Re-examining the Profitability of Moving Average Rules in Various Financial Markets

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Abstract

Previous studies find evidence both in favor and against the usefulness of the moving average (MA) strategies, while a final conclusion is yet to be made. This thesis investigates the performance of MA strategies versus the passive buy-and-hold (BH) strategy, in the commodity, currency, stock and bond markets. To measure the outperformance, we simulate the out-of-sample returns to the MA strategies for all four financial markets. Moreover, possibly for the first time, we provide out-of-sample tests of the performance of MA strategies when a sell signal is a signal to short the underlying asset. In addition, we use a combination of many trading rules and MAs. Our findings are that MA strategies statistically significantly outperform the BH strategy in the commodity markets, and seem to perform well in the currency markets. In the stock and bond markets, the MA strategies do not work well, and even underperform the BH strategy in some cases. For the MA strategies with short sales, we find similar remarks regarding the outperformance, but the risk and mean returns are higher in general. Additionally, we observe that MA strategies rely on bear market states to outperform the BH strategy.

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1 Introduction

To trade in financial assets can be very profitable if the timing is right, you want to buy when the price is low and sell when the price is high. However, investors cannot see into the future. Therefore, investors use methods to identify when prices are high and low. One traditional method of identifying the proper time to buy and sell a financial asset is technical analysis.

Technical analysis represents a methodology that examines past price data to forecast the future financial asset price movements. One basic principle within technical analysis is that prices move in trends, which is the reason for the existence of trend following strategies. Trend followers buy (sell) the financial assets when the price trends upwards (downwards) to gain profits (reduce losses). To follow a trend sounds like a simple concept, but in reality it is difficult to identify trends because of the large fluctuations in the financial asset prices. A popular mathematical approach to "smooth"price fluctuations to highlight the underlying trend is the "moving average (MA)", which we use in this study. To be able to know when to buy and sell a financial asset one needs to select a trading rule. The trading rule generates buy and sell signals. There exist many different trading rules, ranging from the simple "Price minus MA rule", to more complex rules, such as the "MA Convergence/Divergence rule".

Previous studies provide various results about the performance of MA strategies. On the one hand, Brock, Lakonishok, & LeBaron (1992), Levich & Thomas (1993), Faber (2007) and Kilgallen (2012), among other researchers, find that MA strategies outperform the passive buy-and-hold (BH) strategy. On the other hand, Sullivan, Timmermann, & White (1999) and Zakamulin (2014), among others, find that the MA strategies do not outperform the BH strategy.

Now, we will elaborate on some of the weaknesses in previous studies concerning the performance of MA strategies. Most of the previous studies overrate the performance of the MA strategies due to "data-snooping" from in-sample tests, e.g. Faber (2007) and Kilgallen (2012), among others. The "data-snooping" problem occurs when researchers use a set of data more than once for model selection ("data-mining"), and when researchers use trading rules from previous studies that report good performance with the respective rule (Zakamulin, 2017). Moreover, multiple studies e.g. Naved & Srivastava (2015) and Glabadanidis (2016), do not take in account that to switch between the risky and risk-free asset imposes a transaction cost. In addition, a vast number of studies draw conclusions based on parametric tests. The weakness with the use of a parametric test is that it relies on a number of assumptions to report valid results. Many datasets do not meet these assumptions and i.e. the results are not valid. Some studies even leave out tests for statistical significance, which makes it difficult to conclude on the validity of the results. Moreover, some studies manage not to use a real risk-adjusted performance measure, such as Kilgallen (2012). This makes it difficult to compare the real performance between different trading strategies. Further, Kilgallen (2012) does not assume that the proceeds when invested in a foreign currency can earn the risk-free rate of the respective country.

The goal of this study is to overcome the weaknesses of previous studies. To do so, we provide a more accurate measurement of the true performance of MA strategies. In addition, we extend previous research with some new methodology. Now, we present how we overcome the weaknesses of previous studies, and then we present the new methodology:

To overcome the weaknesses of previous studies we perform both in-sample and out-of-sample tests, where we draw no conclusions on the performance of the MA strategies from the in-sample tests, but we select the best performing trading rules from the in-sample period and use them in the out-of-sample tests. With the use of out-of-sample (forward) test, one tests the performance on how a technical trader behaves in reality, which generates more reliable results of the true performance of MA strategies. The out-of-sample test cope with the data-snooping problem. We provide results on the true performance of MA strategies in four different financial markets, possibly for the first time. Faber (2007) and Kilgallen (2012) also test the performance of the MA strategies in different financial markets, but only with the use of in-sample tests. We include four financial markets to give an overview of the true performance of MA strategies in the respective financial markets. We use the non-parametric "stationary bootstrap" test, with Sharpe ratio as performance measure to test for statistically significant outperformance. The reasoning is that one can use the stationary boostrap test when time series are non-normal or serial dependent, which would invalidate the results in a parametric test. In addition, we include realistic transaction costs for each financial market.

One new methodology in this study is that we combine multiple trading rules and MAs (see Table 3). We find it realistic to assume that in reality a technical trader has many MA strategies to choose from and that the technical trader chooses the best performing strategy in a back-test. More specifically, for the out-of-sample tests, we evaluate the performance of each single MA strategy in the in-sample period, and the trading signal at the end of the month is the signal from the strategy with the best performance in the in-sample period. This study is probably the first to do so. Another new methodology in this study is that we provide out-of-sample results where a sell signal is a signal to sell the financial asset short. We also make a realistic assumption that an investor invests the proceeds of a foreign currency into a risk-free asset in the respective country.

We address the weaknesses of previous studies and want to re-examine the profitability of MA rules in various financial markets. Consequently, we emphasize on one issue throughout the thesis: "Are moving average strategies able to outperform the passive buy-and-hold strategy in the respective markets: Commodity, exchange rate, stock and bond markets?"

Our findings are that MA strategies outperform the BH strategy in the commodity and currency markets with statistical significance. The introduction of short sales seems to improve the performance in the commodity markets, but also seems to be beneficial for some currencies. For the stock and bond markets, the MA strategies do not outperform the BH strategy. In most of the cases the MA strategies even underperform the BH strategy. Further, when we analyze bull and bear markets for the financial assets, we observe that the MA strategies rely on bear markets to outperform the BH strategy.

The rest of the thesis is organized as follows: Section 2 addresses relevant and important literature. Section 3 provides the methodology for the findings. Section 4 presents the data we use. Section 5 gives the results for bull and bear markets, in-sample, out-of-sample and out-of-sample test with short sales, for each of the respective markets. Section 6 discusses the findings and Section 7 presents our concluding remarks.

2 Literature review

The main principle behind technical analysis is to examine past price data to forecast future financial asset prices in order to know when to "buy low and sell high", hence, generate profits. According to Wong, Manzur, & Chew (2003) the methods date back to the 1600s when the Japanese rice traders use it on the Dojima Rice Exchange. The usefulness of technical analysis, such as the moving average (MA) strategy, is widely discussed in modern finance after the introduction of the Efficient Market Hypothesis (EMH). Fama (1970) claims that even in a weak form of market efficiency, technical trading rules should be fruitless. On the one hand, studies such as Fama & Blume (1966), Sullivan et al. (1999) and Bauer Jr & Dahlquist (2001), among others, doubt the usefulness of technical trading strategies. On the other hand, Park & Irwin (2007) state that the majority of previous studies find positive results regarding technical trading strategies. The effectiveness of the technical trading strategies is still widely discussed. The modern studies still improve, typically by an increase of the number of trading strategies, and use of more complex statistical tests with either conventional statistical tests or bootstrap methods. They also improve by the use of parameter optimization and out-of-sample verifications. Further in this literature review, we give an overview of some studies regarding the performance of the MA strategies. The structure of the review is organized as follows: Firstly, we present literature concerning the stock and bond markets. Further, we present literature concerning the commodity and currency markets. The studies are sorted from the oldest to the newest. At the end, we present some additional remarks.

2.1 Performance in the stock and bond markets

Brock et al. (1992) use historical data from Dow Jones Index from 1897 to 1986, and provide positive results in the stock markets for technical trading strategies, including MA strategies. The study suggests that the explanation for the positive results lays in either market inefficiency, or by time-varying returns. The study only conducts in-sample tests, which tend to overrate the performance of the trading rules. They also use popular trading rules, which imply data-snooping bias. This is because the popular rules became popular since they perform well with in-sample tests. Hence, the study has several weaknesses, which suggest that the study is not good enough to report the true performance of technical trading rules.

Later Bessembinder & Chan (1998) re-examine the study from Brock et al. (1992) by the use of data from Dow Jones Index and find that the MA strategies have market timing properties and generate profits, but the break-even transaction costs for the strategies are smaller than the real-life transaction costs. Another study by Sullivan et al. (1999) reassess the study by Brock et al. (1992) and finds that the performance of the MA strategies is not significant. The study concludes that market timing does not work in stock markets by the use of out-of-sample tests in addition to back-tests with correction.

Fifield, Power, & Donald Sinclair (2005) analyze the performance of two technical trading strategies by the use of index data from eleven European stock markets from January 1991 to December 2000. The study reports that in emerging markets, some technical trading rules outperform their passive counterparts after adjusting for transaction costs. Moreover, the results indicate that the performance of MA strategies varies dramatically across the different stock markets.

Faber (2007) tests the MA strategies on monthly returns for different financial assets such as the Standard and Poor Composite index, Goldman Sachs Commodity Index and the US Government 10-Year Treasury Bonds. The study reports good performance of the MA strategies in the stock and bond markets (and also for commodity markets). The study obtains results from in-sample tests. The study also excludes transaction costs and statistical tests for outperformance, hence, the results are not valid.

Zakamulin (2014) tests the real-life performance of the MA strategies by the use of out-of-sample tests and realistic transaction costs for US stocks and bonds. The study reveals that the MA strategies are less risky, but in general generate lower returns, which consequently give lower capital growth. Further, he concludes that the performance of MA strategies is highly overstated due to data-mining and neglect of important market frictions.

A recent study by Naved & Srivastava (2015) investigates the performance of five different MA strategies in the Indian stock market. They use daily data from 2004 to 2014 and find that all trading rules for in-sample test perform better than the buy and hold (BH) strategy. They also find that shorter look-back periods generate higher returns. This study does not test the real performance, since they exclude transaction costs. The study also overrates the performance of the MA strategies by the use of in-sample test.

2.2 Performance in the commodity and currency markets

Lukac, Brorsen, & Irwin (1988) provide positive results by application of 12 technical trading systems in the currency and commodity markets from 1978 to 1984. The sample-period in the study is relatively short, which makes the results poor in reliability.

Levich & Thomas (1993) investigate the performance of technical trading rules for five currencies dating from 1976 to 1990. By the use of bootstrap methods, they find statistically significant positive results, even after adjusting for transaction costs. They also extend the research with sub-periods, and find that the performance of the technical trading rules declines over the period. Yet again, they rely on the use of in-sample tests, which implies data-mining bias.

Olson (2004) reports risk-adjusted profits of the MA strategies for 18 currencies in the 1970s and 1980s, but the profits decline during the 1990s to near zero. The study conducts both in-sample and out-of-sample tests with statistical tests to support the results about the outperformance. Olson (2004) does not considers the possibility that lack of bear markets in the 1990s is the reason for the profit decline of the MA strategies.

Kilgallen (2012) tests the performance of MA strategies across currency and commodity markets (and also for global stock indices). The study finds that MA strategies outperform the BH strategy by generation of lower risk combined with equal or higher returns. The study obtains results with an in-sample test and the results are not tested statistically. There is not even an use of a real risk-adjusted performance measure, which makes it difficult to evaluate the real outperformance. This makes the results very questionable, and the study is too inadequate to be reliable.

2.3 Additional remarks

Another study we would like to mention is a study by Zakamulin (2015). The study reports that the market's dynamics is changing over time. It also reports that the MA strategies outperform the BH strategy in bear states of the market, while it underperforms in the bull states of the market. These remarks argue that the performance of the MA strategies is uneven over time and across financial assets. We elaborate on this remark further in this study.

Park & Irwin (2007) report that among 95 earlier studies, 56 of them report positive results in regard to technical analysis, 20 studies find negative results while 19 of them indicate mixed results. Park & Irwin (2007) report results regardless of whether the studies use in-sample or out-of-sample tests, statistical tests, and whether there is an use of realistic transaction costs.

This literature review documents studies that on the one hand report both strong evidence of predictive power and high returns of technical trading rules, and on the other hand studies that remain more skeptical about the true performance of technical trading rules. By the investigation of these studies, we find that the results on the performance of the MA strategies are dependent on many factors. Some of the factors are whether the studies adjust the results for transaction costs, or whether the studies use in-sample or out-of-sample tests, what kind of statistical test they use (parametric or non-parametric), and which kind of market and time period the strategies apply in. From this, we can sum up that the studies on the performance of MA strategies are inconclusive and consist of several weaknesses. The most common weaknesses in earlier studies are to overrate the performance of the MA strategies by the exclusion of transaction costs or to only conduct in-sample tests. Not to use a statistical test, or to use parametric tests to report the statistical significance of the results, are also common weaknesses. Therefore, there is a need of further research in this area, to build on and extend the existing knowledge, and consequently determine the real-life performance of technical trading rules in financial markets.

3 Methodology

3.1 Moving averages

The idea of the technical analysis is to use historical prices to predict the price movements in the future. There is a belief between technical analysts that prices move in trends. If the price trend is positive (negative) it is time to buy (sell) the financial asset in order to gain profits (reduce losses). To follow a trend sounds like a simple concept, but in reality it is difficult to identify trends because of the large fluctuations in the financial asset prices. Moving average (MA) is a mathematical approach within technical analysis, to forecast the price trend. Financial traders all over the world use the MA method as a tool in their analysis. The purpose of the MA is to remove the noise from the financial asset prices random fluctuations. The "smoothing" is done by firstly choose a number of historical prices (look-back period), and then to calculate the average for the period. These averages are calculated in many ways, and by a chosen trading rule they generate buy signals when the trend is calculated to be positive, and sell signals when the trend is negative.

In reality there is a large amount of different types of MAs, with the numbers still increasing. Due to the limitations of this thesis we will only study some of them.

3.1.1 Simple Moving Average

The simple moving average (SMA) compute the arithmetic mean of prices in the defined look-back period n. Let P_t be the price of the financial asset at time t. Formally we compute this type of MA by:

$$SMA_t(n) = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i} \tag{1}$$

From the formula you can observe that each price from the look-back period has the same weight.

3.1.2 Linear Moving Average

Linear moving average (LMA) is another method to calculate the MA. While SMA is calculated by giving each price an equal weight, LMA is calculated by a fixed (linear) increase in weights as the historical prices come closer to the current period. This method is developed in the belief that more recent prices include more relevant information about the future price fluctuations.

With the same expressions as for the SMA, we formally compute the LMA by:

$$LMA_t(n) = \frac{\sum_{i=0}^{n-1}(n-i)P_{t-i}}{\sum_{i=0}^{n-1}(n-i)} \tag{2}$$

3.1.3 Exponential Moving Average

The weakness of LMA is the rigidness of the increasing weight. Exponential moving average (EMA) copes with this weakness. EMA uses an exponential weight with a decay factor (lambda). The decay factor is a smoothing parameter which can be adjusted to preferred sensitivity of the recent prices. Let the decay factor be λ, and with the same notations as for the SMA and LMA, we calculate the EMA by:

$$EMA_t(n) = (1-\lambda)\sum_{i=0}^{\infty}\lambda^i P_{t-i}, \text{ where } \lambda = \frac{n-1}{n+1} \tag{3}$$

3.2 Trading rules

To generate a profit, a trader wants to buy when the price of the risky asset is low and sell when the price is high. Similarly to reduce a loss, the trader wants to sell the risky asset before the price trends downward significantly. A trend following strategy, such as the MA strategy, typically switches between the financial asset and a risk-free asset, depending on whether the price trends upwards or downwards.[1] To decide when it is time to invest in or sell the risky asset, we need a trading rule that generates buy and sell signals. A buy signal is a signal to buy the financial asset (or stay invested in the financial asset), whereas a sell signal is a signal to invest in the risk-free asset (or to stay invested in the risk-free asset). The generation of buy and sell signals is a two step process. First, one needs to compute the value of the technical trading indicator by the use of past prices including the last closing price. The second step is to translate the value of the technical trading indicator into trading signals. All trading rules we consider in this thesis, generate buy signals for positive values of technical trading indicators. Otherwise, sell signal is generated. There exists a wide range of trading rules based on MAs. In this thesis we focus on the following trading rules:

[1] A more risky, and less typical strategy, is to short the financial asset when the price trends downwards.

3.2.1 Momentum rule

Momentum rule (MOM) is the simplest and most basic market timing rule. The trading rule is not based on MAs, but is closely related to the rules of MAs. This rule compares the last observed closing price P_t with the closing price $n-1$ periods ago, P_{t-n+1}. In this case n denotes the size of the window that is between the last closing price and the comparing price. Formally, we compute the indicator for momentum trading rule by:

$$Indicator_t^{MOM(n)} = MOM_t(n) = P_t - P_{t-n+1} \tag{4}$$

This rule assumes that if the price has increased over the last $n-1$ period, the price will continue to increase, and the opposite if the price has decreased. The indicator indicates the price-trend at time t.

3.2.2 Price minus Moving Average rule

The Price minus Moving Average rule (P-MA rule) is one of the oldest, simplest and most used MA rules in practice. There exists a wide range of scientific literature that documents the superiority of the MA strategy, over the passive buy and hold (BH) strategy. Some well known examples are Brock et al. (1992), Faber (2007) and Kilgallen (2012).

This rule identifies the trend of the price by comparing the last closing price with the value of a chosen MA. A buy signal is simply generated when the closing price is higher than the value of the MA, and a sell signal is generated when the closing price is below the value of the MA. Formally we denote P_t as the closing price and MA_t as the MA at time t and n as the window size in months. We compute the indicator for the Price minus Moving Average rule at time t by:

$$Indicator_t^{P-MA(n)} = P_t - MA_t(n) \tag{5}$$

3.2.3 Moving Average Crossover rule

Moving Average Crossover Rule (MAC) was considered already in 1935 by Gartley (1935). The MAC rule tries to avoid noise and false trading signals, which arguably occur frequently in the Price minus MA rule, by the use of two MAs in the generation of the trading signal. The two MAs consist of the short MA with window size s, and the long MA with window size l, where

$l > s$. From this, we calculate the MAC trading rule by:

$$Indicator_t^{MAC(s,l)} = MAC_t(s,l) = MA_t(s) - MA_t(l) \tag{6}$$

The crossover occurs when a short MA is either below or above a long MA. Traders typically use SMA with a short window of 50 days and a long window of 200 days. In this thesis, we also use EMA and LMA, and test for several window lengths. When the shorter MA crosses above the longer MA, we get a “golden cross”, which indicates a bull market and when the shorter MA crosses below the longer MA we get a “death cross”, which indicates a bear market. There is an obvious relationship between MAC rule and Price minus MA rule, where they are equal when the short window is equal to one (see Formula (5) and (6)).

3.2.4 Moving Average Envelope

Another trading rule that tries to reduce the number of false trading signals is the Moving Average Envelope (MAE). More specifically, this rule consists of a lower and upper boundary for the MA to generate trading signals. These boundaries are specified with a percentage (%). Denote $MA_t(n)$ as the computed MA of prices, n as the window size and p as the percentage for the envelope. We then compute the lower (L_t) and upper (U_t) boundary for the MA by:

$$L_t = MA_t(n) \times (1 - p), \quad U_t = MA_t \times (1 + p) \tag{7}$$

When the price lies within the lower and upper boundary, no trading takes place. A buy (sell) signal is generated when the last price is higher (lower) than the upper (lower) limit. When the price trends steadily, the MA is close to the last price. This will in many cases cause that even small fluctuations may generate false trading signals. The MAE trading rule will generate fewer false trading signals when the price trends steadily, because the boundaries demand stronger trends to generate trading signals. On the other side, the reduction of false trading signals is at the expense of a longer delay in the trend recognition.

3.2.5 Moving Average Convergence/Divergence rule

A more complex trading rule, the moving average convergence/divergence rule (MACD), is proposed by Appel (2005). This rule originally consists of a combination of three EMAs. The first step is to calculate the MAC indicator by using two EMAs:

$$MAC_t(s,l) = EMA_t(s) - EMA_t(l) \tag{8}$$

From the MAC rule, a buy (sell) signal is generated when the shorter MA is above (below) the longer MA. Appel (2005) suggests to generate buy (sell) signals in cases where the shorter MA increases (decreases) faster than the longer MA. More specifically, he looks at the changes in the MAC indicator from time $t-1$ to time t. He discovers too many false trading signals by this method, and suggests that the directional movement by MAC needs to be confirmed by a delayed and smoothed version of MAC. The result was the technical MACD rule, that we compute by:

$$Indicator_t^{MACD(s,l,f)} = MAC_t(s,l) - EMA_t(f, MAC(s,l)) \tag{9}$$

The notations are as from before, but we introduce f as the final window size. The trading signals are generated if the trend either strengthens or weakens. If the price moves up, with an increasing speed, the shorter MA will increase faster than the longer MA. That is, if the shorter MA lies above (below) the longer MA, the shorter and longer MAs are diverging (converging). If for example the value of MAC is increasing, there will be a buy signal anyway, regardless of the location of the shorter and longer MAs.

The MACD rule devises to react on the fluctuations in the price trends. Because of this, the MACD rule suits best for prices that change direction of trend often. In contrast, if the prices trend steadily, only small fluctuations in prices may generate many false trading signals.

3.3 Transaction costs

Transaction costs are expenses that occur when buying or selling a financial asset. With active trading strategies, transaction costs have a significant impact on the performance of the strategy, therefore it is essential to use a good estimate of the transaction cost, for the outperformance test of MA strategies to be valid. The transaction costs in capital markets mainly consist of spread, commissions and market impact costs. Since transaction costs vary by type of the investor, liquidity of the asset and the size of the trades, in different markets, we have set the transaction costs in this thesis to a fixed percentage for the respective markets we analyze. On the one hand, Balduzzi & Lynch (1999) reveal that transaction costs normally lie between 0.01 and 0.50 percent in the stock market, but reports 0.50 percent to be a representative average one-way transaction cost. On the other hand, Chan & Lakonishok (1993), Knez & Ready (1996) and Lynch & Balduzzi (2000), among others, suggest a midpoint transaction cost of 0.25 percent. We find 0.25 percent to be reasonable. LeBaron (1999) suggests that an average one-way transaction cost of 0.10 percent is reasonable in foreign exchange markets. In the commodity market, Kilgallen (2012) finds 0.10 percent to be a reasonable average one-way transaction cost. For intermediate- and long-term bonds Edwards, Harris, & Piwowar (2007) find 0.10 percent to be a reasonable average one-way transaction cost. For treasury bills one normally assumes that transaction costs are not present, because the bid-ask spread is close to zero and they are highly liquid.

3.4 Calculating the return

The return of the different trading rules is a result of the buy and sell signals generated by the trading strategies. If the value of a technical trading indicator is positive (negative), the trend is believed to be positive (negative), which results in a buy (sell) signal. Formally, we express the trading signal at time t as follows:

$$\text{Signal}_t = \begin{cases} \text{Buy} & \text{if} \quad \text{Indicator}_{t-1} > 0 \\ \text{Sell} & \text{if} \quad \text{Indicator}_{t-1} \leq 0 \end{cases} \tag{10}$$

Further, we let $(R_1, R_2, R_3, \ldots, R_t)$ be the total return of the risky financial asset, and $(r_{f1}, r_{f2}, r_{f3}, \ldots, r_{ft})$ is the risk-free rate of return for the same sample period. We find that the return of the MA strategy at time t is affected by the buy and sell signals that are generated when we impose an average one-way transaction cost of τ. The relationship is that if we have buy (sell) signal for two subsequent periods , we get return R_t (r_{ft}), but when first a buy (sell) signal is generated and a sell (buy) signal is generated for the next period, one switches from the risky asset (risk-free asset) to the risk-free asset (risky asset), and this imposes a transaction cost of τ. Therefore this leaves the return of the risky asset (risk-free asset) minus the transaction cost. The return from the MA strategy in the presence of transaction costs over $t + 1$ is given by:

$$r_{t+1} = \begin{cases} R_{t+1}, & \text{if} \quad (\text{Signal}_{t+1} = \text{Buy}) \quad \text{and} \quad (\text{Signal}_t = \text{Buy}), \\ R_{t+1} - \tau, & \text{if} \quad (\text{Signal}_{t+1} = \text{Buy}) \quad \text{and} \quad (\text{Signal}_t = \text{Sell}), \\ r_{ft+1}, & \text{if} \quad (\text{Signal}_{t+1} = \text{Sell}) \quad \text{and} \quad (\text{Signal}_t = \text{Sell}), \\ r_{ft+1} - \tau, & \text{if} \quad (\text{Signal}_{t+1} = \text{Sell}) \quad \text{and} \quad (\text{Signal}_t = \text{Buy}). \end{cases} \tag{11}$$

As an extension, we want to see if it is possible to achieve a higher return by shorting the risky asset when a sell signal is generated. To short the risky asset imposes double transaction costs and double risk-free return, because when a sell signal is generated after a buy signal the investor lends the risky asset and sells it, which creates an additional transaction cost to the existing sale. In addition, the proceeds from the sale of the lent risky asset is spent to invest in the risk-free asset, hence we get double risk-free return. We find a similar relationship when a buy signal is generated after a sell signal, where the investor needs to buy an additional risky asset to pay back the loan from the short sale. This also imposes a double transaction cost. We calculate the return of the MA strategy with short-selling as follows:

$$r_{t+1} = \begin{cases} R_{t+1}, & \text{if} \quad (\text{Signal}_{t+1} = \text{Buy}) \quad \text{and} \quad (\text{Signal}_t = \text{Buy}), \\ R_{t+1} - 2\tau, & \text{if} \quad (\text{Signal}_{t+1} = \text{Buy}) \quad \text{and} \quad (\text{Signal}_t = \text{Sell}), \\ 2r_{ft+1} - R_{t+1}, & \text{if} \quad (\text{Signal}_{t+1} = \text{Sell}) \quad \text{and} \quad (\text{Signal}_t = \text{Sell}), \\ 2r_{ft+1} - R_{t-1} - 2\tau, & \text{if} \quad (\text{Signal}_{t+1} = \text{Sell}) \quad \text{and} \quad (\text{Signal}_t = \text{Buy}). \end{cases} \tag{12}$$

3.4.1 Applying the return calculation for exchange rates

Since the different assets we analyze have different characteristics, we need additional explanation for how we calculate the return of some of the assets. For the foreign exchange rates we assume that the buy and sell signals are triggered according to the rules above, but when a switch is triggered, it switches between to hold cash in USD and to hold the foreign currency. A buy signal is a signal to switch to (or hold) the foreign currency. When the trader holds the foreign currency we assume that the cash is invested at the foreign risk-free asset. A sell signal is a signal to switch to (or hold) the USD. When the trader holds the USD we assume that the cash is invested into the risk-free asset in the US. This method is consistent with Kilgallen (2012), among others, but we use a more realistic method by the assumption that the proceeds are not simply held as cash, but invested in a risk-free asset. We calculate the return of exchange rates as follows:

$$r_{t+1} = \begin{cases} R_{t+1} + r_{ftf}, & \text{if} \quad (\text{Signal}_{t+1} = \text{Buy}) \quad \text{and} \quad (\text{Signal}_t = \text{Buy}), \\ R_{t+1} + r_{ftf} - \tau, & \text{if} \quad (\text{Signal}_{t+1} = \text{Buy}) \quad \text{and} \quad (\text{Signal}_t = \text{Sell}), \\ r_{ft+1}, & \text{if} \quad (\text{Signal}_{t+1} = \text{Sell}) \quad \text{and} \quad (\text{Signal}_t = \text{Sell}), \\ r_{ft+1} - \tau, & \text{if} \quad (\text{Signal}_{t+1} = \text{Sell}) \quad \text{and} \quad (\text{Signal}_t = \text{Buy}). \end{cases} \tag{13}$$

From the formula it follows that the investor gets the risk-free rate of return from the foreign country, given as r_{ftf}, when invested in the foreign currency.

For the stock indices S&P 500 and DJIA, and the long-term and intermediate-term US government bond indices, the return of dividends are included as the total return when the trader is invested, but for the computation of the trading signals we use capital returns.

For all other datasets we only have available total returns, for which will follow a regular way to calculate the trading signals and returns.

3.5 Performance measurement

One of the most famous performance measures is the Sharpe ratio, which is a measure of how well a risky asset performs, relative to the risk it imposes. The Sharpe ratio was formulated by William Sharpe (1966) and it is widely in use to compare the performance of different risky assets. The Sharpe ratio is developed from, and justified by the market portfolio theory by Markowitz (1952). A high return is often associated with high risk, and a low return is often associated with low risk. The Sharpe ratio makes it possible to compare the performance relative to the risk the investor imposes. This means that a high Sharpe ratio is good, because the investor gets a high return relative to the risk of the investment. Sharpe ratio is given by:

$$Sharpe\ ratio = \frac{E[r_j - r_f]}{\sigma_{(r_j - r_f)}} \tag{14}$$

Where $E[r_j]$ is the expected return of the risky asset, r_f is the risk free rate and $\sigma_{r_j - r_f}$ is the total volatility. $E[r_j - r_f]$ is the excess return of the risky asset, and the standard deviation is a measure of how much the price of the risky asset deviates, where a high standard deviation is associated with high risk and a low standard deviation is associated with low risk.

The justification of the usage of the Sharpe ratio is based on a number of assumptions such as normally distributed returns, existence of a risk-free asset and the absence of any limitations on borrowing and lending. Some, or all of these assumptions can be violated in reality. For example the assumption about the existence of a risk-free asset is critical. In reality, there is no risk-free asset. Even the government Treasury bills may default. In reality, there are many performance measures to choose from which deals with these assumptions. However, there is much literature that documents that the choice of performance measure does not influence the evaluation of different risky portfolios. For instance, Eling & Schuhmacher (2007), Auer (2015) and Zakamulin (2017) find that the correlation between the rank between a set of performance measures (including the Sharpe ratio) is extremely positively correlated. Hence, from a practical point of view, the choice of performance measure will not have a crucial influence on our results.

3.6 Identifying bull and bear markets

In the financial language bull markets denote a period of rising prices, and bear markets denote a period of falling prices. There is no generally accepted financial literature on how to formally define bull and bear markets. The financial analysts are divided into two distinct groups. One of the groups insist that to qualify for a bull (bear) market, the stock price should increase (decrease) noticeable. For example, a bull (bear) market is ongoing when the price increase (decrease) more than 25 percent from the previous local minimum (maximum). The other group identifies bull (bear) markets when the price has been rising (falling) over a certain period of time (e.g 3 or 6 months).

Because there is no unique solution on how to define bull and bear markets, there exist different methods on how to identify the state of the market. In this thesis, we use a data algorithm by Pagan & Sossounov (2003) to detect the bull and bear markets. This method is closely related to the formal dating method by Bry & Boschan (1971), which one can use to identify the business cycles turning points. This algorithm is based on some complex rules to determine the initial turning points of raw data, and on some censoring operations. To identify initial turning points, one first needs to set a window length of $\tau_{window} = 8$ months on both sides of a date to identify peaks and troughs as higher and lower points in the window. Further, one determines the turning points by the selection of the highest of multiple peaks and the lowest of multiple troughs. The censoring operations require to eliminate the peaks and troughs for the first and last $\tau_{censor} = 6$ months, the cycle that lasts for less than $\tau_{cycle} = 16$ months and phases which last for a shorter period than $\tau_{phase} = 4$ months.

3.7 Statistical test for outperformance

3.7.1 Hypothesis test

In this part, we provide the methodology we use to test statistically for outperformance. Denote SR_{MA} and SR_{BH} as the values of Sharpe ratios of the MA strategy and the corresponding BH strategy. The first step is to calculate whether the performance of the MA strategy is better than the BH strategy. We simply compute this by:

$$\Delta = SR_{MA} - SR_{BH} \tag{15}$$

To only look at the differences in Sharpe ratios when one evaluates the performance, is not enough. The reason is that we consider that the returns from the BH and the MA strategies are two random variables. Therefore, the outperformance may be only due to chance or luck. We need to formulate the outperformance hypothesis to test the differences statistically. The goal is to test if the active MA strategies outperforms the passive BH strategy statistically. We formulate the null and alternative hypothesis to test this as follows:

$$H_0 : \Delta \leq 0 \quad versus \quad H_A : \Delta > 0 \tag{16}$$

The conclusion from the hypothesis tests should be to reject, or not to reject the null hypothesis (H_0). The conclusion depends on how likely H_0 is to be true. From the tests the outcome is the p-value which is the probability of H_0 to occur. In a scientific paper one typically sets a requirement of five percent significance level to be able to reject the H_0. This means that the statistical tests must provide that the MA is better than the BH by more than 95 percent probability to reject H_0. More easily explained, it means that the outperformance that is produced by the MA strategy has less than five percent chance to be false.

3.7.2 Parametric test

Parametric tests are based on the assumption that the random variables to be tested (SR_{MA} and SR_{BH}) follow a bivariate normal distribution. More explicit, each of the Sharpe ratios follows a normal distribution and is correlated. This kind of test is called "Parametric", because it assumes that both of the random variables have the same probability distribution which is parametrized by mean and standard deviation.

A parametric test is typically a "test statistic", which is a standardized value that is calculated from the sample data. The p-value from a parametric test can be calculated quickly, but it is based on a number of assumptions. In addition to the assumption that the return distributions are normal, the parametric test also assumes independent time series, and require a large sample size to be valid. Financial econometric literature document that the return distributions are non-normal, and often serial dependent. Therefore, these simple parametric tests are usually invalid.

When one select Sharpe ratio as the performance measure, one can use the the Jobson & Korkie (1981) test with the Memmel (2003) correction. Let ρ be the correlation coefficient over a sample of size T. The test assumes joint normality of two series of excess returns and can be computed as follows:

$$z = \frac{SR_{MA} - SR_{BH}}{\sqrt{\frac{1}{T}[2(1-\rho)+\frac{1}{2}(SR_{MA}^2 + SR_{BH}^2 - 2\rho^2 SR_{MA} SR_{BH})]}}, \tag{17}$$

which is asymptotically distributed as a standard normal if the sample size is large enough.

3.7.3 Non-parametric test

Non-parametric tests are most often computer-intensive randomization methods to estimate the distribution of a test statistics. These tests do not make a number of assumptions regarding the probability distribution. Non-parametric tests are slower than parametric tests, but are more accurate, distribution free and can be used regardless of the choice of performance measure.

Bootstrap test is the most popular method of computer-intensive randomization. The method is based on resampling original data. We first denote the time series of Sharpe ratios for the MA strategy and the BH strategy as $(x_1^{MA}, x_2^{MA}, \ldots, x_n^{MA})$ and $(x_1^{BH}, x_2^{BH}, \ldots, x_n^{BH})$. The standard bootstrap by Efron (1979), consists of drawing random resamples with replacement from the time series. Further, the Sharpe ratios are paired up (x_t^{*MA}, x_t^{*BH}) in the original data, observed at the same time. After this, the random resamples are drawn R times, and we compute the performance SR_{MA} and SR_{BH} every time, along with the difference $\Delta^* = SR_{MA} - SR_{BH}$. The p-value of the hypotheses tested (from Formula (16)) is the ratio of negative values in the difference Δ^*.

If the data is serially dependent, one can resample the data with blocks of data instead of individual observations. This is completed to avoid breaking up the dependence when performing the bootstrap method. Further, one can randomly select block lengths. This method is called stationary bootstrap, and is provided and closer described by Politis & Romano (1994). In this thesis, we choose to use the stationary bootstrap method in order to calculate the respective p-values. This is consistent with Sullivan et al. (1999), Qi & Wu (2006), Kirby & Ostdiek (2012), among others. We use 10 000 resamples, with random block lengths equal to the mean of the optimal block length. The challenge with this model is to select an optimal block length, but we decide to calculate the optimal block length by the method described by Patton et al. (2009).

The use of this method gives the advantages as follows:

- One can use the method with any preferred performance measure.

- One can use the method even if the series are non-normal or contain serial dependence.

- The method is accurate, even with small sample size.

3.8 Back & forward tests

3.8.1 Back-testing trading rules

Back-test of trading rules, also called in-sample test, is to use historical data to simulate the return of the different MA trading rules, in order to select the rule with the best performance. Easily explained, it is just to run the trading rules (which generate buy and sell signals) through the historical data sample and calculate the Sharpe ratio for the period. Further, one selects the best performing trading rule based on the Sharpe ratio. The process of finding the best trading rule among many alternative trading rules is referred to as "data-mining".

The problem that occurs when one uses the "data-mining" technique, is that it systematically overstates the true performance of the best trading rule. In finance, this form of systematic error when one evaluates the performance of a trading rule in a back-test is called "data-mining bias". Data-mining bias comes from the random fluctuations in returns. More specifically, the observed performance of a trading rule is the sum of two components: the true outperformance and the randomness:

$$\text{Observed outperformance} = \text{True outperformance} + \text{Randomness}. \tag{18}$$

The randomness from the observed outperformance, can be referred to as "good luck" or "bad luck". While the good luck improves the outperformance of a trading rule, bad luck worsen the outperformance of a trading rule. Moreover, the data-mining process tends to spot a rule that benefits most from good luck. This is the reason why the technique overstates the true performance of the best trading rule. To give a result that reflects the true performance of a trading rule, there exist several methods on how to adjust the p-value based on the number of trading rules included. Romano & Wolf (2005), Harvey & Liu (2014) and Harvey & Liu (2015) describe some of the methods on how to perform a correct statistical multiple back-test.

The main advantage with back-tests is that they exploit the full sample-period. Since longer sample size increases the accuracy of any statistical test, back-tests decrease the chance to miss profitable trading rules. On the other side, the methods to adjust p-values increase the chance to miss profitable trading rules. The data-mining bias decreases with sample size that increases. This is due to the idea that larger sample size lessens the effect from the randomness. [2] The data-mining bias increases by the addition of more rules to test, but to add a new rule does not decrease the performance of the best rule in a back-test. If the new rule performs worse than the best rule, the performance of the best trading rule remains the same. If the new rule performs better than the best trading rule, it becomes the trading rule that performs best.

In this thesis, we choose to present our findings from the in-sample test in order to report the best trading rules. We also use the in-sample method as the "training set" for the walk-forward test, which we present in the next section.

3.8.2 Forward-testing trading rules

To cope with the data-mining bias problem in a back-test of trading rules, one solution is to perform a forward test of the trading rules. Since the best performing trading rule in a back-test is overstated when using multiple trading rules, the rule must be tested and validated with the use of an additional sample of data, to provide an unbiased estimate of its performance, which is a forward test.

The first step is to segment the historical data into a "training" set, referred to as "in-sample period", and a "validation" set, often referred to as "out-of-sample period". We recall that the back-test is also referred to as in-sample test. Similarly, the forward test is referred to as an out-of-sample test. We start with the full historical data sample $[1, T]$, we split it into in-sample period $[1, s]$ and out-of-sample period $[s, T]$, where T is the last observation in our data sample and s denotes the split observation. Then, the procedure is to calculate the best performing trading rule for the in-sample-period $[1, s]$. Further, we discover the best performing rule from the in-sample-period, which we evaluate for the out-of-sample data $[s, T]$.

When we implement this test in practice, the in-sample segment of the data is changed during the test period. With the assumption that the market dynamics change over time, one should use a rolling in-sample window (Zakamulin, 2017). Zakamulin (2015) finds strong evidence that the market's dynamics changes over time. This kind of out-of-sample test is often referred to as a walk-forward test, or an out-of-sample test with a moving window. This methodology closely follows the walk-forward tests in Lukac et al. (1988), Lukac & Brorsen (1990) and Zakamulin

[2] This only holds if we assume that the market's dynamics does not change over time

(2014), among others. We now denote p as the step size of how much the window moves. After we determine the best trading rule for the in-sample period $[1, s]$, we simulate the returns for the trading rule for $[1 + s, s + p]$. Then, the procedure of selecting the best trading rule is repeated using a new, moved, in-sample window $[1 + p, s + p]$. The length of the in-sample period will always be equal to s, but each time we do the selection of the best trading rule procedure, the in-sample window is moved forward with the step size of p. The idea behind this moving window when assuming that market's dynamics changes over time, is that more recent information is more valuable when selecting trading rules, than the more distant information.

The out-of-sample methodology closely resembles how a real-life trader could behave. At every point in time, the trader has the historical data available to make the decision of which trading rule to use for the next period. With the out-of-sample test, we do not test whether a specific trading rule outperforms the passive BH strategy, but we test whether a trader can outperform the passive BH strategy by the use of a set of trading rules and follow the trading rule that performs best.

While the methodology of the out-of-sample test is relatively straightforward, there is one unresolved remark. The choice of split date[s], has a huge impact on the results. This is reported in Rossi & Inoue (2012) and Zakamulin (2014). Zakamulin (2014) argues for why this is the case. The main point on why the change of split date sometimes changes the results of the performance in the out-of-sample test, is that the outperformance delivered by any trend following strategy is highly non-uniform. A trend following strategy underperforms the passive BH strategy in bull (upward trend) markets, and outperforms the passive BH strategy in bear (downward trend) markets. This means that the choice of split date cannot be random. More specific, a researcher should include both bull and bear markets in both in-sample and out-of-sample segments. If this is not the case, the strategy is not well suited to detect changes in trends.

In this thesis, we try to be as objective as possible. We study bull and bear markets for all datasets, and find ten years to be a reasonable period for the in-sample segments. For all out-of-sample tests, we use a one month rolling window.

4 Data

In this section of the thesis, we present the data that we use for our analysis. We try our best to select data based on three criteria: 1. The sample period should include as long historical period as possible. 2. The sample period should be as identical as possible, within and across the asset classes. 3. There should be a manageable number of datasets within each asset class. Based on the criteria we are left with a total amount of 42 datasets (including 36 financial assets) and 21 504 observations, most of them from January 1971 until December 2015. The datasets are from different financial markets, and we divide them into commodity, currency, stock and bond markets. We also need proxies on risk-free rates for countries involved in the currency trading. In Table 1, we provide descriptive statistics for the commodity and currency markets. In Table 2, we provide the descriptive statistics of the stock and bond markets, in addition, we provide the risk-free proxies for the foreign currencies.

Datasets	σ	μ	**Min**	**Max**
Commodities				
Gold	5,92	0,79	-22,37	28,79
Oil	9,48	0,81	-32,70	134,60
Cocoa	7,01	0,52	-20,30	75,62
Silver	8,44	0,73	-39,50	73,16
Gas	11,05	1,04	-33,33	61,26
Coffee	7,88	0,52	-29,71	52,61
Palm Oil	7,73	0,43	-29,31	31,53
Soybeans	6,30	0,40	-29,79	37,69
Beef	4,49	0,29	-16,30	25,62
Chicken	2,03	0,35	-5,42	11,02
Sugar	6,07	0,41	-26,08	47,60
Tobacco	1,74	0,29	-4,75	7,01
Commodity indices				
Energy Commodities	10,57	0,96	-28,38	187,40
Non-energy Commodities	2,88	0,27	-18,39	11,78
Precious Metals	5,71	0,71	-22,36	58,26
Exchange rates				
USD/NOK	2,43	0,07	-5,60	14,07
USD/SEK	2,55	0,12	-6,87	14,81
USD/JPY	2,65	-0,16	-9,99	8,40
USD/CAD	1,43	0,07	-5,83	11,95
USD/ZAR	3,42	0,62	-12,53	21,11

Table 1: This table reports the summary for data on the commodity and currency markets. The sample period covers from January 1971 until December 2015 for all datasets. All data is presented monthly in percentage. μ is the average return, σ is the standard deviation, and Min and Max report the maximum and minimum return for the respective dataset. All datasets contain 540 observations.

4.1 Commodity data

The World Bank has monthly prices available for commodities and commodity indices.[3] Spot prices are available from back to 1960, but we choose the period from January 1971 until December 2015. This is because many of the prices only exhibited little or none fluctuation during the

[3] The data for commodities is easily found and downloaded at http://www.worldbank.org/en/research/commodity-markets

Datasets	σ	μ	Min	Max
6 portfolios				
Small firms - low value	7,56	0,97	-32,39	59,54
Small firms - neutral value	7,02	1,26	-30,05	62,20
Small firms - high value	8,20	1,46	-33,83	83,58
Big firms - low value	5,33	0,91	-28,87	33,74
Big firms - neutral value	5,71	0,97	-28,15	51,89
Big firms - high value	7,19	1,19	-45,11	67,78
Single Stocks				
Coca Cola	6,27	1,15	-29,01	25,71
General Electrics	7,00	1,15	-27,78	25,12
Chevron Corporation	6,68	1,13	-17,63	36,30
Consolidated Edison	6,15	1,16	-52,50	45,00
Walt Disney Co	8,79	1,36	-37,92	41,52
McDonald's Co	7,10	1,42	-29,64	43,15
Stock indices				
S&P 500	5,05	0,86	-29,43	42,91
DJIA	5,29	0,91	-29,88	40,46
Bond indices				
Long-term US bond index	3,11	0,77	-11,24	15,23
Intermediate-term US bond index	1,61	0,64	-6,41	11,98
Risk-free proxies				
Risk-free US	0,28	0,40	0,00	1,35
Risk-free Norway	0,33	0,54	0,08	2,01
Risk-free Sweden	0,33	0,51	0,00	2,59
Risk-free Japan	0,19	0,20	-0.01	0,55
Risk-free Canada	0,33	0,49	0,01	1,59
Risk-free South-Africa	0,33	0,79	0,20	1,65

Table 2: This table reports the summary for data on the stock and bond markets, including the risk-free proxies of the foreign currencies. The sample period covers from January 1971 until December 2015 for all datasets, except the bond indices, which last until December 2011. All data is presented monthly in percentage. μ is the average return, σ is the standard deviation, and Min and Max report the maximum and minimum return for the respective dataset. All datasets contain 540 observations, except the bond data which contain 492 observations.

gold exchange standard by Bretton Woods (see Eckes Jr(2012)). Only after the collapse of the gold exchange standard in 1971, commodity prices started to fluctuate. Based on our selection criteria, we end up with 12 commodities and three commodity indices.

4.2 Currency Data

Federal Reserve Bank of St. Louis has available data on many exchange rates. We use monthly prices based on US dollar. All exchange rates are the noon buying rates in New York City for cable transfers payable in foreign currencies. In currency data, we were limited by the fact that we need data on both the exchange rate, and a proxy for the risk-free rate for each country for the whole sample period. Before the collapse of the gold exchange standard most currencies were fixed. It was first from 1971, after the collapse, that prices of currencies were fluctuating with the supply and demand. There is no point to apply moving average (MA) strategy on fixed prices. Our main sample period is therefore from January 1971 until December 2015, and left us with five currencies. The data include closer description and is free for all to download.[4]

4.3 Stock market data

For stock market data our data consist of 14 assets. The data include six portfolios sorted on size and book-to-market, six single stocks and two stock indices from the US stock market. As we try to maintain the same sample period across assets, our sample period for stock markets is also from January 1971 until December 2015. Ken French Data Library has available value-weighted returns for 6 portfolios sorted on size and book-to-market. [5] The portfolios include all stocks from NYSE, AMEX and NASDAQ. Yahoo Finance has readily available historical monthly closing prices adjusted for dividends, for our six single stocks.[6] The companies we use for single stocks are available in Table 2 for descriptive statistics. We include these single stocks because they have sufficient historical data. Data on the S&P 500 is provided by Amit Goyal.[7] The S&P 500 is a value-weighted stock index which is based on the market capitalization of 500 large US companies. For the Dow Jones Industrial Average Index (DJIA) the data is also available for all to download by S&P Dow Jones Indices LLC.[8] DJIA is an index which consists of 30 large US corporations, which at all times are selected to represent a cross-section of the US industry. The dividends for DJIA until 1987 by Barron[9] are interspersed with the data by S&P Dow Jones Indices LLC. The two datasets for indices are both provided with capital return and dividends.

4.4 Bond data

The bond data is from the Ibbotson SBBI 2012 Classic Yearbook. It includes data from two bond indices. More specifically, long-term and intermediate-term US government bond indices. We use the sample period from January 1971 until December 2011, which is the closest period available to our main sample period. The datasets contain both monthly capital returns and dividends.

[4] The data for currencies is easily found and downloaded at https://fred.stlouisfed.org/categories/95.

[5] The data for value-weighted returns for 6 portfolios sorted on size and book-to.market are available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[6] The data for single stocks are easily found and downloaded at https://finance.yahoo.com/.

[7] The data for the S&P Index is available at http://www.hec.unil.ch/agoyal/.

[8] The data for the Dow Jones Industrial Average Index is available at http://www.djaverages.com.

[9] The data for the DJIA dividends until 1987 are available at http://online.barrons.com.

4.5 Data for risk-free rate of returns

The data for the proxy of monthly risk-free rate of returns is generated from different sources. For Japan, Canada and South-Africa we find monthly treasury bills as the best estimate for risk-free rate of returns. The data for the one month treasury bills from January 1971 to December 2015 is available at Federal Reserve Bank of St. Louis.[10] For Norway, we use short-term interest rates from January 1971 until January 1986. For the rest of the sample period, we use one month NIBOR until December 2015. All data until December 2013 is available at Norges Bank.[11] From December 2013 one month NIBOR is available at Oslo Bors.[12] For Sweden we use short-term interest rates until January 1987 and one month STIBOR from February 1987. Swedish data for interest rates is available at Sveriges Riksbank.[13] We include all these risk-free proxies because we need them when we use MA strategies in currency trading. When a buy signal in the currency is generated, the trader places the currency and generates the return of the risk-free rate. For sell signals in all the respective financial markets, we assume that the money is placed in a risk-free asset in US. The data for the monthly US risk-free proxy from January 1971 to December 2015 is provided by Ken French Data Library.[14] This rate is equal to the one month T-bill rate from Ibbotson and Associates Inc.

5 Empirical results

In this section, we present the results we obtain from the in-sample and out-of-sample tests, described in the previous sections. Firstly, we present some key plots from the algorithm for bull and bear market cycles, within each financial asset class. Further, we provide the results from the in-sample test. Then, we present the results from the out-of-sample tests. The out-of-sample test is the so called "walk-forward" test with a moving in-sample window. The results begin with commodities, followed by exchange rates, stocks and bonds, in the respective order.

In the previous sections, we introduced many different moving averages (MAs) and trading

[10] The data is found and downloaded at https://fred.stlouisfed.org/categories/32264. Find the correct country and the 1 month treasury bill for the correct period.

[11] The data is found and downloaded at http://www.norges-bank.no/en/Statistics/Interest-rates/.

[12] The data is downloaded at https://www.oslobors.no/markedsaktivitet//details/NIBOR1M.NIBOR/overview.

[13] The data for short-term interest rates is available at http://www.riksbank.se/sv/Riksbanken/Forskning/Historisk-monetar-statistik-for-Sveriges/Volume-II-House-Prices-Stock-Returns-National-Accounts-and-the-Riksbank-Balance-Sheet-16202012/ and the data for one month STIBOR is available at http://www.riksbank.se/sv/Rantor-och-valutakurser/Sok-rantor-och-valutakurser/.

[14] The risk-free rate for US is downloaded at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

rules. Further, we use them to test the performance of the trading rules compared to the passive buy-and-hold (BH) strategy. For all trading rules, except the momentum (MOM) rule, one needs to select a type of MA. Remember that n denotes the window size, s denotes the short window size, l denotes the long window size, f denotes the final window size and p denotes the percentage of the boundary. Also remember that $P - MA$ rule is equivalent to $MAC(1, l)$. All sizes are in whole numbers with a sequence of one and we let n and l go from two to 18, s and f from one to eight and p from one to ten. We present the combination of trading rules and MAs, with the amount of strategies we test for each trading rule in Table 3.

	Moving average type			**Number**
Trading rule	**SMA**	**LMA**	**EMA**	**of strategies**
MOM(n)	-	-	-	17
P-MA(n)	P-SMA(17)	P-LMA(17)	P-EMA(17)	51
MAC(s,l)	SMAC(91)	LMAC(91)	EMAC(91)	273
MAE(n,p)	SMAE(170)	LMAE(170)	EMAE(170)	510
MACD(s,l,f)	SMACD(756)	LMACD(756)	EMACD(756)	2268
SUM	-	-	-	3119

Table 3: Shows the trading rules we use in this thesis. Under Trading rule, we find the trading rule, with the respective window size intervals in parenthesis. The window sizes are n months in [2;18], s in [2;8], l in [2;18], p in [1;10] and f in [1;8]. Under Moving average type, we find the trading rules with different moving averages and the number of strategies for each trading rule in parenthesis. The Number of strategies, gives the total number of trading strategies for each trading rule, with the SUM at the bottom.

We recall that we use a total of 3120 trading strategies, which include the BH strategy (see Table 3). We obtain all p-values by the use of the stationary bootstrap method by Politis & Romano (1994). The method consists of drawing 10 000 random resamples, with random block length, equal to the value of the optimal block length. We calculate the optimal block length by the method described in Patton et al. (2009). Further, we use the Sharpe ratio as the performance measure, and the presentation of all values will be in annual numbers.

All returns for the MA strategies are simulated with a 0.10 percent one-way transaction cost, except for stock assets which are simulated with a 0.25 percent one-way transaction cost. A sell signal is usually a signal to sell the asset and move to the risk-free asset (or stay invested in the risk-free asset), but we also investigate the performance when a sell signal triggers to sell the financial asset short.

5.1 Commodities

5.1.1 Bull and bear market cycles

In this section we present the bull and bear market cycles for the best and worst performing assets, based on the p-values and Sharpe ratios from the out-of-sample test. The purpose of this is to draw a picture for the reader of why active trading strategies may perform better or worse for certain assets. The bull and bear market cycles are identified by the use of the data algorithm by Pagan and Sossounov (2003) (see Section 3.6). Bull and bear market cycles for all commodities are readily available in appendix.

By the investigation of the bull and bear market cycles, we observe that the MA strategies perform better for assets with longer bear states of market cycles. Figure 1 shows bull and bear market cycles for gold (bad performing with MA strategies) and one can see that the bull markets have an aggressive upward trend, while the bear markets have a weak downward trend. This leaves us with the fact that the traders do not lose much money when invested in bear markets, but the MA strategy make the trader lose capital gain in the bull markets, because of the lag time.

Figure 2 presents bull and bear market cycles for beef price (good performing with MA strategies). There are long periods of bull markets, but for most of the bear markets the price falls noticeable. Already here one can indicate that the MA strategy would save the trader for many bigger losses in the bear markets. The reason for this, is that the sell signal created by MA strategy, tells the investor to sell the asset before the bottom of the downward trend.

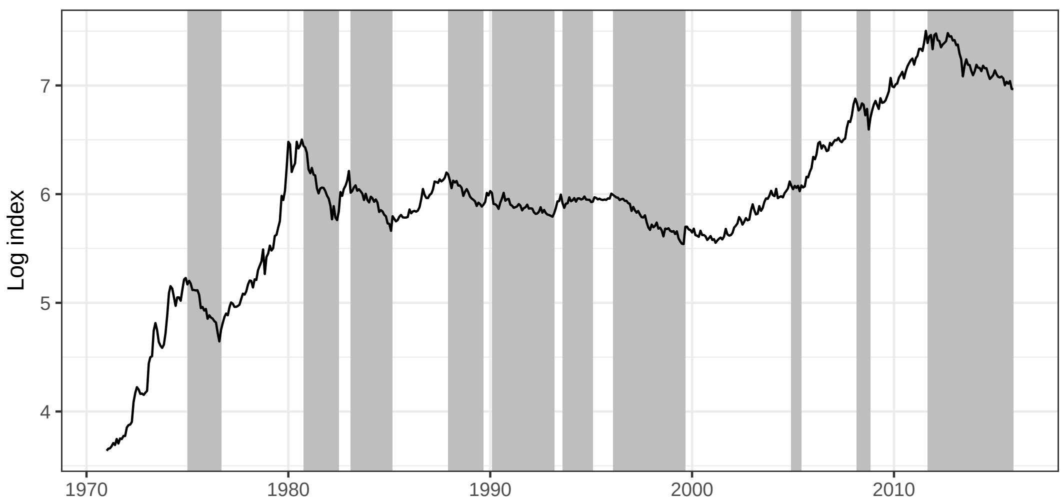

Figure 1: Bull and bear market cycles for gold in the period from January 1971 to December 2015. The shaded areas are indicating bear market phases.

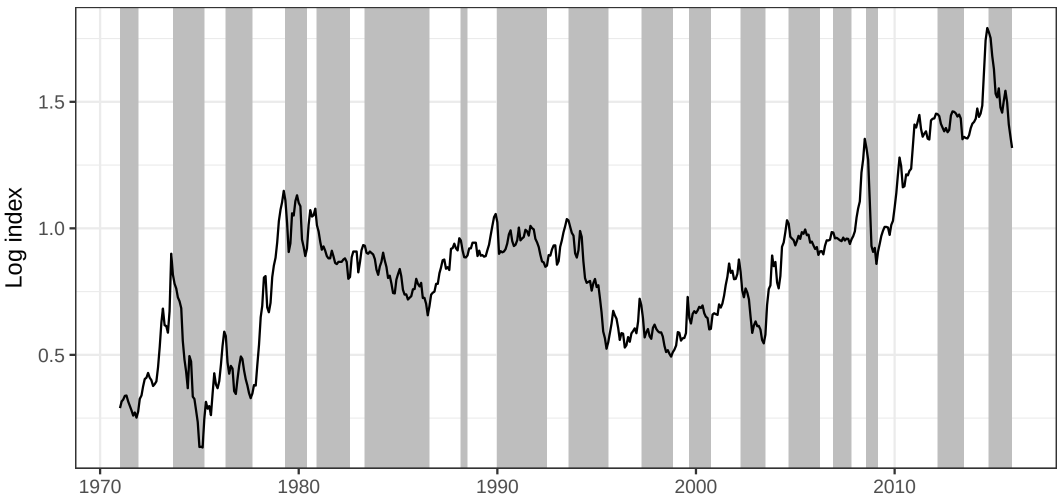

Figure 2: Bull and bear market cycles for beef in the period from January 1971 to December 2015. The shaded areas indicate bear market phases.

5.1.2 In-sample results

	Sharpe			Best	Time
Datasets	**BH**	**MA**	**P-value**	**strategy**	**invested**
Commodities					
Gold	0,15	0,46	**0,00**	SMACD(8,18,8)	0,53
Oil	0,16	0,60	**0,00**	SMACD(1,4,2)	0,48
Cocoa	-0,00	0,41	**0,00**	LMACD(1,4,2)	0,45
Silver	0,12	0,46	**0,00**	SMAE(2,2)	0,50
Gas	0,20	0,46	**0,00**	SMACD(1,4,3)	0,49
Coffee	0,03	0,60	**0,00**	LMAE(2,1)	0,49
Palm Oil	0,02	0,63	**0,00**	SMACD(1,2,2)	0,51
Soybeans	-0,08	0,44	**0,00**	SMACD(1,16,2)	0,54
Beef	-0,13	0,66	**0,00**	LMACD(1,4,7)	0,53
Chicken	-0,12	0,67	**0,00**	SMACD(1,2,7)	0,63
Sugar	-0,01	0,47	**0,00**	LMACD(1,18,2)	0,55
Tobacco	-0,18	0,43	**0,00**	LMAC(2,3)	0,56
Commodity indices					
Energy Commodities	0,16	0,55	**0,00**	LMACD(1,2,8)	0,57
Non-energy Commodities	-0,21	0,63	**0,00**	P-EMA(3)	0,53
Precious Metals	0,14	0,50	**0,00**	P-SMA(2)	0,50

Table 4: In-sample results from the back-test test for Commodities for the period from January 1973 to December 2015. Sharpe BH and MA is the Sharpe ratio, P-value is the respective p-value from the stationary bootstrap test. Best strategy is the best performing strategy and Time invested is the fraction of time invested in the asset by the best performing strategy. P-values in bold are significant at a five percent significance level.

Table 4 shows the best trading strategy in a back-test from January 1971 until December 2015. The returns for these strategies are simulated with the assumption that the trader switches to the risk-free rate of return, when a sell signal is generated. We find that all the Sharpe ratios are higher for the best MA strategies, than for the BH strategy. This is because the best performing MA strategies produce lower standard deviation (lower risk) or a higher mean return, or in some cases both. Further, we find that all p-values are very low and close to zero. The exceptions are Gas and the Energy index, which have a slightly higher p-value. However, they are still significant at a five percent significance level, if one does not adjust the p-value for the number of tested strategies. The low p-values indicate that the best performing MA trading strategies perform better than the BH strategy for this asset class in a back-test. We also observe that there is no single trading rule that is represented in several assets, but the MACD rule is over-represented as the best strategy. This is because the MACD strategy is represented with 2268 out of 3120 strategies. It leaves us with the fact that in a back-test there will be higher probability of a MACD rule to fit as the best strategy. But generally for most of the commodities and commodity indices the best performing MA strategy has a relatively short look-back-period. On average the best performing strategy is invested only around 50 percent of the time, which results in a much lower standard deviation.

5.1.3 Out-of-sample results without short sales

In this section, we present the results from the walk-forward test for commodities. The rolling 10 year in-sample period lasts from March 1973 until February 1983. Consequently, the period from March 1983 to December 2015 is the out-of-sample period. Table 5 reports higher mean returns, lower standard deviation and higher Sharpe ratios for all commodities and commodity indices. It also reports that for the MA strategies, ten out of 12 of the commodities and two out of three of the commodity indices produce statistically significant p-values (at a five percent level) from the stationary bootstrap tests. The MA strategies outperform their passive counterpart when we trade in these commodities. In this case, the MA strategy is a “high return, low risk” strategy.

5.1.4 Out-of-sample results with short sales

In this section, we provide results from the walk-forward test, where the asset is sold short when a sell signal is generated (recall Section 3.4). The rolling in-sample period is from March 1973 to February 1983, with the out-of-sample period from March 1983 to December 2015. Table 6 reports much higher mean returns for the MA strategies than for the BH strategy. The standard deviations are pretty similar for both the BH- and the MA strategy. Consequently, all Sharpe ratios are higher for the MA strategies. This leads to the fact that seven out of 12 commodities and two out of three commodity indices still are statistically significant (at a five percent level)

Datasets	μ BH	μ MA	σ BH	σ MA	Sharpe BH	Sharpe MA	P-value
Commodities							
Gold	4,06	4,87	15,52	12,30	0,02	0,09	0,28
Oil	5,04	10,58	29,11	19,88	0,04	0,34	**0,01**
Cocoa	3,78	7,22	20,13	15,46	-0,00	0,22	**0,03**
Silver	3,29	8,71	22,15	17,53	-0,02	0,28	**0,00**
Gas	8,12	12,62	43,21	33,43	0,10	0,26	0,08
Coffee	4,08	11,52	27,43	22,83	0,01	0,34	**0,00**
Palm Oil	4,69	10,66	26,30	19,82	0,03	0,35	**0,01**
Soybeans	2,96	7,09	18,25	13,71	-0,05	0,24	**0,01**
Beef	2,16	7,13	13,64	10,29	-0,12	0,32	**0,00**
Chicken	3,97	7,71	7,53	6,23	0,02	0,63	**0,00**
Sugar	1,09	5,72	10,81	8,38	-0,25	0,23	**0,00**
Tobacco	2,06	3,93	6,19	4,55	-0,28	0,03	**0,01**
Commodity indices							
Energy Commodities	3,70	9,33	24,52	17,10	-0,00	0,32	**0,00**
Non-energy Commodities	2,01	6,11	9,25	6,47	-0,19	0,35	**0,00**
Precious Metals	3,33	4,58	13,38	10,62	-0,04	0,07	0,17

Table 5: Out-of-sample results from the walk-forward test for commodities with 10 years moving in-sample period and the out-of-sample period from January 1983 to December 2015. All numbers are presented annually in percentage. μ BH and MA is the mean return of the buy and hold strategy and the moving average strategy, σ BH and MA is the standard deviation, Sharpe BH and MA is the Sharpe ratio , P-value is the respective p-value from the stationary bootstrap test. P-values in bold are significant at a five percent significance level.

Datasets	μ BH	μ MA	σ BH	σ MA	Sharpe BH	Sharpe MA	P-value
Commodities							
Gold	4,06	8,25	15,52	15,61	0,02	0,29	0,12
Oil	5,04	15,55	29,11	28,85	0,04	0,41	0,08
Cocoa	3,78	11,25	20,13	20,12	-0,00	0,37	0,06
Silver	3,29	11,27	22,15	22,12	-0,02	0,34	**0,05**
Gas	8,12	16,61	43,21	43,06	0,10	0,30	0,21
Coffee	4,08	19,05	27,43	27,13	0,01	0,56	**0,00**
Palm Oil	4,69	17,19	26,30	25,94	0,03	0,52	**0,03**
Soybeans	2,96	7,89	18,25	18,25	-0,05	0,22	0,13
Beef	2,16	13,49	13,64	13,37	-0,12	0,72	**0,00**
Chicken	3,97	11,08	7,53	7,29	0,02	1,00	**0,00**
Sugar	1,09	9,52	10,81	10,75	-0,25	0,53	**0,00**
Tobacco	2,06	6,00	6,19	6,23	-0,28	0,36	**0,00**
Commodity indices							
Energy Commodities	3,70	15,54	24,52	24,25	-0,00	0,48	**0,03**
Non-energy Commodities	2,01	10,98	9,25	9,02	-0,19	0,79	**0,00**
Precious Metals	3,33	6,32	13,38	13,45	-0,04	0,19	0,16

Table 6: Out-of-sample results from the walk-forward test for Commodities with short sales allowed, with 10 years moving in-sample period and the out-of-sample period from January 1983 to December 2015. All numbers are presented annually in percentage. μ BH and MA is the mean return of the buy and hold strategy and the moving average strategy, σ BH and MA is the standard deviation, Sharpe BH and MA is the Sharpe ratio , P-value is the respective p-value from the stationary bootstrap test. P-values in bold are significant at a five percent significance level.

based on the results from the stationary bootstrap test. The MA strategies combined with short selling, also outperform the BH strategy for the commodity market.

Table 7 provides us with the difference between the MA strategies with- and without short sales. More specifically, the Δ is the Sharpe ratio reported with short sales minus the Sharpe ratio reported with short sales prohibited. We see that for 14 out of 15 assets, the introduction of short sales produce higher Sharpe ratios from the walk-forward test.

	Sharpe		
Datasets	**MA**	**MAS**	Δ
Commodities			
Gold	0,09	0,29	0,20
Oil	0,34	0,41	0,07
Cocoa	0,22	0,37	0,15
Silver	0,28	0,34	0,06
Gas	0,26	0,30	0,03
Coffee	0,34	0,56	0,22
Palm Oil	0,35	0,52	0,17
Soybeans	0,24	0,22	-0,02
Beef	0,32	0,72	0,40
Chicken	0,63	1,00	0,38
Sugar	0,23	0,53	0,31
Tobacco	0,03	0,36	0,33
Commodity indices			
Energy Commodities	0,32	0,48	0,16
Non-energy Commodities	0,35	0,79	0,44
Precious Metals	0,07	0,19	0,11

Table 7: Changes in Sharpe ratio with the extension of short selling the assets for commodities. Δ is the change in Sharpe ratio, which is the Sharpe ratio from the results obtained with short sales allowed minus the Sharpe ratio from the results obtained when short sales are prohibited. MA reports the Sharpe ratio of the moving average strategy without short sales, whereas MAS reports the Sharpe ratio with short sales.

5.2 Exchange rates

5.2.1 Bull and bear market cycles

Based on the p-values and Sharpe ratios, we are left with Japanese Yen (JPY) to perform best of the currencies and South African Rand (ZAR) to perform worst of currencies based on the outperformance of the MA strategies. From Figure 3, we find that there are multiple clear bear markets, where the price decreases significantly. As we have observed before, MA strategies perform better for assets with clear bear states. In Figure 4, we find that the market is in bull state for most of the period, and the bear states do not trend heavily downwards. The MA strategies will lose capital gains because of the lag time when a bear state becomes bull. When the downward trend is not large enough, the investor could be better off by simply staying invested through the bear states.

5.2.2 In-sample results

Table 8 provides the best strategy for exchange rates in a back-test, from January 1971 until December 2015. We find similar results as for commodities, where the Sharpe ratio is higher for

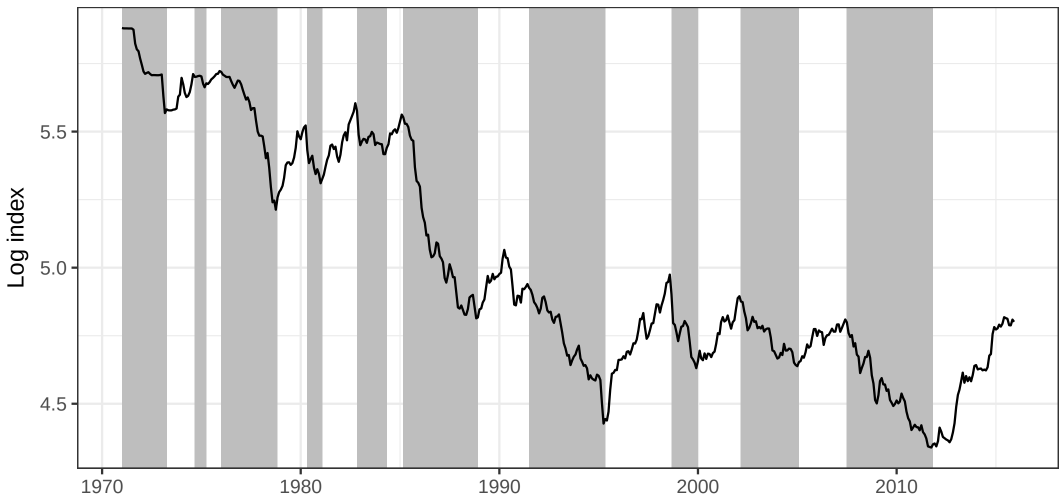

Figure 3: Bull and bear market cycles for USD/JPY in the period from January 1971 until December 2015. Shaded areas indicate bear market phases.

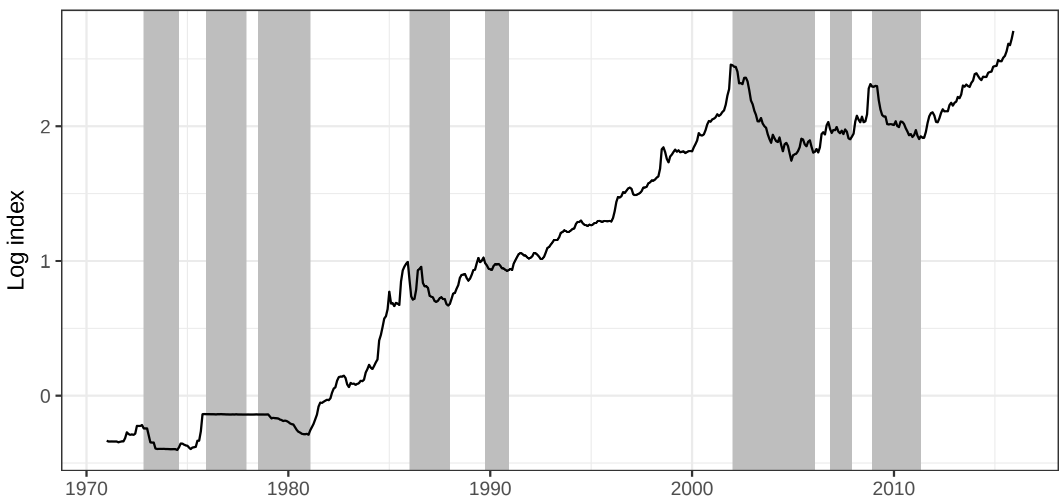

Figure 4: Bull and bear market cycles for USD/ZAR in the period from January 1971 until December 2015. Shaded areas indicate bear market phases.

all the best MA strategies, compared to the BH strategy. Also here the results report very low p-values, where Canadian Dollar (CAD) and ZAR have the highest. As for commodities, the p-values are significant at a five percent significance level, if we do not adjust for the number of trading strategies. For exchange rates, the P-MA rule is overrepresented for the best trading strategies. The time invested is close to the same for all currencies, around 50 percent, with the exception of ZAR with 56,2 percent.

Datasets	Sharpe BH	Sharpe MA	P-value	Best strategy	Time invested
Exchange rates					
USD/NOK	0,34	0,82	**0,00**	LMACD(1,12,2)	0,50
USD/SEK	0,36	0,78	**0,00**	P-SMA(2)	0,49
USD/JPY	-0,44	0,36	**0,00**	P-EMA(2)	0,49
USD/CAD	0,40	0,73	**0,01**	SMACD(1,13,2)	0,51
USD/ZAR	1,04	1,22	**0,02**	P-EMA(9)	0,56

Table 8: In-sample results from the back-test test for exchange rates for the period from January 1973 to December 2015. Sharpe BH and MA is the Sharpe ratio, P-value is the respective p-value from the stationary bootstrap test. Best strategy is the best performing strategy and Time invested is the fraction of time invested in the asset by the best performing strategy. P-values in bold are significant at a five percent significance level.

Datasets	μ BH	μ MA	σ BH	σ MA	Sharpe BH	Sharpe MA	P-value
Exchange rates							
USD/NOK	7,63	8,16	8,89	6,46	0,43	0,67	**0,03**
USD/SEK	6,57	7,12	9,08	6,64	0,31	0,50	0,07
USD/JPY	-0,25	5,67	9,15	6,27	-0,44	0,30	**0,00**
USD/CAD	5,33	6,44	5,50	4,02	0,28	0,66	**0,00**
USD/ZAR	19,40	16,29	13,30	11,50	1,18	1,10	0,83

Table 9: Out-of-sample results from the walk-forward test for exchange rates with 10 years moving in-sample period and the out-of-sample period from January 1983 to December 2015. All numbers are presented annually in percentage. μ BH and MA is the mean return of the buy and hold strategy and the moving average strategy, σ BH and MA is the standard deviation, Sharpe BH and MA is the Sharpe ratio , P-value is the respective p-value from the stationary bootstrap test. P-values in bold are significant at a five percent significance level.

5.2.3 Out-of-sample results without short sales

In Table 9, the results from the forward-test are listed. The results show higher mean returns and lower standard deviation for all currencies except ZAR, hence the Sharpe ratio is higher for all currencies except ZAR. By the use of a significance level of five percent, one finds that the Sharpe ratios for MA strategies are statistically significantly larger than BH strategy for NOK, JPY and CAD. The p-value for SEK is 7,1 percent, and is also close to be significant.

5.2.4 Out-of-sample results with short sales

Table 10 lists the results of exchange rates with the extension of short sales. The MA strategies still outperform the BH strategy for two out of five of the currencies, with statistically significantly higher Sharpe ratios. By the introduction of short sales, we observe that the risk increases for all assets. One can see the difference in the Sharpe ratio for the MA strategies with- and without short sales in Table 11. By the introduction of short sales, the Sharpe ratio is lowered for NOK, SEK and ZAR. However, the two currencies with the highest significance level from the forward test without short sales, JPY and CAD, increase the Sharpe ratio.

	μ		σ		Sharpe		
Datasets	**BH**	**MA**	**BH**	**MA**	**BH**	**MA**	**P-value**
Exchange rates							
USD/NOK	7,63	8,86	8,89	8,71	0,43	0,58	0,25
USD/SEK	6,57	7,17	9,08	8,99	0,31	0,38	0,40
USD/JPY	-0,25	11,61	9,15	8,92	-0,44	0,88	**0,00**
USD/CAD	5,33	7,85	5,50	5,25	0,28	0,77	**0,01**
USD/ZAR	19,40	12,14	13,30	13,75	1,18	0,61	1,00

Table 10: Out-of-sample results from the walk-forward test for exchange rates with short sales allowed, with 10 years moving in-sample period and the out-of-sample period from January 1983 to December 2015. All numbers are presented annually in percentage. μ BH and MA is the mean return of the buy and hold strategy and the moving average strategy, σ BH and MA is the standard deviation, Sharpe BH and MA is the Sharpe ratio , P-value is the respective p-value from the stationary bootstrap test. P-values in bold are significant at a five percent significance level.

	Sharpe		
Datasets	**MA**	**MAS**	Δ
Exchange rates			
USD/NOK	0,67	0,58	-0,10
USD/SEK	0,50	0,38	-0,13
USD/JPY	0,30	0,88	0,58
USD/CAD	0,66	0,77	0,11
USD/ZAR	1,10	0,61	-0,49

Table 11: Changes in Sharpe ratio with the extension of short selling the assets for exchange rates. Δ is the change in Sharpe ratio, which is the Sharpe ratio from the results obtained with short sales allowed minus the Sharpe ratio from the results obtained when short sales are prohibited. MA reports the Sharpe ratio of the moving average strategy without short sales, whereas MAS reports the Sharpe ratio with short sales.

5.3 Stocks

5.3.1 Bull and bear market cycles

Figure 5 and Figure 6 illustrate the bull and bear market cycles from the two stock prices for Consolidated Edison and Walt Disney Co. The illustrations show that for both stocks there is predominance of bull markets. Notice that Walt Disney Co have more and longer lasting bear markets then Consolidating Edison. This leads us to believe that the MA strategies perform better with Walt Disney Co. Bull and bear markets for the other stock prices and stock indices are readily available in appendix (not presented in order to save space, and they do not add any new remarks).

5.3.2 In-sample results

Table 12 provides the best strategies for stocks in a back-test, from January 1971 to December 2015. Also here we find higher Sharpe ratios for the best MA strategies, compared to the BH strategy. However, where the p-values are close to zero for most of the best strategies for currencies and commodities, this is not the case for stocks. Big firms-neutral value, Big firms-

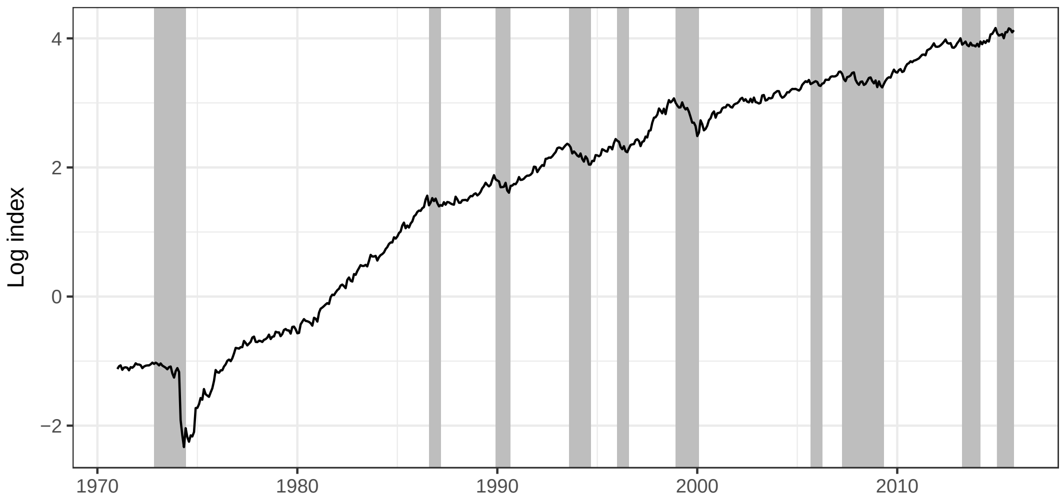

Figure 5: Bull and bear markets for Consolidated Edison in the period from January 1971 until December 2015. Shaded areas indicate bear market phases.

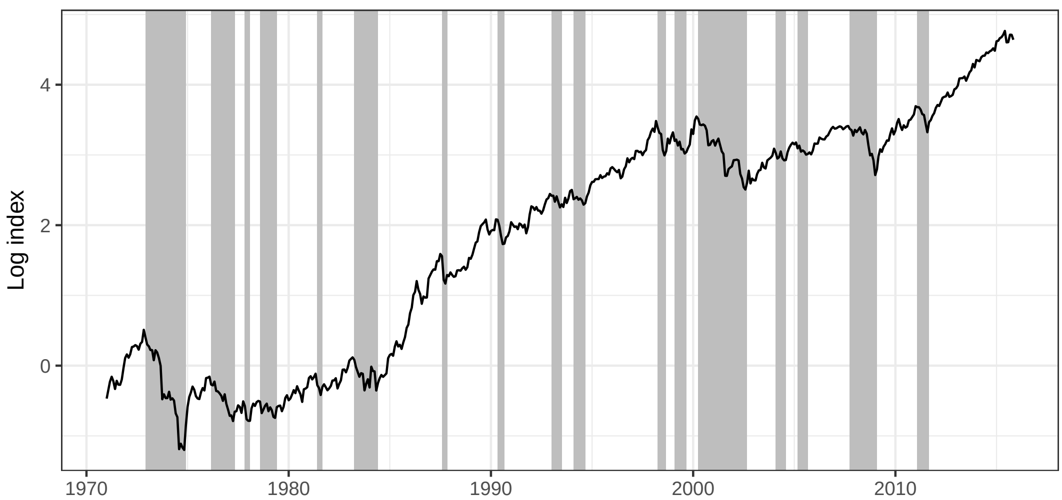

Figure 6: Bull and bear markets for Walt Disney Co in the period from January 1971 until December 2015. Shaded areas indicate bear market phases.

high value, Coca Cola, Chevron Corporation, McDonald's Co and DJIA do not have significant p-values at a five percent level, even before one adjusts the p-values for the number of trading strategies. MACD and MAE are overrepresented for the best strategies, which is natural, because MAE stands for 510 and MACD stands for 2268 of the total strategies tested. We also find that the time invested is longer than for commodities and exchange rates, where the average time invested is close to 60 percent, which leaves a higher standard deviation.

Datasets	Sharpe BH	Sharpe MA	P-value	Best strategy	Time invested
6 portfolios					
Small firms - low value	0,25	0,58	**0,01**	LMACD(1,3,6)	0,59
Small firms - neutral value	0,57	0,86	**0,03**	LMACD(1,2,8)	0,62
Small firms - high value	0,63	0,96	**0,01**	EMACD(1,14,3)	0,64
Big firms - low value	0,36	0,55	**0,02**	SMAE(13,3)	0,59
Big firms - neutral value	0,48	0,64	0,13	SMACD(6,14,4)	0,63
Big firms - high value	0,49	0,66	0,09	EMAE(4,3)	0,63
Single Stocks					
Coca Cola	0,38	0,51	0,13	SMAC(7,9)	0,59
General Electrics	0,36	0,56	**0,03**	SMAE(5,7)	0,54
Chevron Corporation	0,35	0,44	0,14	SMAE(6,9)	0,58
Consolidated Edison	0,45	0,68	**0,04**	EMAE(11,4)	0,60
Walt Disney Co	0,33	0,59	**0,02**	LMACD(4,5,2)	0,59
McDonald's Co	0,40	0,57	0,06	EMAE(3,7)	0,60
Stock indices					
S&P 500	0,39	0,59	**0,05**	SMAC(2,10)	0,59
DJIA	0,42	0,50	0,24	SMAC(8,17)	0,59

Table 12: In-sample results from the back-test test for stocks for the period from January 1973 to December 2015. Sharpe BH and MA is the Sharpe ratio, P-value is the respective p-value from the stationary bootstrap test. Best strategy is the best performing strategy and Time invested is the fraction of time invested in the asset by the best performing strategy. P-values in bold are significant at a five percent significance level.

Datasets	μ BH	μ MA	σ BH	σ MA	Sharpe BH	Sharpe MA	P-value
6 portfolios							
Small firms-low value	8,85	8,46	23,05	14,77	0,22	0,32	0,28
small firms-neutral value	14,04	11,62	17,68	11,03	0,58	0,71	0,25
Small firms-high value	14,92	13,61	18,27	12,23	0,61	0,80	0,13
Big firms-low value	11,87	6,75	15,80	10,49	0,51	0,28	0,93
Big firms-neutral value	11,92	8,41	15,01	9,54	0,54	0,48	0,63
Big firms-high value	12,39	7,94	17,04	10,65	0,51	0,39	0,77
Single stocks							
Coca Cola	15,77	11,03	20,83	16,39	0,58	0,44	0,88
General Electrics	14,11	9,29	24,58	16,62	0,42	0,33	0,74
Chevron Corporation	12,83	5,90	20,73	12,80	0,44	0,16	0,98
Consolidated Edison	12,74	9,86	17,03	12,28	0,53	0,50	0,60
Walt Disney Co	17,88	12,88	28,07	20,25	0,50	0,45	0,67
McDonald's Co	15,74	12,52	21,24	17,52	0,56	0,50	0,72
Stock indices							
S&P 500	11,60	7,61	15,02	10,62	0,52	0,35	0,88
DJIA	12,24	6,42	14,90	10,15	0,57	0,26	0,98

Table 13: Out-of-sample results from the walk-forward test for stocks with 10 years moving in-sample period and the out-of-sample period from January 1983 to December 2015. All numbers are presented annually in percentage. μ BH and MA is the mean return of the buy and hold strategy and the Moving average strategy, σ BH and MA is the standard deviation, Sharpe BH and MA is the Sharpe ratio , P-value is the respective p-value from the stationary bootstrap test. P-values in bold are significant at a five percent significance level.

5.3.3 Out-of-sample results

The out-of-sample results for stocks in Table 13, show that the BH strategy has a higher Sharpe ratio than the MA strategies, for most of the assets. None of the Sharpe ratios for the MA strategies are significantly higher than for BH strategy, when we use a significance level of five percent. We also produce the results with short sale of the asset when a sell signal is generated. This gives even worse results, so we choose to leave this out of the thesis in order to save space.

5.4 Bonds

5.4.1 Bull and bear market cycles

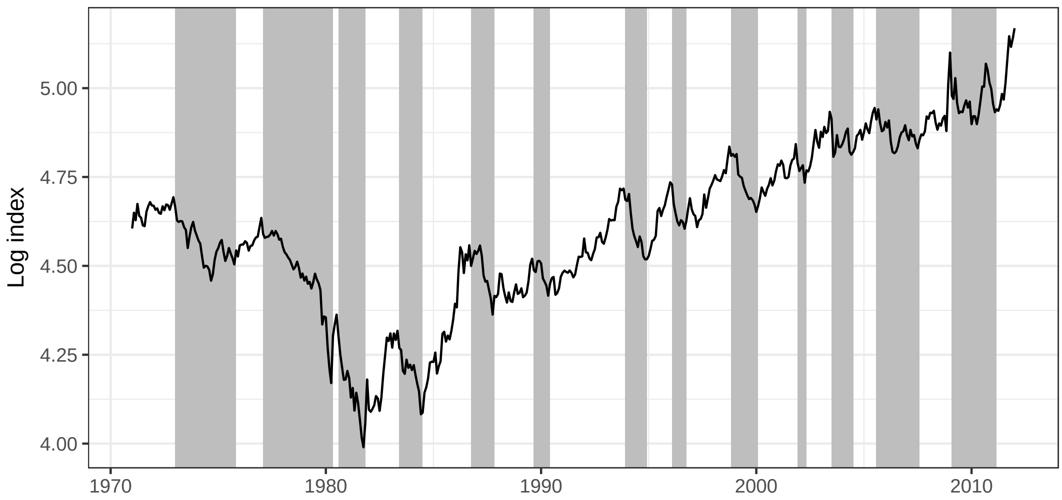

Figure 7: Bull and bear market cycles for Long-term US government bond index in the period from January 1971 to December 2015. Shaded areas indicate bear market phases.

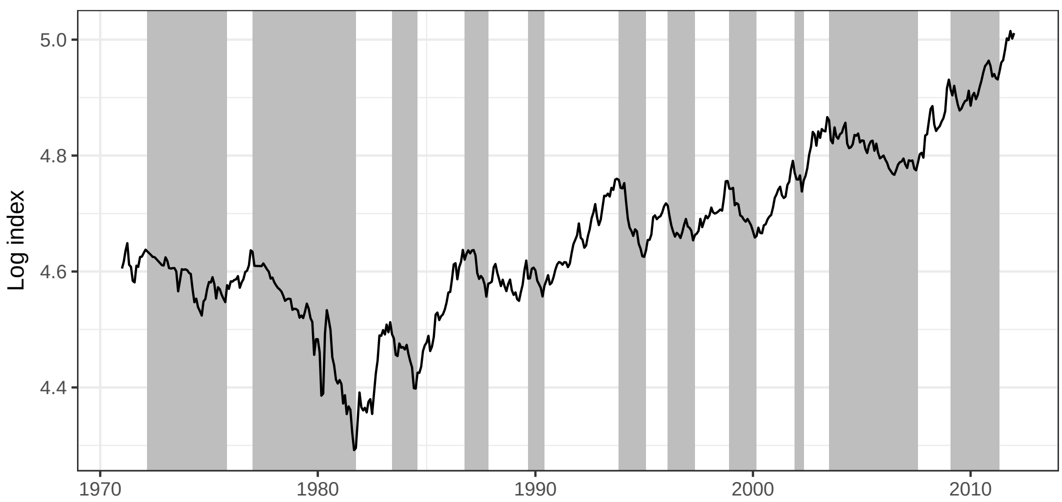

Figure 8: Bull and bear markets for Intermediate-term US government bond index in the period from January 1971 to December 2015. Shaded areas indicate bear market phases.

It is useful to inspect the bull and bear markets before we test the performance of the MA strategies in the bond markets. We have observed from before that the bull and bear markets influence the performance of the MA strategies. From Figure 7 and Figure 8 one can observe that there is predominance of bull markets in the most recent period, which leads us to believe that MA strategies do not work well with these series. Intermediate-term bonds have longest series of bear periods, and we believe it to perform better than the Long-term bonds when one uses MA strategies.

5.4.2 In-sample results

Datasets	Sharpe BH	Sharpe MA	P-value	Best strategy	Time invested
Bond indices					
Long-term US bond index	0,37	0,44	0,25	MOM(13)	0,52
Intermediate-term US bond index	0,45	0,60	0,08	SMAE(5,3)	0,51

Table 14: In-sample results from the back-test test for bonds for the period from January 1973 to December 2011. Sharpe BH and MA is the Sharpe ratio, P-value is the respective p-value from the stationary bootstrap test. Best strategy is the best performing strategy and Time invested is the fraction of time invested in the asset by the best performing strategy. P-values in bold are significant at a five percent significance level.

Table 14 provides the best strategies for Long-term and Intermediate-term bonds in a back-test from January 1971 until December 2011. The best MA strategies are invested in the bonds for slightly more than half of the period. The rest of the time, when a sell signal is generated, we assume that the trader is invested in a risk-free asset. The Sharpe ratio for the best MA strategy is higher for both bonds, but not enough to statistically support outperformance at a five percent level. From the Sharpe ratio, we observe that the best MA strategy produces much higher outperformance for the Intermediate-term bonds than for the Long-term bonds.

5.4.3 Out-of-sample results

Table 15 presents the results from the walk-forward test. The rolling ten year in-sample period lasts from March 1973 to February 1983, which leaves us with the out-of-sample period from March 1983 to December 2011. The results for the bonds produce lower mean return, lower standard deviation and lower Sharpe ratio for both bond indices. Specifically, the MA strategies underperform the BH strategy in these bonds. The results for the walk-forward test with the extension of short sales, produce even worse results for the MA strategies (these results are not reported in order to save space).

Datasets	μ BH	μ MA	σ BH	σ MA	Sharpe BH	Sharpe MA	P-value
Bond indices							
Long-term US bond index	10,30	7,62	10,52	7,88	0,57	0,42	0,86
Intermediate-term US bond index	7,70	6,11	4,80	3,78	0,71	0,48	0,96

Table 15: Out-of-sample results from the walk-forward test for bonds with 10 years moving in-sample period and the out-of-sample period from January 1983 to December 2011. All numbers are presented annually in percentage. μ BH and MA is the mean return of the buy and hold strategy and the Moving average strategy, σ BH and MA is the standard deviation, Sharpe BH and MA is the Sharpe ratio , P-value is the respective p-value from the stationary bootstrap test. P-values in bold are significant at a five percent significance level.

6 Discussion

The findings from the in-sample tests show that for all 36 assets, the best performing moving average (MA) strategy generates higher Sharpe ratio than the buy and hold (BH) strategy. Brock et al. (1992), Faber (2007) and Kilgallen (2012), among others, also find MA strategies to perform better than the BH strategy when they use in-sample tests. For most of the assets, the MA strategies significantly outperform the BH strategy. In reality, the back-test tests whether some of the 3119 MA strategies fit the price fluctuations better than the single BH strategy. When we test for that many strategies, the chance for one of them to have a better goodness of fit than the BH strategy is high. To draw conclusions based on the in-sample tests, would imply a data-mining bias, if one does not adjust the p-value for the number of strategies (Zakamulin, 2017). We therefore choose not to give any concluding remarks about the outperformance based on the in-sample results. However, the in-sample results are important for the selection of the best performing strategies in the in-sample period, which we use in the out-of-sample tests. We also find it important to report these results since most previous studies only report in-sample results.

Further, we discuss our findings from the forward (out-of-sample) tests. For commodities we find positive results for outperformance of the BH strategy by the use of MA strategies. We find statistical evidence for the outperformance for 12 out of 15 assets, with a significance level of five percent. These results are consistent with the conclusions from Lukac et al. (1988), Faber (2007) and Kilgallen (2012), among others, but we cope with the weaknesses of their studies and reinforce the conclusion on the superior performance of the MA strategies in the commodity markets. Moreover, we conduct a forward-test with short sale of the asset. We could not find any previous studies that implement short sales, so this study is possibly one of the first to do so. The implementation of short sales improves the performance of the MA strategies with as high as 0.44 in Sharpe ratio for the non-energy commodity index. The only asset that does not benefit from the short sales is soybeans, with a marginally reduction of 0.02 in Sharpe ratio. However, there is a reduction in statistical significance for the outperformance from 12 to nine out of 15 assets. The results show that the MA strategies that are highly significant in the out-of-sample tests without short-sales, benefit by shorting the asset when a sell signal occurs. The shorting-strategy increases the mean return more than the risk it imposes (standard deviation), hence the increase in the Sharpe ratios. For further research, it would be interesting to investigate the performance if one invests the proceeds from the commodity asset when a sell signal is generated, into single stocks or a fund, instead of the risk-free asset. The reasoning is that commodities and stocks are negatively correlated (Zakamulin, 2017), and could potentially improve the performance.

For exchange rates, the results from the walk-forward tests report that MA strategies statistically significantly outperform the BH strategy for three out of five exchange rates at a five percent significance level. The results are consistent with the conclusions by Levich & Thomas (1993), Olson (2004) and Kilgallen (2012), among others, which report substantial profits of MA strategies in foreign exchange markets. As for commodity markets, we cope with the weaknesses of their studies and reinforce the conclusion that the MA strategies outperform the BH strategy in the currency markets. The extension with short sales improves the performance of the MA strategies for JPY and CAD, but now only two out of five assets are statistically significant. For JPY the Sharpe ratio increases with as much as 0.579. We observe that the introduction of short sales is more risky for all exchange rates, but generate a higher return for four out of five currencies with the MA strategies.

For the stock markets, the results from the walk-forward tests report that the MA strategies statistically significantly outperform the BH strategy for zero out of 14 assets. There are actually eleven out of 14 assets that have a lower Sharpe ratio with the MA strategies than for the BH strategy. The results show poor performance of the MA strategies for the stock markets. These results disagree with most previous studies, such as Brock et al. (1992), Fifield et al. (2005), Kilgallen (2012), Naved & Srivastava (2015), among others. The reason for the contradictory results is due to the weaknesses of their studies. The majority of previous studies tend to overstate the performance of the MA strategies with data-snooping and exclusion of transaction costs. This study copes with these weaknesses with out-of-sample tests and real-life transaction costs. For the stock markets, we only agree with a minority of previous studies such as Sullivan et al. (1999) and Zakamulin (2014) who also use out-of-sample tests. Nevertheless, we only test the performance of the MA strategies for 14 assets in the stock markets which consist of thousands of assets. We cannot rule out the possibility that the MA strategies perform better than the BH strategy for other stocks, portfolios and stock indices.

The reported results for bond markets are virtually the same as for stock markets. For both bond indices, the MA strategies perform worse than the BH strategy in the walk-forward test. This disagrees with most previous studies, such as Faber (2007), among others. Our results are consistent with the results in Zakamulin (2014), who also conducts tests of the real-life performance of the MA strategies with out-of-sample tests and transaction costs. Moreover, we find very few previous studies on the performance of the MA strategies by the use of out-of-sample tests in the bond markets. For further research it would be interesting to study more bond assets, over longer sample periods.

Some academics remark that the MA strategies perform better (worse) during bear (bull) market phases. The reason why MA strategies perform better in bear market phases, is that they produce sell signals to avoid losses. Consequently, MA strategies perform worse in bull market phases, because of the lag time before the MA strategy actually generate a buy signal when the prices rise. A recent study by Zakamulin (2015) documents that all trading rules generate false trading signals, in both bull and bear market phases. Too many of those false trading signals, make it possible for the MA strategies to perform even worse than the BH strategy. We find it reasonable to assume that the false trading signals and a predominance of bull market phases, is the reason for the poor results of the MA strategies from the walk-forward tests, for the bond indices, most of the stock assets, and a few of the assets from the currency and commodity markets. We also find it reasonable to assume that the good performance of the MA strategies in the commodity and currency markets can be explained by longer lasting bear market phases and that prices decrease more significantly during the bear phase, in addition to fewer false trading signals. We observe a clear connection between market phases and the performance of the MA strategies in our figures of the bull and bear markets for the financial assets. However, we do not test the connection statistically in this thesis, but it would be interesting for further research.

7 Conclusion

The goal of this study is to overcome the weaknesses of previous studies, which tend to overrate the performance of moving average (MA) strategies by the use of in-sample tests, exclusion of transaction costs and the lack of valid statistical tests. In addition, we want to extend previous research with some new methodology. Further, we emphasize on one issue throughout the thesis: "Are moving average strategies able to outperform the passive buy-and-hold strategy in the respective markets: Commodity, exchange rate, stock and bond markets?"

We overcome the weaknesses of previous studies by the use of out-of-sample tests that cope with the data-snooping problem. Further, we use the non-parametric stationary bootstrap test, with Sharpe ratio as performance measure, to test for statistically significant outperformance. Faber (2007) and Kilgallen (2012) test the performance of MA strategies in different financial markets, but only with the use of in-sample tests. We provide results on the true performance of MA strategies in four different financial markets, possibly for the first time. In addition, we include realistic transaction costs for each financial market.

To extend previous research, we provide some new methodology. One new methodology is that we report all our results with the use of a combination of multiple trading rules and MAs. Further, we include MA strategies with short sales for the out-of-sample tests, and lastly we make the realistic assumption that an investor invests the proceeds of a foreign currency in a risk-free asset in the respective country.

For the stock and bond markets we find that the MA strategies are not able to outperform the buy and hold (BH) strategy. In most of the cases the MA strategies even underperform the BH strategy. MA strategies seem to be fruitless in the stock and bond markets. These conclusions disagree with the majority of previous studies such as Brock et al. (1992), Faber (2007), and Kilgallen (2012), among others. Our conclusion is similar to what Sullivan et al. (1999) and Zakamulin (2014) conclude on the stock and bond markets based on out-of-sample tests.

For commodity and currency markets, the MA strategies seem to have superior performance over the BH strategy. This conclusion agrees with most previous studies such as Lukac et al. (1988), Levich & Thomas (1993) and Kilgallen (2012) among others. However, we report new findings by the introduction of short sales with the MA strategies. We find that to short the financial asset generally improves the performance in the commodity markets, but it also imposes a higher risk (standard deviation). Further, shorting in the exchange rate markets seems to be beneficial for some currencies, only.

As a final remark, we observe that the MA strategies rely on bear markets in order to outperform the BH strategy. For further research it would be interesting to test the connection between bull and bear markets and the performance of MA strategies statistically.

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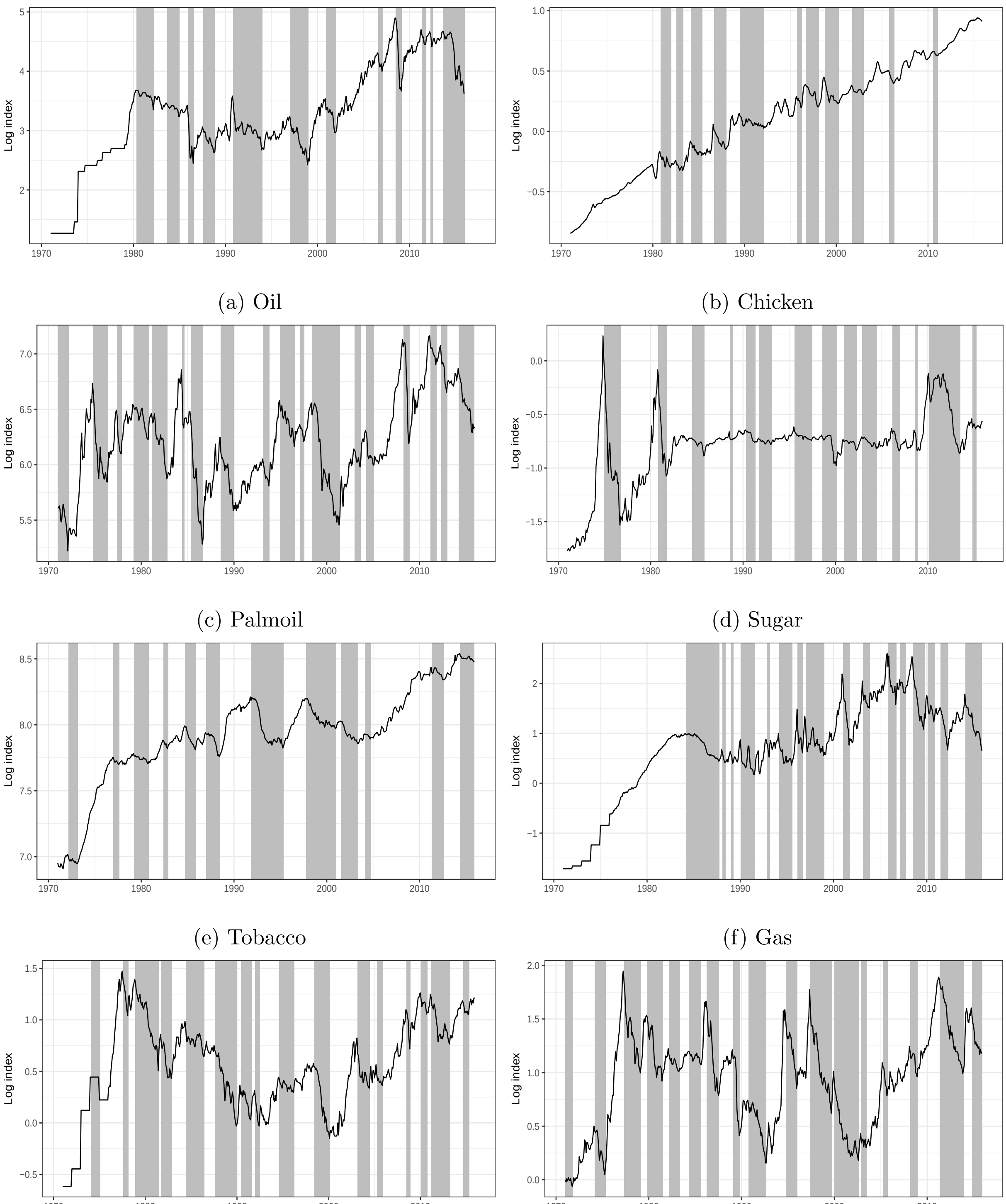
Appendices

Bull and bear markets

In this section we present the bull and bear markets that were not presented in the thesis.



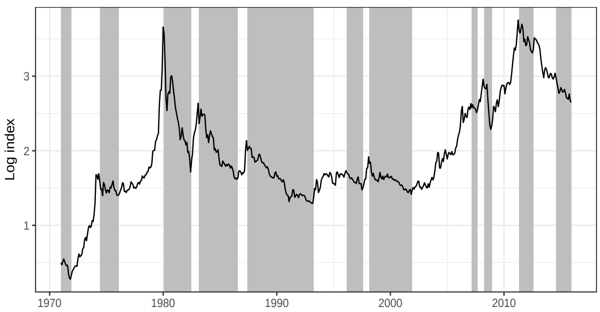
(a) Oil (b) Chicken

(c) Palmoil (d) Sugar

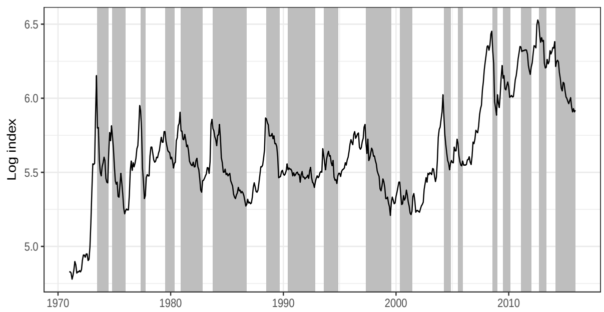
(e) Tobacco (f) Gas

(g) Cocoa (h) Coffee

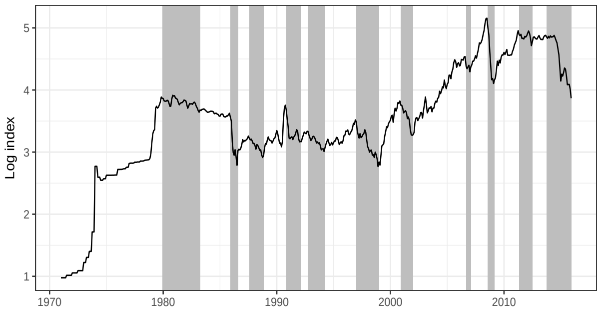
Figure 9: Bull and bear market cycles in the period from January 1971 until December 2015. Shaded areas indicate bear market phases



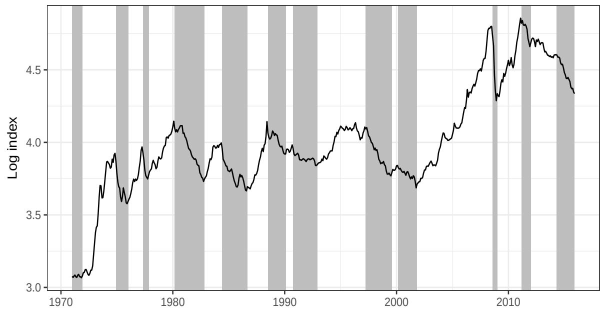
(a) Silver



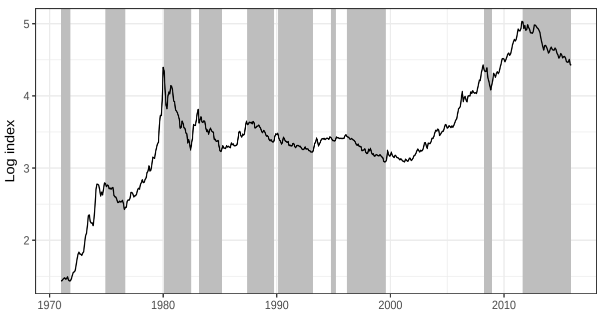
(b) Soybeans



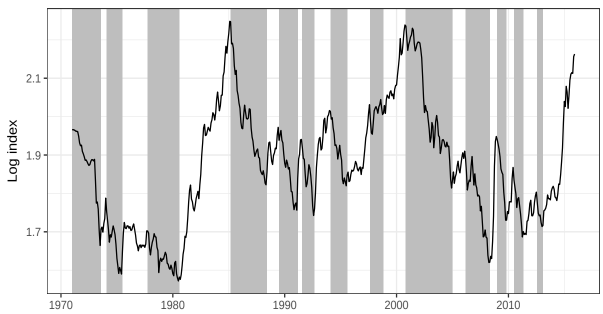
(c) Energy



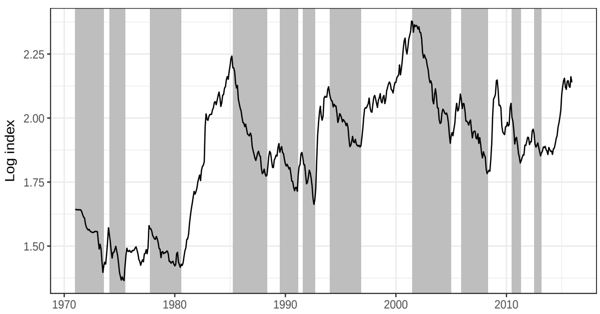
(d) Non-energy



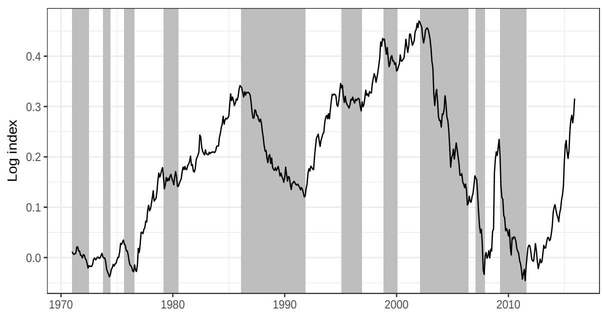
(e) Precious metals



(f) USD/NOK

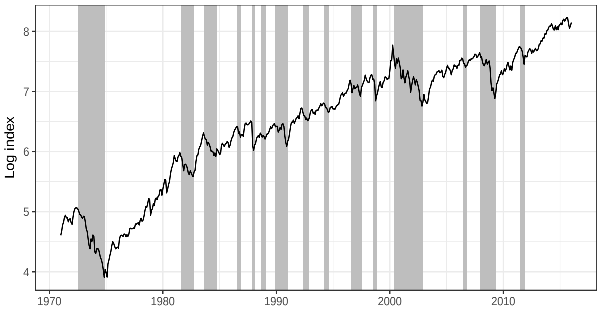


(g) USD/SEK

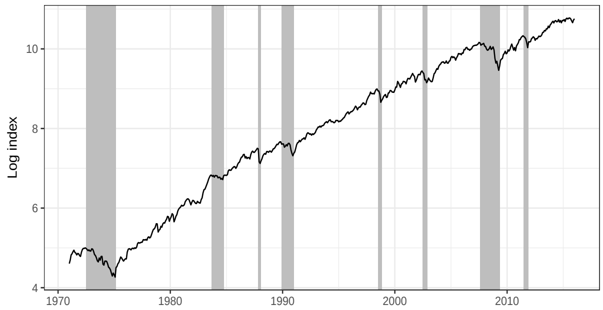


(h) USD/CAD

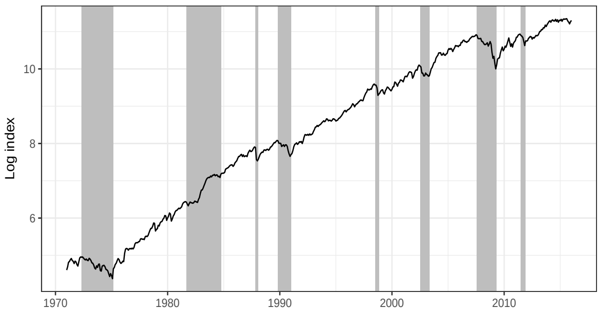
Figure 10: Bull and bear market cycles in the period from January 1971 until December 2015. Shaded areas indicate bear market phases



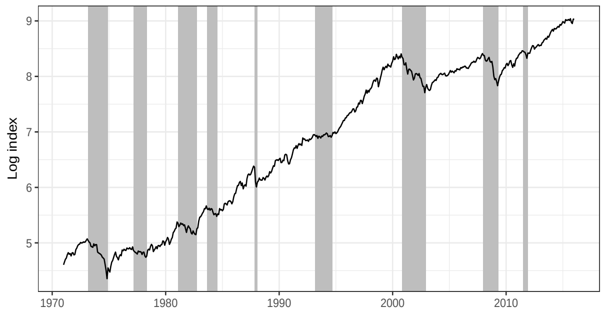
(a) Small firms - low value



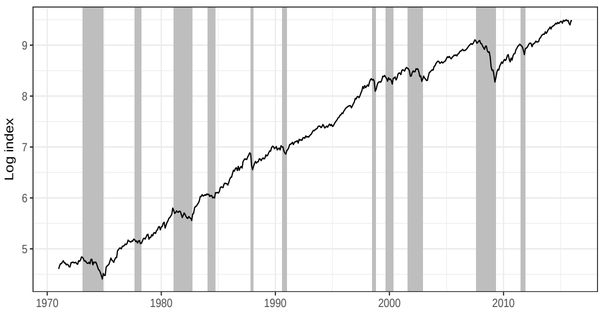
(b) Small firms - neutral value



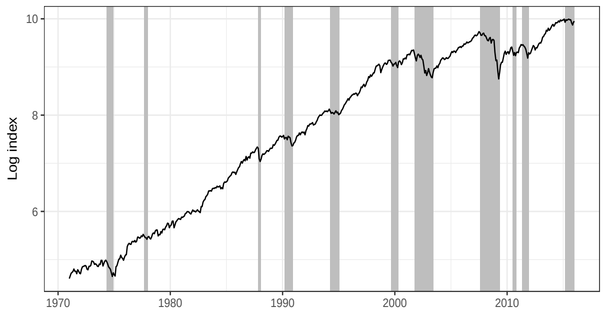
(c) Small firms - high value



(d) Big firms - low value

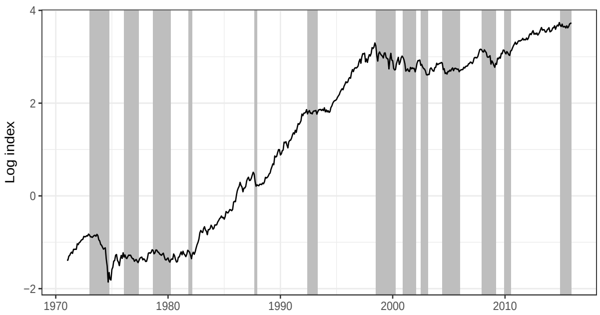


(e) Big firms - neutral value

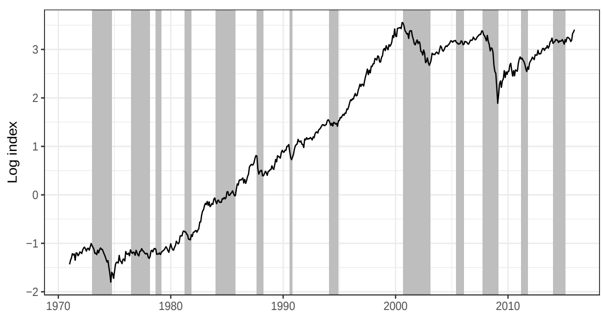


(f) Big firms - high value

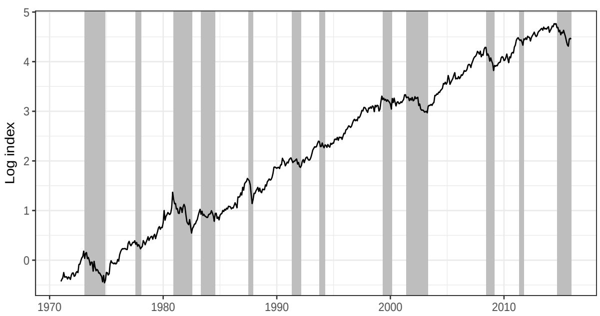
Figure 11: Bull and bear market cycles in the period from January 1971 until December 2015. Shaded areas indicate bear market phases



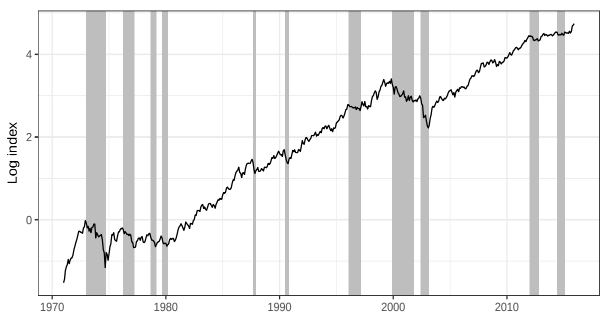
(a) Coca Cola



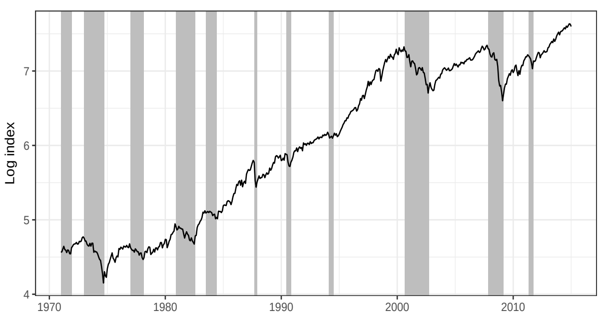
(b) General Electrics



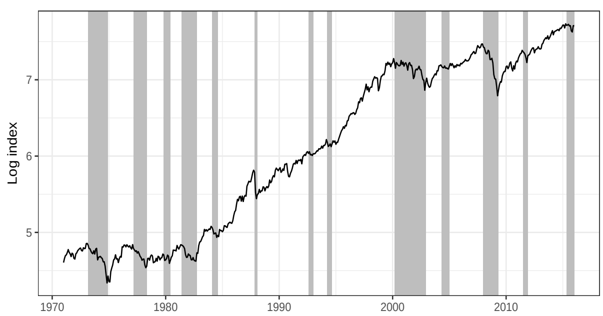
(c) Chevron Corporation



(d) McDonald's Co



(e) S&P 500



(f) DJIA

Figure 12: Bull and bear market cycles in the period from January 1971 until December 2015. Shaded areas indicate bear market phases

Detailed out-of-sample results without short sales

In this section we will present detailed out-of-sample results for all the financial assets.

Gold	BH	MA
Mean returns %	4.062	4.868
Std. deviation %	15.516	12.301
Minimum return %	-17.383	-17.383
Maximum return %	17.347	13.053
Skewness	0.204	-0.107
Kurtosis	1.206	2.979
Average drawdown %	12.108	8.430
Average max drawdown %	18.506	17.566
Maximum drawdown %	48.264	38.453
Performance	0.017	0.086
P-value		0.276
Rolling 5-year Win %		44.910
Rolling 10-year Win %		29.197

Oil	BH	MA
Mean returns %	5.035	10.582
Std. deviation %	29.106	19.879
Minimum return %	-32.700	-17.873
Maximum return %	45.799	45.699
Skewness	0.131	1.469
Kurtosis	3.059	10.915
Average drawdown %	25.441	12.382
Average max drawdown %	27.966	20.463
Maximum drawdown %	72.232	25.482
Performance	0.042	0.341
P-value		0.014
Rolling 5-year Win %		71.557
Rolling 10-year Win %		77.737

Gas	BH	MA
Mean returns %	8.117	12.620
Std. deviation %	43.213	33.433
Minimum return %	-33.333	-33.055
Maximum return %	61.261	61.161
Skewness	0.719	1.140
Kurtosis	2.604	7.537
Average drawdown %	40.738	21.915
Average max drawdown %	40.738	34.364
Maximum drawdown %	85.781	71.925
Performance	0.100	0.264
P-value		0.080
Rolling 5-year Win %		64.371
Rolling 10-year Win %		58.759

Silver	BH	MA
Mean returns %	3.286	8.713
Std. deviation %	22.151	17.528
Minimum return %	-19.293	-19.293
Maximum return %	29.749	29.749
Skewness	0.397	0.865
Kurtosis	1.853	6.222
Average drawdown %	31.960	13.296
Average max drawdown %	31.960	19.477
Maximum drawdown %	71.764	35.634
Performance	-0.023	0.279
P-value		0.002
Rolling 5-year Win %		57.784
Rolling 10-year Win %		72.263

Cocoa	BH	MA
Mean returns %	3.781	7.217
Std. deviation %	20.132	15.460
Minimum return %	-17.702	-17.702
Maximum return %	25.969	25.969
Skewness	0.329	0.558
Kurtosis	0.943	5.112
Average drawdown %	26.076	8.987
Average max drawdown %	26.076	14.668
Maximum drawdown %	68.057	33.877
Performance	-0.001	0.221
P-value		0.027
Rolling 5-year Win %		55.689
Rolling 10-year Win %		55.474

Coffe	BH	MA
Mean returns %	4.084	11.524
Std. deviation %	27.432	22.825
Minimum return %	-29.709	-16.931
Maximum return %	52.607	52.607
Skewness	1.361	2.434
Kurtosis	6.435	13.627
Average drawdown %	33.583	12.570
Average max drawdown %	33.583	19.297
Maximum drawdown %	79.696	54.237
Performance	0.010	0.338
P-value		0.000
Rolling 5-year Win %		74.850
Rolling 10-year Win %		81.752

Table 16: Out-of-sample results for commodities. Transaction cost of 0.10 percent. In-sample period of ten years, from January 1973 to December 1982 with use of one month rolling window. The out of sample period is from January 1983 to December 2015.

Beef	BH	MA
Mean returns %	2.161	7.126
Std. deviation %	13.641	10.285
Minimum return %	-16.303	-15.054
Maximum return %	15.393	15.393
Skewness	0.141	0.678
Kurtosis	2.408	7.045
Average drawdown %	16.842	6.328
Average max drawdown %	18.407	12.954
Maximum drawdown %	43.094	26.752
Performance	-0.120	0.322
P-value		0.000
Rolling 5-year Win %		91.317
Rolling 10-year Win %		96.350

Sugar	BH	MA
Mean returns %	1.089	5.715
Std. deviation %	10.805	8.375
Minimum return %	-12.765	-12.765
Maximum return %	18.181	18.181
Skewness	0.418	1.433
Kurtosis	5.660	14.646
Average drawdown %	20.543	3.978
Average max drawdown %	20.543	8.628
Maximum drawdown %	52.379	34.748
Performance	-0.250	0.227
P-value		0.000
Rolling 5-year Win %		100.000
Rolling 10-year Win %		100.000

Tobacco	BH	MA
Mean returns %	2.055	3.933
Std. deviation %	6.189	4.547
Minimum return %	-4.745	-4.390
Maximum return %	7.013	6.913
Skewness	0.204	0.460
Kurtosis	0.656	3.537
Average drawdown %	5.858	3.526
Average max drawdown %	9.146	6.042
Maximum drawdown %	32.056	13.625
Performance	-0.283	0.029
P-value		0.013
Rolling 5-year Win %		65.569
Rolling 10-year Win %		77.372

Chicken	BH	MA
Mean returns %	3.968	7.712
Std. deviation %	7.525	6.234
Minimum return %	-5.424	-5.424
Maximum return %	11.017	11.017
Skewness	0.816	1.316
Kurtosis	2.851	7.122
Average drawdown %	8.464	2.047
Average max drawdown %	13.360	5.554
Maximum drawdown %	19.434	10.323
Performance	0.022	0.626
P-value		0.000
Rolling 5-year Win %		99.401
Rolling 10-year Win %		100.000

Palmoil	BH	MA
Mean returns %	4.693	10.658
Std. deviation %	26.300	19.822
Minimum return %	-29.313	-29.413
Maximum return %	31.529	31.429
Skewness	0.222	0.901
Kurtosis	2.409	8.419
Average drawdown %	30.422	11.028
Average max drawdown %	30.422	19.885
Maximum drawdown %	79.285	45.775
Performance	0.034	0.345
P-value		0.007
Rolling 5-year Win %		81.737
Rolling 10-year Win %		91.971

Soybeans	BH	MA
Mean returns %	2.957	7.085
Std. deviation %	18.251	13.708
Minimum return %	-22.593	-15.498
Maximum return %	28.897	28.797
Skewness	0.476	1.483
Kurtosis	4.160	11.867
Average drawdown %	32.608	11.162
Average max drawdown %	32.608	17.339
Maximum drawdown %	48.159	41.016
Performance	-0.046	0.239
P-value		0.010
Rolling 5-year Win %		66.766
Rolling 10-year Win %		74.088

Table 17: Out-of-sample results for commodities. Transaction cost of 0.10 percent. In-sample period of ten years, from January 1973 to December 1982 with use of one month rolling window.The out of sample period is from January 1983 to December 2015

Energy index	BH	MA
Mean returns %	3.701	9.330
Std. deviation %	24.521	17.097
Minimum return %	-28.375	-19.547
Maximum return %	41.187	41.087
Skewness	0.155	1.522
Kurtosis	3.775	12.808
Average drawdown %	20.328	9.494
Average max drawdown %	31.521	20.164
Maximum drawdown %	72.413	38.633
Performance	-0.004	0.324
P-value		0.004
Rolling 5-year Win %		74.251
Rolling 10-year Win %		71.533

No-energy index	BH	MA
Mean returns %	2.009	6.105
Std. deviation %	9.245	6.470
Minimum return %	-18.389	-7.548
Maximum return %	10.543	10.543
Skewness	-0.715	0.745
Kurtosis	6.542	4.962
Average drawdown %	12.131	3.261
Average max drawdown %	15.700	7.283
Maximum drawdown %	40.536	19.367
Performance	-0.193	0.354
P-value		0.000
Rolling 5-year Win %		82.335
Rolling 10-year Win %		100.000

Precious metals index	BH	MA
Mean returns %	3.331	4.580
Std. deviation %	13.383	10.621
Minimum return %	-13.105	-13.105
Maximum return %	14.307	14.307
Skewness	0.266	0.747
Kurtosis	0.926	3.813
Average drawdown %	15.134	8.167
Average max drawdown %	15.134	12.469
Maximum drawdown %	46.554	24.867
Performance	-0.035	0.073
P-value		0.165
Rolling 5-year Win %		44.910
Rolling 10-year Win %		58.029

Table 18: Out-of-sample results for commodity indices. Transaction cost of 0.10 percent. In-sample period of ten years, from January 1973 to December 1982 with use of one month rolling window. The out of sample period is from January 1983 to December 2015.

USD/NOK	BH	MA
Mean returns %	7.628	8.157
Std. deviation %	8.885	6.456
Minimum return %	-4.960	-4.364
Maximum return %	14.689	14.589
Skewness	0.597	1.847
Kurtosis	2.001	10.401
Average drawdown %	5.148	2.007
Average max drawdown %	11.161	4.589
Maximum drawdown %	27.778	6.732
Performance	0.432	0.673
P-value		0.028
Rolling 5-year Win %		88.323
Rolling 10-year Win %		100.000

USD/SEK	BH	MA
Mean returns %	6.568	7.117
Std. deviation %	9.076	6.639
Minimum return %	-6.839	-5.644
Maximum return %	12.729	12.629
Skewness	0.617	1.801
Kurtosis	2.022	9.482
Average drawdown %	6.503	3.127
Average max drawdown %	11.497	5.592
Maximum drawdown %	32.106	11.425
Performance	0.306	0.503
P-value		0.071
Rolling 5-year Win %		74.850
Rolling 10-year Win %		88.686

USD/JPY	BH	MA
Mean returns %	-0.245	5.667
Std. deviation %	9.146	6.272
Minimum return %	-9.973	-7.035
Maximum return %	8.462	8.362
Skewness	-0.332	0.349
Kurtosis	0.811	3.127
Average drawdown %	16.183	3.039
Average max drawdown %	16.183	6.364
Maximum drawdown %	57.882	11.251
Performance	-0.442	0.297
P-value		0.000
Rolling 5-year Win %		99.401
Rolling 10-year Win %		100.000

USD/CAD	BH	MA
Mean returns %	5.326	6.441
Std. deviation %	5.498	4.022
Minimum return %	-5.816	-3.220
Maximum return %	12.137	12.137
Skewness	0.619	2.786
Kurtosis	7.612	25.627
Average drawdown %	1.905	1.173
Average max drawdown %	5.105	2.639
Maximum drawdown %	28.070	6.141
Performance	0.280	0.658
P-value		0.002
Rolling 5-year Win %		78.743
Rolling 10-year Win %		84.672

USD/ZAR	BH	MA
Mean returns %	19.399	16.286
Std. deviation %	13.297	11.503
Minimum return %	-11.568	-11.568
Maximum return %	21.978	21.978
Skewness	1.179	1.812
Kurtosis	6.392	10.497
Average drawdown %	4.293	3.172
Average max drawdown %	12.514	8.921
Maximum drawdown %	35.207	20.613
Performance	1.183	1.097
P-value		0.827
Rolling 5-year Win %		23.054
Rolling 10-year Win %		32.482

Table 19: Out-of-sample results for exchange rates. Transaction cost of 0.10 percent. In-sample period of ten years, from January 1973 to December 1982 with use of one month rolling window. The out of sample period is from January 1983 to December 2015.

Coco Cola	BH	MA
Mean returns %	15.772	11.033
Std. deviation %	20.833	16.394
Minimum return %	-19.099	-19.179
Maximum return %	22.280	20.621
Skewness	-0.132	0.068
Kurtosis	1.300	3.726
Average drawdown %	6.855	7.874
Average max drawdown %	18.101	16.075
Maximum drawdown %	49.887	37.816
Performance	0.577	0.444
P-value		0.880
Rolling 5-year Win %		6.886
Rolling 10-year Win %		22.628

Mc Donalds	BH	MA
Mean returns %	15.735	12.519
Std. deviation %	21.242	17.520
Minimum return %	-25.673	-15.504
Maximum return %	18.257	15.966
Skewness	-0.280	-0.016
Kurtosis	0.793	0.838
Average drawdown %	9.627	10.449
Average max drawdown %	24.198	21.276
Maximum drawdown %	69.382	42.734
Performance	0.562	0.496
P-value		0.718
Rolling 5-year Win %		40.719
Rolling 10-year Win %		46.350

Consolidated Edison	BH	MA
Mean returns %	12.739	9.860
Std. deviation %	17.027	12.279
Minimum return %	-14.224	-13.942
Maximum return %	20.815	13.149
Skewness	-0.022	0.065
Kurtosis	0.527	2.305
Average drawdown %	8.030	6.140
Average max drawdown %	20.006	13.701
Maximum drawdown %	44.271	23.349
Performance	0.526	0.496
P-value		0.601
Rolling 5-year Win %		48.204
Rolling 10-year Win %		64.234

General Electrics	BH	MA
Mean returns %	14.108	9.291
Std. deviation %	24.578	16.615
Minimum return %	-27.782	-23.217
Maximum return %	25.124	19.234
Skewness	-0.227	0.418
Kurtosis	1.436	3.609
Average drawdown %	7.969	8.493
Average max drawdown %	22.910	16.381
Maximum drawdown %	81.076	32.190
Performance	0.420	0.330
P-value		0.743
Rolling 5-year Win %		26.946
Rolling 10-year Win %		31.387

Chevron Corporation	BH	MA
Mean returns %	12.826	5.895
Std. deviation %	20.732	12.803
Minimum return %	-17.633	-15.504
Maximum return %	24.531	16.804
Skewness	0.182	0.259
Kurtosis	1.029	3.847
Average drawdown %	8.920	8.394
Average max drawdown %	25.027	16.489
Maximum drawdown %	39.741	36.872
Performance	0.435	0.163
P-value		0.975
Rolling 5-year Win %		21.856
Rolling 10-year Win %		0.000

Walt Disney Co	BH	MA
Mean returns %	17.880	12.880
Std. deviation %	28.068	20.253
Minimum return %	-28.710	-28.710
Maximum return %	34.551	34.551
Skewness	-0.019	0.525
Kurtosis	1.707	6.137
Average drawdown %	14.066	10.165
Average max drawdown %	31.980	21.135
Maximum drawdown %	64.685	43.712
Performance	0.501	0.448
P-value		0.674
Rolling 5-year Win %		50.898
Rolling 10-year Win %		63.869

Table 20: Out-of-sample results for single stocks. Transaction cost of 0.25 percent. In-sample period of ten years, from January 1973 to December 1982 with the use of one month rolling window. The out of sample period is from January 1983 to December 2015.

Small Firms - low value	BH	MA
Mean returns %	8.852	8.461
Std. deviation %	23.048	14.771
Minimum return %	-32.390	-14.770
Maximum return %	28.330	18.920
Skewness	-0.418	0.146
Kurtosis	2.337	2.464
Average drawdown %	14.115	7.554
Average max drawdown %	27.076	16.268
Maximum drawdown %	63.716	35.144
Performance	0.219	0.316
P-value		0.280
Rolling 5-year Win %		61.677
Rolling 10-year Win %		77.372

Small firms - medium value	BH	MA
Mean returns %	14.040	11.621
Std. deviation %	17.684	11.032
Minimum return %	-27.930	-11.150
Maximum return %	16.550	16.300
Skewness	-0.873	0.315
Kurtosis	3.435	2.789
Average drawdown %	7.999	4.240
Average max drawdown %	24.693	11.513
Maximum drawdown %	50.367	32.228
Performance	0.578	0.709
P-value		0.252
Rolling 5-year Win %		77.246
Rolling 10-year Win %		88.321

Small firms - high value	BH	MA
Mean returns %	14.915	13.612
Std. deviation %	18.270	12.234
Minimum return %	-27.730	-16.030
Maximum return %	17.250	17.000
Skewness	-1.007	0.128
Kurtosis	3.376	3.635
Average drawdown %	7.990	4.917
Average max drawdown %	25.206	12.737
Maximum drawdown %	59.970	29.819
Performance	0.607	0.802
P-value		0.126
Rolling 5-year Win %		75.449
Rolling 10-year Win %		89.781

Big firms - low value	BH	MA
Mean returns %	11.874	6.754
Std. deviation %	15.803	10.494
Minimum return %	-23.180	-13.840
Maximum return %	14.440	10.790
Skewness	-0.603	-0.178
Kurtosis	2.129	2.610
Average drawdown %	7.175	5.330
Average max drawdown %	21.465	12.328
Maximum drawdown %	50.345	24.381
Performance	0.511	0.281
P-value		0.934
Rolling 5-year Win %		36.527
Rolling 10-year Win %		24.818

Big firms - medium value	BH	MA
Mean returns %	11.920	8.405
Std. deviation %	15.011	9.540
Minimum return %	-20.240	-10.310
Maximum return %	13.220	10.710
Skewness	-0.752	0.022
Kurtosis	2.793	2.710
Average drawdown %	5.719	4.352
Average max drawdown %	19.256	10.412
Maximum drawdown %	56.392	23.969
Performance	0.541	0.482
P-value		0.628
Rolling 5-year Win %		25.749
Rolling 10-year Win %		30.657

Big firms - high value	BH	MA
Mean returns %	12.393	7.935
Std. deviation %	17.041	10.646
Minimum return %	-22.200	-19.620
Maximum return %	17.770	9.770
Skewness	-0.882	-0.956
Kurtosis	2.903	5.727
Average drawdown %	5.860	4.906
Average max drawdown %	21.809	13.411
Maximum drawdown %	62.585	30.623
Performance	0.505	0.388
P-value		0.772
Rolling 5-year Win %		25.150
Rolling 10-year Win %		28.832

Table 21: Out-of-sample results for 6 portfolios sorted on size and book-to-market from the walk-forward test. Transaction cost of 0.10 percent. In-sample period of ten years, from January 1973 to December 1982 with the use of one month rolling window. The out of sample period is from January 1983 to December 2015.

Long-term bonds	BH	MA
Mean returns %	10.297	7.620
Std. deviation %	10.521	7.875
Minimum return %	-11.240	-6.490
Maximum return %	14.430	11.450
Skewness	0.090	0.589
Kurtosis	1.912	3.481
Average drawdown %	4.543	3.417
Average max drawdown %	10.938	6.634
Maximum drawdown %	14.898	10.112
Performance	0.568	0.420
P-value		0.855
Rolling 5-year Win %		17.483
Rolling 10-year Win %		0.885

Intermediate-term bonds	BH	MA
Mean returns %	7.702	6.106
Std. deviation %	4.797	3.780
Minimum return %	-3.340	-3.340
Maximum return %	4.850	4.750
Skewness	-0.130	0.083
Kurtosis	0.123	2.374
Average drawdown %	1.879	1.603
Average max drawdown %	3.942	3.296
Maximum drawdown %	6.913	7.364
Performance	0.712	0.482
P-value		0.961
Rolling 5-year Win %		22.378
Rolling 10-year Win %		16.814

Table 22: Out-of-sample results for bonds from the walk-forward test. Transaction cost of 0.10 percent. In-sample period of ten years, from January 1973 to December 1982 with the use of one month rolling window. The out of sample period is from January 1983 to December 2015.

Detailed out-of-sample results with short sales

In this section we will present detailed out-of-sample results with the extension of short sales for all the financial assets.

Gold short	BH	MA
Mean returns %	4.062	8.247
Std. deviation %	15.516	15.606
Minimum return %	-17.383	-17.383
Maximum return %	17.347	14.521
Skewness	0.204	-0.486
Kurtosis	1.206	1.296
Average drawdown %	12.108	7.448
Average max drawdown %	18.506	19.846
Maximum drawdown %	48.264	44.857
Performance	0.017	0.285
P-value		0.122
Rolling 5-year Win %		54.491
Rolling 10-year Win %		62.409

Oil short	BH	MA
Mean returns %	5.035	15.545
Std. deviation %	29.106	28.847
Minimum return %	-32.700	-29.464
Maximum return %	45.799	45.599
Skewness	0.131	0.605
Kurtosis	3.059	2.812
Average drawdown %	25.441	13.070
Average max drawdown %	27.966	27.964
Maximum drawdown %	72.232	69.786
Performance	0.042	0.407
P-value		0.082
Rolling 5-year Win %		68.862
Rolling 10-year Win %		56.569

Cocoa short	BH	MA
Mean returns %	3.781	11.247
Std. deviation %	20.132	20.122
Minimum return %	-17.702	-17.702
Maximum return %	25.969	25.969
Skewness	0.329	0.028
Kurtosis	0.943	0.947
Average drawdown %	26.076	10.623
Average max drawdown %	26.076	23.104
Maximum drawdown %	68.057	47.801
Performance	-0.001	0.371
P-value		0.057
Rolling 5-year Win %		63.772
Rolling 10-year Win %		64.964

Silver short	BH	MA
Mean returns %	3.286	11.273
Std. deviation %	22.151	22.121
Minimum return %	-19.293	-19.293
Maximum return %	29.749	29.549
Skewness	0.397	0.334
Kurtosis	1.853	1.682
Average drawdown %	31.960	13.284
Average max drawdown %	31.960	29.666
Maximum drawdown %	71.764	42.351
Performance	-0.023	0.338
P-value		0.047
Rolling 5-year Win %		53.293
Rolling 10-year Win %		60.219

Gas short	BH	MA
Mean returns %	8.117	16.606
Std. deviation %	43.213	43.060
Minimum return %	-33.333	-49.591
Maximum return %	61.261	61.061
Skewness	0.719	0.087
Kurtosis	2.604	2.698
Average drawdown %	40.738	18.115
Average max drawdown %	40.738	30.067
Maximum drawdown %	85.781	95.894
Performance	0.100	0.298
P-value		0.208
Rolling 5-year Win %		64.072
Rolling 10-year Win %		52.920

Coffe short	BH	MA
Mean returns %	4.084	19.048
Std. deviation %	27.432	27.130
Minimum return %	-29.709	-16.931
Maximum return %	52.607	52.607
Skewness	1.361	1.383
Kurtosis	6.435	5.895
Average drawdown %	33.583	9.607
Average max drawdown %	33.583	24.079
Maximum drawdown %	79.696	37.576
Performance	0.010	0.562
P-value		0.001
Rolling 5-year Win %		71.557
Rolling 10-year Win %		81.022

Table 23: Out-of-sample results for commodities, with the extension of short sales. Transaction cost of 0.10 percent. In-sample period of ten years, from January 1973 to December 1982 with the use of one month rolling window. The out of sample period is from January 1983 to December 2015.

Palmoil short	BH	MA
Mean returns %	4.693	17.192
Std. deviation %	26.300	25.941
Minimum return %	-29.313	-29.513
Maximum return %	31.529	31.329
Skewness	0.222	0.266
Kurtosis	2.409	2.406
Average drawdown %	30.422	11.275
Average max drawdown %	30.422	27.262
Maximum drawdown %	79.285	48.901
Performance	0.034	0.515
P-value		0.025
Rolling 5-year Win %		74.850
Rolling 10-year Win %		86.131

Soybeans short	BH	MA
Mean returns %	2.957	7.894
Std. deviation %	18.251	18.254
Minimum return %	-22.593	-16.755
Maximum return %	28.897	28.697
Skewness	0.476	0.511
Kurtosis	4.160	3.944
Average drawdown %	32.608	9.754
Average max drawdown %	32.608	19.837
Maximum drawdown %	48.159	55.576
Performance	-0.046	0.224
P-value		0.127
Rolling 5-year Win %		58.383
Rolling 10-year Win %		58.029

Beef short	BH	MA
Mean returns %	2.161	13.488
Std. deviation %	13.641	13.373
Minimum return %	-16.303	-15.054
Maximum return %	15.393	16.163
Skewness	0.141	0.252
Kurtosis	2.408	2.243
Average drawdown %	16.842	5.212
Average max drawdown %	18.407	14.160
Maximum drawdown %	43.094	26.486
Performance	-0.120	0.724
P-value		0.000
Rolling 5-year Win %		94.012
Rolling 10-year Win %		99.635

Chicken short	BH	MA
Mean returns %	3.968	11.078
Std. deviation %	7.525	7.290
Minimum return %	-5.424	-5.424
Maximum return %	11.017	11.017
Skewness	0.816	0.565
Kurtosis	2.851	2.620
Average drawdown %	8.464	2.751
Average max drawdown %	13.360	7.406
Maximum drawdown %	19.434	13.051
Performance	0.022	1.001
P-value		0.000
Rolling 5-year Win %		95.509
Rolling 10-year Win %		100.000

Sugar short	BH	MA
Mean returns %	1.089	9.524
Std. deviation %	10.805	10.753
Minimum return %	-12.765	-12.765
Maximum return %	18.181	18.181
Skewness	0.418	0.560
Kurtosis	5.660	5.111
Average drawdown %	20.543	3.907
Average max drawdown %	20.543	11.600
Maximum drawdown %	52.379	35.206
Performance	-0.250	0.532
P-value		0.000
Rolling 5-year Win %		99.401
Rolling 10-year Win %		100.000

Tobacco short	BH	MA
Mean returns %	2.055	6.001
Std. deviation %	6.189	6.233
Minimum return %	-4.745	-5.909
Maximum return %	7.013	6.813
Skewness	0.204	0.042
Kurtosis	0.656	0.686
Average drawdown %	5.858	3.371
Average max drawdown %	9.146	7.503
Maximum drawdown %	32.056	18.945
Performance	-0.283	0.357
P-value		0.001
Rolling 5-year Win %		68.263
Rolling 10-year Win %		72.628

Table 24: Out-of-sample results for commodities, with the extension of short sales. Transaction cost of 0.10 percent In-sample period of ten years, from January 1973 to December 1982 with the use of one month rolling window. The out of sample period is from January 1983 to December 2015.

Energy index short	BH	MA
Mean returns %	3.701	15.542
Std. deviation %	24.521	24.254
Minimum return %	-28.375	-25.709
Maximum return %	41.187	40.987
Skewness	0.155	0.681
Kurtosis	3.775	3.460
Average drawdown %	20.328	10.776
Average max drawdown %	31.521	24.778
Maximum drawdown %	72.413	68.352
Performance	-0.004	0.484
P-value		0.030
Rolling 5-year Win %		72.455
Rolling 10-year Win %		52.920

Non-Energy index short	BH	MA
Mean returns %	2.009	10.975
Std. deviation %	9.245	9.018
Minimum return %	-18.389	-7.548
Maximum return %	10.543	18.549
Skewness	-0.715	0.986
Kurtosis	6.542	5.744
Average drawdown %	12.131	3.298
Average max drawdown %	15.700	8.105
Maximum drawdown %	40.536	11.935
Performance	-0.193	0.793
P-value		0.000
Rolling 5-year Win %		84.431
Rolling 10-year Win %		100.000

Precious Metals index short	BH	MA
Mean returns %	3.331	6.316
Std. deviation %	13.383	13.448
Minimum return %	-13.105	-13.527
Maximum return %	14.307	13.234
Skewness	0.266	0.055
Kurtosis	0.926	0.816
Average drawdown %	15.134	10.078
Average max drawdown %	15.134	18.651
Maximum drawdown %	46.554	34.100
Performance	-0.035	0.186
P-value		0.163
Rolling 5-year Win %		50.599
Rolling 10-year Win %		65.328

Table 25: Out-of-sample results for commodity indices, with the extension of short sales. Transaction cost of 0.10 percent In-sample period of ten years, from January 1973 to December 1982 with the use of one month rolling window. The out of sample period is from January 1983 to December 2015.

USD/NOK short	BH	MA
Mean returns %	7.628	8.859
Std. deviation %	8.885	8.713
Minimum return %	-4.960	-8.830
Maximum return %	14.689	14.689
Skewness	0.597	0.292
Kurtosis	2.001	2.400
Average drawdown %	5.148	3.279
Average max drawdown %	11.161	8.426
Maximum drawdown %	27.778	21.048
Performance	0.432	0.578
P-value		0.249
Rolling 5-year Win %		64.970
Rolling 10-year Win %		68.613

USD/SEK short	BH	MA
Mean returns %	6.568	7.169
Std. deviation %	9.076	8.994
Minimum return %	-6.839	-7.276
Maximum return %	12.729	12.529
Skewness	0.617	0.410
Kurtosis	2.022	1.999
Average drawdown %	6.503	5.039
Average max drawdown %	11.497	10.542
Maximum drawdown %	32.106	14.580
Performance	0.306	0.375
P-value		0.395
Rolling 5-year Win %		54.192
Rolling 10-year Win %		61.679

USD/JPY short	BH	MA
Mean returns %	-0.245	11.608
Std. deviation %	9.146	8.921
Minimum return %	-9.973	-7.035
Maximum return %	8.462	10.413
Skewness	-0.332	0.496
Kurtosis	0.811	0.779
Average drawdown %	16.183	2.979
Average max drawdown %	16.183	7.702
Maximum drawdown %	57.882	11.779
Performance	-0.442	0.876
P-value		0.000
Rolling 5-year Win %		99.401
Rolling 10-year Win %		100.000

USD/CAD short	BH	MA
Mean returns %	5.326	7.854
Std. deviation %	5.498	5.248
Minimum return %	-5.816	-4.146
Maximum return %	12.137	12.137
Skewness	0.619	1.157
Kurtosis	7.612	8.241
Average drawdown %	1.905	1.745
Average max drawdown %	5.105	4.964
Maximum drawdown %	28.070	7.544
Performance	0.280	0.767
P-value		0.013
Rolling 5-year Win %		58.683
Rolling 10-year Win %		55.474

USD/ZAR short	BH	MA
Mean returns %	19.399	12.141
Std. deviation %	13.297	13.751
Minimum return %	-11.568	-19.445
Maximum return %	21.978	21.978
Skewness	1.179	0.262
Kurtosis	6.392	6.665
Average drawdown %	4.293	7.180
Average max drawdown %	12.514	14.517
Maximum drawdown %	35.207	47.834
Performance	1.183	0.608
P-value		0.999
Rolling 5-year Win %		13.473
Rolling 10-year Win %		14.234

Table 26: out-of-sample results for exchange rates, with the extension of short sales. Transaction cost of 0.10 percent In-sample period of ten years, from January 1973 to December 1982 with the use of one month rolling window. The out of sample period is from January 1983 to December 2015.

Reflection note

In this thesis, we have tested the performance of moving average strategies, which is a popular method within technical analysis to predict future financial asset prices. Using complicated methods, we have compared the real-life performance of 3119 moving average strategies to the simple buy and hold strategy. More specifically, we have tested the market timing ability of moving average strategies in the stock, bond, commodity and currency markets using monthly returns pending from January 1971 to December 2015. We also extended previous research with new methodology by testing the out-of-sample performance of the moving average when a sell signal is a signal to short the underlying asset. In our research, we found statistical evidence to support good performance of the moving average strategies in the commodity and currency markets. For the bond and stock market, we were unable to find any evidence of good performance from the moving average strategies. For some assets, the moving average strategies even underperformed the simple buy-and-hold strategy.

The process of writing this thesis have been educational. I have learned to use complex programming methods in both R and Latex. We find previous subjects from our bachelor and master program necessary to be able to conduct the analysis and writing this thesis. Especially subjects on statistics, mathematics, finance, econometrics and method were important. I want to point out that the master program of finance could contain more programming and more practical finance courses in order to improve the relevance of the learning outcome.

Further in this reflection note, I will elaborate on how this topic relates to international trends, innovation and responsibility dimensions. To be able to do that, I will not focus on the specific moving average strategies, but the broader theme about technical trading and portfolio management.

Technical trading and portfolio management are influenced by international forces. The last decades the financial markets all over the world have become more interconnected through internet and globalization. In the recent years, it has become more publicly available to trade in financial assets across the world, which lead to a more globalized financial market. The globalization leads to dependencies between the financial markets which was observed when the American market collapsed, and lead to a worldwide global financial crisis. Another international force by the growing technology development is that the market information is constantly available to all interested financial analysts. With tons of financial information available for all, one can argue for the efficient markets, but I still believe it exists a potential of profit opportunities, if one is better than others to process the most relevant information.

I believe that technical trading and portfolio management will be influenced heavily by innovation in the coming years. Traditional day-trading is on its way out, and new trading strategies are coming in. One of them is algorithm trading, sometimes also referred to as trading robots. New technology has made it possible to set parameters for when a stock (or other securities) is to be traded. Using computer programs and algorithms, regular traders can perform thousands of orders per second. Another new form of trading is the social trading. Social networks have changed both the way we communicate, but also the information processes. The concept of social trading is that one can see live, who trades in what and when. You can for example, as a hobby investor, follow the best performing traders.

Technical trading and portfolio management also relate to responsibility. A recent ethical dilemma was just brought up to court where a student and a day-trader manipulated a trading robot to generate profits. This brought up the questions if it is legal to be smarter than an automatic algorithm trading robot. They were both convicted, but is that fair? Another relation to responsibility is that many people who invest in shared investment such as mutual funds, do not have the insight to know what is good and what is not. There is a lot of examples when financial advisors have advised expensive funds, and put themselves and their incentives in front of the costumers needs. Further, most studies on the moving average strategy provides positive results regarding the performance, which may be one of the factors of why the strategy increase in popularity. What is for sure is that the performance of the strategy is uneven over time and between assets. The ethical dilemma arises when institutions and practitioners promise improvement in peoplesâ investments by using such strategies, when the strategy in some cases even underperform the buy and hold strategy. I believe that the topic is highly relevant today, there are large amounts of money managed by portfolio managers, and portfolio managers should handle others equity with responsible manners.