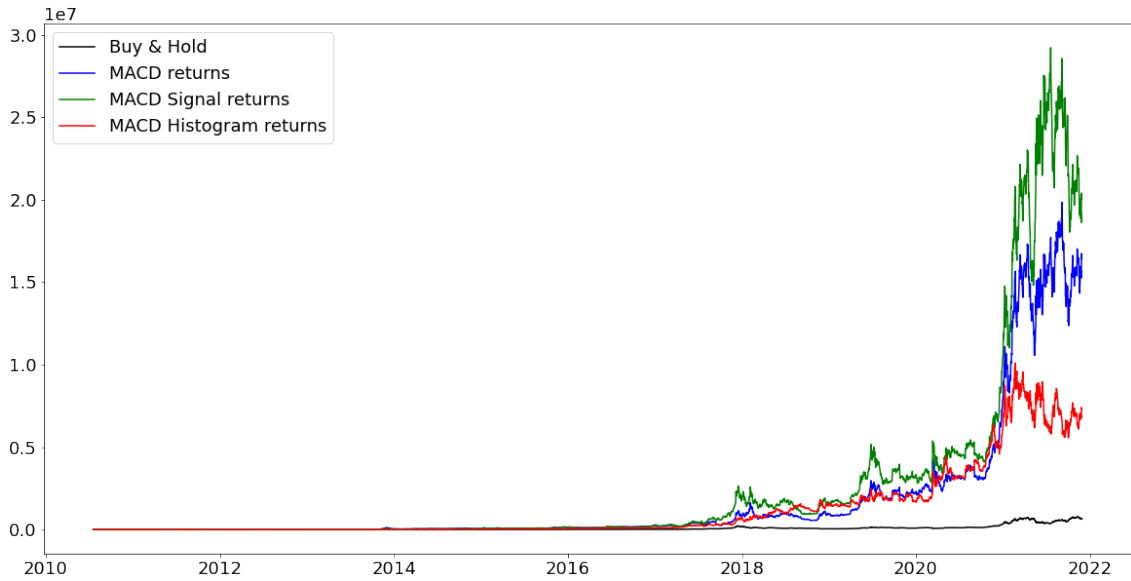
### Appendix C4 Bitcoin trading range breakout daily trading



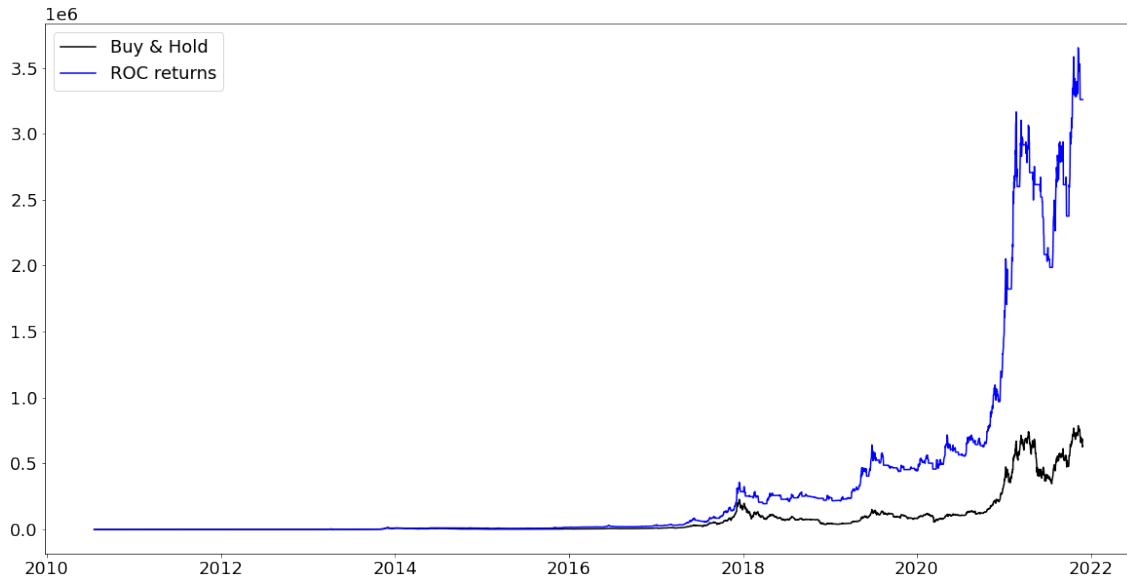
### Appendix C5 Bitcoin MACD daily trading (long or out)



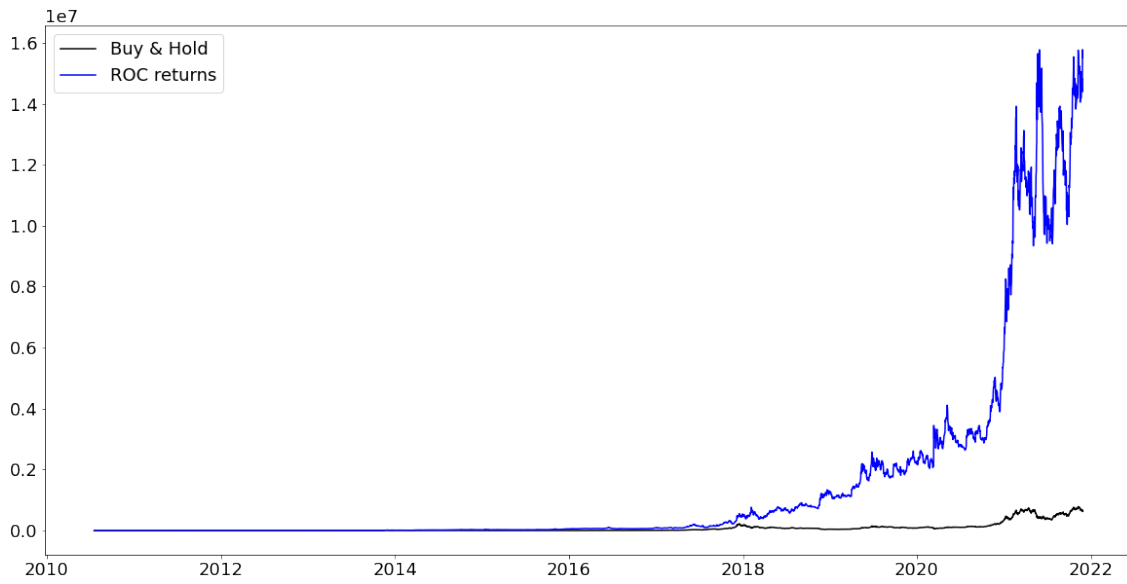
### Appendix C6 Bitcoin MACD daily trading



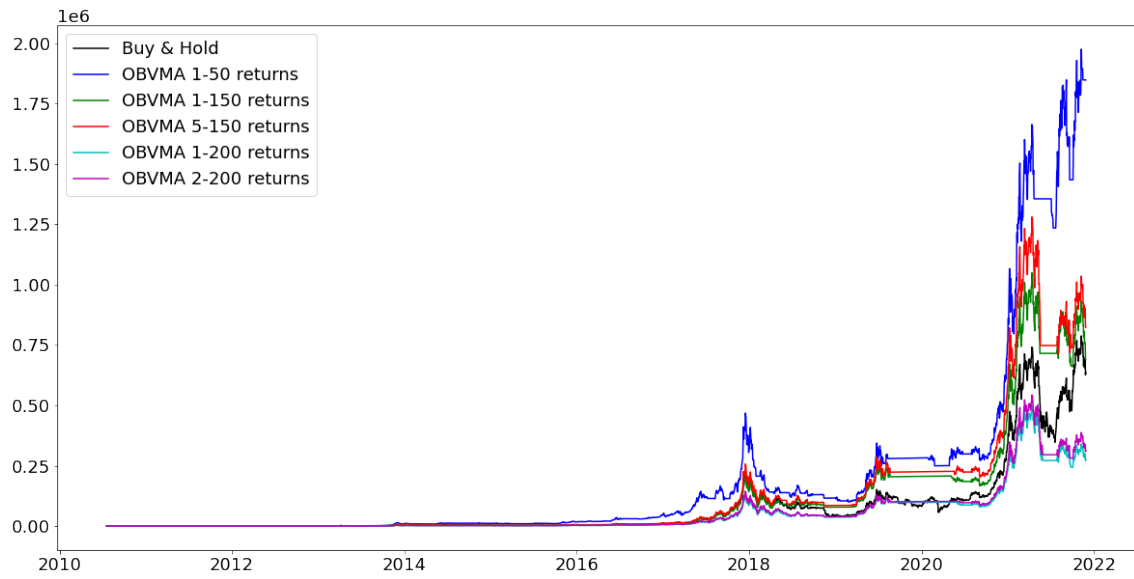
### Appendix C7 Bitcoin rate of change daily trading (long or out)



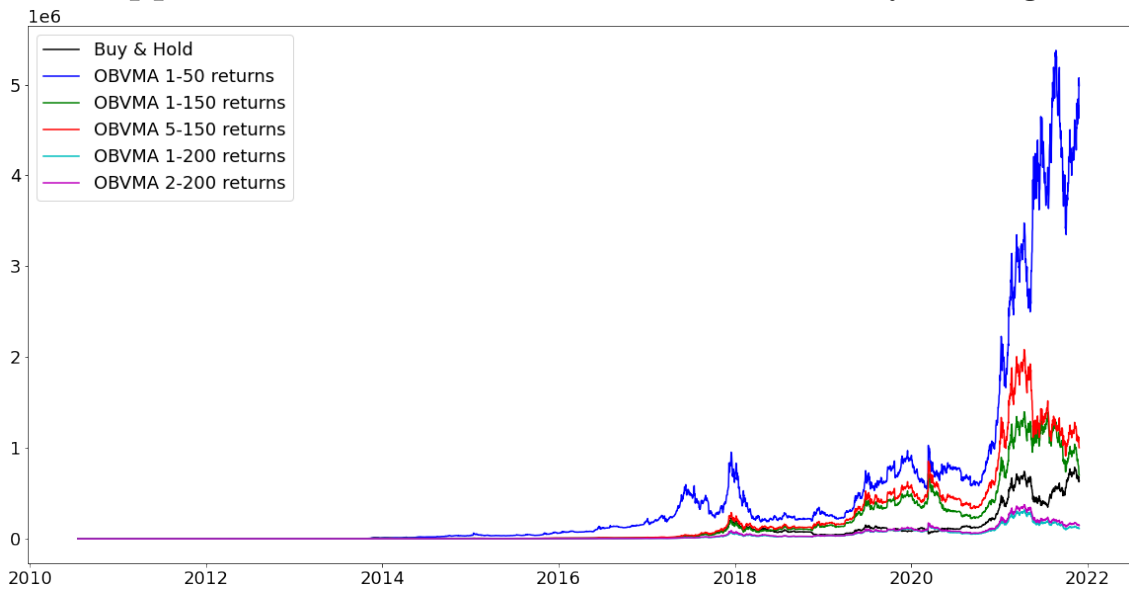
### Appendix C8 Bitcoin rate of change daily trading



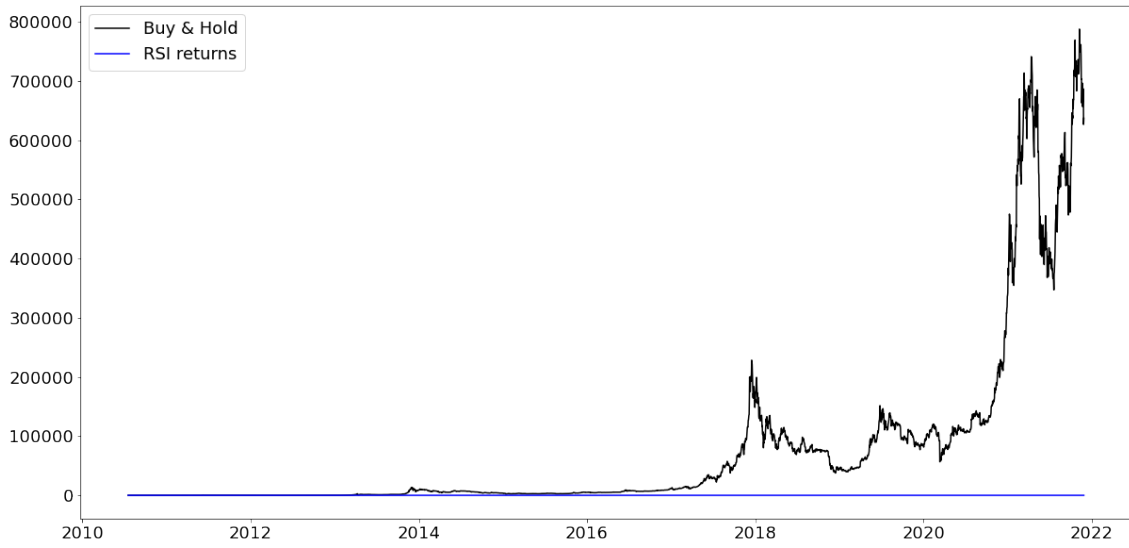
### Appendix C9 Bitcoin on-balance volume daily trading (long or out)



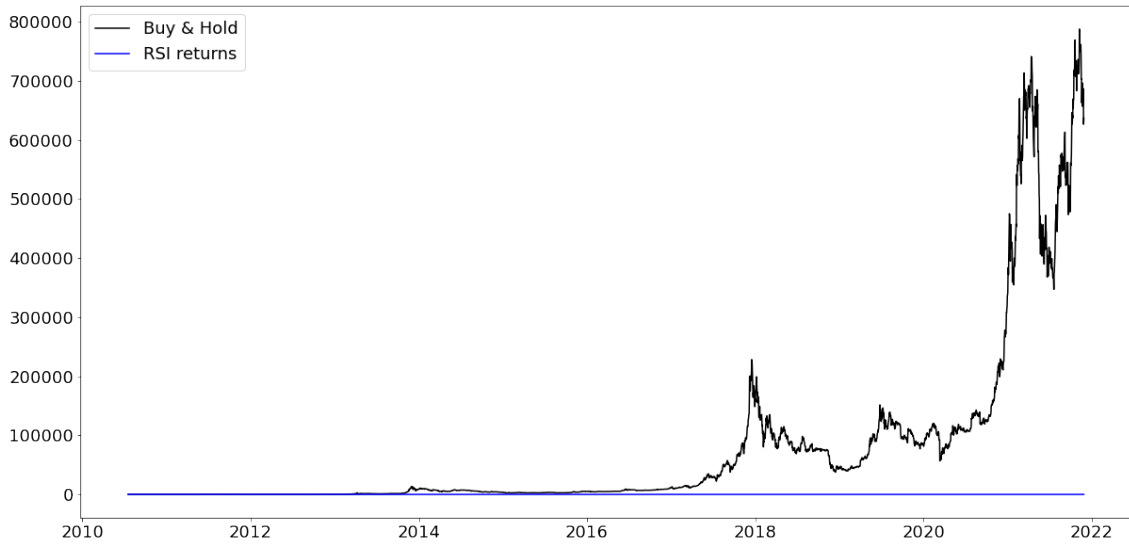
### Appendix C10 Bitcoin on-balance volume daily trading



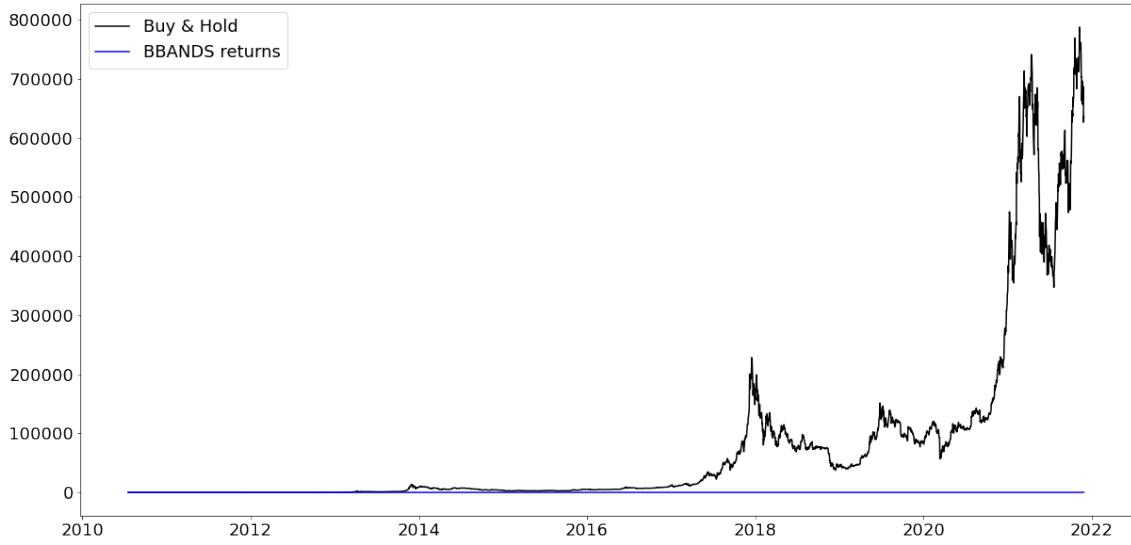
## Appendix C11 Bitcoin relative strength index daily trading (long or out)



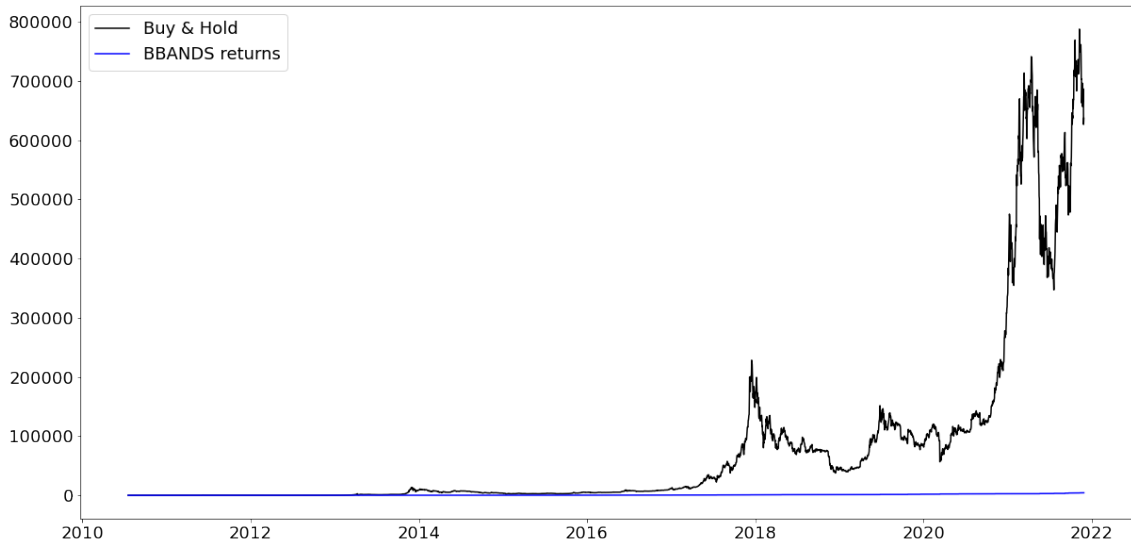
## Appendix C12 Bitcoin relative strength index daily trading



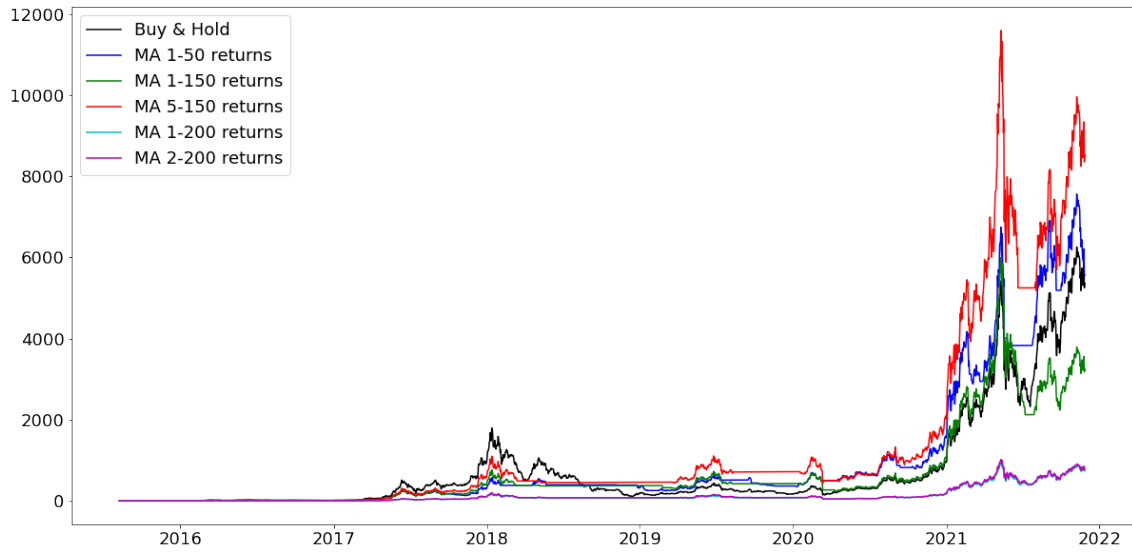
### Appendix C13 Bitcoin Bollinger bands daily trading (long or out)



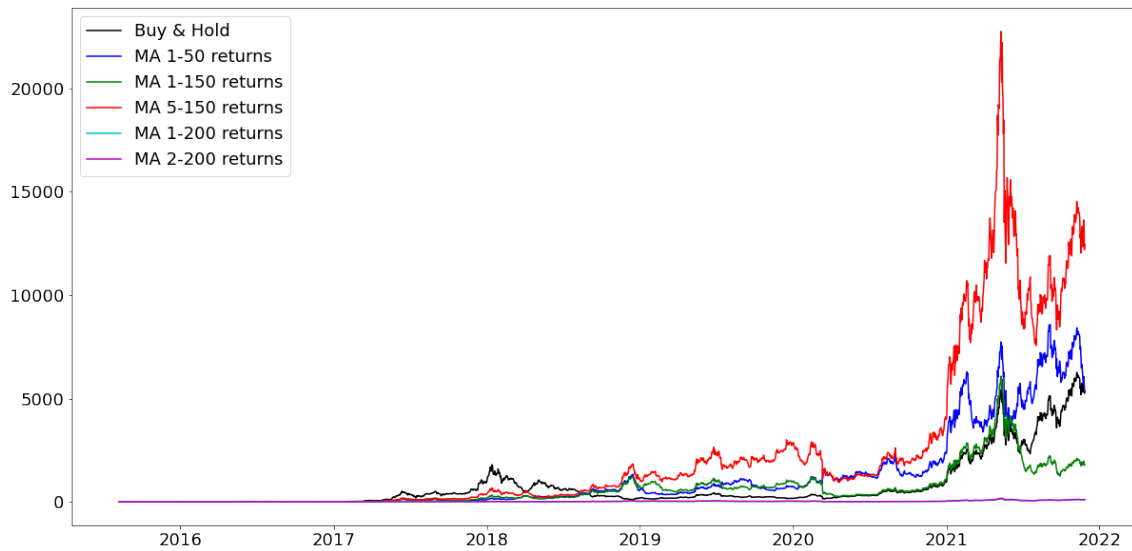
### Appendix C14 Bitcoin Bollinger bands daily trading



### Appendix D1 Ethereum moving average daily trading (long or out)

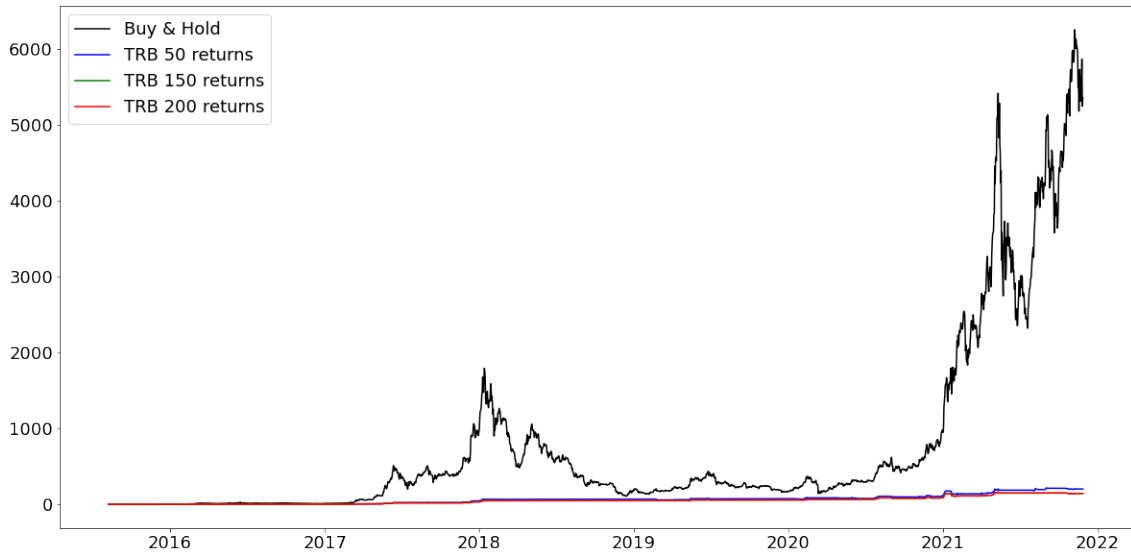


### Appendix D2 Ethereum moving average daily trading





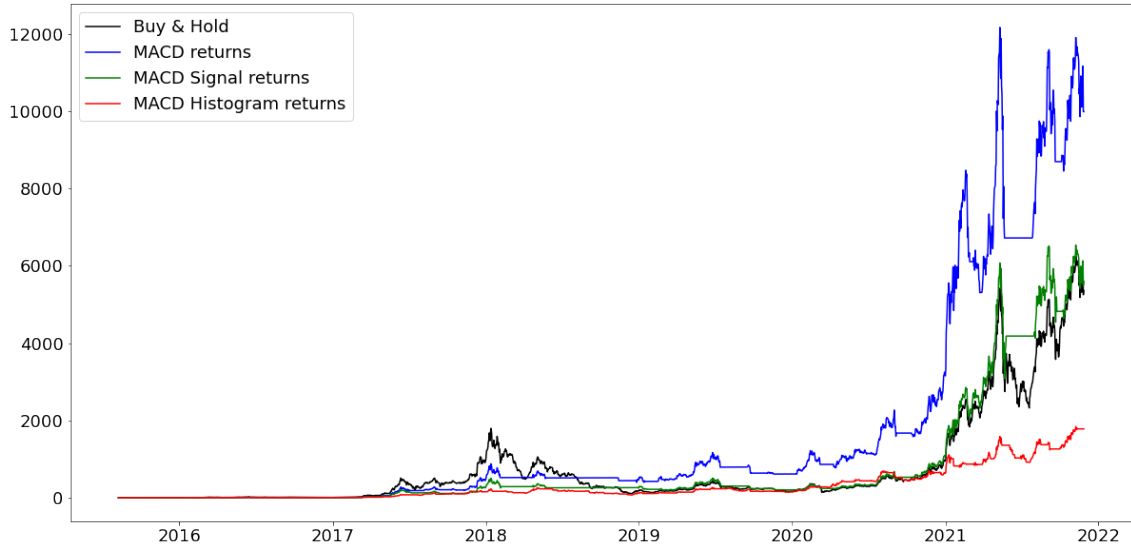
### Appendix D3 Ethereum trading range breakout daily trading (long or out)



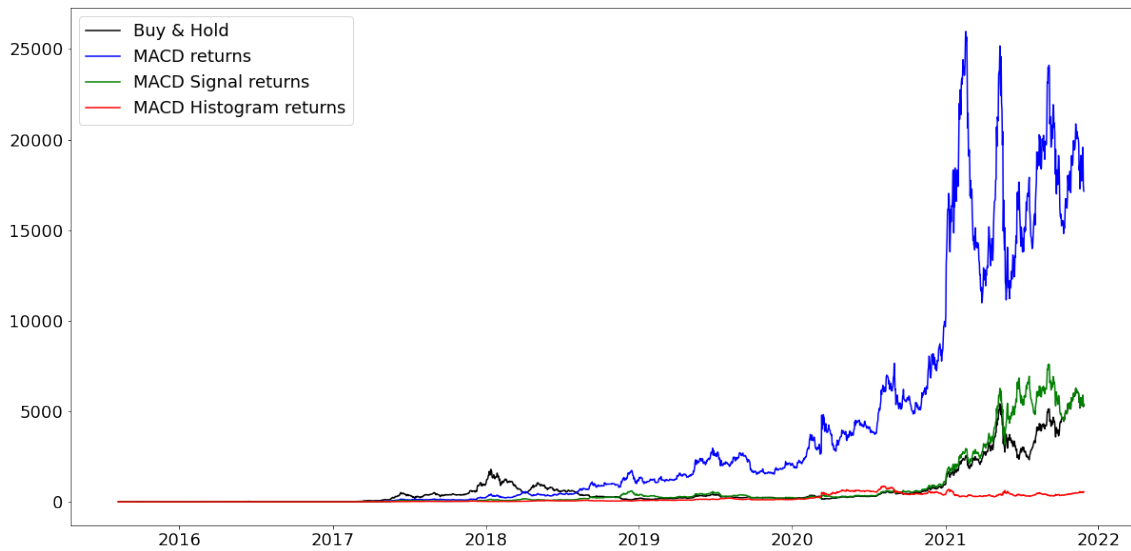
### Appendix D4 Ethereum trading range breakout daily trading



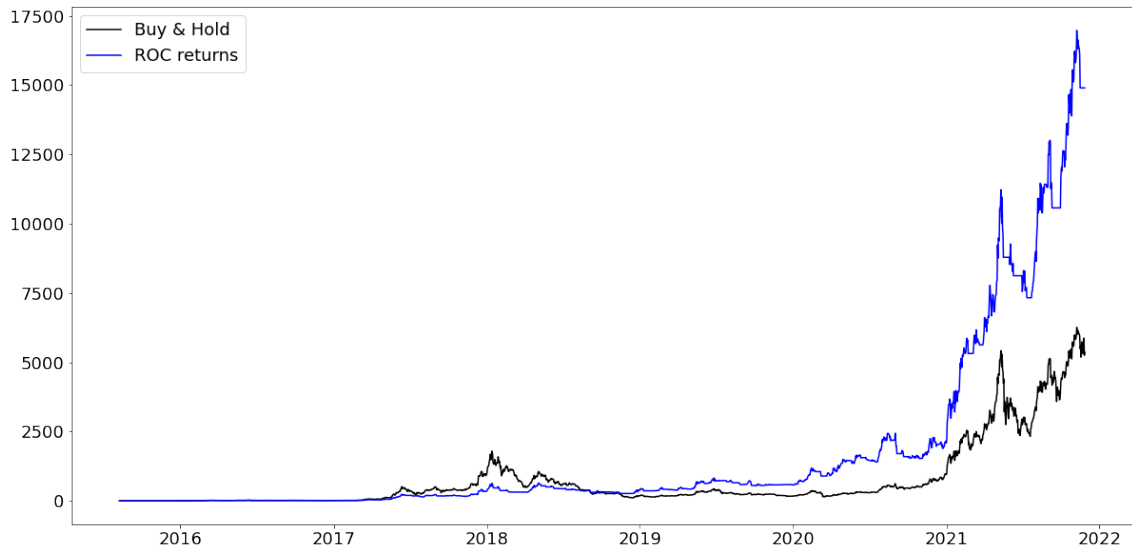
### Appendix D5 Ethereum MACD daily trading (long or out)



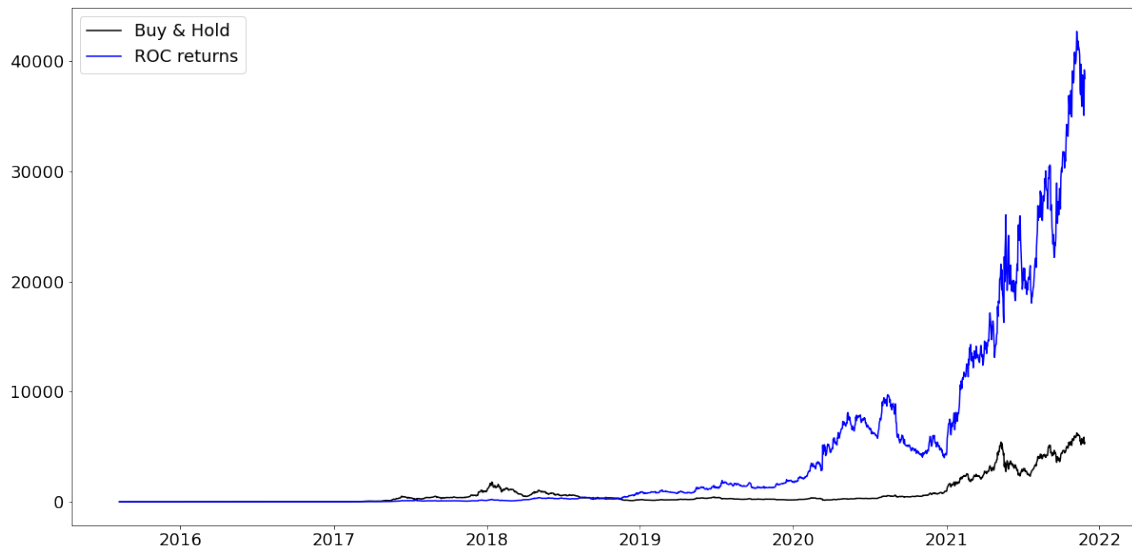
### Appendix D6 Ethereum MACD daily trading



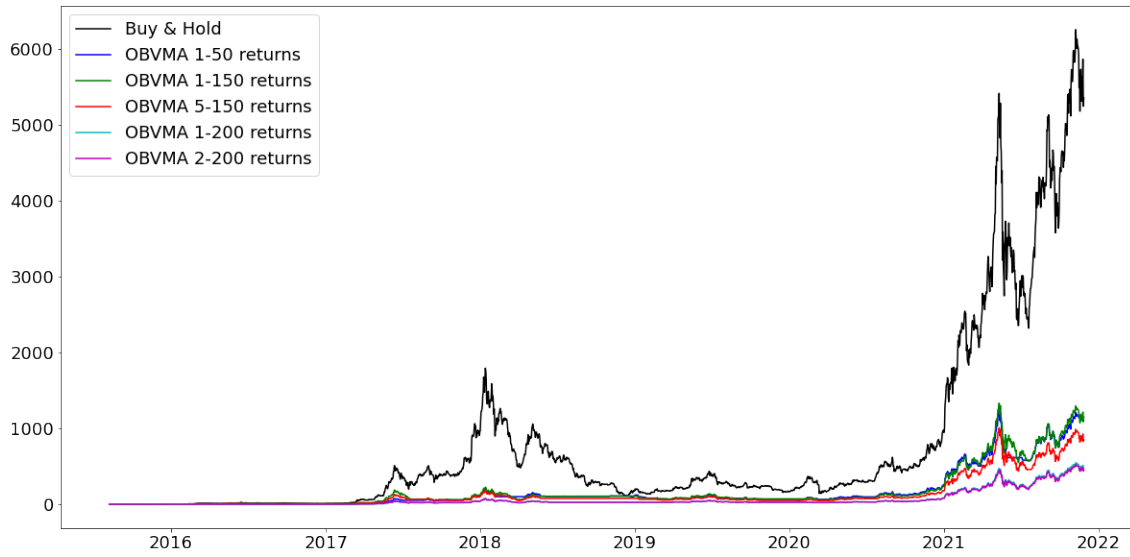
### Appendix D7 Ethereum rate of change daily trading (long or out)



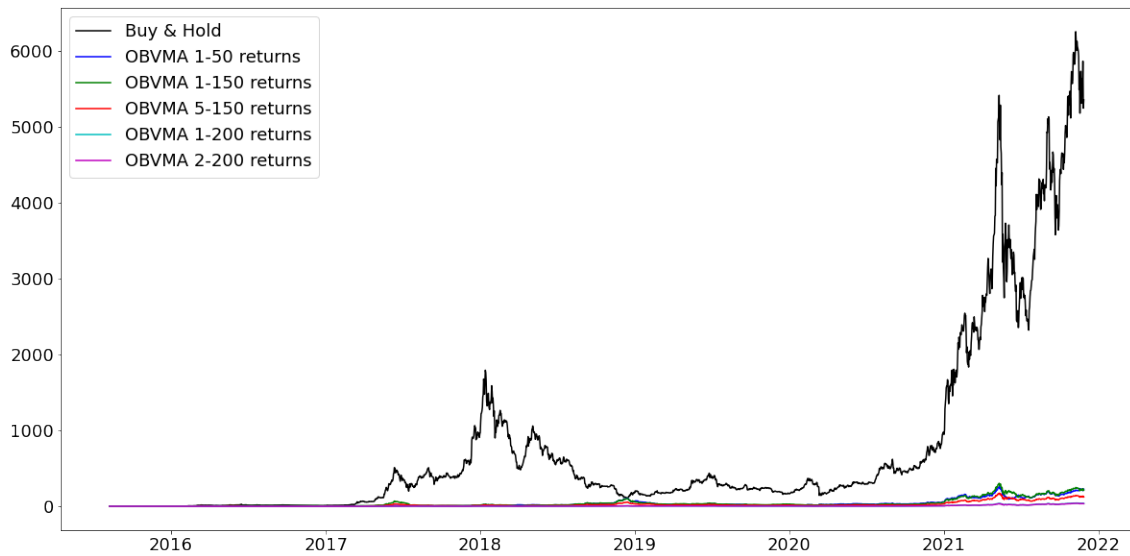
### Appendix D8 Ethereum rate of change daily trading



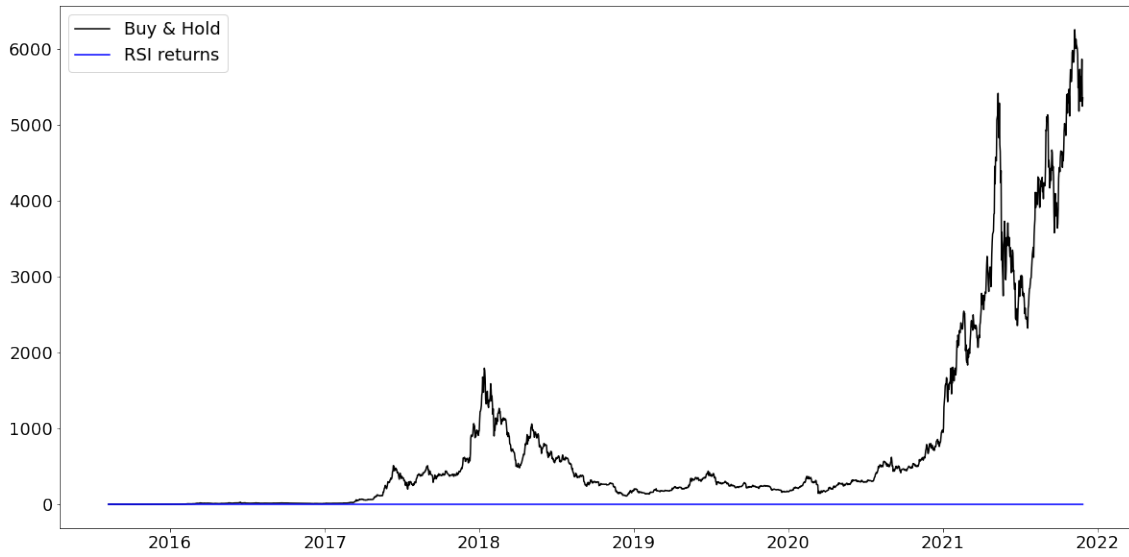
## Appendix D9 Ethereum on-balance volume daily trading (long or out)



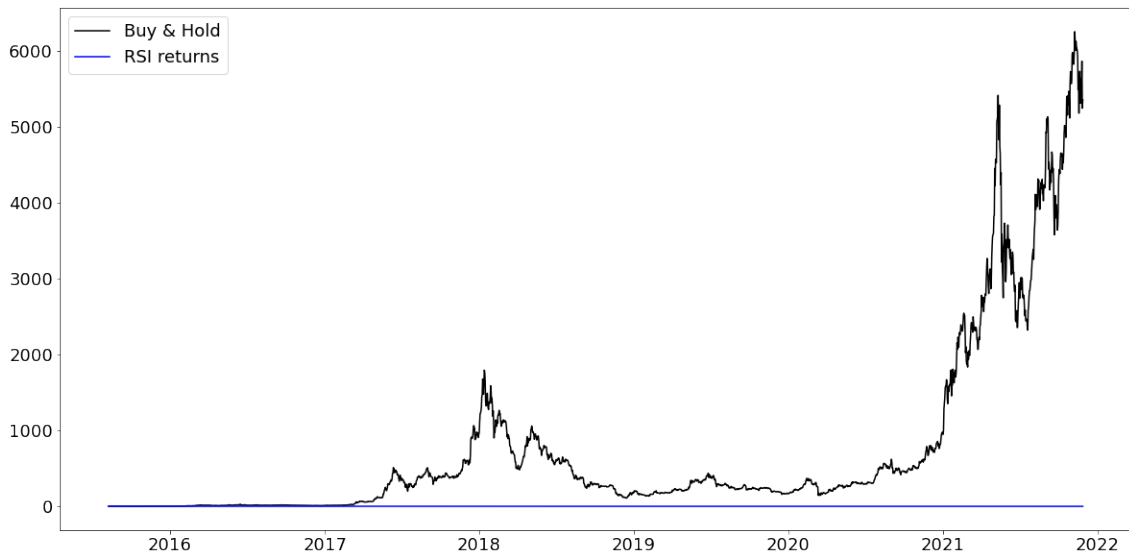
## Appendix D10 Ethereum on-balance volume daily trading



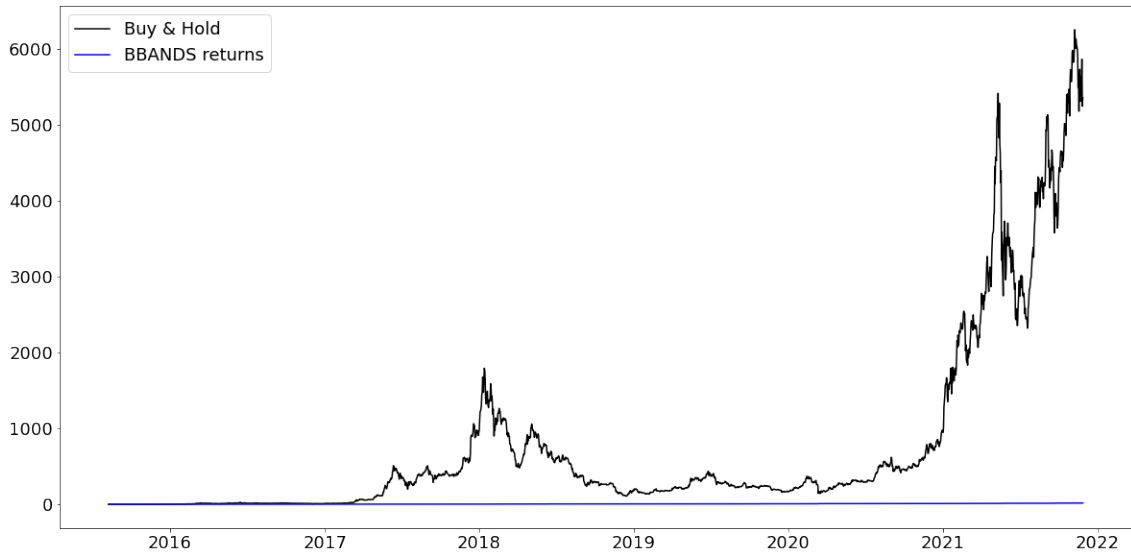
### Appendix D11 Ethereum relative strength index daily trading (long or out)



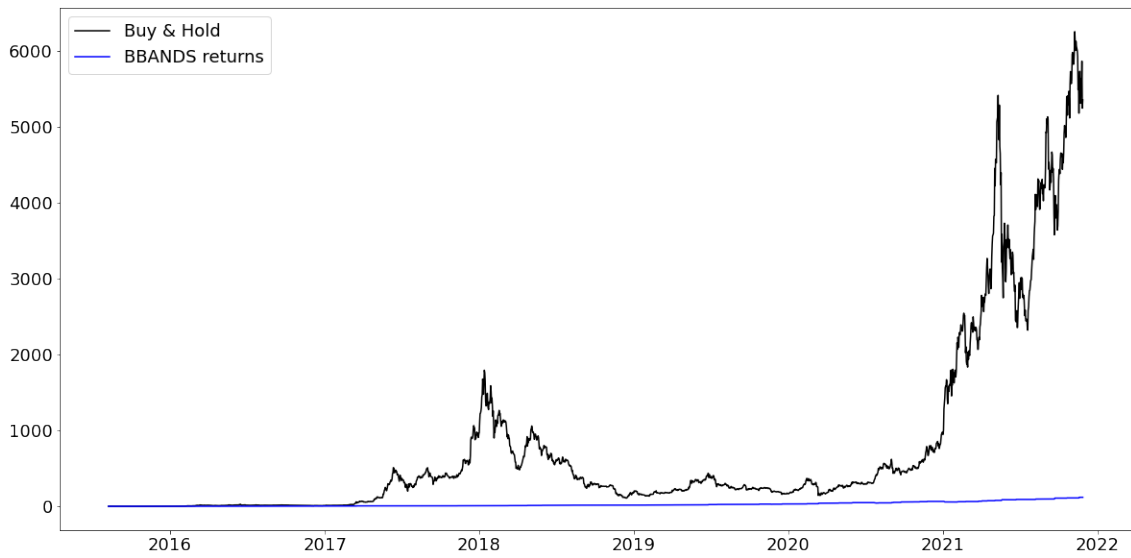
### Appendix D12 Ethereum relative strength index daily trading



### Appendix D13 Ethereum Bollinger bands daily trading (long or out)



### Appendix D14 Ethereum Bollinger bands daily trading



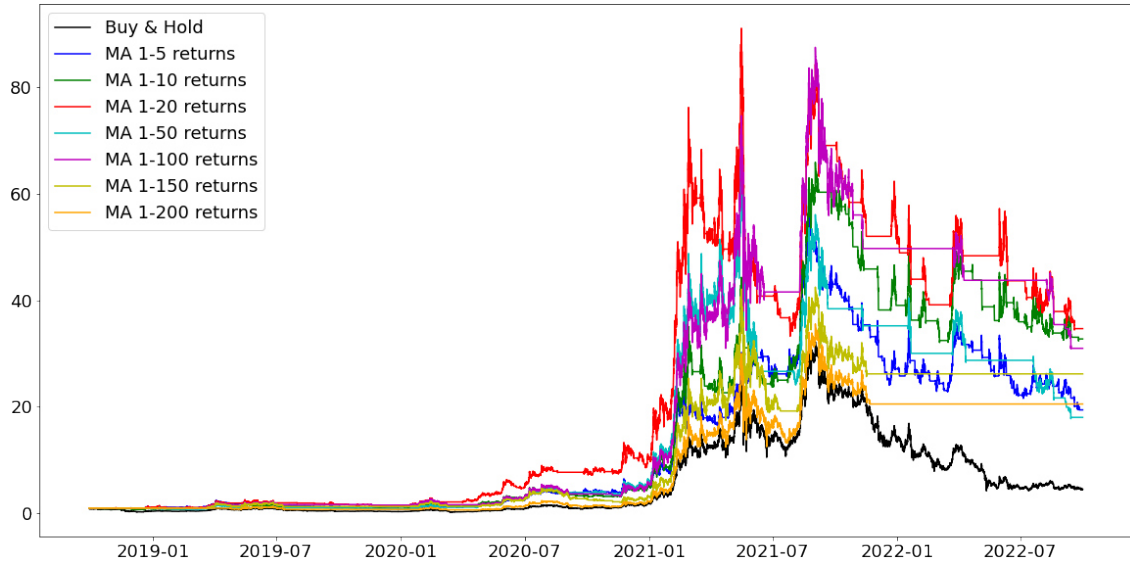


# Appendix B

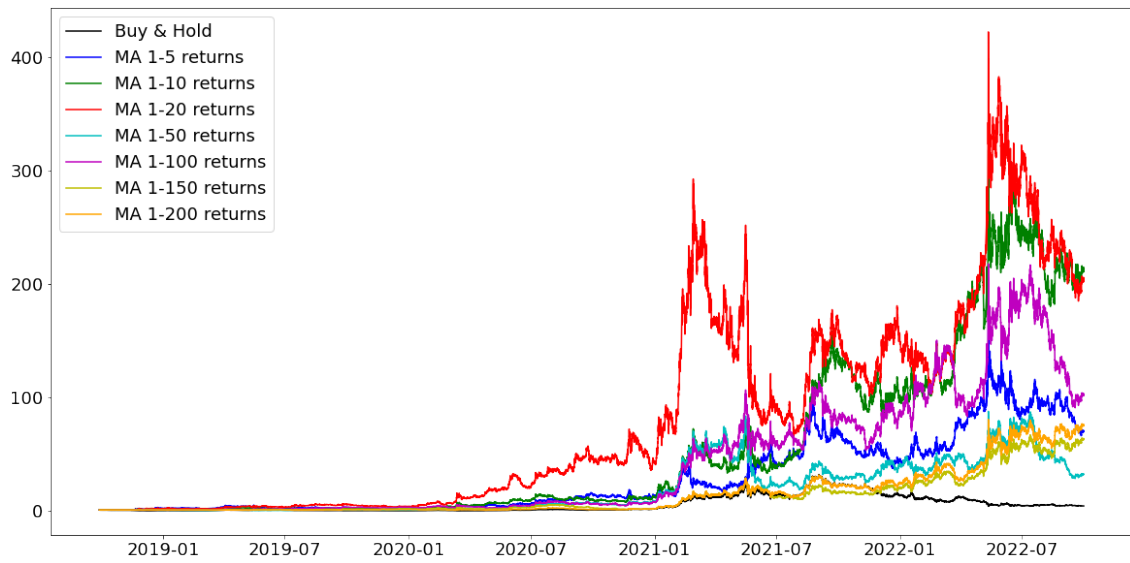
## Appendix to Chapter 4



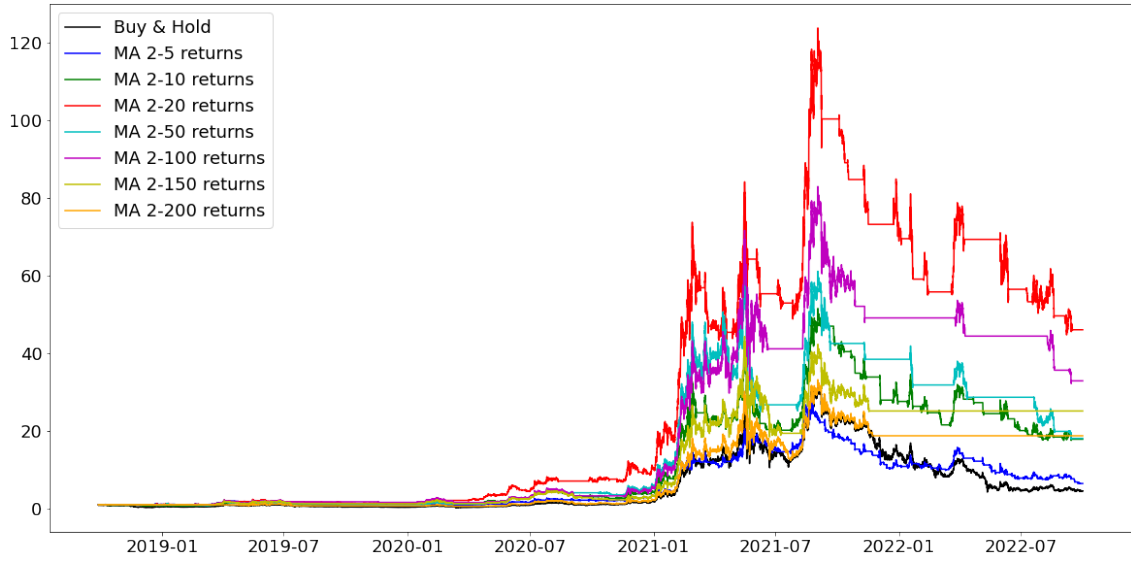
## Appendix A1 Cardano moving average trading 1-x (long or out)



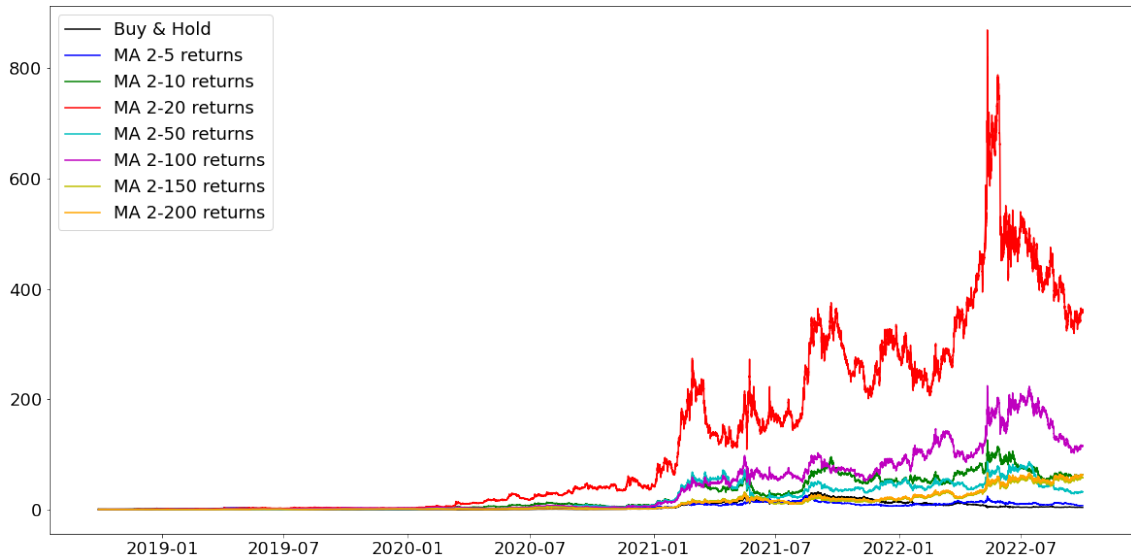
## Appendix A2 Cardano moving average trading 1-x



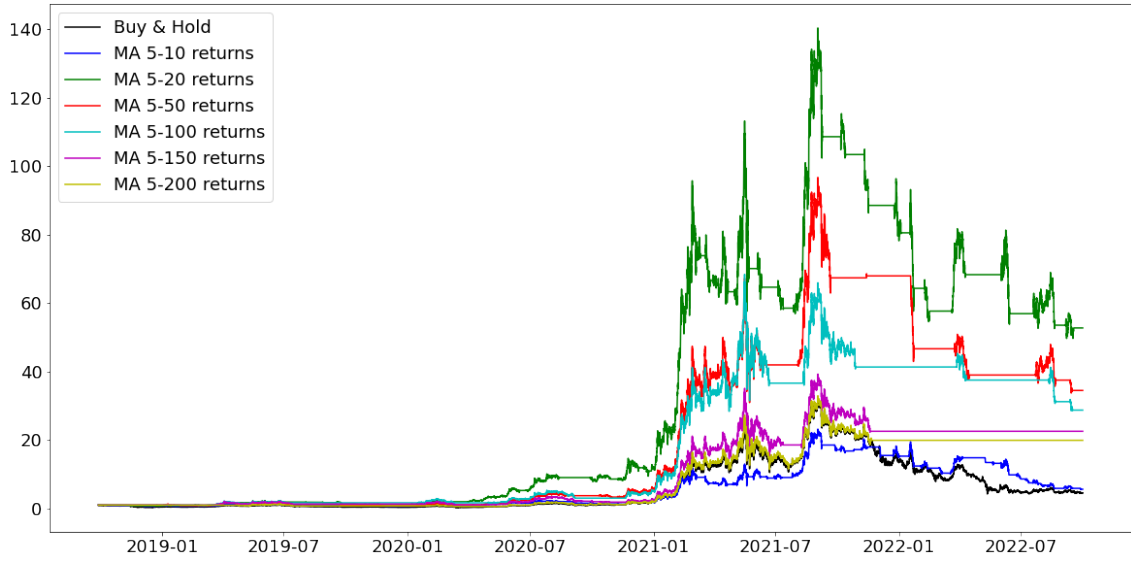
### Appendix A3 Cardano moving average trading 2-x (long or out)



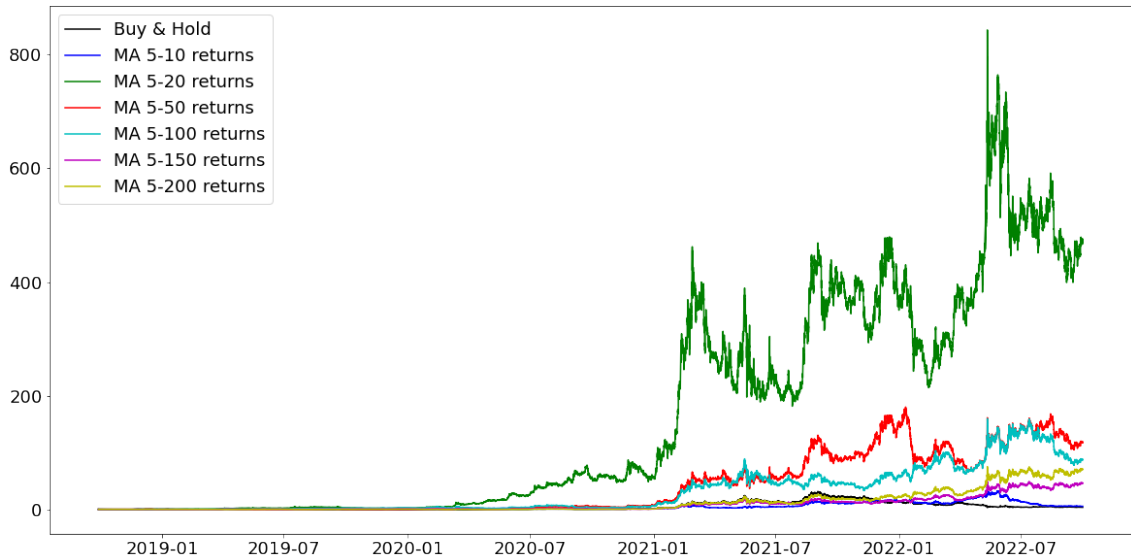
### Appendix A4 Cardano moving average trading 2-x



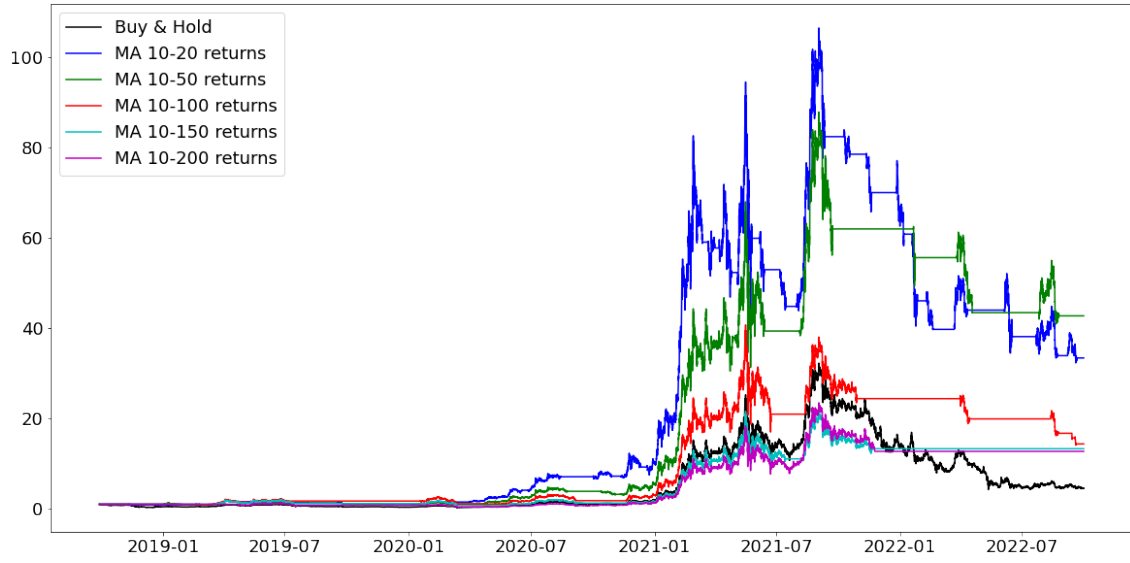
### Appendix A5 Cardano moving average trading 5-x (long or out)



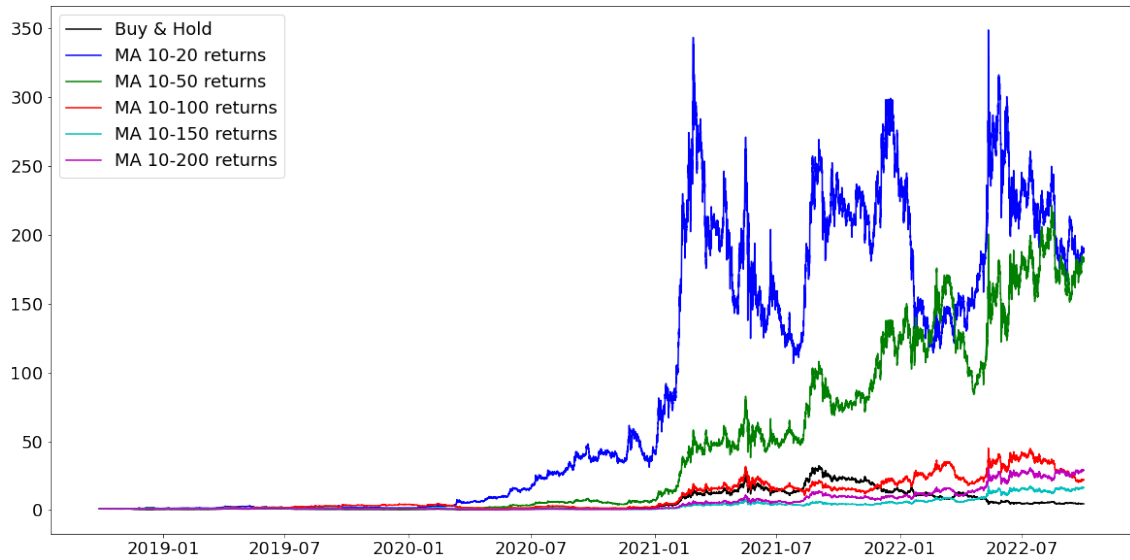
### Appendix A6 Cardano moving average trading 5-x



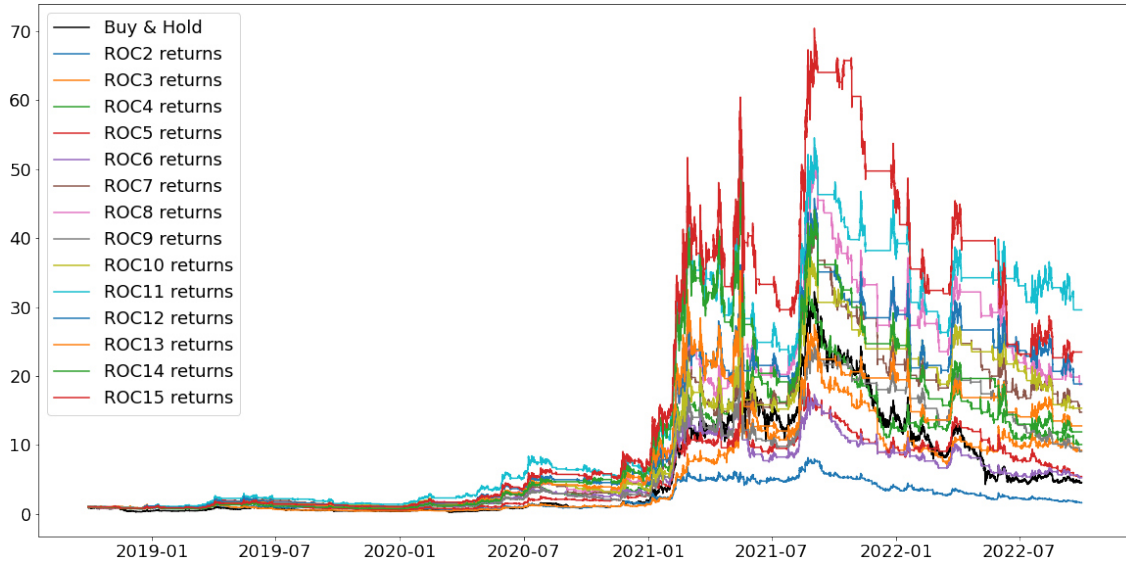
## Appendix A7 Cardano moving average trading 10-x (long or out)



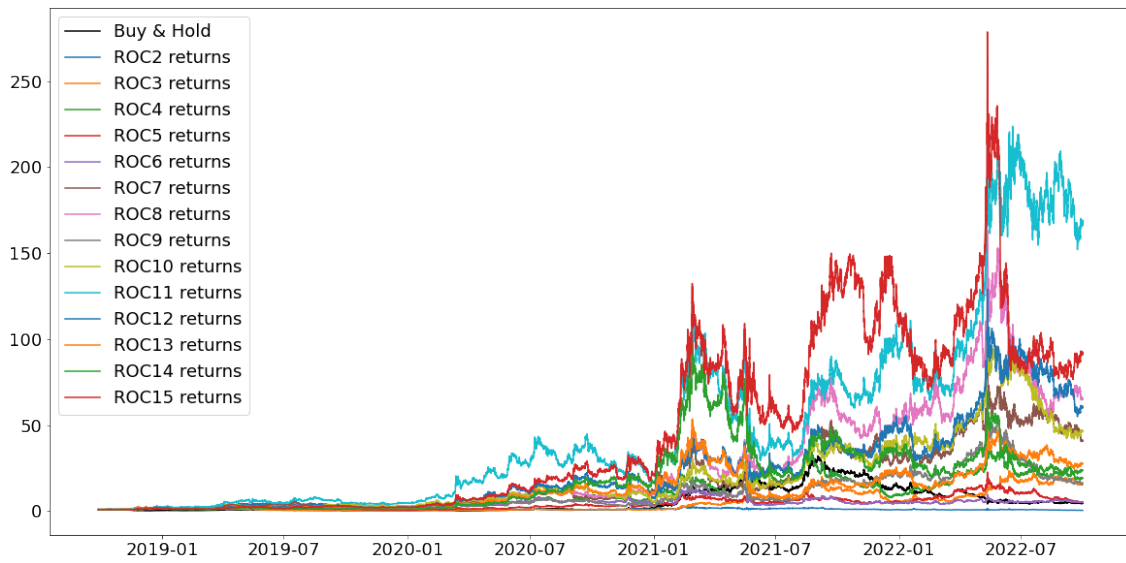
## Appendix A8 Cardano moving average trading 10-x



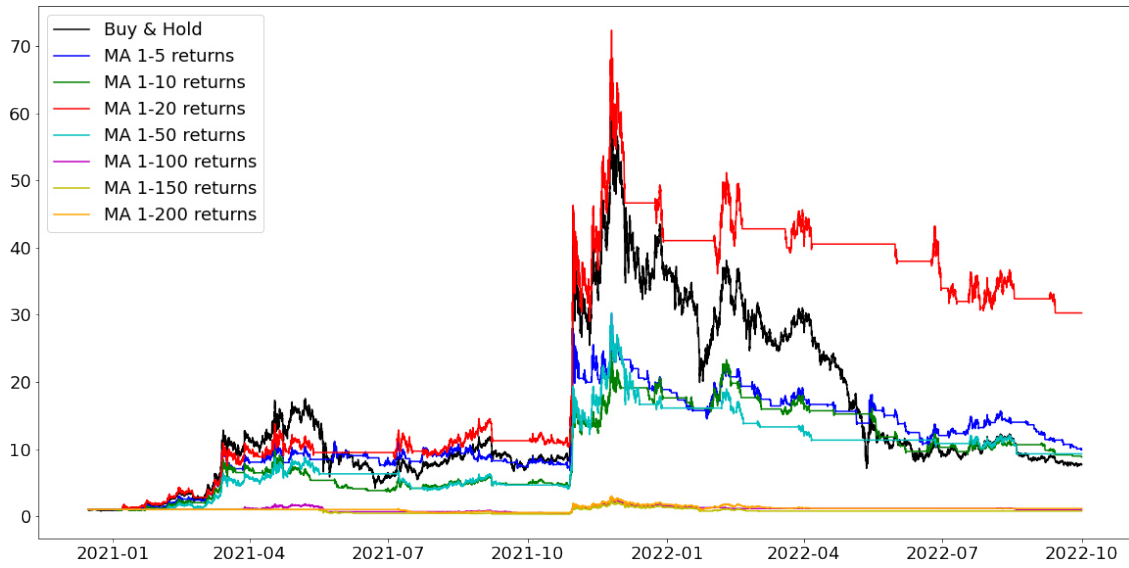
### Appendix A9 Cardano rate of change trading (long or out)



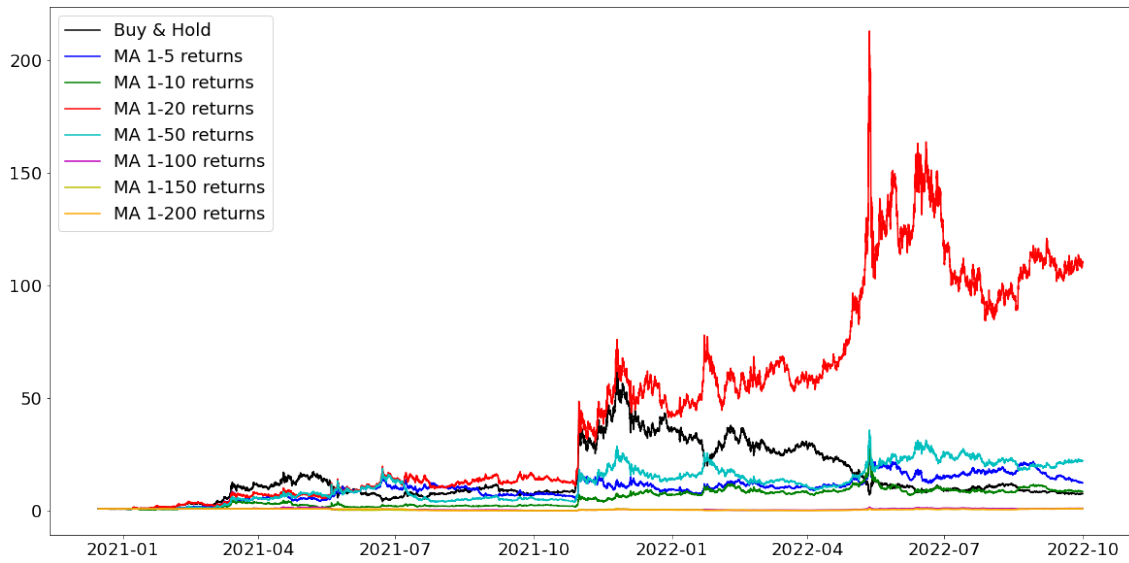
### Appendix A10 Cardano rate of change trading



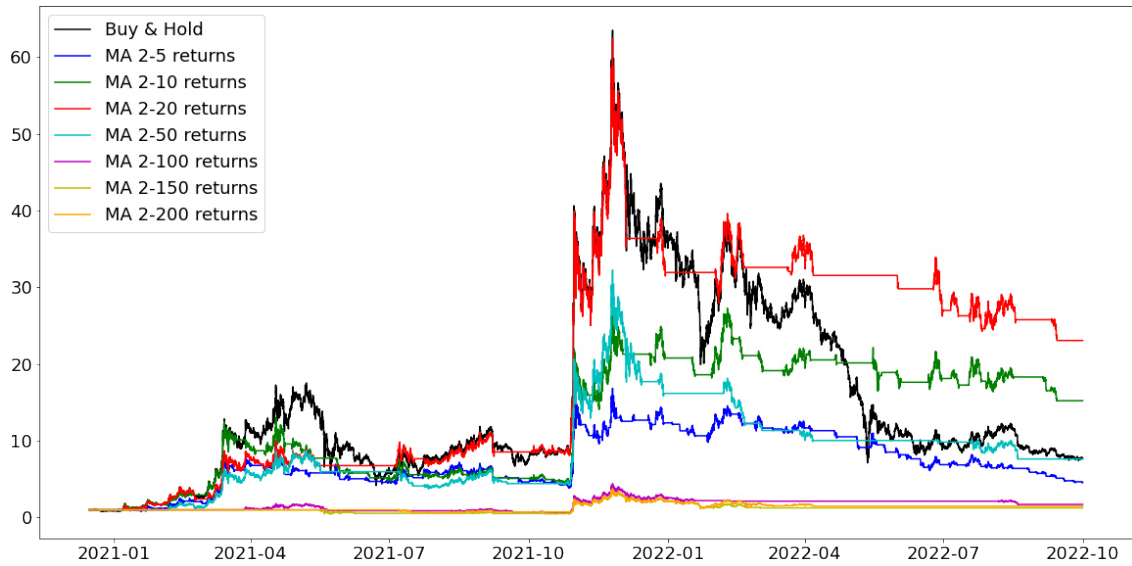
## Appendix B1 Decentraland moving average trading 1-x (long or out)



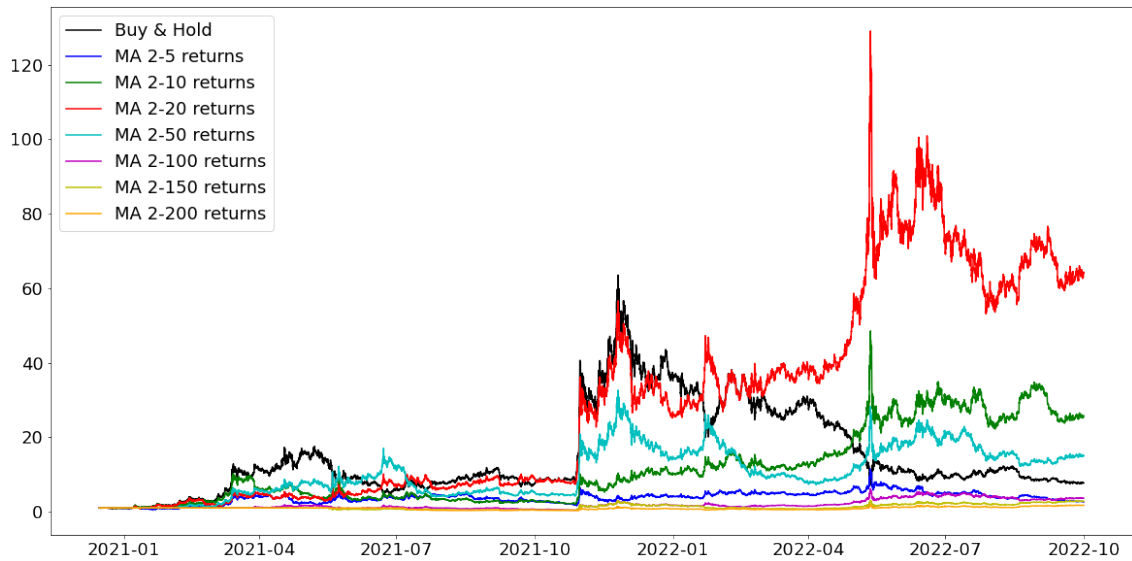
## Appendix B2 Decentraland moving average trading 1-x



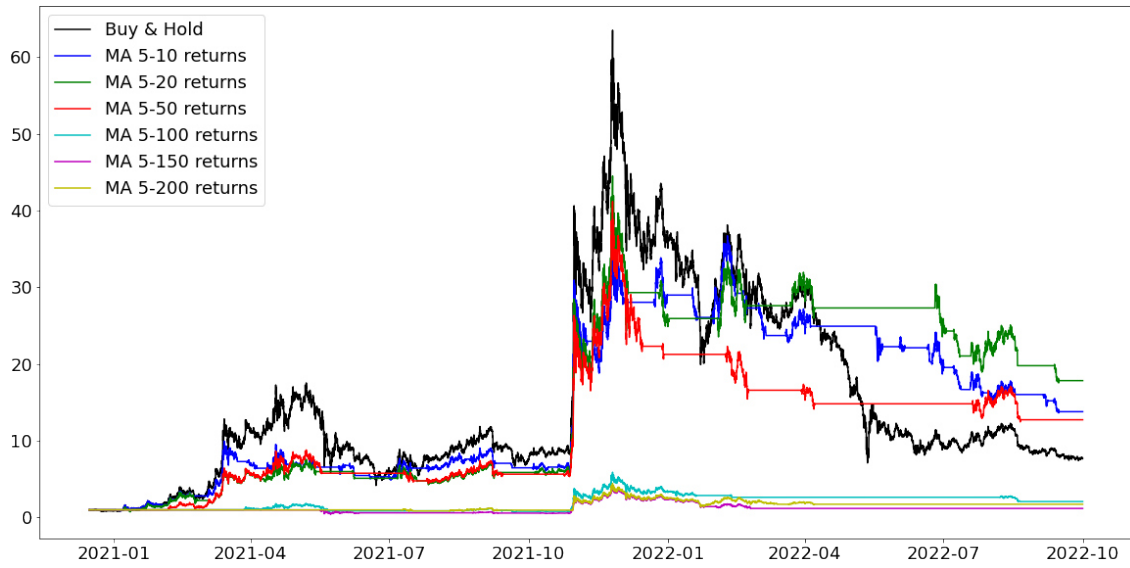
### Appendix B3 Decentraland moving average trading 2-x (long or out)



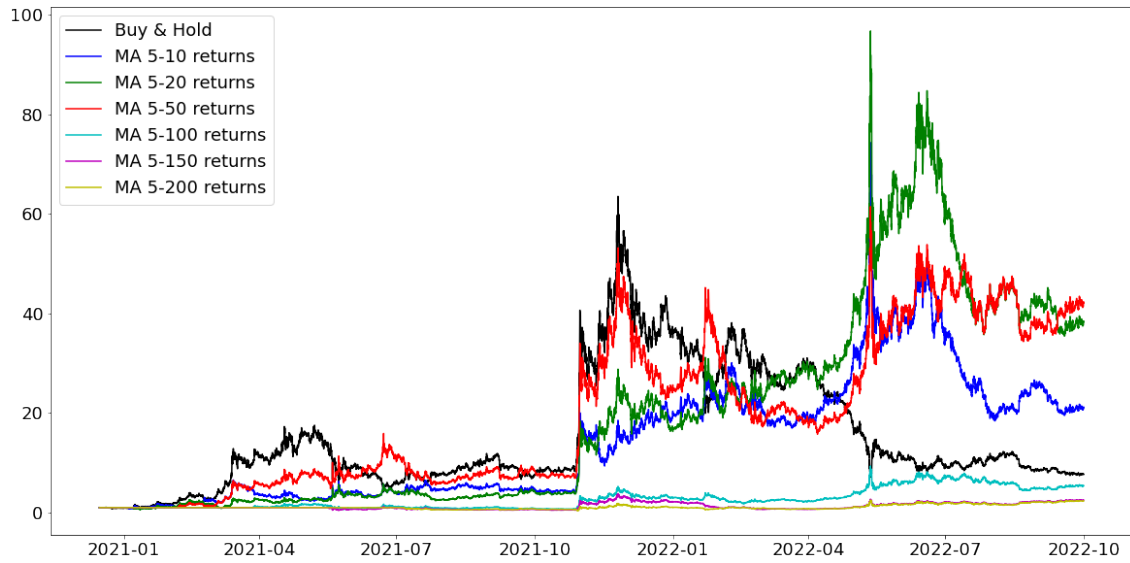
### Appendix B4 Decentraland moving average trading 2-x



## Appendix B5 Decentraland moving average trading 5-x (long or out)

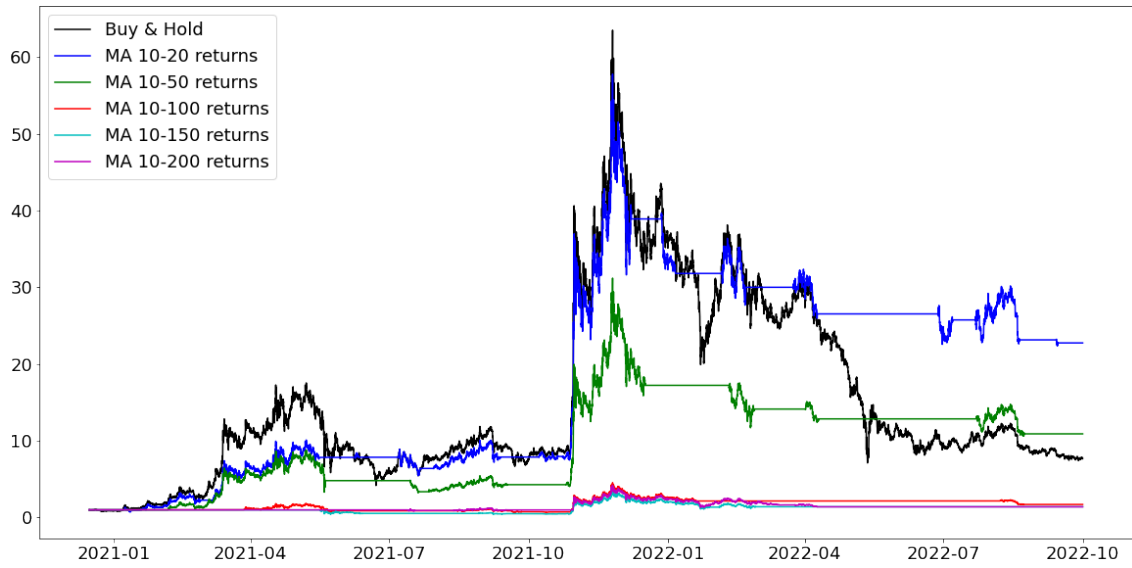


## Appendix B6 Decentraland moving average trading 5-x

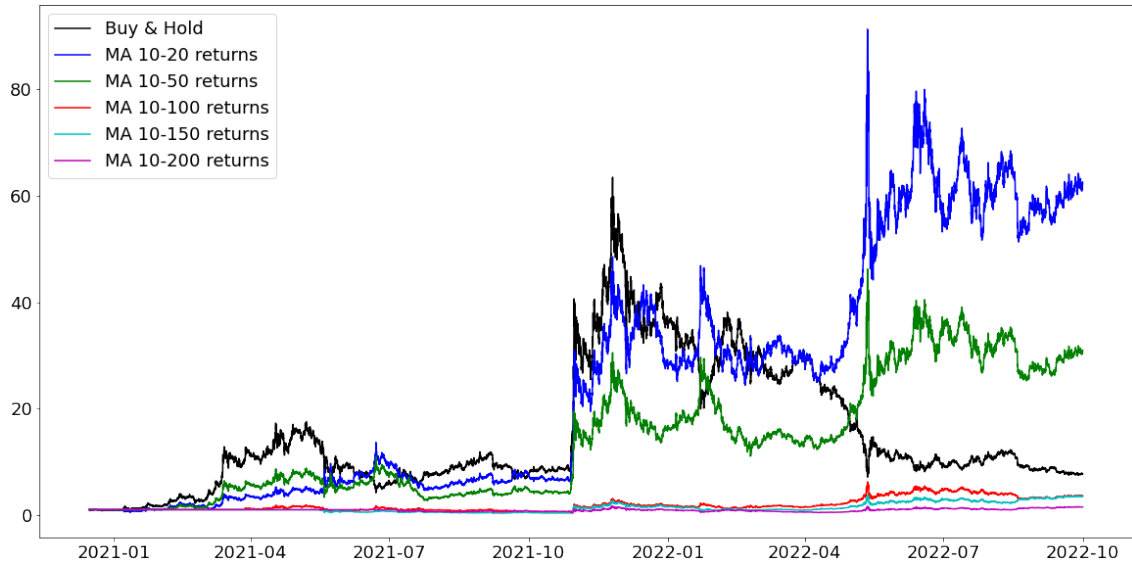




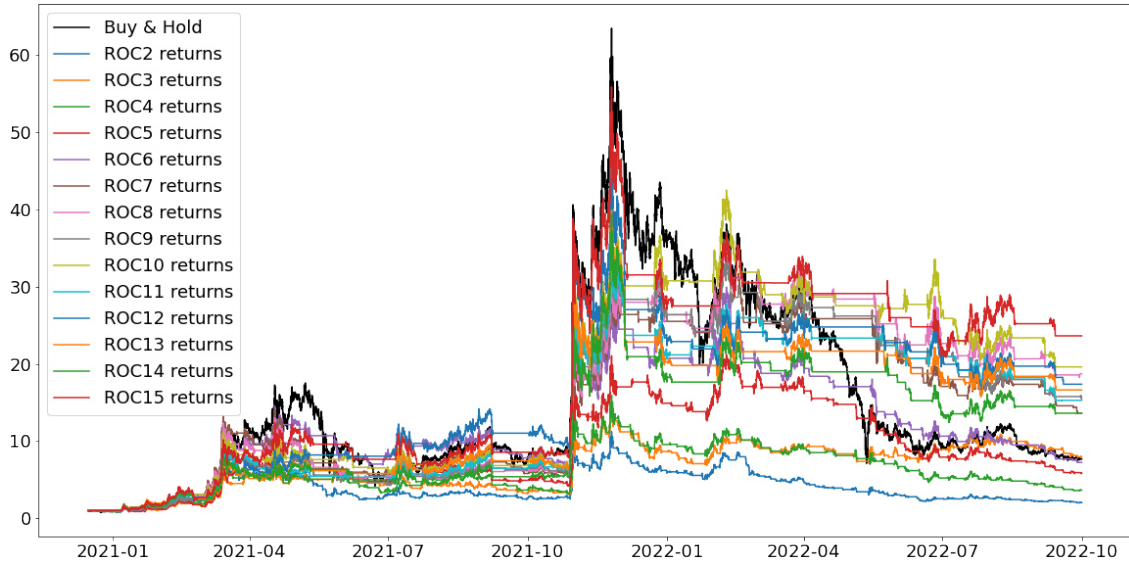
## Appendix B7 Decentraland moving average trading 10-x (long or out)



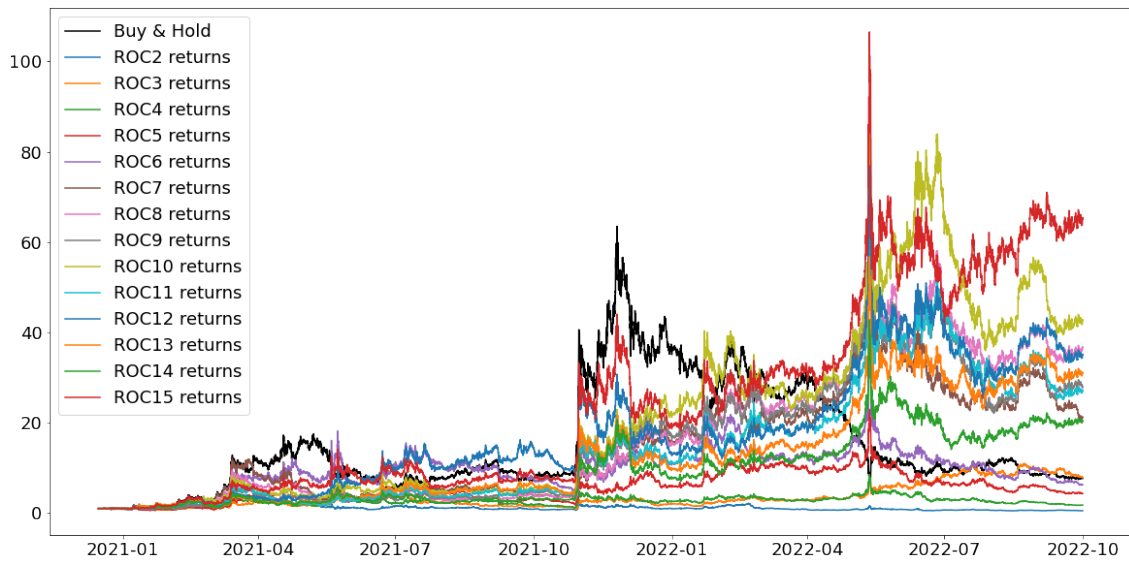
## Appendix B8 Decentraland moving average trading 10-x



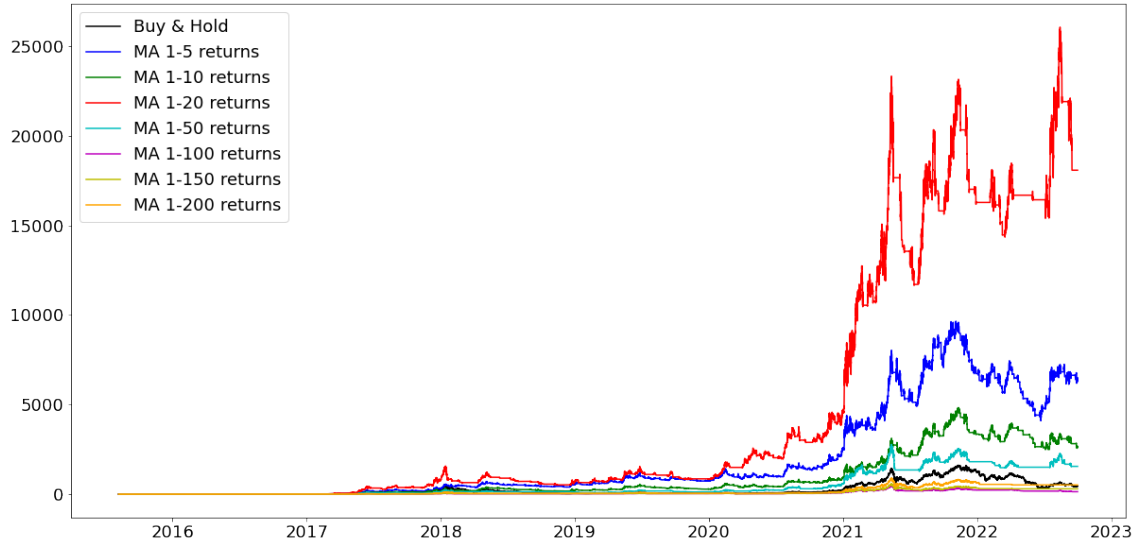
## Appendix B9 Decentraland rate of change trading (long or out)



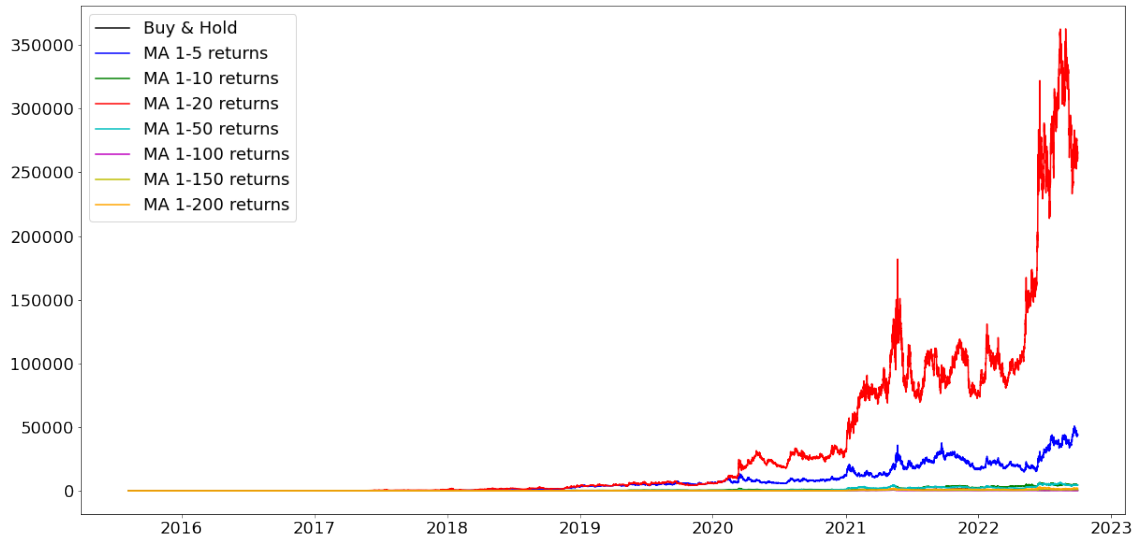
## Appendix B10 Decentraland rate of change trading



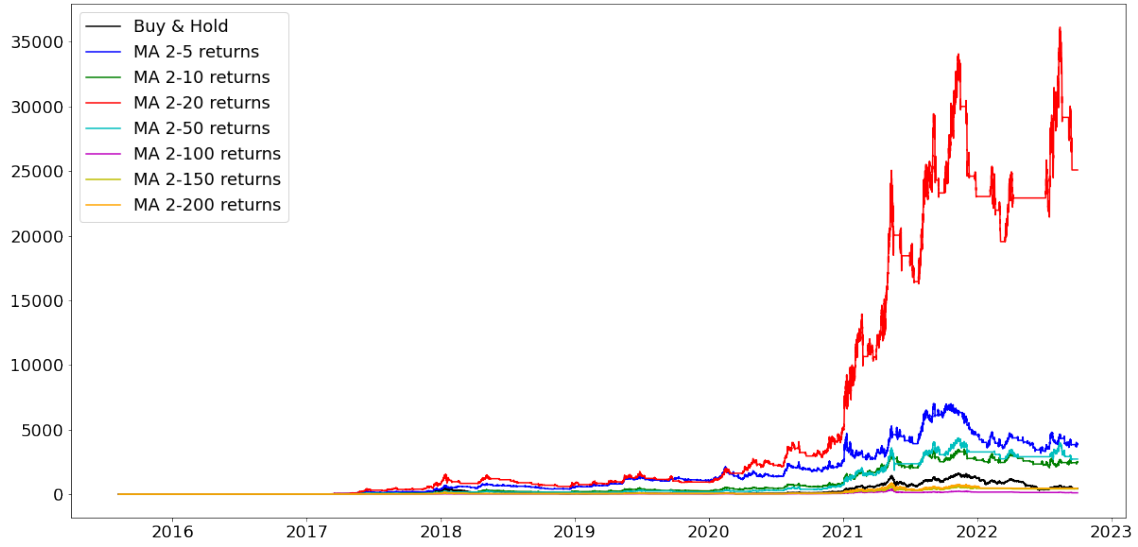
## Appendix C1 Ethereum moving average trading 1-x (long or out)



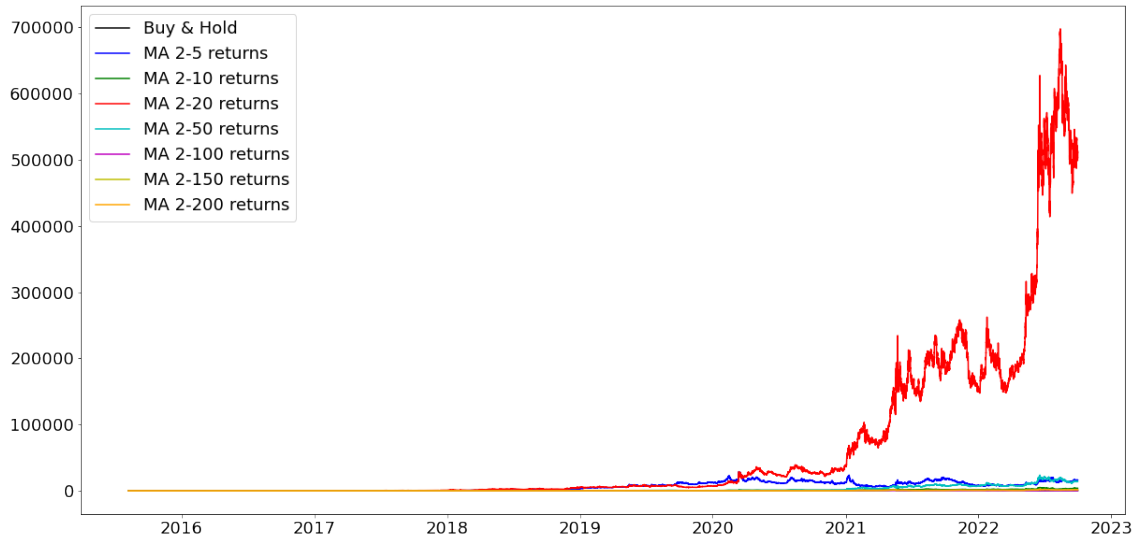
## Appendix C2 Ethereum moving average trading 1-x



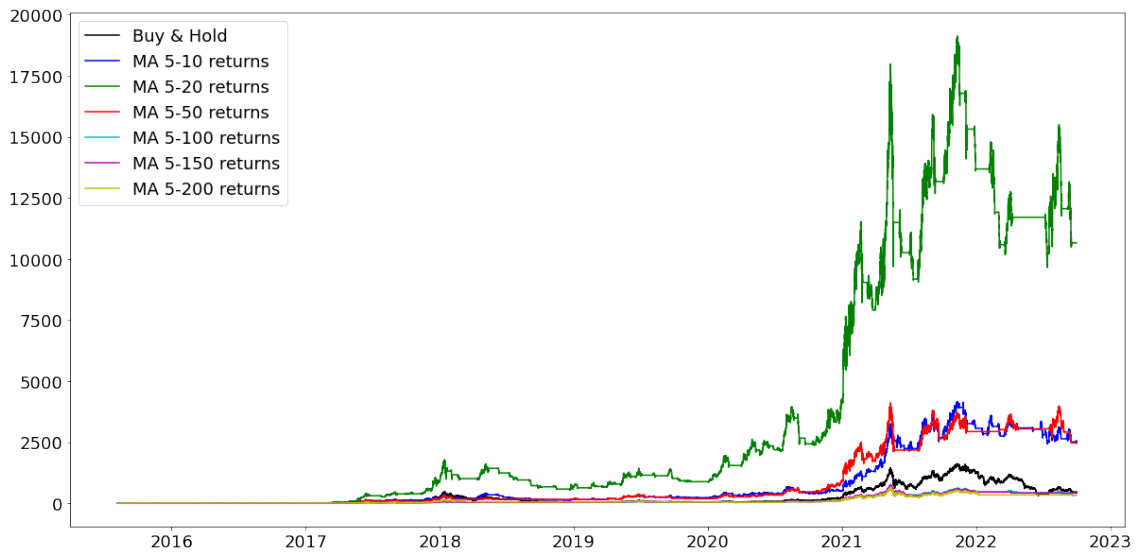
### Appendix C3 Ethereum moving average trading 2-x (long or out)



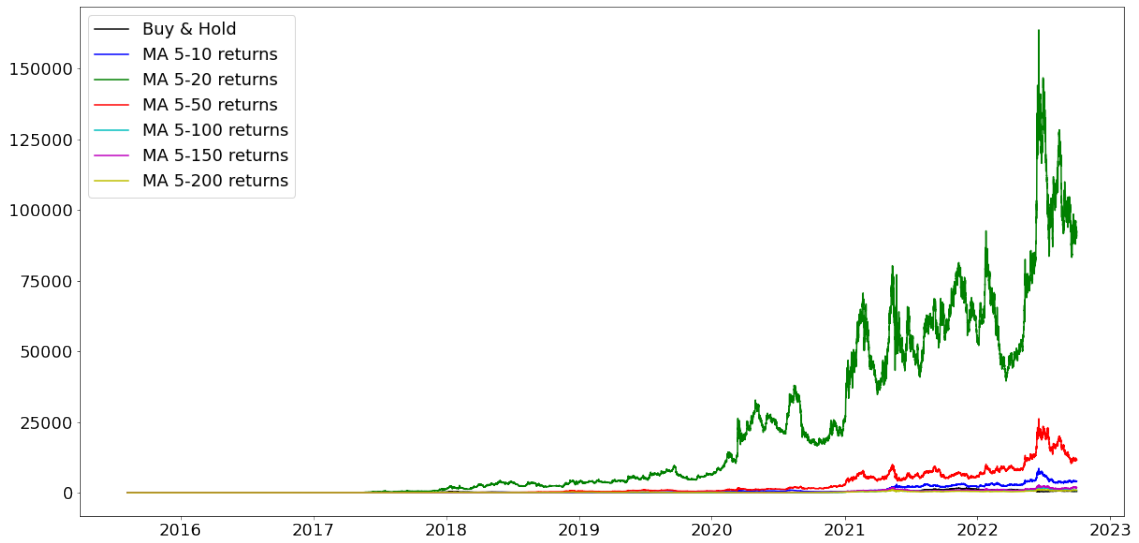
### Appendix C4 Ethereum moving average trading 2-x



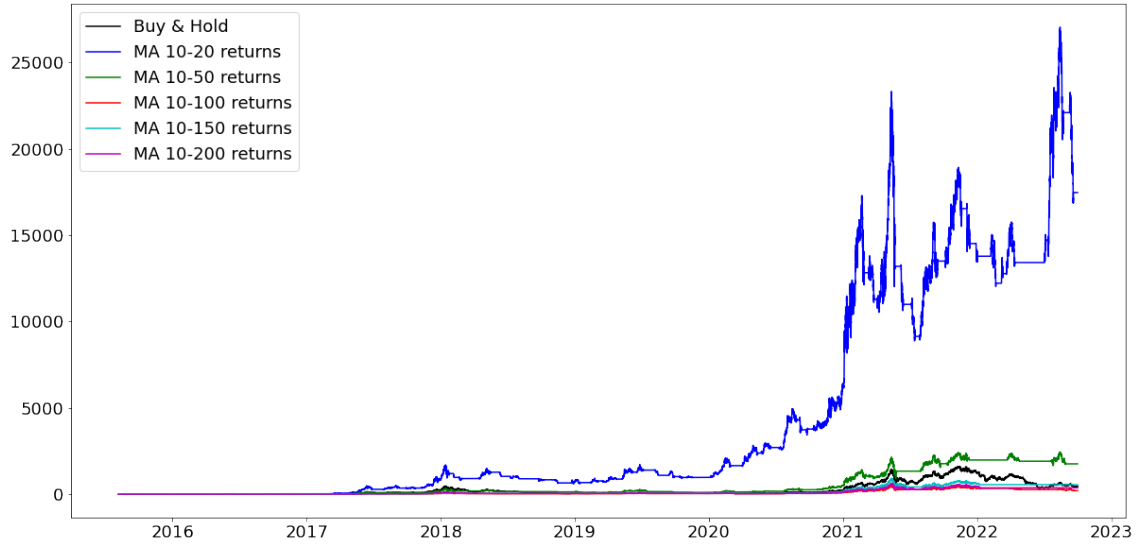
### Appendix C5 Ethereum moving average trading 5-x (long or out)



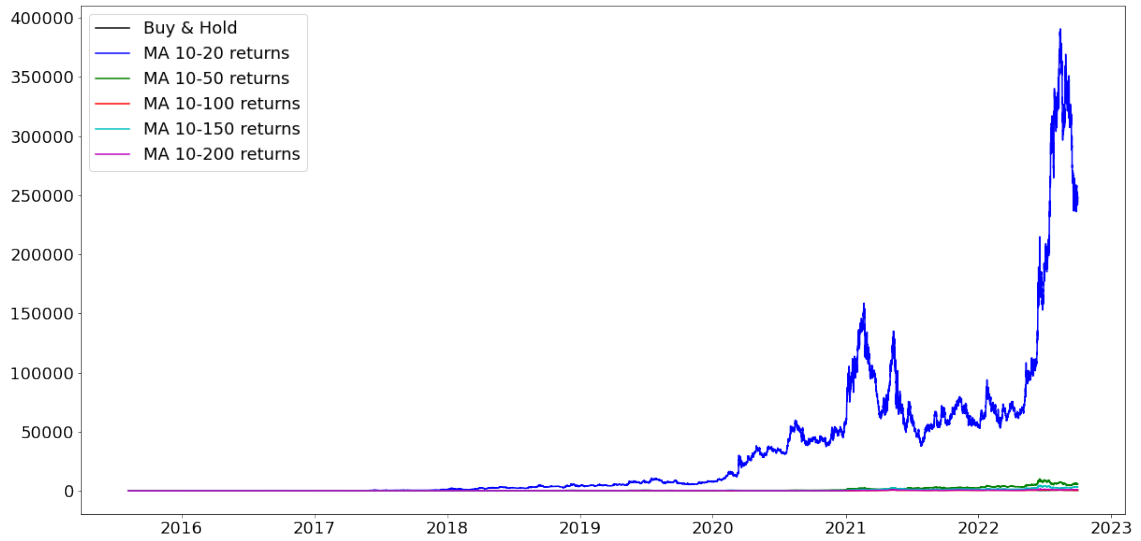
### Appendix C6 Ethereum moving average trading 5-x



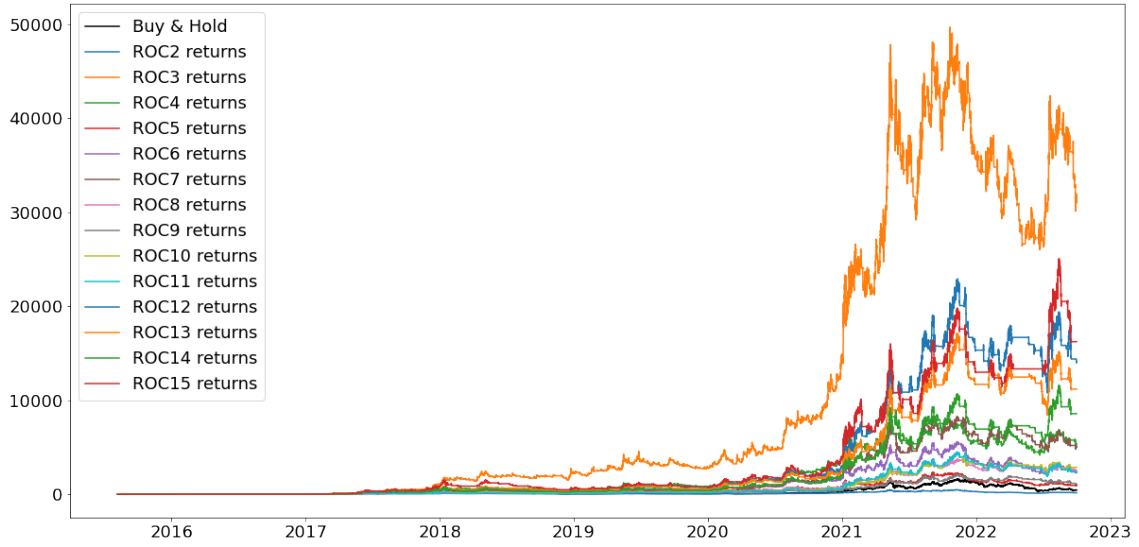
### Appendix C7 Ethereum moving average trading 10-x (long or out)



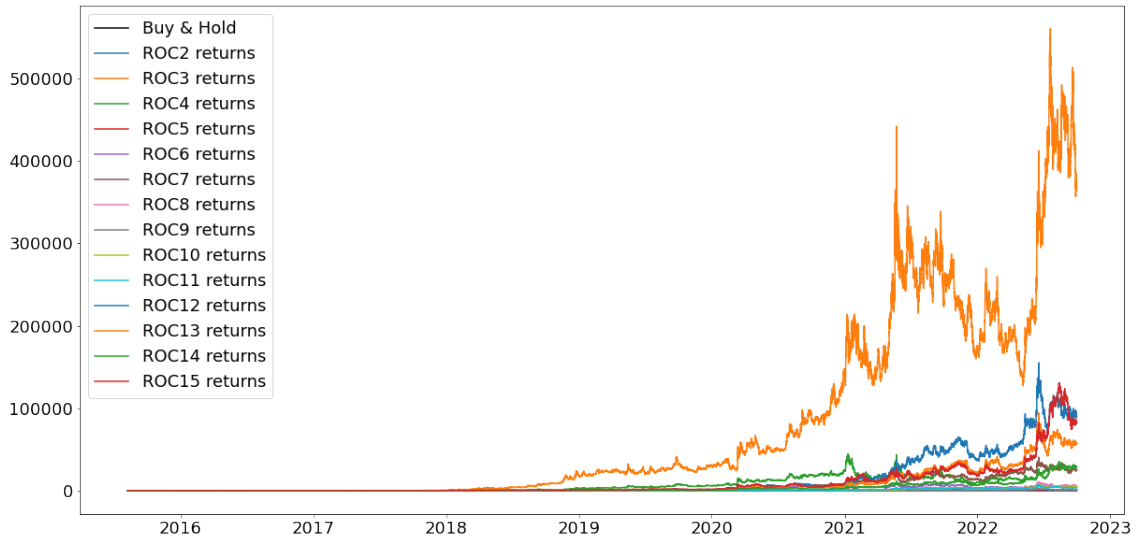
### Appendix C8 Ethereum moving average trading 10-x



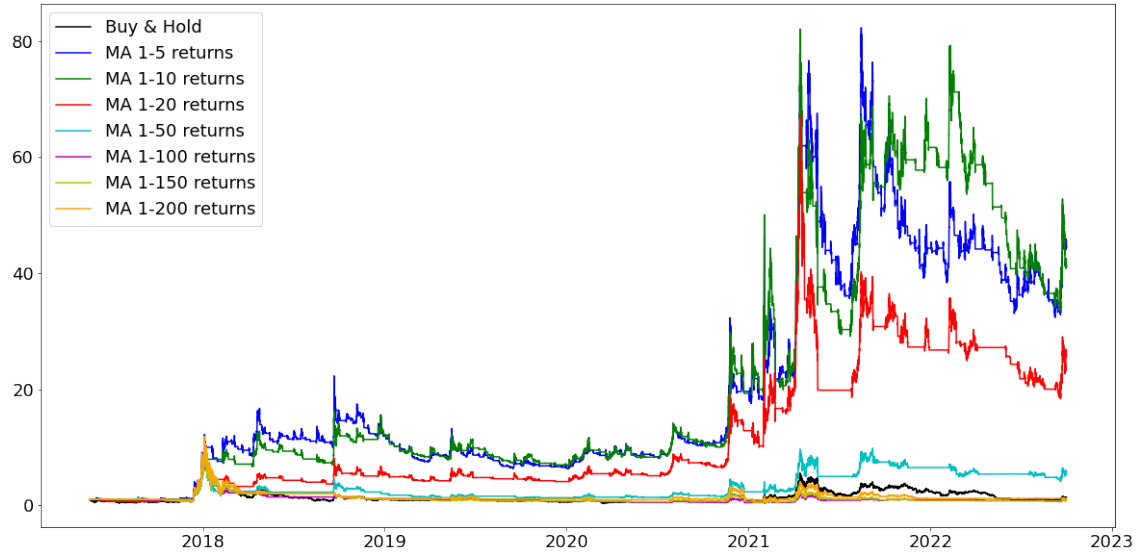
### Appendix C9 Ethereum rate of change trading (long or out)



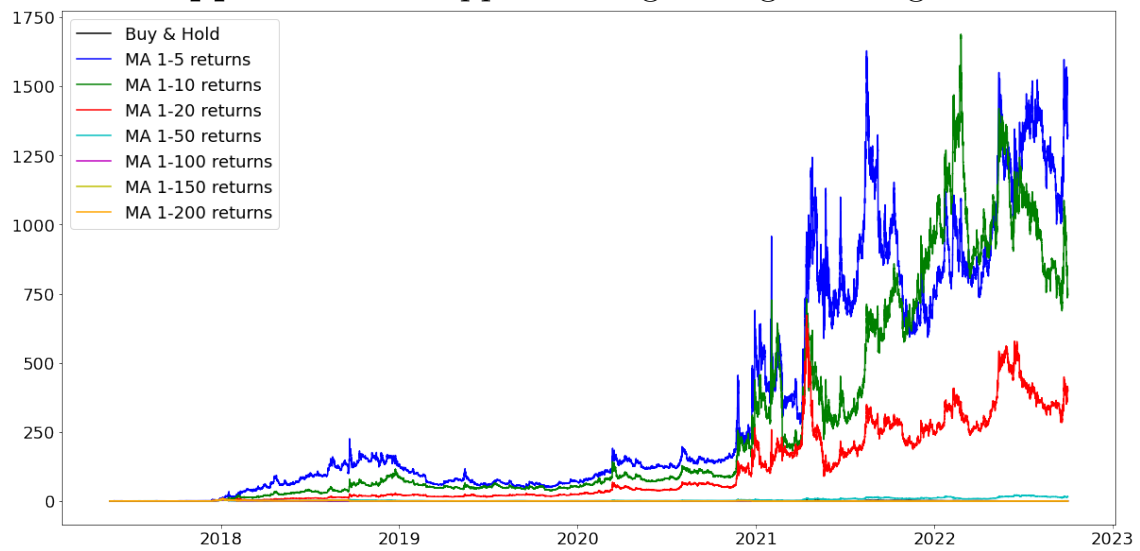
### Appendix C10 Ethereum rate of change trading



### Appendix D1 Ripple moving average trading 1-x (long or out)

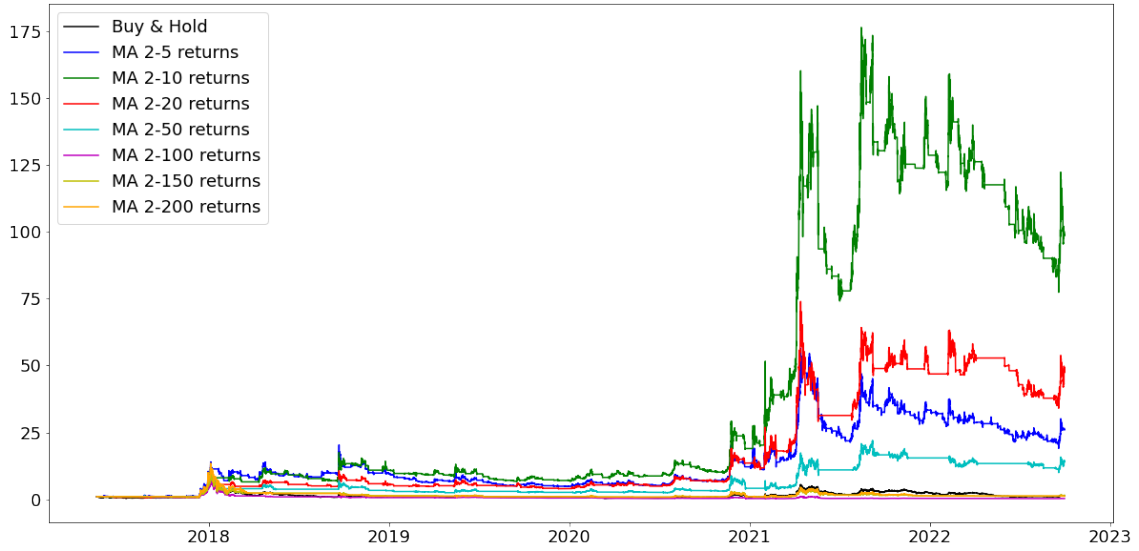


### Appendix D2 Ripple moving average trading 1-x

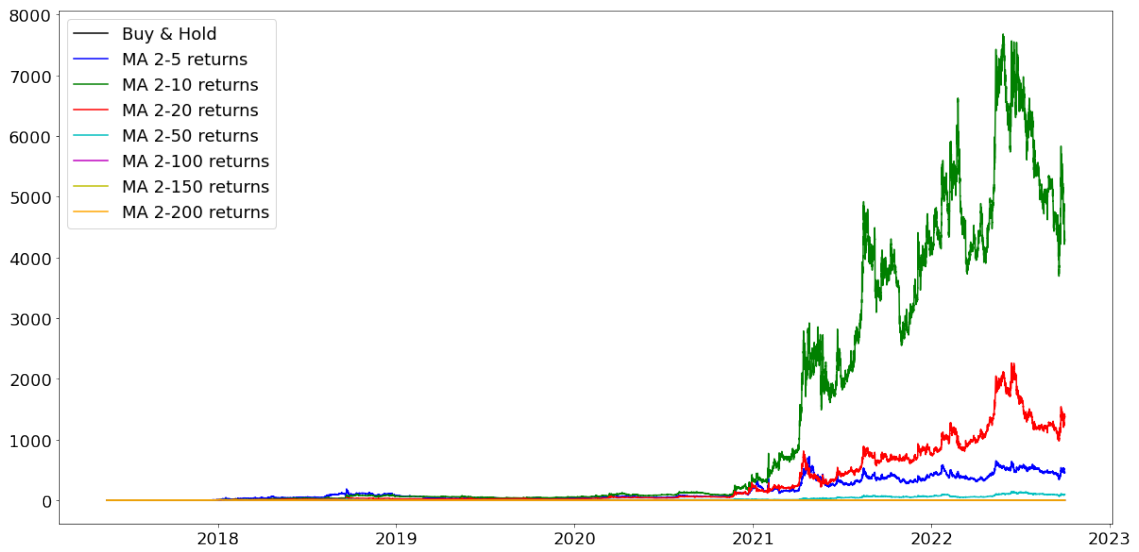




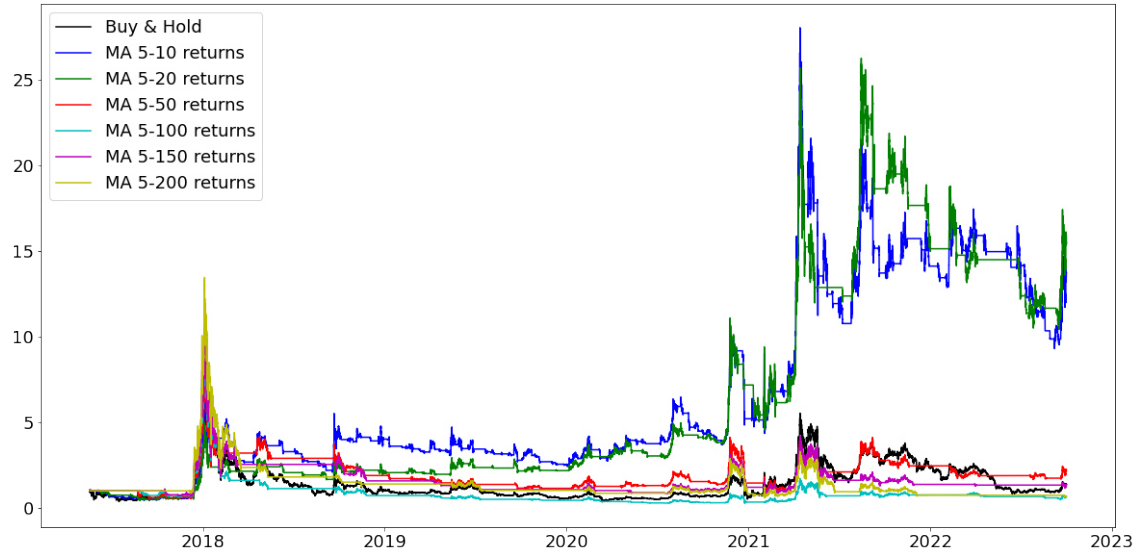
### Appendix D3 Ripple moving average trading 2-x (long or out)



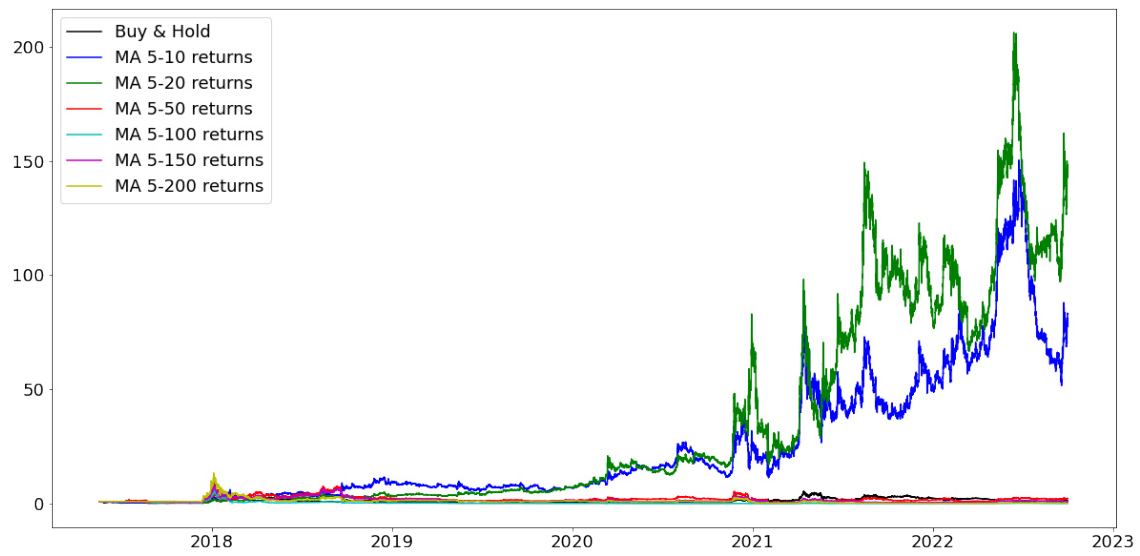
### Appendix D4 Ripple moving average trading 2-x



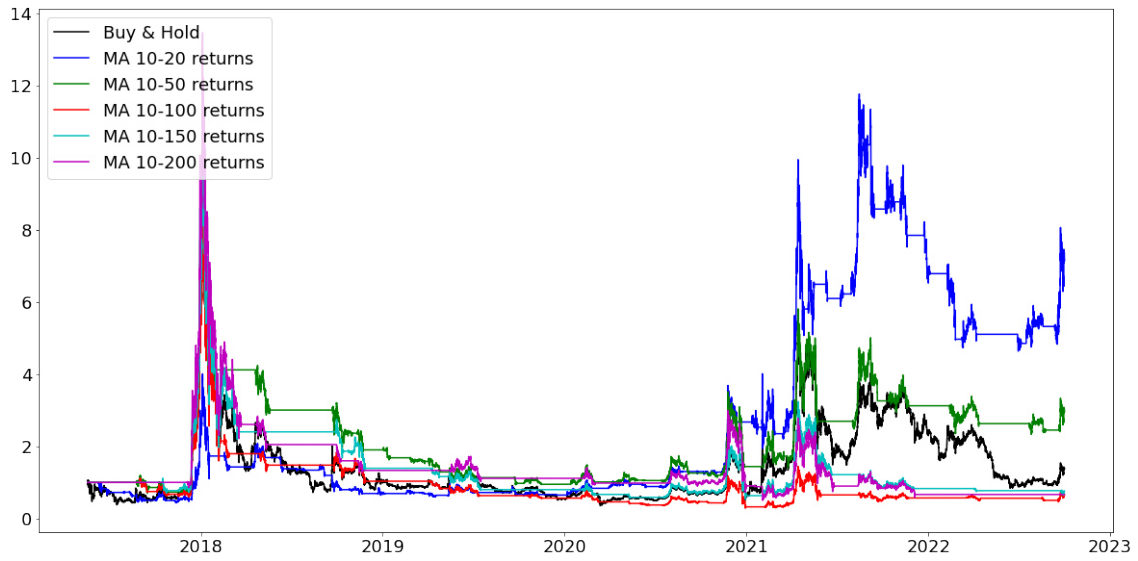
### Appendix D5 Ripple moving average trading 5-x (long or out)



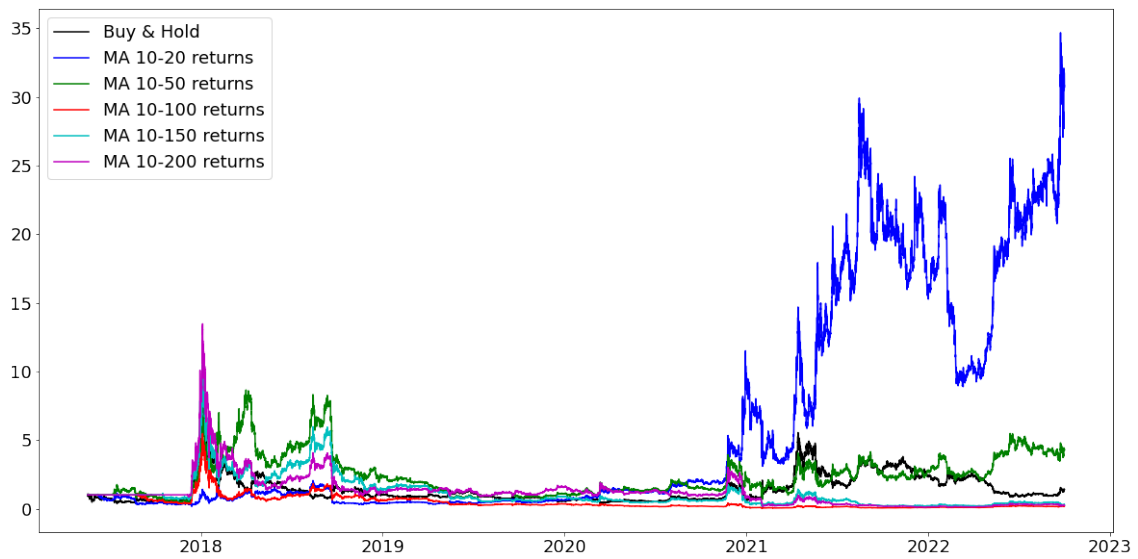
### Appendix D6 Ripple moving average trading 5-x



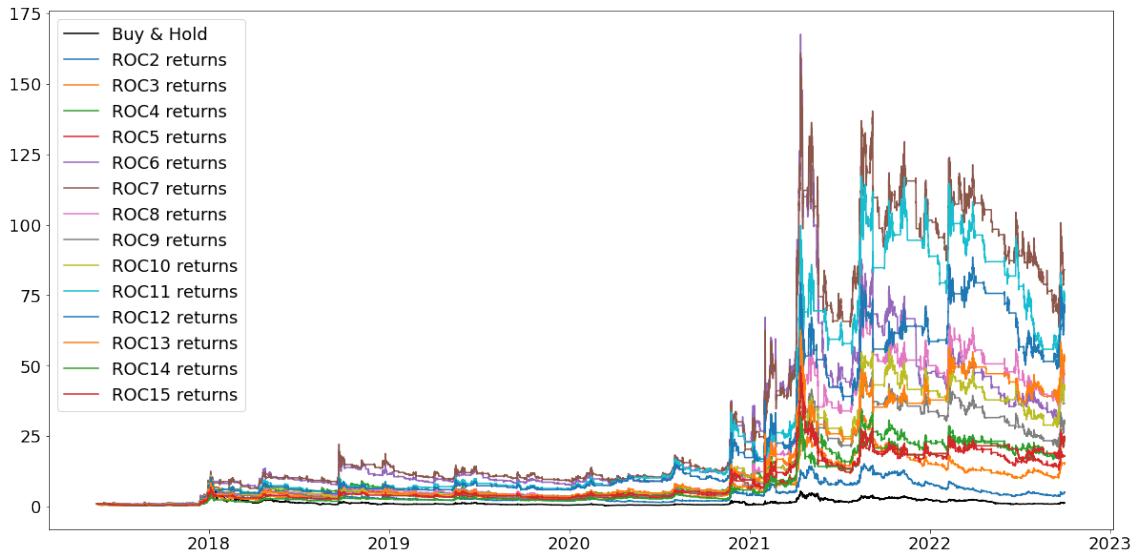
### Appendix D7 Ripple moving average trading 10-x (long or out)



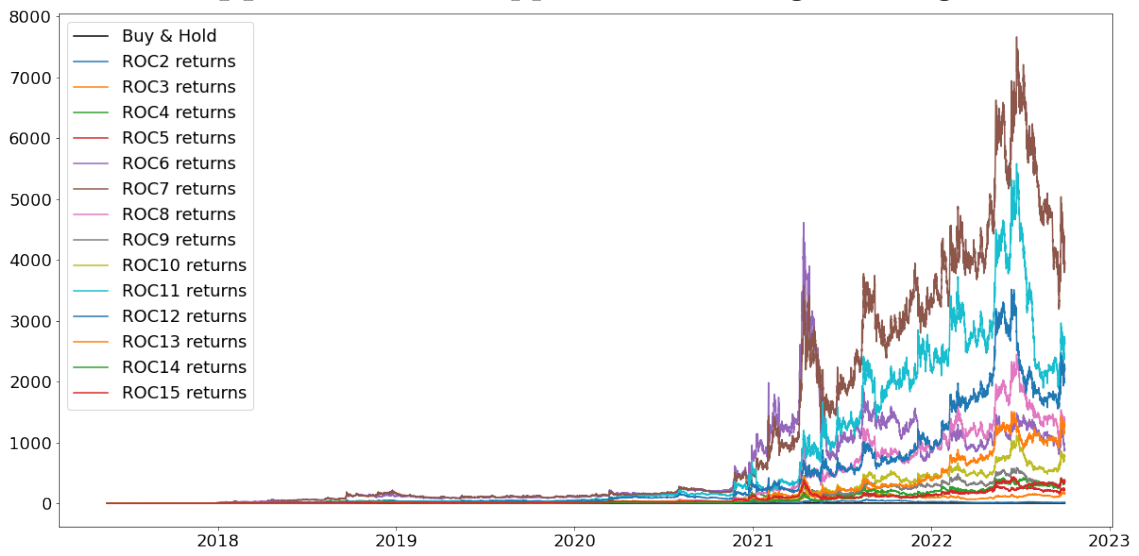
### Appendix D8 Ripple moving average trading 10-x



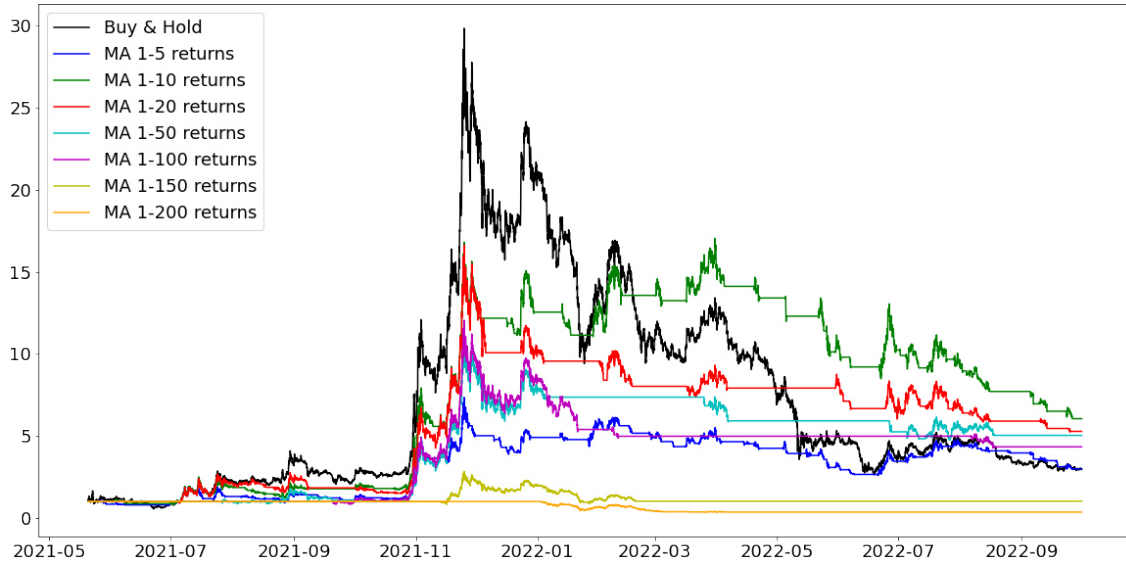
### Appendix D9 Ripple rate of change trading (long or out)



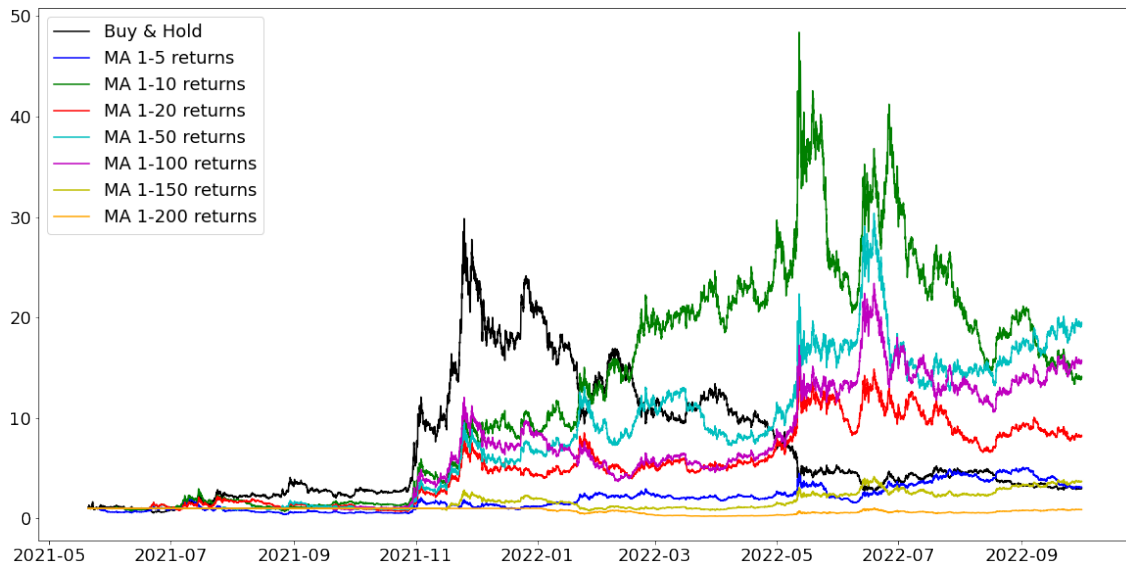
### Appendix D10 Ripple rate of change trading



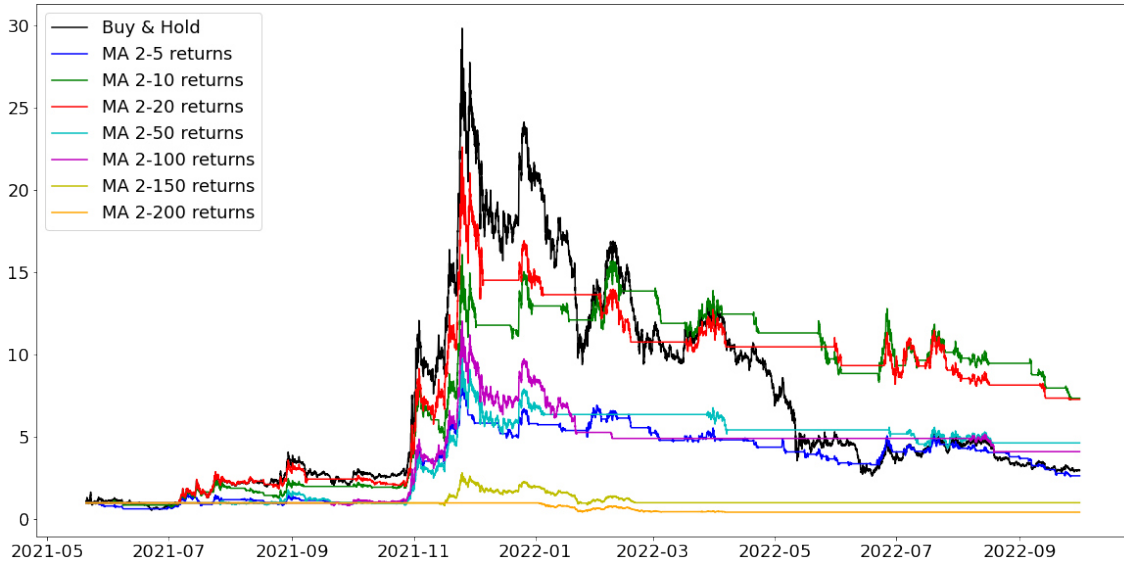
### Appendix E1 Sandbox moving average trading 1-x (long or out)



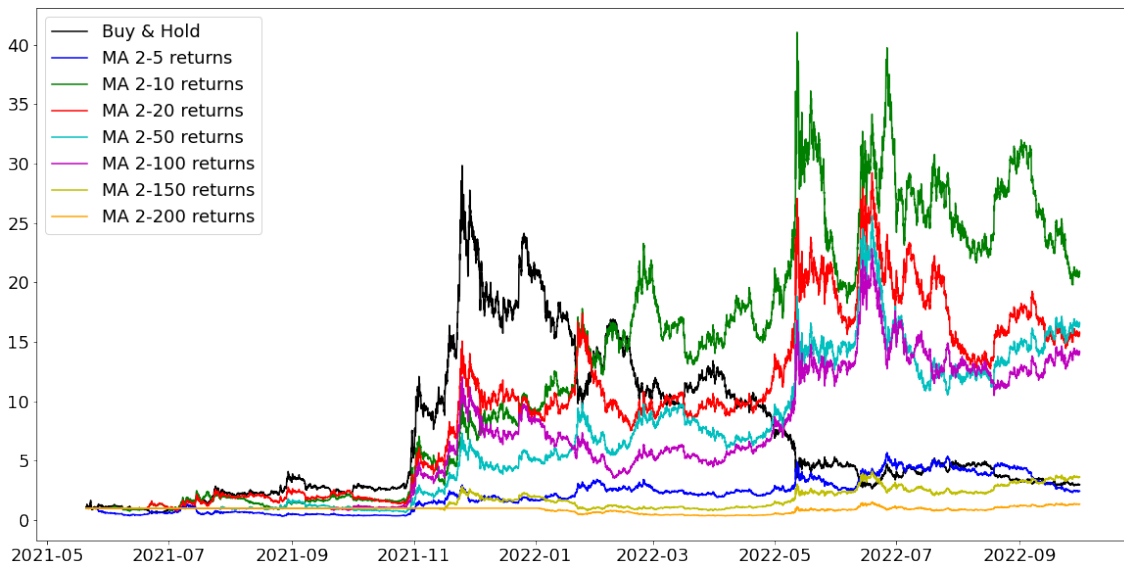
### Appendix E2 Sandbox moving average trading 1-x



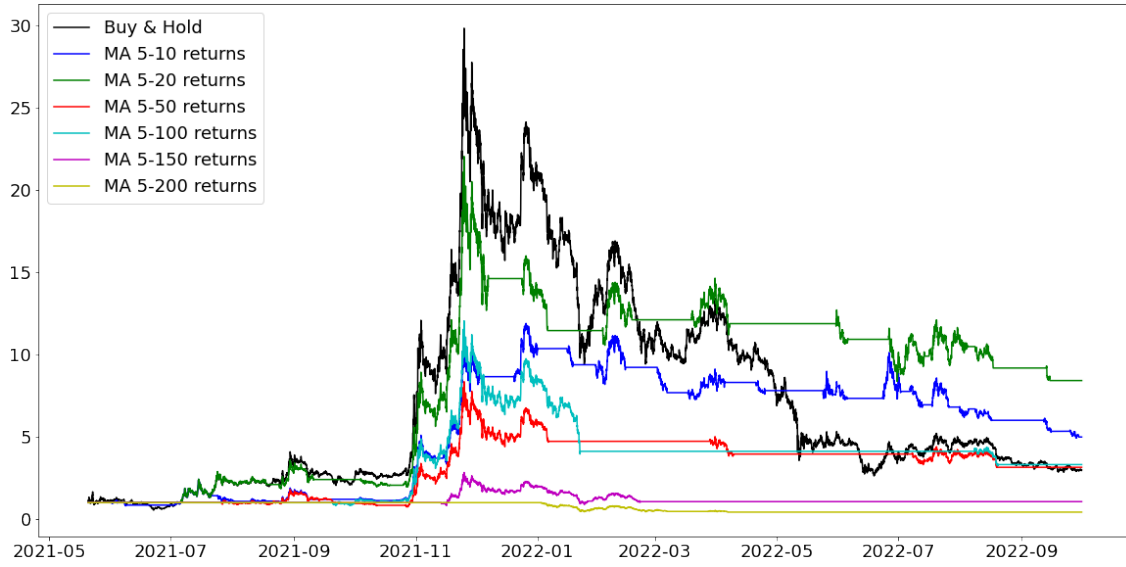
### Appendix E3 Sandbox moving average trading 2-x (long or out)



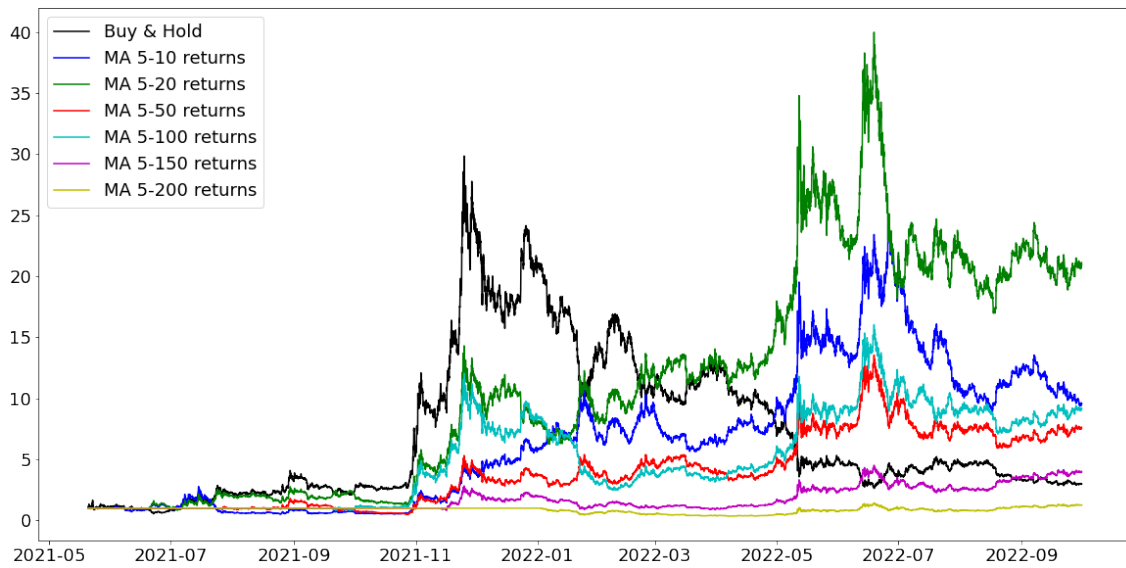
### Appendix E4 Sandbox moving average trading 2-x



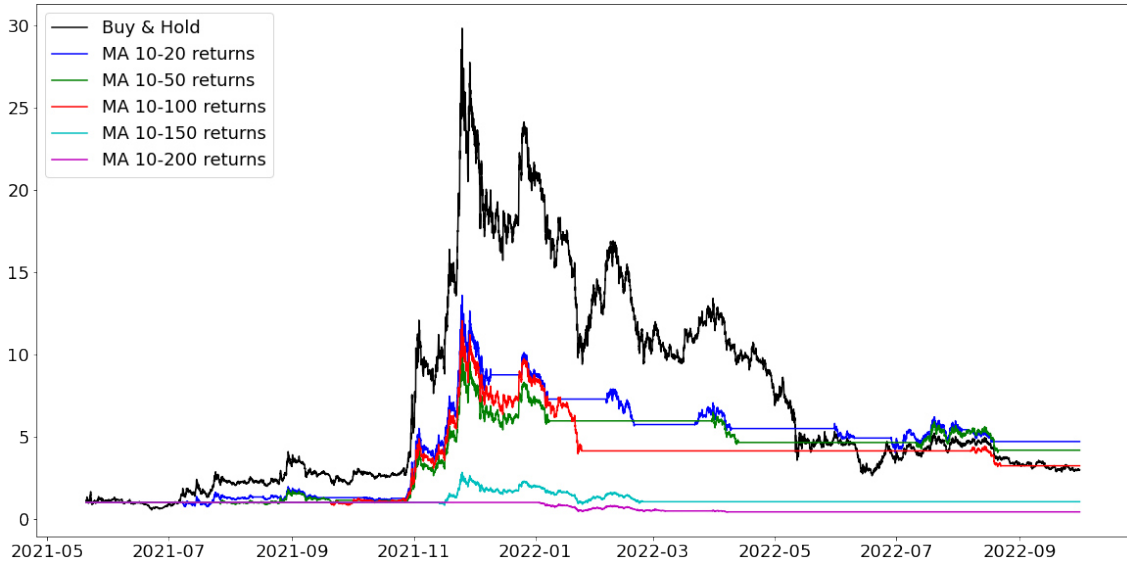
### Appendix E5 Sandbox moving average trading 5-x (long or out)



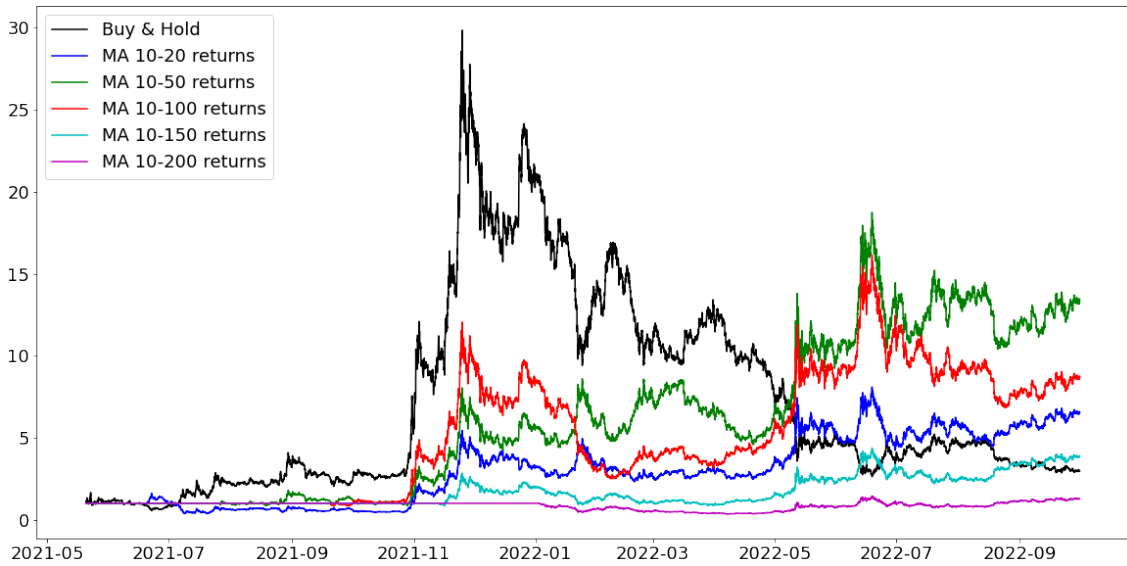
### Appendix E6 Sandbox moving average trading 5-x



### Appendix E7 Sandbox moving average trading 10-x (long or out)

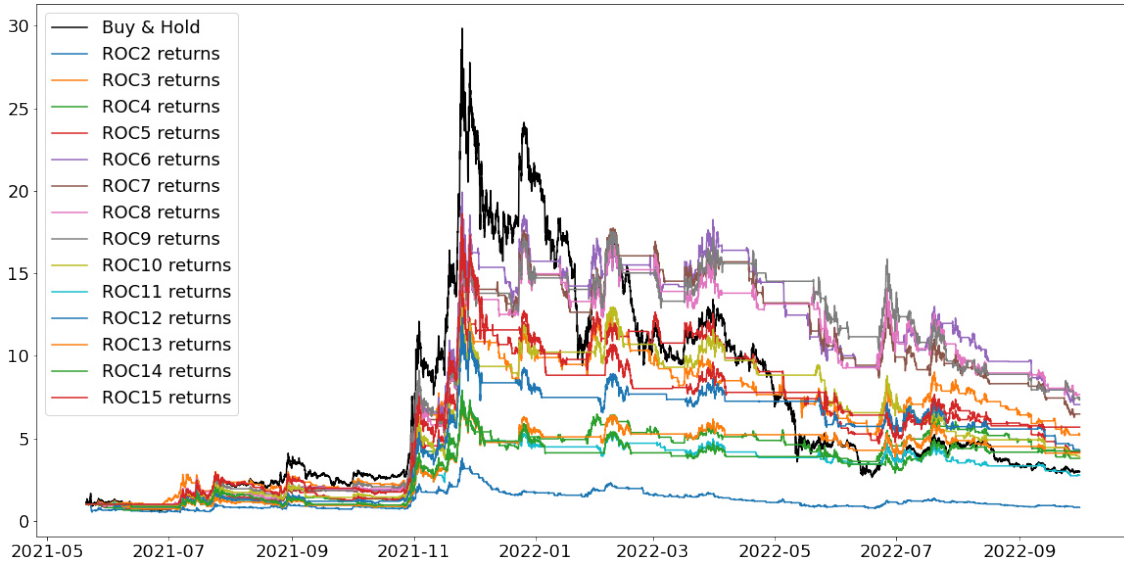


### Appendix E8 Sandbox moving average trading 10-x

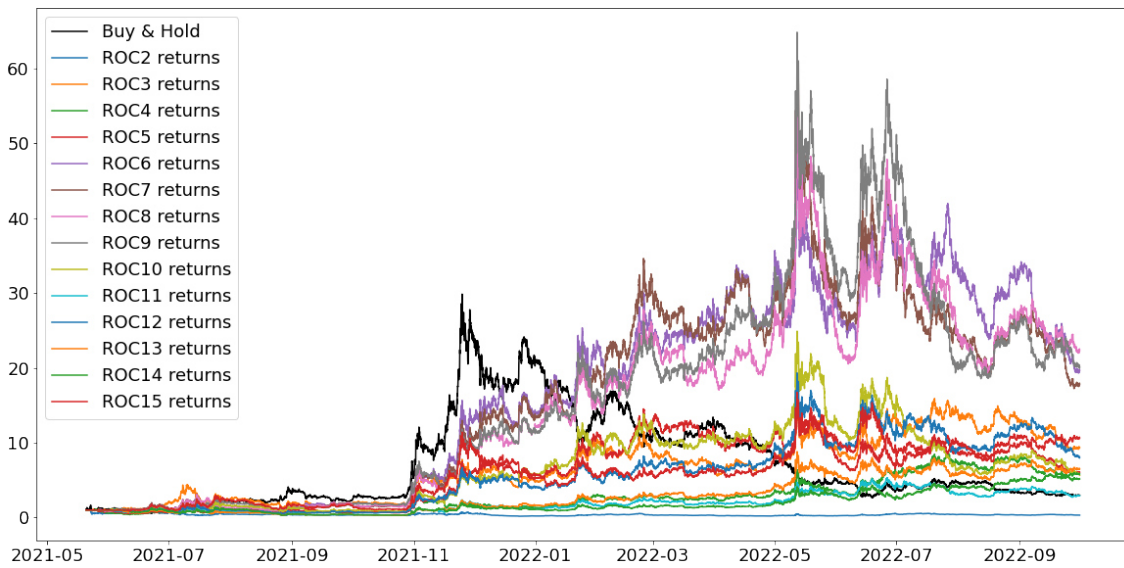




### Appendix E9 Sandbox rate of change trading (long or out)



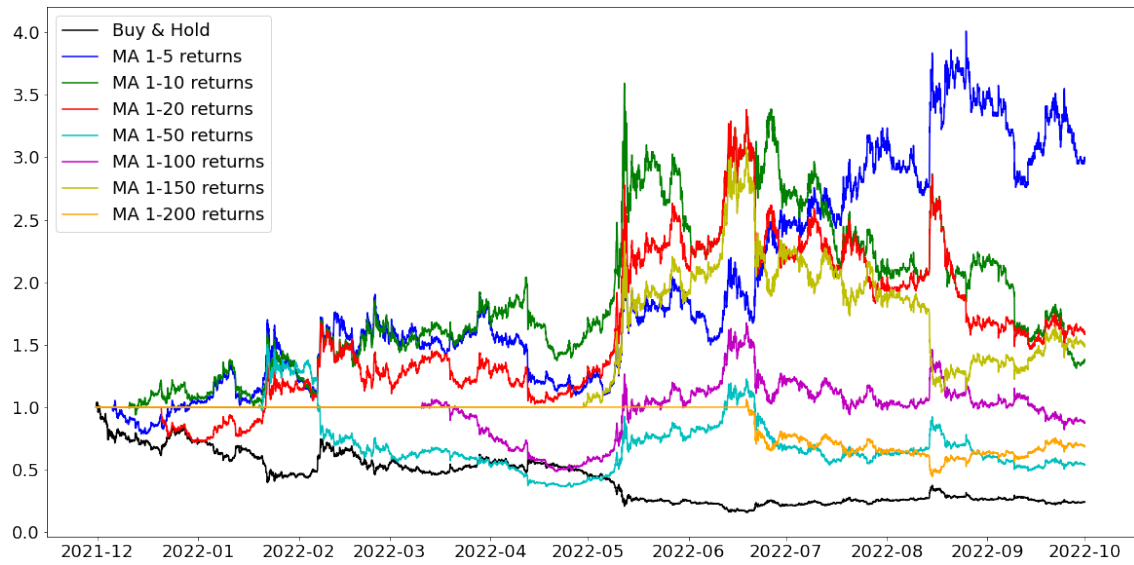
### Appendix E10 Sandbox rate of change trading



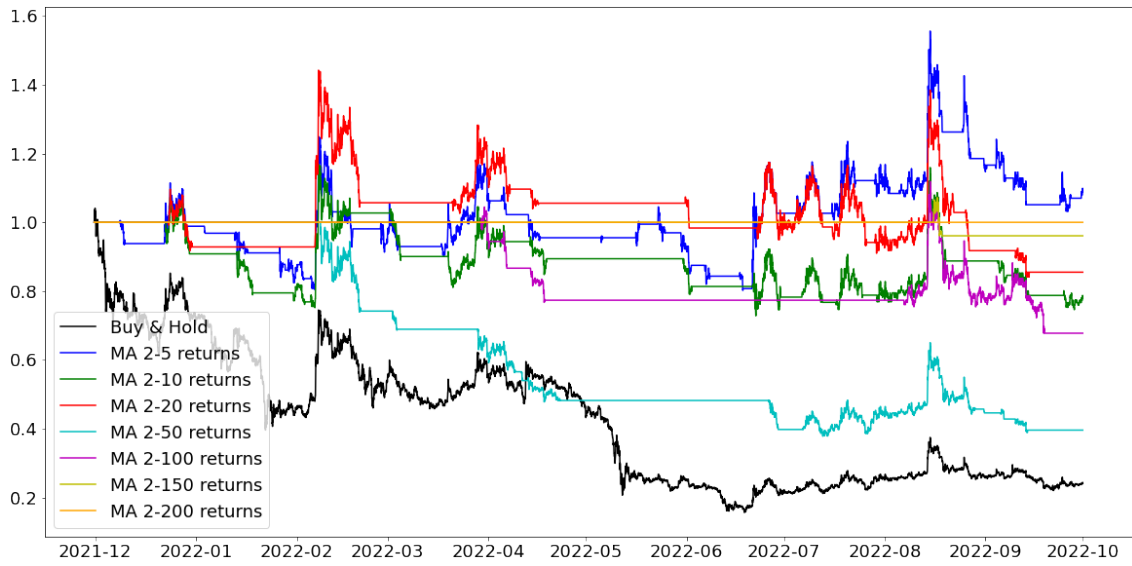
### Appendix F1 Shiba Inu moving average trading 1-x (long or out)



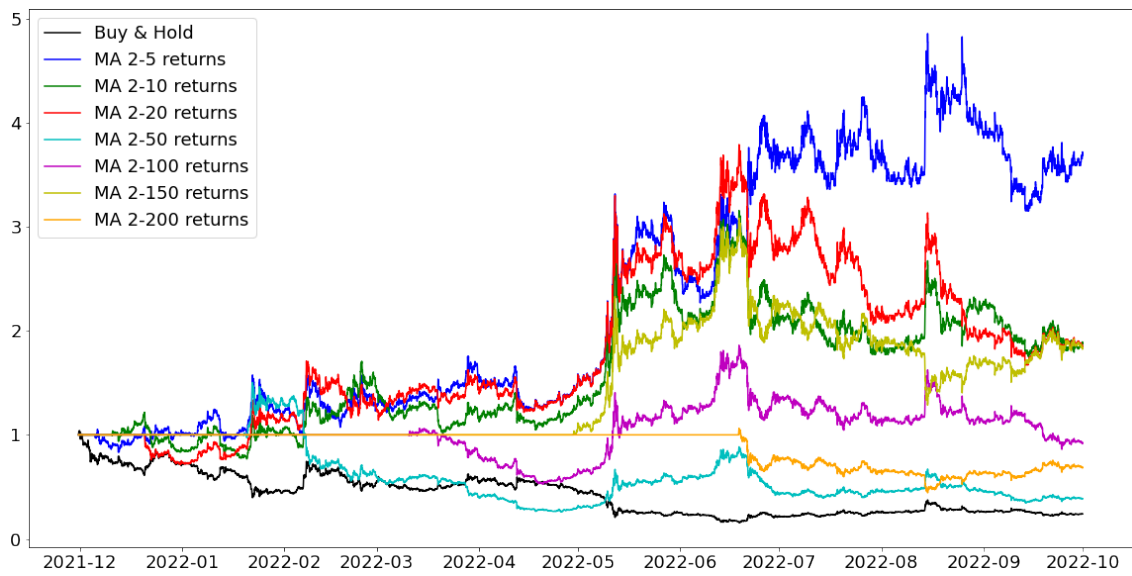
### Appendix F2 Shiba Inu moving average trading 1-x



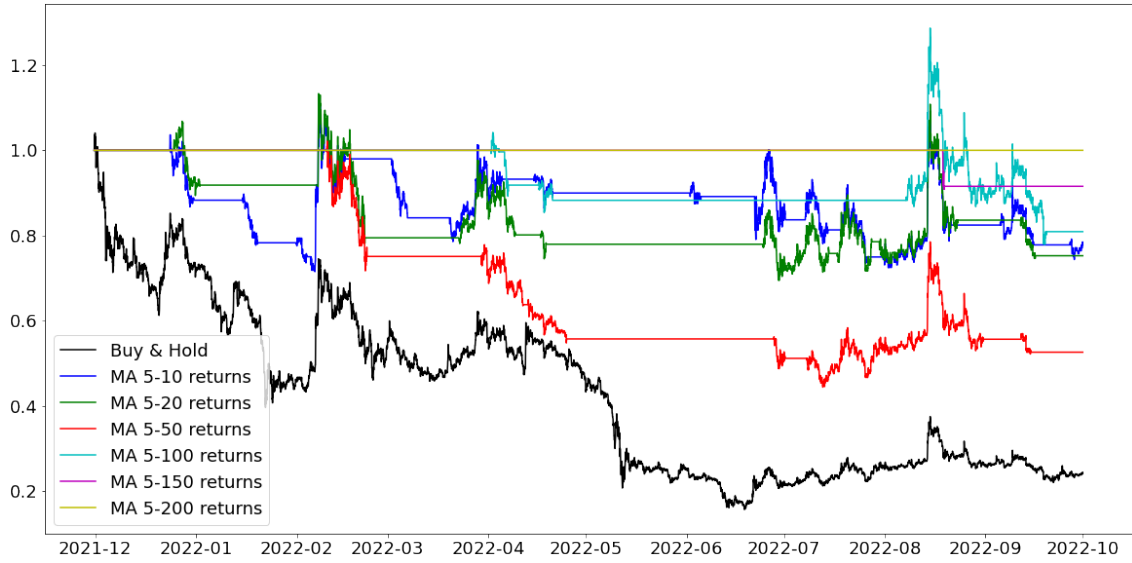
### Appendix F3 Shiba Inu moving average trading 2-x (long or out)



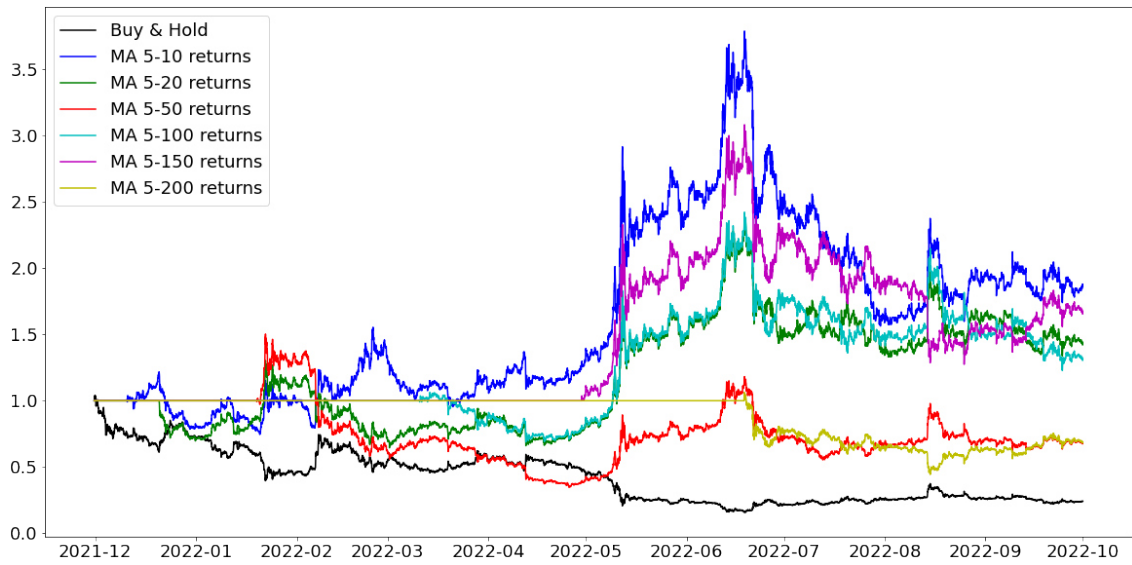
### Appendix F4 Shiba Inu moving average trading 2-x



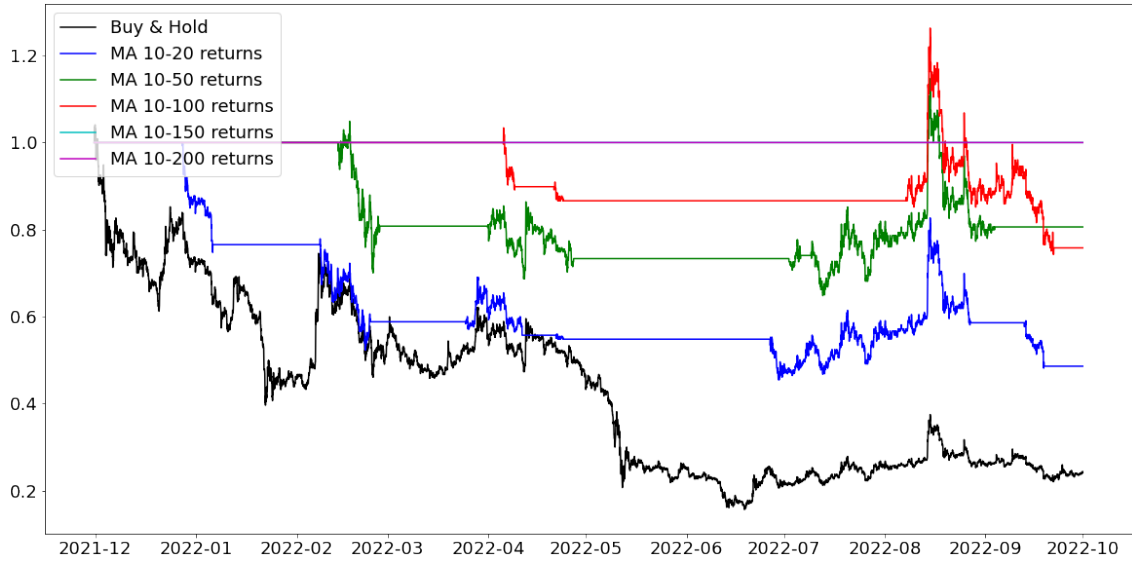
### Appendix F5 Shiba Inu moving average trading 5-x (long or out)



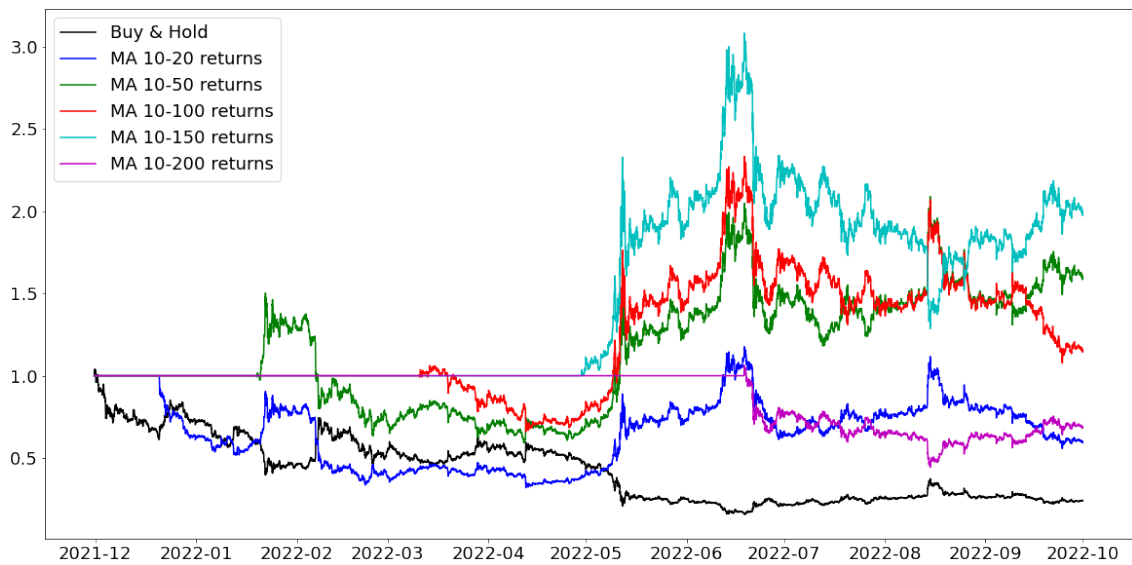
### Appendix F6 Shiba Inu moving average trading 5-x



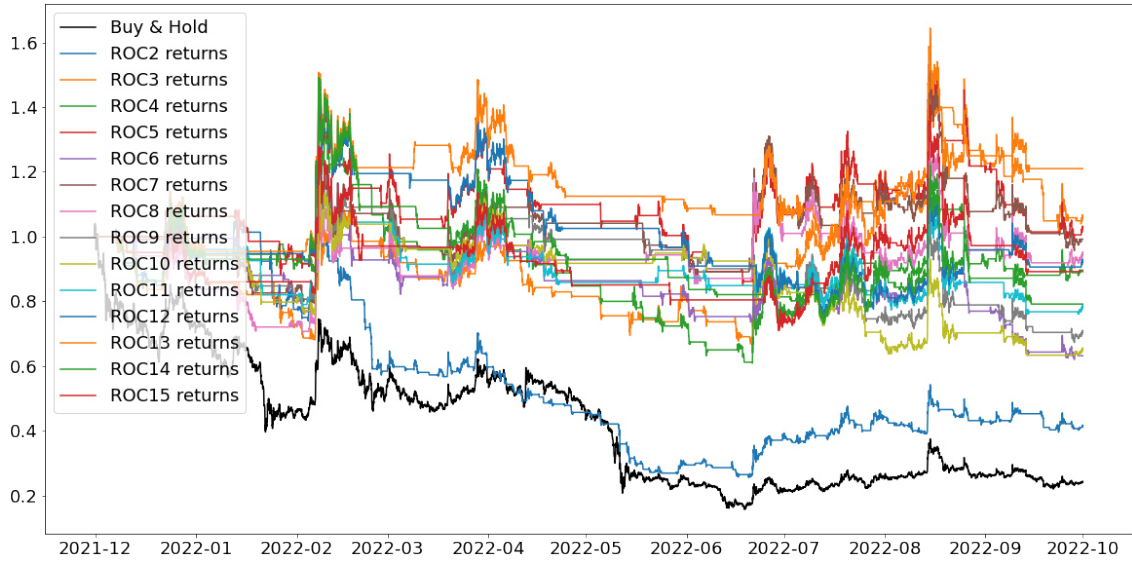
### Appendix F7 Shiba Inu moving average trading 10-x (long or out)



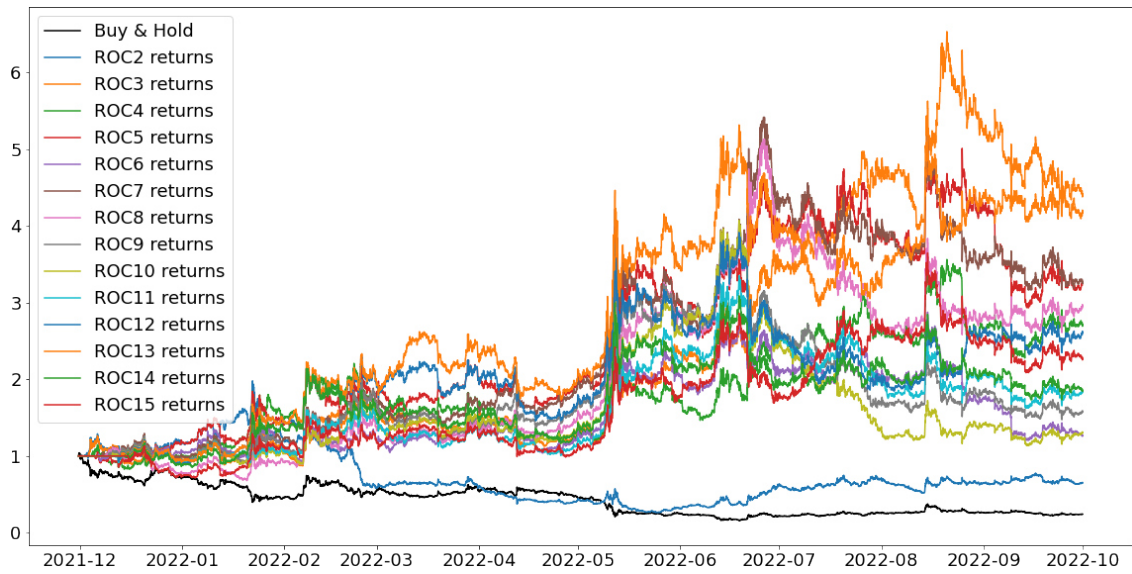
### Appendix F8 Shiba Inu moving average trading 10-x



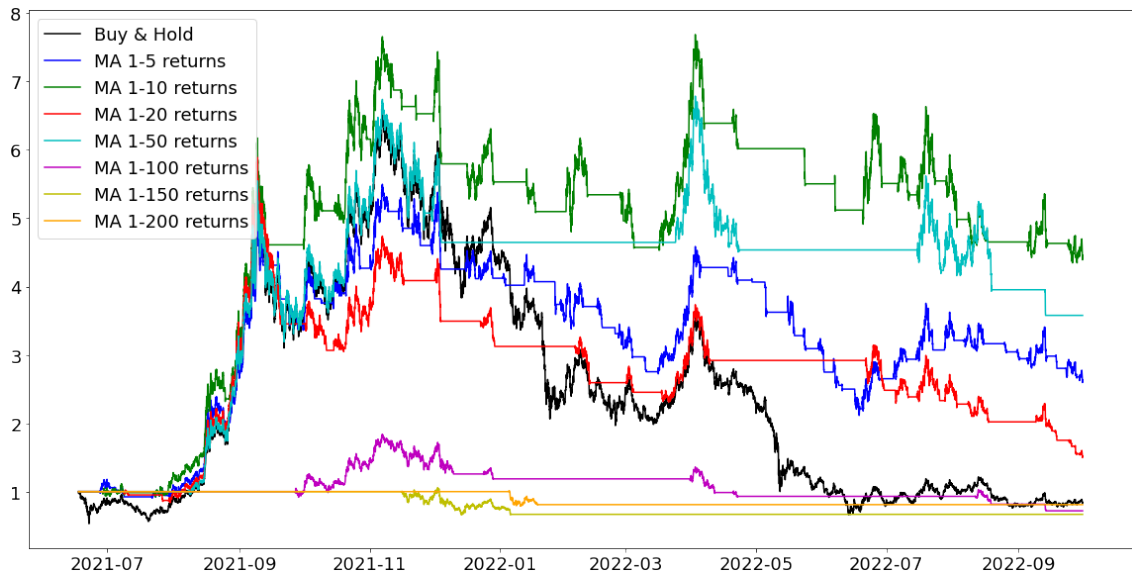
### Appendix F9 Shiba Inu rate of change trading (long or out)



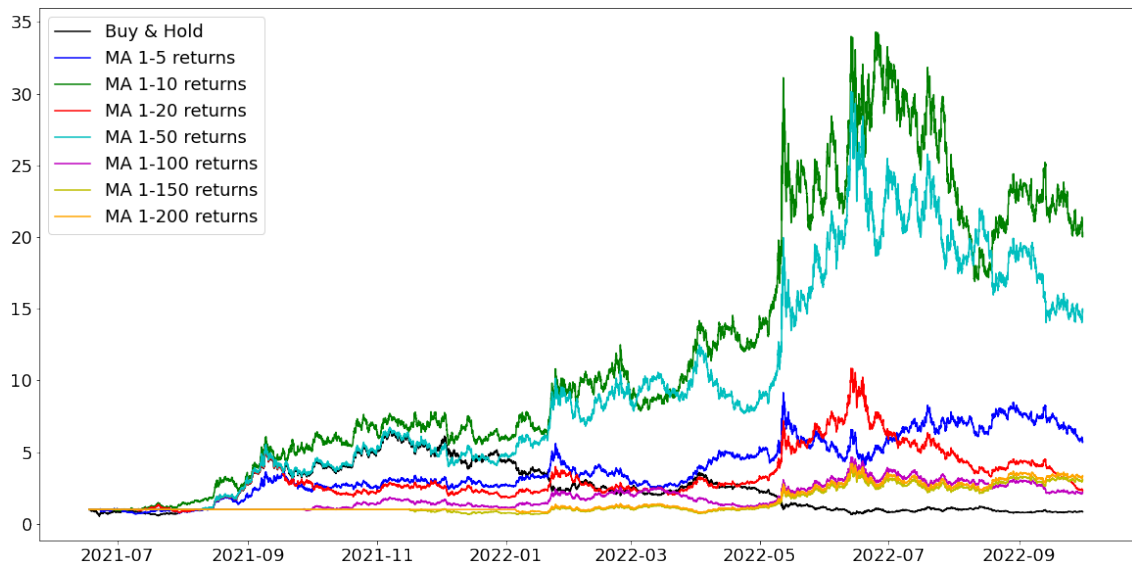
### Appendix F10 Shiba Inu rate of change trading



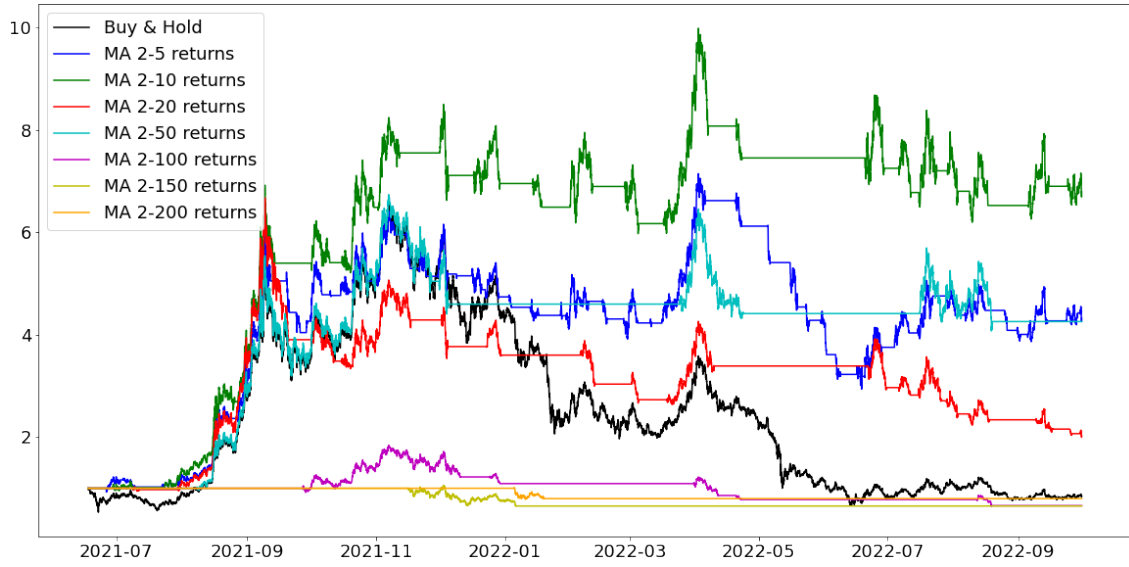
### Appendix G1 Solana moving average trading 1-x (long or out)



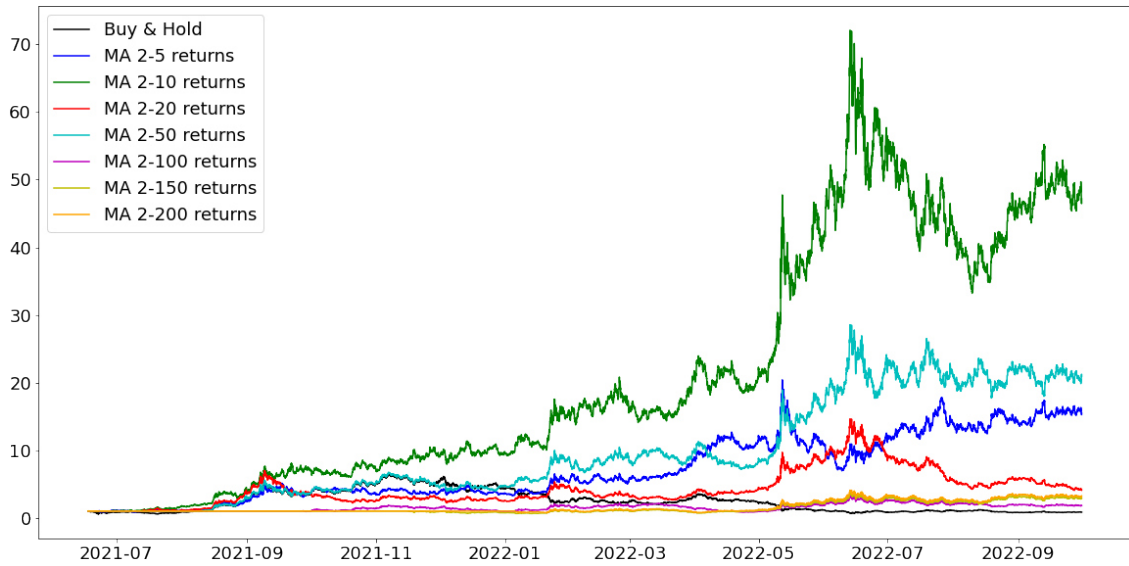
### Appendix G2 Solana moving average trading 1-x



### Appendix G3 Solana moving average trading 2-x (long or out)



### Appendix G4 Solana moving average trading 2-x

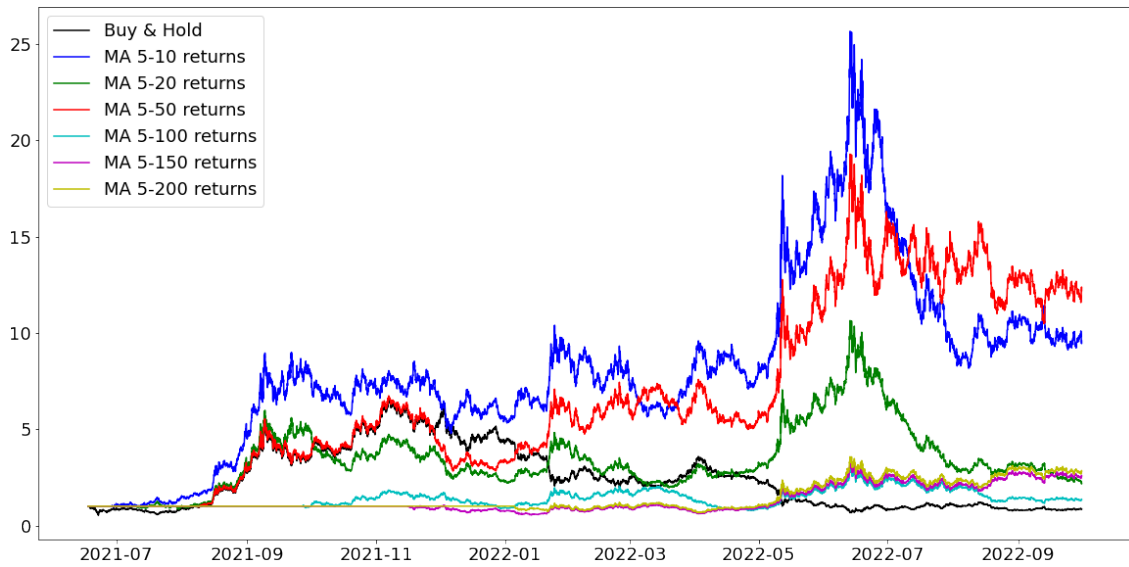




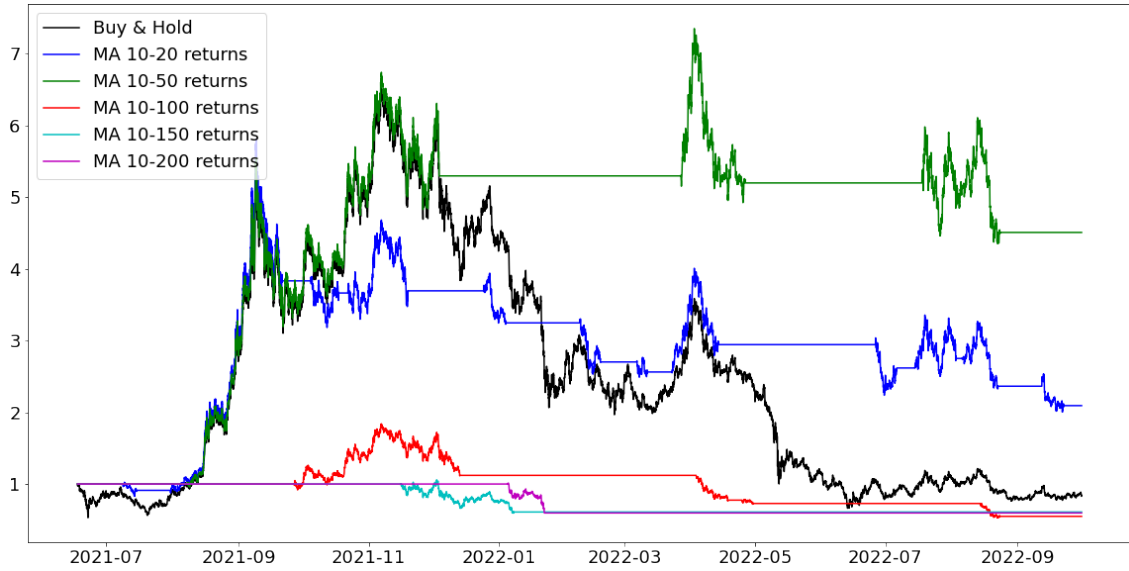
### Appendix G5 Solana moving average trading 5-x (long or out)



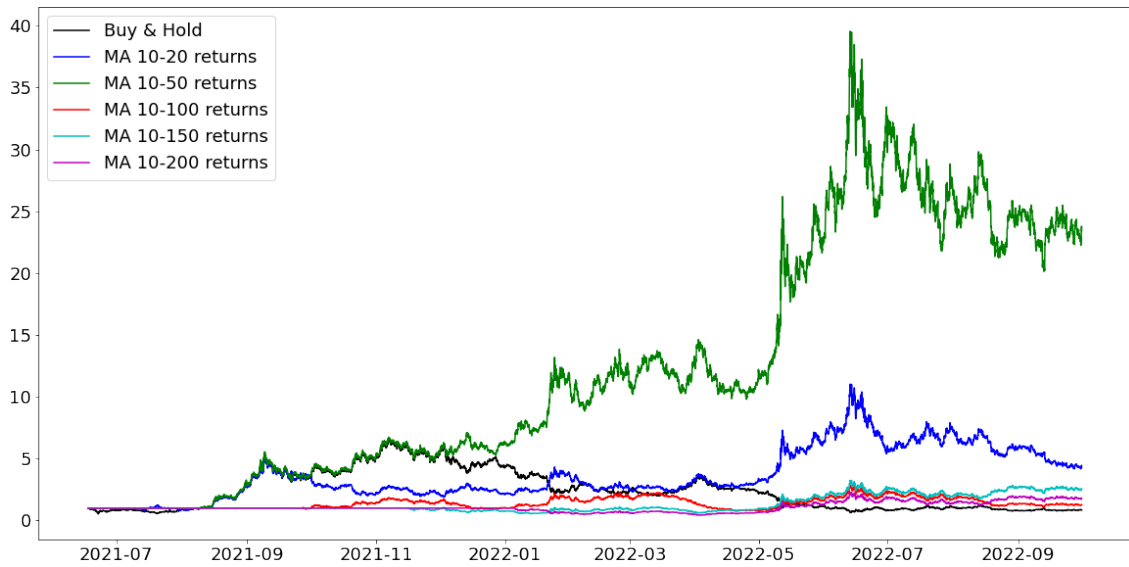
### Appendix G6 Solana moving average trading 5-x



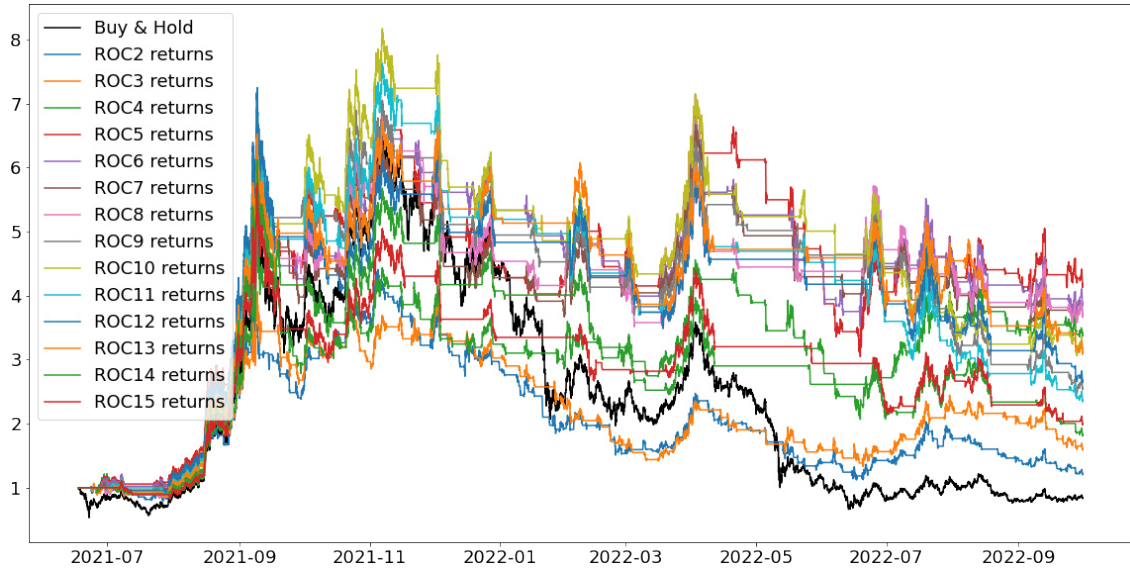
### Appendix G7 Solana moving average trading 10-x (long or out)



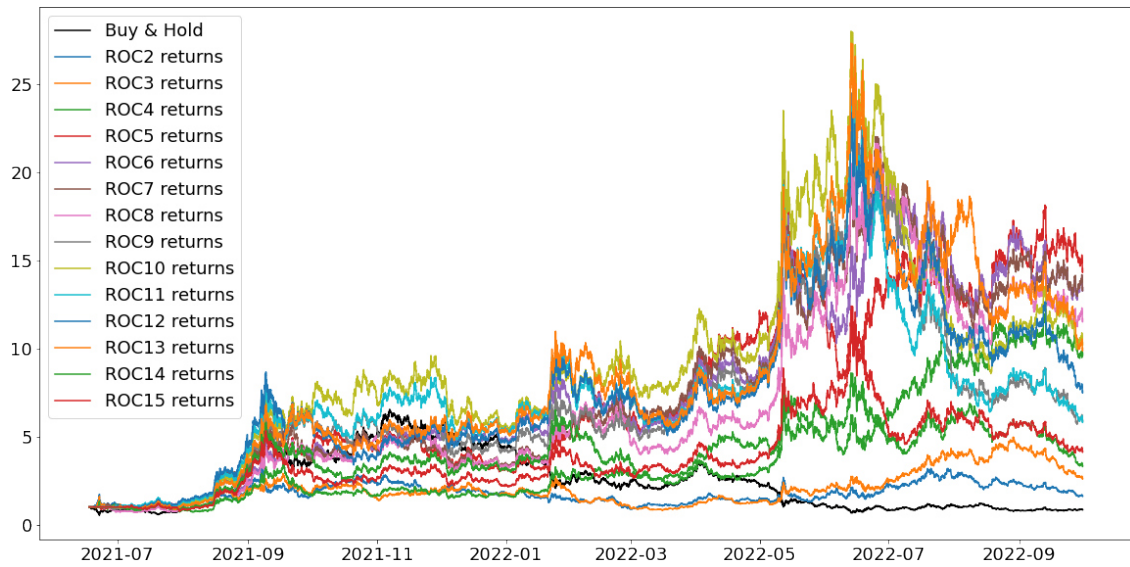
### Appendix G8 Solana moving average trading 10-x



## Appendix G9 Solana rate of change trading (long or out)



## Appendix G10 Solana rate of change trading



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