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Bachelor Thesis

Technical Trading with the Strongest Trading Signal in the Cryptocurrency Market: A Day-to-day Analysis

Winston Bartle (12768928)
winston.bartle@student.uva.nl

Daniel Roelfsema (Supervisor)
d.roelfsema@uva.nl

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Statement of Originality

This document is written by Winston Bartle (12768928) who declares to take full responsibility for the contents of this document.

I declare that the text and the work presented in this document are original and that no sources other than those mentioned in the text and its references have been used in creating it.

The Faculty of Economics and Business is responsible solely for the supervision of completion of the work, not for the contents.

Acknowledgement and Dedication

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Abstract

Never before has the importance of technical trading indicators in asset markets been more evident than it is today as the cryptocurrency market's high daily volatility portends either big investment returns or losses. This study looked at the profitability of day-trading the strongest signalling cryptocurrencies using five trading indicators. The strongest signal was established using two ways, both of which are based on imposing additional limits on previously established technical trading rules. According to the Sharpe Ratio, a 'combined signal' method outperformed the buy-and-hold strategy of the top six (by market capitalization) cryptocurrencies. However, using data from two additional cryptocurrency utility categories, the 'combined signal' technique, despite providing a higher Sharpe Ratio, was statistically insignificant by bootstrapping, indicating possible market efficiencies. This article also looked at its own definition of the strongest signal by comparing relative signals across several coins. The results, however, did not show a substantial out-performance over the buy-and-hold strategy.

Keywords— Technical Trading Rules, Cryptocurrency, Sharpe Ratios, Strongest Signal, Bootstrapping

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1 Introduction

Bitcoin's value has increased by more than 8,000 percent since its inception in 2009 as the world's first decentralized currency (Nakamoto, 2008). Bitcoin, a digital money that can only be exchanged via the internet, has benefited from the unprecedented rise in access to digital technology brought about by the mobile phone boom. Even though majority are low market capitalization and "minor" coins, about 20,000 additional digital cryptocurrencies are exchanged globally 24 hours a day.

As the market becomes flooded with new coins investors proliferate in an effort to find new coins they can at least replicate a portion of the gains Bitcoin experienced. As most are speculators who mostly do not understand the fundamentals of the coins chosen, Technical Analysis (TA) has never been more important in the discipline of trading. Originating in its earlier forms in 17th century Amsterdam, the modern TA is frequently attributed to Charles Dow's work. He was among the first to notice that individual assets and markets frequently move in trends that could be segmented and investigated. This scientific approach was used by traders to select suitable assets to trade as well as estimate and forecast future stock prices. It could also be utilized to determine entrance and exit positions, allowing for high returns. To date, there are thousands of different technical indicators available to use, which begs the question - which indicator should investors use to achieve the greatest returns? How accurate are the existing indicators? It would make sense to then alleviate the burden on investors by utilizing these signals to create a freshly enhanced, strongest signal.

Traditionally day-traders look for the most volatile stock in the most volatile markets available to them. Given the newness of cryptocurrencies and the absolute numbers of new investors marching in and out of coins by the hour, volatility is guaranteed 24 hours a day on every cryptocurrency exchange. Using effective day-trading strategies investors may comprehend and utilize this volatility to generate profits. This is further supported from previous literature that heightened volatility results in higher average Bitcoin returns (Thies & Molnár, 2018).

This study evaluated if daily purchasing and selling of the cryptocurrency with the strongest signal can beat a buy-and-hold strategy of a diversified portfolio of cryptocurrencies of identical weighting. The paper defined the strongest signal in two ways: first, by selecting only the coin with the strongest relative trading rule signal, and second, by selecting the coins for which at least a certain percentage of the 11 distinct trading rules suggest a buy signal. Various parameters were implemented for the Simple Moving Average, Trading Range Breakout, Moving Average Convergence Divergence, Rate of Change, and Bollinger Bands in this study. The performances of the strategies were computed using the Sharpe Ratio which was further simulated by using Ledoit and Wolf (2008)'s bootstrapping approach to draw statistical inference.

In this four-part thesis, the paper starts off by reviewing significant findings in literature reported over the years. Subsequently, in chapter 3, the various technical indicators on which our ultimate models are based on are outlined. As well in that chapter, we explained the source of our data and the performance metric used to evaluate and compare the different trading strategies. At Chapter 4 the results of trading on our strategy of purchasing the strongest signaled coins are presented. The chapter is split into two sections: firstly the results obtained when our strongest signal was defined by what we call the Strongest Relative Signal method, and secondly, the results obtained when our strongest signal was defined by a Combined Trading Signal approach. Chapter 5 describes in-depth our findings as well as the limits of our research, along with suggestions for future research.

2 Theoretical Framework

Traders seeking an income from the trading of financial assets usually position themselves in one of two camps, either the fundamentalist or the technical analyst. The former arrives at an intrinsic value of the target asset by reviewing its macro and micro economic environment against its actual performance but in the case of cryptocurrencies, intrinsic value data sources are unclear due to the lack of history and predictive signals (Detzel, Liu, Strauss, Zhou, & Zhu, 2021). The technical analyst seeks to predict price movements by analyzing the market data captured over the lifespan of the target asset such as historical prices and volumes. Cryptocurrency investors tend to focus on the technical aspect of trading.

Seven notable technical trading strategies were applied to the daily Bitcoin closing prices from July 17, 2010 to December 31, 2018, by Gerritsen, Bouri, Ramezanifar, and Roubaud (2020) including Moving Average and Trading Range Breakout (Brock, Lakonishok, & LeBaron, 1992), Moving Average Convergence Divergence (J. J. Murphy, 1999), Rate of Change (Taylor & Allen, 1992), On-balance Volume (Granville, 1963), Relative strength index (Wong, Manzur, & Chew, 2003), and the Bollinger Band method (Bollinger, 2002), resulting in guidelines that suggest to the investor if a bullish or bearish trend is likely. The Sharpe Ratio performance of each rule was assessed. Throughout the study, which included periods of intense market action, only one of the seven, namely the Trading Range Breakout rule, regularly outperformed the buy-and-hold strategy. It was postulated the reason for this could be that breakout trading allows investors to take positions in the early phases of a trend. If that proves true, this method can be a catalyst for significant price movements.

Additionally, Corbet, Eraslan, Lucey, and Sensoy (2019) studied the Moving Average and Trading Range Breakout rules using minute-scale data on Bitcoin returns. The Moving Average rule offered statistically significant and worthwhile indications with purchase signals outperforming sell signals. Hudson and Urquhart (2021) discovered, with over 15000 trading rules, that predictability is absent for Bitcoin in the out-of-sample period, but persists for three other cryptocurrencies. Moreover, Grobys, Ahmed, and Sapkota (2020) explored the Moving Average rule on 11 cryptocurrencies with data between 2016 and 2018 by starting a purchase order when indicated and holding it until a sell signal is suggested. Grobys et al. (2020) found that a 20-day Moving Average rule generated a greater return when compared to a buy and hold strategy, particularly when trading range breakout and Moving Average signals are executed immediately. However, employing a strategy that is too simple, such as spontaneous action after receiving a signal, as was done by many older studies, may be too elusive when potential transaction costs and price slippages are considered.

To date, few papers have examined the profitability of trading rules that operate across both Bitcoin and Altcoins (coins or cryptocurrency initiatives other than Bitcoin). Examining the profitability of passive Bitcoin investing (hodling is now the accepted term) against investing in an equal-weighted cryptocurrency portfolio, Rantanen et al. (2015) found that the diversification exceeded their Sharpe Ratio. Furthermore, the Sharpe Ratio exceeded that achieved on a single investment into Bitcoin. Jiang and Liang (2017) extended earlier research by utilizing Deep Reinforcement Learning to build an ideal trading strategy profile on the top 100 coins of the cryptocurrency market. The research was found to have generated a return ten times that of a standard diversified investment in less than two months. However, that technique demands computer power that is largely out of the reach of the general population. This prompted Rohrbach, Suremann, and Osterrieder (2017) to investigate whether basic momentum trading on a cryptocurrency portfolio can produce equally high returns. Their study used an Exponential Moving Average indicator with varying smoothing ratios on a cross-sectional portfolio of six cryptocurrencies where three coins are purchased and three are sold during each re-balancing period. The relative intensity of the application of the momentum rules dictated purchase and sell signals and the results produced astonishingly high returns.

When comparing the two strategies used in Rohrbach et al. (2017), the author demonstrated that momentum strategies yielded a greater risk-adjusted return. The research was done on the assumption that returns are normally distributed. Such an assumption is not wholly applicable when returns are time-series in nature due to the presence of volatility clustering in financial assets. Compounding the potential error in the normal distribution assumption is the fact that Rohrbach et al. (2017) conducted their analysis across six cryptocurrencies (one of which is no longer traded today) between 2014 and 2017, a time period when cryptocurrencies were viewed as highly speculative assets (Kristoufek, 2013).

Various previous studies have found mixed performance of different trading rules, with Grobys et al. (2020); Corbet et al. (2019) identifying Moving Average as the most informative trading rule while Gerritsen et al. (2020) identified Trading Range Breakout and Moving Average Convergence Divergence as the most profitable. Because of this discrepancy it is difficult to generalize which technical trading rule an investor should employ. This is particularly pertinent given that there is no theory to guide an investor's decision on the numerous trading rules. For instance, there is no theoretical justification for using the Moving Average rule over the Bollinger Band rule. This is further reiterated by numerous academics and analysts who claimed that a single trading rule alone should not be used to make trading decisions (J. Murphy, 2012).

Consequently, it makes sense to integrate these distinct technical trading indications in order to aid the individual investor. Previous research (Lento, Gradojevic, et al., 2007) has explored such methods of combining signals on the DJIA and NASDAQ markets. The paper found that by having at least seven of twelve individual signals issue a buy signal, the combined signal approach was able to generate excess returns against the buy-and-hold strategy in four different markets. A result so intriguing, as the application of a separate trading rule alone was unable to consistently generate excess returns. This shows that by simply using the common trading rules' signal as basis and imposing additional requirements to make the signals consistently stronger, it is possible to realize a bigger profit than would otherwise be attainable.

This research aimed to fill the gap by answering the question: "Is day trading on coins with the strongest technical trading signal, more profitable than buying and holding an equally weighted portfolio of coins?" The paper was designed to prove or disprove the premise that day trading cryptocurrencies using trading rules will result in a different Sharpe Ratio than the purchase and holding of an equally weighted diversified portfolio of coins. Although such a benchmark portfolio may appear simplistic, Brauneis and Mestel (2019) discovered that its Sharpe Ratio surpassed single cryptocurrencies and more than 75 percent of the more robust mean-variance optimal portfolios.

3 Methodology

In this chapter we first discussed the data used and how it was acquired. Then we covered the numerous technical trading rules, their definitions and how this paper defined our model. This was followed by an explanation of the procedures used to answer our research question.

3.1 Data

Historical prices for all coins investigated were obtained on R Core Team (2022) using the package by Stoeckl (2022) which retrieves the data from CoinMarketCap (2022). We used the 3-month US Treasury bills as a proxy for the risk-free rate of return. These daily rates were collected from Fred (2022). As cryptocurrencies, unlike the bond market, are traded seven days a week, the preceding Friday's treasury bill rate is treated as the weekend risk-free rate.

This study focused on the trading of six coins with the strongest trading signal, the signal drawn from the closing price data. This data was confined to the coin's earliest historical data of the list. The first list of six coins considered was the six overall highest cryptocurrencies by market capitalization. Two were eliminated because, having only debuted on August 8, 2020, we felt that by increasing the sample size we could minimize the sampling error. They were replaced by the next two biggest by market capitalization coins.

Numerous studies by Urquhart (2016); Zhang, Wang, Li, and Shen (2018); Bouri, Gupta, and Roubaud (2019); Al-Yahyaee, Mensi, and Yoon (2018) demonstrated that cryptocurrency markets particularly in the early stages are fairly inefficient. Therefore this paper also added two more lists of six largest coins by market capitalization from each of the two categories of Defi and NFT. As these markets imploded in 2020 as a result of Covid-19, it was believed that the markets are very inefficient thereby more meaningful to technical trading. Furthermore the two categories were believed to have had attracted different types of investors. Defi (Schär, 2021) coins are native currencies of decentralized platforms that offer financial services without having to go through brokers or banks via the use of smart contracts on a blockchain. It is clear to be an effective investor of defi one needs to understand the coins's use case implying some knowledge of finance and computing is required. NFT-Metaverse (Kiong, 2022) coins are native currencies of platforms that govern the trading of Non-Fungible-Tokens. They have grown in popularity since 2021, especially among younger investors as this category of coins may appeal to ordinary risk-taking investors and young individuals who enjoy trading in-game collections.

The final list of coins studied together with the date periods used of the respective categories can be found in the appendix of Table 8 along with descriptive statistics of the daily log-returns for each. The mean, variance, skewness, kurtosis, range, median, IQR, and the Shapiro-Wilk normality test statistic (W-stat) were reported. Furthermore the log-prices of the 18 coins are displayed in Figures 4, 5 and 6 of the appendix. The equal-weighted daily log returns for the NFT-Metaverse group are the highest at 1.33% ($t = 4.03$; $p < .001$). The kurtosis for all the coins suggests a leptokurtic distribution. A high W-stat for all the categories of coins rejects the log-returns following a normal distribution.

3.2 Technical Trading Rules

Discussed in this chapter are the characteristics and formulation of the five most common technical trading rules. They serve as the backbone to the models used in this paper in order to help answer our research question.

3.2.1 Simple Moving Average

The first of the five rules used in this paper is the Moving Average rule which has been shown in numerous studies (e.g., Corbet et al. (2019)) to be a helpful indicator. By smoothing the data and generating an average price over a rolling time period n (1), it is possible to discern the direction of current price trends without being influenced by short-term price fluctuations. The Moving Average smoothing function is defined as:

$$MA(P_i)_{t,n} = \frac{1}{n} \left(\sum_{j=t+1-n}^{t} P_{i,j} \right) \tag{1}$$

When the price at time t exceeds the n-period Moving Average, a buy signal is generated. This is visually portrayed on Figure 1, which shows the price-trend of Bitcoin, where the blue line depicts the Simple Moving Average, $MA(P_{\text{Bitcoin}})_{t,15}$. When the price at any given day is above this blue line, a buy signal is signaled.

Figure 1: Moving Average 15 for Bitcoin $MA(P_{\text{Bitcoin}})_{t,15}$

The 15, 20, 30, 50, 100, and 200 day are the most popular time periods. Since our focused is on day trading, the shorter Moving Averages - 15, 30 and 50 were used. As different cryptocurrencies trade at different price ranges, to compare the change in price to its Moving Average, a transformation function is needed. A proposed function ($MA(P_i)^{norm}_{t,n}$), the normalized Moving-Average relative change, is then defined as:

$$MA(P_i)^{norm}_{t,n} = \frac{P_{i,t} - MA(P_i)_{t,n}}{MA(P_i)_{t,n}} \tag{2}$$

In the article by Detzel et al. (2021), the author carried out a predictive regression of the daily Bitcoin return on the log price to Moving-Average ratios. The results showed a positive correlation between the return and the log price to Moving-Average ratios. With this result, this paper defined the strongest signaled coin (c_t) at time t to be the coin with the highest normalized Moving-Average value.

3.2.2 Trading Range Breakout

The Trading Range Breakout rule, commonly known as support and resistance levels, is the second prominent technical trading method discussed in Brock et al. (1992). This rule measures the highest price, also known as Resistance level, at which an asset has traded in the preceding n days. The Resistance level function, $RES(P_i)_{t,n}$, is defined as:

$$RES(P_i)_{t,n} = MAX(P_{i,t-1}, \dots, P_{i,t-n}) \tag{3}$$

When trading decisions are made around the Resistance level it was assessed to be the best technical trading rule for Bitcoin data in the research by Gerritsen et al. (2020). For this study we used a mix of short, middle to long time horizon of 30, 50 and 150 days for n. A purchase signal is issued when the price of a cryptocurrency exceeds its recent maximum (3). For comparability reasons the function was normalized to a relative change:

$$RES(P_i)_{t,n}^{norm} = \frac{P_{i,t} - MAX(P_{i,t-1}, \dots, P_{i,t-n})}{MAX(P_{i,t-1}, \dots, P_{i,t-n})} \tag{4}$$

As there wasn't any literature at the time of this paper that explains the relative strength of this indicator, this paper defined the strongest signaled coin (c_t) at time t to be the coin with the highest normalized Resistance function value.

3.2.3 Moving Average Convergence Divergence

The third trading rule used is a momentum indicator known as Moving Average Convergence Divergence (MACD) (J. J. Murphy (1999)). It works by comparing two Moving Averages in order to discover changes in the asset's momentum. This rule can be subdivided into three parts: the Moving Average Convergence Divergence (MACD) line, the MACD signal line, and the MACD Histogram. The three components are all derivations of the Exponential Moving Average (EMA)(5), which is a version of the Simple Moving Average defined previously with the caveat that it gives a greater weight to the most recent closing price. The MACD line is constructed by taking the difference between the 12-period EMA and the 26-period EMA (6). Likewise, for comparability reasons, the MACD function was normalized by relative change as was also done in (Appel and Appel (2008))(7). The MACD signal line is then constructed by taking a 9-period EMA of the MACD line (8). Lastly, the MACD histogram is obtained by subtracting the MACD signal line from the MACD line

(9).

$$EMA(P_i)_{t,n} = \left(P_{i,t} \times \frac{2}{1+n}\right) + EMA(P_i)_{t-1,n}\left(1 - \frac{2}{1+n}\right) \tag{5}$$

$$MACD_t = EMA_{t,12} - EMA_{t,26} \tag{6}$$

$$MACD_t^{norm} = \frac{MACD_t}{EMA_{t,26}} \tag{7}$$

$$MACDSIG_t^{norm} = EMA\left(MACD_t^{norm}\right)_{t,9} \tag{8}$$

$$MACDHIST_t^{norm} = MACD_t^{norm} - MACDSIG_t^{norm} \tag{9}$$

Figure 2: Three MACDs indicators for Bitcoin Price

On Figure 2, with the focus on the graph below the price trend, the MACD line (6) is represented by the blue line in the figure, and the orange line represents the MACD signal line. As the name suggests, the histogram represents the MACD histogram indicator with green signal indicating that the MACD line is above the MACD signal line thereby indicating an uptrend is likely. A purchase signal is generated for each of the three sub-divided rules of the trading when its relevant metric exceeds zero. As MACDs are a measurement of momentum, this paper assumed that the farther above the MACDs are from zero, the larger the momentum and therefore the strongest signaled coin (c_t) at time t is defined to be the coin that has the largest normalized MACDs function value.

3.2.4 Rate of Change

The rate of change trading rule (Taylor & Allen, 1992), mathematically the easiest rule, compares the current price to its value n days ago (10). Nine days is a typical time span to compare. A buy signal generated if the normalized rate of change exceeds zero. This paper assumed that the larger the nine day percentage increase in price, the stronger the signal and therefore the strongest signaled coin (c_t) at time t is the coin with the highest normalized rate of change value.

$$ROC(P_i)_t^{norm} = \frac{P_{i,t} - P_{i,9}}{P_{i,9}} \tag{10}$$

3.2.5 Bollinger Band

The last indicator used in this study, a counter trend indicator, is the Bollinger Band method (Bollinger, 2002). This rule contains envelopes plotted twice the standard deviation level above and below the Simple Moving Average of the asset price. The lower band function value, $BB(P_i)_t$, is defined as:

$$BB(P_i)_t = MA(P_i)_{t,20} - 2\sigma_{P_i,20} \tag{11}$$

The notation $\sigma_{P_i,20}$ refers to the standard deviation of coin i over the most recent 20-day period. The idea of this rule is that the price of an asset will tend towards the Moving Average line. Therefore if the price of an asset at time t is below this lower band a buy signal is initiated. The further below the price from its Bollinger lower band a coin is, the greater the would be the return should the price of the coin return to its Moving Average and therefore this paper defined the strongest signaled coin (c_t) at time t as the coin with smallest normalized lower band function value. The normalized lower band function value, $BB(P_i)_t^{norm}$ is defined as:

$$BB(P_i)_t^{norm} = \frac{P_{i,t} - BB(P_i)_t}{BB(P_i)_t} \tag{12}$$

The Figure 3 of the daily Bitcoin data can be seen with two coloured lines. The orange line is the 20 day Moving Average which is then used to calculated the lower Bollinger Band line (11) as represented by the blue line. Should the price be below this blue line, the price of the asset tends to move back upwards, meaning if the price of an asset at time t is below this lower band, a buy signal is initiated.

Figure 3: Bollinger Band on daily Bitcoin Data

3.2.6 Finalized Class of Functions

After introducing the various technical trading principles and their related normalized function formulas; our model, which will be further discussed in Section 3.4, will necessitate the use of a total of 11 normalized trading rule functions, which can be summarized in a class and referred to as $TR(P_i)^{norm}_{k,t}$ for ease of reference (13).

$$\begin{aligned} TR(P_i)^{norm}_{k,t} = \{ & MA(P_i)_{t,15}, MA(P_i)_{t,30}, MA(P_i)_{t,50}, RES(P_i)^{norm}_{t,30}, RES(P_i)^{norm}_{t,50}, \\ & RES(P_i)^{norm}_{t,150}, MACD^{norm}_t, MACDSIG^{norm}_t, MACDHIST^{norm}_t, \\ & ROC(P_i)^{norm}_t, -BB(P_i)^{norm}_t \} \end{aligned} \tag{13}$$

3.3 Performance Evaluation

In order to measure the performances of the profitability of the various different trading strategies a performance metric is proposed. This study used the Sharpe Ratio measured based on the daily log returns from using trading strategy k (R_k) and the risk-free rate R_f to assess the performance of the various trading rules. The ex-ante formula for the Sharpe

Ratio as derived by Sharpe (1966) for rule k is:

$$S_k = \frac{\mathbb{E}(R_k - R_f)}{\sqrt{\mathbb{V}(R_k - R_f)}} \tag{14}$$

The Sharpe Ratios of the trading strategies are compared to a buy-and-hold strategy (BH) of a diversified 1/N portfolio as the benchmark to evaluate their relative performance. Using the Ledoit and Wolf (2008) bootstrapping method we deduce statistically the difference between the Sharpe Ratio of cryptocurrency returns based on trading strategy k and portfolio returns based on a buy-and-hold strategy. Bootstrapping is a statistical process that re-samples a single dataset in order to generate a large number of simulated samples. Using these new simulated sample we can compute standard errors, confidence intervals, and hypothesis testing. It is advantageous to employ a bootstrap approach in order to overcome the shortcomings of a z-test or t-test method as this method is not vulnerable should the returns not meet the theoretical assumptions: Bootstrap methods are not based on certain assumption regarding the distribution of the data hence they are well-suited for the analysis of returns (Ruiz & Pascual, 2002). This technique provides reliable statistical estimations, which is critical when using data to make judgments. Furthermore, as our test sample data is of a time series nature, block bootstrapping is used as it is able to account for autocorrelation and conditional heteroskedasticity. The hypothesis test is defined as follows:

$$\begin{aligned} H_0: &\quad S_k - S_{BH} = 0 \\ H_1: &\quad S_k - S_{BH} \neq 0 \end{aligned}$$

This hypothesis is evaluated by computing a two-sided p-value using M=1000 bootstrap re-samples of the log-returns and then generating the resulting bootstrap p-values using Ledoit and Wolf (2008) method. The bootstrapping process used in Ledoit and Wolf (2008) is based on Politis and Romano (1992)'s circular block bootstrap method whereby blocks of the trading strategy and buy-and-hold return pairs $(r_{t,k}, r_{t,BH})'$, $t = 1, \ldots, N$ are re-sampled with replacement.

3.4 Procedure

Recall that this study was to determine the profitability of day trading on the coins with the strongest signal. The following two subsections of this chapter represents the core of our model. We defined the strongest signal in two ways: in paragraph 3.4.1 the strongest signal was defined according to this paper's definition of the Strongest Relative Signal Trading while in paragraph 3.4.2 it was defined by the said Combined Trading Signal Trading.

As large exchanges such as Binance had halted offering futures trading to residents of a number of countries due to local regulatory requirements, short positions are difficult to execute. As a result, the strategies employed in the subsequent paragraphs will only utilize the purchase signal generated by the trading rules.

3.4.1 Strongest Relative Signal Trading

The first step in classifying the strongest signaled coin is to isolate, for each of the trading rules, which of a category's six coins gives the strongest relative signal on that particular day. The coin with the strongest relative signal (c_t) which is mathematically defined as:

$$c_t = ARGMAX_i \left(TR(P_i)_{k,t}^{norm} \right)$$

will then be purchased at the start of the day t and sold at the end of the day t, generating a log-return of $r_{c_t,t}$. The log-return for a coin i is defined as $r_{i,t} = ln(p_{t+1}) - ln(p_t)$. If a number of cryptocurrencies shared the day's strongest signal the coin with the biggest market capitalization would be purchased. For days without a buy signal, the investor is presumed to have invested in a risk-free asset yielding the risk-free rate. The sequence of log-returns for a trading rule k is then $\{r_{k,t}\}_{t=1}^{N}$, whereby

$$r_{k,t} = \mathbb{1}(TR(P_{c_t})_{k,t}^{norm} > 0) \cdot r_{c_t,t} + \left(1 - \mathbb{1}(TR(P_{c_t})_{k,t}^{norm} > 0)\right) \cdot r_{f,t}$$

With this sequence of returns, the performance of 33 (11 different Trading rules of different parameter values across three categories) trading strategy is then evaluated and compared to the equally weighted portfolio buy-and-hold benchmark by the performance evaluator as discussed in 3.3.

As this method of defining the strongest signal is brand new and have not be discussed in other literature at the time of this paper, this paper also tested this method when applied onto the more matured stock market. This was done so to investigate the performance of such a strategy as being a more matured market compared to the cryptocurrency one could expect that such a trading strategy may not generate as high a return. However, because the stock market is seen to be less volatile, the strategy with the highest relative signal trading could potentially perform better than on the cryptocurrency market.

3.4.2 Combined Trading Signal Trading

The second way of classifying the strongest signaled trade is by combining all 11 technical trading signals. Integrating the signals and applying the most agreed upon position decreases the risk associated with selecting and depending on a single rule at any particular time. With this integrated signal, the coins which satisfies the indicator on day t is bought in equal amount at the beginning of the day and sold at the end of day t.

The trading strategy with the combined signal approach is as follows: daily, the coins that have a majority consensus to buy will be bought in equal amounts but if no majority can be reached, the risk free asset yielding the 3-month T-Bill risk free rate is then invested instead. This is noted by the indicator function, $\text{Combined}_{i,t}(n^*, b\%)$ whereby for each day every coin has to have at least n^* of the 11 separate trading rules providing a buy signal to only then be considered a buy for this combined trading rule (15). The $b\%$ on the other hand represents the band such that for each of the 11 separate trading rules, a buy signal is only signaled if the normalized trading rule indicator $TR(P_i)_{k,t}^{norm}$ exceeds the band by $b\%$. The reason for this is to avoid any 'whiplash' of signals which could be a false positive indication of the trend which may then lead to a noisy-bias combined trading signal.

$$\text{Combined}_{i,t}(n^*, b\%) = \begin{cases} 1 & \text{if } \left\{\sum_{k=1}^{11} \mathbb{1}\left(TR(P_i)_{k,t}^{norm} > \frac{b}{100}\right)\right\} \geq n^*, \\ 0 & \text{if otherwise.} \end{cases} \tag{15}$$

A total of 12 ($n^* = 5, 6, 7, 8 \;\; \& \;\; b = 0, 0.5, 1$) different combinations of combined trading rule conditions for each coin category was used to generate a sequence of returns $\{r_t\}_{t=1}^{N}$, whereby

$$r_t = \left\{\frac{1}{|\text{Combined}_t(n^*, b\%)|} \sum_{i=1}^{6} \left(\text{Combined}_{i,t}(n^*, b\%) r_{i,t}\right)\right\} + \left(1 - \text{Combined}_t(n^*, b\%)\right) r_{f,t}$$

With this sequence of returns the performance of 36 trading strategies (12 for each cryptocurrency utility list of coins) is then evaluated and compared to the equally weighted portfolio buy-and-hold benchmark by the performance evaluator as discussed in 3.3.

4 Results

Presented here are the findings of the two approaches covering the three categories of cryptocurrencies detailed in section 3.4. The three list of six coins and a list of six stocks traded according to the Strongest Relative Signal rule are presented at 4.1 and in 4.2 the results of the application of the Combined Trading Strategy.

4.1 Strongest Relative Signal

The Strongest Relative Signal trading strategy was applied to four separate lists of six assests: The six largest overall cryptocurrency coins by market capitalization, the six largest Defi coins, six largest NFT-Metaverse coins and six largest technology stocks.

Four results tables were generated. Each show the results of the 11 different trading rules applied on the respective category of assets. The first column links the Sharpe Ratio to the relevant trading strategies. The difference in basis points between the Sharpe Ratio of a trading strategy and a buy-and-hold strategy is displayed in the second column. The third column contains the *p*-values that were obtained using a bootstrapping procedure of 1000 simulations in accordance with Ledoit and Wolf (2008) methodology. The buy-and-hold strategy presented in the last row is the buy and hold an equally weighted average of the six coins of that category.

Table 1 displays the Sharpe Ratios of the 11 different trading rules applied on the six largest overall cryptocurrency. For all the trading rules except the Trading Range Breakout rules the Sharpe Ratios trail those of the buy-and-hold benchmark. However the disparities are not statistically significant. The Trading Range Breakout rule resulted in an average out-performance in the Sharpe Ratios over the buy-and-hold strategy of 1.23 basis points however this out-performances are not statistically significant. On the other hand, the Rate of Change trading rule was significant at 10% that its Sharpe Ratio is lower than the buy-and-hold benchmark. Investors should therefore avoid applying the Rate of Change trading rule when selecting for the Strongest Signal coin from this list of six coins. They should instead consider the Trading Range Breakout method as these had a much higher Sharpe Ratio.

Table 1: Sharpe Ratios (SR) for Strongest Relative Signal given employed on the 6 largest overall coins by market capitalization

	Top 6		
TA rule	SR	ΔSR	p-value
Moving Average			
MA15	.0207	-3.530	.1329
MA30	.0214	-3.460	.2078
MA50	.0204	-3.560	.1618
Trading Range Breakout			
TRB30	.0750	1.900	.5135
TRB50	.0671	1.110	.7123
TRB150	.0631	.7100	.8292
MACD			
MACD	.0366	-1.940	.4156
MACD_Signal	.0198	-3.620	.1469
MACD_Hist	.0370	-1.900	.4535
Rate of Change	.0140	-.4200*	.0749
Bollinger Band	.0376	-1.840	.5145
Buy and hold	.0560		

$^{*}p <\ .1$, $^{**}p <\ .05$, $^{***}p <\ .01$

We then applied the same Strongest Relative Signal trading approach on the six largest Defi category coins. Table 2 displays the Sharpe Ratio achieved against the 11 trading rules. Unlike the previous list of six coins none yielded a greater Sharpe Ratio over the buy-and-hold benchmark. With the exception of Moving Average 15, the trading rules did not show any statistical significance in difference in Sharpe Ratios. Moving Average 15 had a significant under-performance of 8.80 basis points over the buy-and-hold strategy while the MACDs Sharpe Ratios were the closest to the buy-and-hold benchmark. Investors seeking to invest in this category of coins should therefore consider utilizing the MACDs indicators and avoiding the Moving Average 15 as well as Bollinger Band method.

Table 2: Sharpe Ratios (SR) for Strongest Relative Signal given employed on the 6 largest Defi coins by market capitalization

	Defi		
TA rule	SR	ΔSR	*p*-value
Moving Average			
MA15	.0149	-8.800*	.0570
MA30	.0782	-2.470	.6164
MA50	.0707	-3.220	.5504
Trading Range Breakout			
TRB30	.0483	-5.460	.3257
TRB50	.0440	-5.890	.3127
TRB150	.0326	-7.030	.1578
MACD			
MACD	.0997	-.3200	.9301
MACD_Signal	.0998	-.3100	.9501
MACD_Hist	.0817	-2.120	.6603
Rate of Change	.0469	-5.595	.2048
Bollinger Band	.0133	-8.959	.1419
Buy and hold	.1029		

$^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

The last of the three cryptocurrency lists of six coins is the NFT-Metaverse group. As presented at Table 8 this category had both the largest daily log-returns and, as shown in Table 3, a high Sharpe Ratio of 0.2034. The Sharpe Ratio was obtained via the Strongest Relative Signal trading strategy of the 11 different trading rules. However, similar to the results from the Defi Category list, none of the 11 trading rules yielded a greater Sharpe Ratio over the buy-and-hold benchmark. Although not all the trading rule's had significant under-performance the best among the 11 trading rules, the Moving Average 50 was still 5.820 basis points less than the buy-and-hold's Sharpe Ratio. Investors should therefore consider avoiding this strategy on the NFT-Metaverse list of coins and instead consider buying and holding.

Table 3: Sharpe Ratios (SR) for Strongest Relative Signal given employed on the 6 largest NFT-Metaverse coins by market capitalization

	NFT-Metaverse		
TA rule	SR	ΔSR	*p*-value
Moving Average			
MA15	.1139	-8.95*	.0340
MA30	.1337	-6.970	.1329
MA50	.1452	-5.820	.2278
Trading Range Breakout			
TRB30	.1443	-5.910	.2158
TRB50	.1171	-8.630*	.0649
TRB150	.1212	-8.240*	.0979
MACD			
MACD	.1314	-7.170	.1608
MACD_Signal	.1419	-6.150	.2098
MACD_Hist	.1171	-8.630*	.0669
Rate of Change	.1435	-5.990	.1928
Bollinger Band	.1124	-9.100*	.0849
Buy and hold	.2034		

$*p < .1$, $**p < .05$, $***p < .01$

Lastly, the Strongest Relative Signal strategy approach was applied to the list of the six largest technology stock companies. As mentioned in section 3.4, the reason for the inclusion of the stock market was to see how such a strategy would perform on the more mature and less volatile stock market.

Table 4 presents the Sharpe Ratios of the 11 trading rules applied to the daily stock returns of the six largest technology companies by market capitalization. A total of 1046 observations spanning October 2017 till November 2021 were used. The six stocks are: Apple, Microsoft, Amazon, Tesla, Google and Nvidia.

Though, with the exception of the Moving Average Convergence Divergence trading rule, the Sharpe Ratios of trading rules trail those of the buy-and-hold benchmark in every application the differences are not statistically significant. The MACD trading rule had a Sharpe Ratio greater than the buy-and-hold but this too is not statistically significant ($\Delta SR = .0118; p = .6634$). It is worth noting that although the results did not out-perform the buy-and-hold strategy the closer Sharpe Ratios and smaller $p-$values may suggest that the Strongest Relative Signal strategy performs better on the stock market. This could be attributable to the lower volatility of the stock market therefore investors can consider using this strategy when trading in the stock market.

Table 4: Sharpe Ratios (SR) for Strongest Relative Signal employed on the 6 largest technology sector stocks.

	Technology Stocks		
TA rule	SR	ΔSR	*p*-value
Moving Average			
MA15	.0693	-.7700	.7872
MA30	.0629	-1.410	.6214
MA50	.0564	-2.060	.4565
Trading Range Breakout			
TRB30	.0470	-3.005	.3936
TRB50	.0419	-3.510	.3317
TRB150	.0627	-1.430	.6474
MACD			
MACD	.0888	1.180	.6494
MACD_Signal	.0740	-.2960	.8901
MACD_Hist	.0626	-1.440	.6394
Rate of Change	.0717	-.5300	.8172
Bollinger Band	.0701	-.6000	.8541
Buy and hold	.0770		

*$p <$ .1, **$p <$ .05, ***$p <$ .01

These results show that the Strongest Relative Signal strategy approach had mixed success in out-performing the diversified buy-and-hold strategy. Although there were instances where one trading rule did out-perform the buy-and-hold the lack of generalization and the lack of across the board statistically significant results suggest that investors are better off buying and holding a diversified portfolio of coins. In the next section, the paper discussed the results obtained when the strongest signal is defined by combining all the 11 trading rule signals.

4.2 Combined Trading Rule strategy

The 12 Combined Trading Rule trading strategies, Combined($n^*, b\%$), were applied across the six largest cryptocurrency coins by market capitalization, the six largest Defi coins and the six largest NFT-Metaverse coins. The results are shown in the next three tables.

The first column indicates the Sharpe Ratio linked with the trading rules. The difference in basis points between the Sharpe Ratio of a technical trading rule and a buy-and-hold strategy is displayed in the second column. The third column contains the *p*-values that were obtained using a bootstrapping procedure of 1000 simulations in accordance with Ledoit and Wolf (2008)'s methodology. Lastly, the fourth column displays the average number of coin(s) bought per day. The buy-and-hold strategy presented in the last row is the buy and hold an equally weighted average of the six coins of that category.

Table 5 presents the Sharpe Ratios of 12 different trading rules profiles applied to the daily cryptocurrencies returns of the six highest coin by market capitalization. A total of 1521 observations spanning October 2017 till November 2021 were used. Compared to the buy-and-hold benchmark, the Sharpe Ratios for all the combined trading rules strategies produced a higher Sharpe Ratio. However, only two strategy profiles, the Combined(5,0.5%) and Combined(7,1%), had a statistically significant increase over the buy-and-hold strategy. The profile of the Combined strategy that yielded the highest Sharpe Ratio was the Combined(7.1%), meaning that at least 63.6% of the individual trading rules must indicate a buy signal with a band of 1%. This result suggests the investors are better off day-trading with the aid of Combined(7,1%) trading strategy.

Table 5: Sharpe Ratios (SR) for the combined TA rules for the top 6 market capitalization category.

	Top 6			
Combined Condition	SR	ΔSR	p-value	MB
Combined (5, 0%)	.0786	2.255	.2937	2.536
Combined (5, 0.5%)	.0959	3.986*	.0669	2.368
Combined (5, 1%)	.0906	3.462	.1099	2.186
Combined (6, 0%)	.0798	2.373	.3117	2.155
Combined (6, 0.5%)	.0732	1.716	.4975	1.976
Combined (6, 1%)	.0692	1.320	.5844	1.805
Combined (7, 0%)	.0714	1.536	.5214	1.560
Combined (7, 0.5%)	.0872	3.113	.1998	1.254
Combined (7, 1%)	.1086	5.257**	.0440	.9901
Combined (8, 0%)	.0862	3.017	.2827	.6272
Combined (8, 0.5%)	.0810	2.495	.3796	.5384
Combined (8 1%)	.0719	1.584	.5984	.4714
Buy and hold	.0560			

$^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

We subsequently applied the same Combined Signal trading approach on the six largest Defi category coins. Table 6 displays the Sharpe Ratios of 12 distinct trading rule profiles applied to the daily returns of this category. A total of 422 samples spanning October 2020 till November 2021 were used. Unlike the result earlier, all combined trading rules profile except the Combined$(7, 0.5\%)$ had a lower Sharpe Ratio compared to the buy-and-hold strategy. Though the bootstrapped p-value did not indicate a significant difference between the trading rule strategys Sharpe Ratio and the buy-and-hold Sharpe Ratio benchmark. The Combined$(7, 0.5\%)$ strategy profile yielded the highest Sharpe Ratio which is higher than the Sharpe Ratio of the buy-and-hold strategy($\Delta SR = .0141\,;\ p = .7363$). However this is not significant. Among the other combined strategy profiles, the profile Combined$(7, b\%)$ yielded higher/closer Sharpe Ratios to the buy-and-hold. In Table 5, the results showed the Combined$(7, b\%)$ yielded a significantly higher Sharpe Ratio to its buy-and-hold. This might indicate that having at least seven of the eleven trading rules might be the best. Investors should therefore consider investing with the Combined$(7, b\%)$ strategy profile should they be interested in the Defi Category of coins.

Table 6: Sharpe Ratios (SR) for the combined TA rules for Defi category.

	Defi			
Combined Condition	SR	ΔSR	p-value	MB
Combined (5, 0%)	.0738	-2.911	.6713	3.090
Combined (5, 0.5%)	.0758	-2.709	.6973	2.936
Combined (5, 1%)	.0717	-3.118	.6314	2.756
Combined (6, 0%)	.0812	-2.165	.6494	2.592
Combined (6, 0.5%)	.0784	-2.453	.6014	2.412
Combined (6, 1%)	.0713	-3.153	.5015	2.270
Combined (7, 0%)	.0836	-1.928	.6993	1.919
Combined (7, 0.5%)	.1170	1.409	.7832	1.647
Combined (7, 1%)	.0985	-0.438	.9191	1.370
Combined (8, 0%)	.0460	-5.689	.2857	.7938
Combined (8, 0.5%)	.0504	-5.244	.3556	.7204
Combined (8 1%)	.0414	-6.150	.2807	.6611
Buy and hold	.1029			

$*p < .1$, $**p < .05$, $***p < .01$

Lastly we applied the same Combined Signal trading approach on the six largest NFT-Metaverse category coins list. Table 7 records the Sharpe Ratios of 12 distinct trading rule profiles applied to the daily returns of 392 observations spanning November 2020 till November 2021.

The combined trading rule strategies were found to be both below and above the benchmark buy-and-hold strategys Sharpe Ratio. The combined trading rule, Combined$(5, 0\%)$ yielded the greatest Sharpe Ratio ($SR = .2138\,;\ \Delta SR = 1.038\,;\ p$=.7732); nevertheless, the bootstrapped statistics did not give any significant conclusion. Compared to the Strongest Relative Signal approach on the NFT-Category, the Sharpe Ratios have improved substantially.

Table 7: Sharpe Ratios (SR) for the combined TA rules for NFT category.

	NFT			
Combined Condition	SR	ΔSR	*p*-value	MB
Combined (5, 0%)	.2138	1.038	.7732	3.327
Combined (5, 0.5%)	.2098	.6437	.8571	3.204
Combined (5, 1%)	.2017	-.1629	.9560	3.089
Combined (6, 0%)	.1974	-.5947	.8851	2.883
Combined (6, 0.5%)	.2002	-.3227	.9331	2.747
Combined (6, 1%)	.1922	-1.115	.7722	2.638
Combined (7, 0%)	.1868	-1.657	.6883	2.077
Combined (7, 0.5%)	.1926	-1.079	.8012	1.796
Combined (7, 1%)	.1940	-.9365	.8402	1.612
Combined (8, 0%)	.1362	-6.719	.1828	0.987
Combined (8, 0.5%)	.1398	-6.360	.2018	.9235
Combined (8 1%)	.1462	-5.718	.2428	.8801
Buy and hold	.2034			

$^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

Clearly the Combined Signal strategy approach improved the Sharpe Ratios obtained with the Strongest Relative Signal strategy. In certain instances, for example, when investing in the six overall largest coins by market capitalization, significant out-performance to the diversified buy-and-hold strategy were witnessed. Of the two sides of defining the strongest signal, the Combined Signal strategy can be seen as the more superior strategy. In that regard, investors should therefore consider using this strategy when day-trading in the cryptocurrency market.

5 Conclusion and Discussion

The objective of this study was to explore the profitability of day trading on the strongest signaled coin(s) in the cryptocurrency market. The strongest signal was defined in two ways: firstly, by assessing the relative signal across all six coins and picking the one with the highest normalized function value, and secondly, by looking at the combined signal and picking the coins which satisfied a certain percentage of individual trading signals.

Our research highlighted two important findings. While the Sharpe Ratios produced by trading (using the strongest relative signal method for all trading rules and across all three cryptocurrency categories) were statistically insignificant compared to the basic Long Term profitable buy-and-hold portfolio strategy (and this proved to the the case also for the stock market), trading using a combined signal technique especially with certain specification can out-perform the buy-and-hold strategy.

The most successful market for implementing the strongest signal trading is with the top six cryptocurrencies. More particularly, the Combined$(7, 0.5\%)$ and Combined$(7, 1\%)$ trading strategies as these two out-perform the buy-and-hold strategies in both the top six overall and Defi categories. The latter was also significant at 5%. Investors keen to consider cryptocurrency trading should therefore consider day-trading using the Combined Signal Approach on the six largest cryptocurrencies by market capitalization.

5.1 Comparing previous literature

Contrary to expectations, the investigation did not provide evidence that the Strongest Relative Signal technique would differ from an equally diversified buy-and-hold strategy. Consistent with Gerritsen et al. (2020)'s research, our findings indicated that the Sharpe Ratios for the Trading Range Breakout technical analysis were higher than those of the buy-and-hold strategy. That the difference was not statistically significant could be attributable to the choice of statistical inference approach utilized in our investigation. Perhaps a different method to that of Ledoit and Wolf (2008)'s bootstrapping procedure would yield more accurate findings. However, this bootstrapping approach investigated by Ledoit and Wolf (2008) is found to be fairly relevant, because the bootstrap is adjusted for volatility clustering and autocorrelation which is typically found in stock and mutual fund returns.

Nonetheless, the findings of this study's Combined Signal Approach provided some evidence that employing such a technical indicator on cryptocurrencies, specifically the six cryptocurrencies with the largest market capitalization, results in a statistically significant out-performance over the buy-and-hold strategy. The success of this technique is consistent with other published works (Lento et al., 2007; Lento, 2008, 2007) albeit their papers focused on investing in single asset in other markets such as DJIA, S&P500 and Asian Stock Market.

5.2 Analysis of Strongest Relative Signal Trading

A perplexing finding of our analysis was the poor performance of the Strongest Relative Signal trading method. The explanations and processes for building the strategy in section

3.2 were intuitive, but the results revealed an under-performance of up to nine basis points in the Sharpe Ratios.

A visual investigation was then conducted to investigate any interesting results that could help shed some light on the result. Reviewed first were all the buy decision's; the difference between the six coin's average return and the return realized from purchasing the strongest signaled coin. The graphs of these difference in returns are in Appendix at Figure 7,8 and 9. The investigation showed the difference between the returns of the buy signal to the average returns weren't as big as we anticipated. We then investigated the standard deviation of the returns from the various technical trading rules against the buy-and-hold positions: The bar chart at Figure 13 refers. It was established that for all the three categories the returns from the trading rules had much higher volatility as compared to the buy-and-hold strategy. This was not a surprise as the buy-and-hold volatility will be lower due to diversification but the difference was clearly enough to pull the Sharpe Ratio down. Given the way Sharpe Ratios are calculated that could explain why the Strongest Relative Trading Strategy despite on average earning a higher mean return, the risk adjusted return is lower than the buy-and-hold strategy.

5.3 Analysis of Combined Trading Signal Trading

An important finding was the success of the Combined Trading Signal method. This was especially true in the market of the six largest cryptocurrency by market capitalization where the combined strategy profiles yielded a larger Sharpe Ratio compared to the buy-and-hold benchmark. A review was then conducted to investigate for all the buy decisions the difference between the six coins average return and the returns realized from the combined strategy profiles. This is presented in Figures 10, 11 and 12 of the Appendix. The graphs show that there are quite a number spikes above the zero line, especially for the NFT-category, implying that there were many occasions when the combined strategy daily returns resulted in a higher return than the average returns of all the six coins. A difference between the Strongest Relative Signal and Combined Signal approach is that there were fewer buy signals in the latter. We also investigated the standard deviation of the returns realized from the Combined Signal strategy. The results, depicted in the Appendix, Figure 14, revealed that unlike the standard deviation of the returns from the Strongest Relative Signal trading the volatility from the Combined Signal trading were closer to the buy-and-hold strategy with the exception of the NFT-coins. The Combined Trading strategy applied on the NFT-

Metaverse cateogry was seen to produce returns that were less volatile than the Strongest Relative signal Approach but it is still more volatile than the buy-and-hold strategy. Yet from the Sharpe Ratios reported in Chapter 4.2 the Sharpe Ratios obtained from Combined Trading is very close to the buy-and-hold's. This implied that the excess returns generated is much larger than that of the buy-and-hold however once the returns are risk adjusted it doesn't fair as well as buying and holding.

To summarize, not only is the Combined Signal Trading approach relatively less volatile, it was able to generate a higher excess return and higher Sharpe Ratios over the buy-and-hold strategy. This should further emphasize the success of applying the Combined Signal Trading approach in day trading.

5.4 Limitations of research and suggestions for further research

Although a considerable number of data points were collected and analyzed for each category there may be concerns regarding the construct validity of this study. Only in late 2020, for instance, were the categories Defi and NFT-metaverse introduced. This occurred the same year as the most recent Bitcoin halving - A four-yearly event which sees the production rate and therefore the remuneration levels of bitcoin minors halved. That is significant for, as Meynkhard (2019)'s study revealed, the price of Bitcoin climbs exponentially, peaking 12 to 16 months after halving. Given Bitcoin's dominance over other cryptocurrencies (Kulal, 2021) this may explain why a variety of technical trading strategies failed to out-perform the buy-and-hold approach. It is suggested that when the Defi and NFT markets are more developed the data collected for these two very different asset classes will yield a far more accurate analysis.

Moreover, despite one of this study's classification that the strongest signal would be the one with the largest relative technical indicator signal, this intuitive definition is not supported by any literature. In order for investors to compare and empirically choose a cryptocurrency to trade, it is suggested that future studies examine additional definitions of a coin with the strongest signal so that they can compare and select a cryptocurrency with more certainty.

As the Combined Signal Approach trading seemed to have shown some evidence of out-performance over the buy-and-hold, a future study should also seek to examine a more robust assessment of the best quantity of trading signals to combine on a daily basis. We suggest utilizing a more complex technique such as deep reinforcement learning or artificial neural networking as well the ability to collect as looking at finer interval data such as hourly intraday trading. One may also investigate the potential for dynamic combination trading rules modelled along the lines of Creal, Koopman, and Lucas (2013)'s Generalized Autoregressive Score (GAS) framework which updates the choice of weights according to the highest likelihood at each time step. Another potential avenue for future research to look into is instead of focusing on only the buy-signals, one could repeat the test on only the sell signals on day short selling. Though short selling, as discussed in Chapter 3, is rather difficult to execute it may be something worth looking into.

To conclude, the Combined Signal Approach showed some signs of out-performance over the buy-and-hold strategy and therefore managers of hedge funds and ordinary investors can utilize the results of this study to their advantage while trading cryptocurrencies.

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A Appendix

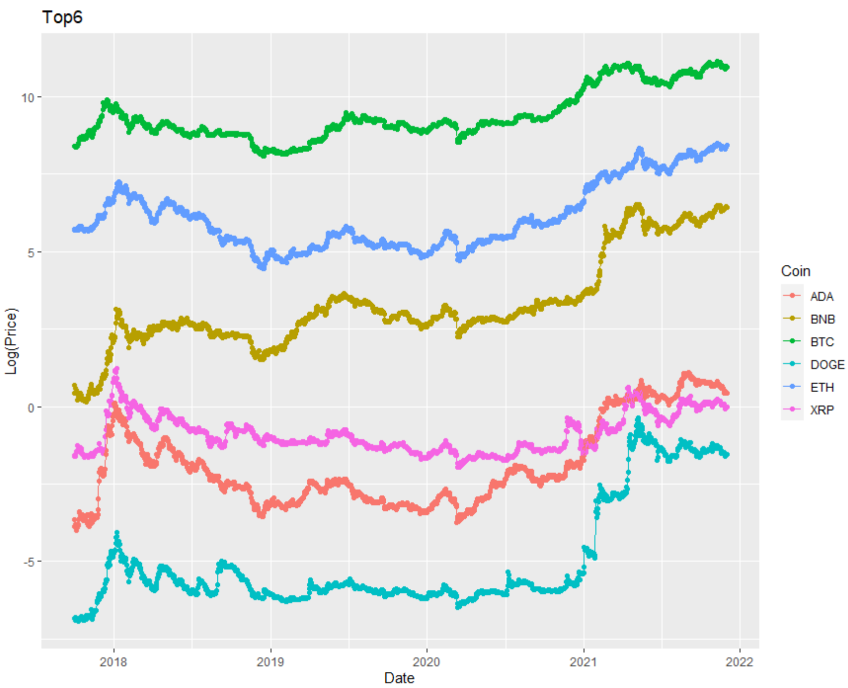

Figure 4: Log Price of the Top6 Coins

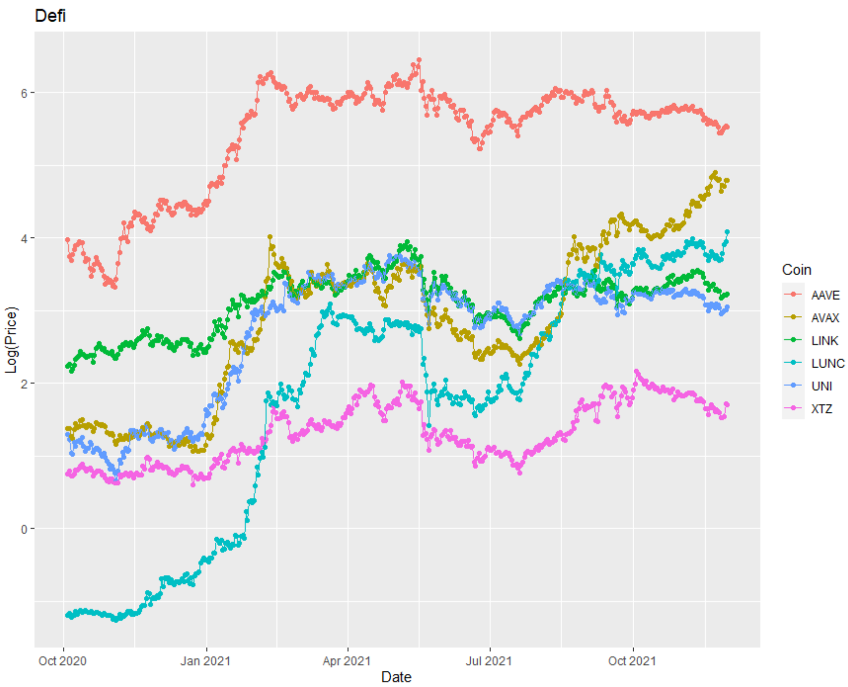

Figure 5: Log Price of the Defi Category Coins

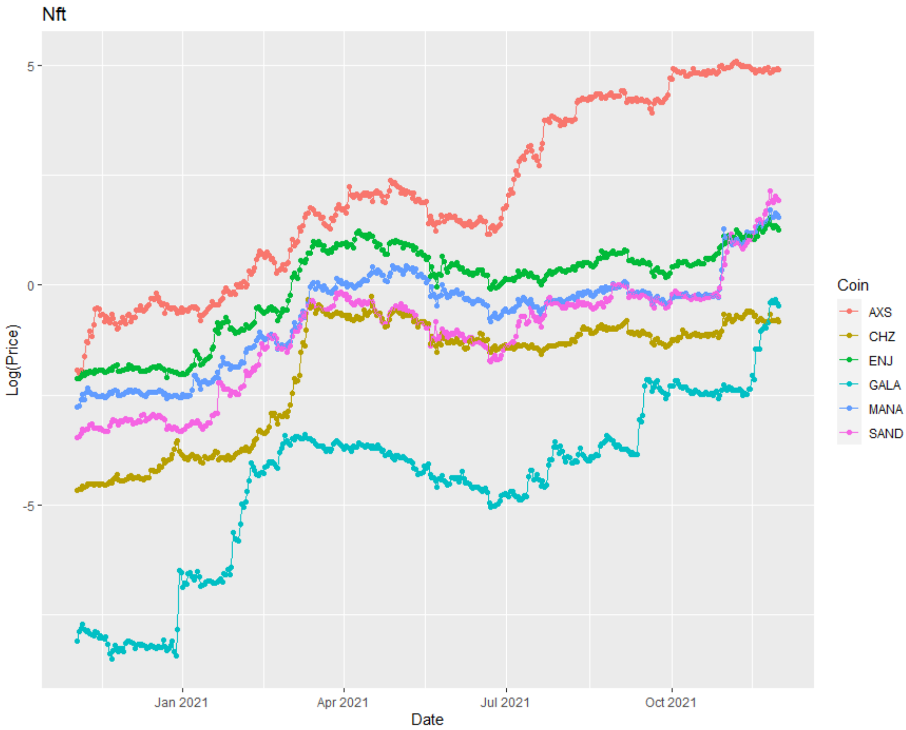

Figure 6: Log Price of the NFT Category Coins

Table 8: Summary Statistics Of Log-returns For Each Coin

	N	Mean	Std.Dev	Skewness	Kurtosis	Range	Median	IQR	W-stat
01/10/17 - 30/11/21	**TOP 6 MARKETCAP COINS**								
BTC	1521	.1684	4.175	-.8576	15.38	68.98	.1930	3.608	.9134***
ETH	1521	.1794	5.246	-1.005	13.54	78.55	.1543	4.938	.9229***
BNB	1521	.3952	6.374	.3736	15.96	107.2	.1251	5.500	.8737***
XRP	1521	.1036	6.738	.8507	18.70	115.7	-.081	4.504	.8157***
ADA	1521	.2688	7.235	1.908	25.26	136.5	.082	6.100	.8528***
DOGE	1521	.3477	8.282	4.893	85.15	203.1	-.053	4.352	.6812***
Equal-Weight	1521	.2439	4.130	-.4259	11.17	65.00	.2494	3.811	.9215***
04/10/20 - 30/11/21	**DEFI CATEGORY COINS**								
LUNC	422	1.253	9.484	.7308	12.09	112.9	.5834	8.403	.8841***
AVAX	422	.8090	8.728	.6387	8.919	101.4	.4647	8.335	.9323***
LINK	422	.2349	7.0792	-.7100	7.759	74.16	.5970	8.190	.9600***
UNI	422	.4161	7.699	.4000	7.583	78.38	.3796	8.532	.9426***
XTZ	422	.2266	7.195	-.5851	7.895	71.23	.4646	6.921	.9460***
AAVE	422	.3676	7.575	-.2278	5.821	68.04	.2992	8.887	.9713***
Equal-Weight	422	.5512	5.352	-.9078	9.332	60.80	.9470	5.575	.9377***
03/11/20 - 30/11/21	**NFT-METAVERSE CATEGORY COINS**								
MANA	392	1.098	10.00	2.317	22.37	130.2	.5573	8.983	.8535***
SAND	392	1.376	10.64	.9713	9.766	116.1	.5552	9.233	.9054***
AXS	392	1.742	11.16	.8087	6.283	102.9	.7148	10.36	.9340***
GALA	392	1.941	14.81	3.462	24.13	167.0	-.9123	10.08	.7296***
CHZ	392	.9809	9.702	1.482	14.27	117.2	.8721	8.033	.8550***
ENJ	392	.8627	9.109	.4477	7.550	88.50	.5401	8.798	.9319***
Equal-Weight	392	1.333	6.553	.1543	6.466	64.18	1.071	6.474	.9587***

Note. For purpose of readability analysis above was done in percentage points (i.e. $r_{i,t} \times 100$) was used. Each Category's Equal-Weighted row provides a study of the mean return on six coins in that category.
$^{***}p < .01$

Figure 7: Return difference between mean return and Strongest Relative Signal return (Top6)

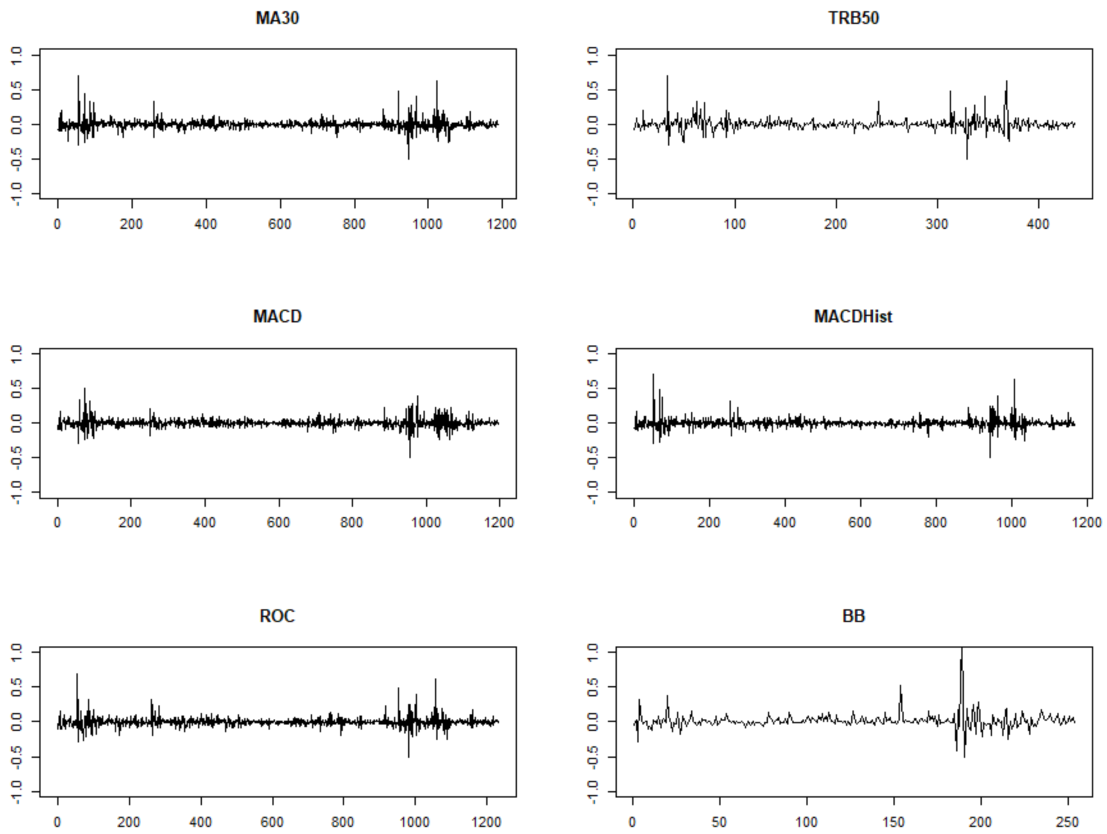

Figure 8: Return difference between mean return and Strongest Relative Signal return(Defi)

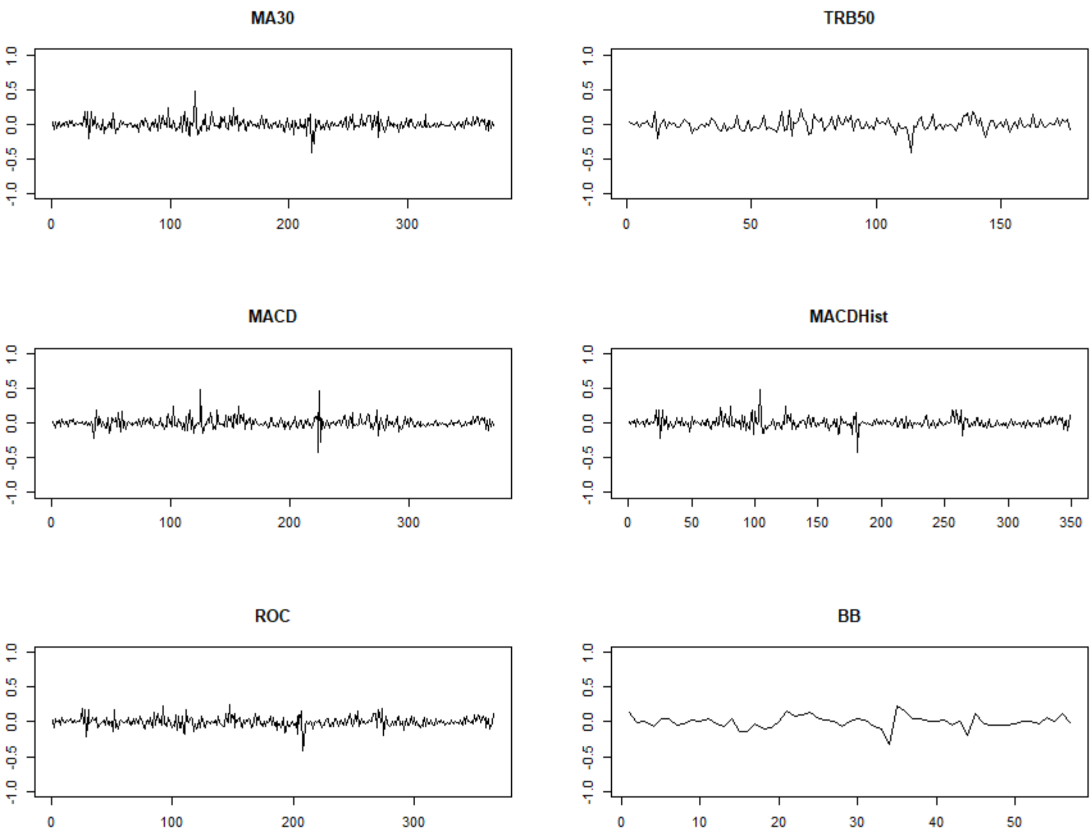

Figure 9: Return difference between mean return and Strongest Relative Signal return (NFT)

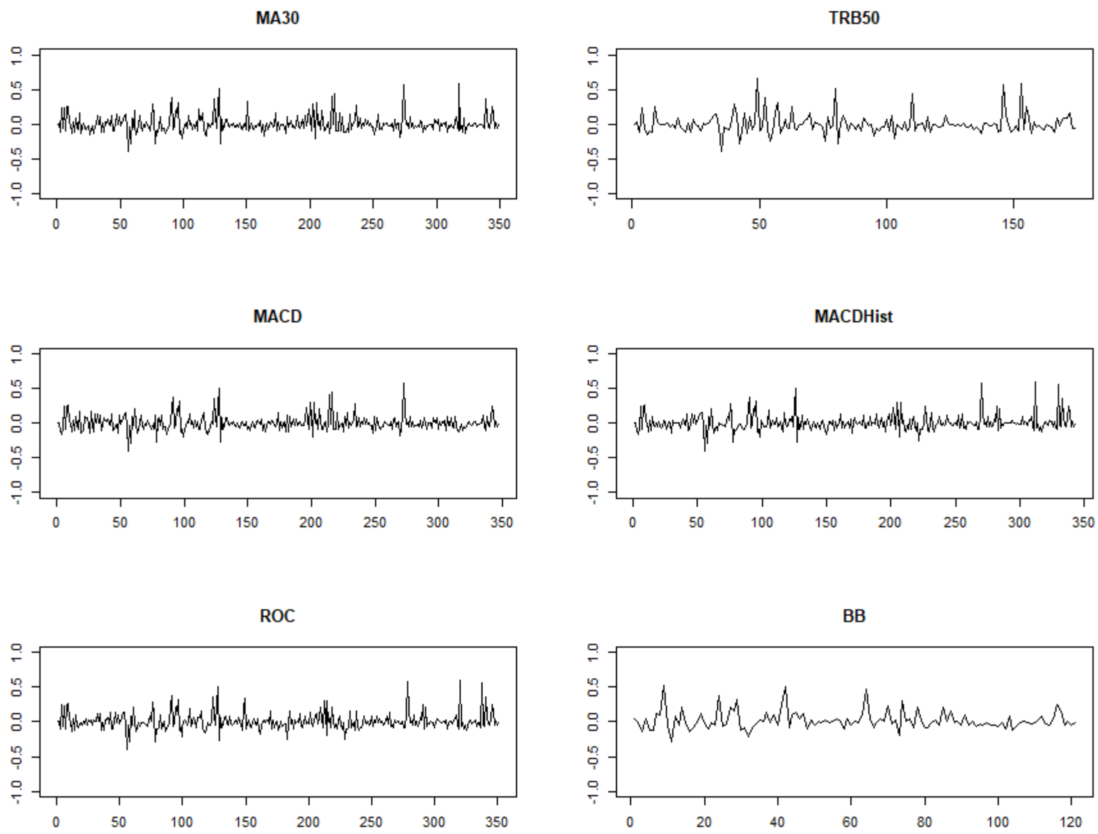

Figure 10: Return difference between mean return and Combined Signal Trading return (Top6)

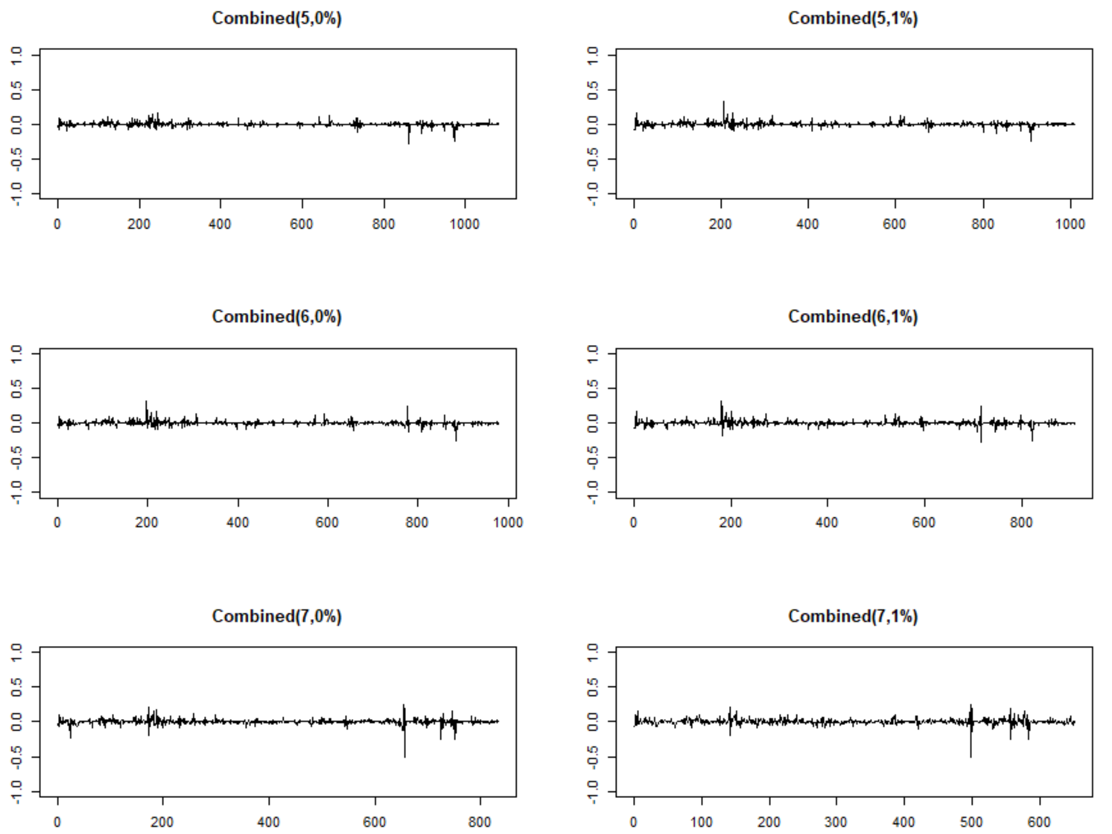

Figure 11: Return difference between mean return and Combined Signal Trading return(Defi)

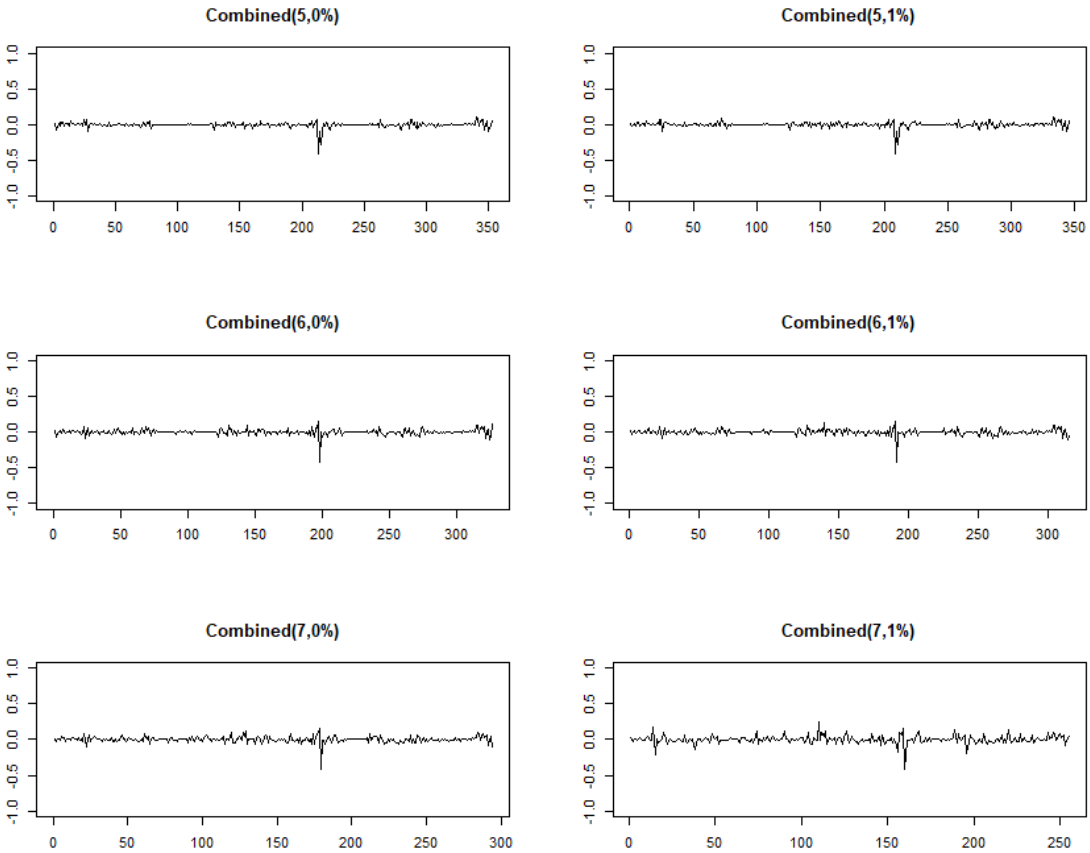

Figure 12: Return difference between mean return and Combined Signal Trading return (NFT)

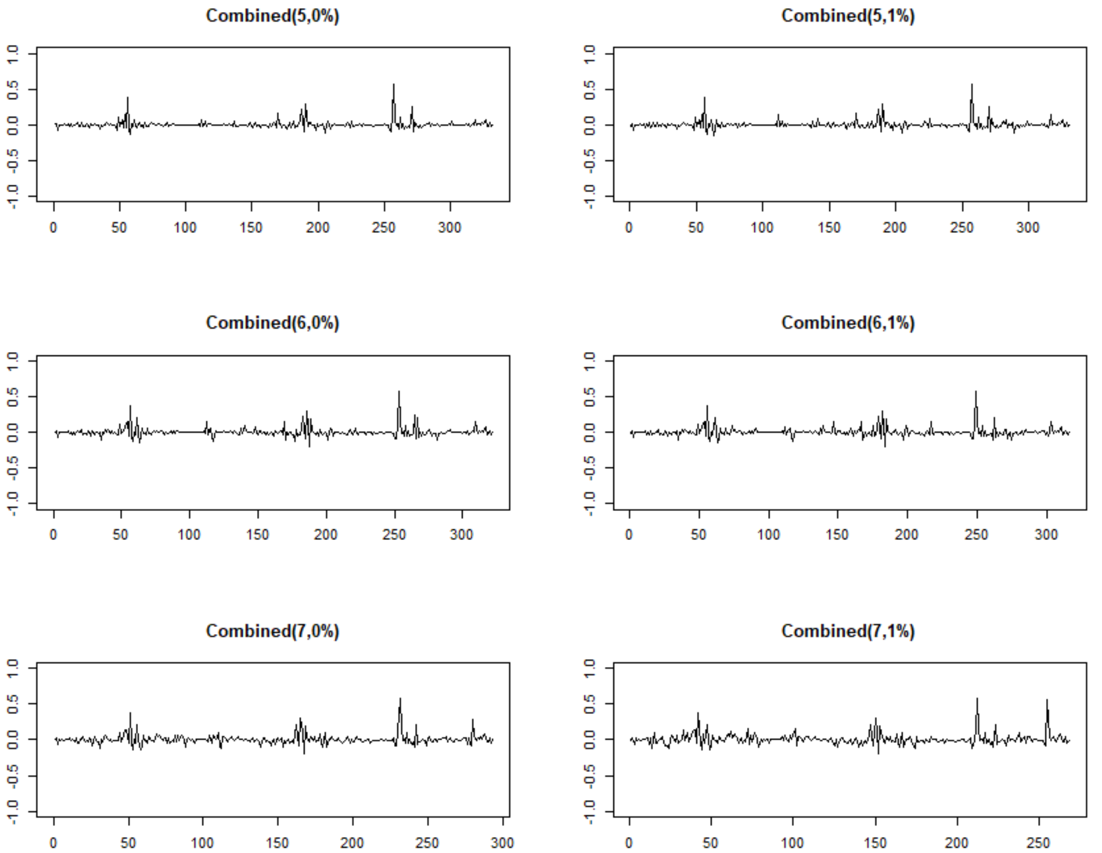

Figure 13: Returns Standard Deviation Strongest Relative Signal

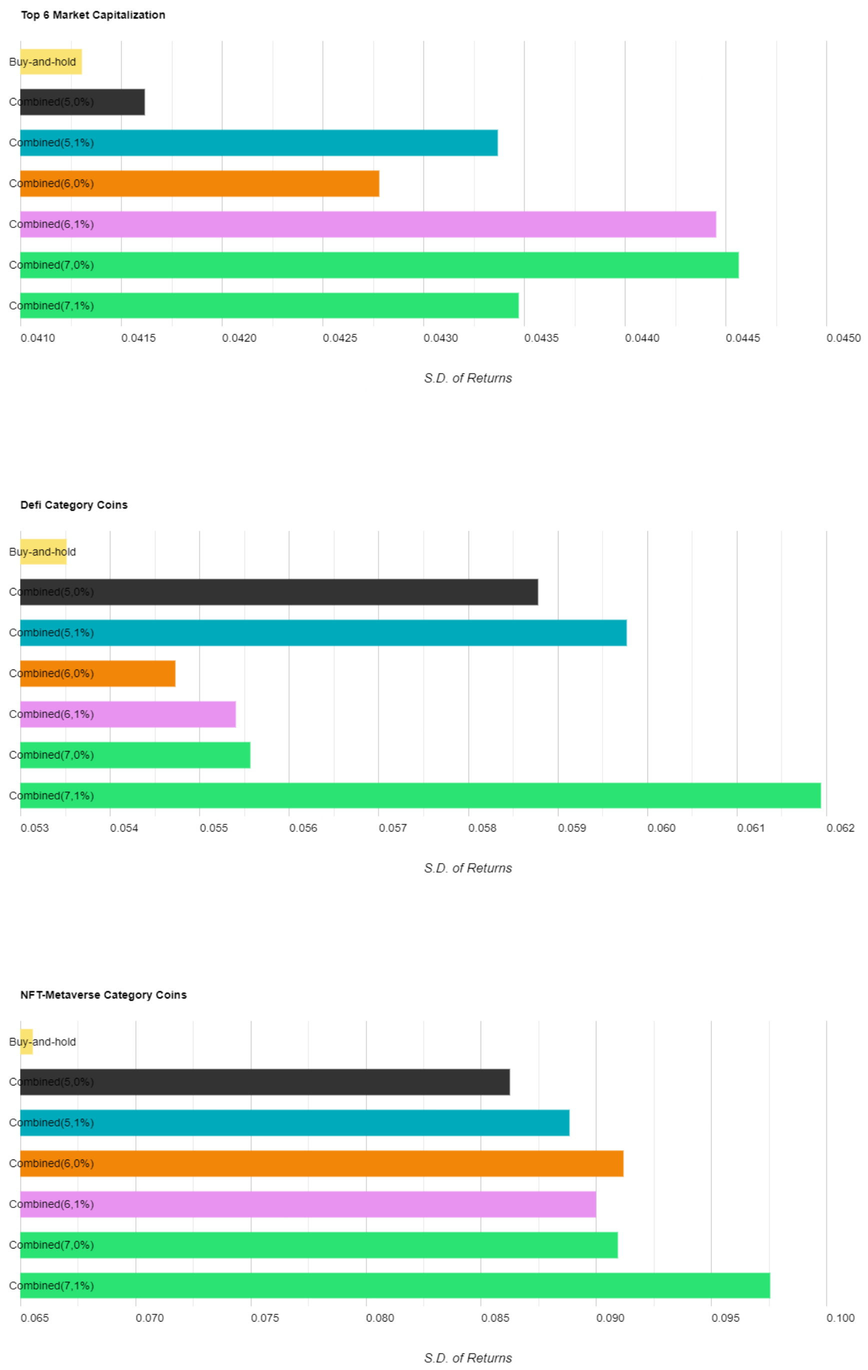

Figure 14: Returns Standard Deviation Combined Trading Signal