Lappeenranta-Lahti University of Technology
School of Business and Management
Strategic Finance and Analytics

Effectiveness of technical trading strategies on intraday bitcoin markets

Master's Thesis

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ABSTRACT

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The purpose of this thesis is to learn if it's possible to gain higher risk-adjusted profits than buy-and-hold -strategy on intraday bitcoin markets using moving averages or trading range breakout. Data used is price notations of bitcoin with 1-minute interval from 2017 to 2019.

There were many strategies that statistically significantly outperformed buy-and-hold -strategy even when trading fees were reduced. Different methods such as stop-loss and bands were able to significantly reduce volatility of returns. However, same trading rules don't work well in different market conditions. Results from the train-set and test-set differed largely and were therefore not valid. Also, none of the strategies were able to outperform CCi30 cryptocurrency index when fees were reduced.

Therefore, while some support was found to conclude that outperforming the index is possible, more data and research would be needed to validate these results.

TIIVISTELMÄ

Tekijä:	Visa Tanner
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Tämän tutkielman tarkoituksena on tutkia, onko liukuvien keskiarvojen tai tuki- ja vastustasojen (eng. trading range breakout) avulla mahdollista saavuttaa ylituottoa osta-ja-pidä -strategiaan verrattuna päivänsisäisessä kaupankäynnissä bitcoin-markkinoilla. Käytetty data sisältää bitcoinin minuutin väliset hintanoteeraukset vuodesta 2017 marraskuulle 2019.

Tutkielmassa löytyi useita strategioita, jotka tuottivat tilastollisesti merkitseviä ylituottoja osta-ja-pidä -strategiaan verratessa jopa kaupankäyntikulut huomioidessa. Volatiliteettia saatiin laskettua tilastollisesti merkitsevästi käyttämällä metodeita, kuten stop-loss. Samat strategiat eivät kuitenkaan toimineet erilaisten markkinatrendien aikana ja tulokset treeni- ja testidatoissa erosivat toisistaan merkittävästi. Yksikään strategioista ei myöskään voittanut suurimpien kryptovaluutoiden arvoa seuraavaa CCi30 indeksiä, jos kaupankäyntikustannukset otettiin huomioon.

Osta-ja-pidä strategian voittaminen on tämän tutkielman perusteella mahdollista tietyissä tapauksissa, mutta lisää aineistoa ja tutkimusta tarvittaisiin, jotta tuloksia voitaisiin pitää valideina.

TABLE OF CONTENTS

TABLES

FIGURES

APPENDICES

1. INTRODUCTION

1.1 Background

While efficient market hypothesis states that all available information is reflected to the prices of the asset, large number of researches are conducted stating otherwise. Finding new efficient trading strategies is what differs winning investors from losing ones and has huge industry built around it. With better movement of information, more data can be easily gathered to base decisions on and at the same time more people have access to the markets. Stock-markets are largely researched for anomalies and ways to beat the markets, but there are also other less researched investment opportunities. One of those is cryptocurrencies.

Cryptocurrencies are relatively recent subject and there has been a lot of discussion around it. Value of any currency is based on the trust of its value in trading. In that way, cryptocurrencies don't differ from any other payment method. However, the anonymity currently provided by many cryptocurrencies, makes much of the trading those are used for quite shady. Industry is however rising, and multiple exchanges make investing in cryptocurrencies easier than ever. It is also easy to say that investing in one of cryptocurrencies, bitcoin would've been worthy in early days of it. When at the beginning of bitcoin around 2010, with investment of $1 000 one could've been easily able to buy 100 000 bitcoins, the value of 100 000 bitcoins in 2019 has varied between 330 million dollars and 1.3 billion dollars. While there are many examples of hugely successful investments, annual profits that have been made by bitcoin are still exceptional. While critical minds might call whole concept of cryptocurrencies bubble, it has provided, and might still provide very profitable investment opportunities.

Main idea behind this thesis is to study how well two different technical indicators can be utilized in intraday trading of bitcoin. There are large number of different technical indicators found in literature, but two of the most commonly used are moving average and trading range breakout. These will be used in this thesis.

1.2 Contribution of thesis

This thesis follows very simple theoretical framework. The methodology of this thesis is connected to the one used by Gerritsen et al. (2019). They concluded similar research on technical trading rules on daily Bitcoin-markets. Data they used was however much larger including six years of very differently behaving less volatile markets Technical trading rules chosen to be used in this thesis will come directly from the rules they found to be most promising in daily bitcoin-markets. These are trading range breakout and moving averages. These rules will be modified to find larger scale of models and account for the fact that 1-minute intervals will be used instead of daily prices.

Following research gaps are meant to be filled with this thesis:

1. How do the technical trading strategies proposed for daily markets by Gerritsen et al. (2019) perform in intraday markets?
2. Can the technical analysis in intraday cryptocurrency markets consistently overperform the index?

Another research that has affected the structure of this thesis is the literature review of technical analysis on stock markets conducted by Farias Nazário et al. (2017). They found that there are many papers on the subject lacking on some generally accepted procedures. For example, some of the researches didn’t account for risk at all, but instead measured efficiency of the strategy just by profits. Other notable thing in previous literature was for example lack of accounting transaction costs while talking about profitability. In this thesis, I’ve included transaction costs and used different measurements of risk.

Main idea behind all theory has been to keep the research as closely connected to reality as possible. This means that all methods used, could be used in real life. Structure of the empirical part in this thesis can be seen as limitation process. Number of different trading strategies are limited by different rules until solution to research questions can be concluded. Limiting structure is presented on Figure 1.

Figure 1. Structure of the empirical analysis

1.3 Definitions

There are some constantly used acronyms and terms that are worth defining. These are mostly used in empirical part of the study.

Moving averages (MA)

Moving averages used in this thesis are interpreted in the format **MA1-250**. In example, this means short moving average of 1 period (current closing price) and long moving average of 250 periods. Periods are always 1-minute ticks, so 250 periods mean 4 hours and 10 minutes. Other acronyms regarding moving averages are **SMA** meaning short moving average and **LMA** meaning long moving average.

Trading range breakout (TRB)

In the thesis trading range breakout is shortened as **TRB.** When talking about single trading range breakout strategy, format such as **TRB600** is used, meaning the trading range breakout rule using 600-period support and resistance levels. Periods are always 1-minute ticks.

SKASR, ASR, SR and IR

All these are acronyms used from different Sharpe ratios. **SKASR** means Skewness and Kurtosis Adjusted Sharpe ratio, which is more discussed in section 2.3. **ASR** is used as acronym for Adjusted Sharpe ratio and **SR** for regular Sharpe ratio. **IR** is used as an acronym for Information Ratio discussed more in section 2.3.7.

1.4 Research questions

Value of trading model is directly comparable to profits it can gain. More deeply, by profits one can gain, for the risk. By just comparing different investment opportunities, cryptocurrencies can be thought as a very risky investment if risk is measured by volatility, as usually is. While investors except more return for more risky assets, this leads to following research question:

Can the intraday trading strategies utilizing moving averages or trading range breakout outperform the buy-and-hold strategy in cryptocurrency markets?

This can be led to three sub-questions:

How can the strategies in question compete against the index?

How do the trading fees affect results of these strategies?

How does utilizing stop-loss or bands affect returns of these strategies?

With these questions I'll try to answer whether technical analysis holds value in bitcoin-markets and more widely cryptocurrency markets.

1.5 Limitations of the study

Few limitations should be acknowledged in this thesis. First of all, data to be used is not fully complete. While all measures have been taken to fill the gaps there are in the data, those still might have small effects on the results of this study. Data also represents prices of just one exchange. While observing very volatile markets, there might be differences in price changes compared to traditional markets with larger trading volumes. Exchange where data is gathered is not close in volume to the largest ones on the markets. This might affect price changes or add lag to adaptations on new market information. This is considered not to be a large problem in purposes of this thesis. Other caveat of lower volume markets is the fact that prices are more exposed to market manipulations. There might be cases when the used closing price doesn’t fully represent real price of the asset at that point of time due unusual orders.

It should also be acknowledged that strategies tested in this thesis might not be completely protected from data snooping bias. Measure taken to avoid this is to generate strategies separately from the data those are tested in. However, it’s noteworthy that even this measure might not fully protect results from this bias. This is especially true because with shorter test set, all possible trends might not be fully represented.

Tested strategies are gathered so that those would present large scale of different strategies and the best one of those would give at least a good idea of what type of strategy would be profitable. However, with limited computational resources, it would be too consuming to find the best individual strategy. While this might simultaneously add some protection against data-snooping bias, it also means that the best strategy proposed in this thesis might not be the best strategy overall.

When considering outperforming index, the used index is the key factor. In case of cryptocurrencies, this is not very straightforward. First, there are not very many indices that follow cryptocurrencies. Secondly, weighting in used indices will have quite heavy effects on the results. It’s notable that measured by market cap, bitcoin is the largest cryptocurrency by large margin. It also correlates heavily with other large cryptocurrencies. R-square from linear regression shows that 59 percent of index movement in 2017-11/2019 can be explained by bitcoin. Comparison with the index is also not perfect as this thesis doesn’t introduce any alternative investment choices. This means, performance against index relies only on how well prices of bitcoin can be predicted and can therefore not be concluded to give full picture of all technical trading rules performance against the index.

Cornish-Fisher expansion is used to account for excess kurtosis and skewness in some of the returns. This holds some limitations that are more thoroughly discussed later in the methodology. Briefly, dealing with non-normally distributed returns are taken into account by introducing distribution with corrected quantiles. There are however cases where some limitations cannot be fulfilled. This means that statistic (SKASR) calculated based on these quantiles is not fully valid. This problem doesn’t affect any results that are significant for purpose of this thesis and the results affected are shown as bolded in appendices.

In this thesis, risk-free rate is not used. Returns originate from intraday data in which case, risk-free rate is not usually used. Returns are however converted to daily returns to decrease skewness and excess kurtosis. In this case, using risk-free rate could be reasoned. Not using risk-free rate has small effect on results. 3-month T-bill rate during the period has been 2.4% p.a. at its highest. Using this would have very minimal effect on any of the results presented.

1.6 Structure of the thesis

Literature and methods surrounding the subject of the thesis will be covered in section 2. Covered are the subjects directly connected to technical analysis, including methods used in this thesis. The object of the theoretical background is to provide different viewpoints of the topics including critical views towards the subjects assessed. Also, different subjects around the methods and usefulness of those are covered.

In section 3 is short introduction of bitcoin and the data used in the analysis. While there is not large amount of data sources or data, this mainly covers key statistics of the data in question as well as where it's obtained.

Methodology of this thesis is covered before empirical analysis in section 4. There are some methodological choices that are explained as well as reasoning around structure of the thesis. Introduction of different statistical tests is also done in this section.

Actual empirical analysis is done in section 5. There will be brief analysis of different variables and some statistical tests to justify usage of those. Actual analysis is divided in six sections. In first four, strategies are tested only on train set. This section includes two estimations of best trading strategies for scenarios excluding and including trading fees. In latter parts, these strategies are tested with the test data to assess validity of obtained results.

At the end of this thesis, the conclusions are pointing out the results and their competence with current research of the subject. This is combined with possible future research topics.

2 THEORETICAL BACKGROUND

2.1 Efficient market hypothesis

Father of efficient market theory is thought to be Eugene Fama, Nobel-prize awarded economist who in his Ph.D. thesis (1965) discussed stock market behavior; especially how past prices affect future prices[1]. He found buy-and-hold strategy constantly beating all technical analysis methods proposing that stock market movements follow random walk. He's proposal was that random walk hypothesis holds. That means all significant information is at given time reflected to the stock price. In his words "If the random walk model is a valid description of reality, the work of the chartist, like that of the astrologer, is of no real value in stock market analysis". (Fama, 1995)

The work was later continued and expanded to other forms of efficient markets namely semi-strong form where concern is the speed adjustment lag after publicly available information is published. This research was conducted by following stock splits and price adjustments before and after these. While there were price anomalies before stock splits, reasons behind these anomalies were concluded to be companies tendency to split stocks at especially good times. (Fama, 1970)

In more recent literature, efficient market theory has had huge popularity. It has also had more and more critical claims. There are many studies of stock markets over the world showing different markets are not weak-form efficient meaning past behavior of the market can reflect future. For example Lo and MacKinlay (2002) used simple volatility-based specification test to find out that weekly stock market returns of CRSP NYSE-AMEX index didn't follow random walk. Similarly Mishra et al. (2014) found that Indian stock markets are mean-reverting meaning they tend to adjust towards the long-time mean. More broad test was conducted also for S&P 500, Nikkie225, Hang Seng, FTSE 100, IBOVESPA, NASDAQ-100, BSE 200 and S&P CNX NIFTY indexes by Dsouza and Mallikarjunappa (2015). They conducted series of tests founding that none of these indexes were normally distributed violating random walk model and volatility of indexes was more affected by negative shock than positive.

[1] There is also less technical article 'Random Walks in Stock Market Prices' (Fama, 1995) based on that thesis

While many of the studies suggest that random walk hypothesis doesn't hold, similarly many studies suggest the opposite. Especially, many of the studies conducted in indexes of developed countries seem to provide at least some proof for random walk model. Following propositions of Grossman and Stiglitz (1980) this can be due the cost of information. When information is easily available and cheap, markets tend to be more efficient. But while this is not the case in many of the markets, the efficient market hypothesis cannot hold. The difference between theory in developed countries and developing countries or BRICK-countries were further examined by Gümüs and Zeren (2014). Analyzing stock markets of G20-countries utilizing different unit-root tests depending on linearity form of the markets, they found that stock markets contained unit root consistent with weak-form efficiency in Germany, USA, Argentina, Australia, France, India, UK and Italy. However, hypothesis of unit root was not confirmed in Brazil, China, Indonesia, South Korea, Canada, Mexico, Russia and Turkey. They also came up with conclusion that development level of the country is connected to weak-form efficiency. Similar results for non-weak-form efficiency of markets in Russia, China, Poland and Romania were earlier obtained also by Hasanov and Omay (2007).

2.2 Technical analysis

Technical analysis means predicting future price movements by past prices or trends. It differs majorly from fundamental analysis, where stock price is calculated by fundamental information from company and operating environment. Two of the most used technical trading rules are moving averages and trading range breakout. One of the earlier studies utilizing these two was conducted by Brock et al. (1992) who conducted research on Dow Jones Index from 1897 to 1986. In that research, they were able to find strong support for these technical strategies. While being largely cited research, actual idea of using past prices to predict future comes much further from the history. Efficiency of these rules especially on stock markets is highly researched topic.

2.2.1 Moving averages

Large part of financial research conducted using technical analysis at least includes moving averages in their analysis (Farias Nazário et al., 2017). Usually two different averages are used. Long moving average (LMA) and short moving average (SMA). These are interpreted in format ‘SMA-LMA’. For example, MA 1-200, means short moving average of 1 period and long moving average of 200 periods. Moving averages can be written in following equation

$$MA_{t,n} = \frac{1}{n}\sum_{i=t-n+1}^{t} C_i = \frac{C_t + C_{t-1} + \cdots + C_{t-n+2} + C_{t-n+1}}{n}, \tag{1}$$

in which $MA_{t,n}$ is *n* period moving average at period *t* and C_i the closing price for period *I* (Wong et al., 2003).

Basically buying- or selling-signals come from crossing short and long moving averages. Buying-signal when SMA crosses LMA from below and selling-signal when SMA crosses LMA from above. (Brock et al., 1992)

Most used moving average rule is MA 1-200. Other widely used rules are 1-50, 1-150, 5-150 and 2-200. Basic idea of all these is the same; smooth out volatile series of data. One problematic scenario using moving averages is when prices go sideways. In that case short and long moving averages are close and there is large amount of sell- and buy-signals as moving averages are more probable to cross each other often. For these reasons many times bands are used, and signals generated only when band is crossed. For example, 1-percent band would mean that buy-signal is only generated when SMA ± 1% completely crosses LMA ± 1% from below. This would eliminate some of the false signals. (Brock et al., 1992)

It is worth noting that using shorter moving averages will result in more signals. 1-period moving average (current closing price) will cross long moving average much more often than longer moving average. Same is true for longer moving average. Shorter period results in more buy- and sell-signals which is especially problematic in sideways movement of markets and might need bands to counter false signals as Brock et al. (1992) suggest.

As an example, Figure 2 shows last half an hour Bitcoin prices from 24.9.2019. With MA 5-200 short moving average crosses long moving average 23.37 assigning sell-signal. In this figure, crossing MA:s are followed by lowering trend as theory suggests.

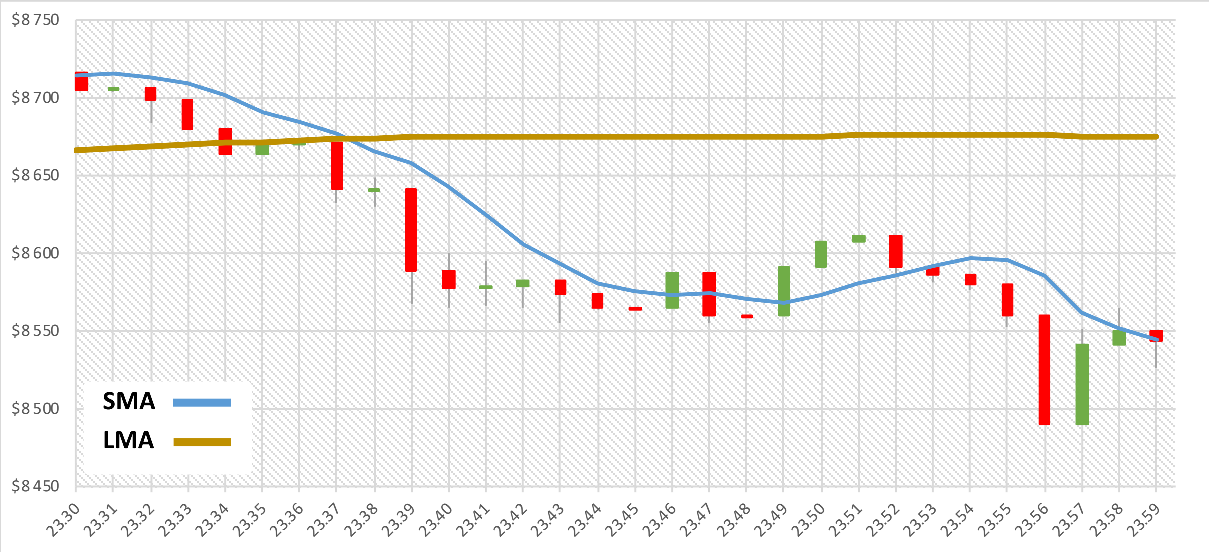

Figure 2. Candlestick chart with example of SMA crossing LMA from above (MA 5-200)

Another case where short moving average crosses long MA from below is presented in Figure 3. There short moving average crosses long moving average from below. By theory this is interpreted as beginning of uptrend and buy-signal would be assigned.

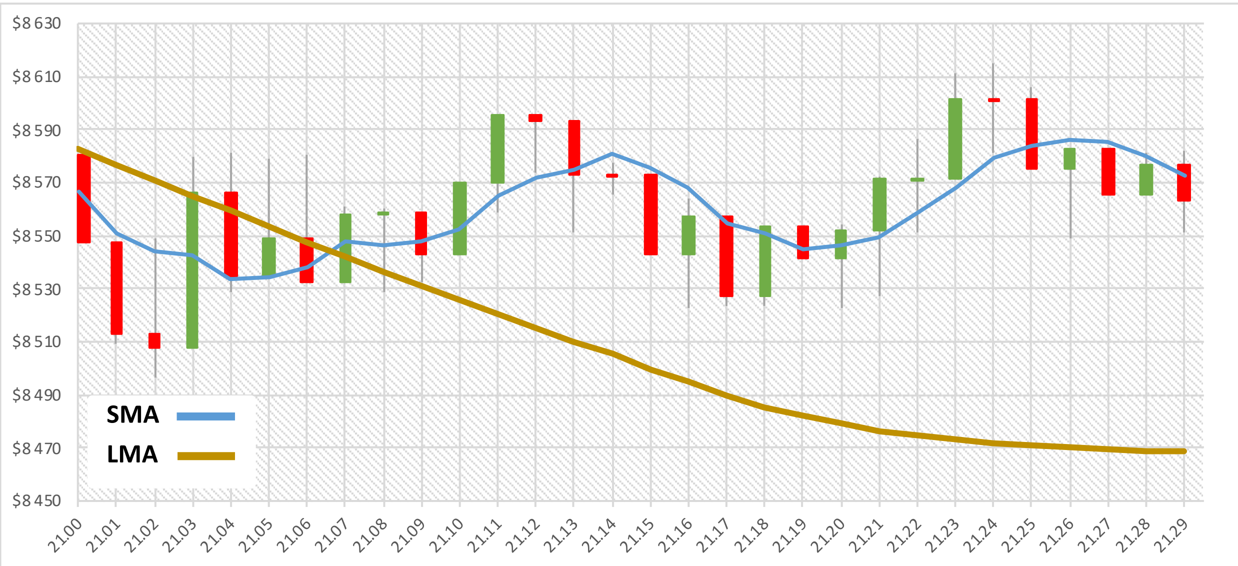

Figure 3. Candlestick-chart example of SMA crossing LMA from below (MA 5-200)

2.2.2 Trading range breakout

Trading range breakout is very simple rule. It uses maximum of *n* periods back as resistance level and minimum of *n* periods back as support level. Buying or selling signals are issued if resistance or support levels are crossed respectively. Usual values for *n* are 50, 150 or 200 (Brock et al., 1992). Simple mathematical representation for support and resistance levels following Gerritsen (2016) are

$$SUPPORT_{i,t} = MIN(C_{i,t-1}, C_{i,t-2}, \cdots, C_{i,t-n-1}),$$

$$RESISTANCE_{i,t} = MAX(C_{i,t-1}, C_{i,t-2}, \cdots, C_{i,t-n-1}),$$

where $SUPPORT_{i,t}$ is the support level of I at the time t and n is periods used.

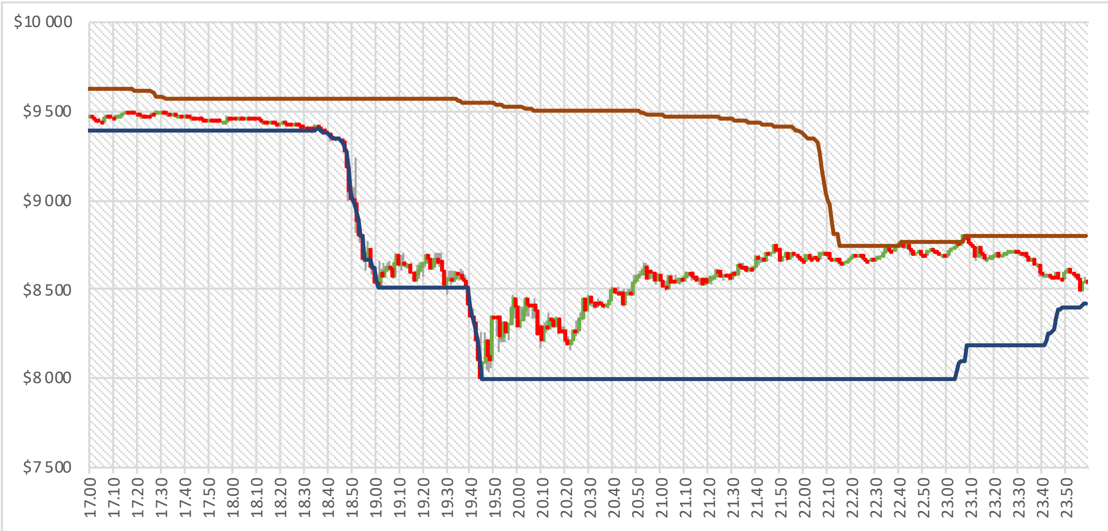

Figure 4. Example of 200-period resistance- and support-levels on bitcoin

Figure 4 shows 200-period resistance- and support-levels on bitcoin. With 1-minute intraday-data shorter periods results in large number of breakouts especially with sideways moving data. This is not hoped as so-called fake breakouts will become even larger issue. The problem is that these are not always real signs of price breakout. Brooks (2011) estimated that as many as 80% of price breakout attempts fail. According to him, same percentage holds also for fails in changing the trend direction.

That might be the reason why many of the intraday studies are focused on so-called opening range breakout (ORB). This means breakout to either direction at the opening of the market. This has been founded to be highly successful technical trading strategy in many of the researches. Holmberg et al. (2013) studied this in intraday-trading of oil futures and while finding it to be successful even without optimal exit-strategy, they questioned strategies success in less volatile markets. Tsai et al. (2019) tested similar ORB strategy for different futures including Dow Jones Industrial Average, Standard & Poor's 500 and NASDAQ. They concluded strategy to be successful and outperform also TRB strategy. This strategy was also successful in periods before and after 2007 financial crisis. Opening range breakout in bitcoin is however not possible as the trading doesn't have time limits. There are however some significant differences with bitcoin trading volumes during the day.

TRB haven't been tested with bitcoin on intraday data. Gerritsen et al. (2019) tested strategy with daily data of bitcoin and found it to outperform other technical strategies. They tested strategy (as well as six other technical trading strategies) for daily bitcoin prices from period of 2010 to 2018. There were three scenarios they tried, one being the scenario where short selling is possible and other two being scenarios where short selling is not possible. As a result, TRB was found to outperform buy-and-hold strategy in all scenarios. Without short selling possibility, outperformance was statistically significant with 95% confidence limits. Performance was measured using Sharpe ratio. Other technical trading strategies tested were moving averages, moving average convergence divergence, rate of change, on-balance volume, relative strength index and Bollinger band method. All of these were found to be less efficient than TRB, but moving averages were the second best.

2.3 Risk-return tradeoff

2.3.1 Sharpe ratio

While usual goal of different trading strategies is to provide profits, it's important to take into account how those profits are generated. For this, there are multiple different tools. Most common and widely known is reward-to-variability ratio introduced by Sharpe (1966) and more commonly known as Sharpe ratio. Sharpe showed that this ratio was effective in ranking mutual fund performances against Dow Jones Industrial Average Index. Ratio can be defined as follows:

$$SR_i = \frac{r_i - r_f}{\sigma_i^{\frac{ER}{|ER|}}}. \tag{2}$$

Basically, it takes excess returns (returns deducted by risk free rate) and divides that with standard deviation of the asset. Included on the equation is also the correction for the Sharpe ratio by Israelsen (2005), where volatility is raised in the power of -1 in case of negative excess returns.

As in this thesis, risk-free rate is not used, ratio is calculated as follows:

$$SR_i = \frac{r_i}{\sigma_i^{\frac{r_i}{|r_i|}}}. \tag{3}$$

2.3.2 Adjusted Sharpe ratio

Usage of the Sharpe ratio has also seen a lot of critical discussion. Much of the recent critique has to do with the distribution of the returns in financial assets. While Sharpe ratio might be effective way of measuring portfolio or asset performance, it also has few assumptions. Most importantly, returns must be normally distributed. As we are explaining risk by standard deviation, non-normally distributed returns distort this. Especially in cases like hedge funds, returns might be largely skewed. (Mistry and Shah, 2013). For this reason, there has been many attempts to make adjustments to original Sharpe ratio. One of these is Adjusted Sharpe ratio (ASR) introduced by Pézier (2004, p. 44). It penalizes for excess kurtosis and negative skewness. Negatively skewed returns result in too high Sharpe ratio as standard deviation embellishes risk. Ratio is defined as (Mistry and Shah, 2013):

$$ASR_i = SR_i \left[1 + \left(\frac{S}{6}\right) SR_i - \left(\frac{E}{24}\right) SR_i^2\right]. \tag{4}$$

Kurtosis can also be very high as in many cases, especially hedge funds tend to have very large number of small positive returns. Adjusted Sharpe ratio is more widely discussed by Pézier and White (2006). They tried to find optimal hedge portfolio allocations with Sharpe ratio, Adjusted Sharpe ratio and Omega ratios. In their research, portfolios created by both Sharpe and Adjusted Sharpe ratio were very closely matching.

By the terms of equation, it's notable that sign of the ASR differs from the sign of Sharpe ratio in cases where:

$$\left(\frac{E}{24}\right) SR_i^2 > 1 + \left(\frac{S}{6}\right) SR_i. \tag{5}$$

This tends to result in situations where exceptionally high Sharpe ratios lead to very negative ASR as larger divisor of excess kurtosis cannot compensate for Sharpe ratios power of two. Therefore, some more precise methods are also needed.

2.3.3 Modified Sharpe Ratio

Another modification worth discussing here is Modified Sharpe Ratio (MSR). Value at Risk (VaR) is largely used method utilizing cumulative normal distribution to measure risk in investments. While it uses cumulative normal distribution making it crucial that the investment itself is normally distributed, Favre and Galeano (2002) introduced Modified Value-at-Risk. Original Value-at-Risk can be stated as equation

$$VaR = n\sigma W dt^{0.5}, \tag{6}$$

where n is standard deviation from cumulative normal distribution at $1-\alpha/2$. σ is yearly standard deviation, W is amount at risk and dt year fraction. In modified Value-at-Risk, return distribution is modified to take into account skewness and kurtosis. Method for this was originally introduced by Cornish and Fisher (1937)[2]. Following formula is used to get skewness- and kurtosis-corrected distribution:

$$z_{CF} = z_c + \frac{1}{6}(z_c^2 - 1)S + \frac{1}{24}(z_c^3 - 3z_c)K - \frac{1}{36}(2z_c^3 - 5z_c)S^2 \tag{7}$$

following

$$MVaR = W(\mu - z_{CF}\sigma) \tag{8}$$

This was further expanded to Modified Sharpe Ratio by Gregoriou and Gueyie (2003) in form of following equation:

$$MSR = \frac{r_i}{MVaR}. \tag{9}$$

MSR behaves similarly to ASR in a way that it penalizes excess kurtosis and negative skewness.

2.3.4 SKASR

Skewness and kurtosis adjusted Sharpe ratio is another tool using Cornish-Fisher expansion. It was originally developed by Pätäri, and uses following formula (Pätäri et al., 2012):

$$SKASR = \frac{r_i}{SKAD_i^{(r_i/|r_i|)}}, \tag{10}$$

where skewness and kurtosis adjusted distribution $SKAD = {}^{z_{CF}}/_{z_c} * \sigma$. Also included is the correction for negative returns, where $SKAD$ is powered by returns divided by the absolute value of those (Israelsen, 2005). This is to account for same problem earlier shown to occur with Sharpe ratio in case of negative returns.

[2] The method is more widely known as Cornish-Fisher expansion

2.3.5 Cornish-Fisher expansions limitations

As Cornish-Fisher expansion is used in few occasions to modify distribution to account for skewness and kurtosis, it's important to discuss limitations surrounding it, most importantly window of validity.

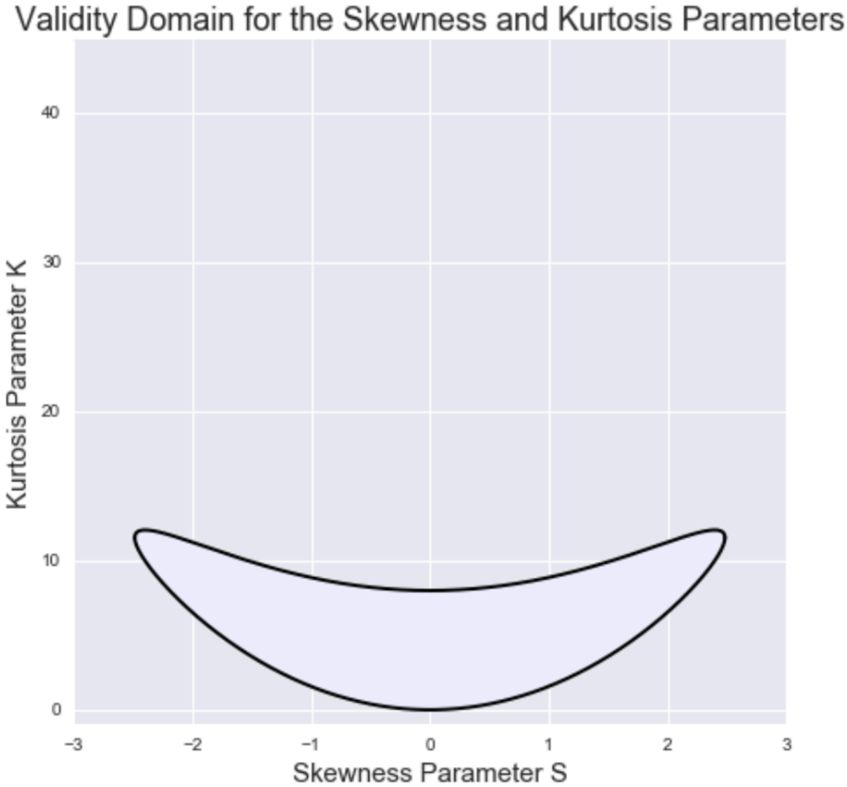

Figure 5. Window of validity for parameters in Cornish-Fisher expansion

Figure 5 presents area where Cornish-Fisher -expansion presents valid results. This means that transformation is increasing in the way that order of the quantiles in the distribution are conserved. Skewness parameter S must be in absolute values below $6(\sqrt{2}-1) = 2.485$. Kurtosis must be:

$$4\left(1+11s^2-\sqrt{s^4-6s^2+1}\right) < K < 4\left(1+11s^2+\sqrt{s^4-6s^2+1}\right), \tag{11}$$

where $s = \frac{S}{6}$.

If these windows are not satisfied, order of quantiles in the distribution are not conserved and resulting distribution is not fully valid. This will affect results and make comparison of SKASR or Modified Sharpe ratio biased. (Didier, 2014)

2.3.6 Winsorization

While trying to conserve as much of the distribution of returns as possible, some modifications will need to be made to fit results in the window of validity of Cornish-Fisher - expansion. For this reason, winsorization will be utilized. Winsorization originates from Epstein (1954) who tested removing samples from distribution to obtain more valid results[3]. These can be seen as outliers. In this case, these are not outliers such as calculation errors would be, but rather values with very high influence on certain components calculated. In these cases, removing those completely will not be very beneficial. Method proposed by Malik (2017) is to change these extreme values to correspond the values at the suggested endpoints of the data. While dealing with very large data, replacement of certain percentile of endpoints doesn't affect data a lot, but at least decreases the problems faced with high excess kurtosis and skewness.

2.3.7 Information ratio

When comparing Sharpe ratios, it's easy to forget that we are actually comparing just proposed strategies to other proposed strategies. This leaves out some important information and doesn't actually answer the question if strategy is overperformer or underperformer in cryptocurrency markets. There are some indexes following different cryptocurrencies values. One of those is CCI30 (2019), which follows 30 largest cryptocurrencies (Figure 6).

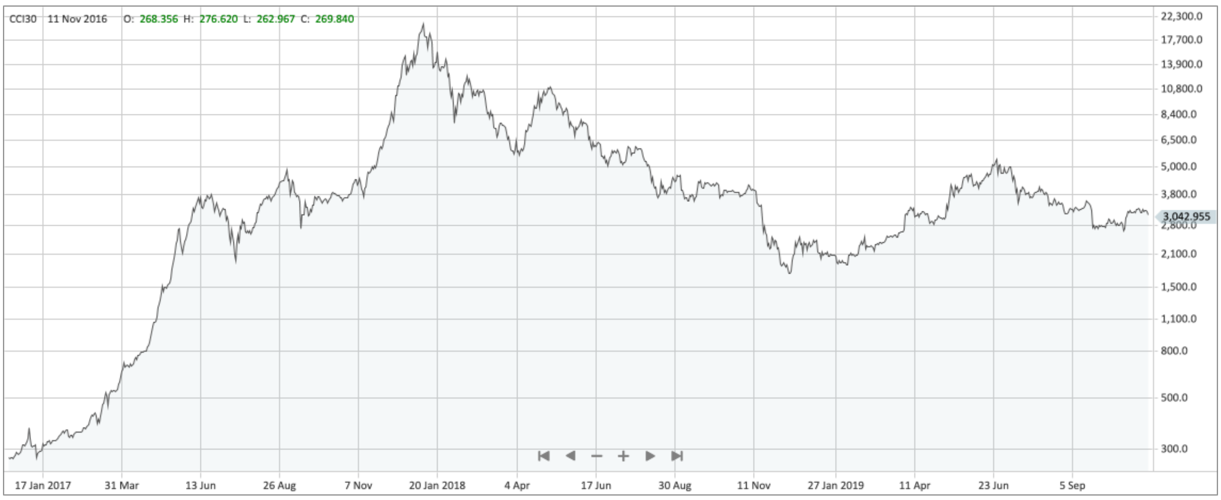

Figure 6. CCi30 Index

[3] Process of completely removing values is actually called truncation instead of winsorization

The index started from the beginning of 2017 and arbitrary starting point was set to beginning of 2015 at value of 100.

Different strategies including buy-and-hold can be compared to this index by using Information Ratio. As the index follows same markets that we are investing in, only way to overperform index is by changing weights of the investments based on information possessed by investor. Same level of market risk is maintained.

Information ratio is investments signal-to-noise ratio where noise can be thought of as a residual risk. Information ratio can be defined as follows:

$$IR = \frac{\alpha_{annual}}{{\omega_{annual}}^{ER/|ER|}}, \tag{12}$$

where, α_{annual} is the annualized intercept from regressing excess portfolio returns against excess benchmark returns. ω_{annual} is the annualized residual (noise) from the same regression. (Grinold and Kahn, 1992)

This can also be written in (maybe simpler) format:

$$IR = \frac{\overline{ER}}{{\hat{\sigma}_{ER}}^{\frac{ER}{|ER|}}}, \tag{13}$$

where $\overline{ER}$ is the arithmetic average of historical excess returns and $\hat{\sigma}_{ER}$ is the standard deviation of the same excess returns, also called tracking error. (Goodwin, 1998)

Same problems with negative excess returns are faced with IR as with any of the Sharpe ratio modifications. Therefore Israelsen (2005) modification can be included in tracking error also with IR.

2.3.8 Bootstrapping

While Sharpe ratio falls behind in non-normally distributed returns, bootstrapping has gained more and more popularity in recent researches. It is technique where original data is replaced with so called bootstrap-sample. This is called resampling, and was originally introduced by Efron (1979) and based on other popular resampling-method called jackknife. He focused on the problem of finding unknown sampling distribution of variable based on the observed data and came up with the resampling method where original sample is resampled with replacement[4] to obtain sample of same size as original. Underlying statistics are calculated, and process is repeated multiple times to come up with distribution of wanted underlying statistic. These can be presented in format of histogram. One popular usage of bootstrapping is to provide confidence intervals for the mean.

Basis behind bootstrapping is probability theory called law of large numbers (LLN). LLN states that as the number of trials approaches infinity, mean of those trials approaches theoretical mean of the underlying distribution. For LLN to hold, it's important that series is stationary. This means that distribution of the sequences taken from series stay same over time. There are various tests for stationarity of the series, one of the most used being augmented Dickey Fuller Test (ADF) which tests if the series contains unit root (e.g. is stationary). Another notable thing to observe is weak form dependency meaning the correlations of observations x_t and x_{t+h} of the series should approach zero sufficiently fast as $h \to \infty$.

While original bootstrap has been largely used, it doesn't work in case of time-series. Resampling of time-series would lead to loss of correlation of consecutive observations. For this reason, there are multiple propositions for time-series bootstrapping. Non-parametric bootstraps were first introduced independently by Künsch (1989) and Liu and Singh (1992) and later developed by research conducted by Politis and Romano (1994). They focused on stationary time-series and proposed model where instead of individual observations, blocks containing number of consecutive observations were used to account for correlation between consecutive observations (Politis and Romano, 1994). This means that dependence between observations is conserved.

For the block bootstraps there are number different methods. Most widely used is probably circular block bootstrap by Politis and Romano (1992) which removes 'edge effect' buy first forming circle from time-series. Results in all of those depend on optimal block-length (Ledoit and Wolf, 2008).

Ledoit and Wolf (2008) proposed block length selection algorithm where optimal block length can be found from fitting semi-parametric model[5] and by trial and error finding block length that minimizes confidence interval of parameter of interest. However, this can be quite time-consuming and might not always lead to optimal block-length. Politis and White (2004) on

[4] Replacement meaning that same observations can occur multiple times in bootstrap-distribution. This is differentiating factor from original jackknife method.

[5] Such as VAR or GARCH

the other hand proposed method to find optimal block length by minimizing mean square error of the bootstrap sample. It can be easily implemented in automatic calculations.

2.4 Stop-loss

Stop-loss is risk avoiding strategy where investment is exited after certain loss threshold is reached. It is intended (but argued) to be able to reduce left tail of the profit distribution (McKeon and Svetina, 2017). There are multiple research papers on the subject. As technical analysis itself, using stop-loss contradicts efficient market hypothesis. If markets movements can be explained by random-walk, there is no point in using stop-loss. This has been researched for example by Kaminski and Lo (2014) who found out that returns of stop-loss strategy, with random-walk return-generating process, were negative. However, in the same research they found that stop-loss strategies were profitable with momentum or regime-switching models. While random-walk hypothesis has been tested in many occasions with mixed results, there is no consensus on if it holds. In simplest form, stop-loss can mean exiting investment if price of it drops under certain threshold. For example, if price of long (short) position drops (rises) over 1%, investment can be sold (bought). There are also more technical stop-loss strategies such as trailing stop-loss where stop loss level is adjusted based on the highest value of investment. In this thesis I'm only interested in regular stop-loss. While also lot of opposing views exist, there are a lot of evidence that stop-loss strategies can be beneficial especially in high-volatility investments. Many of research contradicting usage of stop-loss strategies are based on the formerly discussed efficient market hypothesis. One such research was conducted by Gollier (1997). He discusses evidences against stop-loss and bang-bang theory in portfolio optimization. More recent researches seem to back stop loss -strategies in many cases. Lei and Li (2009) conducted tests on several different stop-loss strategies on NYSE and AMEX stocks from 1970 to 2005 coming up to results backing usage of stop-loss strategies. While profits or losses were not significantly affected, risk-level of portfolio was significantly lowered.

3 DATA

3.1 Bitcoin

Cryptocurrencies are relatively recent topic with first software for bitcoin mining released in 2009 and initial article from pseudonym Satoshi Nakamoto released in 2008. Based on the article written by Nakamoto, Bitcoin is based on the idea of cutting third party from the money transactions. (Nakamoto, 2008) Bitcoin was also first large release using so called blockchains. After it, multiple other cryptocurrencies have been published using same technology. These contain cryptocurrencies such as Ethereum, Ripple XRP, Bitcoin Cash, Tether and Litecoin. As of September 2019 cryptocurrencies have total market capitalization of over 250 billion dollars (CoinMarketCap, 2019). Three largest cryptocurrencies with their market capitalizations are shown in Table 1.

Table 1. Prices and market capitalizations of three largest cryptocurrencies (CoinMarketCap, 2019).

Name	Price	Market Cap.	Market Cap. %
Bitcoin	$9,696.83	$174,100,582,433	68.53%
Ethereum	$196.75	$21,224,359,250	8.35%
Ripple XRP	$0.27	$11,499,528,535	4.53%

These hold more than 80 % of total market capitalization bitcoin being largest of them with 68% market cap. It is worth mentioning that there are over 1000 different smaller cryptocurrencies on the markets 14 of which have market cap of over 1 billion US dollars.

Kidd and Brorsen (2004) discuss the fact that returns from technical analysis have fallen and find two main reasons behind this. Decrease in price volatility and increase in the kurtosis of price changes when markets are closed. In comparison to many other financial assets there are few major differences in Bitcoin. It can be traded around the year 24 hours per day and it has very high volatility as shown in Table 2.

Table 2. Annual volatility of Bitcoin 2016-2019

Year	Volatility
2016	49.40%
2017	94.30%
2018	84.30%
2019	71.10%

There are also no safety mechanisms such as trading halt or volatility halt auction period to decrease volatility (as there is no third party). Therefore, based on the findings of Kidd and Brorsen (2004), bitcoin can be seen as very potential candidate for technical analysis. While not being as largely researched as stock-markets, multiple researches are conducted using technical trading rules on bitcoin or other cryptocurrencies.

One research on the topic was done by Huang et al. (2018) who used classification tree with 124 different technical indicators. While being much more complex model, they did find highly profitable strategy with lower volatility compared to buy-and-hold strategy. They focused on estimating price change range and optimizing their trading strategy based on these findings.

3.1.1 Correlation with other cryptocurrencies

Efficient portfolio trading strategies rely heavy on correlations between investments we invest in. Low correlations will result in more efficient diversification. While cryptocurrencies can add good diversification to portfolio that holds other (non-cryptocurrency)-investments, popular cryptocurrencies are highly correlated to other popular cryptocurrencies (Table 3). For this reason, similar trading strategies probably work on other cryptocurrencies also, but very efficient cryptocurrency portfolio would be quite difficult to accomplice especially in case the liquidating the assets is considered.

Table 3. Correlation matrix of three cryptocurrencies 12.11.2018-27.9.2019

	CloseBTC	CloseLTC	CloseETH
CloseBTC	1		
CloseLTC	0.77	1	
CloseETH	0.84	0.93	1

3.2 Data used

Intraday data of the bitcoin prices with 1-minute intervals will be used from 1.1.2017 to 20.11.2019. The data is acquired from Cryptodatadownload (2019) and uses US based Gemini Cryptocurrency Exchange as a source. It has total of 1 443 374 quotes with opening, closing prices and high/low prices as well as volume. While there are 1 517 760 minutes in the time period, the data is missing 74 386 quotes. While this could be fixed by using previous prices for missing periods, it would increase possibility of wrong buy/sell signals as the prices would have higher probability of changing drastically on periods where previous data is missing. Instead, the data for all missing spots is filled with available hourly data and then filled forward to account for the gaps. While there are still larger movements in those spots, it doesn't affect results significantly. There were two gaps in data that lasted more than a day. First one was 15.11.2018-7.12.2018 and second 8.7.2019-15.7.2019. On top of these, there are some shorter gaps in 2019. From 1.1.2017 to 23.8.2018 there are no missing data.

Table 4. Descriptive statistics of the closing prices of bitcoin 2017-2019

	2017	2018	2019
n	525 600	490 107	427 667
Min.	$ 752.01	$3 126.88	$3 341.60
Max.	$19 999.00	$17 221.96	$13 850.00
Average	$3 967.22	$7 738.18	$7 213.85
Median	$2 567.29	$7 099.07	$7 985.94
St. Dev.	$3 978.84	$2 334.16	$2 764.34
Turnover	$ 13 822 170 917	$ 13 025 443 336	$ 4 631 368 841
Turnover (BTC)	₿ 2,922,939	₿ 1,560,614	₿ 658,984

Some descriptive statistics of the data used can be seen in Table 4. As seen, standard deviation of the prices is very high in all years under observation. Notable is the decrease in turnovers in 2019. This is probable to lead partly from the fact that exchange where data is obtained raised trading fees in 2019. While there is also high volatility in trading volumes over time, this doesn't explain the lower volumes in the exchange as the combined trading volumes in 2019 have been in all-time high. Higher trading volume have historically also affected the price of the bitcoin positively, but causality on this is left to be researched in other studies.

3.3 Data division

For purpose of avoiding apparent problem of data-snooping bias, different set of data needs to be used to assess model performance. For this reason, year 2019 is left out of the original sample and best rules are assessed with data from years 2017 and 2018. The validity of the model is then examined using data from 2019. With this process the desired solution is that the rules work similarly also with 2019 data.

There can be some discussion about the size of the training and testing sets. The apparent problem in case of bitcoin is that data from earlier years shows much lower volatility and trading volumes. As told, these strategies have been earlier tested with the daily data ranging back to 2010. It's considered decision to use only the data that shows similar behavior as today. Otherwise very probable outcome would've been that models either don't work similarly well in future data or multiple timeframes and train sets would've been needed to account for the data of different nature. Using data with 1-minute interval will provide decent number of quotes and should be enough to answer the research questions. If not, it's probable that more historical data wouldn't make the situation better, but rather more data from the future would be needed.

4 METHODOLOGY

Purpose of this section is to provide some answers about the frame this thesis is built on. Some reasoning behind certain decisions are also presented. Actual research of this thesis is built around simple structure provided in Figure 1.

4.1 Calculations

Moving averages for different ranges are saved to the data as own variables. Same is done for support- and resistance-levels. Data is also expanded with buy and sell signals gathered by technical trading rules. When moving averages cross each other, buy or sell signal is saved. When price breaks resistance or lowers below support-level, buy- or sell-signal is saved respectively. These rules are compared separately.

Moving averages to be tested are shown in Table 5.

Table 5. Different short - and long moving averages to be tested

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
SMA	1	2	5	10	20	30	40	50	60	70	80	90	100	
LMA	50	100	150	200	250	300	350	400	450	500	750	1000	1250	1500

For these all different combinations where LMA is at least two times that of SMA will be included. While Brock et al. (1992) suggested four different combinations, with today's computational power it's easy to include much more combinations into calculation. It's also notable that number of sell- and buy-signals reduces drastically when higher LMA:s are included. While usual transaction cost of subsequent buy- and sell-transaction (or sell- and buy-transaction aka. short-sell) is about 0.2%-units, reducing transactions will be in most cases very preferable. In this thesis highest LMA to be included is 1500-minute LMA. With data being highly trending at some points, too high LMA:s would result in higher profits, but results would be more probably biased. Another way to reduce probability of data-snooping bias is the division of data explained earlier. Both, the training period and the testing period introduced would in perfect scenario be longer.

Resistance- and support- ranges are shown in Table 6.

Table 6. Different resistance- and support-levels tested

	1	2	3	4	5	6	7	8	9	10	11	12	13
TRB	60	120	180	240	300	360	420	480	540	600	800	1000	1200

While in case of moving averages, all combinations are tested, length of resistance- and support- levels are always the same. This reduces number of different strategies tested for each resistance and support level substantially. Total number of different strategies tested for each different rule is shown in Table 7.

Table 7. Number of strategies tested

Strategy	No fees	Fees	Total
SMA1	126	126	252
SMA2	126	126	252
SMA5	126	126	252
SMA10	126	126	252
SMA20	126	126	252
SMA30	117	117	234
SMA40	117	117	234
SMA50	117	117	234
SMA60	108	108	216
SMA70	108	108	216
SMA80	99	99	198
SMA90	99	99	198
SMA100	99	99	198
TRB60	9	9	18
TRB120	9	9	18
TRB180	9	9	18
TRB240	9	9	18
TRB300	9	9	18
TRB360	9	9	18
TRB420	9	9	18
TRB480	9	9	18
TRB540	9	9	18
TRB600	9	9	18
TRB800	9	9	18
TRB1000	9	9	18
TRB1200	9	9	18
Total	**1611**	**1611**	**3222**

4.2 Returns

The return calculations in this thesis will be arithmetic. While logarithmic returns wouldn't make huge change in the results, there are few reasons behind using arithmetic returns.

First of all, data is very volatile. In small changes, differences between logarithmic and arithmetic returns are not very high, it will make much larger change in case of logarithmic returns. For example, price change from \$1000 to \$1500 which is not unseen in case of bitcoin would result in logarithmic return of $\ln(1500) - \ln(1000) = 0.4055$ and arithmetic return of 50%. These changes would cumulate noticeably over time.

Secondly, we can't always be sure for returns to have unit root and price of the asset doesn't seem to follow log-normal distribution hence taking one benefit of using logarithmic returns away.

To calculate the profit of the strategies, fixed bet will be used. This means calculations will be done using fixed $1000 bet and winnings will not be re-invested. This removes the worry that the trends would affect results obtained. When comparing to buy-and-hold strategy, it actually also gives buy-and-hold strategy advantage as it's essentially cumulative returns of all periods.

4.3 Winsorization

Winsorization was discussed earlier as a tool to make returns skewness and kurtosis fit inside window of validity of Cornish-Fisher expansion. In the case of this thesis, this will be used only in cases it's necessary. This means, all variables will be tested for skewness and kurtosis and smallest possible tails will be cut out to make data fit the model used. To remove largest excess kurtosis in returns, daily returns are calculated based on intraday returns. This is done to make it possible to fit the data in window of validity. Data is however still not perfectly normally distributed, and we can't actually calculate tails by utilizing cumulative normal distribution. Hence the following method will be used:

1. Returns will be tested to satisfy following conditions:

   Condition 1:

$$|S| \leq 6(\sqrt{2} - 1), \tag{14}$$

   where Fisher's skewness

$$S = \frac{1}{T}\sum_{i=1}^{T} \frac{(r_{it} - \bar{r}_i)^3}{\sigma}. \tag{15}$$

   Condition 2:

$$4(1 + 11s^2 - \sqrt{s^4 - 6s^2 + 1}) < K < 4(1 + 11s^2 + \sqrt{s^4 - 6s^2 + 1}), \tag{16}$$

   where $s = S/6$.

2. If conditions are met, step 3 will be taken. If not, both ends of the distribution sorted by value will be trimmed in following fashion:

   1:

$$r_1 \dots r_{Np} = r_{Np}$$

   2:

$$r_{N(1-p)} \dots r_N = r_{N(1-p)},$$

   where N is the number of observations in r_i and p starts from 0.0005 (0.05%) and increases by 0.0005 in each iteration.

3. SKASR and Adjusted Sharpe ratio will be calculated.

Maximum value of skewness is therefore ± 2.485. Maximum value of kurtosis when skewness is 0, is 8. For maximum values of ± 2.485 in skewness, maximum allowed value of kurtosis is 11.55. With high number of observations, this doesn't affect data in noticeable manner, but we are able to find acceptable values for skewness and kurtosis. Process is shown below.

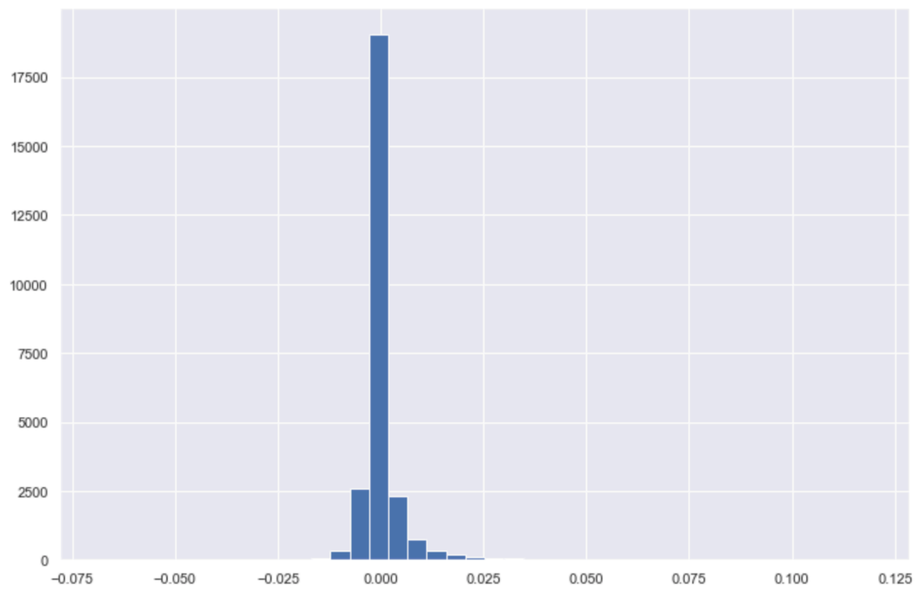

Figure 7. Distribution of the variable before corrections

Figure 7 shows distribution with high kurtosis of 52 and skewness of 4.9. This doesn't fit inside window of validity in Cornish-Fisher expansion. 0.05% tails are trimmed. This reduces kurtosis to 30.3 and skewness to 4.2. This isn't enough. After few iterations, trimming tails by 1.3%, we come up with distribution shown in Figure 8.

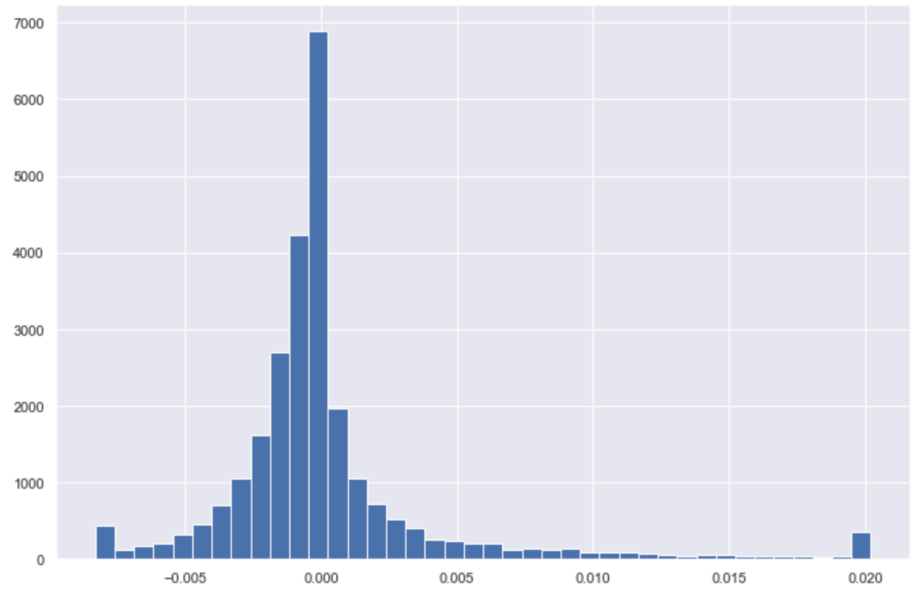

Figure 8. Return distribution with tails trimmed

This results in skewness of 2.4 (which is less than $6(\sqrt{2}-1)$) and kurtosis of 8.58 (which is less than 11.55 that would be allowed for skewness of 2.4). Calculations will be completed with this return distribution.

4.4 Performance measurement

Performance of different strategies compared to buy-and-hold strategy is compared using actual profit as well as SKASR, adjusted Sharpe ratio and traditional Sharpe ratio. Different modifications of Sharpe ratio are empirically justifiable, as in many cases returns provided by strategies hold major excess kurtosis. While Sharpe ratio doesn't penalize for this, SKASR and ASR does provide better measurement of the performance. In usual case, returns have high number of small positive or negative observations.

4.5 Statistical testing

In hypothesis testing, I'll be utilizing few statistical tests. With all statistical tests risk level α of 5% is used. The tests will be two-sided and therefore critical Z-value (in case of Z-tests) is 1.96. The tests are presented here.

4.5.1 T-test

Main test to be used is t-test for two independent samples. It tests if means of two samples is equal or not.

For this, equality of variances of two independent samples needs to be assessed. This is done by Levene's test for equality of variances (Levene, 1960). With this thesis we are constantly working with data that is not normally distributed. Many researches suggest that Levene's test is most robust in cases where data is non-normally distributed while for example Bartlett's test struggles in these cases (Brown and Forsythe, 1974; Lim and Loh, 1996). Modification, suggested by Brown and Forsythe to be best, is used[6]. This means that instead of means of the groups, medians of the groups are used. Null hypothesis of the test is following:

$$H0\text{: } variances\ of\ groups\ i = 1, \dots, n\ are\ equal,$$

$$\sigma_1^2 = \cdots = \sigma_i^2$$

Test statistic for Levene's test is defined as follows:

$$W = \frac{(N-k)}{(k-1)} * \frac{\sum_{i=1}^{k} N_i (Z_{i\cdot} - Z_{\cdot\cdot})^2}{\sum_{i=1}^{k} \sum_{j=1}^{N_i} \left(Z_{ij} - Z_{i\cdot}\right)^2}, \tag{17}$$

where

$Z_{ij} = \left|Y_{ij} - \tilde{Y}_i\right|$, in which $\tilde{Y}_i$ is the median of the ith group, Y_{ij} value of jth case in ith group,

k is the number of groups of the samples,

N is the number of cases and N_i is the number of cases in ith group,

$$Z_{i\cdot} = \frac{1}{N_i} \sum_{j=1}^{N_i} Z_{ij}\,, \tag{18}$$

$$Z_{\cdot\cdot} = \frac{1}{N} \sum_{i=1}^{k} \sum_{j=1}^{N_i} Z_{ij}\,. \tag{19}$$

[6] Making the test used, more strictly speaking, Brown-Forsythe test

W statistic approximately follows F distribution with degrees of freedom $k-1$ and $N-k$ and null hypothesis is rejected when $W > F(\alpha, k-1, N-k)$.
Independent sample t-test is done depending on results of Levene's test. Regardless of that, null hypothesis of t-test is as follows:

$$H0\colon means\ of\ two\ samples\ are\ equal,$$
$$\bar{X}_1 = \bar{X}_2$$

If variances are equal, pooled variance estimator and Student's t-test is used:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{s_p * \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}, \tag{20}$$

where pooled variance estimator

$$s_p = \sqrt{\frac{(n_1 - 1)s_{X_1}^2 + (n_2 - 1)s_{X_2}^2}{n_1 + n_2 - 2}}. \tag{21}$$

T-statistic is compared to Student's t-distribution with degrees of freedom $n_1 + n_2 - 2$. If the t-statistic is higher than the critical value from t-distribution, H0 of equal means is rejected.

In case of unequal variances, Welch's t-test is conducted (Welch, 1947). T-statistics for the test is obtained by following equation:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{s_{\bar{\Delta}}}, \tag{22}$$

where

$$s_{\bar{\Delta}} = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}. \tag{23}$$

T-statistic is compared to Student's t-distribution with degrees of freedom calculated as:

$$d.f. = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{\left(\frac{s_1^2}{n_1}\right)^2}{n_1 - 1} + \frac{\left(\frac{s_2^2}{n_2}\right)^2}{n_2 - 1}}. \tag{24}$$

One last t-test to be used is paired sample t-test. This is used when testing effects of certain modifications to the returns when data itself stays intact, but some values of it are affected. T-test for paired samples is constructed as follows:

$$t = \frac{\bar{X}_D}{\frac{s_D}{\sqrt{n}}}, \qquad (25)$$

where $\bar{X}_D$ is the average of differences and s_D standard deviation of differences. Degrees of freedom of $n-1$ are used when comparing t-statistic to Student's t-distribution.
It's worth mentioning that while critical values of Student's t-distribution are usually tabled to 120 degrees of freedom, it constantly approaches normal distribution as n increases.

4.5.2 Jobson-Korkie Z-test

To test equality of Sharpe-ratios, Jobson-Korkie Z-test will be used (Jobson and Korkie, 1981). Test was later corrected and simplified by Memmel (2003). The nullhypothesis for the test is:

$$Sh_i - Sh_j = 0$$

Asymptotic variance of the distribution of Sharpe ratio is obtained by following formula:

$$\theta = \frac{1}{N}\left[2 - \rho_{ij} + \frac{1}{2}\left(Sh_i^2 - Sh_j^2 - 2Sh_iSh_j\rho_{ij}^2\right)\right], \qquad (26)$$

where ρ_{ij} is correlation coefficient from returns of i and j. Z-test statistic is calculated by:

$$\frac{Sh_i - Sh_j}{\theta}. \qquad (27)$$

Instead of difference of Sharpe ratios, Jobson and Korkie used transformed difference calculated by $\widehat{Sh_{ij}} = s_j\overline{r_i} - s_i\overline{r_j}$. They however concluded this to provide only marginal improvement in case of small samples. In the case of this thesis, samples are large enough and regular difference is used. The SKASR is tested instead of regular Sharpe ratio.

4.5.3 Correlation tests

For all correlation testing, Spearman's rank correlation is used (Spearman, 1904). This is again due the normality assumption of Pearson's correlation which is met in none of the cases of this thesis. Spearman's rank correlation is same as Pearson's correlation, but where ranks of the numbers are used instead of actual numbers. Formula is following[7]:

[7] This is formula when obtained ranks are unique, otherwise Spearman correlation is calculated as Pearson with ranks

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}, \qquad (28)$$

where d_i is the difference of two ranks in each observations and n is the number of observations.

4.6 Strategies and implementation

When buy- or sell-signal is issued, transaction is set to be done next minute after the signal with closing price of that minute. While automized system would probably be able to conduct trade even faster, this is done to make sure all trades would be possible to do also in real life. Three different categories will be used, and profit and risk-adjusted profit calculated for these. Different categories to be used are shown in Table 8. Bands are used both ways. This means that buy-signal will be issued when $SMA * (1 - band) > LMA * (1 + band)$. Similarly sell-signal is issued when $SMA * (1 + band) < LMA * (1 - band)$. While reasoning behind bands is to reduce false signals, usage of band also greatly reduces number of transactions (and thus transaction costs).

Table 8. Different bands, stop-losses and fees to be used

Band	0%	0.1%	0.5%
Stoploss	0%	1%	2%
Fee	0	0.1%	

Model to compare results on will be buy-and-hold. Return will be compared between the model suggested by technical analysis and buy-and-hold strategy. Statistical difference between those will be concluded from Jobson-Korkie Z-test.

4.7 Transaction costs

As expected, usual downfall of different simple technical trading strategies are fees. In this research, three different scenarios are tested. Firstly, strategy without transaction costs. While this must be included, it's clear that in real life situations, these strategies would not work. Number of transactions in two-year timeframe differs from few hundred to tens of thousands based on band used and especially short moving average used. It's therefore clear that best strategies without fee will differ greatly from strategies deducting a fee. Fee used in this thesis is 0.1%. 0.1% fee is based on actual transaction fee used in many of the cryptocurrency exchanges. One of such exchanges is world's largest crypto exchange Binance (2019) (Russo, 2018). However, fees can differ, and higher monthly turnover lowers fees. While deduction is in many cases significant, it also requires usually very high monthly turnover. For example, in exchange such as Coinbase Pro, fees can go as low as 0.04%/0.00% with monthly turnover higher than 1 billion dollars (Coinbase Pro, 2019). Even though, this is not impossible case in institutional investing, I don't include these scenarios in this thesis. Also, while many of the exchanges charge much higher fees, it's not beneficial for purposes of this research to take these into account. It's more than clear that any intraday trading strategy fails if exchanges such as Coinbase Pro with low turnover (0.50% fee) are used.

Most exchanges also differentiate between maker and taker. This is, if client makes order not instantly matched, client is considered maker and fee is lower. On the other case, if order is instantly matched, client is considered as taker and higher fee is used. In case of intraday trading, orders must usually be instantly matched, and taker-fees will be used.

General fees could go lower for example if ETF:s could be utilized in trading. For now, U.S Securities and Exchange Commission (SEC) has continuously rejected all Bitcoin ETF proposals (Gurdus, 2019). By their point of view, Bitcoin markets are not mature and large enough to support a fund. Their main concern lies on market manipulation possibilities.

4.8 Data division

As observable from Figure 9 different phases in price patterns can be seen. Following bullish markets from beginning of the period, original bubble popped in late 2017 following mostly bearish markets for year of 2018 with some sideways drift in autumn.

Figure 9. Bitcoin price and market cap for the period

Comparison of results will be done between train set of 2017-2018 and test set of 2019 until 20.11.2019. While assumptions of obtaining risk-free rate during times when capital is not invested have been done in many previous literatures, it will not be used in this thesis.

Short selling is not possible in many of the crypto exchanges, and it is therefore considered not to be possible. There are futures markets for bitcoin trading but at this point many platforms don’t provide opportunity for short selling. This would further distract main point of the thesis. Also, in institutional investing, short selling is usually limited.

5 EMPIRICAL ANALYSIS

This thesis is built around a concept that markets are not efficient and moving averages can provide some additional information on market movements. With volatilities as high as with bitcoin, this is likely scenario. We can easily plot market movements after certain signals to see, if those seem to hold any information. At the same time, while exit strategy is not set to be n periods after buy or sell signal, it's easy to see how actual movements compare to the ones needed to make profit even with fees added. If we consider fee to be 0.1%, we can easily see that at least 600 periods after buy or sell signals, there seems to be no possibility to make profit in proposed strategies below (Figure 10). Considering one-time purchase to be $1 000, fees to be paid would always be $2 (0.2%) at minimum and linearly go higher when investment price rises.

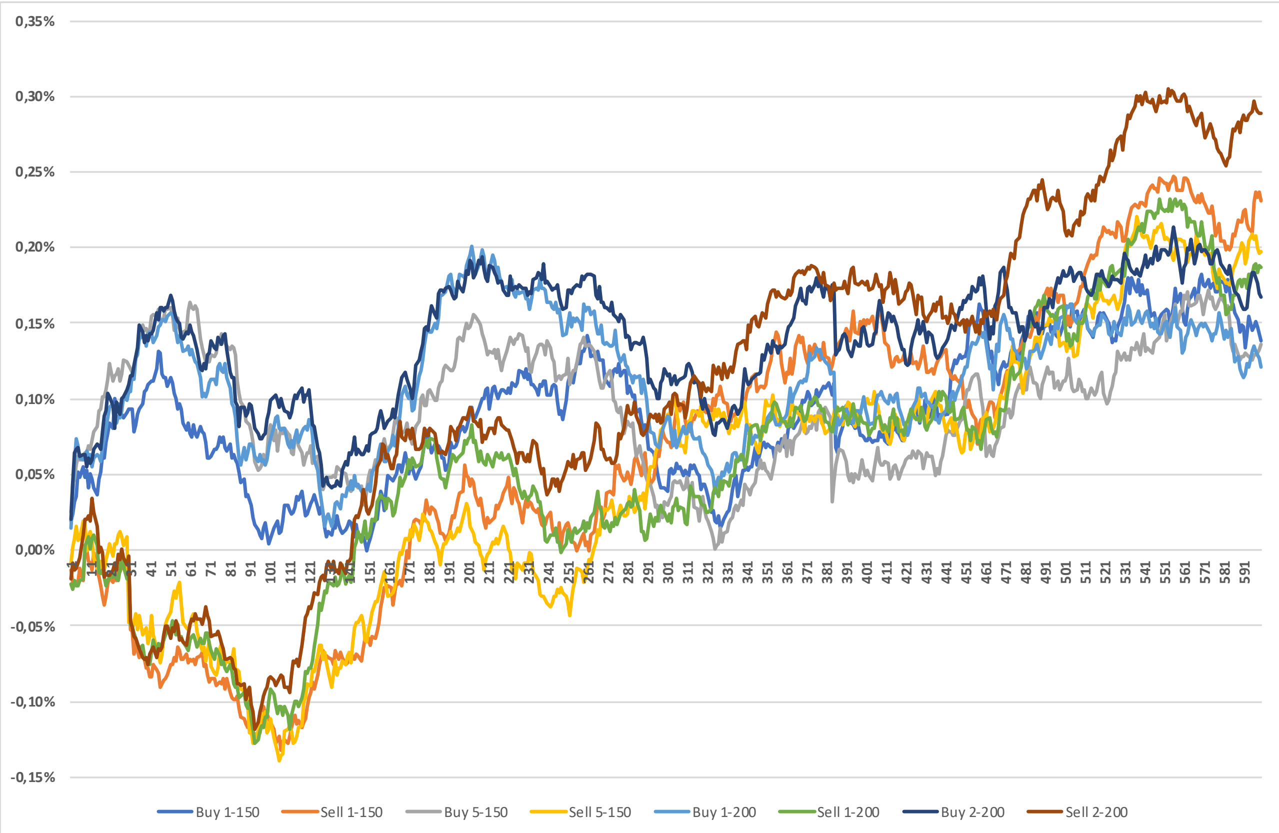

Figure 10. Average returns for different periods after buy- or sell -signal with 0.05% band

However, if we don't consider fees to be a problem and consider market movements after a signal to be always similar, smart investor would always sell his security around period ~50 (e.g. 50 minutes after the signal) or at period ~200 whichever would be averagely closer to next buy- or sell signal. Similarly, after sell signal, shorting if possible, would provide highest profits around period 100. Graph seems to show, that signals provide information at least on short time trends but are mixed up after short time. After 10-hour period, highest profiting signal of these examples would be to buy when MA2-200 tells to sell. This however would be very clear case of data-snooping and would be very probably not too well-fitting strategy on future data.

5.1 Number of signals and trading fees

As mentioned before, fees are lethal in very many intraday trading strategies. This is purely based on number of trades. While in regular buy-and-hold strategy, investor is supposed to pay two fees, one at entrance and second at exit, in intraday-trading, these fees are a lot bigger factor. This will lead to fact that considering fees, in most cases, strategy including smaller number of trades will be more profitable strategy. With this being the case, it's important to understand the effect that moving averages have on number of trades they signal. As is clear, shorter the moving averages are, higher number of trades they signal. 1-period moving average crosses 50-period moving average much more frequently than 10-period moving average crosses the same long moving average (Figure 11).

Figure 11. Number of trades signaled without band by different combinations of SMA and LMA

5.1.1 Bands

This fact leads to need to regulate number of trades to be conducted. This is especially true in shorter moving averages that can suggest number of trades of over 25 000. This would add minimum of over 50 000 to the fees. In this research, number of trades or especially ‘false signals’ have been limited by introducing bands to moving averages. Two bands are suggested, one being 0.1% and another being 0.5%. Number of trades with these bands can be seen in Figure 12 and Figure 13 below.

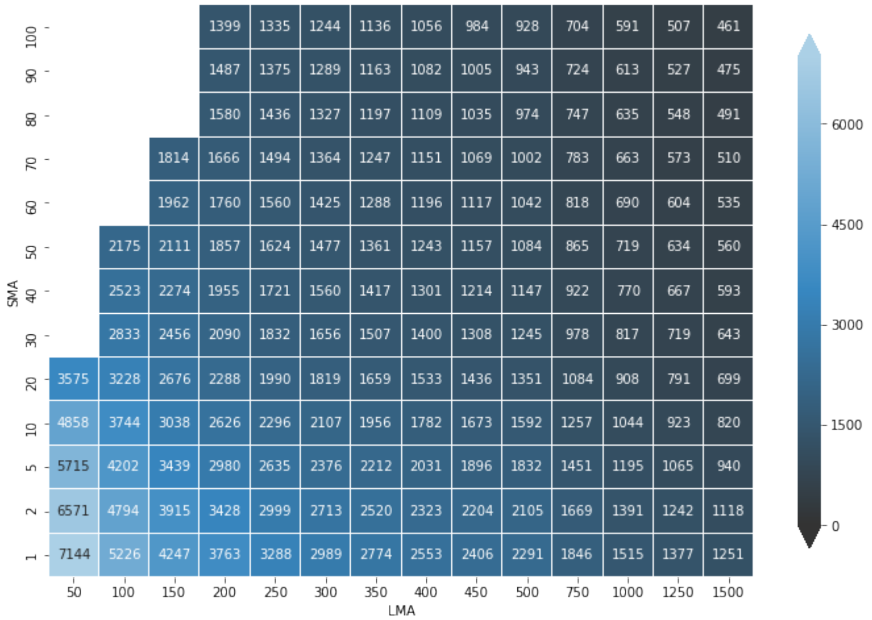

Figure 12. Number of trades signaled with 0.1% band by different combinations of SMA and LMA

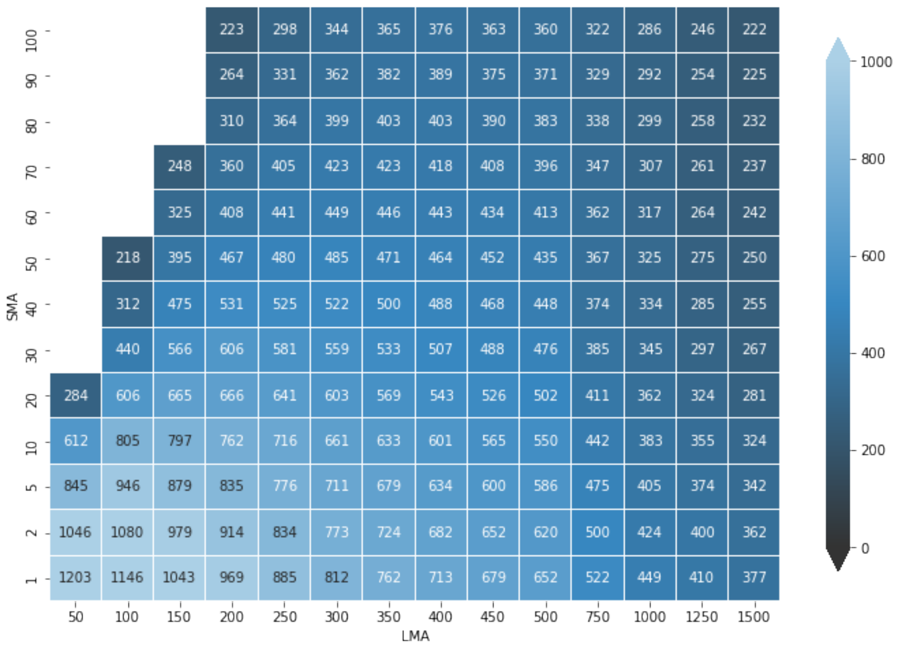

Figure 13. Number of trades signaled with 0.5% band by different combinations of SMA and LMA

Another aspect surrounding usage of bands is if they affect average profit or loss of individual trades. This can be interpreted from following heatmaps.

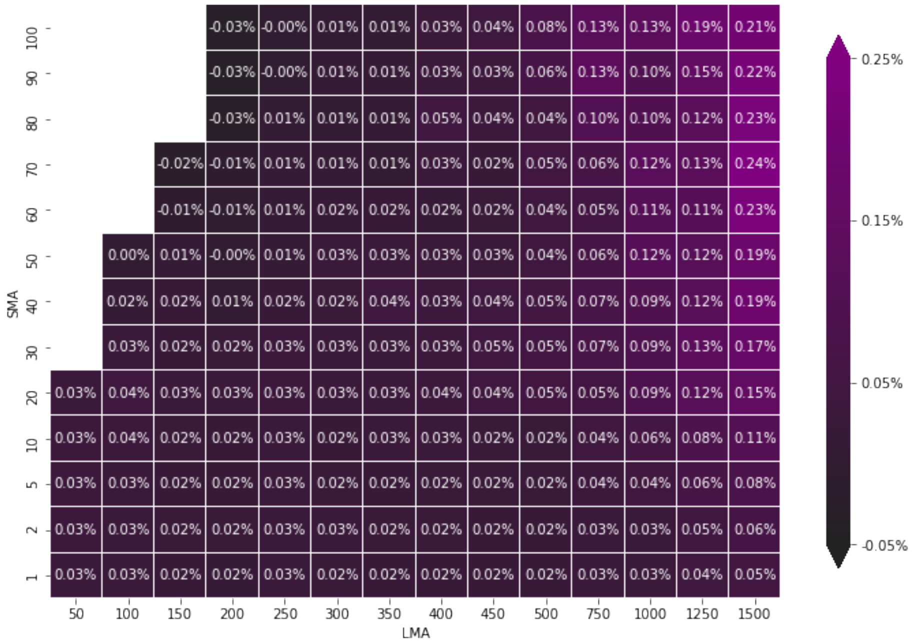

Figure 14. Average profits from different strategies without band

Without band, it’s easy to see that while longest moving averages make largest average profits, even those would struggle if fees would be included in strategies. Only five of the strategies would have even theoretical chance to conduct small profits with 0.1% fee. Smallest moving averages however purely rely on number of trades as the returns from those are very small and wouldn’t even theoretically be able to handle trading fees. (Figure 14)

When band of 0.1% is introduced, returns rise in most of the cases. This is especially evident in largest long moving averages many of whose would be able to make at least theoretical profit. Simultaneously average losses from combinations which made losses in no-band scenario will be even worse. (Figure 15)

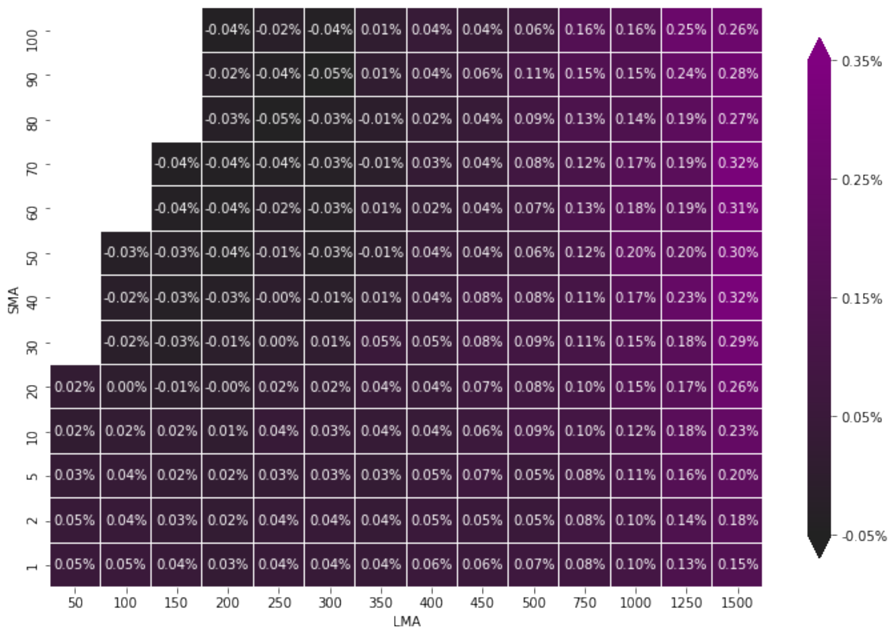

Figure 15. Average profits from different strategies with 0.1% band

Even greater affect can be seen with profits including 0.5% band (Figure 16). With these results it’s nothing but evident that average number of trades need to be limited to have any chance to obtain returns from any strategy.

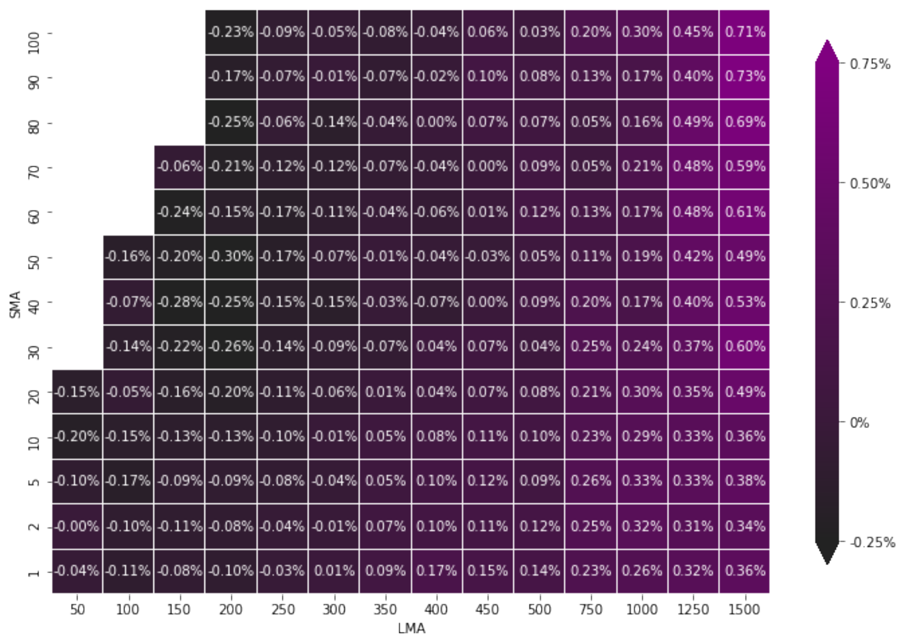

Figure 16. Average profits from different strategies with 0.5% band

This can further be confirmed by testing equality of mean returns with independent sample t-test. Between 0% band and 0.1% band null hypothesis of equal variances is rejected in all cases utilizing Levene’s test of equal variances. Further, Welch’s t-test of equality of means of two samples with unequal variances provides p-values presented in Figure 17.

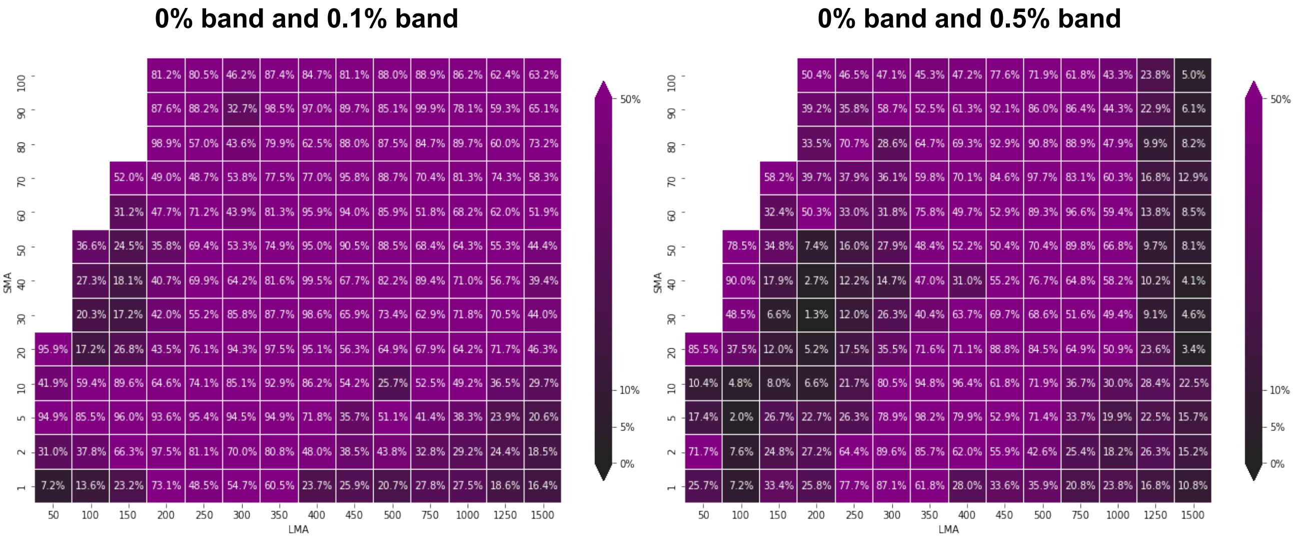

Figure 17. P-values of Welch's t-test for equality of means in returns of 0% band, 0.1% band and 0.5% band

Returns between two first strategies don’t differ significantly in any of the cases. Smallest p-value of 7.2% is between returns on strategy MA1-50 in which average returns grew from 0.03 to 0.05. It can be concluded that there is not very strong empirical support for usage of 0.1%-band.

Similarly, differences of returns between 0% band and 0.5% band don’t differ significantly in most of the cases. In cases, we are most interested in, when fees are introduced, returns however differ significantly.

5.2 Stop-loss

Usage of stop-losses in further analysis can also be justified by testing equality of returns with stop-losses and without them. In this case, as stop-loss doesn’t affect number of returns, those are considered paired and can be tested with paired sample t-test. P-values provide evidence that stop-loss levels do affect returns in some cases (Figure 18). However, there doesn’t seem to be any recognizable patterns in relationships. On the other hand, all statistically significant differences in the graph comparing no stop-loss to 1% stop-loss, are positive suggesting that large number of trades with small profit-potential would be affected positively by including stop-loss to trading strategy. This can be further examined from t-values on Figure 19. By the order of tested values, positive t-values suggest that strategy including stop-loss performed better than the one without it.

In case of 2% stop-loss, larger number of returns seem to be affected negatively by the stop-loss. MA1-500 -strategy didn't have any utilized stop-loss trades and is therefore empty.

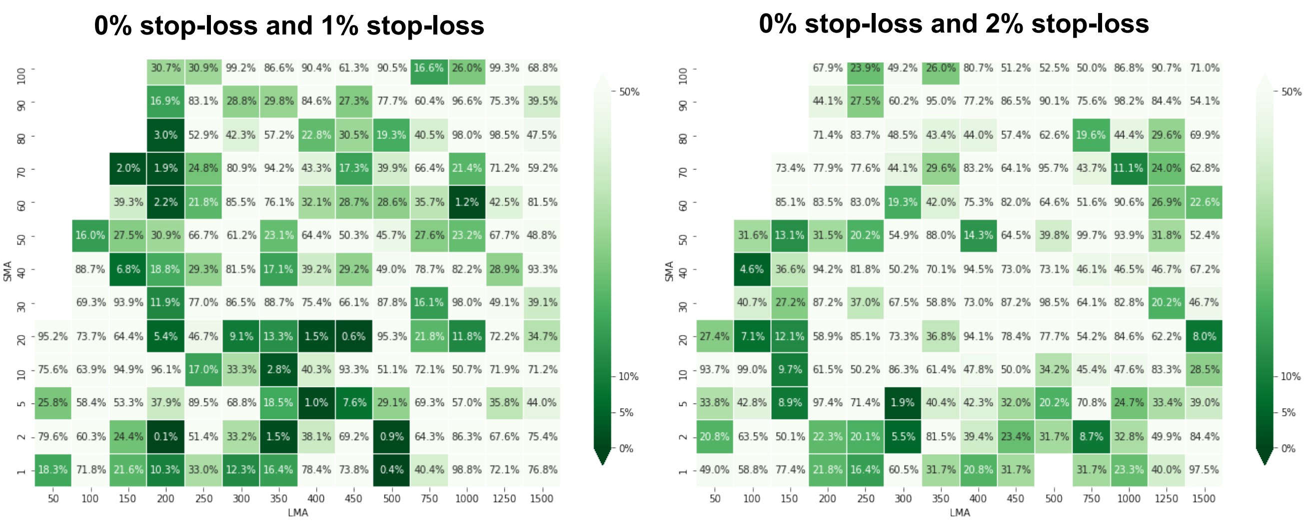

Figure 18. P-values of t-test for equality of means in returns of 0% stop-loss, 1% stop-loss and 2% stop-loss

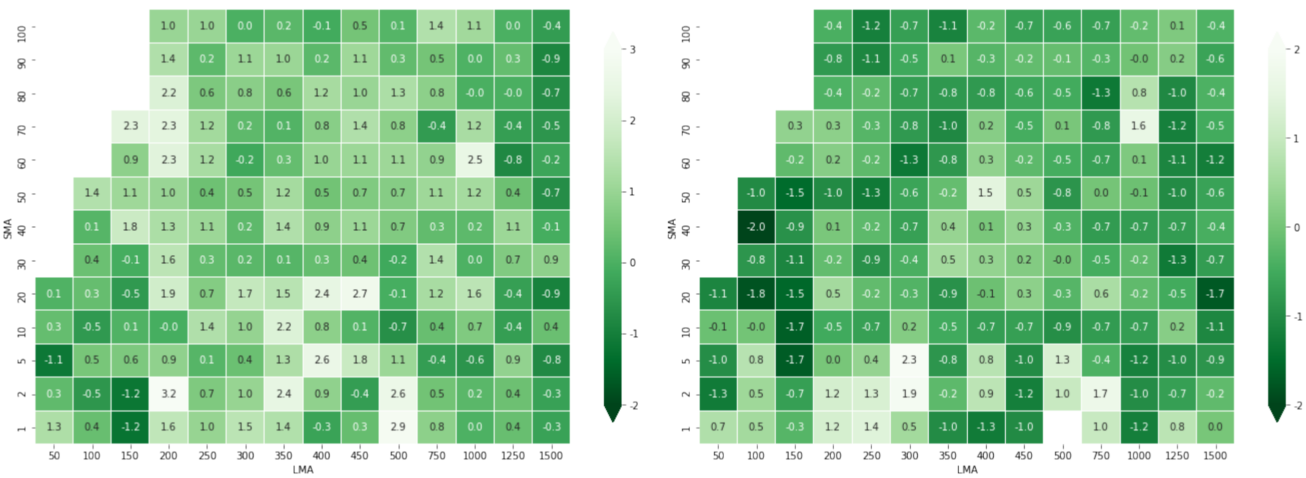

Figure 19. T-values of t-test for equality of means in returns of 0% stop-loss, 1% stop-loss and 2% stop-loss

Trading fees do not affect number of trades different strategies introduce, but just the profitability of these strategies. For that reason, all tests presented above do hold in all scenarios used below.

5.3 Buy-and-hold

As the research question of this thesis is to assess if any of the strategies can overperform buy-and-hold strategy, it's worthwhile to assess baseline by first checking performance of buy-and-hold strategy. As seen earlier on Figure 9 returns on it are very volatile. Volatility in different years of bitcoin were shown in Table 2.

For buy-and-hold, daily closing prices are used. No corrections are needed to data as there is no problems with excess kurtosis or skewness (Figure 20). Same tests were used for this strategy as for the rest of strategies. Annual volatility of buy-and-hold strategy for period of 2017-2018 was 90,3%. SKASR gives strategy Sharpe ratio of 1.75. In case of buy-and-hold returns are cumulative as all returns will always stay in cumulating more returns.

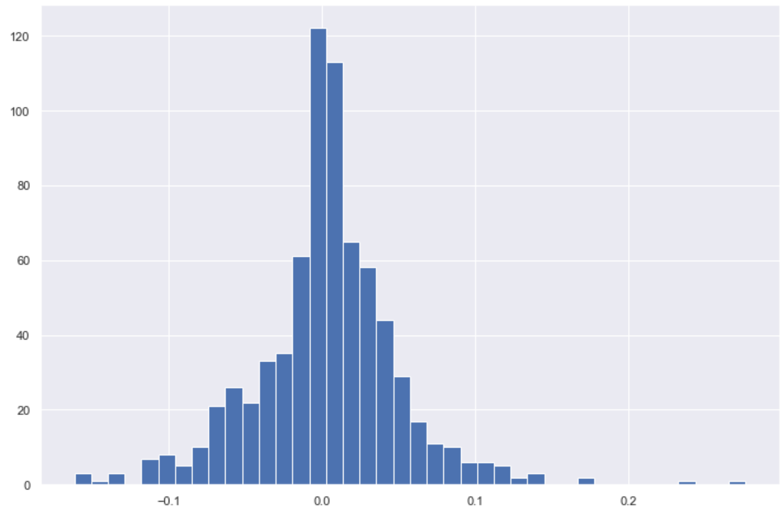

Figure 20. Histogram of distribution for buy-and-hold returns

Sharpe ratio of the strategy is noticeable low. This is largely due very high volatility. Regular Sharpe ratio for buy-and-hold strategy is 1.81 and adjusted Sharpe ratio is 1.9. These can be seen as baseline for comparing other strategies (Table 9). Same statistics are used also in case when fees are added as the affect fees would have on buy-and-hold strategy are minimal.

Table 9. Performance statistics for buy-and-hold strategy on train set

	Annual profit	Annual volatility	SKASR	Adjusted sharpe	Sharpe
Buy-and-hold	164.1%	90.3%	1.75	1.9	1.81

5.4 Without transaction costs

First scenario to be tested is one where no trading fees are included. Stop-losses of 1% and 2% are included as well as the strategy without stop-loss. Also, all bands are included in testing. All strategies on this section are tested only on a train set.

5.4.1 Moving averages

Not surprisingly five highest profiting MA strategies are the ones with smallest moving averages. Highest profiting strategy introduces total of 26 042 buy-signals While being undesirably large number of signals due the real-world trading costs, these strategies are easily able to beat buy-and-hold strategy profit-wise if fees aren't considered. Best profiting strategy was the one with MA1-50, 0%-band and 1% stop-loss. As tested earlier, stop-loss doesn't hold any statistically significant value with this strategy. Other MA1-50 strategies with 0%-band are within $90 from highest profiting strategy. This strategy won the market by clear margins in all scenarios except extreme bullish market. In the end of 2017, market price rose drastically beating temporarily all introduced strategies.

Strategies are able to make profits also on extreme market movements such as ones at the end of 2017, but these profits seem to be not as high as in less volatile markets. Its also noteworthy that all introduced strategies seem to not be too profiting in markets of 2018. Almost all profits in train set are made in 2017.

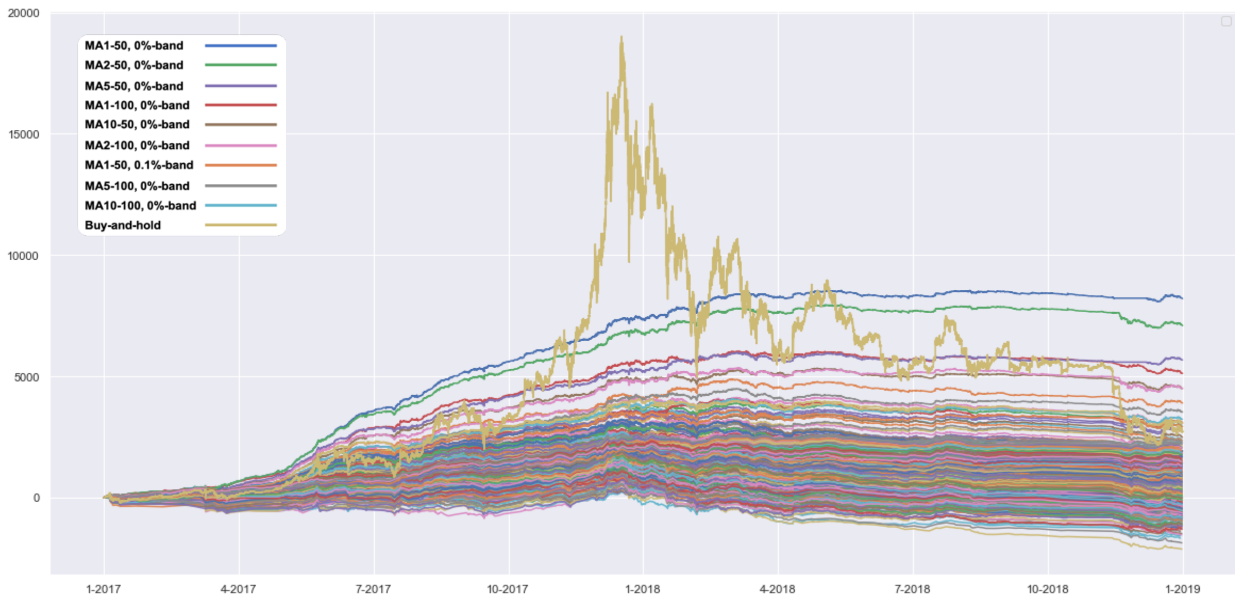

Figure 21. All no-fee MA strategies not including stop-losses

Figure 21 presents all different strategies not including stop-losses. Just few of those stand out and beat the buy-and-hold strategy. Most strategies also follow very similar paths not making clear profits at any point. Also, of those standing out only one, MA1-50 makes good profits also with the band.

In no fees -scenario, same strategies will in most cases profit much smaller amounts if bands are introduced limiting number of trades. This is especially clear in MA5-100 where number of trades would drop drastically from 11 276 to 946 with 0.5% band turning the profits of $3 527 to losses of ~$1 676 and strategy completely useless.

Relationship between number of trades conducted and profits is clear. This can further be examined by Spearman correlation matrix (Table 10).

Table 10. Spearman correlation matrix of key-statistics

	trades	profits	profits_avg	skewness	kurtosis	SMA	LMA
trades	1.0***						
profits	0.32***	1.0***					
profits_avg	-0.26***	0.7***	1.0***				
skewness	0.11***	0.5***	0.29***	1.0***			
kurtosis	0.7***	0.43***	0.01***	0.35***	1.0***		
SMA	-0.38***	-0.37***	-0.03*	-0.25***	-0.23***	1.0***	
LMA	-0.41***	0.48***	0.8***	0.32***	-0.02**	0.14***	1.0***

***1% **5% *10%

Most correlations are statistically significant with 1% risk level. Number of trades and returns have positive correlation coefficient of 0.26. Other notable correlations are the negative correlation of short MA and returns as well as positive correlation between long MA and returns. Especially latter suggests that while rising LMA reduces number of trades, there are also some strategies profiting decently with smaller number of trades. All-in-all most of the strategies do suggest less than 10 000 trades. All tested strategies can be examined in scatterplot from Figure 22.

Figure 22. Scatter plot of number of trades and returns without fees and different LMA:s

By filtering to strategies with less than 10 000 trades, subtle patterns can be seen (Figure 23). Especially in LMA, it's easy to see that larger LMA:s do perform better than smaller LMA:s. This is in line with previous tests including bands. Longer LMA:s returns are positively affected while bands are introduced. Returns provided by all SMA:s with small LMA:s are especially badly affected by bands.

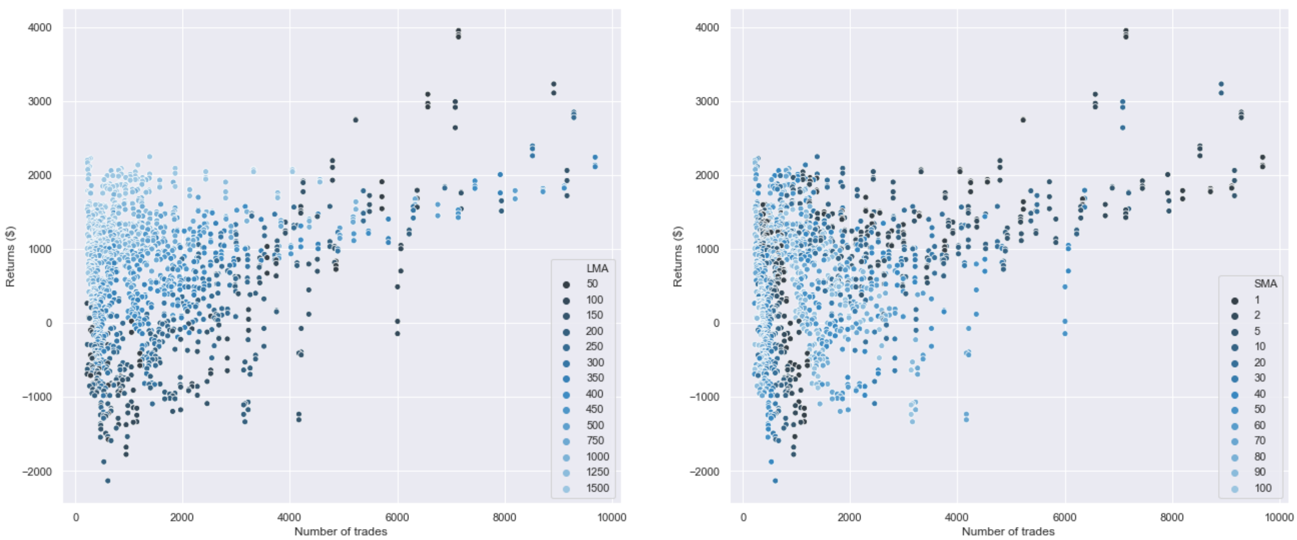

Figure 23. Filtered scatter plots of strategies with under 10 000 trades against returns

It's important to discuss also risk included in these strategies. Risk-adjusted returns are calculated by regular Sharpe ratio, Adjusted Sharpe ratio and skewness and kurtosis adjusted Sharpe ratio. Skewness and kurtosis adjusted Sharpe ratio is the one that will be used to rank strategies and others are there for good measure.

Table 11. Statistics for 10 best MA strategies on train set without fee ranked by SKASR.

Note: Memmel Z shows statistical significance of difference between SKASR of the strategy and SKASR of the buy-and-hold (1.75). When it's in absolute values larger than 1.96 (95% CI), difference is statistically significant. In many cases, ASR is negative. This is caused by high Sharpe ratio used in calculations as described in section 2.3.2.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio
MA1-50	0.0%	1%	26042	$8,271.4	0.03%	21.2 min	65%	414%	7.82	31.6	-4.82	6.41
MA1-50	0.0%	2%	26042	$8,227.3	0.03%	21.2 min	64%	411%	7.81	31.6	-4.41	6.38
MA1-50	0.0%	0%	26042	$8,188.6	0.03%	21.2 min	65%	409%	7.28	31.0	-10.25	6.28
MA2-50	0.0%	0%	21666	$7,090.7	0.03%	25.8 min	68%	355%	5.28	27.8	-4.15	5.20
MA2-50	0.0%	1%	21666	$7,107.7	0.03%	25.8 min	69%	355%	5.14	27.3	-5.65	5.18
MA5-50	0.0%	0%	16471	$5,654.6	0.03%	33.2 min	62%	283%	4.94	26.5	5.60	4.55
MA2-50	0.0%	2%	21666	$7,013.0	0.03%	25.8 min	69%	351%	4.90	26.8	-5.12	5.11
MA5-50	0.0%	1%	16471	$5,453.1	0.03%	33.2 min	61%	273%	4.90	26.5	8.51	4.49
MA5-50	0.0%	2%	16471	$5,530.9	0.03%	33.2 min	62%	277%	4.90	26.6	5.59	4.48
MA1-100	0.0%	1%	18481	$5,169.8	0.03%	30.2 min	60%	258%	4.76	26.7	8.70	4.30

Ranking strategies by SKASR will first of all show how volatile all proposed strategies are (Table 11). All of the 10 best strategies have volatilities of over 60%. This means that even though, these strategies make very decent profit in no-fee scenario, risk is also high. Highest skewness and kurtosis corrected Sharpe ratios are on those strategies that profited best. These also differ statistically significantly from SKASR of buy-and-hold strategy as Jobson-Korkie Z is over the critical value of 1.96. Ten best strategies don't have any corrections done by winsorization, as all return distributions fitted inside the window of validity of Cornish-Fisher expansion.

Highly right-tailed returns make SKASR differ quite a lot from Sharpe ratio. Relationship between the two can be more closely examined from Figure 24. Sharpe ratio clearly over-estimates risk-adjusted return for some left-tailed models. More detailed statistics for thirty strategies with best SKASR can be seen in Appendix 1.

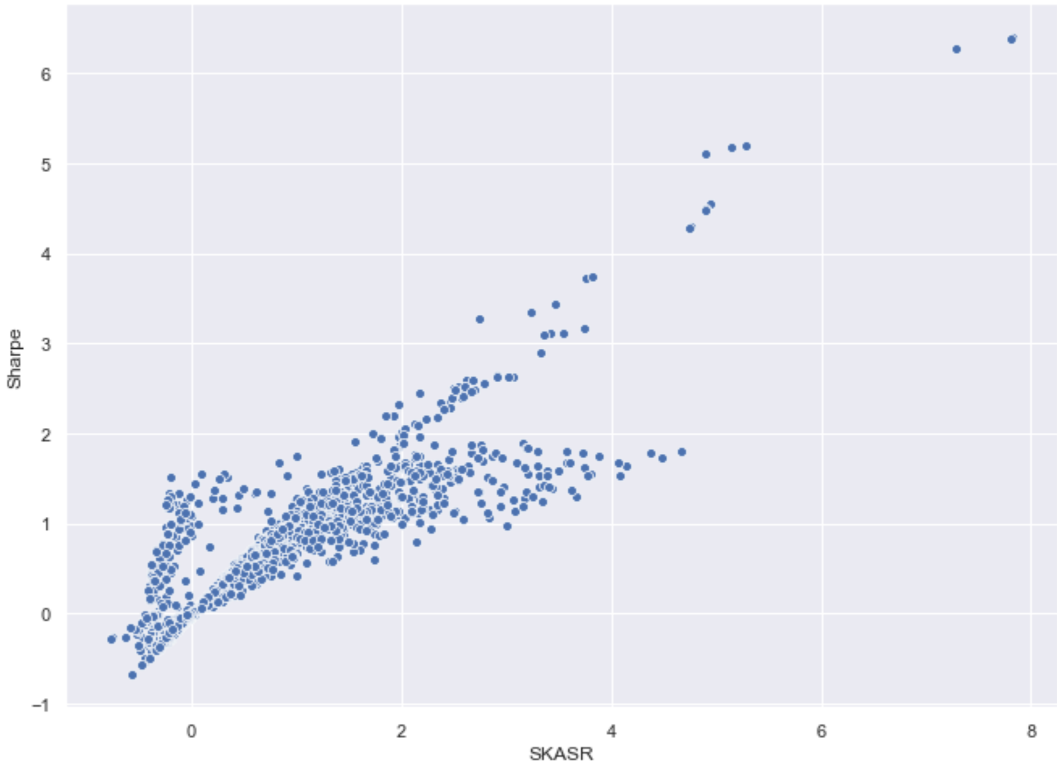

Figure 24. Scatter plot of Sharpe ratio and SKASR

Note: Some Sharpe values and SKASR values have different sign. This is due the winsorization in which small number of high values are replaced. In some cases, winsorizising even few high returns changes profits to losses.

It can be concluded that other strategies than buy-and-hold work better in no-fee scenario on train set. This is especially true because in real life, reasonable investor would invest money to ETF:s or other steady profit-yielding securities when money is not invested in bitcoin. In 20 best performing strategies, time invested in bitcoin ranges between 50-60%. For example, best performing MA1-50 strategy has money on bitcoin 550 861 minutes accounting 52.4% of the two-year timeframe. Easily liquidatable investment could provide almost additional 1 years return.

5.4.2 Trading range breakout

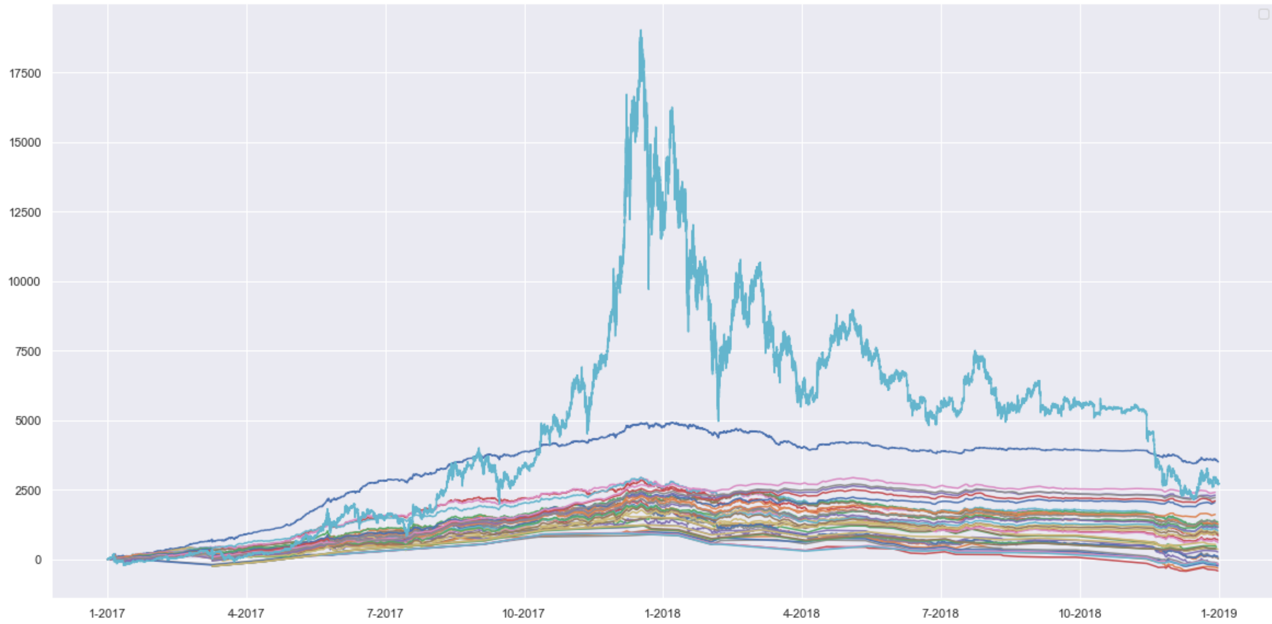

Figure 25. All no-fee TRB strategies

Different strategies utilizing trading range breakout don't seem to perform very well. Profit wise only one of those is able to beat buy-and-hold strategy; the one with 60 lag resistance and support levels. Best strategy profited total of $3 506 with considerably high number of trades at 5 215. Annual volatility of strategy in question was 58%. TRB-strategies seemingly include smaller volatilities compared to previously presented MA strategies,

Regularly, best performing TRB-strategies do suggest much smaller number of trades. This also leads to much longer holding periods. (Table 12) As in case of MA, SKASR of best TRB strategies differ statistically significantly from that of buy-and-hold.

Table 12. Statistics for 10 best TRB strategies on train set without fee ranked by SKASR

Note: Memmel Z shows statistical significance of difference between SKASR of the strategy and SKASR of the buy-and-hold (1.75). When it's in absolute values larger than 1.96 (95% CI), difference is statistically significant.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio
TRB60	0.0%	0%	5215	$3,506.1	0.07%	103.7 min	58%	175%	3.24	13.9	4.73	3.03
TRB800	0.1%	0%	265	$1,618.2	0.61%	2016.2 min	58%	81%	3.21	14.6	1.15	1.40
TRB60	0.0%	1%	5215	$3,169.2	0.06%	100.4 min	55%	158%	3.11	13.0	4.40	2.86
TRB60	0.0%	2%	5215	$3,399.1	0.07%	103.2 min	58%	170%	3.03	12.3	4.17	2.93
TRB480	0.0%	2%	675	$1,359.9	0.20%	758.7 min	56%	68%	3.00	12.8	1.37	1.22
TRB800	0.0%	0%	362	$2,051.9	0.57%	1538.9 min	57%	103%	2.97	12.6	1.59	1.79
TRB600	0.0%	2%	526	$1,944.1	0.37%	970.3 min	54%	97%	2.79	11.1	-0.11	1.79
TRB1000	0.0%	0%	286	$2,099.6	0.73%	1960.4 min	58%	105%	2.70	10.3	1.07	1.81
TRB300	0.1%	1%	633	$1,028.0	0.16%	609.0 min	47%	51%	2.45	7.8	1.22	1.09
TRB300	0.0%	1%	1095	$1,500.3	0.14%	421.8 min	50%	75%	2.44	7.7	1.83	1.49

Stop-losses are much more presented in best-performing TRB-strategies than best-performing MA-strategies. Of the best performing 30 strategies 20 used stop-loss. Of those, 11 were 2% stop-losses and 9 1% stop-losses. While there are no statistically significant differences in profits using different stop-loss levels, using either of those results in statistically significantly lower volatility.

Table 13. Effect of stop-losses and bands to average profits, volatility and SKASR in TRB without fees

Note: Values represent averages of all MA strategies using shown rule. Values are tested for statistically significant differences against other values using t-test. Only volatility differences between different stop-losses are statistically significant. All differences between different bands are statistically significant.

Stop-loss	Profit	SKASR	Volatility
0%	42.3%	0.84	59.8%
1%	40.1%	0.61	36.6%
2%	34.2%	0.85	45.1%
Band	Profit	SKASR	Volatility
0%	79.9%	1.44	53.4%
0.1%	48.1%	0.72	51.2%
0.5%	-11.4%	-0.02	36.1%

Profits however seem to get smaller while using either of stop-losses, but as stated, those differences are not statistically significant. In case of bands, usage also decreases volatility statistically significantly. However simultaneously profits get statistically significantly lower which also affects SKASR. There are only nine usages of 0.1% band in top-30 strategies. More detailed statistics on thirty best strategies can be seen in Appendix 5.

5.4.3 Conclusions of the best no fee strategies

Sharpe ratio is common way to measure risk-adjusted returns of single strategy, and SKASR showed that in no fee scenario, top-strategies of both, MA and TRB, outperformed buy-and-hold which had SKASR of 1.75. We can further look if any of best strategies were able to compete against the markets by looking at Information Ratios. In this, Cryptocurrencies Index 30 will be used as a benchmark index. Daily returns of the strategies are quite closely normally distributed. This means we can easily bootstrap distributions for calculated Information Ratios and therefore obtain quite accurate confidence intervals.

Information ratio for ten best performing unique strategies based on SKASR was calculated. Additionally, IR was calculated for buy-and-hold strategy. Only best-performing unique strategies were chosen. Most of the best-performing strategies were different combinations of MA1-50 strategy, and only the best performing with 1% stop-loss and 0% bands is presented. All best-performing strategies in case of no fees were different MA-strategies.

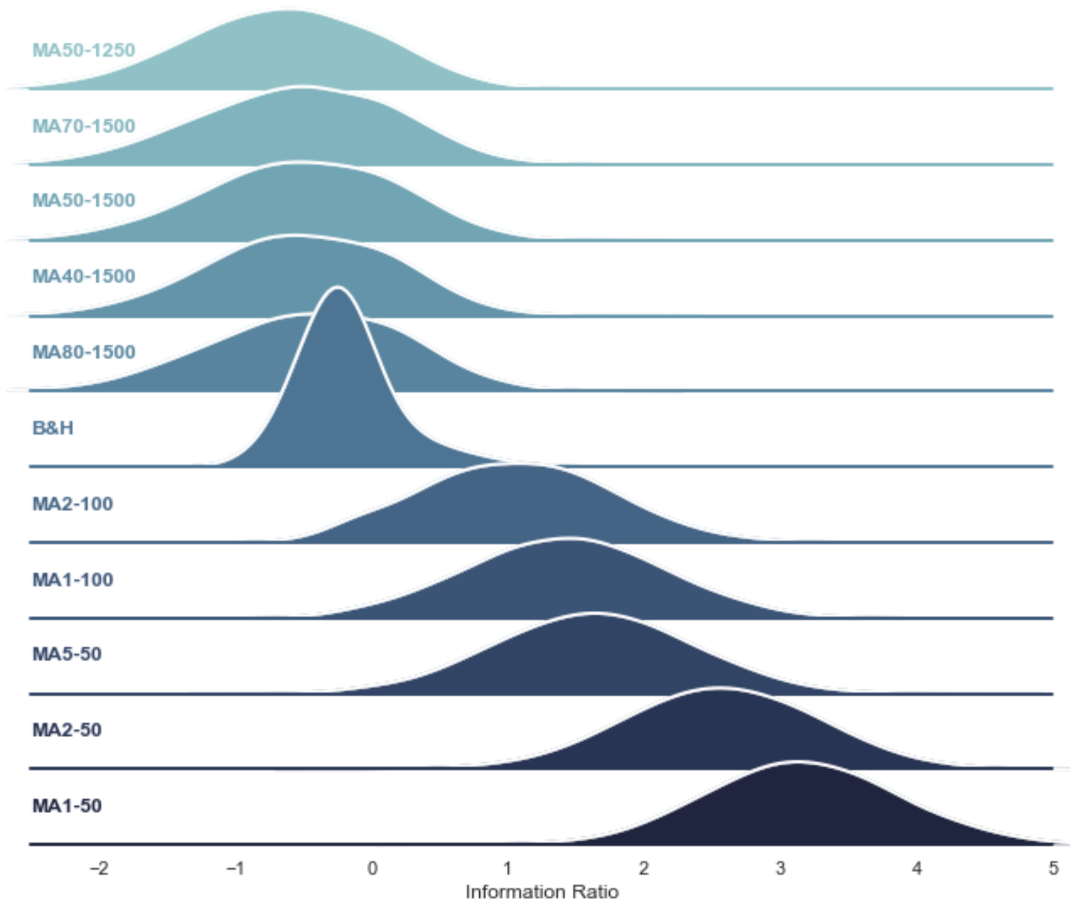

Figure 26. Approximate bootstrapped distributions of ten best Information ratios of unique strategies without fee

Note: Distributions represent Information Ratios calculated from 10 000 samples. Each unique sample is drawn from original values using circular block bootstrap with optimal block length calculated following Politis and White (2004).

With 10 000 iterations, IR distributions shown in Figure 26 were obtained. Buy-and-hold strategy doesn't completely follow normal distribution and stands therefore out and might have somewhat biased confidence intervals. All confidence intervals and Information Ratios are shown in Table 14.

Table 14. Rules without fees tested with IR:s and confidence intervals of those

Note: Confidence intervals are calculated as an average from bootstrap-samples. Therefore, bootstrapping doesn't decrease the confidence intervals as each unique sample is still the size of original data.

Strategy	Band	Stop-loss	IR	Lower CI	Upper CI
MA1-50	0.0%	1%	3.16	1.76	4.59
MA2-50	0.0%	0%	2.57	1.27	3.96
MA5-50	0.0%	0%	1.63	0.30	3.05
MA1-100	0.1%	1%	1.42	-0.01	2.82
MA2-100	0.0%	2%	1.05	-0.32	2.33
B&H	-	-	-0.19	-1.20	0.28
MA80-1500	0.5%	0%	-0.46	-1.74	1.00
MA50-1500	0.5%	0%	-0.52	-1.77	0.98
MA40-1500	0.1%	0%	-0.52	-1.70	0.95
MA70-1500	0.5%	0%	-0.55	-1.86	0.96
MA50-1250	0.5%	0%	-0.65	-1.91	0.79

Only three Information Ratios are over 0 with 95% confidence limits. Those three, MA1-50, MA2-50 and MA5-50 stand also above the buy-and-hold strategy with IR:s of 1.76 - 4.59, 1.27 – 3.96 and 0.3 – 3.05 respectively. Strategies other than three mentioned are not able to significantly outperform index in no fee -scenario. Also buy-and-hold strategy loses to index.

5.5 With transaction costs

Second scenarios to be tested are the ones including 0.1% trading fee. This fee is taken from buying and selling. This means effective fee on profiting trades is at least 0.2% and linearly increases with more profitable trades.

5.5.1 Moving averages

Trading fees complicate situation quite a lot. Even with 0.1% trading fee, large number of trades will make gaining profit impossible. Plotting returns makes change more than evident. This can be observed from Figure 27.

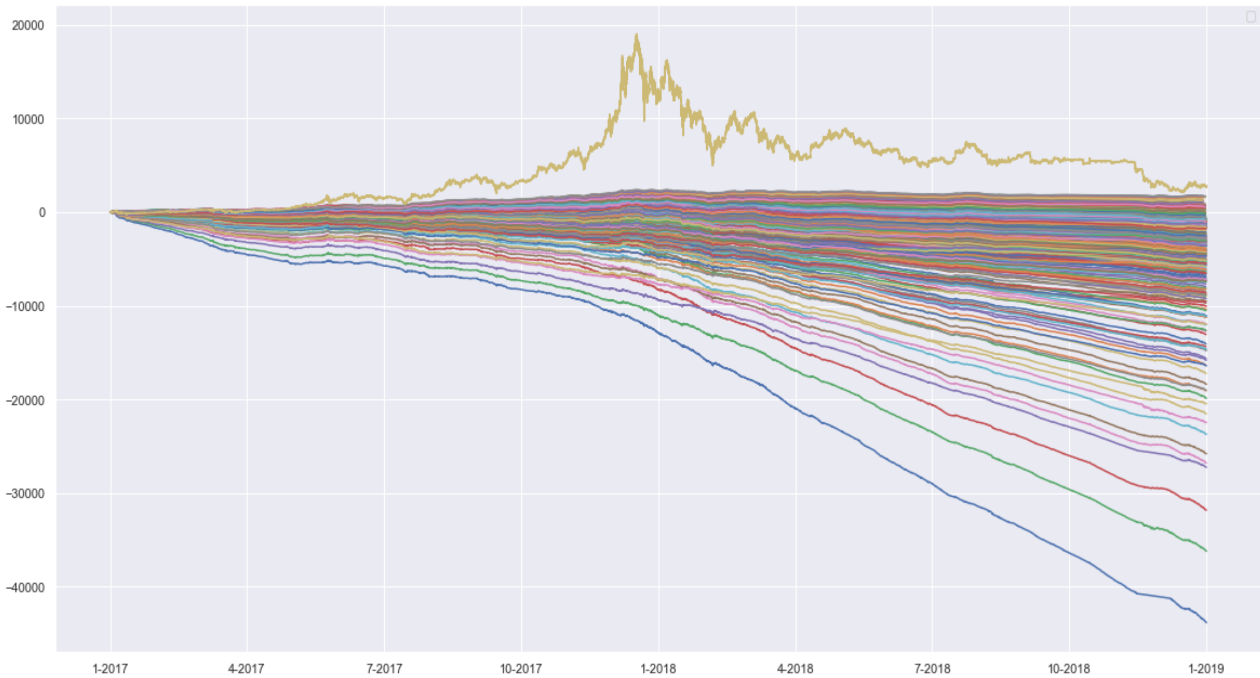

Figure 27. Returns from different MA strategies on train-set with fees.

With fees very important factor is the return from single trade as it must in average match the fees. None of the strategies can win buy-and-hold -strategy profit wise. This means all possible benefits of using these strategies lay on risk aversion. Both, stop-loss and bands seem to be effective in that.

Table 15. Effect of stop-losses and bands to profits, volatility and SKASR in MA with fees

Note: Values represent averages of all MA strategies using shown rule. Values are tested for statistically significant differences against other values using t-test. Only volatility differences between different stop-losses are statistically significant. All differences between different bands are statistically significant.

Stop-loss	Profit	SKASR	Volatility
0%	-180.2%	-0.98	61.6%
1%	-172.5%	-1.21	52.5%
2%	-180.7%	-1.1	58.8%
Band	**Profit**	**SKASR**	**Volatility**
0%	-358.4%	-2.36	61.8%
0.1%	-133.5%	-0.69	58.5%
0.5%	-41.5%	-0.24	52.7%

Volatility differences between each stop-loss level are statistically significant. However, none of the profit differences or differences in SKASR are statistically significant. With bands all differences are statistically significant. However, causality in these is more probable to go through number of trades. (Table 15)

Plotting number of trades against profits reveal quite a lot about the effect fees have on profits (Figure 28).

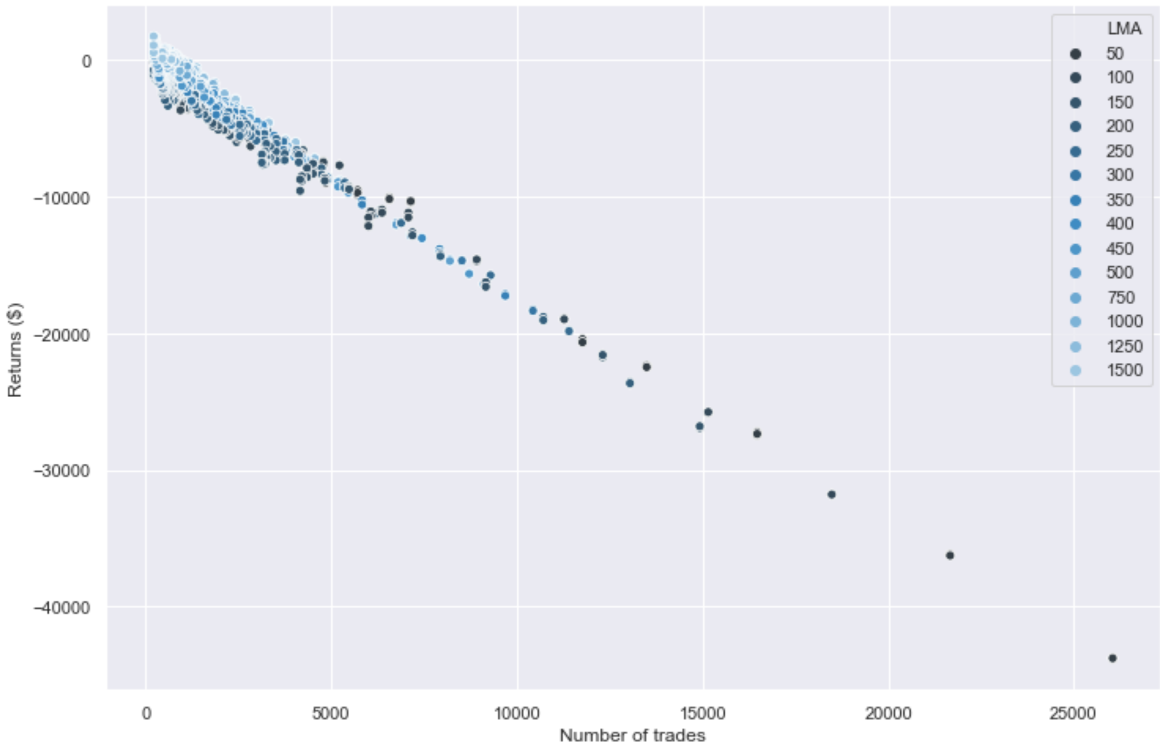

Figure 28. Scatter plot of number of trades and returns with fees and different LMA:s

Number of trades and profits have almost complete linear relationship. All strategies that have smaller number of trades are either combinations of longer MA:s or smaller MA:s with number of trades limited by bands. Very few of the strategies are able to make any profits as seen on the left top-corner of the figure.

Table 16. Spearman correlation matrix of key statistics from MA strategies with fees

	trades	profits	profits_avg	skewness	kurtosis	SMA	LMA	holding_time	vol_annual
trades	1.0***								
profits	-0.9***	1.0***							
profits_avg	-0.26***	0.61***	1.0***						
skewness	0.11***	0.03***	0.29***	1.0***					
kurtosis	0.7***	-0.55***	0.01***	0.35***	1.0***				
SMA	-0.38***	0.32***	-0.03*	-0.25***	-0.23***	1.0***			
LMA	-0.41***	0.69***	0.8***	0.32***	-0.02**	0.14***	1.0***		
holding_time	-1.0***	0.9***	0.27***	-0.1***	-0.69***	0.38***	0.41***	1.0***	
vol_annual	0.32***	-0.27***	-0.08	-0.32***	0.16***	-0.24***	-0.08	-0.34***	1.0***

***1% **5% *10%

Correlation matrix in Table 16 reveals more about the effect different key statistics have on strategies profit-making potential. As expected, all different variables limiting number of trades are highly correlated with profits. Other expected results are positive effect of skewness and negative effect of kurtosis in profits, as theory suggests.

Ranking different strategies by their SKASR reveals that best strategy, MA20-1500 was able to make 83% annual profit with annual volatility of 55%. (Table 17)

Table 17. Statistics for 30 best MA strategies with fee ranked by SKASR

Note: Memmel Z shows statistical significance of difference between SKASR of the strategy and SKASR of the buy-and-hold (1.75). When it's in absolute values larger than 1.96 (95% CI), difference is statistically significant.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio
MA20-1500	0.5%	0%	281	$1,660.3	0.59%	2016.0 min	55%	83%	4.16	18.7	1.42	1.50
MA60-1500	0.5%	0%	242	$1,683.3	0.70%	2429.1 min	58%	84%	3.80	16.9	1.37	1.46
MA100-1500	0.5%	0%	222	$1,753.0	0.79%	2645.1 min	58%	88%	3.79	16.9	1.48	1.51
MA90-1500	0.5%	0%	225	$1,745.8	0.78%	2624.5 min	58%	87%	3.52	15.4	1.41	1.51
MA80-1500	0.5%	0%	232	$1,608.9	0.69%	2530.4 min	57%	80%	3.34	14.3	1.38	1.41
MA50-1500	0.5%	0%	250	$1,502.1	0.60%	2333.6 min	58%	75%	2.93	11.4	1.26	1.31
MA70-1500	0.5%	0%	237	$1,472.5	0.62%	2470.3 min	58%	74%	2.69	9.5	1.18	1.27
MA40-1250	0.5%	0%	285	$1,183.2	0.42%	2012.7 min	57%	59%	2.54	8.3	1.16	1.04
MA50-1250	0.5%	0%	275	$1,211.1	0.44%	2069.1 min	57%	61%	2.45	7.4	1.16	1.05
MA80-1250	0.5%	0%	258	$1,260.3	0.49%	2243.8 min	58%	63%	2.36	6.6	1.17	1.09

Appendix 3 reveals that average profits from best 30 strategies range from 0.08% to 0.79%. Highest number of trades at 699 is done by MA 20-1500 strategy. Average holding times are also much longer than in no fee -scenario, in all most profitable cases more than 10 hours. In long moving averages, it's also notable that first strategy not using long moving average of at least 1000 doesn't fit to the list. Ranked by SKASR, first strategy using LMA750 is 43th. Out of 1494 tested strategies only 185 were able to make any profits. Of those, only 5 didn't use either bands or stop-losses. Actually 23 best profiting strategies used highest band of 0.5%. However, still 11 best strategies had statistically significantly higher risk-adjusted profit compared to buy-and-hold -strategy.

5.5.2 Trading range breakout

TRB strategies show results quite similar to the ones of MA strategies. However, because TRB strategies introduced smaller number of trades from the beginning, the negative results don’t stand out so clearly. There are also few different strategies that are able to make decent profits even with fees (Figure 29). None of those can however beat profits of buy-and-hold strategy. Best profiting strategy is the one with 1200-lag resistance and support levels, 0.1% band and 2% stop-loss. While making only 187 trades, it did have very good average profit of 1.04% cumulating total of $1 941 profits with annual volatility of 49%. Worst of TRB strategies were the 60-lag strategies without bands, which had over 5 000 trades signaled. Of those, the one using 1% stop-loss, made losses of $7 260.

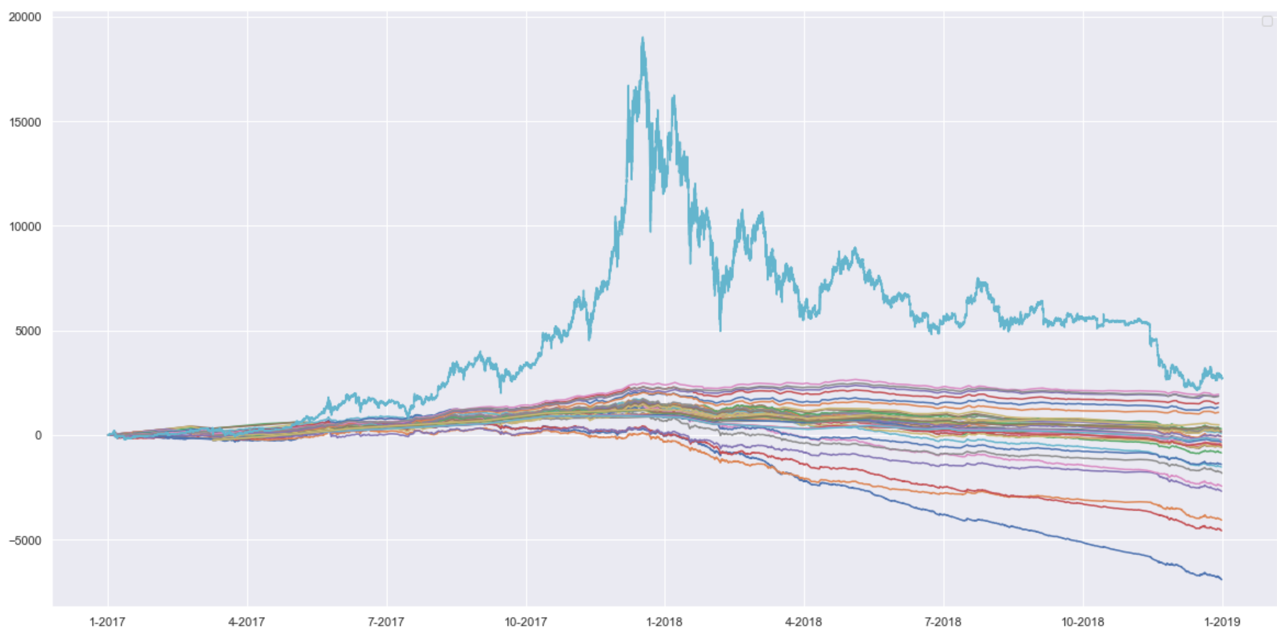

Figure 29. Returns from different TRB strategies with fees.

It’s not worth graphing how number of trades affect profits as that is evident. On the other hand, it’s worth noting that TRB strategies need much less help of the bands to limit number of trades. This doesn’t prove that these rules would work better when fees are introduced, but rather that number of trades signaled was smaller from the beginning. This makes it also much easier for strategies with shorter lag to have chance of making profits. Compared to MA-strategies, there is much larger variety in the best strategies. Longer lags are however still overpresented. This means that there aren’t any strategies, included in this research, that would somehow manage to signal short-time price movements large enough to make profits after trading fees. This is not surprising.

Table 18 presents ten best TRB strategies ranked by SKASR. More detailed table is found from Appendix 4. Of TRB strategies, only six have higher SKASR than buy-and-hold strategy. Of these only four differed statistically significantly from the SKASR of buy-and-hold. 44 out of the 118 tested TRB strategies were able to make profits. This is much higher proportion than the one with MA:s. Average holding times are quite similar in best MA strategies and best TRB strategies. 30 best TRB strategies also introduce average holding time of more than 10 hours.

It's worth noting that in case of TRB, more of the strategies had problems fitting inside window of validity of Cornish-Fisher expansion. The problematic strategies were the ones that had very few trades and therefore high kurtosis. Best performing strategies that I'm mostly interested in however didn't have this problem and therefore no measures need to be taken to account for this.

Table 18. Statistics for 10 best TRB strategies with fee ranked by SKASR

Note: Memmel Z shows statistical significance of difference between SKASR of the strategy and SKASR of the buy-and-hold (1.75). When it's in absolute values larger than 1.96 (95% CI), difference is statistically significant.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio
TRB1000	0.1%	0%	214	$1,874.3	0.88%	2551.1 min	55%	94%	4.92	21.7	1.05	1.70
TRB1200	0.0%	0%	234	$1,931.6	0.83%	2389.5 min	55%	97%	3.00	11.9	1.72	1.76
TRB1200	0.1%	0%	187	$1,844.9	0.99%	2885.3 min	55%	92%	2.25	5.5	1.31	1.67
TRB800	0.1%	0%	265	$1,086.7	0.41%	2016.2 min	58%	54%	2.00	2.9	1.06	0.94
TRB1000	0.0%	0%	286	$1,526.2	0.53%	1960.4 min	58%	76%	1.84	1.1	1.16	1.32
TRB800	0.0%	0%	362	$1,326.6	0.37%	1538.9 min	57%	66%	1.83	1.0	1.27	1.16
TRB600	0.0%	2%	526	$891.1	0.17%	970.3 min	54%	45%	1.18	-7.6	0.76	0.82
TRB1200	0.1%	2%	187	$1,941.2	1.04%	2420.3 min	49%	97%	1.18	-7.4	0.67	2.00
TRB1200	0.0%	2%	234	$1,651.8	0.71%	2010.2 min	50%	83%	0.88	-11.7	0.57	1.65
TRB420	0.1%	2%	478	$381.2	0.08%	1019.7 min	55%	19%	0.87	-12.5	0.36	0.35

5.5.3 Conclusions of the best 0.1%-fee strategies

As was without the fees, ranked by the SKASR, best strategies including fees can outperform by-and-hold. This is again largely due the positively skewed returns in technical strategies compared to the negatively skewed returns of buy-and-hold. Strategies introduced also had significantly lower volatility than buy-and-hold. In case of no fees, best strategies used moving averages. When fees are used, most of the unique strategies use also moving averages. Out of best performing strategies, eight use moving averages, worst one having SKASR of 2.54. Worst included TRB strategy has SKASR of 3.

Information ratios of best strategies reveal that none of them seem to have any chance of outperforming the index. Best strategy based on information ratios is buy-and-hold. All other strategies are clear underperformers against the index. (Figure 30)

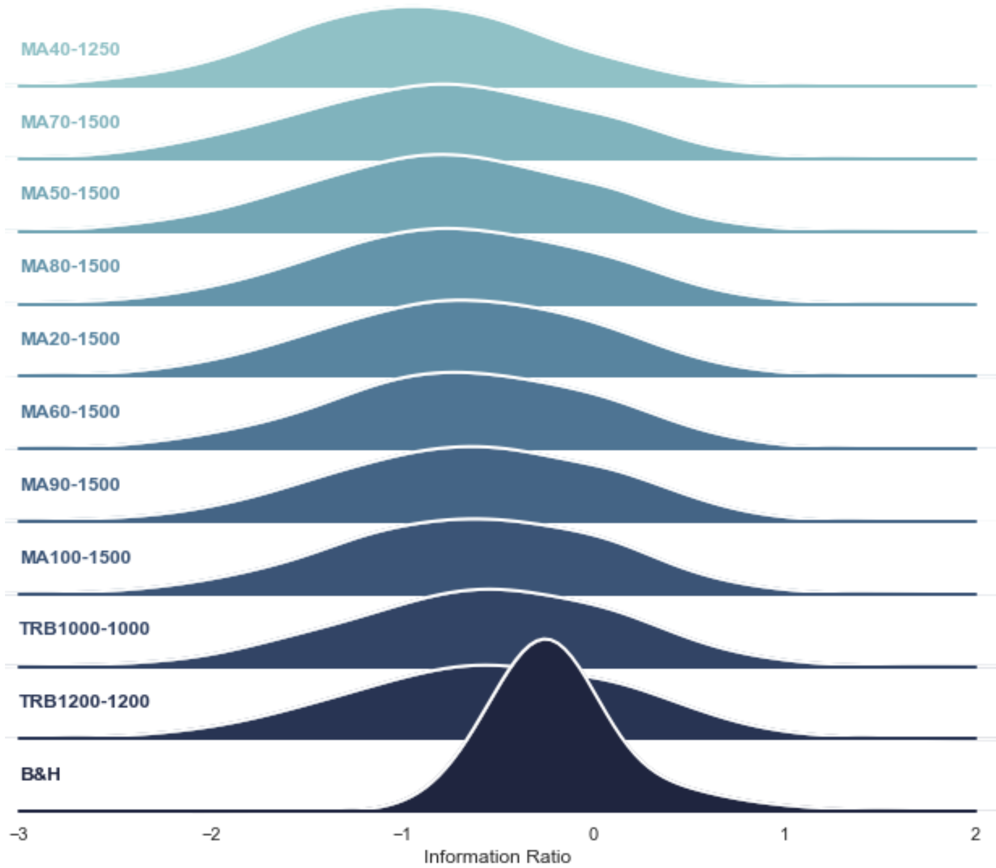

Figure 30. Approximate bootstrapped distributions of ten best Information ratios of unique strategies with fee

Note: Distributions represent Information Ratios calculated from 10 000 samples. Each unique sample is drawn from original values using circular block bootstrap with optimal block length calculated following Politis and White (2004).

If it’s not clear from the figure, looking at confidence intervals of different IR:s reveals that confidence intervals overlap zero (Table 19). Simultaneously, confidence intervals overlap each other. Further testing with larger data would need to be used to see how bad these strategies actually perform against the index, but it can still be concluded that performances are not very good.

Table 19. Rules with fees tested with IR:s and confidence intervals of those

Note: Confidence intervals are calculated as an average from bootstrap-samples. Therefore, bootstrapping doesn't decrease the confidence intervals as each unique sample is still the size of original data.

Strategy	Band	Stop-loss	IR	Lower CI	Upper CI
MA40-1250	0.5%	0%	-0.949	-2.29	0.44
MA70-1500	0.5%	0%	-0.806	-2.14	0.72
MA50-1500	0.5%	0%	-0.784	-2.07	0.65
MA80-1500	0.5%	0%	-0.719	-2.06	0.75
MA20-1500	0.5%	0%	-0.694	-1.97	0.78
MA60-1500	0.5%	0%	-0.677	-1.95	0.76
MA90-1500	0.5%	0%	-0.654	-1.94	0.81
MA100-1500	0.5%	0%	-0.646	-1.89	0.78
TRB1000	0.1%	0%	-0.568	-1.88	0.87
TRB1200	0.0%	0%	-0.547	-1.81	0.96
B&H	-	-	-0.181	-1.23	0.27

5.6 Validity of the results

To conclude the research, same tests are conducted on test set containing range of 1.1.2019 – 20.11.2019. As previously, we can set the baseline to be buy-and-hold -strategy. In the period it had annualized volatility of 72.2%. This is substantially lower than on the two previous periods. SKASR of buy-and-hold in 2019 is 1.45. This is due the returns being lower at annualized rate of 119.5%. Differences between different Sharpe ratios are not very large as can be seen from Table 20.

Table 20. Performance statistics for buy-and-hold strategy on test-set

	Annual profit	Annual volatility	SKASR	Adjusted sharpe	Sharpe
Buy-and-hold	119.5%	72.2%	1.45	1.47	1.47

5.6.1 Performance without fees

If we look at the strategies that performed well on no-fee scenario, it can be seen that performance is quite closely correlating with number of trades strategy conducted. For these strategies to be in any way valid, same strategies should also perform similarly well with test-set. It can be easily seen that this is not the case. While number of trades is in almost perfect linear relationship between the two, returns don't seem to have noticeable linear relationship. (Figure 31) This seems to suggest that MA strategies don't work similarly on the unknown data.

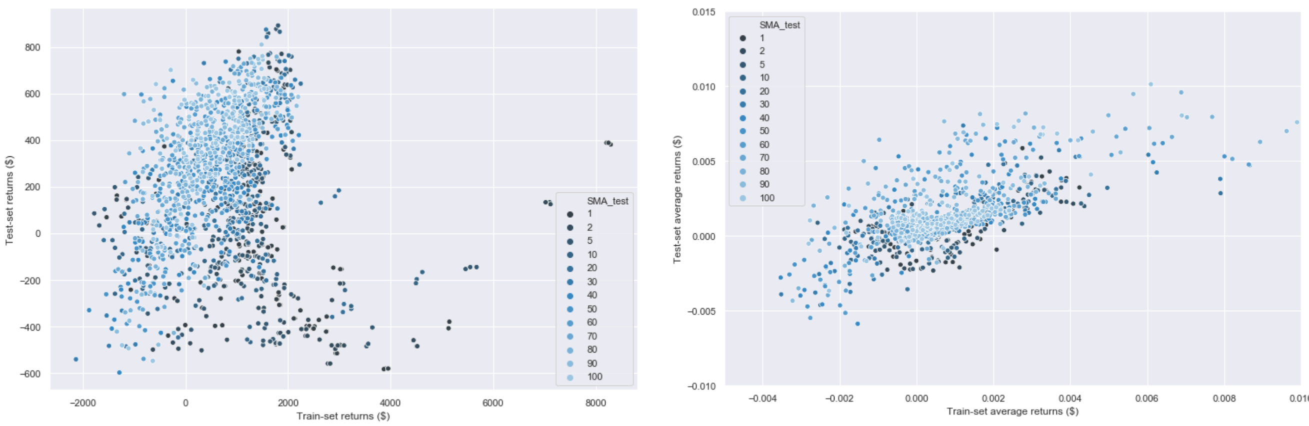

Figure 31. Scatterplot of differences in returns without fee between train- and test-set

Most of the best-performing strategies in the test-set are mediocre in train-set and best performing strategies of the train set are with few exceptions below average on test-set. To get better hold of what differs between the two sets, we can look at Spearmans correlation matrix Table 21.

Table 21. Correlation matrix of key statistics between train- and test-set without fee

Test set \ Train set	trades	profits	profits_avg	skewness	kurtosis	holding_time	vol_annual	SKASR	a_sharpe	sharpe
trades	0.98***	0.4***	-0.12**	0.16***	0.71***	-0.98***	0.28***	0.07	-0.02***	0.37***
profits	-0.32***	0.24***	0.58***	0.09	-0.08***	0.33	-0.1***	0.39***	0.41***	0.25***
profits_avg	-0.49***	0.19***	0.61***	0.08**	-0.21***	0.5***	-0.2***	0.35***	0.42***	0.22***
skewness	0.82***	0.51***	0.03	0.43***	0.77***	-0.82***	0.04***	0.16***	0.04***	0.51***
kurtosis	0.89***	0.42***	-0.07*	0.31***	0.75***	-0.89***	0.1***	0.08***	-0.03***	0.41***
holding_time	-0.97***	-0.36***	0.17***	-0.23***	-0.74***	0.97***	-0.19***	-0.04**	0.06	-0.34***
vol_annual	-0.57***	-0.29***	0.05***	-0.05	-0.46***	0.59***	-0.14***	-0.13***	-0.09***	-0.27***
SKASR	-0.61***	-0.15***	0.37***	-0.26***	-0.47***	0.61***	-0.19***	0.24***	0.36***	-0.14***
a_sharpe	-0.45***	0.01	0.36***	-0.12***	-0.33***	0.46***	-0.15***	0.12***	0.26***	0.03
sharpe	-0.3***	0.25***	0.58***	0.08	-0.07***	0.31	-0.09*	0.4***	0.42***	0.26***

***1% **5% *10%

While all correlations are statistically significant with 1% risk-level, it's easy to note that only number of trades, average holding time and kurtosis have high correlation coefficients between the two sets. Annual volatility on the other hand is negatively correlated. This means that linear relationship between variables on different sets is negative; strategies in train set with lower volatility than others have on the test-set higher volatility than others. This is probable to also be somewhat linked to quite low correlation coefficients between different Sharpe ratios on two sets. It's also worth reminding that most of the profits on the train set were done in first half of the period. Year 2017 was more or less side drift with all strategies. It's clear that year 2017 was preferable for technical trading and same characteristics of market couldn't be utilized in later periods.

It can also be examined how the same strategies behave in different sets. By plotting same strategies rank (ranked by SKASR) in both sets, it can easily be seen that these strategies don't work similarly on test data (Figure 32). Ten strategies with average smallest and largest absolute differences in ranks are shown in Table 22.

Table 22. Most stable and least stable rules ranked by absolute difference of rank in train- and test-set without fees

Note: Rules are ranked according to difference of average rank in both sets. If rule is 100th best in train set and 200th best in test-set, difference is 100. Averages are taken from all of the rules using same moving averages or support- and resistance -levels. Smaller average difference means that rule performs more consistently in both sets. This is preferred result.

Best rules	
Rule	**Difference**
MA10-350	137.3
MA10-1000	152.8
MA10-1250	189.1
MA10-750	192.7
TRB540	202.0
MA5-1250	217.7
TRB480	221.8
MA50-150	223.3
TRB360	225.7
TRB420	226.9

Worst rules	
Rule	**Difference**
MA1-50	1238.0
MA1-100	1211.7
MA2-100	1168.2
MA2-50	1116.7
MA5-50	1077.8
MA5-100	1055.3
MA10-50	768.3
TRB60	747.3
MA2-150	671.0
MA10-100	666.0

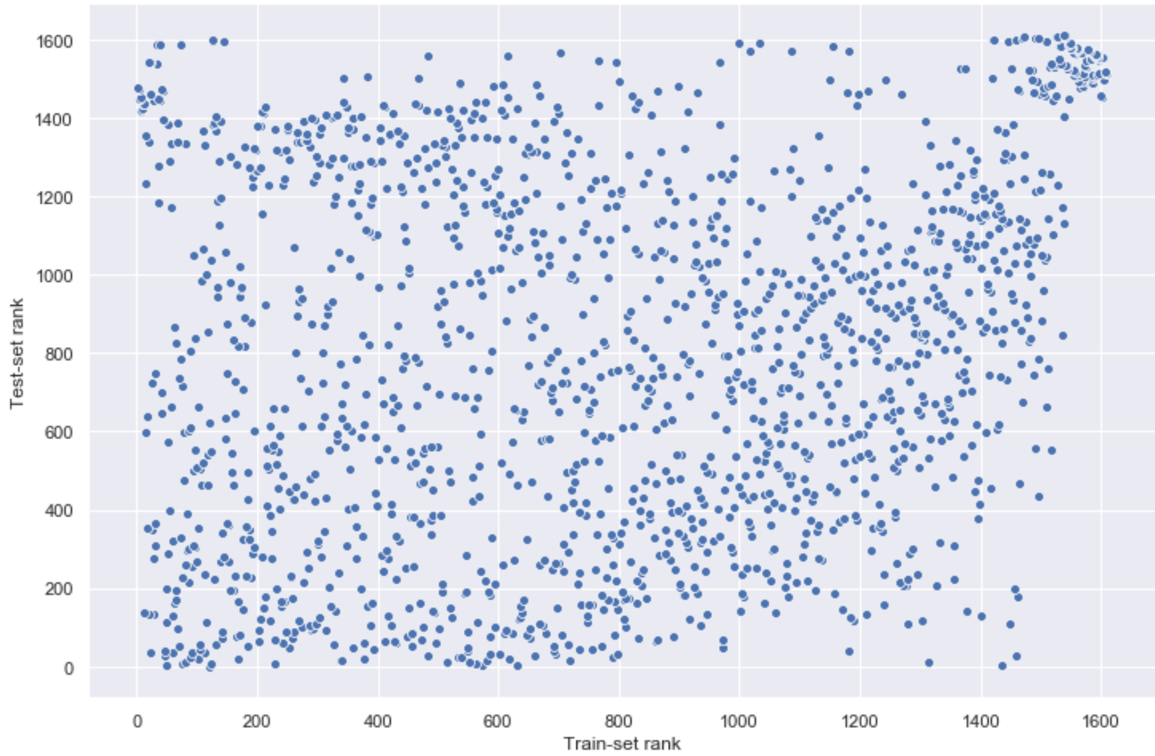

Figure 32. Different no-fee strategies and their ranks in train- and test-set

Note: If performance in both sets would be similar, plot would show linear relationship between train-set rank and test-set rank.

There were still some strategies which were able to perform decently on test-set. These can be examined more closely on Appendix 5. However, it's not worth discussing these more as it's clear that validity of the proposed strategies is not good on new data.

5.6.2 Performance with fees

When fees are considered, rules seem to perform much more consistently in train set and test-set. It's obvious that profits have much higher correlation as number of trades are still highly correlated between the sets. That's because of the fact that number of trades affect profits directly when fee is deducted from every trade. When effect the number of trades have is considered, we are left with very similar results as in case of no fees. The average profit pattern can be seen in Figure 33.

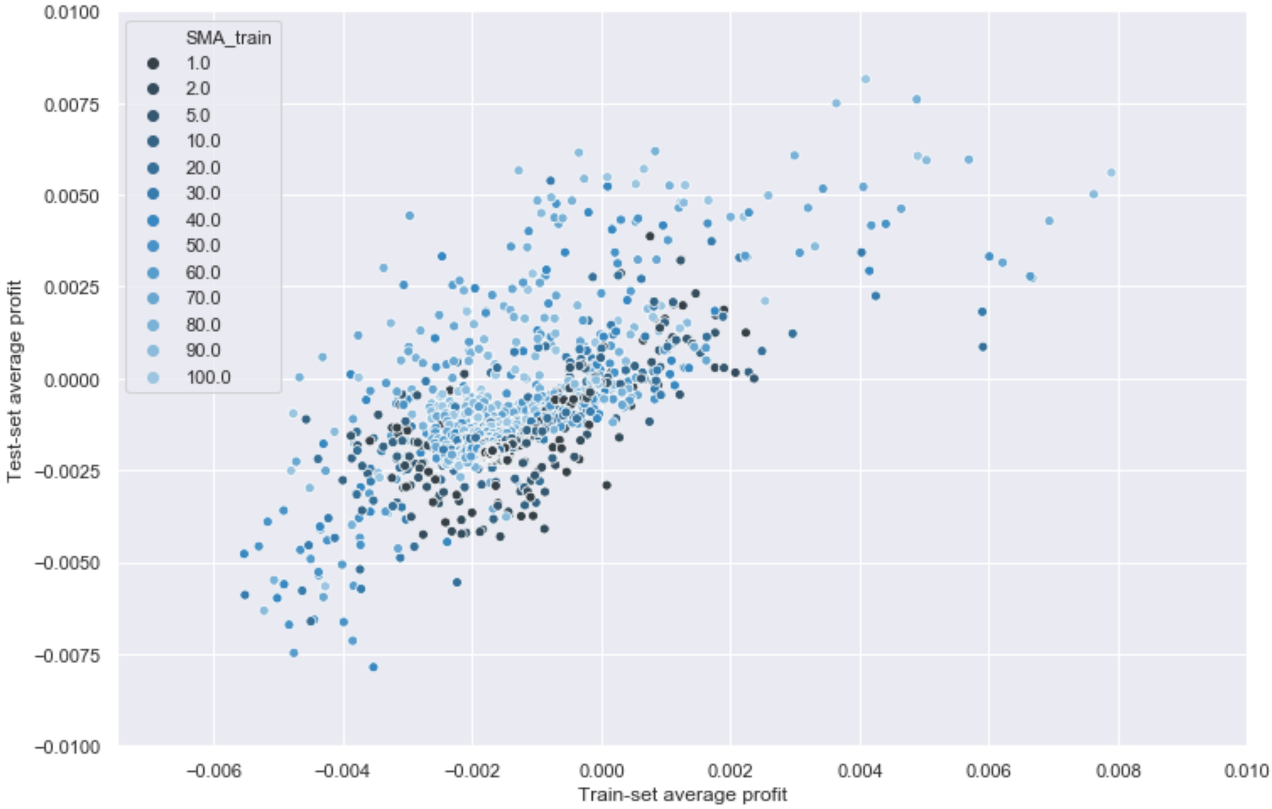

Figure 33. Scatterplot of differences in returns with fee between train- and test-set

Table 23 shows more clearly that number of trades done, and amount of fees reduced because of those has quite a large effect on correlations between different sets. All statistics that are affected by profits are very closely correlating. This includes also all different Sharpe ratios.

Table 23. Correlation matrix of key statistics with fee between train- and test-set

Test set \ Train set	trades	profits	profits_avg	skewness	kurtosis	holding_time	vol_annual	SKASR	a_sharpe	sharpe
trades	0.98***	-0.83***	-0.12**	0.16***	0.71***	-0.98***	0.28***	-0.85***	0.43***	-0.84***
profits	-0.93***	0.92***	0.38***	-0.08***	-0.61***	0.93***	-0.28***	0.89***	-0.34***	0.92***
profits_avg	-0.49***	0.66***	0.61***	0.08**	-0.21***	0.5***	-0.2***	0.57***	-0.09**	0.66***
skewness	0.82***	-0.63***	0.03	0.43***	0.77***	-0.82***	0.04***	-0.78***	0.37***	-0.63***
kurtosis	0.89***	-0.73***	-0.07*	0.31***	0.75***	-0.89***	0.1***	-0.82***	0.34***	-0.73***
holding_time	-0.97***	0.84***	0.17***	-0.23***	-0.74***	0.97***	-0.19***	0.88***	-0.42***	0.84***
vol_annual	-0.57***	0.46***	0.05***	-0.05	-0.46***	0.59***	-0.14***	0.49***	-0.41***	0.46***
SKASR	-0.92***	0.82***	0.2***	-0.27***	-0.71***	0.92***	-0.21***	0.9***	-0.37***	0.82***
a_sharpe	0.34***	-0.36***	0.03	0.17***	0.34***	-0.34***	0.15***	-0.35***	0.81***	-0.36***
sharpe	-0.93***	0.92***	0.38***	-0.08***	-0.61***	0.93***	-0.28***	0.9***	-0.34***	0.92***

***1% **5% *10%

Rules with fees are seemingly more consistent also when watching differences of ranks in different sets (Table 24). This is however also purely specious as can easily be seen from Figure 34.

Table 24. Most consistent and least consistent rules ranked by absolute difference of rank in train- and test-set with fees

Note: Rules are ranked according to difference of average rank in both sets. If rule is 100th best in train set and 200th best in test-set, difference is 100. Averages are taken from all of the rules using same moving averages or support- and resistance -levels. Smaller average difference means that rule performs more consistently in both sets. This is preferred result.

Best rules	
Rule	**Difference**
MA5-250	23.6
MA1-150	25.3
MA1-1500	26.4
MA10-1000	28.4
MA1-1000	30.0
MA30-450	45.3
MA1-250	46.7
MA20-1250	49.1
MA20-150	56.6
MA10-300	60.6

Worst rules	
Rule	**Difference**
MA60-1500	358.1
MA70-1500	341.7
MA50-1500	304.4
MA40-1500	292.0
MA80-1500	269.2
MA30-1500	265.9
TRB420	261.4
TRB1000	259.4
TRB1200	258.3
MA80-300	255.3

Figure 34. Different 0.1% fee strategies and their ranks in train- and test-set

Rules with high number of trades are consistently bad in both of the sets for apparent reasons. Ranks of the rules with smaller number of trades are just as inconsistent as in the case of no fees. Thirty best test-set strategies can be seen in Appendix 6.

6 CONCLUSIONS

The objective of this thesis was to conclude if certain intraday technical trading strategies could outperform buy-and-hold -strategy in bitcoin-markets. While earlier research suggested that there were some strategies that were able to outperform buy-and-hold, this thesis provides some support to this. With train-set of 2017-2018, it was clear that if fees wouldn't be an issue, there were number of rules that were able to outperform buy-and-hold -strategy in both, profits and risk-adjusted profits. The effectiveness was mostly based on high number of small-profit trades conducted. When fees were included, there were still number of strategies performing well. Even though, none was able to outperform buy-and-hold profit wise, decreased risk made Sharpe of some strategies such as MA20-1500 higher than the one of buy-and-hold.

However even in case of no fees, best strategies were only able to make clear profits in certain market conditions, namely bullish conditions of 2017. These market conditions were not met in test-set of 2019. It was very clear that performance of the strategies couldn't be repeated in the test-set. This makes validity of the results very questionable. Without fees, many of the strategies still outperformed buy-and-hold in risk-adjusted profits. This was not the case when fees were considered. In that case none of the strategies could perform better than buy-and-hold in test-set, no matter which performance measurement was used.

The answer to research question is therefore: **yes, some strategies are able to outperform buy-and-hold even when fees are considered.** More research and evidently more data are however needed to assess validity problems faced.

Information ratios showed effectively that only three combinations of the strategies were significantly able to outperform the index when no transaction costs were considered. With transaction costs, none of the strategies were able to compete against the index and buy-and-hold -strategy was the only one performing even decently. This thesis doesn't therefore provide support that winning the index would be possible.

Both, bands and stop-losses were able to significantly reduce volatility especially when fees were used. Effects on the profits in case of stop-losses were not statistically significant. Bands on the other hand averagely affected returns by decreasing both losses and profits.

6.1 Further research topics

It's evident that more research is needed on the cryptocurrencies. The strategies proposed in this thesis didn't perform similarly in train set and test set. The problem is most probably in amount of data. When more high-volatility data of bitcoin markets is gained, strategies could be tested again as there was still some evidence that outperforming the buy-and-hold strategy was possible even with fees considered. Another benefit that higher amount of data would have is, that there would be less problems with the distributions of returns.

Distribution of the returns was quite problematic in many cases. Usage of data manipulation such as winsorization was justified to account for non-normal distributions, but it would be more preferable if these kinds of technics could be avoided. There are technics to calculate risk-adjusted returns for non-normal and non-iid data. One of those is to fit semiparametric model to the data and use bootstrapping. This could provide more accurate results.

Other technics to find working technical trading rules should also be considered. Especially artificial intelligence has been the hot topic for several years and has been used in multiple researches. When technical analysis divides opinions, neural networks and other implications of artificial intelligence are no different. It's also very apparent that when overfitting should be avoided also with artificial intelligence, there should be sufficiently large amount of data.

This thesis tested only the bitcoin. When considering outperforming the index, other cryptocurrencies should also be considered. Using only bitcoin is major setback on this, as other cryptocurrencies could've provided more returns when money was not invested in bitcoin. This would've also provided much more evidence to back or reject the usage of technical analysis on cryptocurrency markets.

7 REFERENCES

Binance, 2019. Fee Schedule [WWW Document]. Binance. URL https://www.binance.com/en/fee/schedule (accessed 11.16.19).

Brock, W., Lakonishok, J., LeBaron, B., 1992. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. J. Finance 47, 1731–1764. https://doi.org/10.2307/2328994

Brooks, A., 2011. Five-minute breakout solution. Futur. News Anal. Strateg. Futur. Options Deriv. Traders 40, 32–36.

Brown, M.B., Forsythe, A.B., 1974. Robust Tests for the Equality of Variances. J. Am. Stat. Assoc. 69, 364–367. https://doi.org/10.2307/2285659

CCI30, 2019. Cryptocurrency Index 30 | CCi30 [WWW Document]. URL https://cci30.com/ (accessed 11.19.19).

Coinbase Pro, 2019. Fees [WWW Document]. Coinbase Pro. URL https://support.pro.coinbase.com/customer/en/portal/articles/2945310-fees (accessed 11.8.19).

CoinMarketCap, 2019. Cryptocurrency Market Capitalizations [WWW Document]. URL https://coinmarketcap.com/ (accessed 9.24.19).

Cornish, E.A., Fisher, F.R.S., 1937. Moments and Cumulants in the Specification of Distributions [WWW Document]. URL https://wilma.finna.fi/lut/PrimoRecord/pci.jstor_archive_3510.2307%2F1400905 (accessed 11.7.19).

Cryptodatadownload, 2019. Gemini Exchange Data [WWW Document]. URL http://www.cryptodatadownload.com/data/northamerican/ (accessed 9.26.19).

Didier, M., 2014. A User’s Guide to the Cornish Fisher Expansion [WWW Document]. URL https://wilma.finna.fi/lut/PrimoRecord/pci.crossref10.2139%2Fssrn.1997178 (accessed 11.15.19).

Dsouza, J.J., Mallikarjunappa, T., 2015. Do the Stock Market Indices Follow Random Walk? Asia-Pac. J. Manag. Res. Innov. 11, 251–273. https://doi.org/10.1177/2319510X15602969

Efron, B., 1979. Bootstrap Methods: Another Look at the Jackknife. Ann. Stat. 7, 1–26.

Epstein, B., 1954. Truncated Life Tests in the Exponential Case. Ann. Math. Stat. 25, 555–564.

Fama, E.F., 1995. Random Walks in Stock Market Prices. Financ. Anal. J. 51, 75. https://doi.org/10.2469/faj.v51.n1.1861

Fama, E.F., 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. J. Finance 25, 383–417. https://doi.org/10.2307/2325486

Fama, E.F., 1965. The Behavior of Stock-Market Prices. J. Bus. 38, 34–105. https://doi.org/10.1086/294743

Farias Nazário, R.T., e Silva, J.L., Sobreiro, V.A., Kimura, H., 2017. A literature review of technical analysis on stock markets. Q. Rev. Econ. Finance 66, 115–126. https://doi.org/10.1016/j.qref.2017.01.014

Favre, L., Galeano, J.-A., 2002. Mean-Modified Value-at-Risk Optimisation With Hedge Funds. EDHEC Bus. Sch.

Gerritsen, D.F., 2016. Are chartists artists? The determinants and profitability of recommendations based on technical analysis. Int. Rev. Financ. Anal. 47, 179–196. https://doi.org/10.1016/j.irfa.2016.06.008

Gerritsen, D.F., Bouri, E., Ramezanifar, E., Roubaud, D., 2019. The profitability of technical trading rules in the Bitcoin market. Finance Res. Lett. https://doi.org/10.1016/j.frl.2019.08.011

Gollier, C., 1997. On the Inefficiency of Bang-Bang and Stop-Loss Portfolio Strategies. J. Risk Uncertain. 14, 143–154. https://doi.org/10.1023/A:1007725428360

Goodwin, T.H., 1998. The information ratio. Financ. Anal. J. Charlottesv. 54, 34–43.

Gregoriou, G.N., Gueyie, J.-P., 2003. Risk-Adjusted Performance of Funds of Hedge Funds Using a Modified Sharpe Ratio [WWW Document]. URL https://wilma.finna.fi/lut/PrimoRecord/pci.crossref10.3905%2Fjwm.2003.442378 (accessed 11.7.19).

Grinold, R.C., Kahn, R.N., 1992. Information Analysis. J. Portf. Manag. N. Y. 18, 14.

Grossman, S.J., Stiglitz, J.E., 1980. On the Impossibility of Informationally Efficient Markets. Am. Econ. Rev. 70, 393.

Gümüs, F.B., Zeren, F., 2014. Analyzing the Efficient Market Hypothesis with the Fourier Unit Root Tests: Evidence from G-20 Countries. Ekon. Horizonti Kragujev. 16, 219–230.

Gurdus, L., 2019. Bitcoin ETF hits another snag, and approval won’t come “anytime soon,” says researcher [WWW Document]. CNBC. URL https://www.cnbc.com/2019/10/15/bitcoin-etf-hits-another-snag-and-approval-wont-come-anytime-soon.html (accessed 11.11.19).

Hasanov, M., Omay, T., 2007. Are the Transition Stock Markets Efficient? Evidence from Non-Linear Unit Root Tests. Cent. Bank Rev. 2 1–12.

Holmberg, U., Lönnbark, C., Lundström, C., 2013. Assessing the profitability of intraday opening range breakout strategies. Finance Res. Lett. 10, 27–33. https://doi.org/10.1016/j.frl.2012.09.001

Huang, J.-Z., Huang, W., Ni, J., 2018. Predicting bitcoin returns using high-dimensional technical indicators. J. Finance Data Sci. https://doi.org/10.1016/j.jfds.2018.10.001

Israelsen, C.L., 2005. A refinement to the Sharpe ratio and information ratio. J. Asset Manag. 5, 423–427. https://doi.org/10.1057/palgrave.jam.2240158

Jobson, J.D., Korkie, B.M., 1981. Performance Hypothesis Testing with the Sharpe and Treynor Measures. J. Finance 36, 889–908. https://doi.org/10.2307/2327554

Kaminski, K.M., Lo, A.W., 2014. When do stop-loss rules stop losses? J. Financ. Mark. 18, 234–254. https://doi.org/10.1016/j.finmar.2013.07.001

Kidd, W.V., Brorsen, B.W., 2004. Why have the returns to technical analysis decreased? J. Econ. Bus. 56, 159–176. https://doi.org/10.1016/j.jeconbus.2003.08.001

Kunsch, H.R., 1989. The Jackknife and the Bootstrap for General Stationary Observations. Ann. Stat. 17, 1217–1241.

Ledoit, O., Wolf, M., 2008. Robust performance hypothesis testing with the Sharpe ratio. J. Empir. Finance 15, 850–859. https://doi.org/10.1016/j.jempfin.2008.03.002

Lei, A.Y.C., Li, H., 2009. The value of stop loss strategies. Financ. Serv. Rev. Atlanta 18, 23–51.

Levene, H., 1960. Robust tests for equality of variances., in: Contributions to Probability and Statistics: Essays in Honor of Harold Hotelling, Ed. I. Olkin, S. G. Ghurye, W. Hoeffding, W. G. Madow, and H. B. Mann. Menlo Park, CA: Stanford University Press., pp. 278–292.

Lim, T.-S., Loh, W.-Y., 1996. A comparison of tests of equality of variances. Comput. Stat. Data Anal. 22, 287–301. https://doi.org/10.1016/0167-9473(95)00054-2

Liu, R.Y., Singh, K., 1992. Moving blocks jackknife and bootstrap capture weak dependence, in: Exploring the Limits of Bootstrap. John Wiley & Sons, pp. 225–248.

Lo, A.W., MacKinlay, A.C., 2002. Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test, in: A Non-Random Walk down Wall Street. Princeton Univ. Press, Princeton.

Malik, M.B., 2017. Weighted Inspection Sampling Methods Based on Winsorization. Qual. Manag. J. Milwaukee 24, 37-45,5.

McKeon, R., Svetina, M., 2017. Protecting against Loss: Protective Put Strategies versus Stop-Loss Strategies. J. Invest. N. Y. 26, 65–76. http://dx.doi.org.ezproxy.cc.lut.fi/10.3905/joi.2017.26.3.065

Memmel, C., 2003. Performance Hypothesis Testing with the Sharpe Ratio (SSRN Scholarly Paper No. ID 412588). Social Science Research Network, Rochester, NY.

Mishra, A., Mishra, V., Smyth, R., 2014. The Random-Walk Hypothesis on the Indian Stock Market. IDEAS Work. Pap. Ser. RePEc St Louis.

Mistry, J., Shah, J., 2013. Dealing with the Limitations of the Sharpe Ratio for Portfolio Evaluation. J. Commer. Account. Res. New Delhi 2, 10–18.

Nakamoto, S., 2008. Bitcoin: A Peer-to-Peer Electronic Cash System.

Pätäri, E., Leivo, T., Honkapuro, S., 2012. Enhancement of equity portfolio performance using data envelopment analysis. Eur. J. Oper. Res. 220, 786–797. https://doi.org/10.1016/j.ejor.2012.02.006

Pézier, J., 2004. Risk and Risk Aversion, in: The Professional Risk Managers' Handbook. Wilmington DE: PRMIA Publications.

Pézier, J., White, A., 2006. The Relative Merits of Investable Hedge Fund Indices and of Funds of Hedge Funds in Optimal Passive Portfolios. ICMA Cent. Discuss. Pap. Finance DP2006-10.

Politis, D.N., Romano, J.P., 1994. The stationary bootstrap. J. Am. Stat. Assoc. Alex. 89, 1303.

Politis, D.N., Romano, J.P., 1992. A General Resampling Scheme for Triangular Arrays of α-Mixing Random Variables with Application to the Problem of Spectral Density Estimation. Ann. Stat. 20, 1985–2007.

Politis, D.N., White, H., 2004. Automatic Block-Length Selection for the Dependent Bootstrap. Econom. Rev. 23, 53–70. https://doi.org/10.1081/ETC-120028836

Russo, C., 2018. Crypto Exchanges Are Raking in Billions of Dollars. Bloomberg.com.

Sharpe, W.F., 1966. Mutual Fund Performance. J. Bus. 39, 119. https://doi.org/10.1086/294846

Sortino, F.A., Price, L.N., 1994. Performance Measurement in a Downside Risk Framework. J. Invest. Fall 1994, 59–64.

Sortino, F.A., van der Meer, R., 1991. Downside Risk. J. Portf. Manag. N. Y. 17, 27.

Spearman, C., 1904. The proof and measurement of association between two things. Int. J. Epidemiol. 39, 1137–1150. https://doi.org/10.1093/ije/dyq191

Tsai, Y., Wu, M., Syu, J., Lei, C., Wu, C., Ho, J., Wang, C., 2019. Assessing the Profitability of Timely Opening Range Breakout on Index Futures Markets. IEEE Access 7, 32061–32071. https://doi.org/10.1109/ACCESS.2019.2899177

Welch, B.L., 1947. The Generalization of `Student's' Problem when Several Different Population Variances are Involved. Biometrika 34, 28–35. https://doi.org/10.2307/2332510

Wong, W.-K., Manzur, M., Chew, B.-K., 2003. How rewarding is technical analysis? Evidence from Singapore stock market. Appl. Financ. Econ. 13, 543. https://doi.org/10.1080/0960310022000020906

8 APPENDICES

Appendix 1. Best performing MA strategies without fees on train set

Note: Corrected skewness and corrected kurtosis show values of skewness and kurtosis after winsorization. Min. kurtosis and max. kurtosis show minimum and maximum values of kurtosis fitting inside Cornish-Fisher expansion window of validity. Tail-correction show percentage of tails trimmed to get accepted values of skewness and kurtosis.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio	Skewness	Kurtosis	Corrected skewness	Corrected kurtosis	Min. kurtosis	Max. kurtosis	Tail-correction
MA1-50	0.0%	1%	26042	$8,271.4	0.03%	21.2 min	65%	414%	7.82	31.57	-4.82	6.41	1.08	4.74	1.08	4.74	1.82	9.01	0.0%
MA1-50	0.0%	2%	26042	$8,227.3	0.03%	21.2 min	64%	411%	7.81	31.60	-4.41	6.38	1.08	4.71	1.08	4.71	1.84	9.02	0.0%
MA1-50	0.0%	0%	26042	$8,188.6	0.03%	21.2 min	65%	409%	7.28	30.99	-10.25	6.28	1.02	5.29	1.02	5.29	1.62	8.90	0.0%
MA2-50	0.0%	0%	21666	$7,090.7	0.03%	25.8 min	68%	355%	5.28	27.83	-4.15	5.20	0.68	5.16	0.68	5.16	0.71	8.40	0.0%
MA2-50	0.0%	1%	21666	$7,107.7	0.03%	25.8 min	69%	355%	5.14	27.33	-5.65	5.18	0.62	5.39	0.62	5.39	0.61	8.34	0.0%
MA5-50	0.0%	0%	16471	$5,654.6	0.03%	33.2 min	62%	283%	4.94	26.46	5.60	4.55	0.67	3.35	0.67	3.35	0.71	8.40	0.0%
MA2-50	0.0%	2%	21666	$7,013.0	0.03%	25.8 min	69%	351%	4.90	26.77	-5.12	5.11	0.51	5.28	0.51	5.28	0.40	8.23	0.0%
MA5-50	0.0%	1%	16471	$5,453.1	0.03%	33.2 min	61%	273%	4.90	26.54	8.51	4.49	0.59	2.49	0.59	2.49	0.55	8.31	0.0%
TRB600	0.0%	2%	16471	$5,530.9	0.03%	33.2 min	62%	277%	4.90	26.56	5.59	4.48	0.69	3.35	0.69	3.35	0.75	8.42	0.0%
MA1-100	0.0%	1%	18481	$5,169.8	0.03%	30.2 min	60%	258%	4.76	26.66	8.70	4.30	0.61	2.26	0.61	2.26	0.59	8.33	0.0%
MA1-100	0.0%	0%	18481	$5,152.2	0.03%	30.2 min	60%	258%	4.74	26.64	8.29	4.29	0.62	2.38	0.62	2.38	0.60	8.34	0.0%
MA1-100	0.0%	2%	18481	$5,154.6	0.03%	30.2 min	60%	258%	4.74	26.64	8.29	4.29	0.62	2.38	0.62	2.38	0.60	8.34	0.0%
TRB540	0.5%	0%	232	$2,072.5	0.89%	2530.4 min	57%	104%	4.67	20.79	1.58	1.80	2.55	13.07	2.31	9.05	9.03	11.97	1.0%
MA50-1500	0.5%	0%	250	$2,001.6	0.80%	2333.6 min	58%	100%	4.48	20.05	1.26	1.73	2.37	10.73	2.37	10.73	9.64	12.05	0.0%
MA40-1500	0.1%	0%	593	$1,990.3	0.34%	958.1 min	56%	100%	4.38	19.61	1.57	1.78	2.23	8.96	2.23	8.96	8.31	11.82	0.0%
MA50-1500	0.1%	0%	560	$1,847.4	0.33%	1014.5 min	56%	92%	4.14	18.57	1.47	1.64	2.28	9.52	2.28	9.52	8.76	11.92	0.0%
MA50-1250	0.5%	0%	275	$1,760.6	0.64%	2069.1 min	58%	88%	4.09	18.36	1.48	1.53	2.31	9.44	2.31	9.44	9.09	11.98	0.0%
MA70-1500	0.5%	0%	237	$1,946.0	0.82%	2470.3 min	58%	97%	4.06	18.21	1.14	1.68	2.36	11.45	2.36	11.45	9.62	12.05	0.0%
MA40-1500	0.0%	0%	1023	$2,005.5	0.20%	562.4 min	58%	100%	3.89	17.37	1.70	1.74	2.1	8.06	2.10	8.06	7.26	11.50	0.0%
MA2-100	0.0%	2%	15154	$4,587.1	0.03%	36.9 min	61%	229%	3.82	22.94	5.08	3.75	0.44	2.88	0.44	2.88	0.30	8.17	0.0%
MA1-400	0.5%	1%	713	$1,479.8	0.21%	844.4 min	48%	74%	3.81	18.00	1.80	1.55	2.1	6.85	2.10	6.85	7.25	11.50	0.0%
MA2-100	0.0%	0%	15154	$4,569.5	0.03%	36.9 min	61%	228%	3.80	22.80	5.02	3.74	0.43	2.9	0.43	2.90	0.29	8.17	0.0%
MA80-1250	0.5%	0%	258	$1,775.8	0.69%	2243.8 min	58%	89%	3.78	16.85	1.42	1.53	2.28	9.75	2.28	9.75	8.76	11.92	0.0%
MA2-100	0.0%	1%	15154	$4,509.6	0.03%	36.8 min	61%	225%	3.76	22.47	5.12	3.72	0.4	2.8	0.40	2.80	0.25	8.14	0.0%
MA1-50	0.1%	2%	7144	$3,948.4	0.06%	75.4 min	62%	197%	3.75	21.42	1.23	3.18	1.11	5.9	1.11	5.90	1.93	9.07	0.0%
MA30-1250	0.5%	0%	297	$1,855.3	0.62%	1933.2 min	57%	93%	3.75	16.67	1.50	1.62	2.2	9.17	2.20	9.17	8.04	11.75	0.0%
TRB480	0.0%	0%	805	$2,063.4	0.26%	713.7 min	58%	103%	3.73	16.53	1.60	1.79	2.06	8.45	2.06	8.45	7.00	11.41	0.0%
MA1-500	0.5%	1%	652	$1,236.6	0.19%	962.5 min	47%	62%	3.66	16.79	1.38	1.31	2.34	9.45	2.34	9.45	9.38	12.02	0.0%
MA2-1000	0.5%	2%	424	$1,598.4	0.38%	1351.5 min	58%	80%	3.62	16.01	1.55	1.37	1.71	16.9	2.21	8.21	8.13	11.77	0.2%
MA60-1500	0.1%	0%	535	$1,935.7	0.36%	1061.3 min	57%	97%	3.60	15.80	1.25	1.69	2.21	10.5	2.21	10.50	8.19	11.79	0.0%

Appendix 2. Best performing TRB strategies without fees on train set

Note: Corrected skewness and corrected kurtosis show values of skewness and kurtosis after winsorization. Min. kurtosis and max. kurtosis show minimum and maximum values of kurtosis fitting inside Cornish-Fisher expansion window of validity. Tail-correction show percentage of tails trimmed to get accepted values of skewness and kurtosis.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio	Skewness	Kurtosis	Corrected skewness	Corrected kurtosis	Min. kurtosis	Max. kurtosis	Tail-correction
TRB60	0.0%	0%	5215	$3,506.1	0.07%	103.7 min	58%	175%	3.24	13.85	4.73	3.03	0.51	2.24	0.51	2.24	0.41	8.23	0.00%
TRB800	0.1%	0%	265	$1,618.2	0.61%	2016.2 min	58%	81%	3.21	14.58	1.15	1.40	1.33	16.72	2.26	11.52	8.62	11.89	0.30%
TRB60	0.0%	1%	5215	$3,169.2	0.06%	100.4 min	55%	158%	3.11	13.01	4.40	2.86	0.57	2.22	0.57	2.22	0.50	8.28	0.00%
TRB60	0.0%	2%	5215	$3,399.1	0.07%	103.2 min	58%	170%	3.03	12.33	4.17	2.93	0.43	2.43	0.43	2.43	0.29	8.17	0.00%
TRB480	0.0%	2%	675	$1,359.9	0.20%	758.7 min	56%	68%	3.00	12.80	1.37	1.22	2.3	17.06	2.19	8.44	7.98	11.73	0.15%
TRB800	0.0%	0%	362	$2,051.9	0.57%	1538.9 min	57%	103%	2.97	12.61	1.59	1.79	1.47	10.49	1.76	7.83	5.01	10.60	0.15%
TRB600	0.0%	2%	526	$1,944.1	0.37%	970.3 min	54%	97%	2.79	11.11	-0.11	1.79	2.25	16.08	2.25	16.08	8.52	11.87	0.00%
TRB1000	0.0%	0%	286	$2,099.6	0.73%	1960.4 min	58%	105%	2.70	10.26	1.07	1.81	1.5	13.47	1.79	9.96	5.19	10.68	0.30%
TRB300	0.1%	1%	633	$1,028.0	0.16%	609.0 min	47%	51%	2.45	7.84	1.22	1.09	1.93	23.1	2.13	8.68	7.53	11.59	0.15%
TRB300	0.0%	1%	1095	$1,500.3	0.14%	421.8 min	50%	75%	2.44	7.66	1.83	1.49	1.79	17.24	1.56	4.45	3.86	10.06	0.15%
TRB360	0.0%	1%	918	$1,580.1	0.17%	491.8 min	49%	79%	2.24	5.61	0.11	1.61	2.19	17.22	2.19	17.22	7.97	11.72	0.00%
TRB240	0.1%	1%	753	$993.4	0.13%	518.6 min	44%	50%	2.21	5.28	1.29	1.12	1.92	6.93	1.92	6.93	5.96	11.01	0.00%
TRB1200	0.1%	0%	187	$2,218.6	1.19%	2885.3 min	55%	111%	2.12	4.35	1.37	2.00	2.53	18.27	1.74	4.92	4.84	10.52	4.15%
TRB540	0.0%	2%	600	$1,508.9	0.25%	852.4 min	54%	75%	2.00	2.95	0.67	1.41	2.1	15.41	2.10	15.41	7.28	11.51	0.00%
TRB240	0.0%	1%	1366	$1,226.9	0.09%	342.4 min	47%	61%	1.99	2.79	1.63	1.30	1.39	3.74	1.39	3.74	3.05	9.66	0.00%
TRB540	0.0%	1%	600	$1,648.7	0.27%	705.6 min	47%	82%	1.97	2.63	-1.66	1.74	2.33	24.1	2.33	24.10	9.23	12.00	0.00%
TRB360	0.0%	2%	918	$1,249.3	0.14%	568.1 min	54%	62%	1.92	2.00	1.40	1.16	1.6	11.3	1.57	5.20	3.94	10.10	0.15%
TRB420	0.0%	2%	778	$1,094.8	0.14%	665.8 min	54%	55%	1.91	1.89	1.17	1.01	2.01	14.63	1.86	7.00	5.61	10.87	0.15%
TRB600	0.1%	2%	353	$1,464.6	0.41%	1334.7 min	55%	73%	1.78	0.36	0.29	1.32	2.37	20.98	2.37	20.98	9.70	12.05	0.00%
TRB300	0.0%	2%	1095	$1,324.0	0.12%	484.6 min	55%	66%	1.54	-2.56	1.45	1.20	1.17	10.62	1.03	2.91	1.67	8.93	0.15%
TRB480	0.1%	0%	426	$1,155.5	0.27%	1270.3 min	62%	58%	1.49	-3.20	1.05	0.93	1.57	14.32	1.69	7.43	4.56	10.40	0.15%
TRB360	0.1%	2%	553	$718.8	0.13%	873.9 min	52%	36%	1.48	-3.33	0.83	0.69	1.89	13.51	1.99	7.64	6.50	11.23	0.15%
TRB240	0.0%	2%	1366	$1,280.7	0.09%	388.5 min	53%	64%	1.45	-3.66	1.45	1.21	0.84	2.55	0.84	2.55	1.11	8.62	0.00%
TRB1200	0.0%	0%	234	$2,401.1	1.03%	2389.5 min	55%	120%	1.34	-5.14	1.11	2.18	2.37	15.92	1.20	2.35	2.28	9.26	7.15%
TRB420	0.0%	1%	778	$1,088.1	0.14%	558.9 min	44%	54%	1.34	-5.12	1.01	1.23	1.29	10.15	1.29	10.15	2.61	9.43	0.00%
TRB540	0.1%	2%	386	$1,248.5	0.32%	1236.5 min	54%	62%	1.33	-5.25	0.49	1.15	2.18	21.27	2.18	21.27	7.92	11.71	0.00%
TRB120	0.0%	1%	2718	$1,151.1	0.04%	186.8 min	52%	58%	1.33	-5.17	1.34	1.11	0.77	1.84	0.77	1.84	0.92	8.52	0.00%
TRB600	0.0%	0%	526	$1,347.1	0.26%	1069.2 min	61%	67%	1.30	-5.61	1.11	1.11	1.29	11.06	1.23	7.32	2.38	9.31	0.15%
TRB360	0.0%	0%	918	$1,217.9	0.13%	600.8 min	58%	61%	1.28	-5.84	1.15	1.05	1.35	10.63	1.10	4.62	1.89	9.05	0.15%
TRB540	0.1%	0%	386	$923.3	0.24%	1401.0 min	62%	46%	1.26	-6.12	0.87	0.74	1.4	13.38	1.84	9.71	5.44	10.79	0.15%

Appendix 3. Best performing MA strategies with fees on train set

Note: Corrected skewness and corrected kurtosis show values of skewness and kurtosis after winsorization. Min. kurtosis and max. kurtosis show minimum and maximum values of kurtosis fitting inside Cornish-Fisher expansion window of validity. Tail-correction show percentage of tails trimmed to get accepted values of skewness and kurtosis.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio	Skewness	Kurtosis	Corrected skewness	Corrected kurtosis	Min. kurtosis	Max. kurtosis	Tail-correction
MA20-1500	0.5%	0%	281	$1,660.3	0.59%	2016.0 min	55%	83%	4.16	18.69	1.42	1.50	2.36	9.94	2.36	9.94	9.61	12.05	0.00%
MA60-1500	0.5%	0%	242	$1,683.3	0.70%	2429.1 min	58%	84%	3.80	16.91	1.37	1.46	2.34	10.21	2.34	10.21	9.35	12.02	0.00%
MA100-1500	0.5%	0%	222	$1,753.0	0.79%	2645.1 min	58%	88%	3.79	16.87	1.48	1.51	2.49	12.99	2.29	9.04	8.83	11.94	0.85%
MA90-1500	0.5%	0%	225	$1,745.8	0.78%	2624.5 min	58%	87%	3.52	15.37	1.41	1.51	2.46	12.51	2.26	9.51	8.63	11.89	0.70%
MA80-1500	0.5%	0%	232	$1,608.9	0.69%	2530.4 min	57%	80%	3.34	14.28	1.38	1.41	2.43	12.8	2.26	9.40	8.62	11.89	0.70%
MA50-1500	0.5%	0%	250	$1,502.1	0.60%	2333.6 min	58%	75%	2.93	11.44	1.26	1.31	2.25	10.46	2.25	10.46	8.51	11.87	0.00%
MA70-1500	0.5%	0%	237	$1,472.5	0.62%	2470.3 min	58%	74%	2.69	9.53	1.18	1.27	2.25	11.2	2.25	11.20	8.50	11.86	0.00%
MA40-1250	0.5%	0%	285	$1,183.2	0.42%	2012.7 min	57%	59%	2.54	8.26	1.16	1.04	2.22	8.87	2.22	8.87	8.22	11.79	0.00%
MA50-1250	0.5%	0%	275	$1,211.1	0.44%	2069.1 min	57%	61%	2.45	7.43	1.16	1.05	2.2	9.17	2.20	9.17	8.07	11.75	0.00%
MA80-1250	0.5%	0%	258	$1,260.3	0.49%	2243.8 min	58%	63%	2.36	6.61	1.17	1.09	2.16	9.46	2.16	9.46	7.75	11.66	0.00%
MA30-1250	0.5%	0%	297	$1,261.9	0.42%	1933.2 min	57%	63%	2.21	5.12	1.20	1.10	2.05	8.83	2.05	8.83	6.92	11.38	0.00%
MA1-1500	0.5%	2%	377	$715.9	0.19%	1567.1 min	58%	36%	1.83	0.95	0.84	0.62	1.41	12.96	2.25	9.22	8.50	11.86	0.15%
MA60-1250	0.5%	0%	264	$1,103.7	0.42%	2141.2 min	57%	55%	1.80	0.60	1.05	0.96	1.99	8.77	1.99	8.77	6.45	11.21	0.00%
MA40-1500	0.5%	0%	255	$1,700.0	0.67%	2290.6 min	57%	85%	1.77	0.24	1.12	1.50	2.54	10.86	1.74	4.91	4.86	10.53	3.30%
MA70-1250	0.5%	0%	261	$1,058.8	0.41%	2211.3 min	58%	53%	1.76	0.12	0.99	0.91	2.06	9.38	2.06	9.38	6.96	11.40	0.00%
MA5-1000	0.5%	2%	405	$713.9	0.18%	1445.2 min	57%	36%	1.62	-1.62	0.80	0.63	1.52	17.34	2.12	7.91	7.45	11.57	0.15%
MA20-1500	0.1%	1%	699	$593.2	0.08%	827.8 min	55%	30%	1.59	-1.98	0.69	0.54	1.83	12.47	2.25	8.57	8.47	11.86	0.15%
MA30-1500	0.5%	0%	267	$1,575.1	0.59%	2124.0 min	55%	79%	1.56	-2.37	1.01	1.43	2.39	9.43	1.68	4.57	4.52	10.38	3.45%
MA2-1500	0.5%	0%	362	$751.5	0.21%	1582.8 min	59%	38%	1.53	-2.75	0.89	0.64	0.96	12.41	1.95	7.42	6.16	11.09	0.15%
MA1-1500	0.5%	0%	377	$843.8	0.22%	1517.1 min	59%	42%	1.47	-3.53	0.92	0.71	1.15	11.15	1.86	7.33	5.57	10.85	0.15%
MA40-1500	0.1%	0%	593	$805.5	0.14%	958.1 min	56%	40%	1.47	-3.53	0.81	0.72	2.05	8.55	2.05	8.55	6.92	11.38	0.00%
MA100-1250	0.5%	0%	246	$1,030.8	0.42%	2385.4 min	58%	52%	1.44	-3.98	0.94	0.89	1.89	9.66	1.89	9.66	5.77	10.93	0.00%
MA2-1000	0.5%	2%	424	$751.3	0.18%	1351.5 min	58%	38%	1.43	-4.11	0.78	0.65	1.53	16.6	2.03	7.87	6.72	11.31	0.15%
MA60-1500	0.1%	0%	535	$866.8	0.16%	1061.3 min	58%	43%	1.40	-4.46	0.82	0.75	2.07	10.15	2.07	10.15	7.01	11.42	0.00%
MA90-1250	0.5%	0%	254	$924.4	0.36%	2291.0 min	58%	46%	1.40	-4.52	0.87	0.79	1.96	9.32	1.96	9.32	6.24	11.12	0.00%
MA10-1500	0.5%	0%	324	$739.5	0.23%	1758.1 min	58%	37%	1.39	-4.61	0.80	0.63	1.35	12.28	1.94	7.25	6.10	11.07	0.15%
MA40-1500	0.1%	2%	593	$631.1	0.11%	957.4 min	58%	32%	1.37	-4.86	0.62	0.55	2.02	13.31	2.20	8.42	8.09	11.76	0.30%
MA50-1500	0.1%	0%	560	$728.5	0.13%	1014.5 min	56%	36%	1.37	-4.87	0.73	0.65	2.12	9.18	2.12	9.18	7.45	11.57	0.00%
MA5-1250	0.5%	2%	374	$495.8	0.13%	1549.6 min	58%	25%	1.33	-5.42	0.58	0.43	1.44	17.08	2.29	9.46	8.84	11.94	0.15%
MA50-1500	0.1%	2%	560	$445.5	0.08%	1016.5 min	57%	22%	1.30	-5.83	0.53	0.39	1.82	11.78	2.33	9.57	9.31	12.02	0.15%

Appendix 4. Best performing TRB strategies with fees on train set

Note: Corrected skewness and corrected kurtosis show values of skewness and kurtosis after winsorization. Min. kurtosis and max. kurtosis show minimum and maximum values of kurtosis fitting inside Cornish-Fisher expansion window of validity. Tail-correction show percentage of tails trimmed to get accepted values of skewness and kurtosis.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio	Skewness	Kurtosis	Corrected skewness	Corrected kurtosis	Min. kurtosis	Max. kurtosis	Tail-correction
TRB1000	0.1%	0%	214	$1,874.3	0.88%	2551.1 min	55%	94%	4.92	21.69	1.05	1.70	1.14	21.42	2.45	11.59	10.68	12.00	0.30%
TRB1200	0.0%	0%	234	$1,931.6	0.83%	2389.5 min	55%	97%	3.00	11.94	1.72	1.76	2.26	15.83	1.91	5.94	5.92	10.99	2.50%
TRB1200	0.1%	0%	187	$1,844.9	0.99%	2885.3 min	55%	92%	2.25	5.51	1.31	1.67	2.42	18.18	1.89	5.98	5.80	10.94	3.20%
TRB800	0.1%	0%	265	$1,086.7	0.41%	2016.2 min	58%	54%	2.00	2.90	1.06	0.94	1.18	16.85	2.14	11.30	7.62	11.62	0.30%
TRB1000	0.0%	0%	286	$1,526.2	0.53%	1960.4 min	58%	76%	1.84	1.08	1.16	1.32	1.37	13.53	1.69	9.84	4.55	10.39	0.30%
TRB800	0.0%	0%	362	$1,326.6	0.37%	1538.9 min	57%	66%	1.83	0.96	1.27	1.16	1.36	10.49	1.67	7.69	4.45	10.34	0.15%
TRB600	0.0%	2%	526	$891.1	0.17%	970.3 min	54%	45%	1.18	-7.64	0.76	0.82	2.15	15.97	2.15	**15.97**	7.64	11.63	0.00%
TRB1200	0.1%	2%	187	$1,941.2	1.04%	2420.3 min	49%	97%	1.18	-7.37	0.67	2.00	4.2	23.17	1.83	5.53	5.42	10.78	3.85%
TRB1200	0.0%	2%	234	$1,651.8	0.71%	2010.2 min	50%	83%	0.88	-11.71	0.57	1.65	3	21.67	1.59	4.11	4.06	10.16	4.00%
TRB420	0.1%	2%	478	$381.2	0.08%	1019.7 min	55%	19%	0.87	-12.51	0.36	0.35	2.51	18.13	2.28	8.76	8.74	11.92	0.30%
TRB540	0.0%	2%	600	$308.1	0.05%	852.4 min	54%	15%	0.80	-13.53	0.36	0.29	2	15.23	2.17	8.23	7.85	11.69	0.15%
TRB1000	0.1%	2%	214	$1,276.2	0.60%	2097.7 min	50%	64%	0.76	-13.56	0.42	1.29	1.44	30.89	1.81	5.35	5.27	10.72	3.70%
TRB540	0.0%	1%	600	$447.9	0.07%	705.6 min	47%	22%	0.51	-17.99	0.46	0.47	2.24	23.91	2.24	**23.91**	8.45	11.85	0.00%
TRB540	0.1%	2%	386	$475.3	0.12%	1236.5 min	55%	24%	0.47	-18.50	0.44	0.44	2.04	21.12	2.04	**21.12**	6.85	11.36	0.00%
TRB800	0.1%	2%	265	$881.6	0.33%	1635.7 min	50%	44%	0.40	-19.10	0.22	0.88	1.76	26.83	1.73	4.78	4.78	10.50	2.65%
TRB480	0.0%	1%	675	$331.7	0.05%	632.4 min	50%	17%	0.39	-20.02	0.34	0.33	2.46	25.25	2.46	**25.25**	10.85	11.95	0.00%
TRB480	0.1%	0%	426	$302.3	0.07%	1270.3 min	62%	15%	0.39	-20.06	0.28	0.24	1.46	14.21	1.58	7.24	3.98	10.12	0.15%
TRB600	0.1%	0%	353	$181.5	0.05%	1529.8 min	62%	9%	0.30	-21.21	0.22	0.15	1.31	13.44	1.73	9.43	4.83	10.52	0.15%
TRB1000	0.0%	2%	286	$1,309.7	0.46%	1623.0 min	50%	65%	0.29	-20.80	0.20	1.30	2.28	20.74	1.36	2.92	2.92	9.59	4.70%
TRB540	0.1%	0%	386	$150.1	0.04%	1401.0 min	62%	8%	0.27	-21.90	0.20	0.12	1.28	13.29	1.72	9.49	4.76	10.49	0.15%
TRB600	0.0%	0%	526	$294.1	0.06%	1069.2 min	61%	15%	0.27	-21.86	0.24	0.24	1.19	11	1.14	7.24	2.03	9.12	0.15%
TRB1200	0.5%	0%	24	$479.8	2.00%	25442.7 min	63%	24%	0.15	-23.22	0.28	0.38	1.97	65.97	1.97	**65.97**	6.34	11.16	0.00%
TRB800	0.5%	0%	29	$319.7	1.10%	20494.9 min	63%	16%	0.10	-24.23	0.23	0.25	1.85	66.71	1.85	**66.71**	5.56	10.84	0.00%
TRB1000	0.5%	0%	27	$318.2	1.18%	22724.2 min	64%	16%	0.10	-24.02	0.23	0.25	1.82	62.64	1.82	**62.64**	5.35	10.75	0.00%
TRB120	0.5%	0%	76	$209.5	0.28%	7279.7 min	67%	10%	0.06	-24.75	0.15	0.16	1.29	60.69	1.29	**60.69**	2.61	9.43	0.00%
TRB180	0.5%	0%	64	$232.3	0.36%	8348.5 min	68%	12%	0.06	-25.06	0.16	0.17	0.99	58.7	0.99	**58.70**	1.53	8.85	0.00%
TRB300	0.5%	0%	50	$164.8	0.33%	10431.2 min	63%	8%	0.06	-25.07	0.13	0.13	1.86	57.73	1.86	**57.73**	5.58	10.85	0.00%
TRB480	0.0%	2%	675	$9.2	0.00%	758.7 min	56%	0%	0.05	-25.47	0.02	0.01	2.2	16.79	2.09	8.19	7.21	11.48	0.15%
TRB420	0.1%	0%	478	$74.5	0.02%	1117.7 min	60%	4%	0.03	-25.99	0.02	0.06	1.7	13.13	1.40	7.30	3.12	9.69	0.15%
TRB1200	0.5%	1%	24	-$140.2	-0.58%	2748.8 min	11%	-7%	0.00	-24.46	-0.01	-0.01	15.42	360.72	15.42	**360.72**	285.53	303.36	0.00%

Appendix 5. Best performing strategies on test-set without fees

Note: Corrected skewness and corrected kurtosis show values of skewness and kurtosis after winsorization. Min. kurtosis and max. kurtosis show minimum and maximum values of kurtosis fitting inside Cornish-Fisher expansion window of validity. Tail-correction show percentage of tails trimmed to get accepted values of skewness and kurtosis. Bolded values on corrected kurtosis show values that could not be fitted inside window of validity with acceptable tail-trimming. SKASR from these is therefore not fully valid.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio	Skewness	Kurtosis	Corrected skewness	Corrected kurtosis	Min. kurtosis	Max. kurtosis	Tail-correction
MA100-500	0.0%	1%	664	$588.6	0.09%	347.1 min	48%	67%	3.51	13.75	0.62	0.61	3.14	18.52	2.35	**9.40**	9.42	12.03	0.4%
MA90-450	0.1%	1%	378	$499.8	0.13%	580.3 min	46%	56%	3.14	11.63	0.55	0.55	3.33	21.51	2.37	9.83	9.70	12.05	0.4%
MA1-50	0.5%	1%	223	$372.4	0.17%	473.9 min	38%	42%	2.93	11.07	0.49	0.48	2.8	14.03	2.44	10.59	10.54	12.02	0.7%
MA20-50	0.1%	1%	945	$749.3	0.08%	228.8 min	47%	85%	2.93	13.43	0.90	0.79	1.63	5.8	1.63	5.80	4.26	10.25	0.0%
MA100-450	0.0%	1%	726	$588.8	0.08%	317.1 min	45%	67%	2.74	10.41	0.63	0.65	3.13	19.41	1.98	6.52	6.39	11.18	0.4%
MA5-1000	0.1%	1%	464	$534.4	0.12%	516.9 min	49%	60%	2.58	8.46	0.48	0.55	2.8	12.59	2.12	**6.15**	7.40	11.55	1.3%
MA100-400	0.0%	1%	787	$546.4	0.07%	294.2 min	47%	62%	2.55	9.45	0.58	0.58	3.25	23.23	2.08	7.97	7.10	11.45	0.4%
MA70-1000	0.0%	0%	511	$447.4	0.09%	480.7 min	51%	51%	2.53	8.21	0.47	0.44	2.48	11.68	2.38	10.76	9.79	12.06	0.4%
MA90-500	0.0%	1%	700	$521.7	0.07%	327.4 min	47%	59%	2.46	8.82	0.54	0.56	3.13	19.35	2.05	7.03	6.90	11.38	0.4%
MA100-1000	0.0%	0%	440	$439.0	0.10%	559.6 min	53%	50%	2.40	7.39	0.45	0.42	2.46	12.11	2.38	10.88	9.74	12.06	0.4%
MA80-1000	0.0%	0%	484	$421.8	0.09%	507.9 min	52%	48%	2.39	7.34	0.44	0.41	2.5	11.93	2.40	10.93	10.00	12.06	0.4%
MA100-500	0.0%	2%	664	$582.3	0.09%	362.8 min	49%	66%	2.39	8.30	0.58	0.59	2.88	17.02	2.07	8.80	7.07	11.44	0.4%
TRB120	0.1%	1%	391	$374.1	0.10%	438.7 min	43%	42%	2.39	8.25	0.41	0.43	3.87	24.88	2.24	**7.62**	8.41	11.84	0.4%
MA100-250	0.1%	0%	427	$701.0	0.16%	550.8 min	51%	79%	2.32	8.18	0.70	0.69	2.52	15.66	1.65	5.81	4.33	10.29	0.4%
MA100-450	0.0%	2%	726	$593.1	0.08%	330.0 min	47%	67%	2.31	7.87	0.62	0.63	2.8	17.01	1.83	6.61	5.42	10.78	0.4%
MA90-750	0.0%	2%	558	$471.2	0.08%	438.9 min	48%	53%	2.30	7.07	0.48	0.49	2.73	14.52	2.18	8.82	7.92	11.71	0.4%
MA90-750	0.1%	2%	301	$442.3	0.15%	799.1 min	49%	50%	2.30	7.03	0.45	0.45	2.77	14.62	2.27	9.40	8.70	11.91	0.4%
MA20-50	0.1%	0%	945	$702.2	0.07%	242.7 min	49%	79%	2.27	8.86	0.79	0.71	1.44	5.98	1.44	5.98	3.29	9.78	0.0%
MA40-1000	0.1%	0%	306	$387.3	0.13%	790.9 min	51%	44%	2.27	6.52	0.40	0.38	2.55	12.24	2.44	11.28	10.55	12.02	0.4%
MA90-1000	0.0%	0%	460	$414.3	0.09%	534.6 min	53%	47%	2.23	6.33	0.42	0.39	2.53	12.59	2.42	11.50	10.25	12.06	0.4%
MA70-450	0.1%	0%	415	$561.2	0.14%	583.5 min	51%	63%	2.22	7.03	0.54	0.55	2.7	14.88	2.01	7.99	6.63	11.28	0.4%
MA50-450	0.1%	1%	457	$362.6	0.08%	495.2 min	48%	41%	2.21	6.65	0.36	0.38	3.07	17.83	2.39	**9.65**	9.92	12.06	0.4%
MA80-1250	0.0%	0%	416	$656.3	0.16%	588.7 min	53%	74%	2.21	6.10	0.48	0.62	3.11	16.16	2.05	7.01	6.87	11.37	1.6%
MA70-750	0.1%	2%	318	$441.0	0.14%	756.9 min	48%	50%	2.16	6.00	0.45	0.46	2.69	14.31	2.21	9.28	8.12	11.77	0.4%
MA100-300	0.1%	1%	408	$406.6	0.10%	507.6 min	46%	46%	2.16	6.35	0.38	0.44	3.58	24.15	2.25	**8.08**	8.55	11.87	0.4%
MA10-1000	0.1%	0%	412	$470.1	0.11%	591.0 min	48%	53%	2.15	5.75	0.44	0.49	2.56	11.26	2.03	**6.26**	6.77	11.33	1.3%
MA20-50	0.1%	2%	945	$650.2	0.07%	242.5 min	49%	73%	2.15	7.97	0.74	0.66	1.44	5.65	1.44	5.65	3.28	9.77	0.0%
MA60-500	0.1%	2%	409	$402.5	0.10%	581.4 min	50%	45%	2.15	6.31	0.38	0.41	3.06	17.36	2.34	**9.46**	9.33	12.02	0.4%
MA70-300	0.1%	0%	496	$617.8	0.12%	484.4 min	50%	70%	2.13	6.66	0.61	0.61	2.7	16.65	1.76	6.57	4.96	10.58	0.4%
MA10-400	0.1%	1%	674	$351.3	0.05%	350.4 min	46%	40%	2.10	6.10	0.40	0.38	2.79	17.76	2.21	8.15	8.19	11.79	0.4%

Appendix 6. Best performing strategies on test-set with fees

Note: Corrected skewness and corrected kurtosis show values of skewness and kurtosis after winsorization. Min. kurtosis and max. kurtosis show minimum and maximum values of kurtosis fitting inside Cornish-Fisher expansion window of validity. Tail-correction show percentage of tails trimmed to get accepted values of skewness and kurtosis.

Rule	Band	Stop-loss	Trades	Profit	Avg. Profit	Avg. holding time	Annual volatility	Yearly returns	SKASR	Memmel Z	ASR	Sharpe ratio	Skewness	Kurtosis	Corrected skewness	Corrected kurtosis	Min. kurtosis	Max. kurtosis	Tail-correction
MA90-1250	0.5%	0%	77	$576.8	0.75%	3020.4 min	50%	65%	1.18	-2.59	0.22	0.57	3.8	21.32	2.23	8.62	8.36	11.83	2.8%
MA80-1250	0.5%	0%	79	$600.1	0.76%	2967.7 min	52%	68%	1.05	-3.94	0.19	0.58	3.8	21.11	2.21	8.32	8.16	11.78	3.1%
MA100-1250	0.5%	0%	75	$610.8	0.81%	3176.4 min	50%	69%	0.97	-4.73	0.20	0.61	3.7	20.6	2.05	7.34	6.89	11.37	3.5%
MA100-1500	0.5%	0%	77	$431.4	0.56%	2983.6 min	51%	49%	0.73	-7.38	0.13	0.42	3.48	19.73	2.19	8.23	8.03	11.74	2.8%
MA50-750	0.5%	0%	98	$392.7	0.40%	2583.7 min	53%	44%	0.64	-8.64	0.11	0.37	3.48	18.35	2.31	9.07	9.03	11.97	2.2%
MA90-750	0.5%	0%	85	$461.7	0.54%	2788.5 min	53%	52%	0.59	-9.20	0.11	0.44	3.54	19.7	2.13	7.75	7.52	11.59	2.8%
MA100-1250	0.1%	0%	204	$340.5	0.17%	1183.4 min	54%	38%	0.58	-9.30	0.11	0.32	3.27	17.54	2.15	7.77	7.71	11.65	1.9%
MA40-750	0.5%	0%	102	$460.9	0.45%	2483.6 min	53%	52%	0.57	-9.48	0.11	0.43	3.52	17.9	2.17	8.21	7.85	11.69	2.2%
TRB600	0.1%	0%	145	$256.9	0.18%	1518.2 min	47%	29%	0.57	-9.10	0.12	0.27	2.82	13.2	2.03	6.81	6.74	11.32	1.6%
MA60-1500	0.5%	0%	83	$230.7	0.28%	2917.1 min	52%	26%	0.51	-9.90	0.10	0.22	3.11	17.9	2.28	10.44	8.82	11.93	1.0%
MA100-750	0.5%	0%	84	$444.3	0.53%	2793.3 min	54%	50%	0.45	-10.84	0.09	0.41	3.44	18.61	2.08	7.51	7.09	11.44	2.8%
MA70-1500	0.5%	0%	82	$258.4	0.32%	2952.5 min	52%	29%	0.43	-10.81	0.07	0.25	3.23	17.97	2.30	9.01	8.96	11.96	2.2%
TRB540	0.1%	0%	155	$151.4	0.10%	1424.8 min	47%	17%	0.40	-11.35	0.07	0.16	2.82	13.61	2.21	8.24	8.15	11.77	0.7%
MA70-1250	0.5%	0%	84	$437.9	0.52%	2860.5 min	52%	49%	0.38	-11.31	0.07	0.42	3.71	20.57	2.19	7.98	7.98	11.73	3.5%
MA80-1500	0.5%	0%	79	$338.7	0.43%	2999.5 min	52%	38%	0.38	-11.26	0.08	0.33	3.19	17.5	2.10	7.86	7.30	11.52	2.8%
MA90-1000	0.5%	0%	84	$401.8	0.48%	2803.7 min	52%	45%	0.37	-11.68	0.07	0.39	3.56	20.11	2.15	8.24	7.69	11.64	2.8%
MA90-1500	0.5%	0%	78	$390.9	0.50%	3051.1 min	52%	44%	0.36	-11.54	0.08	0.38	3.27	18.36	2.03	7.56	6.73	11.32	2.8%
MA70-1000	0.5%	0%	89	$287.4	0.32%	2637.9 min	52%	32%	0.32	-12.17	0.06	0.28	3.49	20.59	2.28	9.62	8.82	11.93	2.2%
MA100-500	0.5%	0%	90	$163.7	0.18%	2617.5 min	55%	18%	0.32	-12.26	0.07	0.15	2.95	17.27	2.29	11.45	8.90	11.95	1.0%
MA70-300	0.5%	0%	91	$106.4	0.12%	2468.9 min	50%	12%	0.28	-13.17	0.07	0.11	2.55	15.04	2.14	11.00	7.60	11.61	0.4%
MA90-1250	0.1%	0%	215	$256.3	0.12%	1122.8 min	53%	29%	0.23	-13.39	0.04	0.24	3.21	17.21	2.18	8.07	7.94	11.72	1.6%
MA50-1500	0.5%	0%	85	$282.0	0.33%	2769.0 min	52%	32%	0.20	-13.31	0.04	0.27	3.08	17.73	2.13	7.67	7.47	11.57	3.1%
MA50-1250	0.5%	0%	90	$378.5	0.42%	2750.1 min	52%	43%	0.17	-13.92	0.03	0.37	3.69	20.39	2.17	8.05	7.86	11.69	3.1%
MA70-500	0.5%	0%	101	$88.5	0.09%	2328.8 min	55%	10%	0.14	-14.39	0.02	0.08	2.85	17.02	2.41	10.92	10.11	12.06	1.0%
MA60-450	0.5%	2%	108	$244.8	0.23%	1963.7 min	52%	28%	0.12	-14.58	0.02	0.23	3.23	17.29	2.12	7.56	7.41	11.55	2.2%
MA100-1000	0.5%	0%	83	$402.2	0.48%	2851.7 min	53%	45%	0.12	-14.47	0.02	0.38	3.56	19.67	2.04	7.72	6.80	11.34	2.8%
TRB480	0.1%	0%	168	$136.4	0.08%	1305.1 min	49%	15%	0.09	-14.97	0.02	0.14	2.96	15.87	2.03	7.42	6.77	11.33	0.7%
MA60-1250	0.5%	0%	88	$366.5	0.42%	2784.1 min	52%	41%	0.08	-14.93	0.01	0.36	3.65	20.46	2.12	7.56	7.45	11.57	3.8%
MA30-750	0.5%	0%	115	$166.8	0.15%	2232.3 min	54%	19%	0.02	-15.79	0.00	0.16	3.24	17.26	2.42	10.61	10.29	12.05	1.9%
MA40-1000	0.5%	0%	100	$212.8	0.21%	2467.4 min	53%	24%	0.00	-15.76	0.00	0.20	3.42	18.62	2.39	9.92	9.88	12.06	1.9%