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MOMENTUM INVESTING WITH MOVING AVERAGES IN THE U.S. STOCK MARKET

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Abstract			
<p>Momentum phenomenon has been one of the hardest market anomaly to be explained by the efficient market hypothesis and the risk based theories. The more recent behavioral theories offer much better explanations for this phenomenon. It is suggested that the investor's over- and underreaction is the key element that generates momentum phenomenon and its profits. Momentum investment strategy is often seen as a method of technical analysis because it focuses on stock price trends and not to company fundamentals. In addition, there are clear similarities between momentum investing and moving average strategy. Both strategies can be seen as a trend-following strategies, so the simultaneous use of these strategies is justified.</p> <p>The target of this thesis is to study if the simultaneous use of moving averages and momentum strategy is economically and statistically viable. In addition, the study investigates if the momentum strategy has been profitable in late 20th and early 21st century and have the recent market crashes affected the profits. As the research shows, the phenomenon is present in the late 20th and early 21st century but the strategy's profits are lower than the earlier literature suggests. One main reason for this finding is the market sensitivity of momentum strategy. This research presents the evidence that the momentum profits are clearly linked to market states and the strategy loses its profitability during the negative market trends. This finding is supported by earlier literature. To overcome this, the study applies moving averages to the momentum strategy to try to time the markets.</p> <p>The previous financial literature have shown that the moving averages have some ability to predict the changing market trends. This study presents more mixed results. It seems that the moving averages can indeed predict positive market trends but cannot predict market crashes. This thesis suggest that the reason for this finding is the severe and relatively short market crashes of the 21st century. In other words, the moving averages are able to recognize more long lasting trends than rapid market movements. The use of moving averages did lower the volatility of the used strategy but did not increase the profits.</p> <p>This research uses average monthly returns to study the momentum effect with 3, 6, 9 and 12 month momentum strategies. S&P 500 Composite Index's 12 month lagged market returns are used to define the market states. In addition, the moving averages strategy uses similar 3, 6, 9 and 12 month strategies with the momentum portfolios to study the market timing ability. The study focuses on the U.S. stock markets, and for this reason, the data in use is random sample of New York Stock Exchange listed companies, which includes 820 company stocks. The study period is from January 1995 to September 2013.</p>			
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Additional information			

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1 INTRODUCTION

1.1 Background

Efficient market hypothesis has had an important role in finance literature in the past decades. This hypothesis means that value of stocks reflects all the available information in the market and the future prices are not predictable (Fama 1970). However, during the last decades this hypothesis has faced a strong criticism in the form of different market anomalies. These anomalies, or phenomena, should not occur if the market would be fully efficient. One of the most important market anomaly, and perhaps the hardest one to explain, in the perspective of efficient market hypothesis, is momentum phenomenon (Fama & French 2008). Momentum refers to a phenomenon that stocks with best (worst) medium term profits will generate the best (worst) profits also in the next 3–12 months in the stock market. In other words, momentum phenomenon suggests that stock prices have clear price trends and it is economically viable to exploit this phenomenon.

As momentum phenomenon focuses simply on stock prices, it can be seen as a technical analysis instead of fundamental analysis. In other words, momentum phenomenon is based on simple trend analysis of stocks and it ignores mostly stock fundamentals, such as earnings, dividends and R&D expenses. For this reason, it is good to take closer look into technical analysis as well when examining momentum phenomenon. Technical analysis can be explained as a study of market actions with charts and few key figures for the purpose of forecasting future price trends. In other words, investors that use technical analysis believe that anything that can affect the stock prices will affect the stock prices, so a study of prices is all that is needed in forecasting future price levels. (Murphy 1999.) The similarities between technical analysis and momentum phenomenon are hereby clearly obvious.

For the average investor, the financial crises of 20th and 21st century have had huge impacts on their stock portfolios'. These crises have caused severe drawdowns in almost all asset classes and the simultaneous loss of value have been around 40 to 60 % (Faber 2007). During these crises, the diversification of portfolios have lost its ability to protect stock portfolios' from the downside risk and large drawdowns. Due

to the short time spans of average investor's portfolios, the recovery from these severe losses is relatively hard or sometimes even impossible. This raises an interesting question, is it wise to be invested in the market during these market crashes, and if not, would it be possible to avoid these market crashes beforehand?

It is suggested, that these market crashes have generated a need for average investor to time the markets, and this way, avoid the large drawdowns and losses. Perhaps the most used, and most simple, strategy is the moving averages methodology. This methodology relies on mechanical trading rules that generate buy and sell signals. In other words, moving averages are one possible method to implement technical analysis. Moving averages tries to estimate changing market trends, and this way, avoid investing during the negative market trends. It triggers signals that protects the portfolio from the drawdowns and advices investing in less riskier assets or even liquidating the position fully into cash. For this reason, moving averages are basically a market timing strategy with a strong relation to momentum phenomenon.

1.2 Earlier Literature

The first observations of momentum phenomenon were made by Jegadeesh and Titman (1993). Their study shows us that the momentum strategy, that buys stocks with best (worst) medium term profits, will generate the best (worst) profits also in the next 3–12 months. The profits of this momentum strategy is approximately 1 % per month during years 1965–1998 (Jegadeesh & Titman 1993, 2001). Even though Jegadeesh and Titman's (1993) study is the first clear evidence of the momentum phenomenon and momentum profits, it is also important to note that their research is inspired by De Bondt and Thaler's (1985) earlier research article, where the momentum strategy is used as a comparison to the studied contrarian strategy.

Most of the finance literature observes momentum phenomenon in the US equity markets it is also found in European equity markets (Rouwenhorst 1998) and even globally (Griffin et al. 2004). The only exception is that momentum cannot be found in many Asian equity markets (Chui et al. 2010), for example Japan (Asness 2011). All of the international results conclude that the momentum profits are approximately 1 % per month. Despite the fact that momentum profits have been approximately one

percent per month in the last century (Jegadeesh & Titman 1993, 2001), there have been one important regularity with market states. As Cooper, Gutierrez Jr and Hameed (2004) observes, momentum phenomenon is clearly linked with market states and market trends. In other words, momentum profits are highest (lowest) in positive (negative) market trends, even though the profits are not linear. Their research shows that during positive market trends, momentum profits are 0.93 %, whereas momentum profits are -0.37 % during negative market trends. Also, Jegadeesh and Titman (2011) and Henker et al. (2012) find that momentum profits are affected by negative market trends. Especially, during the dot-com bubble and 2008's financial crisis momentum profits were close to zero or even negative (Henker et al. 2012, Jegadeesh & Titman 2011). Since the latest published article by Jegadeesh and Titman is from year 2001, this raises a question: have the momentum strategy's profits continued in the 21st century? So far the new results have shown arguments in favor (Jegadeesh & Titman 2011) and against (Henker et al. 2012) Jegadeesh and Titman's (2001) results.

In addition, it has been shown that the momentum profits have regularities with seasonality. For example, Jegadeesh and Titman (1993) discover that momentum profits are constantly negative in January and especially high in April, November and December. In addition to these most cited momentum studies, studies of Grinblatt and Moskowitz (2003), Chordia and Shivakumar (2006) and Marx (2012) have offered strong evidence of this phenomenon and its profits. Because the evidence of momentum phenomenon is so vast, nowadays momentum is widely accepted phenomenon in the financial literature. The oldest evidence of momentum profits even dates to year 1801. (Asness et al. 2014.)

Although, momentum is widely accepted phenomenon in the financial literature, it is still up for debate what generates momentum and momentum profits. The explanation models of momentum varies between two school of thoughts, behavioral and risk based theories. The behavioral explanation models tend to explain momentum with irrational investor behavior, while the rational models tend to explain momentum with compensation to higher risk exposure. Perhaps the most important researches concerning explanation models of momentum are Barberis, Schleifer and Vishny's (1998), Daniel, Hirshleifer and Subrahmanyam's (1998) and Hong and Stein's (1999) articles. Even though, these articles use different factors to explain momentum, all of

the studies are based on the same conclusion that investors' over- and underreaction plays an important role in the process. In addition, Fama and French's (1996) three-factor model can explain several market anomalies but fails to explain momentum. To overcome this problem, Carhart (1997) extended Fama and French's (1996) model with additional risk factor, momentum factor. This four factor model's ability to explain asset prices is much improved and it can take into account momentum phenomenon.

In addition to these school of thoughts, there is also a larger debate between fundamental and technical analysis. Historically speaking, fundamental analysis have had the larger supporter base but during the last decades, as the processing power of computers have increased, also the technical analysis has achieved some recognition in the academic world. For example, momentum phenomenon can be seen as a strong support for technical analysis. In addition, studies of Pruitt and White (1988), Neftci (1991), Neely, Weller and Dittmar (1997), Brown, Goetzmann and Kumar (1998), Gencay (1998) and Chang and Osler (1999) have presented results that offer direct support for the usefulness of technical analysis. These studies suggest that the use of technical analysis can increase the portfolio profits when compared to passive buy-and-hold strategies. Also, several different studies have presented indirect support for technical analysis.

The similarities with technical analysis and momentum phenomenon raises a question: can we beat this unfortunate regularity between momentum phenomenon and market trends with simple technical indicators, or in more detail, with moving averages? As Glabadanidis (2015) shows us, it is possible to increase average returns and decrease volatility of different investing strategies with simple moving averages. Moving averages are technical indicators that are used to spot positive and negative market trends early on and it is perhaps one of the most used tool in technical analysis (Murphy 1999). When spotting changing market trends with one moving average, the idea is that the moving average generates buy (sell) signal when the moving average intersects stock's price chart from the downside (upside). In other words, when using stock's short-term closing day price averages, it is possible to spot changing market trends when the moving average intersects with the stock's price chart. With simpler example, when the stock price is above (below) stocks moving average, then investor

should be in the market (out of the market). There are also possibility to use multiple moving averages at the same time with the same logic. In this case, the moving averages intersect each other and generate buy (sell) signals for the investor.

1.3 Research Problem

Because the results of momentum profits in the 21st century are contradicted and there are clear similarities between technical analysis and momentum phenomenon, or in other words, moving average and momentum strategy are both trend-following strategies (Han et al. 2013), this thesis tries to answer the following research questions:

- Have the momentum profits continued in the 20th and 21st century in the U.S. stock markets?
- Have the different financial crises affected the momentum profits?
- If the crises have affected the profits, can we improve momentum strategy's profits with monthly moving averages?

This thesis hypotheses are derived from these research questions. First hypothesis is that, if the momentum phenomenon is more than just an anomaly, its returns should have continued in the 21st century and should be approximately 1% per holding month. The second hypothesis is that big stock market crashes should affect momentum returns in the 21st century. And lastly the third hypothesis is that, if the market crashes did really affect the returns, then we should be able to use technical analysis' tools to time the market for larger profits and smaller volatility. This third hypothesis is based on the thought that if the moving averages can spot market changes with single stocks, then this method should be possible to use with portfolios. And because the similarities between technical analysis and momentum's trend analysis, these technical analysis' tools, more precisely moving averages, should also work with different momentum portfolios. This way we should be able to increase momentum strategy's profits by leaving the stock markets during market crashes and reap the profits during the positive stock market trends. The research is conducted with similar research setting as Jegadeesh & Titman (1993, 2001) have in their studies. The market states are studied with lagged S&P 500 Composite Index returns and this methodology follows Cooper

et al. (2004) and Henker et al. (2012) framework. In addition, the moving averages are constructed similarly as in Glabadanidis' (2015) study. More detailed description of the methods are presented in the fourth chapter. This study's results indicate that the momentum profits are present in the 21st century but are lower than the theories suggest. One reason for this is the market sensitivity of the momentum portfolios. On the other hand, the simultaneous use of moving averages and momentum portfolios seem to be ineffective strategy when compared to the plain momentum strategy. The results are discussed in more detail in the fifth chapter.

This thesis' aim is also to be able to clarify to the reader the importance of momentum phenomenon to financial markets and how technical analysis can be used as a tool to increase this phenomenon's profits. Also the purpose is to offer some explanation to this phenomenon and its profits so the reader can form a general picture of momentum investing. This thesis will focus fully on U.S. stock markets, even though this phenomenon can be found in different asset classes and in different international markets. Also the focus is solely on price momentum, even though there is valid evidence that earnings momentum and revenue momentum also exists (Chen et al. 2014). All in all, momentum literature is too extensive to fully cover in one thesis, so reader's discretion is advised when making any comprehensive conclusions about momentum phenomenon.

This thesis consists six chapters. The second chapter considers momentum phenomenon in general, and tries to answer in detail what momentum is. I also discuss briefly explanation models of momentum and momentum as a global phenomenon. After this I take a closer look how different market states affect momentum phenomenon and its profits. Lastly I will discuss how the momentum strategy should be implemented in practice. In the third chapter I examine technical analysis in general and especially moving averages. After this I will discuss how the profitability of moving averages and how moving averages can be used as a tool when trying to recognize changes in market trends. Lastly, I discuss the similarities of momentum and moving averages. The fourth chapter describes the research setting, methodology and data in use. This chapter also discusses the process of the research in full detail. The fifth chapter presents the results and comparison of the results with the previous momentum and moving average literature. The last chapter consist discussion of the

results and a summary of this thesis. The chapter has also a brief discussion of possible future research topics.

2 MOMENTUM PHENOMENON

The aim in this chapter, is to answer the question, what momentum and momentum strategy is. At first, I will observe momentum at a general level and after this behavioral and rational models for this phenomenon. In the third subchapter I will take a closer look how momentum is observed globally. After this I will observe momentum in different asset classes and how to use this phenomenon as an investing strategy. In the last subchapter I will analyze how the market states affects the momentum strategy.

2.1 Momentum in General

In finance literature the momentum practically means that stocks with highest (lowest) cumulative returns in the past 3–12 months will continue to outperform (underperform) other stocks in the next 3–12 months. In other words this means that previous good price trend will lead to future good price trend, and vice versa. This phenomenon is observed to be strongest with under 12 month holding periods. After the holding period the momentum strategy starts slowly to lose its profitability. The first observations of this phenomenon were made by Jegadeesh and Titman (1993). Usually this phenomenon is seen as a strong argument against the market efficiency (Jegadeesh & Titman 1993) but Crombrez (2001) states that momentum can be observed even when the markets are efficient and the investors are rational. Mainly momentum is seen as a behavioral phenomenon but few rational explanations have also been suggested.

Momentum is often seen as a market anomaly (Fama & French 1996) but it is important to consider that is it more likely a constant market phenomenon? As Jegadeesh and Titman (2001) shows in their study that momentum has been profitable in several decades so should we call it as an anomaly? As Asness, Frazzini, Israel and Moskowitz (2014) states, oldest evidence of momentum profits goes even back to 1801 U.K. equity data. It is also typical to market anomalies to disappear or get weaker after their discoveries and this is not the case with momentum phenomenon (Jegadeesh & Titman 2001). Nowadays momentum phenomenon is widely accepted and the bigger debate is what generates this phenomenon (Li et al. 2008). These explanation models are discussed more thoroughly in the next subchapter.

Even though most of the finance literature observes this phenomenon in the US equity markets it is also found in European equity markets (Rouwenhorst 1998) and even globally (Griffin et al. 2004). The only exception is that momentum cannot be found in many Asian equity markets (Chui et al. 2010), for example Japan (Asness 2011). The possible reason for this is discussed in the third subchapter.

Jegadeesh and Titman's (1993) study is considered to be the first extensive research about momentum, even though it is not called momentum in their research article. In their research setting Jegadeesh and Titman observe The New York Stock Exchange's (NYSE) and American Stock Exchange's (AMEX) stocks during years 1965–1989 and they rank these stocks by their returns in the previous 3–12 month period. Based on these returns Jegadeesh and Titman form ten equally weighted decile portfolios and track the portfolios for the next 36 months and repeat the whole process again. The results indicate that this strategy is most profitable during the first year holding period. Based on the formation periods returns, the decile portfolio with the highest returns is called the *winner* portfolio and the decile portfolio with lowest returns is called the *loser* portfolio. These two portfolios are momentum strategy's buy and sell side and the investment strategy is to take long (short) position on the winner (loser) portfolio. This is called as the WML (winner minus loser) strategy. The main hypothesis of Jegadeesh and Titman's article is that if the stock prices over- or underreact to market information, then there has to be a profitable investment strategy that is based on historical stock profits. (Jegadeesh & Titman 1993.)

Jegadeesh and Titman (1993) shows that with this momentum strategy, that buys the winner portfolio and short sells the loser portfolio, it is possible to produce statistically and economically significant excess returns with 3–12 month holding periods. With under one month and over two year holding periods this particular investment strategy is unprofitable. They examine especially portfolio with six month formation and holding period and it is able to produce 12.01 annual excess returns. Jegadeesh and Titman also discovered that portfolio with 6/6-strategy turned out to be unprofitable when the holding period is over one year. During the second year holding period this strategy starts to lose its profits and this trend continued to the third year holding period. Based on their research, they conclude that these results indicate that momentum strategy's profits are at least partly temporary. According to Jegadeesh and

Titman, investors' under- and overreaction to market information is too simplistic explanation for the momentum strategy's profits and return reversals and more research is needed to fully understand this phenomenon. (Jegadeesh & Titman 1993.)

Another interesting regularity is the seasonality of the momentum profits. As Jegadeesh and Titman (1993) states, momentum strategy generates approximately 7 % losses in each January. These momentum losses are usually associated with *January effect*. January effect means that in every January, stock markets in general tend to perform well (Cicccone 2011). Because whole stock market tend to perform well in January, momentum phenomenon loses its returns in comparison to the stock market. Even though January is extremely poor month for the momentum strategy, this isn't the only seasonality in momentum phenomenon. This strategy produces close to zero profits in August and good returns in April, November and December. In fact, 96 % of the Aprils are profitable for the momentum strategy. This regularity in Aprils, according to Jegadeesh and Titman (1993), is due to U.S. companies' tax deductions. To qualify for this tax deduction, companies' need to transfer assets, most likely money, to pension funds before 15th of April. If the companies' asset managers follow momentum strategy, then the winner portfolio will get additional positive price pressure. The extremely good profits in November and December are linked to asset managers' habits to sell loser stocks before the end of the year so they will qualify for tax deductions. This will lead again to a price pressure which might generate momentum profits in these months. (Jegadeesh & Titman 1993.) Also in the Jegadeesh and Titman's (2001) newer study the same momentum seasonality is observed. These results have a clear similarities with their 1993 study's results and with similar momentum research and newer data-set the profits in January are again negative.

It is important to mention that momentum has a negative correlation with size, even though the returns are not limited only to small companies (Rouwenhorst 1998). In other words, all size deciles generate momentum profits but the smallest decile has the highest returns. Also Jegadeesh and Titman (2001) observe that both, winner and loser portfolio, tend to be smaller in size than the average stocks in the market. They also test that whether the size factor or illiquidity have any impact on the momentum profits by excluding the smallest decile and stocks with under 5\$ market price. This exclusion of small and low-priced stocks does not have any significant impact on the average

returns, despite the fact that the standard errors are significantly lower. (Jegadeesh & Titman 2001.)

Even though Jegadeesh and Titman's (1993) study is the first clear evidence of the momentum phenomenon and momentum profits, it is also important to note that their research is inspired by De Bondt and Thaler's (1985) earlier research article. De Bondt and Thaler's study examines market, and investor, under- and overreactions as well as market inefficiency using quite similar trend analysis. The article's main focus is in loser portfolio, which includes stocks that have had the lowest profits with 36 month formation period. The more interesting aspect is that they compare these results to the winner portfolio, which includes stocks with the highest profits and with the same formation period. These portfolios, which they use in the article, are very similar to the Jegadeesh and Titman's (1993) winner and loser portfolios, only the formation and holding periods differ. De Bondt and Thaler's (1985) results indicate that with over two year holding period the loser portfolio is more profitable than the winner portfolio, but with less than 12 month holding period the loser portfolio has the higher profits only in January. Another similarity with Jegadeesh and Titman's (1993) research article is that De Bondt and Thaler's (1985) results indicate that the profits of the winner portfolio start to weaken after the first year.

Even though momentum phenomenon has been clearly dominant in the last century, it has been found out that the momentum profits have one significant regularity. Cooper et al. (2004) states that momentum phenomenon's profitability is connected with positive market trends. Also Henker et al. (2012) studies the effects of market states to momentum profits and the results are similar. Even though both studies found this regularity, they also state that the profits were, on average, approximately one percent in each month. In other words, the profits are on average similar as Jegadeesh and Titman (1993, 2001) have stated but the profits varies significantly in different market states. I will study this significant regularity closer in the later subchapters and will discuss if the investor could utilize moving averages to avoid these losses in negative markets states in the third chapter.

De Bondt and Thaler's (1985), and especially Jegadeesh and Titman's (1993) study, can be seen as a foundation of the momentum research. In the last decades momentum

has achieved global recognition in finance literature and Jegadeesh and Titman's (1993) results has been able to replicate time and time again. In addition to stock momentum in U.S. equity markets, momentum can also be found in Real Estate Investment Trusts (Derwall et al. 2009), mutual funds (Grinblatt et al. 1995) and even in commodities futures (Miffre & Rallis 2007) but these asset classes are omitted from the thesis. Also momentum phenomenon can be found in different global markets (Rouwenhorst 1998, Griffin et al. 2004), so it is important to ask what generates these profits. In the next subchapter I will discuss what are the most widely accepted explanation models for momentum.

2.2 Explanation Models of Momentum

In the earlier subchapter I discussed momentum in general but to really understand it we need to take a closer look what generates this phenomenon. Momentum has been very persistent phenomenon in the last decades, so it is important to understand what causes this phenomenon. Most of the explanation models are trying to explain momentum with risk factors or by irrational behavior of the investors with varying results. The efficient market hypothesis has had a major role in finance literature since 1970s which is the foundation of risk based explanation models for momentum. This hypothesis means, that stock prices should reflect all available market information and, due to this, future stock prices should not be predictable. If these conditions are fulfilled then the market is seen as efficient. A faith in this hypothesis started to erode in the 1980s by a discoveries of market anomalies that the hypothesis could not explain (Charlas & Lawrence 2012). A new school of thought raised its head in the 1990s which underlined that investor behavior is biased and need to be taken into an account when analyzing markets. Even though behavioral finance has a firm foothold in a modern finance theory nowadays, efficient market hypothesis is still relevant theory and these school of thoughts more likely complement than rule out each other. In other words, financial markets does not only reflect financial realities and risk factors, it also reflects investors' beliefs and emotions and together they give us a more complete picture how financial markets work.

In this subchapter I will observe both behavioral and rational risk-based models for momentum phenomenon and its profits. First I will take a look at behavioral models

and how the under- and overreaction can generate momentum phenomenon and later on I will observe how risk factors are related to momentum.

2.2.1 Behavioral Explanation Models

Behavioral finance theory tries to understand, and explain, thought process of investors' reasoning and how these affect investors decision process (Chaarlas & Lawrence 2012). As stated in the earlier subchapter, De Bondt and Thaler (1985), as well as Jegadeesh and Titman (1993), present that investors' irrational behavior based on market information has a role in explaining momentum phenomenon. It is also good to note that Jegadeesh and Titman (1993) state in their study that return reversals of momentum portfolios is not a sufficient argument of this investors' overreaction to information and broader explanation models are needed to fully understand momentum phenomenon.

Jegadeesh and Titman (1993) provide as a one possible explanation for momentum that investors who use momentum investment strategy move stock prices away from the long-run values, in other words, they cause the prices to overreact with their buying behavior. They also state that markets' under-reaction to short-term prospects of companies and overreaction to long-term prospects of companies can be another possible explanation for this phenomenon. For example investors may underreact to companies' earnings forecasts and stick to their more ambiguous information that they may use to predict future prospects. Jegadeesh and Titman cannot prove in their study which of these explanations is better in modelling investor behavior and cannot rule out that there can be even more explanations for this phenomenon.

During the last decades, growing numbers of behavioral factors and models have come up to explain momentum. Perhaps the most important researches concerning explanation models of momentum are Barberis, Schleifer and Vishny's (1998), Daniel, Hirshleifer and Subrahmanyam's (1998) and Hong and Stein's (1999) articles. Even though, these articles use different factors to explain momentum, all of the studies are based on the same conclusion that investors' over- and underreaction plays an important role in the process.

Daniel et al. (1998) try to explain in their study investors' behavior with overconfidence. According to their theory, this investors' *overconfidence*, and changes in confidence, is caused by *self-attribution bias*. This means that self-attribution bias affects investors' investment decisions and, because of this, investors believe that investment profits are results of their skills and losses are a result of a bad luck and coincidence. They suggest that investors who suffer from self-attribution bias overreact to private information and underreact to public information, and drive the stock prices higher than the fundamental value. When this overreaction is prolonged, the positive price trend will continue and the momentum profits are generated. According to Daniel et al. (1998) this positive price trend will lead to stock mispricing and generation of momentum phenomenon. To fully explain this phenomenon, Daniel et al. (1998) conclude that the long-term price reversal, which is one of the main characteristics of momentum, is a result of growing public information which gradually reaches the investors and rights the prices back to the fundamental values. (Daniel et al. 1998.)

Daniel et al. (1998) are not the only ones that have explained momentum with investors' over- and underreaction to information. Also Barberis et al. (1998) hypothesize that momentum is generated by investor behavior, and this biased behavior has an impact on short-term and long-term stock prices. They suggest that with under one year investment period stock prices underreact to information and overreact on 3–5 year investment period. In other words, Barberis et al. claim that stocks that have had good historical profits will become overpriced and later on the price will return to its fundamental value. Their model is offering a possible explanation how investors form expectations based on different price trends and how this generates momentum phenomenon. According to Barberis et al. (1998), this model of investor sentiment is based on two key components, conservatism and representativeness heuristics. Conservatism means, in this model, that it is typical for investors to slowly update their beliefs concerning stock information. In other words, investors take new information into consideration but weigh it too little. Representativeness heuristic means, on the other hand, that investors have a tendency to ignore probabilities and they give too much weight to certain characteristics of different stocks. For example, investors have a tendency to classify stocks to growth stocks based on stocks historical returns, despite the fact that only a few companies

keep growing constantly. These tendencies lead to investors' habit to overweight companies' historical earnings, which ultimately leads stock prices to overreact. Barberis et al. (1998) suggest that, based on their model, conservatism causes stock prices to underreact in short-term, as for representativeness heuristic causes prices to overreact to information in long-term and together these key components explain momentum phenomenon and profits. (Barberis et al. 1998.) To support this model, also Moskowitz and Grinblatt (1999) have stated that when new information comes available to the markets, investors tend to be too conservative when making decisions about new companies.

Third important explanation model to mention is Hong and Stein's (1999) theory of under- and overreaction and how these generate momentum. Their model has a significant difference in the approach when compared to Daniel et al. (1998) and Barberis et al. (1998) who explains the phenomenon with investors' biased characteristics. Hong and Stein (1999) suggest that interactions between investors play more important role than the biased traits. Based on their model, heterogenic investors who are active participants in the market are affected by their bounded rationality. In other words, they suggest that in the markets there are two active heterogenic investor groups, *news watchers* and *momentum investors*, who can only process some of the public information at a time. (Hong & Stein 1999.)

These news watchers make their investment decisions based on new private information, which they can observe only by themselves, that reflects the future. This private information will gradually reach all of the news watchers. Their limitation is, that they cannot take into account any current or past price information when making decisions. On the other hand, momentum investors can only take into account past price information when making investment decisions. These investors are limited by the fact that they can only make forecasts that are "simple" functions of the history of past prices. In other words, momentum traders cannot take into account all public information when making decisions concerning future. (Hong & Stein 1999.)

Hong and Stein (1999) show that when the only active participant in the market is the news watchers group, then the stock prices will adjust slowly to the new information. Simply put, there only occurs short-run price underreaction in the market and

momentum investors strive to benefit economically from this situation. One might expect that this reaction of momentum investors would cancel the underreaction of the prices and this would eventually lead to approximately efficient market. As Hong and Stein demonstrate, this assumption is incorrect. According to them, this really leads to quicker response of the prices, but due to this, it will lead to a later overreaction of the stock prices when any new information, related to the stocks, appear to the market. In other words, their model can explain momentum phenomenon because it can capture short-run price continuation and long-run price reversal. Hong and Stein's model can also capture this so called "momentum cycle" where early momentum investors can, and will, make profits but momentum investors who enter the market later will make losses. This is because in the early cycle momentum investors who react to news watchers will push the prices higher and attract more momentum investors. These investors who enter the cycle later will keep pushing the prices higher and eventually the price goes over the long-term fundamental value and price overreaction occurs. In the long run the price will go back to its fundamental value and the momentum investors start to make losses. (Hong & Stein 1999.)

These three presented models try to explain momentum phenomenon with significantly different approaches. There are several other behavioral explanation models that have explained momentum with different factors. For example, Grinblatt and Han (2005) states that momentum is basically based on disposition effect. All in all, it can be said that these models, more or less, are always based on over- and underreaction of the investors, so presenting these models in more detail would not bring any extra benefit to this thesis. One could think that these models are in contradiction with each other, since every model use investors' under- and overreaction as a key factors to explain momentum. Because of this, it is important to notice that these models explain these reactions with different investors' biases. It is naïve to think that investors' biased behavior could be explained with only a few psychological factors. More like, together these models will give a broader picture what generates this phenomenon and drive investors' behavior. As Jegadeesh and Titman (2001) states, even at best behavioral explanation models can only provide a partial explanation to momentum phenomenon. Based on this fact it is important to observe how risk factors can explain momentum and this is studied in the next subchapter.

2.2.2 Rational Explanation Models

In addition to behavioral models, momentum has several explanation models which aim to explain this phenomenon with different risk factors. In other words, these rational models aim to explain momentum, instead of irrational investor behavior, with compensation to investors' additional risk exposure (Li et al. 2008). Often it is expressed that momentum, and other market anomalies that are based on irrational behavior, indicates about market inefficiencies because excess returns these phenomena's generate should, at least, disappear over time. This clearly is not the case (Jegadeesh & Titman 2001). This is problematic in efficient market hypothesis' point of view. This hypothesis proposes that, when markets are efficient, different asset classes should reflect all the available information in their prices and excess returns should not be generated (Fama 1998). This is important thing to notice because rational models aim to explain momentum in efficient market hypothesis' point of view.

For example, Fama and French (1996) created their famous three factor model for asset pricing and for explaining anomalies, for example momentum, that the *Capital Asset Pricing Model* (CAPM) couldn't explain. They state that many market anomalies are related with each other and can be explained with their three factor model. We can see from the results that even though they really can explain many different anomalies momentum is not one of them. In more detail, the three factor model cannot explain short-term price continuation, which is typical to momentum, but instead predicts short-term price reversals. They state that the reason for this might be data mining, irrational investor behavior or their model is faulty. Most likely reason is that the model is insufficient. Despite of this, Fama and French (1996) can duplicate Jegadeesh and Titman's (1993) results with similar research settings. To tackle this problem Carhart (1997) extended Fama and French's (1996) model with additional risk factor, momentum factor. This four factor model's ability to explain asset prices is much improved and it can take into account momentum. Although, Avramov and Chordia (2006) state in their study that Carhart's (1997) four factor model cannot absorb all the momentum in the U.S. stock returns.

Perhaps the most accepted rational explanation to momentum in finance literature is that investors bear significant risk and therefore the excess returns are just

compensation for the higher risk (Li et al. 2008). By using momentum strategy, investors accept this higher risk in compensation of momentum profits. The bigger debate is that what kind of risk the investors are exposed to. For example, Sadka (2006) aims to explain momentum phenomenon and profits with liquidity risk. In other words, investors are exposed to liquidity changes which, is suggested by Sadka, to be one of the sources of momentum profits. It is typical to study momentum without transaction costs, but Sadka states that even when transaction costs are taken into account momentum profits are significant, although smaller. Also Li, Brooks and Miffre (2009) states that usually in momentum literature transaction costs are underestimated but it is possible to generate low-cost momentum strategies that generate excess returns even when transaction costs are taken into account. This statement supports Sadka's (2006) earlier statement. According to Sadka, momentum profits are relatively short-term and are focused in the first few months after the portfolio formation. Because these profits are quite short-term, investors need to make several buy and sell transactions during these first few months to take advantage of momentum strategy efficiently. Due to this, Sadka states that high transaction costs are related to momentum strategy.

Because profitability of momentum strategy is heavily related to transaction costs, Sadka (2006) asks a question, could the momentum profits be related also to liquidity changes. According to him, if unexpected changes in liquidity are related to some market wide systematic variable, momentum profits could be seen as compensation for the taken liquidity risk. This requires that momentum strategy has to be sensitive to unexpected changes in market liquidity. To examine closer the effects of liquidity, Sadka divides liquidity risk to fixed and varied components. According to him, liquidity risk's varied component is usually associated with investors' private information. In other words, when private information increases in the market in relation to public information, then liquidity risk increases and market will become illiquid. This private information in question can only be used by *informed traders*, while *noise traders* rely solely on public information. Based on this, Sadka suggest that when private information increases, in the market, in relation to public information, also the amount of informed traders will increase in relation to all traders. The change, and relation, between these different types of traders defines the magnitude of momentum profits. In other words, the more informed traders there are in relation to the total number of traders, the more illiquid market and the higher

liquidity risk is, and thus the higher the momentum profits are. For this reason, the profits of momentum strategy can be seen as a compensation of market's liquidity risk but when the liquidity risk realizes, the transaction costs increases significantly in the market and the strategy loses its profits. (Sadka 2006.)

We can see from the results that Sadka's (2006) proposed model can explain 40–80 percent of the momentum profits which is significant result. In other words, we cannot discard efficient market hypothesis when explaining momentum, because, according to Sadka, we can explain this phenomenon with risk based factor, at least partially. Another important thing to notice is that Sadka also states that momentum phenomenon has a strong relation to information. In other words, momentum phenomenon is related to how informed traders and noise traders are able to interpret new private and public stock information in the market and how high quality the information is. (Sadka 2006.)

Also Asness, Moskowitz and Pedersen (2013) state in their study that momentum phenomenon has a strong relation with liquidity risk. According to them, momentum and liquidity risk are correlated positively with each other, which is in line with Sadka's (2006) results. According to Asness et al. liquidity risk could also explain excess returns of value investing and the negative relation between momentum and value investing. Value investing refers to an investment strategy that buys stocks of undervalued companies. In other words, the market value of these companies are lower than the book value of the companies. According to this study, liquidity risk correlates positively with momentum phenomenon and negatively with excess returns of value investing, i.e. liquidity risk could explain both of these phenomena, at least partially. In conclusion, Asness et al. can fairly say that liquidity risk and momentum have a strong relation with each other. (Asness et al. 2013.)

All in all we can state that risk based models can explain momentum partially but the behavioral models does a better job when explaining this phenomenon. Despite this fact, behavioral models cannot fully disregard efficient market hypothesis, although these models presents a strong case against it. We can conclude that these models cannot fully explain this phenomenon but together they give us a better picture what factors may lie behind momentum phenomenon's profits. Or perhaps as Qawi (2010)

states, the differences between rational and behavioral explanation models could be dissipated if the risk based models would include factors that would reflect investors' irrational behavior. As we have learned in this thesis, momentum has been an omnipresent phenomenon during the last century and momentum profits have not disappeared after the discovery of this phenomenon. All of the presented models and studies did observe momentum in the U.S. stock markets, so it is important to ask, can we find momentum in other markets as well? In the next subchapter I will take a closer look if momentum can be found globally and how individualism can explain this phenomenon.

2.3 Momentum Globally

As stated earlier, momentum does not only appear in U.S. stock markets, but there is also strong evidence of this phenomenon on international stock markets (Rouwenhorst 1998). If momentum would be present only in U.S. stock markets one could draw a conclusion that it would be just a temporal anomaly. This is not the case. Rouwenhorst studies over 2100 firms from 12 European stock markets between years 1980–1995. The results indicate that Jegadeesh and Titman's (1993) momentum strategy attains approximately 1 % monthly returns in these European stock markets. Also the same momentum strategy generates similar short-term continuation and long-term reversals as in Jegadeesh and Titman's study (1993). All in all, the results of the European momentum are almost identical with the findings in the U.S. stock markets and these momentum portfolios have a significant correlation between each other. (Rouwenhorst 1998.)

Rouwenhorst (1999) also studies momentum returns in emerging stock markets and he finds that the returns are lower, but still significant, than in the developed stock markets. He states that the main reason for this is in the different portfolio formation and in higher transaction costs. Both, Jegadeesh and Titman (1993) and Rouwenhorst (1998) uses top and bottom deciles when forming momentum portfolios but Rouwenhorst (1999) forms the momentum portfolio with stocks from top and bottom 30 %. As we can conclude, from these research articles, momentum phenomenon can be found also in different international stock markets, although there is one exception. The only exception is the Asian markets (Chui et al. 2003 via Chui et al. 2010).

As Chui, Titman and Wei (2010) studies momentum profits in international markets they confirm that there are no momentum phenomenon in the Asian stock markets. According to them, the explanation for this irregularity is in cultural differences between Asian and western cultures, and more precisely in investors' individualism. As they study these cultural differences they observe that western cultures which have momentum phenomenon are more individualist cultures. On the other hand, Asian cultures are more collective cultures and because of the lack of individualism there cannot be found any momentum profits. (Chui et al. 2010.) This view is in line with Daniel et al. (1998) theory of overconfidence and self-attribution bias. As Chui et al. (2010) states, in individual cultures investors are also overconfident and have biased self-attribution. In conclusion, Chui et al. (2010) state that momentum profits are highest in the countries that have individualist cultures and lowest in the collective cultures. It is important to mention that Fama and French (2012) argue against this explanation. They state that also low individualism might generate momentum profits because stock prices react slowly to information. They conclude that this irregularity, that momentum cannot be found in the Asian markets, is more likely a result of simple chance. (Fama & French 2012.)

In addition to these presented articles, momentum phenomenon have been studied also in a global scale. Griffin et al. (2004) studies momentum profits in 40 different markets and he states that momentum profits can be found all over the world with only few minor exceptions. Only a few Asian and South American stock markets does not have any clear signs of momentum phenomenon. (Griffin et al. 2004.) More interestingly Griffin et al. (2004) observes that momentum strategy has some sensitivity to different market states but does not lose its profitability. In the next subchapter I will examine more closely how different market states and changing trends affect momentum profits in the U.S. stock markets.

2.4 Market States and Momentum

Even though momentum has been a dominant phenomenon in several decades in the last century, the profits have not been positive in every year. When observed these profits in 1929–1995, Cooper et al. (2004) note that the profitability of this phenomenon has a clear relation with positively trending market. Also the losses are

linked with negative market trends. In other words, momentum phenomenon's profits disappear when the market is negatively trending. Also Stivers and Sun (2013) states that momentum profits are higher (lower) when the market is experiencing a positive (negative) trend and that the profits are significantly lower when the market is experiencing a transition between these two states. According to Stivers and Sun, this indicates that the medium-term momentum strategies are profitable but the long-term momentum strategies are not because the medium-term strategies are less likely to face market transitions than the longer strategies. This deduction supports the phenomenon that 3–12 month strategies are profitable where the over 12 month strategies are not. Also Asem and Tian (2010) find that the momentum profits are significantly higher within the market states than in market transitions.

Stivers and Sun's (2013), Cooper et al. (2004) and Asem and Tian's (2010) findings are consistent with several behavioral explanation models in which the, already mentioned, overreaction is seen as the main explanation (Daniel et al. 1998, Hong & Stein 1999). Daniel et al. (1998) and Hong and Stein's (1999) models of investors overreaction also suggest that momentum profits are linked with trending markets. In other words, investors tend to be more overconfident when the market is on the rise and this should lead to higher momentum profits. Cooper et al. (2004) uses similar research setting and portfolio formation as Jegadeesh and Titman (1993) and they conclude that the portfolio is only profitable when the stock markets are positively trending. Another important observation is that the momentum profits are not linear. In other words, momentum profits are not highest when the market has the highest increase (Cooper et al. 2004). When the stock market has the highest increase, momentum profits decrease significantly but does not dissipate fully. Their portfolio also have a long-term price reversals so the results are comparable, and similar, with Jegadeesh and Titman's (2001) results.

Henker et al. (2012) perform similar research with Cooper et al. (2004), when observing momentum profits in U.S. stock markets during years 1993–2004. The main goal is to study how different time periods and market states affect the portfolio's returns. This time period is especially interesting because it is relatively short when compared to earlier studies and it includes, for example, dot-com bubble. Dot-com bubble has not been included in any of the earlier studies that are presented in this

thesis. We can see from the results that momentum strategy did not produce statistically significant profits during years 1993–2004. The main reason for this result is the dot-com bubble. During years 1993–2000 the profits were very close to Jegadeesh and Titman's (1993, 2001) results but during years 2001–2004 the profits diminished. During and after the dot-com bubble, momentum profits were merely 0.08 % per each month. Henker et al. (2012) states that momentum phenomenon has a clear relation with stock market movements but not with the U.S. economy's movements. More precisely, Henker et al. states that momentum is linked with stock market trends, which is a similar result than Cooper et al. (2004) results. In other words, during the positive stock market trends, momentum strategy did produce approximately 1 % excess returns, but during negative stock market trends these returns disappeared.

This relation between momentum phenomenon's profits and market trends raises big questions: how this strategy should be implemented in practice and could we possibly predict these changes in market trends? These questions are also the main research questions of this thesis. In this section's last subchapter I will talk how average investor's should use momentum strategy in practice and in the next chapter I will present different technical analysis' tools to predict market changes.

2.5 Momentum Strategy in Practice

As a summary of the momentum strategy and its profits we can state that even if the momentum strategy has been producing significant profits, both economically and statistically, during the last century, we cannot think it as some kind of miracle of the financial world. The profits of momentum strategy are clearly significant in the long run but in the closer inspection we can notice that the profits variate between years and trends. When practicing this strategy, investors should take into account momentum's seasonality and even more importantly, general market trends. Based on this, we can state that using momentum strategy is very tempting during steady stock market growth but during the current European financial crisis we should analyze the markets more closely before making any investments into momentum portfolios. Jegadeesh and Titman's (2011) result support this point of view. They study in their unpublished research paper momentum profits during years 1990–2009. We can note from the results that momentum profits during this timeframe are again approximately 1 % per

month but when we take a closer look we can see that the profits are negative during the last two years, reaching 36.5 % negative annual return in 2009. These two years are especially interesting because the U.S.'s subprime crisis occurred during these years. (Jegadeesh & Titman 2011.)

We can draw a conclusion that momentum strategy's profits have been sensitive to this particular financial crisis and it is very likely that the same applies to European stock markets during the European financial crisis. As the momentum literature has clearly shown us, momentum strategy is really sensitive to changes in market trends and especially to financial crises. To overcome this regularity and to improve momentum strategy's profits investors' should try to estimate these changes in market states and especially market crashes. This way investors could decrease momentum portfolio's volatility and perhaps increase profits by cutting losses. One possible solution to this problem could lay in the field of technical analysis. As stated in the introduction, there are clear similarities between momentum investing and technical analysis. In the next chapter I will take a closer look into technical analysis and moving averages as a tool to predict market changes and after this, I will present the data and methods used in this thesis research setting.

3 TECHNICAL ANALYSIS

The aim of this chapter is to explain what technical analysis is and how the most used technical tool, moving averages, can be used as investment strategies. At first, I will discuss technical analysis in general and after this, I will take a closer look to the moving averages. In the third subchapter, I will observe how the moving averages can be used in spotting changing, and ongoing, market trends. In the last subchapter, I will discuss how the moving averages and momentum phenomenon are related and how these two investment methods can be used jointly.

3.1 Technical Analysis in General

As stated in the earlier chapters, Fama's (1970) efficient market hypothesis has had the most important role during the last decades when explaining the financial markets. According to Kilgallen (2012), this is one of the main reasons why the buy-and-hold strategy is perhaps the most popular investment strategy in the world. When the investors implement this buy-and-hold strategy, they, at least partially, accept the efficient market hypothesis and the assumption that the markets are informationally efficient. This will lead to the assumption that the average investor cannot consistently beat the market, unless they have access to some nonpublic information, so they will settle for classic buy-and-hold strategies. (Kilgallen 2012.)

Even though the efficient market hypothesis has been the most prominent financial theory during the last century, it has not gone unchallenged. Many different price-based phenomena and anomalies have suggested that it is in fact possible to beat the market on risk-adjusted basis. These price-based phenomena are called as technical investment strategies. The interest towards these technical investment strategies, according to Faber (2007), might be the result of the large drawdowns that many global asset classes have experienced during different market crashes. Faber (2007) states that, mathematically speaking, 75 % decline in the asset price would require 300 % future gains to just get back to even. For average investor, this would mean annual returns of 10 % for the next 15 years. Especially the 21st century's dot-com bubble and financial crisis have proven that classic buy-and-hold strategy has its downsides. The

simple quantitative approach, that is called technical analysis, is trying to overcome this by trying to achieve stock like returns with bond like volatility and drawdowns.

Technical analysis and fundamental analysis are the main methods when analyzing stocks and stock markets and when making investment decisions. As the fundamental analysis focuses solely on company fundamentals that generate the stock value, the technical analysis mainly focuses on stock prices and price movements. In other words, technical analysis is a hypernym for simple quantitative methods, which try to forecast future price trends with charts and few key figures (Murphy 1999). According to Murphy (1999), this methodology rests on the idea that anything that can affect the stock prices, will affect the stock prices, so a study of prices is all that is needed in forecasting future price levels. These methods rely mostly on buy and sell signals that are generated by different mechanical trading rules.

According to Hsu and Kuan (2005), technical analysis includes at least 39,832 different trading rules, and with few changes in key parameters, it would be possible to form almost infinite number of trading rules. To simplify this myriad of rules, all the rules are divided into twelve classes. These classes are filter rules, moving averages, support and resistance rules, channel break-outs, on balance volume averages, momentum strategies, head and shoulders strategies, triangle and broadening tops and bottoms strategies, rectangle strategies, double tops and bottoms strategies, learning strategies and vote and fractional position strategies. In addition, also the contrarian strategies of all the classes are considered as technical trading rules. (Hsu & Kuan 2005.)

According to Brock et al. (1992) use of technical analysis as an investment tool is as old methodology as the US stock markets and has been used by many famous Wall Street investors. Even older evidence is found in the 18th century Japan. Legendary rice merchant Munehisa Homma was able to gather large fortunes in the Japanese rice markets using technical methods that he had invented. This particular strategy is nowadays known as the candlestick pattern. (Zhu & Zhou 2009.) Based on these findings, it is justified to say that for centuries the investors have had an urge to forecast stock prices by analyzing past prices and sometimes they have even succeeded. Nowadays technical analysis is widely accepted and adopted by many practitioners

(Zhu & Zhou 2009). Despite this fact, many academics have been very skeptical towards technical analysis (Brock et al. 1992, Zhu & Zhou 2009). For example, Fama and Blume (1966) and Jensen and Bennington (1970) strongly states that technical analysis and especially simple filter rules and relative strength strategies are not profitable. Also, Malkiel (1981: 173) have even stated in his book that “technical analysis is anathema to the academic world.”

According to Zhu and Zhou (2009), this academic resistance towards technical analysis is based on three key elements. Firstly, academics argue that technical analysis is without any theoretical background. Nowadays, this is not completely true. It is true that it is a hard task to form theories that are able to explain theoretically why all of the different technical methods work but there are partial theories for some of the methods. For example, Zhu and Zhou (2009) have suggested that investors risk aversion and stocks’ degree of predictability does affect the optimal use of moving averages and the profitability of the strategy. Also, Hong and Satchell (2015) discover that stocks’ autocorrelation is the main reason why many technical trading rules are so popular. In larger perspective, Faber (2007) have also suggested that the same behavioral models that are able to explain momentum phenomenon are suitable theories for many others technical strategies that uses trend-following methodology.

Secondly, academics and many theoretical studies assume that the stock prices follow random walk. This random walk hypothesis states that the stock prices are not predictable, which automatically rules out the profitability of technical analysis. This same argument fits as well to momentum phenomenon but, as stated in the earlier chapters, there is strong evidence that supports the hypothesis that historical price data can be used in predicting future prices. Also, Brock et al. (1992) and Faber (2007) have shown that the simple moving averages can produce significant profits over the buy-and-hold strategy.

The third and last argument is that the empirical findings concerning technical analysis and its profits are mixed and inconclusive. This is perhaps the most valid argument against technical analysis and is based on the fact that all the earlier research articles concerning technical analysis are done with insufficient data and methods. Also data snooping bias is seen as a reason for the profits of technical analysis (Allen &

Karjalainen 1999). This basically means that when thousands of different strategies are tested simultaneously in the same data set, statistically speaking, some of the strategies will produce statistically significant profits despite the fact that the profits are simply a result of chance. In contrast, Park and Irwin (2007) studied 95 modern research articles about technical analysis and they found that 56 of these did support the technical trading rules, 20 were against and only 19 reported mixed results. Recently, Brock et al. (1992) and Lo, Mamaysky and Wang (2000) and Faber (2007) have also been able to show that when larger datasets and sufficient methodology are used, technical analysis, and especially moving averages, is able to produce significant profits.

It is also suggested that the transaction costs affects the profitability of technical analysis. For example, Allen and Karjalainen (1999) states that the trading rules cannot generate any profits when transaction costs are taken into account. According to Allen and Karjalainen (1999) these results indicate that the markets are efficient and the technical analysis cannot offer any excess returns when compared to buy-and-hold strategies. Bessembinder and Chan (1998) have similar results but they conclude that this does not mean that efficient market hypothesis and technical analysis are in contradiction with each other. According to their study, if technical analysis' predictability of stock returns vanishes when transaction costs are taken into account, it might be an indication that technical analysis work similarly when the markets are efficient. In other words, it is just not useful method for the average investor to implement, because the transaction costs are higher than the profits of the strategy. Bessembinder and Chan (1998) also find out that technical analysis is able to produce significant returns when the transaction costs are excluded, but after the transaction costs this methodology loses its profits. Despite this fact, they conclude that these profits might be, in fact, economically significant for the investors, even though the profits are not statistically significant. This also might explain why technical analysis is so popular methodology.

As stated earlier, technical analysis includes tens of thousands different strategies and most of the results are inconclusive or insignificant after the transaction costs. It is important to understand that this does not mean that all of the different strategies are useless. According to Faber (2007), the most used and studied technical methodology,

the moving averages methodology, and especially the 200-day simple moving average, are able to produce significant returns. Also the results of Glabadanidis (2015) indicate that moving averages are useful methodology in market timing and are able to produce statistically significant returns, even when the transaction costs are taken into account. This master's thesis focuses on this particular methodology of technical analysis because of its popularity. In the next subchapter I will take a closer look into moving averages and its ability to spot changing market trends. I will also discuss how the momentum phenomenon and moving averages are closely related and how these strategies can be used jointly in investing.

3.2 Moving Averages

Moving averages are the most used method in technical analysis, but it is possible to implement this methodology in several different ways (Kilgallen 2012). According to Kilgallen (2012) the most used and the most basic moving average strategy is the 200 day simple moving average. Moving averages basically means that when the stock's closing price is above its, for example 200 day, price average, it indicates that the stock is experiencing a positive price trend and the investor's should invest, or stay invested, in the stock. On the other hand, when the stock's closing price is below its price average, it indicates that the stock is experiencing a negative price trend and the investor's should divest, or stay divested, from the stock. Also, when the stock price and the calculated moving average crosses each other, a buy or sell signal is generated (see Figure 1). If the stock's closing price crosses the moving average from below (above), a buy (sell) signal is generated. Even though it is most common to use closing prices, it is also possible to use other prices as well. Also it is possible to use moving averages with stock returns or even with trading volumes (Nedeltcheva 2015). The term "moving" comes from the simple idea that the new moving averages are calculated daily, weekly, monthly or even yearly. In other words, the calculated average "moves" forward as the times goes by. (Kilgallen 2012.) Although, this thesis focuses solely on using moving averages with stock portfolios, it is important to mention that use of moving averages has been profitable in other asset classes as well (Faber 2007, Kilgallen 2012).

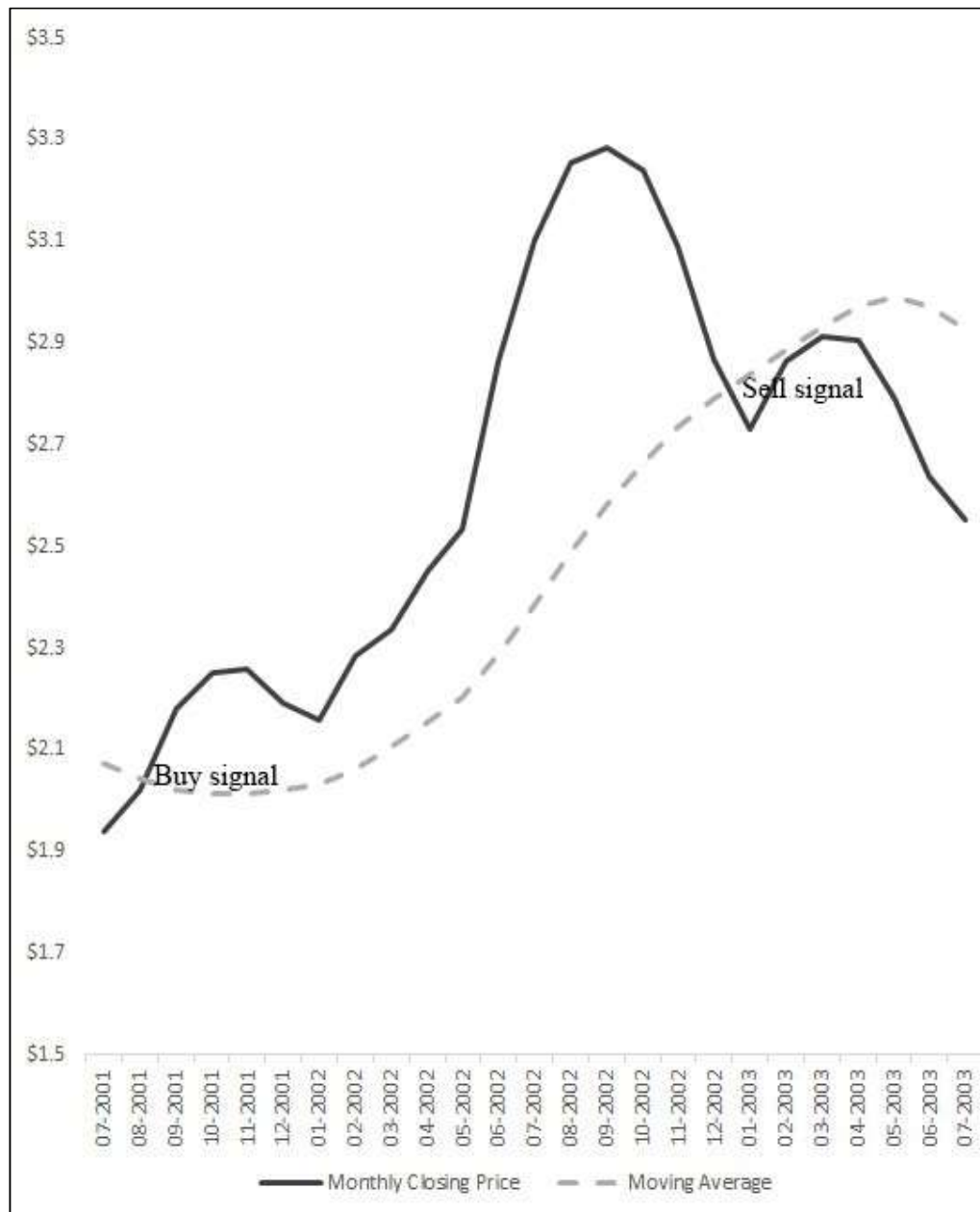


Figure 1. Moving Average Trade Signals

According to Murphy (1999) the popularity of moving averages is based on the fact that this method can be tested very easily and the buy and sell signals are precise and not open for debate. This is also the reason why moving averages are the basis for several different technical strategies. As mentioned earlier, there are numerous ways to implement moving averages. For example, investors can use in addition to simple moving averages, exponential and linear moving averages as well. The only difference between these methods is how the averages are calculated. Simple moving averages

uses simple, or arithmetic averages where exponential and linear moving averages uses exponential and linear averages. It is also quite typical to use two averages together when trying to spot price trends. With two averages, the trading signals occurs when the two averages, which uses different time intervals, shorter and longer, crosses each other. (Murphy 1999.) This thesis focuses mainly on the use of one simple moving averages.

Moving averages are usually seen as a way to spot changing, and progression of, market trends. It is important to understand that moving averages does not anticipate changing market trends but reacts to changing market trends. In other words, moving averages tells us that a positive or negative market trend has begun but only after the fact that the trend has already started. This lag is strongly related to the length of the used moving average. For example, 20 day moving average tracks more precisely with smaller lag than the 200 day moving average. In other words, the sensitivity of the moving averages is higher with shorter moving averages. This also leads to a larger number of trading signals, to higher transaction costs and even perhaps to many false trading signals. In other words, there is always a tradeoff between the sensitivity and the accuracy of the moving averages. Moving averages has also a smoothing effect, as seen in Figure 1, and this feature makes it easier to spot changing market trends. This leads to a much smoother price line when moving averages are used instead of the stock's closing price. (Murphy 1999.)

Although the simple moving average is the most used method by technical analysts, it has faced some criticism. For example, it is criticized that the simple moving average takes into account only the price information from the time period that the moving average is calculated and ignores all the other information. This might lead to a situation where some crucial information is ignored and the investment decision is flawed. Also, it is criticized that the simple moving average gives similar weight to each day's, or month's, price. Some analysts and investors believes that the more recent prices should have much larger weighting when moving averages are calculated. To overcome these problems, the use of exponential and linear moving averages are justified. (Murphy 1999.)

Despite the fact that moving averages have many advantages, when compared to simple stock price and chart analysis, this methodology is not useful all the time. As seen in the Figure 1, moving averages are methodology that follows price trends. This leads to a situation where moving averages works best when the stock market is trending positively or negatively. If the volatility of the stock markets are high, or the price development of the stocks are choppy, moving averages tend to perform poorly. Because of this aspect, it might be quite dangerous for the investor to fully rely on moving averages, when there are no clear consensus of the direction of the stock markets. In other words, if there are no clear stock trend, moving averages is not useful strategy to use. (Murphy 1999.) In the next subchapters I will discuss the profitability of moving averages strategies, how well this methodology can time the markets and how the momentum phenomenon and moving averages are related with each other.

3.2.1 Profitability of Moving Averages

As discussed in earlier, technical analysis in general have generated very mixed results when talked about its ability to produce significant returns over the classical buy-and-hold strategy. Moving averages have produced better results across-the-board, at least when observed without transaction costs and taxes. Perhaps more importantly, the volatility and maximum drawdowns of the moving averages strategies are from one third to two thirds lower than with the buy-and-hold strategy (Kilgallen 2012). In other words, risk adjusted returns are superior when compared to the buy-and-hold strategy. This observation applies to stocks and several different asset classes and commodities (Kilgallen 2012). Also Glabadanidis (2015) observes similar regularities. He states that the simple moving average strategies can indeed generate larger returns with lower volatility when compared to buy-and-hold strategies, even after transaction costs. This phenomenon applies also to all value-weighted decile portfolios that are sorted by market size, book-to-market and momentum factors, only exceptions are the high minus low and the winner minus loser decile portfolios (Glabadanidis 2015). This finding is quite troubling, because momentum phenomenon is especially observed with the winner minus loser portfolio.

Perhaps the most valid evidence of profitability of moving averages strategies are Faber's (2007) and Brock's, Lakonishok's and LeBaron's (1992) studies. Both of these

studies uses over 100 years of U.S. stock data and conclude that moving averages increases profits and lowers volatility and maximum drawdowns. Faber (2007) states that the use of moving averages instead of buy-and-hold strategy increases portfolio's Sharpe ratio from 0.32 to 0.55. Sharpe ratio is a common financial ratio that reflects portfolio's risk adjusted profits, the higher the ratio, the better the portfolio's risk adjusted returns are (Sharpe 1994). On the other hand, Brock et al. (1992) finds that moving averages' buy signals were followed approximately by 12 % market increment and sell signals were followed approximately by 7 % market decrement annually. These results clearly indicates that the moving averages can, at least partially, time the stock markets and reduce the riskiness of the investment portfolio. Even though these two studies are perhaps the most cited papers, because of the validity of the results, concerning technical analysis, there is suggestion that Brock et al. (1992) results are affected by data snooping bias (Ready 2002). According to Ready (2002), the choice of the trading rules Brock et al. (1992) used in their study were chosen because of their popularity in the 1980s. This might be problematic because Ready (2002) states that the popularity of these rules were a result of long-term effectiveness of these particular rules, so when the study period is pre 1980s, as Brock et al. (1992) study period were, these rules are destined to beat the passive investment strategies. On the other hand, Sullivan, Timmerman and White (1999) duplicate Brock et al. (1992) results and find them to be robust of data snooping bias. In fact, Sullivan et al. (1992) state that there are even better trading rules, for the study period, than the strategies which Brock et al. (1992) uses. In addition, also Hsu and Kuan's (2005) results supports both Faber (2007) and Brock et al. (1992) findings. All in all, the consensus is that it seems that the moving averages can, at least partially, time the market and this way increase the profits of the portfolio. The next subchapter takes a closer look at this feature.

3.2.2 Market Timing and Moving Averages

Market timing in general has a great impact on investors' portfolio profits. Estrada (2009) states that if the investor misses the ten best market days of U.S. stock market, the portfolio profits were 65 % smaller than the passive buy-and-hold strategy's profits. On the other hand, if the investor were able to avoid the ten worst market days of U.S. stock market, the profits were 206 % higher than the passive buy-and-hold strategy's profits. The effect is enormous because these days account only for 0.03 %

of the whole study period of 107 years. This explains the average investors need to time the markets. As stated previously, Faber (2007) and Brock et al. (1992) have found that the moving averages can time the stock markets by generating buy and sell signals that have real predictive power. In general, market timing strategies are defined as active strategies that try to offer larger profits, than the classical buy-and-hold strategies, by forecasting stock market movements. The requirement for these particular strategies to work is the assumption that stock prices are predictable and that the markets have price trends. That is why technical analysis, and the use of moving averages, are sometimes called as a trend analysis. (Zakamulin 2014.) As Zakamulin tested the simple moving averages in out-of-sample tests, he found out that the market timing ability are highly non-uniform. In other words, he found out that the moving averages have some predictability but these particular time periods tended to be short. More interestingly, during these time periods, when the simple moving average were able to outperform the passive strategy, the profits of the strategy were significantly higher. On the other hand, the same strategy experienced long time periods when the passive strategy had larger profits. We can deduct from these results that the usefulness, and the market timing ability, of moving averages are highly dependent on the time period of the out-of-sample tests. This is in line with Murphy's (1999) statements that the moving averages works best when the market is experiencing clear, positive or negative, trends. If the market has no clear direction, the moving averages loses its predictability. It is not unusual that these times of uncertainty can last many years.

Hong & Satchell's (2015) results also indicate that the moving averages have predictive power over stock markets but only when the stock prices are experiencing autocorrelation, or in other words, the prices are trending. According to their study, moving averages can identify and exploit these price trends and even amplify them. Another interesting finding is that when the market's level of autocorrelation is high, the longer moving averages work better and vice versa. (Hong & Satchell 2015.) This is logical because the shorter moving averages are more sensitive to the rapid market movements than the longer moving averages. Sadly, the investor cannot know beforehand if the market autocorrelation is high or low and which of the many moving averages strategies is the most useful.

According to Hsieh (2012), the empirical evidence of the moving averages ability to predict markets are irrelevant unless the benefits are bigger than the additional trading costs that the frequent trading involves. To study this, Hsieh (2012) focused on how the moving averages are able to preserve portfolio's value during economic downturns. To be statistically and economically viable, moving averages should be able to protect the investor from negative market shocks and lower the losses and risk in contrast to the passive strategy. As stated earlier, for this to work, the negative market trends should be prolonged. Hsieh's (2012) study period of 1970–2008 involves several prolonged market downturns, for example, oil crisis, the dot-com bubble and the recent subprime crisis, so the results indicate that the moving averages are indeed able to time the markets by avoiding the negative market trends. To study the effect, Hsieh (2012) compared the portfolio returns, standard deviations and Sharpe ratios. All of these parameters indicate that the use of moving averages did slightly increase the profits and lower significantly the riskiness. For example, Sharpe ratio increased from 0.24 to 0.42, which was a result of a much lower standard deviation. These results again indicate that, at least with the selected time frame, moving averages have protective and market timing abilities.

Even though the presented findings largely supports the market timing ability of the moving averages, it is important to understand that this feature is highly dependent on the state that the market is in. If the uncertainty is high and the market does not have any clear direction, this ability vanishes and the profits of moving averages largely disappear. Some researchers have even stated that the usability of moving averages are merely a result of data snooping bias (Zakamulin 2014). For this reason, more research is needed to develop more advanced moving averages strategies that takes account of this allegation. Also, it would be fruitful to test this methodology with different investment strategies, for example momentum, to see if the predictability is more universal feature or just a result of data snooping and random chance. The next subchapter takes a look how the momentum phenomenon and the moving averages are related with each other and is it possible to increase momentum profits with the use of moving averages.

3.2.3 Momentum and Moving Averages

As stated in the earlier chapters, momentum phenomenon, especially time series momentum, and moving averages are closely related with each other. Both of these methods focuses on past average returns of different stocks, so it is justified to say that the similarities are notable. The time series momentum is related to the traditional cross-sectional momentum but there is one key difference. Cross-sectional momentum focuses on group of stocks' relative profits, where the time-series momentum focuses on single stock's own past return (Moskowitz et al 2012). It could be argued that the time series momentum is a special case of the traditional momentum because it only focuses on single stocks where the cross-sectional momentum focuses on group of stocks. It is also good to mention that the same behavioral models of under- and overreaction applies and works also with the time series momentum (Moskowitz et al. 2012). Also, Moskowitz's, Ooi's and Pedersen's (2012) results indicate that the time series momentum is similarly a global phenomenon that can be found in different asset classes and markets.

It could be argued that the moving averages and time series momentum both can identify emerging price trends but different phases of these trends. As described in earlier in this chapter, moving average generates buy and sell signals that indicates that the, positive or negative, price trend has begun. Actually this buy signal can be also described as a methodology where the investor buys earlier losers and sells them when the stock's price have increased. In contrast, time series momentum generates this similar buy signal but a bit later. For example, moving averages focuses on the emerging and changing price trends, where momentum focuses on the continuity of the price trends. In other words, moving averages buys earlier losers and sells them when the price has increased, or when they can be seen as a current winners, and momentum buys these current winners and sells them when the price has increased even higher. More simply put, both of the methodologies generates buy (sell) signals when the stock's current price is higher (lower) than the stock's earlier price but the signal is generated in different phase of this price trend. (Fong & Yong 2005, Hong & Satchell 2015.) According to Hong and Satchell (2015), to both of these methodologies to work, and to generate correct signals, the stock prices have to be predictable and have autocorrelation.

These clear similarities raises a question, could it be possible to use these methodologies together to increase momentum strategy's profits? This aspect have not been studied that much. Perhaps the most relevant study for this thesis is the Glabadanidis' (2015) study that discovers that the use of simple moving averages can lower the riskiness and increase the profits of passive buy-and-hold portfolio. In addition, Glabadanidis (2015) studies if the same regularity applies to portfolios which are constructed by market size, book-to-market and momentum. To study this effect, Glabadanidis sorts the stocks into decile portfolios, which are constructed by the aforementioned factors, and applies 24 month moving average trading rule. In other words, the highest (lowest) decile includes stocks which has the highest (lowest) size, market value or momentum et cetera. In addition, Glabadanidis (2015) forms the High minus Low portfolios which invests to the highest and lowest decile portfolio. In more detail, this particular strategy invests to the highest decile and short sells the lowest decile simultaneously. As already mentioned, his results indicates that the use of 24 month moving averages lowers the standard deviation and increases the profits of all decile portfolios when compared to the passive counterparts. More surprisingly the eleventh portfolio, which is the high minus low portfolio, suffers from the use of moving averages. The returns of this portfolio are lower than the passive counterpart's returns. The results are identical with 6 month, 12 month, 36 month, 48 month and 60 month moving averages. This finding is particularly interesting because momentum phenomenon is strongest with this particular portfolio. Unfortunately, Glanadanidis (2015) does not discuss why the moving averages does not work with this particular portfolio. For this reason, this aspect requires more research to see if this finding is just an anomaly.

As this subchapter points out, the similarities with moving averages and momentum are obvious. Although, the momentum phenomenon is widely accepted and well-studied topic, unfortunately, the use of moving averages with momentum strategy is still relatively new topic despite the similarities. For this reason, more research is needed and this thesis will test if the moving averages work with the momentum portfolios. As Glabadanidis' (2015) findings indicate, even though moving averages work with momentum deciles, it might lose its usefulness with High minus Low portfolios. This finding raises more questions than gives answers. Why the use of moving averages loses its profitability over buy-and-hold strategies, when it is applied

with High minus Low portfolios? This master's thesis tries to address this issue. In addition, I will study if the dot-com bubble or the financial crisis have affected the momentum returns during the 21st century, as Henker et al. (2012) argues. The next chapter presents the study in more detail and describes the data and methods that are used in this study.

4 DATA AND METHODS

This chapter describes the research setting of the study and the methodology that is used. The first section presents the data that is used in the study and explains how the momentum portfolios are formed. After that, it is showed how the different market states are defined, and how the moving averages are formed. And the last section shows how the momentum portfolios with moving averages are formed and used in this study.

This thesis studies similar momentum portfolios as Jegadeesh and Titman (1993, 2001) did in their studies. At first, this research studies how the momentum portfolios perform, with the data in use, and how the many market crashes and negative market trends have affected the profits during the used timeframe. According to several theories, (Henker et al. 2012, Jegadeesh & Titman 2011, Cooper et al. 2004) the momentum profits should be affected by the market changes. To overcome these momentum losses, this thesis uses technical analysis and moving averages when trying to predict these market changes. The reason for these particular methods is the similarities between technical analysis, or more precisely moving average strategy, and momentum investing. Both strategies can be seen as a trend analysis and as a stock price analysis. Based on this, it is justified to use technical analysis' trend tools to identify these market changes. For example, Glabadanidis (2015) uses monthly moving averages with several different investment methods, for example momentum and value investing, to spot market changes beforehand. He is able to beat the classical buy-and-hold strategies with several percentages. This applies to the momentum deciles as well. The method that is used in this thesis, to spot different market changes, is the same method as Glabadanidis uses in his study. The reason why this thesis uses monthly moving averages is the popularity of this particular method (Brock et al. 1992). According to Brock, Lakonishok and LeBaron (1992), moving averages are the most popular strategy used by investors who follow technical analysis' methods. Also the evidence is strong that the moving averages can be used in recognizing market trends (Lo et al. 2000). Also the previous literature review supports this research setting.

4.1 Data

The data that is used in this thesis' research consists random sample of 820 stocks from the New York Stock Exchange (NYSE) and is obtained from the Center for Research in Security Prices (CRSP). The random sample is unbiased, so it accurately represents NYSE. Because this thesis only focuses on price momentum, all the dividends and capital payments to shareholders are excluded. The data consist monthly stock return data which is used in portfolio formation and in calculating moving averages. This data consist monthly closing day prices between January 1994 and September 2013. Because momentum portfolios and moving averages are based on earlier price changes, the actual sample period and the research periods differ. The research period for momentum portfolios and market states is 1.1.1995–30.9.2013. Because moving averages calculations are based on monthly average returns of momentum portfolios, the first possible month for moving average calculation is $1.1.1995+L$, which is the length of the used moving average. The longest moving average that is used in this thesis is 12 months, so for this particular moving average portfolio, the investment period starts at 1.1.1996. To ensure that all of the moving average portfolios' have the same amount of observations, so the results are comparable, the research period for these portfolios' are 1.1.1996–30.9.2013.

4.2 Formation of Momentum Portfolios

The momentum portfolios that are formed in this thesis are based on the same methodology that Jegadeesh and Titman (1993, 2001) uses in their study. At the start of each momentum portfolios' holding period, the returns of the stocks are calculated as a compounded total returns over the formation period, J months. The stocks are ranked based on the J month returns. After the ranking, stocks are split into deciles. The decile with largest returns is called the *winner* portfolio and the decile with lowest returns as the *loser* portfolio. All the portfolios are equally weighted. The momentum strategy involves buying the winner portfolio and selling short the loser portfolio and holding them for K months. This is called the holding period of the portfolio. This particular strategy that buys the *winner* portfolio and short sells the *loser* portfolio is called as Winner minus Loser (*WML*) strategy. This research studies zero-cost portfolios, so no transaction costs are taken into account. The strategy is also seen as

a self-sustaining strategy which means that there is no money infusions or withdrawals during the research timeline.

As Jegadeesh and Titman (1993) states, momentum strategy generates losses with under one month holding period. To overcome this, the momentum strategy that is used in this research skips one month between formation and holding period. This is only significant difference between this thesis' study and Jegadeesh and Titman's (1993, 2001) studies. This is done for the reason, that this way we can minimize effects of market microstructures and bid-ask bounce and maximize momentum strategy's profits (Henker et al. 2012). As stated earlier, Jegadeesh and Titman (1993) uses in their study 3–12 month formation and holding periods. To have comparable results, this thesis will also study momentum portfolios with 3, 6, 9 and 12 month formation and holding periods. In total, 16 different momentum strategies are studied with one month skip period between formation and holding periods. In addition, the momentum portfolios are always formed at the start of holding period and at the start of each month.

In this research, overlapping momentum portfolios are used, as did Jegadeesh and Titman in their studies (1993, 2001). This means that in any given month, each momentum strategy holds multiple portfolios at the same time. For example. 6/6 strategy holds, in every month, portfolios that are selected in the current month t , as well as portfolios that are formed in the previous $K - 1$ months. In other words, all the strategies buys the winner portfolio and short sells the loser portfolio in every month and closes the $t - K$ portfolio.

As stated previously, all the momentum portfolios are equally weighted at the start of the holding period. Naturally, stock values change during the holding period, so the portfolios will not stay as equally weighted. To overcome this issue, Jegadeesh and Titman (1993) rebalances the portfolios monthly. In other words, portfolio's stocks that have performed above average are sold and these profits are used to buy portfolio's stocks that have performed below average. This research follows the same rebalancing method in every month. This will give us the average return of the portfolios that are held in that month. To study if the results are robust and statistically significant, simple t-statistics are calculated and reported.

4.3 Momentum Portfolios and Market States

As stated in the earlier chapters, one of the research questions is to study how different market states affect the momentum profits. As Henker et al. (2012) and Cooper et al. (2004) states, momentum profits are affected by changes in market trends. It seems that momentum strategy's profits are linked with positive market trends and during negative market trends and crashes, momentum profits are highly negative. Also Jegadeesh and Titman (2011) observed this same phenomenon in their study.

To study the effect of different market states, each month during the research timeline needs to be addressed as a "UP" or "DOWN" market. Cooper et al. (2004) defines these two market states with lagged three-year market returns. This will not suit this research, because of a much shorter research period. They also observe, that with two-year and one-year lagged market returns the results are also robust, although different. In this study, it is used one-year lagged market returns to define market states in each month. Also Henker et al. (2012) uses one-year lagged market returns because it should capture more volatile market states than the three-year lagged market returns. UP market occurs when the lagged one-year S&P 500 Composite index's (S&P500) return is positive and DOWN market occurs when the lagged one-year S&P500 index's return is negative. S&P500 index is chosen because it is a single best reflection of overall performance of the U.S economy and the U.S. stock markets (Faber 2007, Nedeltcheva 2015). When we compare these UP and DOWN markets with that month's momentum returns, we can see if the profits occur during the UP markets and if the momentum returns are negative during the DOWN markets. Lastly, average momentum profits are calculated during UP and DOWN markets to fully see if the market states affect the results. This method is fully based on Cooper et al. (2004) and Henker et al. (2012) studies and the results are fully comparable.

4.4 Momentum Portfolios with Moving Averages

In this thesis, moving averages are used to spot changing market trends beforehand. As Glabadanidis (2015) and Han et al. (2013) states, using trading strategies with moving averages will generate better profits than the classical buy-and-hold strategy. The idea is to time the market so the used strategy will be invested (divested) in the

stock market only when positive (negative) market trend is happening. Monthly moving averages are used in this thesis with the momentum portfolios that were described in the earlier subchapter. It is important to mention that moving averages are not a method that is able to time the market perfectly. The following method, of forming moving averages, mimics Glabadaninidis' (2015) and Han et al. (2013) method. The monthly moving average can be defined as follows:

$$A_{jt,L} = \frac{P_{jt-L} + P_{jt-L+1} + \dots + P_{jt-1} + P_{jt}}{L} \quad (2)$$

Where, j is the portfolio at the end of the month t and P_{jt} is the closing price of the studied momentum portfolio and the length of the used moving average is L . The momentum portfolio j 's moving average, at the time t with the moving average's length L is named $A_{jt,L}$. The lengths of momentum portfolio's moving averages that are studied in this thesis are 3, 6, 9 and 12 months. The way these moving averages are used with momentum portfolios in this study is to compare the momentum portfolio's closing price P_{jt} at the end of every month to the portfolio's running moving average $A_{jt,L}$. If the portfolio's return is above the portfolio's moving average, it triggers an investment signal (or signal to stay invested). In other words, if the signal occurs on month t , then the strategy invests to the portfolio in the next month $t + 1$. If the momentum portfolio's closing price is below the portfolio's moving average, it signals to divest in the portfolio (or stay invested in cash) in the following month $t + 1$. When the buy or sell signal occurs, the strategy will invest or divest fully in the portfolio or in the risk-free rate. During these months when the strategy is divested in the portfolio, it is invested in 30-day US Treasury bill. This is seen as a proxy of the risk-free rate. The returns of this momentum portfolio with moving averages strategy can be expressed as follows:

$$\tilde{R}_{jt,L} = \begin{cases} R_{jt}, & \text{if } R_{jt-1} > A_{jt-1,L} \\ r_{ft}, & \text{otherwise} \end{cases} \quad (3)$$

No transaction costs are taken into account in this strategy. Lastly, I will compare the momentum portfolios' returns with and without the moving average to see if it is possible to generate more profits and less losses with moving averages when trying to time the market changes.

As it would be laborious to study all the different momentum portfolios with all the different lengths of moving averages, this thesis studies more closely the 6/6 portfolio, and the two momentum portfolios with the best average returns. If the 6/6 is one of them, then the two second best momentum portfolios are chosen in addition to the 6/6 portfolio. The reason to study especially 6/6 portfolio is, that this particular portfolio is the most studied momentum strategy and it generates approximately 1 % monthly returns. For example, Jegadeesh and Titman (1993, 2001), Cooper et al (2004) and Henker et al. (2012) uses particularly this 6 month formation and holding period in their studies. In addition to basic measures of portfolio returns, the performance of these different momentum portfolios are measured with average monthly return and standard deviation. The statistical significance of the results are measured with simple t-statistics.

In the next chapter, the results of this thesis' research setting are presented and discussed and, in addition, all the necessary tables and graphs of the results are reported. This thesis' results are also compared with earlier momentum and moving average literature to see if the results are similar, and if not, the reasons why the results differ are also discussed. Lastly, this thesis answers the research questions in full detail and interprets the answers.

5 DATA ANALYSIS

The results and findings of this thesis are reported in this chapter, and also the discussion about the results. First subchapter focuses on momentum portfolios' profits during the study period and after that it is shown how the negative market trends of 21st century have affected the momentum portfolios' profits. The results when moving averages are implemented to the momentum portfolios are reported in the last subchapter.

5.1 Momentum Profits in 1995–2013

This subchapter presents the returns of *winner*, *loser* and *WML* portfolios during the years 1995–2013. The stocks are sorted to deciles by their *J*-month lagged returns and the decile with highest (lowest) returns is called as the *winner* (*loser*) portfolio. These portfolios' are held for *K*-months. In addition, the returns of *WML* portfolio (later called the momentum portfolio) is reported also in Table 1. The *WML* portfolio takes simultaneously long position in *winner* portfolio and short position in *loser* portfolio. Table 1 presents the monthly average profits of these three portfolios. The results indicate that ten of the sixteen momentum portfolios' produces statistically significant monthly returns. Perhaps surprisingly, all the returns of the momentum portfolios are lower than the earlier studies suggest (Jegadeesh & Titman 1993, 2001). Despite this, we can still state that the momentum phenomenon is present in the used sample. Another interesting finding is that the *loser* (*winner*) portfolios tend to generate more (less) profits when the holding period gets longer. This is problematic for the momentum portfolios' because the used strategy buys the *winner* portfolio and short sells the *loser* portfolio. In other words, when the returns of *loser* portfolio increases, the momentum portfolios' returns decrease, and vice versa.

As stated in the earlier chapters, use of momentum strategy should generate 1 % monthly average returns, but in this study, the highest return were only 0.47 % with t-statistic of 1.764. The momentum strategy with 3 month formation period does not generate significant returns. One possible reason for the lower returns might be the negative market trends during the 21st century. It is suggested that large market crashes and negative market trends affects the momentum profits negatively (Cooper et al.

2004, Henker et al. 2012). These results indicate that the momentum has been apparent during the late 20th and early 21st century but the phenomenon has weakened significantly. The *Winner* and *Loser* portfolios have managed to generate similar monthly returns than the S&P 500 Composite Index, which generated 0.86 % average monthly returns. All of the returns of *Winner* and *Loser* are highly statistically significant. This indicates that for the average investor, passive index investing would have been better choice than to use the momentum strategy.

The results in Table 1 are in line with Jegadeesh & Titman's (1993) findings, although the momentum effect is weakened. Jegadeesh & Titman (1993) states that the only insignificant portfolio is the 3-3 momentum strategy and the most successful strategy is 12-3 strategy. This applies also to this thesis' results. We can conclude that, in general, momentum strategy works best when the formation period is long and the holding period is short. According to the models that try to explain momentum, the reason behind this effect might be the investors' overreaction. The overreaction drives the prices higher than the fundamental value and this overreaction takes time to accumulate (Daniel et al. 1998). According to Daniel et al. (1998) theory, the overreaction is prolonged and the positive price reaction is continued, so the effect is strongest with longer formation periods. After this, the phenomenon disappears when the public information reaches the investors, which might indicate why the shorter holding periods work better than the longer ones. As stated in the earlier chapters, momentum is strongest in first 12 months and after this the phenomenon disappears gradually (Jegadeesh & Titman 1993). This might also explain why the phenomenon is strongest with close to 12 month formation periods and with short holding periods.

To study more closely why the returns of momentum portfolios are lower and partly statistically insignificant, this study presents the sub-period analysis of the 12-3, 9-3 and 6-6 momentum strategies (See Table 2). 12-3 and 9-3 strategies are picked for the closer analysis because these strategies generated the highest monthly average returns. The 6-6 momentum strategy is picked because it is the most studied momentum strategy and it is seen as a best representative of the other momentum strategies (Jegadeesh & Titman 1993, 2001). The sub-periods in question are five years but the last sub-period is shorter because of the uneven time frame.

Table 1. Returns of Momentum Portfolios

J	Portfolio	K =	3	6	9	12
3	Winner		0.73 % (3.021)***	0.76 % (4.318)***	0.86 % (6.056)***	0.86 % (7.414)***
3	Loser		0.69 % (2.322)***	0.71 % (3.277)***	0.75 % (4.767)***	0.77 % (5.923)***
3	WML		0.04 % (0.206)	0.05 % (0.350)	0.11 % (1.071)	0.09 % (0.983)
6	Winner		0.79 % (3.319)***	0.88 % (4.972)***	0.91 % (6.560)***	0.87 % (7.267)***
6	Loser		0.54 % (1.672)**	0.56 % (2.461)***	0.63 % (3.756)***	0.70 % (5.228)***
6	WML		0.25 % (1.051)	0.31 % (2.049)**	0.29 % (2.326)***	0.18 % (1.687)**
9	Winner		0.95 % (4.099)***	0.17 % (5.625)***	0.97 % (6.863)***	0.91 % (7.387)***
9	Loser		0.51 % (1.567)*	0.08 % (2.147)**	0.63 % (3.710)***	0.74 % (5.612)***
9	WML		0.44 % (1.717)**	0.08 % (2.791)***	0.34 % (2.537)***	0.18 % (1.617)*
12	Winner		0.96 % (4.028)***	0.94 % (5.130)***	0.92 % (6.099)***	0.86 % (6.450)***
12	Loser		0.49 % (1.491)*	0.58 % (2.437)***	0.68 % (3.988)***	0.76 % (5.751)***
12	WML		0.47 % (1.764)**	0.36 % (1.993)**	0.24 % (1.722)**	0.10 % (0.862)

The momentum portfolios are formed based on J -month lagged returns and are held for K -months. The values for J and K are reported in the first row and column. The stocks are ranked based on the performance of J months and are divided into deciles. The worst decile is the *Loser* and the best decile is the *Winner* portfolio. The momentum portfolio, or the Winner Minus Loser (*WML*) is also reported. The t-statistics are reported in the brackets. *, ** and *** presents the significance levels of 10, 5 and 1 %. The profits presented for the zero-cost portfolios are monthly average profits during 1995–2013.

The returns presented in Table 2 indicates that the recent financial crisis and the dot-com bubble have indeed affected the strategies. All of the momentum portfolios are most profitable in years 1995–1999 when the stock markets experienced strong bull markets. Also the *Winner* portfolios' average monthly returns indicates large positive market trend. The average monthly returns were as high as 2.34 %. This is almost 32 % annually. During the same time-period the momentum profits were approximately 1 % monthly. This results supports the earlier momentum literature. Also, the results are very similar to Jegadeesh & Titman's (2001) findings during the same time period.

The dot-com bubble burst in September 2000 resulted a market wide crash and the profits of the studied momentum portfolios declined on average 58 % during years 2000–2004. The impact is massive. This finding supports both Cooper et al. (2004) and Henker et al. (2012) findings that the negative market trends affect momentum profits.

Table 2. Sub-Period Returns of Momentum Portfolios

Strategies	Portfolio	1995–1999	2000–2004	2005–2009	2010–2013	1995–2013
6-6	Winner	1.85 %	0.45 %	0.04 %	1.27 %	0.88 %
		(9.682)***	(1.717)**	(0.079)	(4.298)***	(4.972)***
6-6	Loser	1.13 %	0.14 %	-0.19 %	1.36 %	0.56 %
		(4.809)***	(0.374)	(-0.275)	(4.876)***	(2.461)***
6-6	WML	0.72 %	0.31 %	0.23 %	-0.10 %	0.31 %
		(3.669)***	(1.122)	(0.535)	(-0.434)	(2.049)**
9-3	Winner	2.06 %	0.61 %	-0.16 %	1.41 %	0.95 %
		(5.954)***	(1.757)**	(-0.258)	(3.389)***	(4.099)***
9-3	Loser	1.19 %	0.20 %	-0.41 %	1.26 %	0.51 %
		(3.022)***	(0.321)	(-0.446)	(2.912)***	(1.567)*
9-3	WML	0.88 %	0.41 %	0.25 %	0.14 %	0.44 %
		(2.213)**	(0.788)	(0.366)	(0.549)	(1.717)**
12-3	Winner	2.34 %	0.64 %	-0.27 %	1.22 %	0.96 %
		(6.450)***	(1.878)**	(-0.420)	(2.975)***	(4.028)***
12-3	Loser	1.10 %	0.19 %	-0.32 %	1.15 %	0.49 %
		(2.662)***	(0.314)	(-0.343)	(2.586)***	(1.491)*
12-3	WML	1.24 %	0.45 %	0.05 %	0.07 %	0.47 %
		(3.002)***	(0.826)	(0.070)	(0.267)	(1.764)**

Returns of 6-6, 9-3 and 12-3 momentum strategies are formed based on J -month lagged returns and are held for K -months. The values for J and K are reported in the first row. The stocks are ranked based on the performance of J months and are divided into deciles. The worst decile is the *Loser* and the best decile is the *Winner* portfolio. The momentum portfolio, or the Winner Minus Loser (*WML*), is also reported. The used sub-periods are reported in the columns. The t-statistics are reported in the brackets. *, ** and *** presents the significance levels of 10, 5 and 1 %. The profits presented for the portfolios are monthly average profits during 1995–2013.

In Henker et al. (2012) study, the results also indicate that the returns before the dot-com bubble are close to 1 % but after the year 2000, the returns vanish. This study's results support this finding and the same applies to years 2005–2009. The main reason for the poor results might be the financial crisis of 2008. Perhaps the most interesting finding is that the momentum portfolios have not recovered after these crises. As we focus on the *Winner* and *Loser* portfolios, we can see that the profits have significantly

declined during the bad years and the market have started to recover after 2010. Somehow the years after 2010 are the worst for the momentum portfolios. The earlier literature suggest few possible explanations for this. As Cooper et al. (2004) have stated, momentum profits are not linear. In other words, momentum profits are not highest when the market is experiencing strong and sudden positive trends, but when the stock markets are growing steadily. Another reason might be that the momentum phenomenon is simply a temporary anomaly. Possibly, as the momentum were documented and analyzed thoroughly the investors took advantage of this phenomenon and the returns disappeared as the market “corrected” itself. This theory supports the risk-based model and the efficient market hypothesis. To fully study this, more research and out-of-sample testing is needed in the future.

To study more closely the real effect of these negative market trends to momentum returns, a more thorough market analysis is needed. The next sub-chapter focuses on this by classifying each of the time period’s months to UP or DOWN markets and reporting the average returns during these two market states.

5.2 Changing Market Trends and Momentum Profits

As stated in the previous chapter, the results indicates that the market crashes of 21st century have significantly affected the momentum returns. After the year 2000, the momentum returns have diminished gradually and have not recovered afterwards. To study this effect in more detail, the Figure 2 presents the time series of the best momentum portfolio.

We can see from the Figure 2 that the momentum profits have been clearly sensitive to the market crashes. Despite the fact that the average monthly return of the portfolios are positive, there are many negative periods. For example, the burst of dot-com bubble in September 2000 produced, on average, 7 % monthly average losses for the next six months. Perhaps the clearest evidence of the market sensitivity of this particular momentum portfolio is the 2008’s financial crisis. During and after this market crash, the momentum losses grew to a staggering 25 % per month. Also, we can see the strong bull markets that preceded these market crashes from the time series. Figure 2 points out that the momentum returns have been highly volatile during these times of

uncertainty in the U.S. stock markets. The high volatility of the momentum returns also can explain why the profits have been statistically insignificant during the 21st century.

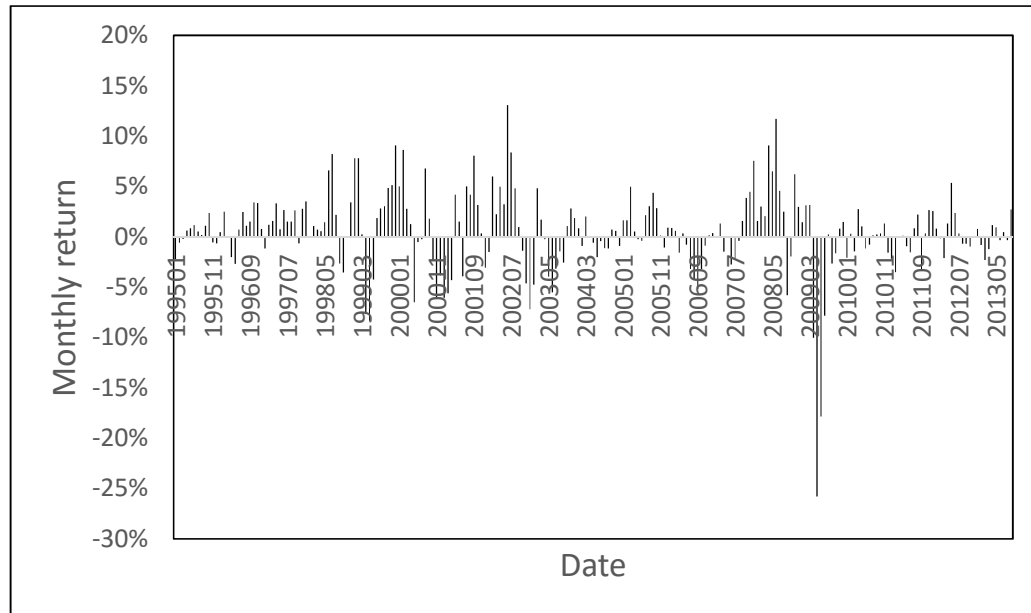


Figure 2. Time Series of WML 12-3 Portfolio Returns

To study the momentum returns during these two major market crashes, to see if the market sensitivity is really behind the weak profits, we need to define the UP and DOWN markets. This methodology follows Cooper et al. (2004) framework. As they use 3 year lagged market returns to define the market states, this study uses 12 month lagged returns of S&P 500 Composite index. The reason for the shorter lagged returns is the much shorter study period. Cooper et al. (2004) also states that the use of shorter horizon should capture smaller market changes between these two market states. UP (DOWN) market occurs when the 12 month lagged market return is positive (negative). These states are defined monthly.

We can see from Figure 3 that this methodology captures well the negative market states of dot-com bubble and 2008's financial crisis. The DOWN markets occurred right after the crises which is logical and, for example, the DOWN states lasted on average 17 months where the UP market lasted on average 42.5 months. This tells us that the crises have been quite short and severe when compared to the UP markets. To

fully understand how the momentum portfolios performed during these two market states, we need to calculate the average monthly returns during these two states. Table 3 and Table 4 reports these results.

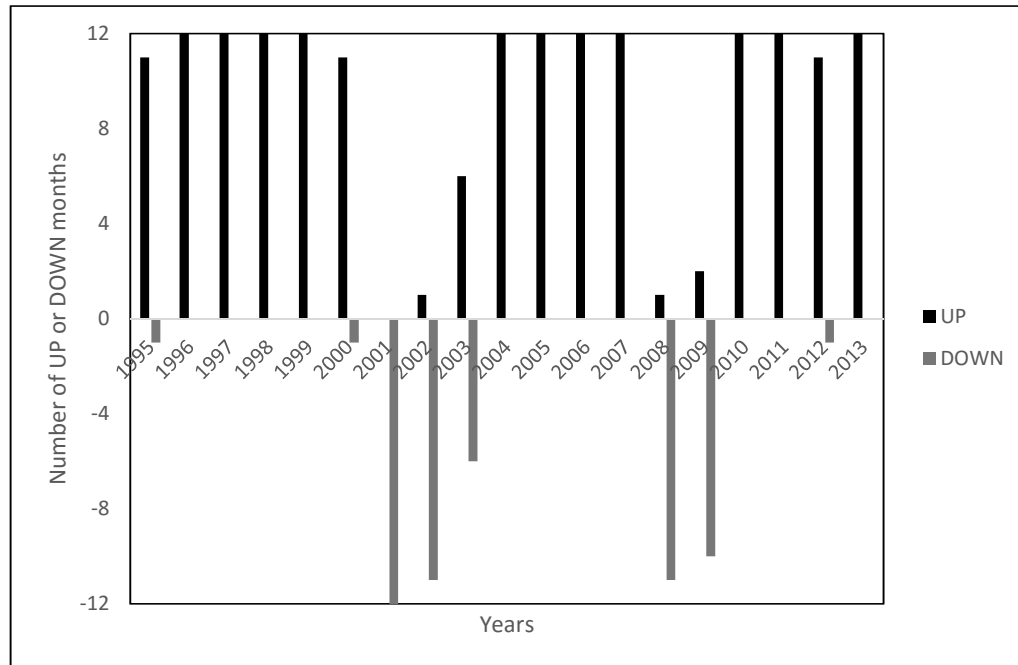


Figure 3. Number of UP and DOWN States

We can see from Table 3 that momentum portfolios generate, on average, higher returns during the UP markets than on the whole study period on average. For example, the best strategy, 12-3 WML portfolio, generates 0.62 % average monthly profits when on the whole study period the average monthly return were 0.47 %. This is 32 % change in the average returns. Also the t-stat increases from 1.764 to 2.914. These are significant changes and we can conclude that the momentum strategy is, on average, market sensitive and generates higher returns during the UP market states.

Again, only the strategies with 3 month formation period are statistically insignificant which also applied when we studied the whole study period. This indicates clearly that the momentum profits are higher during the positive market trends and that the state of the stock market has importance when implementing momentum investing. To study if the momentum profits are linear during the UP market states, more detailed research is needed.

Table 3. Momentum Profits during UP States

J	Portfolio	N=172	K=	3	6	9	12
3	WML			0.07 % (0.427)	0.04 % (0.375)	0.10 % (1.001)	0.06 % (0.635)
6	WML			0.34 % (1.658)**	0.29 % (2.438)***	0.28 % (2.239)**	0.20 % (1.772)**
9	WML			0.53 % (2.643)***	0.10 % (4.372)***	0.39 % (2.890)***	0.30 % (2.506)***
12	WML			0.62 % (2.914)***	0.51 % (4.005)***	0.41 % (3.004)***	0.31 % (2.573)***

The momentum portfolios are formed based on J -month lagged returns and are held for K -months. The values for J and K are reported in the first row and column. The stocks are ranked based on the performance of J months and are divided into deciles. Profits of momentum portfolios (*WML*) are reported during *UP* states. *UP* state is defined when the 12 month lagged return of S&P 500 Composite index is positive. N is the number of observations for *UP* states. The t-statistics are reported in the brackets. *, ** and *** presents the significance levels of 10, 5 and 1 %. The profits presented for the portfolios are monthly average profits during 1995–2013.

Table 4, on the other hand, reports the average monthly profits of the same momentum portfolios and again we can see that 15 of the 16 strategies generate statistically insignificant returns. More interestingly, 6 of the 16 strategies generate negative monthly profits, although five of these results are statistically insignificant. One reason for this insignificance might be the low number of observations, if the study period would be longer and it would include several other market crises, the results might be more prominent. Despite this, the changes are quite dramatic. For example, the 12-12 momentum strategy's profits decline from 0.10 % to -0.61 %. This is staggering -710 % change in the average returns. All in all, we can say, with strong confidence, that the momentum profits are indeed sensitive for negative market states and momentum strategies are only profitable during positive market trends. These results supports both Cooper et al. (2004) and Henker et al. (2012) findings. To increase the robustness of this finding, different lengths of lagged market returns and different market proxies should also be tested.

This market sensitivity of momentum profits raises a question that why the returns are so sensitive? Again, the behavioral models of Daniel et al. (1998) and Hong and Stein (1999) explain this phenomenon really well. Daniel et al. (1998) theory of overconfidence suggests that the investors' overconfidence is stronger during the bull markets and hence, the momentum profits are higher. The opposite applies during the

bear markets. Also, the Hong and Stein's (1999) theory of momentum investors and news watchers can explain this market sensitivity. They suggests that the momentum investors' risk aversion decreases when their wealth increases which leads to a higher returns during the positive market trends. To test these two hypotheses in more detail, investors' confidence and risk aversion levels should be also measured and tested.

Table 4. Momentum Profits during DOWN States

J	Portfolio	N=53	K=	3	6	9	12
3	WML			-0.10 % (-0.156)	0.07 % (0.145)	0.18 % (0.577)	0.26 % (1.140)
6	WML			-0.04 % (-0.051)	0.38 % (0.726)	0.31 % (0.903)	0.09 % (0.331)
9	WML			0.14 % (0.161)	0.04 % (0.404)	0.17 % (0.464)	-0.20 % (0.735)
12	WML			0.01 % (0.011)	-0.14 % (-0.218)	-0.29 % (-0.751)	-0.61 % (-2.125)**

The momentum portfolios are formed based on J -month lagged returns and are held for K -months. The values for J and K are reported in the first row and column. The stocks are ranked based on the performance of J months and are divided into deciles. Profits of momentum portfolios (WML) are reported during $DOWN$ states. $DOWN$ state is defined when the 12 month lagged return of S&P 500 Composite index is negative. N is the number of observations for $DOWN$ states. The t-statistics are reported in the brackets. *, ** and *** presents the significance levels of 10, 5 and 1 %. The profits presented for the portfolios are monthly average profits during 1995–2013.

The feature that momentum profits seems to be sensitive to different market trends, and especially to negative trends, raises a question, would it be possible to avoid these lower returns by timing the markets? One possible solution is to use moving averages to time the markets. Next subchapter combines these two methodologies, momentum and moving averages, and reports these results.

5.3 Momentum Portfolios with Moving Averages in 1996-2013

This section reports the portfolio returns when the momentum and moving averages methodologies are used as a combined strategy. These returns are then compared to the passive counterpart that just implements the same momentum strategy as earlier. The use of moving averages generates buy and sell signals that try to anticipate market movements beforehand. Table 5 reports the results of these two aforementioned strategies. We can see from Table 5 that the strategies that combine momentum and

moving averages generate, on average, smaller returns and smaller standard deviations. Only exception is the 6-6 momentum strategy with 3 month moving average. This might indicate that the shorter moving averages are better at timing the markets than the moving averages with longer time periods. This hypothesis is supported by the finding that the $p1$ is statistically significant. $p1$ indicates the portion when the strategy's buy signal was followed by a positive portfolio return. In other words, $p1$ indicates the proportion how well the strategy were able to spot positive market trends. The 6-6 momentum strategy with 3 month moving averages buy signals were 68 % of the time right. The same did not apply with sell signals. Sell signals were only 45.45 % of the time right. Despite this, the overall performance of this particular portfolio is remarkable. The returns were 30 % higher than the passive counterpart's returns and the standard deviation were 16 % lower. It could be argued that this benefit is lost if we took transaction costs into account but more research is needed for making any further conclusions. The average holding period were less than 5 months which indicates that the amount of transactions with this particular strategy is not particularly high.

Even though the moving averages were not able to increase the profits of the strategies in general, we can still see some regularities in the results. For example, the shorter the moving average, the higher the return and more transactions. This indicates that the shorter moving averages are more sensitive to market changes and react faster than the longer moving averages. This finding supports Glabadanidis' (2015) findings and is in line with the earlier literature. Another interesting finding is that the moving averages are only able to produce statistically significant results with the 6-6 momentum strategy with all of the time lengths. The main reason behind this might be the lower standard deviation of the strategy. For example, Murphy (1999) have stated that the moving averages work best in markets that have clear price trends. This also applies to single stocks and portfolios. If the volatility is high and the trends are more random, the moving averages loses its ability to spot price trends. As the standard deviation is smallest with the 6-6 momentum strategy, the moving averages generates the most reliable buy and sell signals with this strategy. The investment parameter tells that the strategy is "active", on average, 55-60 % of the time. In other words, all of the strategies are invested in the momentum portfolio over half of the time. The number is bit low when compared to Glabadanidis' (2015) findings. The number of

transactions during the study period ranges from 17 to 58. In other words, the average holding period is between 4 and 13 months which is very close to the holding periods of traditional momentum portfolios. We can conclude that because of this, the transaction costs should not be any higher than with the momentum portfolios and the higher profitability of the 6-6 momentum strategy with 3 month moving averages could be utilized.

Perhaps the most interesting finding is that the moving averages that were used in this study were able to spot positive market trends way better than negative market trends. The $p1$ value, that reflects the success rate of the buy signal, were over half the time right with 9 portfolios out of 12. Unfortunately only 2 of these 9 parameters were statistically significant. The main reason for this is the low number of observations, or buy signals. If the study period would include more buy signals, the statistical significance would also increase. With $p2$ parameter, we can see that the success rate of the sell signal were over half the time right with only 1 portfolio. This finding is contradicted with earlier moving averages literature. Also 9 out of 10 parameters were statistically insignificant. Because of the insignificant results, we can only presume that these results might indicate that the moving averages work better with positive trends.

These results raises a question, why the moving averages were not able to spot negative market trends and, on average, did not work with momentum strategy? As said, these findings are contradicted with the earlier literature so no widely accepted theoretical explanations are currently available. Some explanation might be the used market. The stocks in the data are taken from NYSE which is the world largest and one of the oldest stock exchange. According to Allen & Karjalainen (1999), moving averages only work in new stock markets that lacks efficiency. Another reason might be that the results of Glabadanidis (2015) might be biased. In other words, Glabadanidis' results could be only a result of change and data snooping bias. To verify this more research is needed with similar methodology. In addition, Sullivan et al. (1999) states that moving averages can outperform its passive counterparts in relatively short time periods. He continues that in over 10 year out of sample tests, moving averages cannot generate excess returns when compared to the buy-and-hold strategy. This study's research period is almost 18 years so these results might support Sullivan et al. (1999) claims.

Table 5. Returns of Momentum Portfolios with Moving Averages

Portfolio	Strategy	N=213	r	std	Inv	NT	p1	p2
6-6 WML	B-and-H		0.30 % (1.863)**	2.35 %	100%	1	-	-
	MA3		0.39 % (2.889)***	1.97 %	56 %	44	68.00 % (1.689)*	45.45 % (-0.427)
	MA6		0.29 % (2.045)**	2.07 %	59 %	20	70.00 % (1.265)	40.00 % (-0.632)
	MA9		0.29 % (2.035)**	2.08 %	58 %	22	72.73 % (1.508)*	63.64 % (0.905)
	MA12		0.23 % (1.654)**	2.03 %	56 %	20	70.00 % (1.265)	50.00 % (0.000)
9-3 WML	B-and-H		0.44 % (1.634)*	3.93 %	100 %	1	-	-
	MA3		0.37 % (1.571)*	3.48 %	58 %	58	58.62 % (0.928)	37.93 % (-1.300)
	MA6		0.31 % (1.264)	3.58 %	61 %	33	47.06 % (-0.242)	37.50 % (-1.000)
	MA9		0.31 % (1.246)	3.63 %	58 %	25	53.85 % (0.278)	41.67 % (0.577)
	MA12		0.27 % (1.089)	3.62 %	57 %	17	55.56 % (0.334)	50.00 % (0.000)
12-3 WML	B-and-H		0.48 % (1.692)**	4.14 %	100 %	1	-	-
	MA3		0.32 % (1.276)	3.66 %	58 %	57	57.14 % (0.756)	32.14 % (-1.890)**
	MA6		0.29 % (1.169)	3.62 %	58 %	39	50.00 % (0.000)	36.84 % (-1.117)
	MA9		0.36 % (1.416)*	3.71 %	61 %	23	63.64 % (0.905)	36.36 % (-0.905)
	MA12		0.29 % (1.123)	3.77 %	61 %	21	40.00 % (0.632)	30.00 % (-1.265)

The momentum portfolios (*WML*) are formed based on *J*-month lagged returns and are held for *K*-months. The values for *J* and *K* are reported in the first row. *N* is the number of months in the sample period. Profits of *WML* portfolios are reported with buy-and-hold and moving averages strategies, where *r* is the average monthly return of the strategies, *std* is standard deviation, *Inv* is the proportion of months where the strategy is invested in the *WML* portfolio, *NT* is the number of transactions (buy or sell) during the sample period. *p1* indicates the proportion when the buy signal was followed with positive portfolio return and the *p2* indicates the proportion when the sell signal was followed with negative portfolio return. The used moving average strategies are 3, 6, 9 and 12-month strategies. The strategies invest in the momentum portfolio when the strategy generates buy signal and invests in the risk-free rate when the strategy generates sell signal. 30-day U.S. Treasury Bond is the risk-free proxy. The t-statistics are reported in the brackets. *, ** and *** presents the significance levels of 10, 5 and 1 %. *p1* and *p2* are tested against 0.5 and the monthly average returns are tested against zero. The study period is 1996–2013.

Perhaps the best reason for the mixed results is the used methodology. One possible reason for worse performance might be the use of monthly average returns instead of real monthly returns. The reported, and used, momentum profits are average monthly profits of the whole holding period and these masks the real monthly performance of the portfolios. For example, the first holding month could be highly profitable but if the rest of the holding months produce negative profits, the average return of the portfolio would be negative, on average. If we used real monthly profits, the moving average might have produced better results and the amount of correct buy or sell signals could have been higher. Further research is needed to see if this assumption is true.

As earlier mentioned, the moving averages were able to recognize positive market trends but not the negative market trends. As mentioned, this finding does not support Glabadanidis' (2015) findings. He states in his study that the moving averages can recognize both, the positive and negative, market trends with 55 % to 63 % success rate. The reason for this significant difference might be in the time period that was used. This study's results indicates that the positive market trends have been longer and less severe than the negative market trends during the study period. This is in line with the last decades where the dot-com bubble and 2008's financial crisis have lasted only few years but the stock prices plummeted. As stated in the earlier chapters, moving averages lag the real market changes so the buy and sell signals come always after the changes in market trends. In other words, the positive market trends have lasted longer during the study periods, so the moving averages had time to react and generate correct signals, but the short negative market trends had already ended when the moving average gave the false sell signal. In conclusion, the moving averages are useful methodology when the trends continue for longer periods, so the methodology has time to react and time to generate returns. To overcome this, in future studies we could use exponential moving averages that gives extra weight to more recent observations. This way the methodology would be more sensitive and it would spot the changing trends more quickly. On the other hand, this might lead to false signals if the spotted trends does not continue. All in all, there is always a trade-off between the sensitivity and accuracy of the moving averages.

The next chapter includes the summary of this thesis. I will discuss shortly about the theoretical background of momentum phenomenon and technical analysis. After that I will present the main findings of this thesis. Finally I will discuss about the importance of the findings and provide future research questions that arose during the study.

6 SUMMARY

The aim of this thesis was to clarify to the reader what momentum is and what generates this phenomenon and how it is related to moving averages. At first, momentum was observed in more general level and after this the most widely accepted explanation models were introduced. Because of the broadness of this phenomenon, some explanation models and strategies are excluded from this thesis. For the same reason, the focus has been in momentum stocks and U.S. stock markets, even though this phenomenon can be found in several different asset classes and even in international markets.

As stated in the first chapter, momentum phenomenon means that stocks which have generated the highest returns during the past 3–12 months will also generate the highest returns during the next 3–12 months, and vice versa. This phenomenon is able to generate significant returns, on average 1 % per holding month. Although the phenomenon has been omnipresent during the 20th century, its returns have not been monotonic from month to month. When we study these returns more closely, we can observe that these profits are strongly linked with positive market trends. During the negative market trends, momentum phenomenon cannot generate any returns. These results are robust and the studies have been repeated several times with similar results. For this reason, the academic world does not argue whether the phenomenon is real but what causes the momentum phenomenon.

In conclusion, we can state that the presented behavioristic models in this study offer better explanation theories for this phenomenon. This supports earlier literature. The rational models, which are based on risk factors, have without exception some shortcomings. Many academics have also argued that the behavioristic models are insufficient because these models can only explain momentum phenomenon and cannot be extended to explain other market anomalies (Fama 1998). In other words, these models can only explain momentum phenomenon and its features. These models have also faced critique that they are in contradiction with the efficient market hypothesis. We can argue that both, behavioristic and rational models, needs more research so we could form better overall picture which key factors generate this phenomenon. All in all, both of these momentum theories can explain momentum

phenomenon partially, but the behavioral models does clearly a better job. More comprehensive theory for this phenomenon might include both behavioristic and rational factors. As Qawi (2010) states, combination of rational factors and behavioristic factors might dissipate the differences between these two explanation theories. Although, it might be naïve to think that phenomenon, which is apparent in global stock markets and in many different asset classes, could be explain only with one explanation model or factor.

Lastly we can say that, based on this thesis, the key factor behind momentum phenomenon is information. Both, the rational and behavioral models, admits that momentum is strongly related to market information. Behavioral models tries to explain this phenomenon with investor's over- and underreaction to new, public or private, information. On the other hand, in the rational models the type and quality of the new information is related to risk. In other words, the new market information affects the riskiness of the stock markets and the momentum profits, that are generated by this information, can be seen just a compensation to this higher risk.

As stated earlier, both momentum and moving averages can be seen as a trend following strategies. For this reason, technical analysis and moving averages are used with momentum in the study. Technical analysis differs from the classical fundamental analysis significantly. As the fundamental analysis focuses solely on company fundamentals and company related information, technical analysis focuses on stock prices and price movements. The idea behind this is that anything that can affect the stock prices, will affect the stock prices so basic price analysis is all that is needed in forecasting future stock prices. Technical analysis includes tens of thousands of different trading rules but the most used one is moving averages.

Moving averages can be implemented in many different ways but the most used methodology is the simple moving average. Simple moving average generates buy and sell signals when the stock's closing price and the moving average crosses each other. The buy signal indicates to the investor that positive price trend has begun and the investor's should invest, or stay invested, in the stock. The opposite applies to the sell signal. The term moving comes from the simple idea that the moving average "moves" forward as the time goes by. In other words, moving averages are calculated, for

example, monthly and when new monthly data is available, it is taken into the calculation and the oldest monthly data is dropped out.

The profitability of moving averages is still up to debate. The older studies are accused of data snooping bias and that the higher returns of moving averages disappear when transaction costs are taken into account. Newer studies (Kilgallen 2012, Glabadanidis 2015) have been able to show that the use of moving averages lower the volatility and increase the profits when compared to the passive portfolio, even after the costs. It is also stated that the moving averages are useful methodology when the markets are experiencing clear price trends. Because of the partially mixed results, more research is needed to make any conclusions about the profitability of moving averages.

Another interesting feature about the moving averages is their ability to spot changing market trends. The buy and sell signals that this methodology generates, have found to have real predictive power (Brock et al. 1992, Faber 2007). This also implicates that the stock markets are indeed predictable and have autocorrelation. Some researchers (Zakamulin 2014) have stated that even though moving averages seem to have the ability to time the markets, this feature does not work all the time. In other words, the time periods when this market timing works tend to be relatively short. We can conclude that the usefulness, and the market timing ability, of moving averages are highly dependent on the time period of the out-of-sample tests. As Murphy (1999) states, moving averages work best when the market is experiencing clear, positive or negative, price trends. If the market has no clear direction, the moving averages loses its market timing ability.

The similarities between momentum and moving averages are uncanny. Both of these methodologies can be seen as a trend-following strategies that try to time the markets to increase strategy's profits. It could be argued that the moving averages and momentum can identify price trends but different phases of these trends. As explained previously, moving averages generates buy and sell signals that indicates that the price trend has begun. The buy signal can also be described as a methodology where the investor buys earlier losers stocks and sells them when the price level has increased. In contrast, momentum strategy generates similar signal but bit later. For example, moving averages focuses on the emerging and changing price trends, where

momentum focuses on the continuity of the price trends. In other words, moving averages buys earlier losers and sells them when the price has increased, or when they can be seen as a current winners, and momentum buys these current winners and sells them when the price has increased even higher.

Because of these clear similarities, this thesis' study focuses on the methodology where both, momentum and moving averages, are used together. First, the study uses similar methodology as Jegadeesh and Titman's (1993, 2001) studies to investigate the momentum profits during the 1995–2013 time period in the U.S. stock markets. In addition, I studied the effect of the recent market crises' to these profits. Lastly, I combined the momentum strategy with moving averages to see if the returns could be increased with this simple market timing strategy.

The results indicates that the momentum effect has been present but significantly weakened during the study period. Before year 2000, the results are similar to earlier literature. After 2000 the returns have gradually diminished and after 2010, disappeared completely. The main reason behind this are the dot-com bubble and 2008s financial crisis. During these market crashes, the momentum profits were statistically insignificant. The most interesting finding is that after these crises, the momentum profits did not increase as the earlier literature suggests. Main reason is the non-linearity of the momentum profits. In other words, momentum profits are not highest when the market is experiencing strongest positive price trends. This is the case after 2010. After 2008, the U.S. stock markets experienced strong positive price trends which has continued almost to this day. It is suggested that when this trends ceases the momentum profits will return. To study this, more research is needed in the future.

When moving averages and momentum strategy were combined, the results were worse than with the passive counterpart. Only one portfolio were able to produce statistical significant profits that were higher than the passive buy-and-hold strategy's profits. Again, one possible reason for this is the highly volatile markets of 21st century. On the other hand, the use of moving averages did lower the volatility of the portfolio, as the earlier literature suggests. More interestingly, the results indicate that the moving averages have some predictive ability when trying to time the markets, this

feature did work only during the positive market trends. The main reason for this might be the severe market crashes. As stated in earlier chapters, moving averages' signals lag the real market changes so for these signal to work, the emerging trend needs to continue. This were not the case during the market crashes. These crashes were really severe and all of the stock plummeted. Because of the sudden crash, moving averages did not have enough time to react and when the sell signal finally emerged, the crisis were already over. On the other hand, the positive price trends were much less severe and lasted for longer periods so the market timing did work during these positive market trends. Another possible reason for these different results, when compared to the earlier literature, might be the used methodology. The monthly average returns that were used masks the real performance of the portfolios. For example, the real monthly return could differ significantly from the average returns but the use of average returns masks this. If we used the real returns, the results might differ significantly.

All in all, we can conclude that the use of momentum strategy with moving averages were not useful. This methodology might be useful to spot positive market trends beforehand but to fully discuss this, more research is needed. Also, after 2010, the momentum effect has disappeared completely. The future will tell us if the returns have disappeared for good or that will the returns emerge again when the stock markets stabilize. The study also raised new research questions. For example, this same study should be conducted again with the transaction costs to see how the costs affects these strategies. Also, it would be interesting to use whole U.S. stock data, instead of this random sample of NYSE stocks, to see if the results of this study are expandable to apply to the whole U.S. stock markets.

Another interesting topic for future research would be the average investors' ability to use momentum and moving averages in their investment strategies. It is argued that the momentum phenomenon is hard to implement to average investors because of the high transaction costs, especially the costs that comes from the short selling the *loser* portfolio. The used methodology also used monthly rebalancing which generates extra costs to the investor. Also, to have highly diversified momentum portfolio, investors would need to invest in tens or even hundreds of stocks at the same time. This is laborious for the average investors. In conclusion, only the future will tell us that have

the momentum phenomenon disappeared completely or will the returns emerge again in the future. To fully answer this interesting question, more research is needed.

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