Degree Project in Technology

First cycle, 15 credits

Investigation of the potential of the moving average crossover trading strategy

Evaluation of a trading strategy in nine historical time periods

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Bachelor's Programme in Information and Communication Technology
Date: February 5, 2025

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Swedish title: Undersökning av potentialen hos den glidande medelvärdesstrategin
Swedish subtitle: Utvärdering av en handelsstrategi över nio historiska tidsperioder

Abstract

The Moving average crossover strategy (MACS) is a widely used technique in financial markets where two moving averages are used to identify trends and make trading decisions. However, the effectiveness of this strategy largely depends on the chosen length parameters for the moving averages. The moving averages identify trends in a market price and help investors decide when to buy and sell. The moving average crossover strategy uses two averages called the short and long moving averages. The long moving average covers a larger timespan compared to the short moving average. The length parameters for the short and long moving averages are usually set to 40 and 140 but they might not necessarily be the most efficient combination. This study is about investigating the potential of the optimal combination of the two length parameters for the moving averages. We evaluate the performance in historical markets based on the net gain in a financial market following a number of trades. In the study we also compare the MACS to the common and usually profitable strategy of simply buying and holding a security in the same timeframe.

To optimize the length parameters a digital testing environment is created. The environment takes historical data of market prices during a specific period and applies the MACS with adjustable averages lengths on the data uploaded by the user. The environment then creates a 3D-graph measuring net gain or the net loss, that is the increase or decrease in value of an investment as a function of average length of the two moving averages. Historical data for the S and P 500, gold, and bitcoin are used. After finding the optimal moving average crossover length parameters, the strategy's net gain is compared to the outcome of buying and holding the security for the same amount of time. The results show that simply buying and holding a security consistently outperforms the moving average crossover strategy when the standard length parameters of 40 and 140 are used, but the MACS using optimal length parameters often outperforms buying and holding. The results also show that the optimal length for the long and short moving averages often are close to one another.

Keywords

Moving Average Crossover Strategy, Technical Analysis, Market, Trading

Sammanfattning

Glidande medelvärdestrategin (MACS) är en ofta använd strategi inom finansiella marknader där två glidande medelvärden används för att identifiera trender och fatta handelsbeslut. Effektiviteten av denna strategi beror till stor del på de valda längdparametrarna för de glidande medelvärderna. De glidande medelvärderna identifierar trender i marknadspris för värdepapper och hjälper investerare att besluta när de ska köpa och sälja. Den glidande medelvärdestrategin använder två medelvärden, det korta och det långa glidande medelvärdet. Det långa glidande medelvärdet täcker en större tidsperiod jämfört med det korta glidande medelvärdet. Längdparametrarna för det korta och långa glidande medelvärdet är vanligtvis satta till 40 respektive 140 men de värderna måste inte vara den mest effektiva kombinationen. Denna studie undersöker potentialen hos den optimala kombinationen av längdparametrarna för de två glidande medelvärderna. Vi utvärderar resultatet från historiska marknader baserat på nettoavkastningen under en tidsperiod efter ett antal handelsbeslut. I studien jämför vi också MACS med den vanligt använda och ofta lönsamma strategin att helt enkelt köpa och hålla ett värdepapper under en tidsperiod.

För att optimera parametrarna skapas en digital testmiljö. Miljön tar historiska data över marknadspriser under en specifik tidsperiod och använder glidande medelvärdesstrategin med justerbara längdparametrar för medelvärden på den historiska datan som användaren laddar upp. Miljön genererar sedan en 3D-graf som visar nettoökningen eller nettoförlusten, det vill säga värdeökningen eller världeförlusten på en investeringsstrategi som en funktion baserad på längden på de två glidande medelvärderna. Historiska data för SP 500, guld och bitcoin används. Efter att ha hittat de optimala längdparametrarna för glidande medelvärdesstrategin jämförs strategins nettoavkastning med resultatet av att köpa och hålla det valda värdepappret under samma tidsperiod. Resultaten visar att att köpa och hålla ett värdepapper ofta överträffar glidande medelvärdesstrategin när standardparametrarna 40 och 140 används, men att MACS med optimala parametrar ofta överträffar att köpa och hålla. Resultaten visar också att de optimala längderna för det långa och det korta glidande medelvärdet ofta ligger nära varandra.

Nyckelord

Glidande Medelvärden, Teknisk Analys, Marknad, Handel

Acknowledgments

We would like to thank Zhenyu Li for being our supervisor and Håkan Olsson for being our examiner.

Stockholm, February 2025
Olof Olsson Erik Sirborg

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List of Acronyms and Abbreviations

BandH	Buy and Hold. x
BandHS	Buy and Hold Strategy. x
MAC	Moving Average Crossover. x
MACS	Moving Average Crossover Strategy. x
SandP 500	Standard and Poor's 500. x

Chapter 1

Introduction

In this chapter technical analysis and MACS are described along with the problems this study aims to answer. Specific goals and research questions are explained. The research method is described, including the methodology and delimitation, along with the chapter structure.

1.1 Background

A moving average is the average value of a security in a market over a specific period. It is calculated by adding all the price points of a security over a chosen timespan and then dividing by the number of timesteps. These units can range from seconds and minutes to days. The MACS, a popular investment strategy, uses two moving averages, a short and a long one to guide buying and selling decisions. The short moving average covers a smaller timespan, making it more responsive to recent price changes, while the long moving average spans a longer period and thus moves more slowly. Typically, the short moving average length is set to 40 days, and the long moving average to 140 days, though these length parameters can vary based on investor preference [1].

At its core, the MACS aims to identify market trends. The strategy is based on the premise that a price moving in a particular direction will likely continue in that direction, barring any contrary evidence. A declining moving average suggests a general drop in prices, whereas a rising average indicates overall price increases [1]. With the MACS, a "buy" signal, known as a "golden cross," occurs when the short moving average crosses above the long one. Conversely, a "sell" signal, or "death cross," is triggered when the short moving average crosses below the long one [2]. Shorter moving averages typically lead to faster trading and more fluctuations, while longer averages lead to slower trading with fewer swings. The speed of trading with the MACS is influenced by the lengths chosen for the short and long moving averages [3].

A common strategy used in financial markets is the Buy and Hold Strategy(BandHS). BandHS is a passive strategy where the investor buys an asset and holds it for a prolonged period of time. Investors who follow this approach are not concerned with short term fluctuations of an asset's price or technical indicators, instead focusing on increasing value over time. [4]

The goal of all trading strategies is to maximize the returns.[5] The length of the MACS averages directly influences the balance between capturing profitable trends and avoiding false signals. A poorly chosen average length may lead to missed opportunities or unnecessary losses. Optimizing this length parameter can enhance the net gain of the strategy by aligning it more closely with the market's behavior.

1.1.1 Authors division of work

In this thesis Olsson focused on creating the environment while Sirborg focused on gathering sources and writing the report. In most aspects of the thesis the authors have worked together.

1.2 Problem

1.2.1 Original problem and definition

The main problem we focused on was the potential of the MACS compared to the BandHS. Since it would be hard to draw definite conclusions based on data from the past that can't be directly applied to the future, we chose to investigate if the potential exists for the MACS to beat BandHS in the same timeframe. We also wanted to find the optimal parameters for the lengths of the moving averages for the MACS in these timeframes.

1.2.2 Scientific and engineering issues

We wanted to have a real time solution for the testing environment in order to get intuition for how different length parameters could reflect performance. To achieve this we focused on creating an environment where trading results could be seen in real time by changing length parameters. The environment needed to be able to draw how the price of an asset evolved over time along with its moving averages. Another engineering issue was creating a 3D environment that could visualize the effectiveness of various length parameter combinations.

1.3 Purpose

The purpose of this thesis is to find effective moving average strategies in financial markets when using the MACS. The effectiveness of this strategy relies heavily on selecting appropriate moving average lengths. This research aims to systematically evaluate different moving average lengths to identify which combinations yield the highest returns and most reliable signals across various market conditions. The findings may interest private and institutional investors seeking to identify trends and achieve financial gains in the markets.

1.4 Goals

The goal of this study is to find the potential of the MACS. Another objective is to determine the most effective moving average lengths for the MACS based on historical data and market conditions.

1.5 Research Question

When using the MACS, the lengths of the averages can be adjusted, and averages of varying lengths may display differing effectiveness across different market conditions. The primary aim of this paper is to investigate if the MACS, when using optimal length parameters can outperform the BandHS. A secondary aim is to determine the optimal MACS parameters across various market environments and timeframes. To achieve this, an environment was developed to test the MACS length parameters using historical price data. The MACS can accommodate any time unit for its average lengths but for this study we chose days since they are a commonly used time unit. The research questions are:

1. Is it possible for the MACS to beat the buy-and-hold strategy?

2. What are the optimal length parameters for the MACS in various markets?

1.6 Research Methodology

Historical data sets will be used for assets such as stocks, gold, and bitcoin, focusing on end-of-day prices. The testing method will be quantitative, using a digital testing environment to evaluate all possible combinations of moving average lengths within a specified range to identify the optimal combination. Different timeframes for the various assets will be tested.

1.7 Delimitations

This research focuses primarily on the MACS and does not explore other technical indicators or trading strategies. The study is limited to historical data and does not account for future market developments or changes in market conditions that could affect a strategy's performance. The analysis will be conducted on a limited group of assets, and therefore the results might not generally cover all asset types. The research assumes that transaction costs and other trading frictions are negligible, which may not reflect real trading conditions. The moving average lengths tested are also limited to certain time periods.

1.8 Structure of the thesis

Chapter 2: Background. This chapter presents information that describes the concepts used in this thesis, mainly different market strategies and moving averages.

Chapter 3: Method. This chapter describes the method used to get the results for this thesis.

Chapter 4: Results. This chapter presents the results showing the optimal length parameters for the MACS in various situations.

Chapter 5: Conclusions and Future work. The thesis is summarized in this chapter and potential future work is discussed.

Chapter 2

Background

In this chapter the background of this thesis is described. Moving averages, market strategies and previous studies on similar subjects are discussed.

2.1 Finding a moving average

Moving averages can be used to smooth the historical data to show general trends. The moving average at a specific point is calculated by summing up the prizes over a period of n days back and dividing by the number of days, n. The function MA(t) for a moving average can be described with the expression 2.1 where t is a certain timesframe. The value n decides how many time units back in time the average will reach.

$$\mathrm{MA}(t) = \frac{1}{n}\sum_{i=0}^{n-1} x(t-i) \tag{2.1}$$

A larger n will result in a smoother curve of the moving average function and a smaller n will result in a curve that resembles the actual price curve more. When applying the MACS, the length of an average is the number of days into the past that are accounted for. [6]

2.2 Market strategies

In theory market prices should reflect all information available in a market however investment psychology plays a large role in investing. Cognitive bias and emotions often influence investors to make poor financial judgements. Investors have a tendency to not sell investments while being in profit and hold onto losing investments. Market strategies can help offset psychological biases [7].

The BandHS has in general been very rewarding. A one dollar portfolio invested in the DOW Jones industrial average in January 1946 would be worth 116 dollars at the end of 1991. [8] When accounting for inflation, the decrease of a currency's value because of increased supply, the investment's growth becomes smaller but still substantial. The S and P 500 grows an average of 10% per year.[9] In comparison the return of government bonds, which is often called "risk-free" tends to be around 2%. The average inflation in the United States was 3.1 % per year in the last 100 years. The "risk free" return rate of government bonds is thus often not enough for investors to overcome losses from inflation. In general, investments held in indexes like for example the S and P 500 over several generations have massively increased in value even though the investments occasionally substantially decreased in value. All G7 countries have at some point lost 75% of their stock value. Despite this, the BandHS in a stock index will often lead to a net gain greater than what is usually considered a "risk free" investment like government bonds [10]. Overall BandH has proven to be an effective investing strategy which makes comparing strategies like the MACS to it of interest.

Much research has been done on technical analysis in the 21st and 20th centuries. Initial research performed on the MACS in the 1960s found that the rules of the strategy could not outperform BandH but later research found that the MACS could outperform BandH under certain circumstances. The research found that buy signals consistently generated higher returns following sell signals and that the returns of following buy signals were less volatile than when sell signals were followed. Returns following sell signals were often found to be negative [11].

Another study found that the MACS was profitable when tested on various Asian markets in limited timeframes, especially in the markets of non-developed countries. The length parameters in these studies differed somewhat, for example, they used different lengths for their respective moving averages [12]. Compared to the buy-and-hold strategy Faber found that the MACS both provided less returns but also less risk for the invested capital [13]. One study tested the long moving average on the Dow Jones Industrial Average over the 1886-2006 period and found that the market timing strategy outperformed the buy-and-hold strategy. [3]

One of the major drawbacks of the MACS is its assumption that trends can be identified and followed in a market. The strategy might find trends that are not there, or if the market is characterized by volatility trends might be hard to spot or not exist under certain timeframes. The MACS might not always spot opportunities to profit in a volatile market since the market might rapidly change the price before the long or short moving averages can catch up. [14]

Despite the success of buy-and-hold over longer periods of time many top investors, hedge funds and security trading advisors chose to use technical analysis. In falling markets, BandH suffers as a security might take years to recover its price, especially when adjusting the price for inflation. [15]

2.2.1 Summary

In summary a moving average can be used to smooth data trends by averaging a set number of data points. Longer lengths of the average result in smoother slower-moving averages, while shorter lengths create faster moving averages. The MACS uses the crossing of moving averages to signal buy or sell opportunities. Initial studies suggested that the MACS did not outperform the BandHS but later research found it could be effective under certain conditions particularly in volatile or underdeveloped markets. However transaction fees and market volatility often diminish its effectiveness compared to BandHS.

Chapter 3

Method:

In this chapter the method of this thesis, the research question and data gathering method are described. Risks to the validity of the findings are also discussed.

3.1 Research Process

The research process for this thesis was made to test the effectiveness of various MAC strategies in a testing environment. The process was divided into four stages:

1. Literature Review: A literature review was conducted to understand existing research related to MAC strategies. This helped give a foundation for the thesis.

2. Development of the Testing Environment: This next step was to develop a digital testing environment capable of simulating various MAC strategies.

3. Data Collection: Historical market data was collected to serve as the basis for testing.

4. Testing: All possible combinations of moving average lengths in a certain range were tested in the environment and the optimal combinations found.

3.2 Choice of Method:

The choice of method for this thesis was based on the need to test a large amount of MAC strategies. All possible combinations of moving average lengths within the range of 40 units to 300 units for long moving averages, and 10 units to 270 units for short moving averages were tested in the environment. This approach was chosen to cover a wide spectrum of potential strategies and avoid bias. By testing all combinations, the research aimed to find the most effective strategies.

3.3 Data Collection:

The main goal of this study was to find if the MACS has the potential to outperform the market and then draw conclusions based on the effectiveness of the MACS. A quantitative method was best suited for this study since market performance can be heavily dependent on unpredictable swings and general volatility. Large test data can help offset some of the unpredictability in the market. Since manually testing large amounts of moving average length combinations would be infeasible we chose to create a digital environment that can receive historical economic data and create charts. Javascript was used to create the environment. The environment automatically performs the MACS where the length parameters of the averages are based on user input. The environment buys and sells one security at a time and we assume that the environment always has enough currency to make a purchase. After each test the environment returns the total net loss or gain and some graphs showing the result.

3.4 Validity Risks

The validity of the research depends on the relevancy of the historical market data used. Strategies that perform well in the testing environment may not necessarily perform well in real future market conditions. Additionally, the optimal length parameters for the moving averages may be capturing noise rather than actual patterns. The research is limited to historical data so there is a risk that the result might be overfitted to the specific data used and not necessarily reflect future conditions. Market conditions will evolve over time and strategies that worked well in the past may not be effective in the future. The research does not account for external factors that could influence a market such as for example black swan geopolitical events. These risks can affect research validity and its usability to future market conditions.

3.5 Reliability Risks

The research reliability is limited because of historical data. The limits of the historical data set might create a systemic bias in the testing environment. For example the results will only reflect the conditions that existed during the specific timeframes that were tested. This could be remedied by using more data sets covering larger time periods where the goal is to find patterns that are present long term. Longer time periods also helps avoid having unexpected black swan events play a large role in the results.

3.6 Method for analyzing data

This thesis uses a quantitative method for analyzing data. After the digital testing environment runs every possible combination of moving averages lengths in a certain range their returns in the market are compared and the averages yielding the highest return selected.

12 | Method:

Chapter 4

Implementation

In this chapter the implementation of the trading environment and some background on how it was designed are described. The chapter also describes how results are calculated using the environment.

4.1 Digital testing environment functionality:

The environment computes the long and short moving averages using the historical data provided.

Figure 4.1: Plot generated by the testing environment showing the purchasing and selling events

In Figure 4.1, the green line represents the price based on the historical data, the orange line represents the short moving average and the red line represents the long moving average. Green dots represent dates where the short moving average crosses the long and a buy signal is given. Red dots represent dates where the long moving average crosses the short and a sell signal is given.

The environment also generates a 3D-graph to give an overview of all possible parameter combinations of short and long moving averages lengths and their results, shown in Figure 4.2.

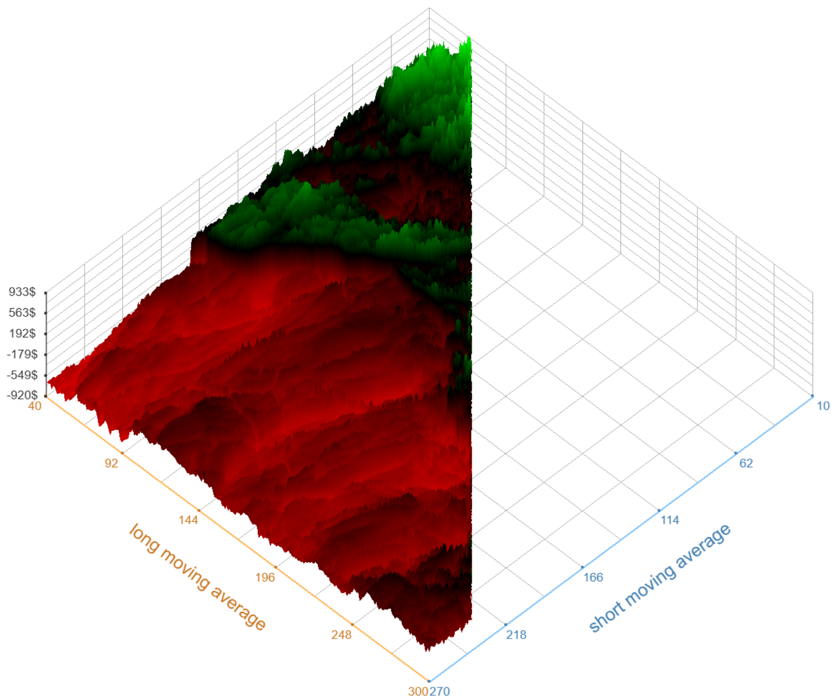

Figure 4.2: Example of a graph generated with the testing environment

The long and short moving averages represent the x and y-axis while the total net gain or loss is represented by the z-axis. The highest point along the z-axis represents the place where the moving averages lengths are optimally adjusted for the data provided and the lowest point represents the worst combination in terms of profitability. The long moving averages lengths start at 40 and the short moving averages lengths start at 10 to ensure that the long moving average always is larger than the short moving average,

After having identified the optimal long and short moving averages lengths the net results were compared to the buy-and-hold strategy where the initial and final purchases happened at the same time as the MACS performed its initial and final purchases.

We chose to investigate the optimal length parameters for the S and P 500, gold and bitcoin. The S and P 500 is a commonly used index tracking the top 500 US companies. Gold has been a means for exchange by humans for thousands of years and is often used as a measure against inflation. Both the S and P 500 and gold are commonly used by traders so finding the optimal length parameters for them is relevant to the purpose of this paper. Bitcoin is a cryptocurrency known for volatility and swing conditions, making it possible for traders to rapidly make huge gains or losses. Optimal length parameters in a volatile market are also relevant to the purpose of the paper since the MACS is often used by traders looking to make quick gains. For the S and P 500 and gold we chose three timeframes: 1980-2020, 2000-2020 and 2010-2020. The timeframes cover a relatively large amount of time which helps remove "noise" from the result. The timeframes also intersect which can help find answers if the same result in a smaller part of the same timeframe. For bitcoin, which only has existed since 2009, we chose three timeframes: 2013-2018, 2018-2023 and 2013-2023.

4.2 Choice of programming language

JavaScript, HTML and CSS were used for the testing environment. HTML and CSS were utilized to create a graphical interface. JavaScript was used to make the interface interactive as well as performing computations related to executing the MACS strategy.

There are other options for simulating a trading strategy on historical timeframes such as Python, Matlab or C++. Ultimately we decided upon Javascript, HTML and CSS due to their convenient way of combining graphical interface with code. Other programming languages could potentially be faster however we found that Javascript was sufficiently fast for our purposes.

4.3 Overview of structure of the testing environment

The testing environment consists of a web application that executes the MACS on a file that is uploaded by the user. The web page has an interface that allows the user to change the length parameters of the MACS that will be executed. Results are displayed for the user on a graph. In order to find the optimal values for the MACS multiple tests with varying length parameters are performed. A matrix representing the profit of each combination of length parameters is generated by the environment after the user inputs data. This matrix can then be exported to another web page that renders a 3D graph of the resulting values.

The range of values of moving averages lengths we decided to test is between 10 - 270 units for short moving averages and 40 - 300 units for long moving averages. In total this is around 30000 possible combinations. We found that a brute force method was sufficiently time efficient to find the optimal length parameters. The environment tested all combinations of the moving averages lengths except those where the long moving average was shorter than the short moving average. The highest net result and lowest were identified along with their coordinates.

The process of testing a certain set of length parameters consists of first creating the two moving average graphs over a selected time period. The next step is to pass those arrays to a function that executes the MACS on the same time period. This function iterates through the period and using the moving averages and the varying price of the stock decides if it should buy or sell a stock at a particular timestep. The resulting data is a list containing how many stocks are bought or sold on each timestep. The process is described in figure 4.1.

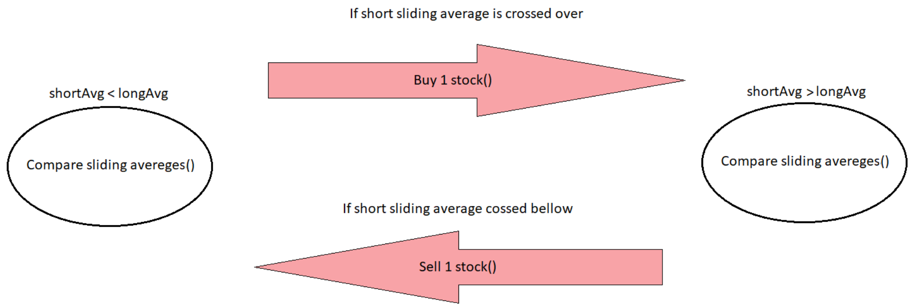

Figure 4.3: Description of how buy and sell events are determined.

The net profit or net loss is found by using the formula 4.1. j stands for each time the environment buys and then sells a stock, while m indicates the total number of times the environment holds a stock. The environment buys and sells one stock at a time and any potential stock the environment still owns at the end of the timeframe is not included in the calculation.

$$\sum_{j=1}^{m} (\text{Sell Price for } j - \text{Buy Price for } j) \tag{4.1}$$

4.4 Computing moving averages in linear time

In our study the MACS is executed a large amount of times on different timeframes. In order to save time in computation and have the results displayed in real time for the efficiency of the code is crucial. The approach to calculating the moving averages plays an important role for the environment to have desired efficiency. In order to compute the moving averages as fast as possible we based the computation on the formula in figure 4.2 instead of the more intuitive definition in figure 2.1. MA(t) is the moving average value on timestep t and x(t) is the market value of t. N is the length of the moving average.

$$MA(t) = MA(t-1) + \frac{x(t) - x(t-N)}{N} \tag{4.2}$$

Computing the moving average using this recursive formula does not require the environment to repeatedly scan back through the timeframe and iterate over N values each step. Instead the sum is computed once for the initial value and for subsequent timesteps only a few computations are required. In this way the recursive formula takes advantage of how the moving average from the previous timestep is closely related to the next. This results in a moving average computation with a time complexity of $O(xlength + N)$ as opposed to $O(xlength \times N)$, where xlength is the length of the timespan and N is the length of the moving average.

Chapter 5

Results and Analysis

In this chapter the results from the trading environment are listed. For each time period of a tested asset a 2D and 3D graph is presented, along with a list of profitability for the optimal and least optimal combinations of moving averages lengths. There is also an analysis section with speculation about the results.

5.1 Major results

The 3D graphs showing the possible combinations of moving averages lengths in a range are shown here. Brighter variants of the color green indicate net gain while red indicates losses. The height value of each 3D graph indicates the relative loss or gain for each length parameter combination. After each 3D graph a diagram shows the coordinates for maximum net gain and minimum net gain along with their result. The results of using the standard averages of 140 and 40 and of using the BandHS over the same timeframe are also shown. The coordinates are presented as (XL, YS). X and Y represent coordinates while L represents the long moving average length and S represents the short moving average length. Below each graph the price difference of the S and P 500 index during the same timeframe is included, meaning the difference in value of the S and P 500 measured between the first day of the timeframe and the last. This was included to compare the optimal MACS to the S and P 500 in the same timeframe.

5.2 S and P 500 from 1980-2020:

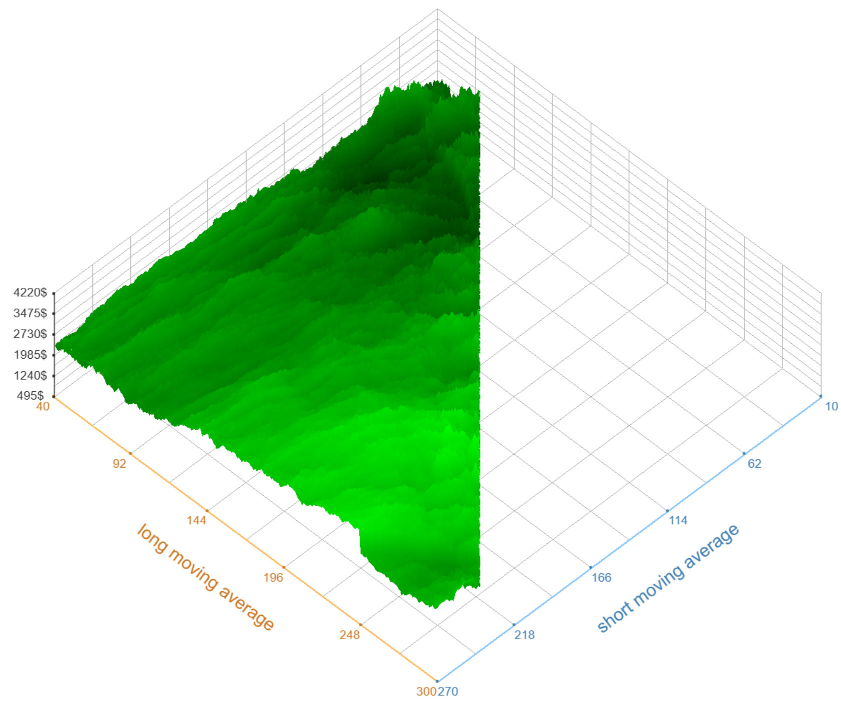

Figure 5.1: The net result obtained with various long and short moving average lengths.

Maximum coordinates:	(227L, 205S)
Minimum coordinates:	(94L, 92S)
Maximum coordinates result:	$4220
Minimum coordinates result:	$495
140, 40 Strategy result:	$1702
S and P price difference in the same timeframe (BandH):	$3650

Table 5.1: Various Results for the S and P 500 1980-2020

Figure 5.2: Optimal trades for the time period 1980 - 2020

The results for the S and P 500 during the 1980-2020 time period show that using the maximum coordinates of (227L, 205S) beats both the 140,40 strategy and BandH the s and p 500 during the same timeframe. The BandHS was beaten by a much smaller margin. The minimum coordinates of (94L, 92S) are very close to eachother.

5.3 S and P 500 from 2000-2020:

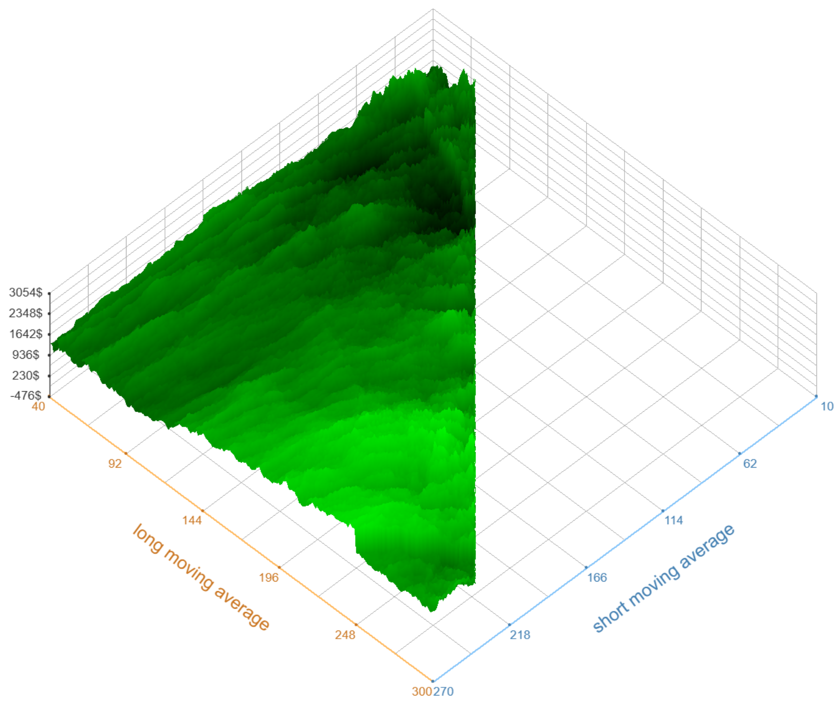

Figure 5.3: The net result obtained with various long and short moving average lengths.

Maximum coordinates:	(221L, 218S)
Minimum coordinates:	(95L, 94S)
Maximum coordinates result:	$3054
Minimum coordinates result:	-$476
140, 40 strategy gain:	$956
S and P price difference in the same timeframe (BandH):	$2301

Table 5.2: Various results for the S and P 500 2000-2020

Figure 5.4: Optimal trades for the time period 2000 - 2020

The results for the S and P 500 during the 2000-2010 time period show that using the maximum coordinates of (221L, 218S) beats both the 140,40 strategy and BandH during the same timeframe. Both the maximum coordinates of (221L, 218S) and minimum coordinates of (95L, 94S) are very close.

5.4 S and P 500 from 2010-2020:

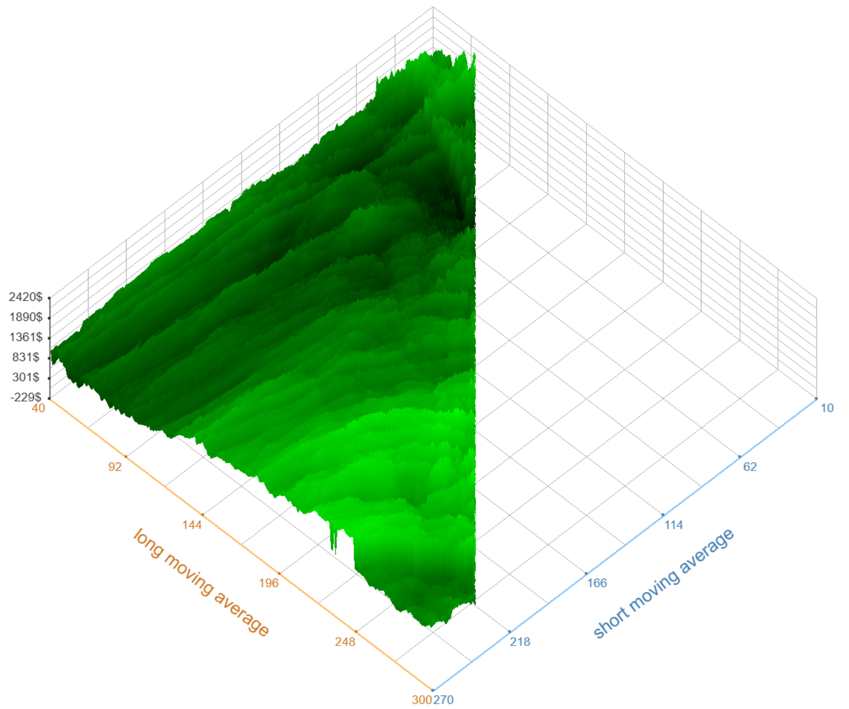

Figure 5.5: The net result obtained with various long and short moving average lengths.

Maximum coordinates:	(211L, 198S)
Minimum coordinates:	(94L, 93S)
Maximum coordinates result:	$2420
Minimum coordinates result:	-$229
140, 40 strategy gain:	$718
S and P price difference in the same timeframe (BandH):	$2624

Table 5.3: Various Results for the S and P 500 2010-2020

Figure 5.6: Optimal trades for S and P 500 for 2010-2020

The results for the S and P 500 during the 2010-2010 time period show that BandH outperforms the coordinates that provide the maximum result for the MACS.

5.5 Gold 1980-2020:

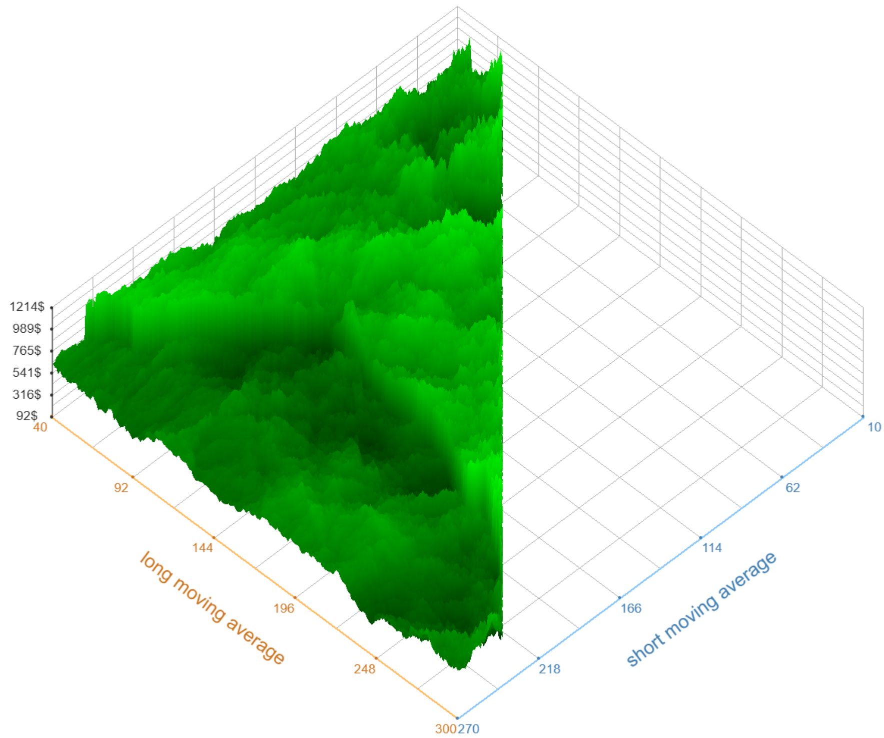

Figure 5.7: The net result obtained with various long and short moving average lengths.

Maximum coordinates:	(70L, 69S)
Minimum coordinates:	(49L, 45S)
Maximum coordinates result:	$1214
Minimum coordinates result:	$92
140, 40 strategy gain:	$636
Gold price difference in the same timeframe (BandH):	$1288

Table 5.4: Various results for gold, 1980-2020

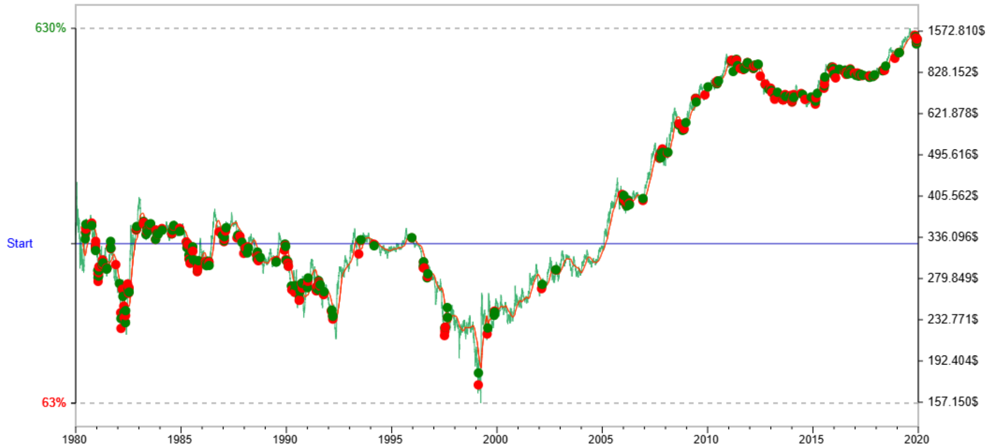

Figure 5.8: Optimal trades for gold using MACS, 1980-2020

The results for gold during the 1980-2020 time period show that BandH outperforms the coordinates that provide the maximum result for the MACS.

5.6 Gold 2000-2020:

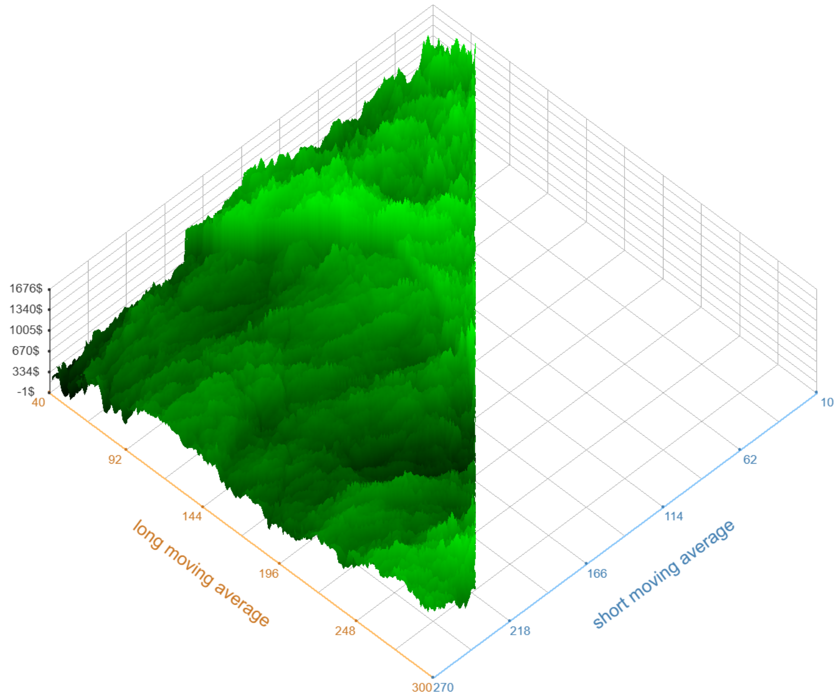

Figure 5.9: The result obtained with various long and short moving average lengths.

Maximum coordinates:	(171L, 167S)
Minimum coordinates:	(205L, 200S)
Maximum coordinates result:	$1676
Minimum coordinates result:	-$1
140, 40 strategy gain:	$1275
Gold price difference in the same timeframe (BandH):	$1621

Table 5.5: Various results for gold, 2000-2020

Figure 5.10: Optimal trades for gold using MACS, 2000-2020

The results for gold during the 2000-2020 time period show that the optimal moving average lengths slightly outperform BandH. The minimum coordinate result is low enough to incur a small loss.

5.7 Gold 2010-2020:

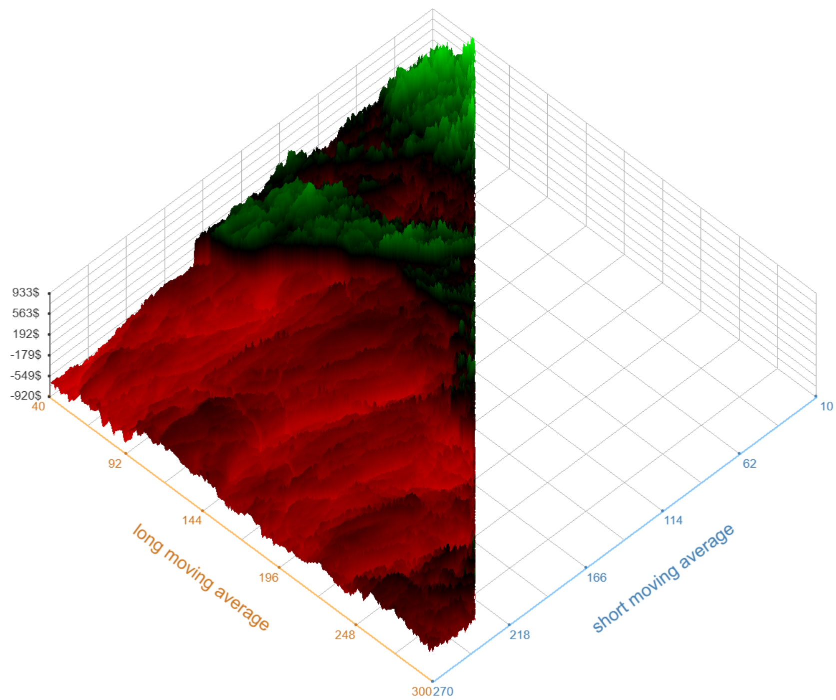

Figure 5.11: The net result obtained with various long and short moving average lengths.

Maximum coordinates:	(40L, 37S)
Minimum coordinates:	(193L, 185S)
Maximum coordinates result:	$933
Minimum coordinates result:	-$920
140, 40 strategy gain:	$239
Gold price difference in the same timeframe (BandH):	$489

Table 5.6: Various results for gold 2010-2020

Figure 5.12: Optimal trades for gold, 2010-2020

The results for gold during the 2010-2020 time period show that the optimal moving averages lengths outperforms BandH and the 140,40 strategy. The period between 2010-2020 seems to have been thought for the gold market as the price difference in that timeframe was relatively small. As with the other results for gold the MACS performed a large amount of trades during the time period.

5.8 Bitcoin 2013-2023:

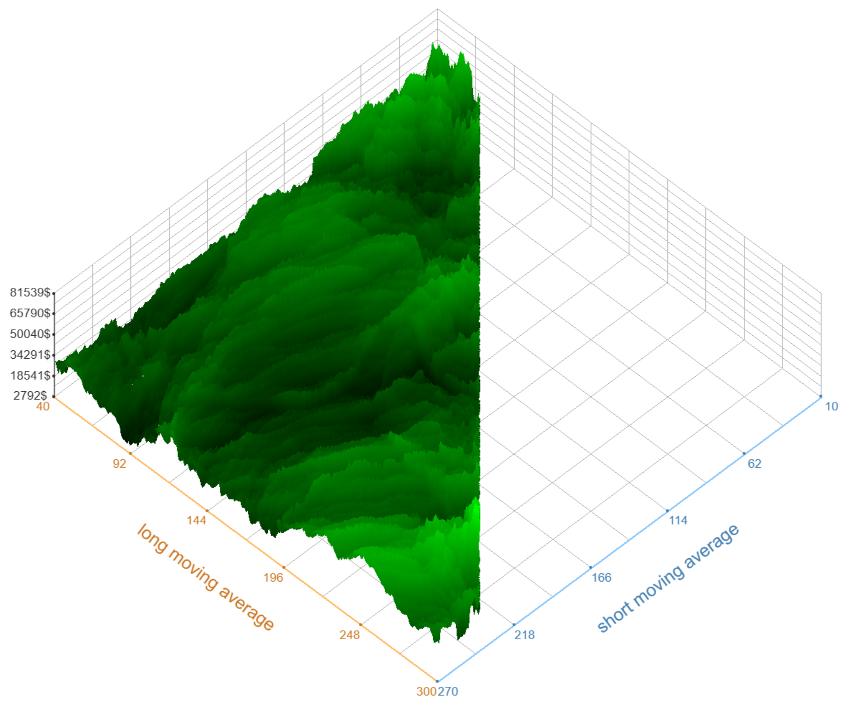

Figure 5.13: The net result obtained with various long and short moving average lengths.

Maximum coordinates:	(253L, 252S)
Minimum coordinates:	(171L, 130S)
Maximum coordinates result:	$81539
Minimum coordinates result:	$2791
140, 40 strategy gain:	$36545
Bitcoin price difference in the same timeframe (BandH):	$42129

Table 5.7: Various results for bitcoin 2013-2023

Figure 5.14: Optimal trades for bitcoin, 2013-2023

The results for bitcoin during the 2013-2023 time period show that the maximum coordinate result can massively outperform BandH. As with the other results the 140, 40 strategy underperforms BandH. Based on the 2d graph the MACS managed to sell at the top of one the peaks making a huge profit.

5.9 Bitcoin 2018-2023:

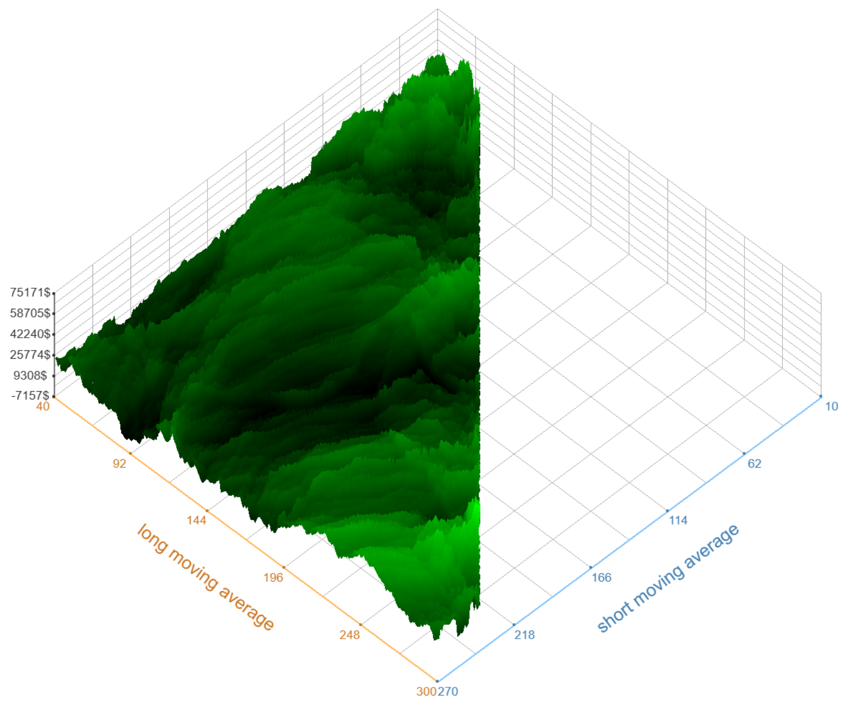

Figure 5.15: The result gain obtained with various long and short moving average lengths.

Maximum coordinates:	(253L, 252S)
Minimum coordinates:	(73L, 63S)
Maximum coordinates result:	$75171
Minimum coordinates result:	-$7157
140, 40 strategy gain:	$24786
Bitcoin price difference in the same timeframe (BandH):	$28561

Table 5.8: Various results for bitcoin 2018-2023

Figure 5.16: Optimal trades for bitcoin using MACS, 2018-2023

Interestingly the maximum coordinates here are the same as for bitcoin during the 2013-2023 period, probably because the timeframes overlap and the value of bitcoin was much lower during the initial period. Because of bitcoins huge swings in value it seems that the MACS can both lead to huge gains and losses as shown by the difference between the maximum and minimum coordinates result.

5.10 Bitcoin 2013-2018:

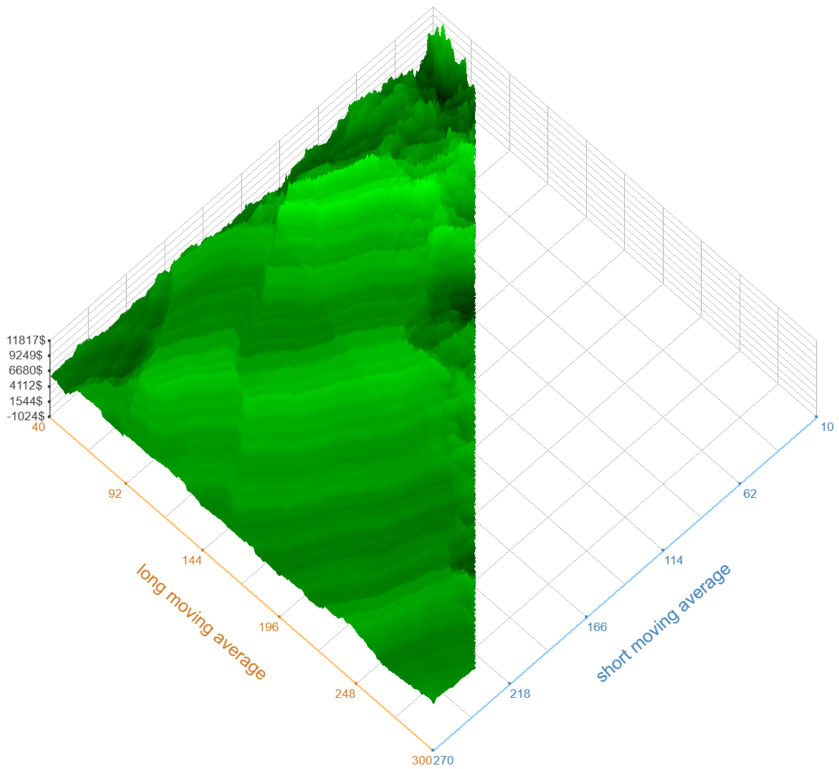

Figure 5.17: Bitcoin, 2013-2018

Maximum coordinates:	(115L, 74S)
Minimum coordinates:	(51L, 25S)
Maximum coordinates result:	$11817
Minimum coordinates result:	$-1024
140, 40 strategy gain:	$3697
Bitcoin price difference in the same timeframe (BandH):	$3812

Table 5.9: Various results for bitcoin 2013-2018

Figure 5.18: Optimal trades for bitcoin using MACS, 2013-2018

Bitcoin experienced a large rise in price during the period 2013-2018 which explains why the minimum coordinates yield a relatively small loss compared to the other bitcoin timeframes. Unlike the other bitcoin timeframes the maximum coordinates here are somewhat far apart at (115L, 74S). The 140,40 strategy is somewhat close to the actual price difference of bitcoin during the time period.

5.11 Analysis

Part of the goal of this thesis was to find the optimal lengths for moving averages. The results presented show that the optimal lengths vary wildly but some trends can be seen. For example in several of the charts the maximum coordinates were two coordinates that were very close to eachother. Two close values leads to the strategy performing a large amount of trades when the market is fluctuating but not when it is moving in a certain direction without much fluctuation. The reason why two values close to eachother often end up successful is probably because the large amount of trades can occasionally generate a very profitable result even if it most of the time ends in a loss for the trader. The large amount of trades could be seen on the 2d graphs. Since the thesis is about identifying the maximum coordinate result it makes sense that it would often be a combination leading to many trades being performed.

In general the tests for the S and P 500 lead to very few trades being performed compared to gold and bitcoin. Gold in particular seemed to have a massive amount of trades required for its optimal MACS. This might be because of gold being somewhat "stable" compared to the s and p 500 and bitcoin and the optimal strategies is thus required to be more aggressive. The S and P 500 is the least fluctuating of the three assets which leads to fewer trades being performed. In almost all cases the maximum MACS could outperform BandH except for gold during the 1980-2020 period. For all the tested timeframes BandH a security outperforms the MACS when the standard (140L, 40S) length parameters are used. However when the optimal length parameters are used the MAC will often outperform BandH.

5.12 Validity Analysis

The main issue affecting the validity of this thesis is the limited number of data sets. The conclusions drawn can therefore only be considered to be valid for the historical data tested. A larger research project could improve on the result by testing a greater number of data sets which could help draw more accurate conclusions about optimizing the MACS.

Chapter 6

Discussion

This chapter discusses the results for the various assets and time periods.

6.0.1 Timeperiod results

This study showed that the MACS can in some cases outperform BandH when using optimal length parameters. Out of the nine timeframes that were tested the optimal MACS outperformed BandH in seven. This doesn't necessarily mean that the MAC is preferable as the vast majority of long and short moving averages lengths would still underperform when tested against BandH.

For the S and P 500 index the results showed that for three different timeframes the optimal long moving average lengths was around 211-227 and the short moving average length around 198-218. This means that the historical data points to the optimal length parameters for the S and P 500 being in this area but is no guarantee that they will remain there in the future.

The optimal length parameters for gold varied more. The result varied from (171L, 167S) to (40L, 37S). This might be because the gold market is less "predictable" than the S and P 500 in the timeframe tested. Over the timeframe tested the S and P 500 often grew massively whereas gold had a more stable growth or in the case of the 2010-2020 period very limited growth.

For bitcoin the results showed that for the period 2013-2023 and 2018-2023 the optimal length parameters were the identical results of (253L, 252S). For the period 2013-2018, when bitcoins value was considerably lower and the market less well known the optimal length parameters were (73L, 63S). This along with the results for the S and P 500 seemed to show that the MACS with optimal length parameters is most efficient in growing markets, like the S and P 500 or bitcoin over the timeframe used.

6.0.2 MACS or BandH

The MACS with optimal length parameters seemed to perform very well in volatile markets like bitcoin as the strategy often managed to sell at the top of market peaks. In markets that sideline more, like the gold market in the timeframe used, BandH often outperformed the MACS even with optimal length parameters. The exception to this seems to be a market in a timeframe with little growth, or decline, as the MACS with optimal length parameters could outperform holding gold in the 2010-2020 period.

In several timeframes the results showed that the optimal length parameters often were numbers close to eachother. For example the optimal length parameters for bitcoin over both the 2018-2023 and 2013-2023 timeframes were (253L, 252S). The optimal length parameters for gold from 2010-2020 were (40L, 37S), or (70L, 69S) for gold from 1980-2020. Judging from the graphs this seems to be because having the two averages be close together allows for the algorithm to ride and profit from large upswings without selling, while also aggressively buying and selling when the market makes many small swings to take small profits each time.

In many cases the short moving average was very large, often close in length to the long moving average. We believe this is the case because of the large amounts of trades that are performed when the two values are close. When a large amount of trades are performed it will often result in a net loss, but can sometimes also result in a large net gain. Since we are looking for the optimal lengths of the two moving averages in this report it makes sense that the short moving average often would be around the same size as the long moving average.

Chapter 7

Conclusions and Future Work

This chapter provides a conclusion for the thesis and gives some suggestions for improvements to the study and future work.

7.0.1 Conclusions

Since markets are volatile and unpredictable, and this study is based on historical data, the definitive conclusion that can be drawn is that MACS has the potential to beat BandH under certain circumstances. In general BandH outperforms the MACS, but the average crossover strategy can outperform BandH under certain rare circumstances.

7.0.2 Suggestions for improvements

One of the goals of this study was picking optimal strategies based on historical data which is affected by previous market conditions. There is no guarantee that those conditions will persist and future market swings might lead to different conclusions being drawn. The historical data can also be impacted by market anomalies which can disrupt the performance of strategies like the MACS. A way of making an improved future study could be to test with a larger dataset and test more types of securities to offset market anomalies. To reduce the reliance on historical data real time testing could help validate the results in current market conditions. To make the simulation more realistic one could include transaction fees which would have the result of reducing the efficiency of the MACS since it often rapidly performs many trades.

7.0.3 Consistency of optimal length parameter pairs across timeframes

The results show that the length parameters for the optimal moving averages lengths vary between different timeperiod and assets, however in 5 out of 9 tests both length parameters were either larger than 200 or every close to 200. This implies that the peak on the 3D graph is usually in this area. Additionally this suggests that larger lengths for moving averages seem to give more returns.

Since the peak on the 3d graph was in a similar point over different timeframes the optimal coordinates seem to be somewhat consistent.

7.0.4 Factors that could impact a real MACS implementation

In some of the combinations of length parameters it appears that the profitability depends on a large amount of small profitable trades as opposed to a few big trades. If transaction fees were accounted for those combinations of length parameters would not generate the same amount of profit as they would in an actual market during the same timespan.

When creating a trading environment more factors could be taken into account since they might affect the result. Factors such as delays in trading and transaction fees might vary under certain circumstances and should be taken into account when optimizing lengths of moving averages for the MACS.

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Appendix

The following is the code for some of the key functions of the digital testing environment:

```
function basicSlidAvgBot2(curve, stopWin, stopLoss, shortLength, longLength){

    var res = [curve.vals.length]

    shortAvg = slideAvg(curve.vals, shortLength);
    longAvg = slideAvg(curve.vals, longLength);

    var shortOver = false;

    var hasbought = false;

    if(shortAvg[parseInt(longLength) + 1] > longAvg[parseInt(longLength) + 1]){
        shortOver = true;
    }
    var boughtPrice = NaN;
    for(var i = parseInt(longLength) + 1; i < curve.vals.length; i++){

        var switched = false;

        if(shortOver){
            if(parseFloat(shortAvg[i]) < parseFloat(longAvg[i])){
                switched = true;
                shortOver = false;
            }
        }else{
            if(parseFloat(shortAvg[i]) > parseFloat(longAvg[i])){
                switched = true;
                shortOver = true;
            }
        }

        if(switched == true && shortOver == true && hasbought == false){
            res[i] = 1;
```

```
                hasbought = true;

                boughtPrice = curve.vals[i];

            }else if(switched == true && shortOver ==false && hasbought == true){
                res[i] = -1;
                hasbought = false;
                boughtPrice = NaN;
            }

            if(!isNaN(boughtPrice) && hasbought && !switched){
                if(is3PercentLarger(boughtPrice, curve.vals[i], stopWin)){
                    res[i] = -1;
                    hasbought = false;
                    boughtPrice = NaN;
                }else if(is3PercentLarger(curve.vals[i], boughtPrice, stopLoss)){
                    res[i] = -1;
                    hasbought = false;
                    boughtPrice = NaN;
                }
            }
        }

    return res
}
och denna :

function getFinalValue(curve, events){

    var vals = curve.vals;
    var boughtStocks = 0;
    var soldStocks = 0;

    var buyAcc = 0;
    var sellAcc = 0;

    var lastBuy = 0;
    for(var i = 1; i < events.length; i++){
```

```
        if(events[i] > 0){
            boughtStocks += events[i]
            lastBuy += events[i] * vals[i];
        }else if(events[i] < 0){

            sellAcc += -events[i] * vals[i]
            buyAcc += lastBuy;
            lastBuy = 0;
            soldStocks += -events[i]
        }
    }
    var vinst2 = (sellAcc - buyAcc);
    return vinst2;
}


function drawCurve(curve, startIndex, endIndex, color, start){

ctx.strokeStyle = color;
ctx.lineWidth = 1;

var margin2 = 75;
var vals = curve.vals;
var highest = curve.highest;
var lowest = curve.lowest;

diffY = curve.highest - curve.lowest;

datapointWidth = endIndex - startIndex;

deltaX = 900 / vals.length;

var procentInPrice = ((curve.vals[0] - lowest) / diffY);
var procentInPixel = (50 + 400 * procentInPrice);

ctx.beginPath();
ctx.moveTo(margin, 500 - procentInPixel);

for(var i = 1; i < endIndex; i++){

    procentInPrice = (curve.vals[i] -
```

```
        lowest) / diffY;
    procentInPixel = 50 + 400 *
        procentInPrice;
    ctx.lineTo(margin+ i * deltaX, 500 -
        procentInPixel);
}

ctx.stroke();
ctx.closePath();


if(start == true){
ctx.strokeStyle = 'gray';
ctx.lineWidth = 1;
ctx.strokeRect(margin, 25, 900, 450);
ctx.strokeStyle = '#1111BB';
procentInPrice = (curve.vals[0] - lowest)
    / diffY;
procentInPixel = 50 + 400 * procentInPrice
    ;
ctx.beginPath();
ctx.moveTo(margin, 500 - procentInPixel);
ctx.lineTo(975, 500 - procentInPixel)
ctx.stroke();

ctx.setLineDash([5, 5]);
ctx.strokeStyle = 'gray';
procentInPrice = (curve.vals[0] - lowest)
    / diffY;
procentInPixel1 = 50;
procentInPixel2 = 450;
ctx.beginPath();
ctx.moveTo(975, 500 - procentInPixel1);
ctx.lineTo(margin, 500 - procentInPixel1)
ctx.moveTo(975, 500 - procentInPixel2);
ctx.lineTo(margin, 500 - procentInPixel2)
ctx.stroke();

ctx.setLineDash([]);
ctx.strokeStyle = 'black';
var numberOfTicks = 9;
var spaceBetweenTicks = 44;
var startX = 975;
var startY = 50;
var lineLength = 5;
ctx.strokeStyle = 'black';
```

```
ctx.beginPath();
ctx.moveTo(startX, startY);
ctx.lineTo(startX, startY + (numberOfTicks * spaceBetweenTicks));
ctx.stroke();

var deltaC = (highest - lowest) / numberOfTicks

for (var i = 0; i <= numberOfTicks; i++) {
    var y = startY + (i * spaceBetweenTicks);

    ctx.beginPath();
    ctx.moveTo(startX, y);
    ctx.lineTo(startX + lineLength, y);
    ctx.stroke();

    ctx.font = '13px Arial';
    ctx.fillText((highest - deltaC * i).toFixed(3), startX + lineLength + 5, y + 4);
}

ctx.strokeStyle = 'black';
 numberOfTicks = 3;
 spaceBetweenTicks = 400/3;
 startX = margin;
 startY = 50;
 lineLength = 5;
ctx.beginPath();
ctx.moveTo(startX, startY);
ctx.lineTo(startX, startY + (numberOfTicks * spaceBetweenTicks));
ctx.stroke();

var procentInPrice23 = (curve.vals[0] - lowest) / diffY;
var procentInPixel23 = 50 + 400 * procentInPrice23;
var middle = 500 - procentInPixel23;
for (var i = 0; i <= numberOfTicks; i++) {
    var y = 0;
    if(i == 0){
        y = 50;
    }else if(i == 1){
```

```
            y = middle;
        }else{
            y = 450;
        }

        ctx.beginPath();
        ctx.moveTo(startX, y);
        ctx.lineTo(startX - lineLength, y);
        ctx.stroke();
        ctx.font = '13px Arial';

        if(y < middle) {
            ctx.fillStyle = 'green';

        }else if(y > middle){
            ctx.fillStyle = 'red';
        }else{
            ctx.fillStyle = 'blue';
        }

        var string = String((-100*((y / middle
          ) - 1)).toFixed(0)) + "%";
        if(y == middle){
            string = "Startpris"
        }
        ctx.fillText(string, startX - ctx.
          measureText(string).width - 5 -
          lineLength, y + 4);
        ctx.fillStyle = 'black';
    }
    ctx.fillStyle = 'black';
    }

    }
```

Listing 1: Code for the digital testing environment

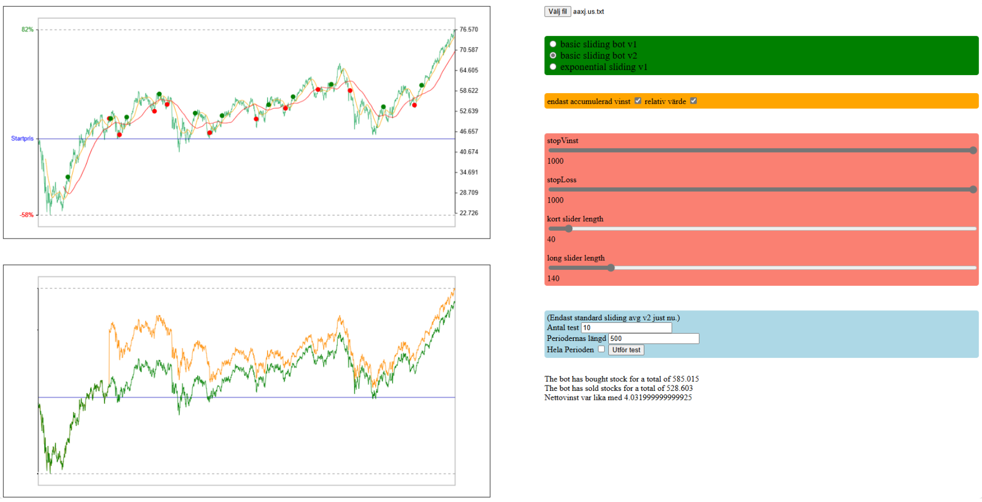

Figure 1: Screenshot of the digital testing environment

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