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Bachelor's Thesis

Financial Behavior and the Momentum Strategy

Authors:
Emil Eliasson
Olle Josefsson
Fredrik Thörning

Supervisor:
Maria Gårdängen

Lund University
School of Economics and Management

Group 14
Department of Business administration
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Abstract

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Authors: Emil Eliasson, Olle Josefsson, Fredrik Thörning

Advisor: Maria Gårdängen

Key words: Behavioral Finance, Momentum Strategy, CAPM, Sharpe Ratio and Trading

Purpose: The authors of this thesis aim to study if it is possible to generate a better Sharpe ratio within the CAPM-theory using a mathematical model to buy and sell a risky asset depending on the market volatility. The authors then aim to explain the changes in volatility by discussing anomalies in the market.

Methodology: In order to fulfill the purpose and to answer the research questions, the methodology of this thesis is heavily based on a mathematical algorithm. The algorithm is set to trade a hypothetic portfolio in order to generate a better result than the index. With primarily the non-traditional theories mentioned below, the result is then compared with the chosen indices.

Theoretical perspectives: Theories used in this thesis can be divided into traditional and non-traditional theories in economics. The traditional perspective is represented by the Efficient Market Hypothesis, EMH, and the Capital Asset Pricing model, CAPM. The non-traditional theories are Behavioral Finance and Herd Behavior.

Empirical foundation: The empiric analyzed in this thesis is based on the performance of the algorithm and the two indices Dow Jones Industrial Average and Standard and Poor's 500. The analyzed period is from the beginning of 1998 until the end of 2017.

Conclusions: The algorithm is able to gain a better Sharpe ratio than the market index on Standard and Poor's 500 but not on Dow Jones Industrial Average. The authors found the cause to be an unreasonable high volatility on Dow Jones Industrial Average in the year of 2000 and 2016. This forces the algorithm to execute unnecessary trades and therefore gain a weak return due to transaction costs.

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Contents

List of Abbreviations

CAPM	**C**apital **A**sset **P**ricing **M**odel
CML	**C**apital **M**arket **L**ine
DJIA	**D**ow **J**ones **I**ndustial **A**verage
EMH	**E**fficient **M**arket **H**ypothesis
IT	**I**nformation **T**echnology
S&P 500	**S**tandard **&** **P**oor's **500**
VIX	**V**olatility **I**nde**x**

Chapter 1

Introduction

1.1 Background

Last year (2017), Richard Thaler was awarded The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel (also known as the unofficial Nobel prize in Economic Sciences) for his contributions within behavioral finance. The motivation from the Nobel committee was "By exploring the consequences of limited rationality, social preferences, and lack of self-control, he has shown how these human traits systematically affect individual decisions as well as market outcomes." (Nobelprize, 2017). Thaler himself describe that the most important impact of his research is that economic models have to considerate that economic agents are humans and that humans are not always rational.

It is interesting with a Nobel Prize winner who is researching the human behavior in relation to economy. Former Nobel prize winners have had research subjects that are closer related to classic economy as taught in academia. In our education we are taught economic theories and models that assume people are rational in their decisionmaking, but here we have a Nobel prize winner who believe otherwise.

How does Thalers work and theories fit into what we learn in the university about financial markets? We learn that markets are efficient, people are rational and according to CAPM there is no need for stock-picking since you can not over-perform the market anyway. If one agrees with Thaler that economic agents are human and humans are not rational, how can an investor take this into consideration? Should you try to time the market knowing that sometimes the economic agents on the market are acting irrational? As an investor you want to make the best possible return to the least amount of risk. In finance, risk is usually measured by the variance or standard deviation of the price. If one could anticipate when the market agents are acting irrational and only be invested in the market when the risk is low, one could possibly gain the same return at a lower risk.

1.2 Problem Statement

The Efficient Market Hypothesis (EMH) is described by Fama (1970) as the price of the market always captures all the information available at the time. The price of an asset is always the correct price and adjusts as new information becomes available at the market. According to this theory there is no use for an investor to waste time on reading information already known to the market in the hope of gaining a return higher than the market return. In other words, there is no use for an investor to invest their money in no other asset than the market portfolio.

Another model, within the same area as the EMH, is the Capital Asset Pricing Model (CAPM). According to Sharpe (1964), the rate of return an investor can expect from investing with a certain amount of risk can be calculated by forming a portfolio of the market portfolio, with expected return $\mathbb{E}[r_m]$, and a risk free asset with return r_f:

$$\mathbb{E}[r_p] = (1 - w) \cdot r_f + w \cdot \mathbb{E}[r_m], \tag{1.1}$$

were $0 \leq w \leq 1$ determines the portion of the available capital invested in the risky asset, the market portfolio. The linear dependence, also refereed to as the capital market line (CML), determines all possible combinations between the risk free asset and the tangent of the efficient frontier. According to the theory, every investment amongst the CML will have the same Sharpe ratio. The derivative of the line is constant. A higher return can then only be achieved if the investor is willing to cope with more risk.

For the theory to be true the Sharpe-ratio of the market portfolio has to remain constant in time, or the incline of the CML will change. As the Sharpe ratio consists of both expected return and risk, none of the two are allowed to vary over time according to the model. It has however been argued, for instance by Cont (2001), that there are empirical results of stylized facts in the stock data that do not agree with the risk being constant. It has been observed that the volatility varies over time and days with high volatility tend to come in waves, forming what is known as volatility clustering.

Why this is the case is not something that gets explained by none of the two theories. To study the financial markets in new light, psychological theories among behavioral finance is a well-fitted choice. Since humans not always are rational, it is not realistic to use theories that stand on the fact that all investors are so (Barberis and Thaler, 2005, p. 1). Within this field, also the theory about herd behavior may be an important theory to understand what happens on the market when it experiences volatility clustering. According to the theory, investors do as other investors do instead of what their own gut feeling or quantitative analysis tells them to do. Prior research within this field has declared herd behavior as one important factor behind investors irrational overtrading (Barber and Odean, 2000).

Theories as the CAPM and the EMH have been dominant within financial research for decades. However there is empirical evidence disproving the models. Since both of them deny the existence of market-anomalies, none of the theories describes the possibilities to trade within them. Instead, the two theories state that it is not possible to beat the market by getting a higher return without increase the level of risk. If those two theories were strictly correct, the market-portfolio would always perform better than investors trying to stock-picking in the long run.

According to an article in Business Insider, a comparison between the American index Standard and Poor's 500 and the well-known investor Warren Buffets company Berkshire Hathaway shows an interesting fact. From 1964 until 2015, the S&P 500 increased its value by 2 300 %. During the same period, Berkshire Hathaway manages to increase its market value by 1 000 000 % (Kiersz, 2016). These results strongly suggest that it is possible to gain a much higher return than the market portfolio. How much risk they took to increase their value by this much is not something that appears from the article and even CAPM supports the fact that it is possible to gain a higher return as long as you take a greater portion of risk (Sharpe, 1964). An interesting thought is however if it is possible to keep the level of return at a lower risk level. This will in turn imply a higher Sharpe-ratio on the investment.

The fact that the variance is changing over time and that periods with higher volatility tend to occur in waves will imply that the Sharpe ratio and thereby the incline of the CML, figure 1.1, to change over time. If the incline of CML changes over time and one is able to predict these changes. It could be profitable to change the portfolio weight, w, over time as well. At times when the risk is lower, it would seem to be more profitable to invest a larger portion of the available capital in the risky asset. At times when the risk is larger, a tinier portion of the capital would be invested in the risky asset in order to prevent huge losses.

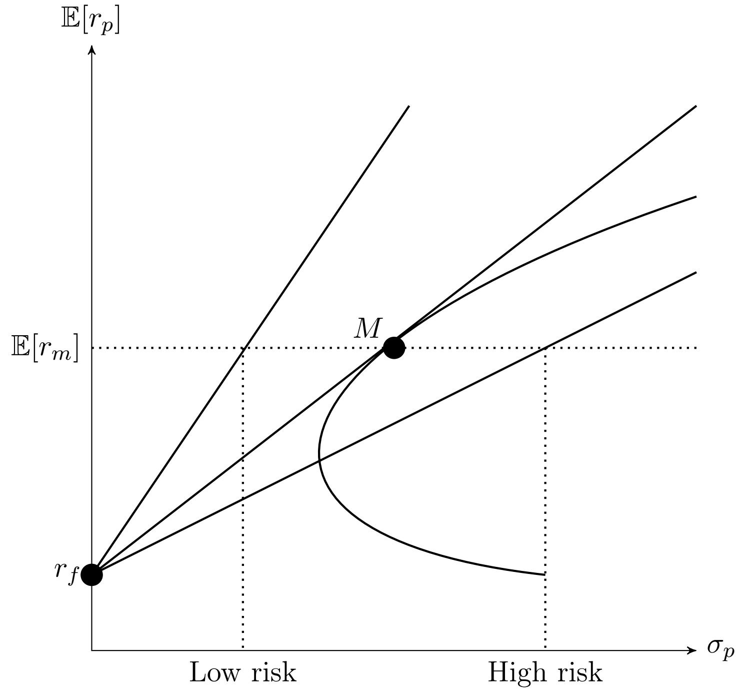

FIGURE 1.1: Capital Market Line (Sharpe, 1964, p. 432). The incline will change as the current volatility in the market varies.

One way to achieve this may be to use the algorithm developed by Eliasson and Hamlin (2018). The algorithm is built on a momentum strategy where the portfolio consists of the same assets as in CAPM, a bank account at a risk free interest rate and an investment in the market portfolio, which could be represented by a broad index. When the market is expected to be volatile, all the money is supposed to be invested in the bank account. When the market on the other hand is characterized by less volatility, all the money should be invested in the index.

1.3 Research question

- Can one gain a better risk adjusted return, in terms of Sharpe-ratio, by anticipating when the market contains more risk and avoid being invested in the market portfolio during these periods of time?
- How do theories within behavioral finance explain the anomalies observed in the financial markets?

1.4 Purpose

The authors of this thesis aim to study if it is possible to generate a better Sharpe ratio within the CAPM-theory using a mathematical model to buy and sell the risky asset depending on the market volatility. The authors then aim to explain the changes in volatility by discussing anomalies in the market.

1.5 Limitations and Scope

This study is limited to only study and analyze the two indices DJIA and S&P 500. It would be possible to also cover other or additional indices to answer the purpose of the study. We have decided to use those two indices since they cover a wide range of companies. The theory of CAPM makes use of a market portfolio and the chosen indices are commonly used to represent the market portfolio making them suitable for this thesis. Another limitation of this study is that we have started measuring the performance from 1998. The reason for this is that we consider this to be a timeframe wide enough to get a good result and contain both bull and bear periods to analyze. Another factor is that it is most recent events that are interesting today and is more likely to represent future market conditions.

1.6 Target Group

The target audience for this paper is persons in academia with a basic understanding of financial economics. Other groups who might find the paper interesting are investors or traders who have a non-academic perspective on markets and want to get another perspective on how to interpret market changes and how to understand them.

Chapter 2

Theory

In this chapter the authors will introduce the theories used in the thesis, which are relevant for the reader to better understand the subject. First the fundamental theories of EMH and CAPM will briefly be described so the reader can refresh their knowledge about these theories. Then, an introduction to the algorithm used to trade follows. The algorithm used is a momentum strategy model to predict future market conditions and the implications of these. The algorithm will only trade indices futures, which usually are good approximation of the market portfolio and therefore will be suitable for the purpose of this thesis. Especially since the market portfolio is used in the CAPM-model. A definition of bear and bull market will be made, as this is fundamental for the trading algorithm as a way of identifying the future market risk at a given day. Lastly, a background on theory of behavioral finance and herd behavior will be presented.

Some parts of this chapter, especially the introduction to the algorithm can be considered quite technical. However, the reader should not fear, as this will not be the main focus of the thesis.

2.1 Definition of Risk Measure

Financial risk can be measured in various numbers of ways. As this thesis aims to improve CAPM developed by Sharpe (1964) it is reasonable to use the same measure of risk. In the article by Sharpe (1964) risk is defined as the volatility, σ, in a financial return series. When the authors of this thesis therefore mention risk it should be understood that this would be the same as the volatility in the market. The risk-adjusted return is therefore defined by the Sharpe-ratio, S_p, which measures the return in the relation to the volatility of the portfolio (Sharpe, 1964, p. 438):

$$S_p = \frac{\mathbb{E}[r_p] - r_f}{\sigma_p}. \tag{2.1}$$

The volatility, σ_p, is measured as the standard deviation of the daily log-returns of the portfolio. The expected value of the portfolio return, $\mathbb{E}[r_p]$, is measured as the mean of the daily log-returns. The two measurements will be used to calculate the average daily Sharpe-ratio, S_p, during the measured period. In this thesis, the annual Sharpe-ratio will be used instead of the daily. The annual Sharpe-ratio is though easily achieved from the daily by multiplying with $\sqrt{252}$, which is the number of trading days per year.

The daily log-return, r_t at time (or day) t, of the portfolio can be calculated given the price of the asset, P, as:

$$r_t = \log(P_t) - \log(P_{t-1}). \tag{2.2}$$

To give the reader a slight intuition for why the log-returns is used instead of ordinary returns one is asked to consider the following toy example: An asset alternates in price between \$50 and \$100 each and every day. The ordinary daily returns, $\frac{P_t - P_{t-1}}{P_{t-1}}$, will then alternate between going down $-50\,\%$ and up $100\,\%$ every other day. The arithmetic average of this return series will yield that the asset on average will have gone up by $\mathbb{E}[r] = 25\,\%$, which we know to be an unrealistic performance given the change in price. In the logarithmic scale the returns will alternate between -0.6931 and 0.6931 yielding an average of $\mathbb{E}[r] = 0$ which will correspond to the actual return in sheer dollars.

2.2 Definition of Bull and Bear Market

The trading-strategy represented depends on the market switching between two states, bull and bear, it is then reasonable to present a definition of the two as they are used in this thesis. Traditionally the bull state implies an optimistic market and the bear state a pessimistic market. The trades of the market portfolio will be made on the incline of the CML, or value of the Sharpe ratio. As argued, the incline will change over time as the volatility will not remain constant, which has been empirically observed in the market by Cont (2001) and others. Since the trades will practically be made on the measured volatility the authors wish to define the state of bull- and bear markets based on volatility as well. Figure 2.1 shows the implied volatility, measured by options on the S&P 500 stock index, also known as VIX.

At times when the volatility is high, the market will be closer to a bear state than a bull state. An example, based on the figure, is between 2008-2010 where the market would be defined as a bear market. The opposite will occur when the volatility is lower. It is worth noting, that there is no explicit value of the volatility where the algorithm decides to switch between a bull and a bear market but the limit is a scale between the lowest measured volatility and the highest. It is, for example, possible for the market to be in a 30 % bull state and 70 % bear state at a given day. As the market states are based on the volatility it will not purely be estimated as when the markets is inclining and declining. The bull market, with a low volatility, will be characterized by a slow and steady growth and the low volatility means that the returns, and thereby the gains and losses, will be small. An unstable market with high volatility will characterize the bear market. The instability in the market means that the losses, but also the gains, in the market will be large.

It is however the case that a low volatility is often a sign of an incline in the market and a higher volatility is a sign of a decline. This is the reason why a slow and steady growth, with low volatility, can be seen as an optimistic bull market. The more unstable and jittery market, with higher volatility, can thereby be seen as the pessimistic market when no one is sure of the value in the market, which often implies a drop in the market portfolio (Maheu and McCurdy, 2000, p. 108).

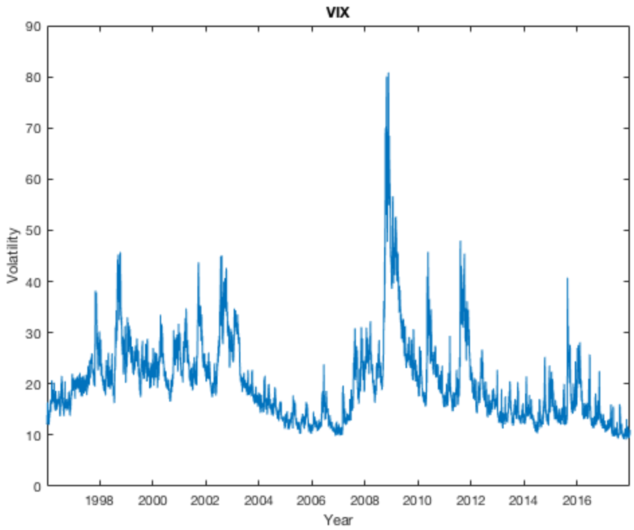

FIGURE 2.1: The estimated volatility between 2 Jan 1998 and 29 Dec 2017 on the S&P 500 stock index (Bloomberg, 2018).

2.3 Efficient Market Hypothesis

The efficient market hypothesis further EMH, builds on the assumption that the market price reflects all known information. In this way, a market can be called efficient if the price in fully reflect the information (Fama, 1970, p. 383); (Brown, 2011, p. 80). According to the theory, it is not possible for any investor to perform better than the market over time. If this is the case, all time and resources spent on stock picking and analyzing different stocks are wasted. To maximize profits, it is better to just hold the passive market portfolio since it is not possible to beat the market (Shleifer, 2000, p. 1).

When the hypothesis first was expressed by Fama (1970), there were doubts about its complete truth. Tests were divided into weak, semi-strong and strong to make it possible to get the bigger picture. The weak and semi-strong tests showed not doubts for the hypothesis reality and there were only limited objections from the strong tests (Fama, 1970, p. 388)

A strict interpretation of the theory implies that information asymmetry does not exist in the market. No investor can have more information than another (Brown, 2011, p. 82). The strict version of EMH neither allows transaction costs (Brown, 2011, p. 80). In his review 1991, Fama, the founder of EMH in 1970, agrees to falsify the strict version. At almost all times, some sort of trading costs exists which indicates that investors have to pay a higher price than the stocks real value (Fama, 1991, p. 1575). On the other hand research done between Famas both articles about the EMH still supports the hypothesis in some form. According to Fama, the market responds quickly to information that is specific to one firm (Fama, 1991, p. 1607).

2.4 Capital Asset Pricing Model

To enable the use of CAPM, Sharpe (1964, pp. 433-434) pinpoints two assumptions. First, there must be a risk-free interest rate to which all investors can borrow money. There must also be some homogeneity in the assumptions and expectations among investors. If those two assumptions are overlooked, the result from using the model will not be satisfying or correct. Prior models to calculate price and expected return did not include any premium from risk. In the Capital Asset Pricing Model (CAPM), Sharpe included risk. According to his theory, if equilibrium is reached, the relation between expected return, $\mathbb{E}[r_p]$, and risk in form of standard deviation, σ_p, is linear (Sharpe, 1964, p. 436). According to the theory about Capital Market Line (CML), a rational investor can only gain higher return if he is willing to take a greater portion of risk (Sharpe, 1964, p. 425):

$$\mathbb{E}[r_p] = r_f + \sigma_p \frac{\mathbb{E}[r_m] - r_f}{\sigma_m} = r_f + \sigma_p \cdot S_m. \tag{2.3}$$

When an investor follows the line, he gains two different returns. According to the first part of the model, the investor is given a return for the time he is giving up his money. This return is represented by the risk-free interest rate, r_f. The other return comes from the risk-premium. This part rests on the investments beta, β, and the difference between the expected return in the market and the risk-free interest rate (Sharpe, 1964, p. 425). Beta is a measure of how the stock has performed in relation to the market based on historical values (Kim and Kim, 2016, p. 268):

$$\mathbb{E}[r_{\text{stock}}] = r_f + \beta(\mathbb{E}[r_m] - r_f). \tag{2.4}$$

The risk-premium included in CAPM is not a measure of the total risk. Since the firm-specific risk can be avoided through diversification, which all rational investors are doing, this is not something that will give the investor a premium (Sharpe, 1964, p. 426).

2.5 Behavioral Finance

Behavioral finance gives a new perspective on how to analyze financial markets. Instead of only consider the traditional economical theories, this perspective also includes psychological aspects (Krishnan and Beena, 2009, p. 27). Behavior finance focuses on that sometimes, people are not rational at fully (Barberis and Thaler, 2005, p. 1). Another thing that the theories of behavioral finance can help explain is why there is so much trading in the market. According to Barberis and Thaler (2005, p. 53), there is much more trading on the market than what can be considered rational. Other research concludes that more trading might lower the return. Transaction costs and bid-ask spread are only partly explanations according to their results. Additional explanations suggest that the new investments performed worse then the ones they had at the beginning (Barber and Odean, 2000). Behavior finance explains this lack of rationality with overconfidence. Traders and investors are overconfident and believe that they have more information and knowledge than the market. This makes them buy and sell even when it would be more rational to refrain (Barberis and Thaler, 2005, p. 53).

When it comes to which stocks to buy or sell the markets behavior are not rational. Research suggests that even though it is more rational to sell prior losers instead of winners with purpose to avoid taxes, investors tend to do the opposite. When we are buying stocks, we tend to buy the first one that draws our attention instead of searching through all the lists. Both these cases are irrational behavior that cannot be explained with traditional theories. Behavioral finance explains it with an irrational belief that the stock will return to prior levels (Barberis and Thaler, 2005, p.54-56). With a traditional economical perspective, it is not possible to explain the difference between market value and fundamental value. According to a economical perspective, there should not be any difference between the prices. While using a broader perspective, it becomes clear that the reasons are based in psychology and cognitive thoughts (Krishnan and Beena, 2009, p. 27).

According to the research by Kahneman and Tversky, humans are more concerned about their eventual losses than their potential gain. Research suggests that some investors prefer a stable state were the value do not chance instead of the risk of losing their money even if it means they will not gain anything either (Christiane Kleinübing Gogoi and daSilva, 2005, p. 47-49).

Other research presented by Kahneman and Tversky concludes that people's assumptions and references to how something will be are important to how we view the final result. If we expect to get money and we get less than we expect, we se it as a loss instead of a minor gain. If we on the other hand expect to lose money but in the end, we do not lose as much as expected, we see it as a gain, not a reduced loss (Kahneman and Tversky, 1979, p. 286).

2.6 Herd Behavior

The phenomenon with herd behavior might be seen as an extension or deepening of behavior finance. The theory sets focus to the fact that humans in some cases act like a big herd and imitate others. If one person goes to the left, it is more likely that also person two goes to the left. When it comes to investing, herd behavior may lead to a lot of investors invest in the same stock or sell the same security (Graham, 1999, p.237). A recently published study has shown that the presence of herd behavior may depend on the markets status. Under crisis or with extreme market conditions, the presence of herd behavior was significantly higher (Asma Mobarek and Keasey, 2014, pp. 125-126). At the same time, another study has shown that regarding IPOs, herding is more common if there is positive news and investors are buying a stock than if investors are selling it (Chao-Shi Wang and Chen, 2017, p. 271). If the investors have access to the same information, this might be the case anyway. There is a difference between consciously copying and a form of chance herding. Chance herding may occur in relation to big changes in the interest rates or after big news that relates to a whole sector (Bikhchandani and Sharma, 2000, p. 281-282). For actions to actually be herd behavior, it requires one of two following criteria's. First, it might be if an investor was alone and without contact with the surrounding, she would not have invested in the stock. But since she knows that a lot of other reputed investors are buying the stock, she does so too. The other scenario is if she had planed to fulfill and investment but refrain since she realizes others wont make the same investment (Bikhchandani and Sharma, 2000; Scharfstein and Stein, 1990, p. 280, p 466). Potential consequenses from herd behavior is extended volatility and increased instability on the market (Asma Mobarek and Keasey, 2014, p. 107).

Bikhchandani and Sharma (2000) suggests three potential explanations to why and how herd behavior occurs. Those are information-based herding, reputation-based herding and compensation-based herding. Information-based herding comes from the theories about information-asymmetry, which means everyone on the market does not have the same access to information. In this case the follower believes someone else has more information about the future return of a stock. According to information-based herding, the follower will copy the first investor's strategy (Bikhchandani and Sharma, 2000, pp. 280-290). Herding based on information asymmetry may also occur when there is so much information on a market for a single investor to handle. When this is the case, investors tend to ignore the facts they actually can manage and instead connects to the herd. This is the reason why cascade liking domino effect can happen on a well-informed market (Graham, 1999, p. 239).

The reputation-based herd is based on career and reputations of investors. No one wants to be the person who sold the stock that everyone else was buying if it later shows that it was a bad decision to sell. The consequences of being the only loser are greater than the gain of being the only winner. Investors therefore prefer to do as others to get protected by the herd. Not only the follower's gain from copying, also the first investor's reputation gets the protection when others are following (Bikhchandani and Sharma, 2000, pp. 290-292). Prior research suggests the same thing. According to Scharfstein and Stein (1990), a bad decision will not have any greater impact on an investor's reputation as long as many other investors did the same investment. Those investors who exclusively care about their reputation will always herd and stay protected of the mass (Scharfstein and Stein, 1990, p. 475).

The third reason why herd behavior occurs is based on how the investor gets compensated. If the compensation not only is based on how the investor performs, but also how she performs in relation to others, herd behavior is more likely. If the investor copies the benchmark, she can not perform worse than the comparable investor which means she wont get less paid. On the other hand she will not perform better either. In order to minimize risks, herd behavior might be the best strategy (Bikhchandani and Sharma, 2000, pp. 292-293). As the career of an analyst evolves, it is likely to assume that also the wage of the analyst increases. The incentives to use herd behavior is therefore likely to be greater among more experienced analysts and investors. When a well-known analyst connects to the herd, her name might also be a trigger that gives the snowball more strength (Scharfstein and Stein, 1990, p. 476).

2.7 Mechanisms for Volatility Clustering

The algorithm used in this study is based on the empirical observed fact of volatility clustering in financial time series. The following sections are intended to supply the reader with a more theoretical base for why volatility clustering appears in financial markets. The fact has been discussed by Cont (2007, p. 8) who builds an artificial financial market consisting of simulated investors trading in the same market, represented in figure 2.2. Each investor has to choose between buying the asset, selling the asset or to do nothing. As every investor is allowed to interact with others, their choice will be affected by the choice of others. Say that the first investor (gray in the figure) chooses to buy the asset. The investor will then interact with two other investors (represented by arrows) yielding a significantly higher probability of them buying the asset as well. These investors will then interact with other investors as the process continues. The behavior give rise to what we above described as herding and herd behavior. The simulations tested yielded similar returns in the simulated market as empirically seen in true market returns (Cont, 2007, pp. 8-10).

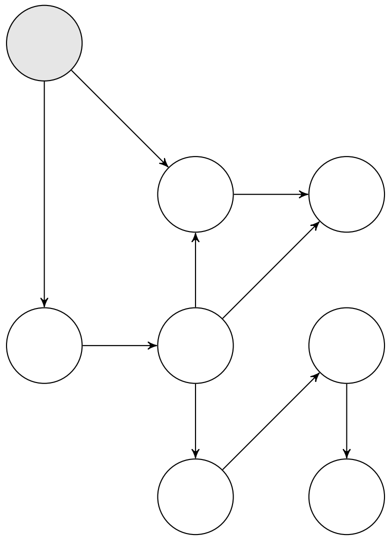

Figure 2.2: Model of simulated investors interacting with each other. Drawn with inspiration from Cont (2007).

2.8 Algorithm

The algorithm used for robotic trading using a momentum strategy in this thesis is heavily based on research by Nystrup (2017) later developed by Eliasson and Hamlin (2018). The following section is meant to give the reader a slight introduction and a brief understanding of the thoughts behind the algorithm. The algorithm will therefore not be explained in full detail and anyone who may be interested in further details are referred to the articles written by Nystrup in his PhD thesis.

The momentum strategy imposes the trader to buy an asset that has a history of yielding a strong return and to sell assets with a history of weaker returns. In this case, the risky asset will consist of the market index. Using this methodology one may assume that assets are continuously switching between two states, one good where you buy the asset and one bad where the asset is sold, namely a bull- and a bear state.

Nystrup, Madsen, and Lindström (2015) argue that the log-returns of a financial time series can be approximated with a normal, or even better, a student t-distribution. Moreover the log-returns will be symmetric around the mean just as the normal and Student's t-distributions are. In this algorithm the returns belonging to the bull market will be assumed to be normal distributed and the returns of the bear market will be assumed to be Student's t-distributed. As mentioned, these distributions will help the algorithm decide if the market is in a bull state, bear state or something in between. The way to achieve this is to estimate the probability of being in the respective state given how well the previous return will fit the distribution in the different states (Baum, 1972, p. 3). To clarify, the reader is asked to consider the following example: The algorithm has estimated the two distributions in figure 2.3. If the price does not move from one day to the next the return will be $r = 0$. The market condition can then be estimated by how well this particular return will fit in the estimated distributions. From figure 2.3 one are able to see that this particular return is more likely to belong to the bear market than the bull. Further investigations will show that the market is at a 94 % chance of being in a bear market and a 6 % chance of being in a bull market on this particular day.

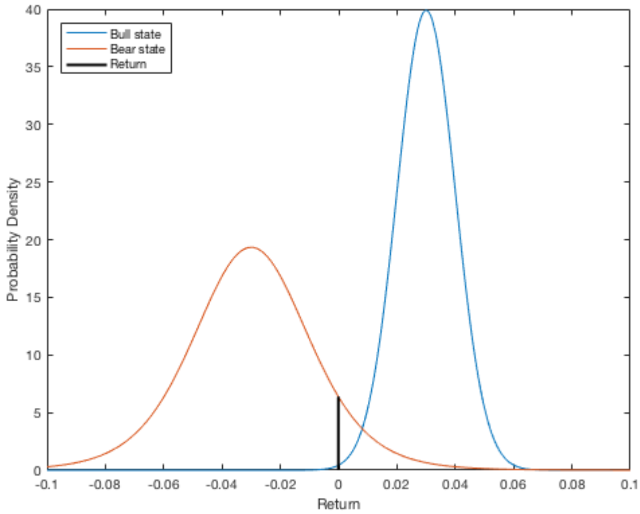

FIGURE 2.3: Illustration of the two distributions and a zero return.

The knowledge of the state the market is currently in gives the algorithm a good chance of making accurate prediction of the market return the next day. Estimations of the future returns from the two distributions, $\hat{r}_{\text{bull}}$ and $\hat{r}_{\text{bear}}$, are to be calculated by the respective expected value. From the two returns, the return of the entire market, r_m, can be calculated. As an example consider the conditions above where the market is at a 6 % chance of being in a bull state and at a 94 % chance of being in a bear state the expected return of the entire market will be:

$$\hat{r}_m = 0,06 \cdot \hat{r}_{\text{bull}} + 0,94 \cdot \hat{r}_{\text{bear}}. \tag{2.5}$$

The future risk in the market, $\hat{\sigma}_m$, can be estimated in similar manner. Please note that the algorithm is able to make predictions for as many days in the future as the user would like. To be able to deal with a reasonable high uncertainty in the predictions made, the investor is recommended to keep the time horizon to just a few days or weeks (Nystrup et al., 2017, p. 3).

The next stage in the process is for the algorithm to decide how much of the available capital to invest in the risky asset. This is denoted by a portfolio weight, $0 \leq w \leq 1$, where $w = 1$ means to place all the capital available in the risky asset and $w = 0$ means to place the full amount in the bank account with a risk free rate, r_f. The algorithm is therefore not allowed to use any leverage or to short sell the asset. The future return of the portfolio, r_p, will therefore be:

$$r_p = (1 - w) \cdot r_f + w \cdot r_m. \tag{2.6}$$

In this particular model the risk free rate is assumed to be $r_f = 0$ for simplification reasons. The assumption is not assumed to be too unrealistic given current rates in the market. The weight is then chosen by maximizing a utility function, $\mathcal{U}(M)$, of the estimated market conditions. The utility function will in practice consist of the estimated future return with a penalty representing transactions costs and risk aversion.

Chapter 3

Method

3.1 Starting points

3.1.1 Limitations of the study

To make our study possible to actualize, we had a few delimitations to take into consideration. The first limitation concerned our strategy. In the beginning of this study, we decided to base the thesis main strategy on the algorithm we got access to from Eliasson and Hamlin (2018). To strengthen our results and the conclusions from them, we would have preferred to use a few different momentum strategies and algorithms. The recourses required to get access to more algorithms and to use them on our chosen index would probably not give this study the credibility that would motivate doing so. At the same time, one strategy is enough to show that beating the market is possible. The results gained from the algorithm will be enough to answer our question, which is the purpose of this thesis.

Another limitation with our study is that we only take two indices into consideration. The indices we choose was, as discussed above, Standard and Poor's 500 index and Dow Jones Industrial Average index. With those two indices, we still cover a lot of companies and different industries. To broaden the perspective, it would be interesting to include other indices from both the U.S but also from other parts of the world. The results from such a study could lead to a discussion about, if there were any significant, differences between continents and countries. Another interesting alignment would be to study a broad range of narrow and industry-specific indices. With that study, it would be interesting to se if there were any differences between different industries. But, as argued in the discussion about our choice of strategy, the purpose of this study will be fully answered with the two chosen indices. With our narrow focus, we will be able to put in more effort in areas that will generate a deeper analysis than what would have been possible otherwise. In our opinion, this prioritization is the most suitable for the purpose and the frame in which the paper is written without exceeding our resources.

The third identified delimitation detected concerns the mathematical part. In this bachelor thesis, the main focus is the financial sector and the financial perspective on the algorithms outcome. Therefore, we have decided to exclude thorough and detailed information and discussions about the mathematics behind the algorithm from the essay and instead limited us to a brief introduction. More details about the mathematical parts can be found in Eliasson and Hamlin (2018) for those who are interested. Since we use the same algorithm, our studies reliability will not be affected in any negative way.

Another limitation for our study concerns the timeframe under which the thesis is written. We will write the whole paper in around ten weeks. This limitation could have a negative effect on the quality on our writhing. As far as we concern, the quality of our results and analysis will not be affected by this. To secure high quality and trustable results, we have, as discussed above, limited the width of our research.

3.1.2 Validity

According to Bryman (2011, pp. 50-51), validity is defined how well the thing meant to be measured corresponds to the thing that actually gets measured. In our case, this will be if our strategy tries to beat the market or not. In this thesis, we will use two indices to represent the market. A further explanation to our indices is to be found bellow but in. The algorithm is created to buy and hold the index when it is in a bull-market and to sell the asset when it enters a bear-market. The data gained from the algorithm will help us see under which conditions the algorithm performed well and when it did not. This will help us understand and explain the conditions of the market.

3.1.3 Reliability

Reliability refers to the possibilities for other students or researchers to redo the study (Bryman, 2011, p. 49). Since all the details about the mathematical formula are to be found in Eliasson and Hamlin (2018), our opinion is that other researchers or students will be able to use this and create the study once again. In the previous chapter, we gave an introduction to the theories we are using to analyze the data. We have also described our interpretation on how we use the different theories. The same chapter also contains definitions of a chosen few concepts important to the study. In the next section, we will in more details go through the different steps we have made and motivate our different choices during this study. This can be used as a guide to those who have doubts in our results or with other purposes are interested in how our results and conclusions are generated.

3.2 Procedure

3.2.1 Theories

In this thesis, we are using the efficient market hypothesis and the capital asset pricing model to describe the common situation with traditional theories. To create and develop a good understanding of our subject, it is important to understand the models that are common in academia today. With the use of EMH we will gain a better understanding of how a market is to be considered as efficient. We will implement the theory in our analysis to consider however the market actually is efficient in line with the theory. Our second theory, CAPM will be used in a similar way. This theory will explain the traditional perspective on how to calculate the risk and expected return. By the use of CAPM we will be able to generate a deeper understanding for our used algorithm, which will be an underlying factor for how this thesis will proceed. The capital market line, generated from CAPM, explains how the algorithm is trading and in which market states it act in different ways. Those two theories can be seen as representatives for the traditional perspective on economics and finance.

We will use the newer theories about behavioral finance and herd behavior to implement a psychological perspective to our findings. According to Barberis and Thaler (2005), a psychological perspective is needed to explain some economical phenomenon. In our belief, our subject with market anomalies requires behavioral theories to fully explain and understand the phenomenon. With the theory about behavior finance we will implement Thalers psychological perspective about irrationality around human investors. To strengthen and deepen our analysis, we have decided to complement the area with a theory about herd behavior. Herd behavior will be the best fitted theory to explain volatility clustering according to both what it is and why it occur. Those two theories will gain a psychological perspective to our thesis and act as a contrast to the primarily theories thought in school and which we have explained above. They will also complete our thesis with a theoretical perspective on the results we expect to generate from the algorithm. With the theories we hope to explain volatility clustering and to generate a better understanding of what happens when investors act irrational and how it can be used to gain advantages over competitors.

3.2.2 Data

The data used in this thesis is collected from two large market indices, namely Dow Jones Industrial Average, figure 3.1, and Standard and Poor's 500, figure 3.3. Data is collected from 3 Jan 1928 to 29 Dec 2017 from the BLOOMBERG terminal, which is available to members of Lund University Finance Society, LINC. As the behavior of the algorithm too far back in time is neither interesting or applicable to the current market the actual trading of the algorithm will be tested for 20 years of time, 2 Jan 1998 to 29 Dec 2017. This is considered to be enough time to truly test algorithm through both bear and bull markets without make the whole thesis a historical overview. The rest of the data set, from 1928 to 1997, will therefore not be used for actual trading but merely to train the algorithm. The volatility index (VIX) is not used in the algorithm, as the volatility can be calculated directly from the return series. The index is used to illustrate the fact that the implied volatility in the market is varying over time. The data is collected from the BLOOMBERG terminal from 2 Jan 1998 to 29 Dec 2017. These two indices were chosen as both of them can be considered to be large and broad. It is also few indices in the world for which data is available for such a long period of time, which is preferred in order to train the model. This was the first factor we needed to consider when we chose from which indices to collect the data. The long time-period needed to train the algorithm excluded some other potential indices. In the two following sections, a brief introduction to the indices will follow.

Dow Jones Industrial Average

Founded 26 May 1896, the Dow Jones Industrial Average covers 30 blue-chip U.S. companies weighted by price. The index measures all sectors except utility and real estate (Spice, 2018a, p. 1). A sector breakdown of the index can be seen in figure 3.2

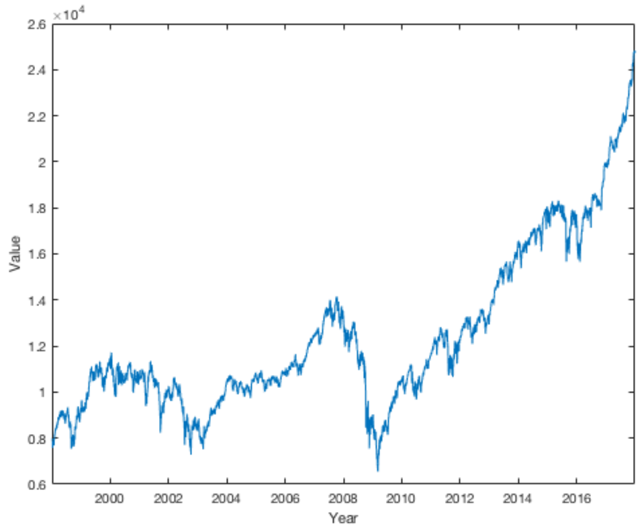

FIGURE 3.1: The value of Dow Jones Industrial Average between the periods 2 Jan 1998 to 29 Dec 2017 (Bloomberg, 2018).

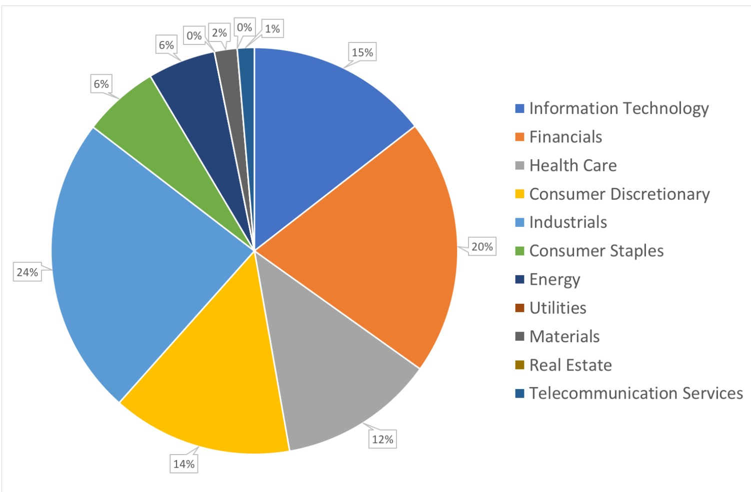

FIGURE 3.2: Sector breakdown according to the GICS standard for the Dow Jones Industrial Average (Spice, 2018a, p. 4).

Standard and Poor's 500

Founded in 1957, but with data collected from 3 Jan 1928, the S&P 500 stock index aims to be a broad index reflecting the entire U.S. market. The index contains 500 of the leading U.S. listed companies and reflects 80 % of the market capitalization (Spice, 2018b, p. 1). A sector breakdown of the index can be seen in figure 3.4

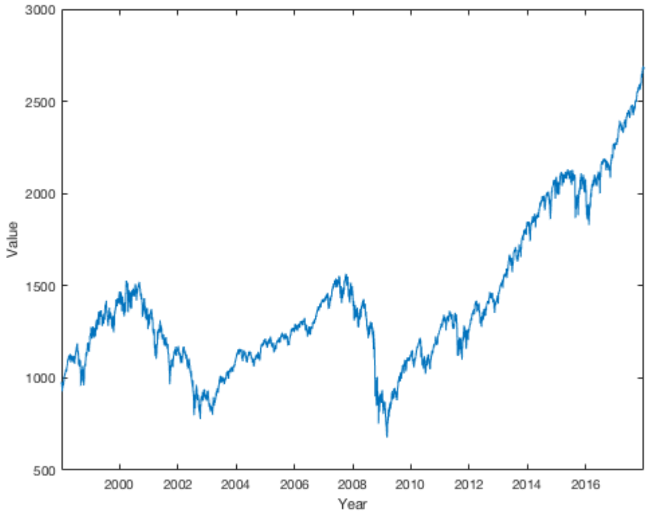

FIGURE 3.3: The value of Standard and Poor's 500 stock index between the periods 2 Jan 1998 to 29 Dec 2017 (Bloomberg, 2018).

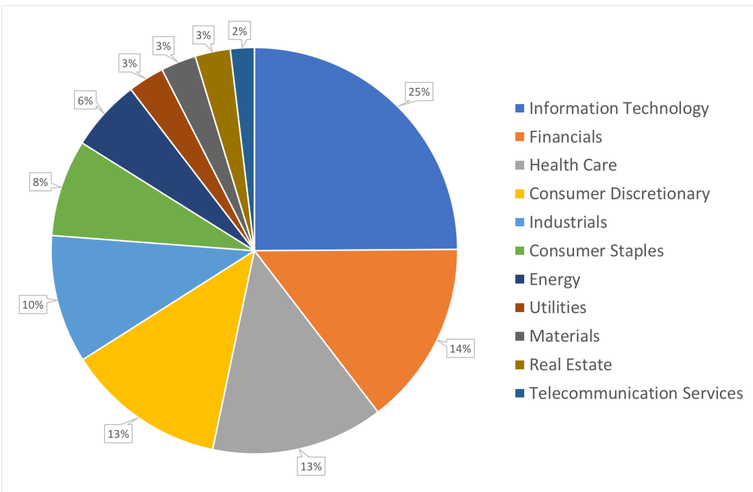

FIGURE 3.4: Sector breakdown according to the GICS standard for the Standard and Poor's 500 stock index as of 29 March 2018 (Spice, 2018b, p. 4)

Indices

The largest difference between the two indices it their size and the way a stock enters or exit an index. As mentioned above, S&P 500 statically contains the 500 most traded companies. DJIA on the other hand uses a committee, which unregularly selects which stocks that should be included (Simons, 2015, p.42). Our hope with those two indices is to have two indices that are constructed in the same market which makes them active under the same conditions. Our belief is that this will create a greater analysis since we will be able to exclude a lot of country-specific activities that otherwise may have affected the results. Most of the companies in the DJIA are also represented in S&P 500. This makes us consider S&P 500 as a broader form of DJIA where only a chosen few of the largest companies are represented. In our analysis this might generate an interesting twist where we will be able to discuss the results with base in these differences. Another factor for making those indices relevant for the study is that both of them cover a large range of industries. Since both indices consist of American companies, we will be able to exclude national differences among our analysis.

Algorithm

The exact algorithm used in this thesis is developed and described by Eliasson and Hamlin (2018). The algorithm can be configured to behave differently in different market situations to fulfill the special requirements of the individual investor. The choices may imply a certain risk- or trading aversion in order to reduce the annual turnover of the portfolio. None of the two are considered in this thesis, as they are not assumed to contribute to the discussion. However, the cost of trading is included with 10 basis points (0.1 %) on the size of the trade, assumed to be reasonable for an institutional investor (Nystrup et al., 2017, p. 15). By including costs for transactions the authors aim to make the results of the thesis more applicable to real market conditions. The algorithm only trades index futures and not individual stocks motivated by its use in CAPM (Sharpe, 1964, p. 435). The portfolio is set to be in long-only mode. This implies that the portfolio is not allowed to use leverage or to short sell the traded asset (Eliasson and Hamlin, 2018, p. 27-28).

Using these settings the algorithm will only trade on the expected return in the market. If the return of the market is calculated to outperform the risk-free rate all the capital will be placed in the index future. If the opposite occurs, the return of the market is calculated to underperform the risk-free rate all the capital will be placed in the bank account. As the risk-free rate is assumed to be $r_f = 0$ in this thesis the algorithm will trade on whether the expected return of the market is expected to be positive or negative. In order to connect the statement to previous discussion about the algorithms calculation of the market state, the algorithm does also calculate what the implication (expected return, volatility, etc.) of the respective state is (Eliasson and Hamlin, 2018, p. 4). The estimates are allowed to vary in time in order to represent the most recent market conditions, but for the most part the bull state is estimated with a positive return and low volatility and the bear state with a negative return and high volatility (Eliasson and Hamlin, 2018, p. 29). To state an example from figure 2.3 in the theory, the estimated market returns were $\hat{r}_{\text{bull}} = 0.03$ and $\hat{r}_{\text{bear}} = -0.03$ in addition to the probability of 6 % of being in a bull state and 94 % of being in a bear state. The estimated return of the entire market the following day will then be:

$$\hat{r}_m = 0.06 \cdot 0.03 + 0.94 \cdot (-0.03) = -0.264$$

which is negative, lower than $r_f = 0$, and the portfolio will therefore be traded to consist of cash only.

It should be noted that even if the algorithm execute trades based on the expected return, the trades are still related to the volatility in the market as stated before. Since the volatility in the bear market is higher than the bull market, returns with a high variance will be estimated as bear returns. Afterwards the future returns will be calculated as negative and not the other way around. In this way the future returns are more so calculated from the current volatility in the market rather than if returns are positive or negative. To get a bit more technical and elaborate on the explanation from the theory, the state of the market is estimated from how well the past returns fit the two distributions for the bull and bear state. As the distribution for the bull state has a positive expected value, the predictions made from this will be positive. As the distribution for the bear market state has a negative expected value the predictions made will be negative. Moreover, as the distribution for the bull state has a low variance, past returns with low volatility will better fit this distribution. As the bear state distribution has a higher variance, past returns with higher volatility will better fit this distribution.

One drawback with the portfolio being allocated to be fully invested in the market or bank account and nothing in between is the scenario when the market is going sideways. If the algorithm is unsure if the market is in a bull or bear state the estimated expected return will fluctuate around zero activating huge and unnecessary trades making the portfolio loose capital due to transaction costs. This may for instance happen just before a financial crisis erupts (Eliasson and Hamlin, 2018, pp. 35-37).

3.2.3 Bubbles

To mediate a deeper understanding on our results and to better understand why the results are as they are, we have chosen to describe the three most result-affecting periods in more detail. All of the periods are characterized and of us described as bubbles that have burst and made the market change from bull state to bear state. Our belief is that we by analyzing those periods in detail will be better equipped to understand the results as a whole. The first bubble, the dot-com bubble primarily affected the Information Technology sector with only minor corrections in other sectors. The bubble still had a notable effect on our indices (Anderson, Brooks, and Katsaris, 2010). The containment to this sector kept the whole financial system intact. This crisis was therefore minor in comparison to the housing bubble where the whole financial system faced a potential collapse and all sectors were affected (Acharya et al., 2009, p. 94). The third bubble analyzed in this thesis is the one that happened in the Chinese market who created turbulence across the worlds financial markets. The crash in the Chinese market did create turbulence and higher volatility in both indices as well, which therefore had an impact on the results that motivate a deeper analysis (Fang and Bessler, 2018).

Dot-com Bubble

The dot-com bubble is known to have burst in 2000 (Anderson, Brooks, and Katsaris, 2010, p. 347). The boom came from speculative investments in IT as the Internet was quite a new phenomenon. The Internet was regarded to change the very fundamentals in the business models for all companies implying these companies could not be evaluated using standard pricing techniques, such as the DCF-method. The companies were mostly active in the Technology Information sector leading to a huge growth in the sector during the boom (Anderson, Brooks, and Katsaris, 2010, pp. 347-349).

Today, it seems obvious that there was no reason for the pricing of these companies to be higher than ordinary pricing methods would imply and the bust eventually came. The Technology Information sector suffered the most from the fall but minor adjustments also affected other sectors (Anderson, Brooks, and Katsaris, 2010, pp. 347-349).

Housing Bubble

The subprime crisis in 2007-2009 started in the U.S. but affected the whole world. The cause of the bubble was that the American housing market turned in 2006 (Acharya et al., 2009, p. 89). The American mortgage industry was built from subprime mortgages with balloon interests continuously refinanced to avoid jumps in the interest rate. The refinancing was built on the assumption that housing prices would continue to appreciate (Acharya et al., 2009, p. 89). As financial institutions relied quite heavily on this assumption a circle of evil was triggered when the housing prices started to decline. When the bubbly assets started to decline the institutions faced a margin call to sell the assets depreciating the value even further, making the financial sector face enormous losses (Acharya et al., 2009, p. 90).

The investment banks were heavily leveraged in the subprime mortgages, which in turn made the losses large enough to make Lehman Brother's file for bankruptcy in 2008 (Acharya et al., 2009, p. 93). As Lehman Brother's were one of the largest investments banks in the U.S. the bankruptcy led to the risk of collapsing the entire financial system. The systematic risk is what made this financial crisis so great (Acharya et al., 2009, p. 94).

China Bubble

From June to August 2015, the Chinese stock market crashed down by 40 percent. The crash led to chain reactions across, primarily Asia, were other markets followed in the downturn. As one of the world's largest economies, things that happens in China do often highly correlate with what happens in the global economy (Fang and Bessler, 2018, p. 752). According to a news article, one explanation for the Chinese turbulence is that the stock market had entered the stage of a bubble. The stocks were rising in a much higher speed than the rest of the economy just prior to the turbulence started (Pilbeam, 2015, p. 15). Another article emphasize the governments attempts to stabilize the market as another factor for making the turbulence and volatility even greater. When the government had raised the liquidity of the market with new money, investors may have seen this as a last opportunity to cash out (Liu, 2015, p. 1). In the market turbulence 2015-2016, the results of Fang and Bessler (2018) conclude that the crash in China were the reason behind other economies downhill.

Chapter 4

Result

In this chapter the authors aim to represent the result of the trading algorithm in the chosen markets DJIA and S&P 500. The goal of the strategy is to reduce risk while still being able maintain the expected return of the market. As a lower risk will increase the Sharpe-ratio, the average portfolio Sharpe-ratio compared to the average Sharpe-ratio of the market can be seen in table 4.1. It should be noted that the Sharpe-ratio is annualized, as there is a difference between daily and annual values. For further illustration, the CML (where the incline is equal to the Sharpe ratio) together with the actual value of the portfolio and the market indices can be seen in figure 4.1 and 4.2. It should also be noted that a transaction cost of 0.1 % of the size of all trades is included in the portfolio, which is assumed to be reasonable by Eliasson and Hamlin (2018, p. 31).

TABLE 4.1: Annualized average Sharpe-ratio of the indices and portfolios from 1998 to 2017.

Traded Asset	Index Sharpe-Ratio	Portfolio Sharpe-Ratio
DJIA	0,301	0,239
S&P 500	0,251	0,484

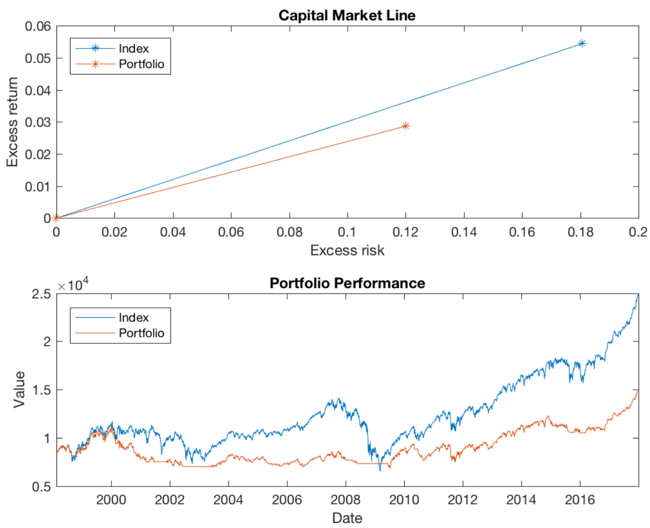

FIGURE 4.1: The CML and trading performance using the momentum strategy on the Dow Jones Industrial Average index.

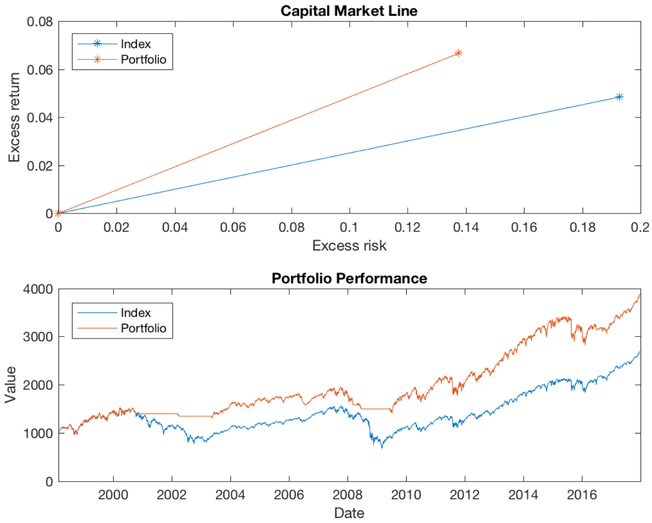

FIGURE 4.2: The CML and trading performance using the momentum strategy on the Standard and Poor's 500 index.

In table 4.1 it can be seen that the Sharpe-ratio is improved by the algorithm on S&P 500 but not on DJIA. The reason is more clearly illustrated in figure 4.1, as the algorithm is able to lower the risk compared to the index but at the cost of lowering the return as well. The resulting Sharpe-ratio will therefore be lowered. The algorithm on S&P 500 is however able to lower the risk while maintaining an equal, and even higher, return as the market index as seen in figure 4.2.

Chapter 5

Analysis

5.1 Bear and Bull

How come there is bear and bull states? If the market always goes up in the long run, why would not everybody agree on this and the market can continue to rise in a slow and controlled way. When observing the graph of the markets performance in figure 3.1 and 3.3, it is clear that the up trends are longer and steadier then the drawdowns, why is that?

5.1.1 Volatility

Volatility is graphically seen by the fluctuations in the price shown in figure 4.1 and 4.2. Some part of the volatility can be explained by the non-traditional economical theories within behavioral finance. Investors can be seen to act like a big herd in buying and selling the assets, which has made the indices fluctuate. Since not all investors share the same opinion about the fundamental value of an asset, the herds are going both up and down (Graham, 1999, p. 237). Depending on the time frame, the volatility can be very different. On a given day, the volatility on a tick-by-tick basis might be relatively large/small but on a daily or weekly basis the price movements on that given day are small/large. In these short time frames the theories about behavior finance is probably not part of the explanation. Today the fluctuations on very short time-frames are usually driven by high-frequency traders or algorithms of some kind that are executing orders on pre-defined rules. Those new techniques make it hard for traditional investors to react to the market changes. A longer time frame does in some means reflect a strategic view on the market and these decisions are still made by humans to a great extent. Here behavioral finance might be able to contribute in trying to understand the volatility on the market. Using the theory of herd behavior described in 2.6 one could possibly understand volatility better.

Volatility could in one way be viewed as herd behavior made visible, or at least it amplifies the volatility in some scene. One can view it as there are different herds and the investors have a hard time to determine which herd to follow. In a financial transaction there are one seller and one buyer. The investor needs to determine which one of the parties in the transaction that is acting right. If the market goes up it was the buyer, if it goes down it was the seller. Imagine that the investor determines to buy the asset and join the buying-herd, but the market goes down. Now the investor feel bad because she was wrong and determines to sell the asset and join the selling-herd, with the consequence of driving the price of the asset further down.

If one imagine that the investor exemplifies several investors then it is easy to understand that she impacts the price of the asset. This amplifies the movement of the price and eventually some investors realize that the fundamental value of the asset is higher which makes them buy it. The price now starts to move up and investors in the selling-herd now want to shift to the buying-herd, which is making money. Another thing that might affect the investor in her decision-making is which assumptions she had on the asset from the beginning. If the investor expected the stock to rise a lot direct and to generate e high return in the short run, the investor might be disappointed even if the return is positive. The high pre-assumptions might make the investor to evaluate the investment as a loss even if the return actually is positive (Kahneman and Tversky, 1979, p. 286). This might be one explanation to why volatility exists even when the market is in bull state.

According to the data reported in figure 4.1 and 4.2, the volatility is higher in DJIA than it is in the S&P 500. The greater volatility might be an explanation to why the algorithms performance differs between the two indices. The volatility shown in the two figures might also be explained with volatility clustering (Cont, 2001). When the majority of investors are in the winning herd the volatility is low, since everyone is making money. The consequence of this being that when the prize turns there are a lot of investors who wants to change herd. Depending on the time before other investors are able to convince the herd that the assets fundamental value is something else then the price the size of the winning herd will be various. This might explain why it would be possible to identify a bull and a bear state using volatility.

5.1.2 Why volatility occur

The bear state usually describe a down trend and the bull state usually describe an up trend, and in this thesis the bear and bull state is defined as a high and a low volatility as described in 2.1 and 2.2. In this chapter, the theories described in 2.5 and 2.6 will contribute to an explanation in how the different states occur. As discussed in the previous chapter the authors discuss the volatility on a longer time frame.

Behavioral finance considers that there are more trading in the market then what is rational (Barber and Odean, 2000). This could be an explanation as to why the volatility is higher during bear markets, investors have a hard time to determine weather they should be invested or not and therefore jump in and out of the market. One possible factor to describe the bear state is loss aversion, which is a theory in behavioral finance. It implies that people in general are more afraid of losing then they enjoy winning (Christiane Kleinübing Gogoi and daSilva, 2005, p. 47-49). This might be a contributory factor as to why bear markets are characterized as shorter in time and more volatile then bull markets. This phenomenon can be observed in both of our indices. In the DJIA, figure 4.1, it is clearly found during and after the housing bubble. The DJIA needed around four years to recover from the big downfall before it was back at the levels as before the bubble burst. A similar relationship can be seen in the S&P 500, figure 4.2. In this index, the fall was not as big but it still took around four years to recover.

Investors sell off in panic when the market starts to go down in order to avoid losing more capital. The fear of losing capital is bigger then the will to gain money and therefor investors are faster to go "all-out" then they are to go "all-in" (Christiane Kleinübing Gogoi and daSilva, 2005, p. 47-49). As the market becomes more volatile and more investors fear the risk of losing ones capital, they to sell their assets which are driving the price down. Alongside, there are investors who are buying as they either are more risk-tolerant, believe that the fundamental value is higher then the traded price or they might not have been invested in the market and therefore have not lost any capital yet. The result is large fluctuations in the price. Herd behavior amplifies this trait even more. If the investor do as other investors and sell, she will at least not be alone in selling and taking a loss. On the other hand investors wants to make money and some join the herd of investors that are buying. As discussed above one way of understanding volatility is as the investors have a hard time determining which herd they should follow. During a bear market it seems as the loss aversion will make more investors join the selling herd, which is why the price on the market is trending down. From a behavioral point of view, the bear state is characterized by pessimism among investors.

Why is the bull state characterized by a lower volatility then? First of all, in modern time, the economy in the world has been going up. It is then reasonable that large companies earn more money and therefore are worth more, which drive the price of the market up. This implies that the market should go up in the long run and one could argue that the rational thing for an investor to do is simply to buy and hold their assets and not sell. Applying the aspects of behavioral finance and herd behavior can help to understand why the bull state is steadier then the bear state. As a bull period follows a bear period it starts off when more and more investors start to buy stocks again. When others start to make money eventually more investors will follow. The investor who is not invested in the market feels the urge to go in on the market and start making money. The loss aversion plays a big role in the bull state as well. Investors who lost a large portion of their capital during the bear period has been scared by this and therefore are more careful about going in to the market again. They fear that the market will start to decline again and they will lose their capital. This would explain why the bull periods usually are longer and steadier then the bear periods, investors are taking it more careful entering the market then when they want out of the market during a bear period. Herd behavior in a bull market could explain why they usually end with a euphoric phase where the price gain is more or less exponential (Leiss, Nax, and Sornette, 2015). When the buying heard is growing bigger and bigger, it has a greater impact on the price and the decisions of investors. An investor who think the price of an asset is higher then the fundamental value of it might change its mind when considering that everyone else seem to have an more optimistic view on the value. The larger the herd is, the more likely it is that the investor ignores its own analysis and goes with the herd. As described in section 2.5 about behavioral finance, the theory consider how investors and traders become overconfident and think they have more information and knowledge then the market. It is more likely this will occur during a bull market because then the investors are making money since the market is going up rather then during a bear market when everyone is losing money. If one consider that the entire herd becomes overconfident then it is easier to understand the euphoric phase in the end of a bull period.

From the results in table 4.1 it can easily be seen that the algorithm is able to improve the risk-adjusted return trading on S&P 500 and not on DJIA. The most intuitive explanation may be that DJIA is to a greater extent effective and correctly priced than S&P 500 making it impossible to predict future movements based on past returns. The authors of this thesis are though inclined, to try explaining the differences on a deeper level.

5.2 Bubbles

To gain a better understanding of our results we have decided to in more detail study and describe the three largest result-affecting periods. What happened in those periods referred to as bubbles that have been described in section 3.2.3? In this section we will discuss differences and similarities between our two indices during those three periods. The purpose with this section is to gain a deeper understanding of why the results are as they are.

5.2.1 Dot-com Bubble

When the dot-com bubble burst in 2000, the two indices chosen for this study reacted in different ways. Our first index, the Dow Jones Industrial Average entered a period of high volatility. In total, the prices went sideways during the period from the start of the bust until 2002, but with shorter ups and downs. This made the algorithm insecure of which state the market expired at the moment. To avoid losses and to still gain on the upturns, the algorithm began to trade a lot which activated unnecessary transaction costs with a weak return as the end result. The S&P 500 on the other hand experienced one big decline after the bust and then continued down until 2003. Before the bubble bust in 2000, the index had viewed a steady growth. Those conditions made it easy for the algorithm to perform with success. As explained in section 2.8 and 3.2.2 about the algorithm, it sells the index when the market is about to enter a decline period and follows the index when the market is going up. When there is one big downfall, the algorithm does not need to trade much to capture the movements in prices. This keeps value into the portfolio since it does not need to activate much transaction costs.

The stocks included in the two indices might explain why the two indices acted in those different ways. By viewing the weight of the different sectors in the two indices, figure 3.2 and 3.4, it is clear that S&P 500 is more heavily weighted in the Information Technology sector than DJIA. In 2018, S&P 500 contained 25 % Information Technology companies in comparison the DJIA with only 15 %. Since those numbers are from 2018, it would probably have looked different back in 2000 as the weighting changes together with the value of the companies. However, it is likely that S&P 500 were more heavily weighted in the technology sector in 2000 as well, especially since there was a boom in the sector. The assumption is confirmed by the value of the indices, figure 3.1 and 3.3, where the value of S&P 500 declines more than DJIA. As explained in sector 3.2.3, it was mostly companies active in Information Technology that were affected by the bubble. If the IT companies were equally big parts in the two indices, they would have behaved more similar. The volatility in DJIA can though be assumed to be higher than normal due to huge movements in price in one sector. The sector weightings may therefore explain the portfolio performance during the dot-com bubble in the two portfolios.

5.2.2 Housing Bubble

The housing bubble of 2008 appears to be similar in the two indices as it affected all sectors in the entire market. Neither of them handled the fall well. As described in section 3.2.3 major financial institutions were so heavily leveraged in the housing market that they risked going bankrupt in the bust. If they had been more reasonable invested as they were in the Internet companies in 2000 the bubble could probably have been contained to the Real Estate sector. In the same manner as the dot-com bubble was contained to Information Technology. When we compare the result of the indices with the algorithms portfolio, we can still detect some differences. In the DJIA, shown in figure 4.1, the index experienced a huge fall in 2008. Before the bubble burst, the index was clearly outperforming our portfolio. But when the downfall stroke, the algorithm were fast with selling the index which made it manage the crisis well and instead of a big loss, the value of the portfolio went sideways. The difference between the portfolio and the index disappeared and in 2009 the portfolios value were higher then the index for a short period. In the S&P 500, the portfolio was not as fast to sell as in the DJIA. In this case, the portfolios value also declined before the portfolio had shifted from owning index to instead place the money at the account with a risk free interest rate. Since the market was volatile in this stage, we believe that the decline of the portfolio consists largely of transaction costs. Early during the crisis, the gap retained since the dot-com bubble in 2000 was much smaller than during the prior period figure 4.2. In this point, the algorithm sold of the asset. According to the results in figure 4.2, it was clearly the last moment of doing so. The index experienced the largest downfall during the bubble at this time. Since the portfolio had sold the asset and placed the money at a risk-free rate, the gap between those two were now greater than before the bubble.

When the market turned up and left the bottom, the portfolio trading the DJIA did not manage to follow the index. In this time, it was the index that outperformed the portfolio. One explanation to this is that the market post 2009 was volatile which activated a lot transaction-costs. This phenomenon, with index beating the portfolio in bull markets is something we will discuss in later sections, primarily 5.1.2. Since the index and the portfolio were at the same level in 2009, it becomes clear that the failure of the algorithm in DJIA does therefore not depend on its ability to cope with the crisis of 2008 but rather the trading after the crisis in the period 2010-2017. This period was also different between the two indices. In S&P 500, the algorithm handled the time until the China bubble discussed bellow, better than the index and managed to extend the difference by raising its value more than the index. Since the algorithm only trade by buying and selling the index, the higher starting point probably explains the reason for why this is possible in 2010. The percentage differences will therefore have a grater effect on the portfolio.

5.2.3 China Bubble

As seen in figure 4.1 and 4.2, the American stock market declined during the second half of 2015 and the beginning of 2016. The results shown in 3.2.3 confirm the domino effect described in section 3.2.3, which created market turbulence across other markets as the explanation. It is likely that the crash in the Chinese market was the driving factor behind the turbulence also in the U.S market. As we will explain in section 5.1.1 about volatility and 5.1 about bear and bull markets, herd behavior is a likely explanation for these events. When the turbulence started in China, which is one of the largest trading partners to the U.S (Petroff, 2016), investors in U.S might have acted irrationally. Investors acting like a herd are then likely to have created higher volatility in both of our studied indexes as well.

We can still see a difference between the two indices also in this bubble. At DJIA, shown in figure 4.1, it is clear that the algorithm performed better than index during the turbulence and avoided the worst ups and downs. At the same time, after the turbulent period, the DJIA had a higher value than when the period started. Since our strategy was to avoid the turbulence, it unforturnately also missed the last upturn. This extended the value difference between the algorithms portfolio and the index more than it was before the turbulence started. During the measured period, the algorithm did not manage to catch up this loss. After the turbulent period, the index still performed better and raised the value more than the portfolio. Since the value of the DJIA was higher before the turbulence, a period of good performance will generate a higher turnout in actual money.

According to figure 4.2, the results from S&P 500 were different. During the turbulence, there were larger changes in value of the portfolio held by the algorithm than in the index. The volatility will though still be the same as the algorithm is only able to place the available capital in the market index with no use of leverage. The relative changes, in percent, will therefore be the same for both the portfolio and the market index. The larger changes in value will be due the fact that the value of the portfolio is higher than the index at this point in time. The algorithm will however start to trade the index back and forth. Since the algorithm is constructed to take transaction costs into consideration, this makes the return and performance of the trading strategy less than otherwise. At the same time, this makes the strategy more trustable and more like how it is in reality than otherwise. Even since the portfolio did perform worse than index due to transaction costs, the value of the portfolio was still higher after the turbulent period, even if not as much as before. A part of this can be explained since the turbulent period ended with an upturn. Also in this case, the index and the portfolio performed quite alike in the rest of the measured period.

As a whole, there were greater turbulence and higher volatility in the DJIA than in the S&P 500. This is one explanation to why the algorithm performed better at the DJIA. Since the turbulence on DJIA were greater, it was easier for the algorithm to calculate and predict the volatility and therefore sell out. In the DJIA, the portfolios value had a minor decline during the turbulence but in comparison to the index, it might be considered as flat.

The higher volatility might have something to do with the number of stocks included in the indices. If one stock is exposed for high volatility and this stock constitute a considerable part of an index, also the index will experience a higher volatility. The DJIA also consists of large global companies, which therefore may be more exposed to the crisis in China.

5.2.4 Performance of the algorithm

To notice that the algorithm performed better in the S&P 500 than in the DJIA does not require any advanced analysis. In the DJIA, it would have been more successful to trust the traditional theories as the efficient market hypothesis and the capital asset pricing models. Both of those theories suggest that it is not possible to outperform the market by stock-picking (Fama, 1970; Sharpe, 1964), which at least was the case with this algorithm and this measured period 4.1. Since the measuring started in 1998, it was only in the turbulent period after the housing bubble that the portfolio showed a higher value than the index. This strongly supports those theories, which in the same way would falsify our hypothesis. On the other hand, none of those theories do not take transaction costs into consideration. As discussed above, we could have made the algorithm perform better just by excluding those additional costs. Since this is not how reality works we have still chosen to include them and stick closer to reality.

On the other hand, in our other index, the S&P 500, the portfolio was at all times during the period 1998-2017 at the same level or above the index. In this index, the strategy for how the algorithm is supposed to trade becomes clear. During the periods when the index is in a bull state and the market is going up, the portfolio is following in the same direction. When the index on the other hand is enters a bear period and the value is sinking, the index is going flat. This becomes clear by viewing the results presented in section 4. The three bubbles discussed above is a clear evidence for this. Before the dot-com bubble, the portfolio is following the index. When the bubble burst, the portfolio is flat which gives the portfolio a lead. This distance is roughly calculated kept until the housing bubble when the same phenomenon can be seen. After this bubble, the lead is even bigger for the algorithm. As discussed in section 5.2.3, the portfolio is rising faster than the index because of the higher value as exists before the China turbulence starts. This is the only time during this measured period when the algorithm has a lower return than the index.

Also table 4.1, showing the results from the Sharpe-ratio, supports the fact that the algorithm failed to beat the DJIA, even not as much as in behalf of the return. Those results shown in table 4.1 are not as obvious. The Sharpe-ratio from the DJIA was 0,301 compared to 0,239 for the portfolio. How this come can be observed in as the capital market line reported in figure 4.1. Here the results show that the DJIA did generate a higher return but it did so at a much higher risk. According to Sharpe (1994, p. 57), the Sharpe-ratio was constructed in order to give an alternative to only consider the return and to set the potential return in relation to the risk. In other way, a high-risk investment would in most scenarios generate a higher expected return. For a risk-averse investor, the algorithm might be viewed as a more interesting investment. But in a strict economical perspective, the index would be considered a better alternative since the Sharpe-ratio was higher.

In the results from S&P 500, the Sharpe-ratio shows an interesting fact. The ratio for the S&P were 0,251 compared to 0,484 for the portfolio (Table 4.1). In this area, the algorithm did beat the market both regarding return and Sharpe-ratio. Figure 4.2 shows that also the risk was lower. In all of the three measured areas, the algorithm did perform better than the index. Those findings support the fact that the algorithm did manage to beat the market. Any investor that in some way would be considered as rational would perform an investment in the index instead of an investment in the algorithms portfolio. Otherwise, the investor would choose to take a greater risk for a smaller expected return.

Chapter 6

Conclusion

To conclude the results of the thesis, one may state that the algorithm has the ability to gain the investor a higher risk adjusted return than a stationary investment in the market index. However, this is not a warranty as the algorithm in some occasions fail to fulfill its purpose. This is the case when trading on DJIA as algorithm fails to deliver as high return as the market index. The reason for this may be incorrect predictions the of bear markets. Since the portfolio is not allowed to use neither leverage nor short selling of the risky asset, the algorithm may outperform the market index because of its ability to trade the risky asset for cash during bear markets. In the bull markets, the algorithm will be fully invested in the market index and therefore contain the same amount of risk as the market. However, during a bear market the portfolio contains zero risk as the entire portfolio consists of cash deposited in the bank account at a risk-free return.

As the portfolio is able to outperform the market index due to the occurrence of bear markets, it is important that the algorithm make correct estimates of the state of the market. From the result and analysis of different bubbles affecting the two market portfolios the authors conclude that the algorithm is able to cope very well with bubbles which has a direct effect to the traded asset. To state an example, the dot-com bubble affects S&P 500 more directly than DJIA. The algorithm does therefore trade S&P 500 better than DJIA during this period of time. Since minor corrections also affects DJIA the algorithm starts to trade the index back and forth during the period activating unnecessary transaction costs making the portfolio loose capital. The conclusion is that transaction costs are a vital aspect to consider when discussing investing strategies.

Another conclusion is that anomalies on the market to some extent can be understood with behavioral finance. Especially when trying to understand why and how anomalies occur that cannot be understood with classical economical theories. Therefore it is of interest for investors to get a basic knowledge on behavioral finance to better understand why other investors sometimes can act irrational.

Chapter 7

Discussion

The results of the algorithm cannot be considered to be entirely true as it is tested on historic data. There is no evidence to support that past market conditions will apply in the future. The historic performance of the algorithm can therefore not be seen as a warranty for future returns. The developers of the algorithm have though attempted to make the results as realistically as possible by including the cost of transactions in the measured performance. The transaction costs are meant to represent the brokerage fee an investor usually pays for trading assets. Other costs that could have been implemented in the model are: holding costs, spread and the fact the price of the asset changes due to trading.

Starting of with the holding costs it may be reasonable to not include them in the model as there is no use of neither leverage or short selling of the risky asset. The cost of holding the asset is usually represented by a form of interest when lending money, for the use of leverage, or lending the asset itself, for short selling. If the model would be made to cover these possibilities, it would be reasonable to include a cost for holding the asset as well.

The spread is not explicitly covered in the model but may considered to be covered in the regular transaction costs. As there also is an uncertainty in what the spread may be this is probably the best estimation that can be made.

Costs due to the price of the asset changing when trading are neither considered in the model as the traded assets, DJIA and S&P 500, are considered to be large enough for the cost to be disregarded. As the price of the asset are determined by supply and demand the price will move if the algorithm for instance aims to buy the asset and thereby increasing the demand. Due to the fact that the chosen indices are so large, the supply of the asset is considered to be so great that the increase in demand is assumed to only have a negligible effect on the price.

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