Momentum in Norway

Traditional and Behavioral Explanations

Master's Thesis

Copenhagen Business School, 2018

M.Sc. FIR & M.Sc. AEF

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Supervisor: Søren Ulrik Plesner

Pages: 97

Characters: 162 379

Hand in date: May 15, 2018

Abstract

In this thesis we investigate whether a trading strategy of buying past winners and selling past losers is profitable. We find that this strategy, often referred to as a momentum strategy, yields positive returns on a 3 - 12 month horizon. More specifically, all 16 strategies yield between 1.95 and 3.39 percent monthly return on average. The thesis documents that the momentum profit is mainly driven by return continuation in loser stocks. Factor models reveal that much of the momentum return can be explained by systematic risk, size and momentum. Thus, we conclude that some of the momentum effect can be attributed to risk. However, the factor models were not able to fully capture abnormal return for all strategies. In order to explain the remaining, unexplained momentum return, we look at overreaction and underreaction as possible behavioral explanations, and find that these can indeed provide some insight into the momentum effect.

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Chapter 1

Introduction

1.1 Motivation

For the last 30 years, the field of behavioral finance has fought to gain credibility in the economics and finance academia. Traditional economists, such as Merton Miller and Eugene Fama, have been reluctant to acknowledge the relevance of the research conducted by behaviorists such as Daniel Kahneman, Robert Shiller and Richard Thaler. However, in 2017, Richard Thaler won the Nobel prize in economics, joining Kahneman and Shiller. With the addition of Thaler, behavioral economists now account for approximately 6% of all economic Nobel prizes ever awarded [1] (Shiller, 2017).

For more than 40 years, the efficient market hypothesis has been the central proposition of finance. This hypothesis, as presented by Eugene F. Fama in 1970, defines an efficient financial market as one where all available information is fully reflected in the security prices. This implies that an average investor cannot hope to consistently beat the market, and that the efforts invested in active money management is in fact wasted. In stead, investors should invest passively in the market portfolio (Shleifer, 2000).

After the efficient market hypothesis was published in 1970, financial academics developed powerful theoretical reasons supporting it. A great number of empirical findings emerged, nearly all of them supporting the hypothesis. The hypothesis became an enormous success.

[1] Also including George Akerlof, Robert Fogel and Elinor Ostrom

The university of Chicago, where Eugene Fama was working, became the world's centre of academic finance. In 1978, Michael Jensen, one of the creators of the hypothesis, declared that there were no other economic proposition with more solid empirical evidence supporting it than the efficient market hypothesis (Shleifer, 2000).

However, researchers soon began to discover anomalies in the market that could not be explained by the theories available. They discovered that investors rarely behave according to the assumptions held in traditional finance theory. One of the assumptions being challenged was the assumption that all market participants are rational and behave accordingly. Everywhere there were evidence of people behaving irrationally - for example by buying lottery tickets. Academics therefore started looking to psychology to explain this behavior that financial theories had failed to explain.

Behavioral researchers claim that financial theory should take account of observed human behavior. By analyzing the discovered anomalies, they found that biases, such as loss aversion and overconfidence, can effect all types of decision-making, with particular implications in relation to money and investing. In many cases, these biases serves us well. However, in an investing situation they may lead us to unhelpful or even hurtful decisions. The extent to which these biases affect the efficiency of markets is still a controversial subject, and traditional economists and behavioral economist are still in disagreement.

1.2 Research question

In light of Richard Thaler winning the Nobel Prize in economics, and behavioral finance gaining foothold as an academic field of finance, we find it interesting and relevant to assess both sides of this ongoing debate between behavioral and traditional economists. We will see to what extent the theory and findings from these two research fields applies to recent events and developments in the Norwegian stock market. More specifically, we want to investigate whether there has existed momentum in the Norwegian market in recent years, and look at the proposed explanations from both parties. We have therefore chosen the following research question:

How can possible momentum effects on the Norwegian stock market be explained by traditional and behavioral finance?

To get a better picture of the structure and purpose of our thesis, we have chosen the following subquestions:

- Does momentum investment strategies generate positive returns in Norway?
- Can the returns from momentum investing be explained by risk?
- Can the returns from momentum investing be explained by behavioral theories?

Our main purpose of this thesis is to investigate the well documented market anomaly that is the momentum effect, and use both traditional and behavioral finance as tools for understanding. We will not go deeply into the efficient markets versus inefficient markets debate, but simply look into the possible ways that the momentum anomaly can be explained.

1.3 Delimitations

While momentum literature comprises different forms of momentum, such as earnings momentum and industry momentum, this thesis' focus is exclusively on momentum in stock prices. Compared to earnings momentum and industry momentum, more empirical research has been conducted on price momentum. As the empirical research on momentum in the Norwegian stock market is fairly scarce, and mostly limited to master theses, we chose to focus exclusively on this market. Empirical research only covers the years until 2013, thus we found it relevant to conduct a study which include the recent years. In particular, this is interesting, as we cover the period before and after the financial crisis.

Our thesis is relatively theoretical as we do not delve into practical issues that a real life investor might meet, such as short sale restrictions, transaction costs, taxes and other implementation considerations. However, we will slightly touch upon the subject of transaction costs and the increased convenience of the non-overlapping method.

Lastly, we have chosen to follow the methodology of Jegadeesh and Titman (1993). All though other there are other methods for momentum trading, we will not discuss these. Most empirical literature, however, follow this method. Therefore, by following Jegadeesh and Titman (1993) our research will easier to compare to previous studies.

1.4 Thesis Structure

This thesis will be divided into six main chapters. We will start with a review of relevant financial theory and empirical research, in order to provide a theoretical base for our analysis. Our analysis will commence with a description of our applied methodology, which will be followed by a presentation of our results and various robustness tests. After this, we will turn to the second part of our research question and look at the different explanations for momentum. Lastly, our thesis will be brought together in a discussion of our findings and finally a conclusion.

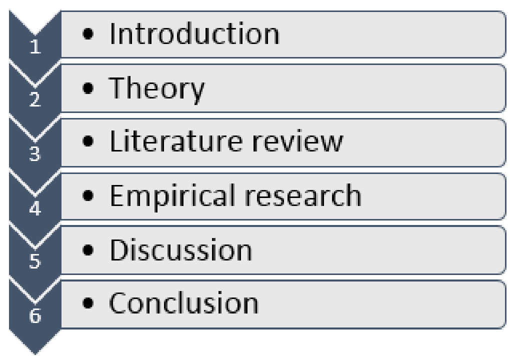

Figure 1.1: Thesis structure

Chapter 2: Theory

The reader will be introduced to the theoretical framework that is relevant for the scope of our thesis. We will start by presenting traditional finance theory that has shaped most of modern finance. Further, we will introduce some of the most important contributions within behavioral finance. We will include only the theories that are relevant for our thesis, which we see as important tools for explaining momentum.

Chapter 3: Literature review

We will present and describe previously documented findings of momentum from both domestic markets and the Norwegian stock market. The chapter will be divided in three, based on the different geographical markets.

Chapter 4: Analysis

The first part of our analysis will start with a thorough presentation of our applied methodology. We will then present the results from our base study, and discuss these. Further, to strengthen our findings, we will conduct various robustness tests. The results from these will be presented and discussed.

The second part of our analysis will consist of the different explanations for the momentum effect. We will start with the risk-based explanations, in which we examine three different factor-models and their ability to explain momentum. We will then turn to the behavioral explanations, where we will present the different explanations that apply to momentum.

Chapter 5: Discussion

Our discussion will bring together the different parts of our analysis, and provide a more clear and consistent discussion of our research question.

Chapter 4: Conclusion

The conclusion will summarize our thesis, and present our answer to the research question.

Chapter 2

Theory

In this chapter we will present academic theories that are relevant for the scope of our thesis. As our approach is focused on both traditional and behavioral finance, this chapter will be divided in two. We will begin the first part of the chapter with a review of the efficient market hypothesis, as it lays the foundation of our thesis. We will then present the different factor-models, which will be used later in the thesis. The second part is dedicated to the subject of behavioral finance. Here we will introduce the two most important pillars that behavioral finance rests on, psychology and limits to arbitrage.

2.1 Traditional Finance Theory

2.1.1 Efficient Markets

In 1970, Eugene Fama presented his theory of efficient markets. The theory states that in an efficient market, asset prices "fully reflect" all available information. After it's launch, the hypothesis became fundamental for great parts of modern finance.

The efficient market hypothesis claims that stock prices always incorporate and reflect all relevant and available information. This is explained by the investors' constant search for profit in a strongly competitive environment. An investor will take advantage of any informational opportunity until the price of the asset reflects this information.

The Efficient Market Hypothesis (EMH) builds on the argument that stock prices should follow a random walk, meaning that price changes are random and unpredictable. If it was possible to predict stock prices, for example an increase, this information would be incorporated in the price of the stock almost immediately, because investors would bid the stock price up to the predicted value (Bodie et al., 2014).

If the price change happens immediately as new information hits the market, and the market is free of friction and transaction costs, this implies that it is impossible to "beat the market", because the stocks always trade on their fair value. The only way an investor can obtain higher returns is by investing in riskier assets.

The efficient market hypothesis rests on several assumptions. The main assumptions include:

1. All market participants have access to the same information immediately.

2. The investors are rational and value the assets perfectly and rationally, so that the price of the assets always equals fair value.

3. If irrational market agents exist, their dispositions will be random and therefore neutralize each other. Otherwise, rational investors will take advantage of the arbitrage opportunity and reduce the mispricing.

4. The market participants all have well defined subjective utility functions (SEU) that they seek to maximize. This means that the choices are being made (1) among a given set of alternatives, (2) with a subjectively known probability distribution and (3) in such a way that it maximizes a given utility function (Savage, 1954).

Another key assumption of the hypothesis is that costs related to research and transactions do not exist. In reality, these costs exist, and there have therefore been made modifications of the hypothesis that take these into account. One example is Jensen's (1978) efficient market hypothesis, which states that asset prices reflect relevant information up to the point where the marginal cost of transaction and research equals the marginal gain of these trades. However, Fama (1991) claims that it is easier to do tests that assume that these costs are zero, as this would make a cleaner benchmark without unnecessary assumptions about the size of the costs (Schouw-Hansen, 2007).

Fama (1970) defines three forms of market efficiency: weak form, semi-strong form and strong form. In markets with weak efficiency, asset prices only reflect *historical* information. In semi-strong markets, current prices fully reflect all *obviously publicly available* information. For a market to be efficient in strong form, the assets prices need to also reflect insider information (Fama, 1970). In this thesis we will refer to "semi-strong efficiency" when talking about efficient markets.

The key point in the efficient market hypothesis is that prices should reflect *available* information. One can always wish for more information about a company's prospects than will be available. Sometimes in retrospect, market prices will turn out to have been absurdly high or low. However, the hypothesis asserts only that at the given time, using the currently available information, we cannot be sure if today's prices will ultimately prove themselves to have been too high or too low. If markets are rational, we can expect the prices to be correct on average (Fama, 1970).

Joint Hypothesis Problem

While many phenomena can be interpreted as a deviation from fundamental value, it is difficult to prove mispricing beyond any reasonable doubt. The reason for this is that the efficient market hypothesis relies on some form of model that specifies the nature of market equilibrium when prices "fully reflect" available information (Fama, 1970). Therefore, testing the efficient market hypothesis also implies a test of the model being used. This makes it impossible to know whether mispricing is due to inefficient markets or simply because the pricing model was incomplete. Thus the efficient market hypothesis is impossible to test.

In the following sections we will present the most acknowledged models for asset pricing, the CAPM and the Fama-French three-factor model. We will also introduce the Carhart four-factor model, which is especially relevant for our thesis as it incorporates momentum as an explanatory variable.

2.1.2 Capital Asset Pricing Model

The CAPM was developed in the early 1960s by William Sharpe (1964), Jack Treynor (1962), John Lintner (1965a, b) and Jan Mossin (1966). It is based on the idea that asset prices should not be affected by all risks. Specifically, risk that can be diversified away should not have impact on asset prices. Some risks, such as a global recession, cannot be eliminated through diversification, which means that even the market portfolio contains some risk. Because of this, the investors need to be compensated for the risk of the market portfolio by earning returns higher than of risk-free assets, such as treasury bills (Bodie et al., 2014). The CAPM involves several assumptions. The most important are that all investors have the same information and are risk averse, striving to minimize risk at a given return.

The CAPM shows the relationship between the un-diversifiable risk, given by beta, the return of the market portfolio, r_m, and the risk-free rate, r_f.

$$r_i = r_f + \beta_a(r_m - r_f) \tag{2.1}$$

As the equation implies, the only risk that is relevant for the price of the asset is the systematic risk, the risk that cannot be eliminated through diversification. The rational investor will hold some mix of the market portfolio and risk-free assets. All possible combinations will have the same sharpe ratio (amount of return per unit of risk) and constitute the Security Market Line (SML).

The difference between the fair expected return of an asset, as given by CAPM, and the actual expected return is called the stock's alpha. If the expected return is higher than given by the CAPM, then the asset has a positive alpha, and the asset is undervalued. With a negative alpha, the asset is overvalued. According to the arbitrage argument, the prices will be adjusted back to fair value by rational investors who take advantage of the mispricing.

For many years the CAPM reigned as the most applied asset pricing model within the finance literature. However, a critical point in the concept of CAPM is the aggregation of risk into one single factor, the market risk. It is reasonable to assume that that other factors may well have an influence on the expected returns. Hence, we will now present two models that extend the CAPM with additional factors.

2.1.3 The Fama-French Three-Factor Model

The most prominent factor-model is the three-factor model developed by Eugene Fama and Kenneth French in 1992. The model seeks to explain the return of an asset with two additions to the CAPM: size and book-to-market (B/M) ratio. When researching, Fama and French (1992) observed that two groups of stocks tended to outperform the market. These were the ”small” stocks and the stocks that had high book-to-market ratio. These factors were added to the CAPM, with SMB (small minus big) to represent size and HML (high minus low) to represent B/M-ratio. The model is given by:

$$r_i = \alpha_i + \beta(r_m - r_f) + \gamma SMB + \delta HML + e_i \tag{2.2}$$

The SMB-factor is designed to capture the extra return that an investor, historically, have received when investing in companies with relatively low market capitalization. The size anomaly was first documented by Banz (1981). In 1992, Fama and French found that small companies tend to yield higher returns than larger companies. This extra return is sometimes referred to as the ”size premium”. The factor is estimated based on a long position in small companies and a short position in big companies.

The HML-factor measures the value premium that the investor receives when investing in companies with high book-to-market ratio. Stocks with a high B/M ratio has a low market value compared to book value and are often referred to as value stocks. Those with a low B/M ratio have a low market value compared to book value and are referred to as growth stocks. Companies with a high book-to-market ratio usually have higher returns than companies with a low ratio. In the model, the factor is created so that one is long in the high B/M stocks and short in the low B/M stocks.

2.1.4 The Carhart Four-Factor model

The Carhart Four-Factor model is a lesser known model, developed by Mark M. Carhart in 1997. Inspired by the work of Jegadeesh and Titman (1993), the model extends the Fama-French three factor model by one factor: momentum. The momentum factor is meant to capture the return on a momentum portfolio with 12 month formation. The four-factor model can be written as:

$$r_i = \alpha_i + \beta r_m + \delta SMB + \gamma HML + \rho PR1YR + e_i \tag{2.3}$$

where the additional factor $PR1YR$ is returns on a value-weighted, zero-investment, factor-mimicking portfolio for one-year momentum in stock returns. This will be more thoroughly explained later in the thesis.

Carhart's model was motivated by the three-factor model's inability to explain variations in momentum portfolio returns. He found that what appeared to be the alpha of many mutual funds could in fact be explained as due to their loadings to market momentum.

2.1.5 Implications of the Efficient Market Hypothesis

Technical Analysis Technical analysis is the statistical analysis of price movement, searching for recurrent and predictable patterns in stock prices. Technical analysts recognize the value of information regarding future economic prospects of the firm, but believe that if the stock price responds slowly enough to new information, the analyst will be able to identify a trend that can be exploited during the adjustment period (Bodie et al., 2014).

The efficient market hypothesis implies that technical analysis is a waste of time. This is because the past history of prices and trading volume is available to anyone at a minimal cost. Therefore, any information that was available from analyzing past prices has already been reflected in the stock prices. When the investors try to exploit their information about a stock's price history, they drive stock levels to the exact level where expected rates of return is proportionate to the risk, and no abnormal returns are obtainable (Bodie et al., 2014).

Fundamental analysis Fundamental analysis seeks to determine the fair value of an asset, by examining related economic, financial and other qualitative and quantitative factors. It represents an attempt to determine the present value of all the payments a stockholder will receive from each share of stock. This way, the analyst tries to find overpriced or underpriced stocks to take advantage of (Bodie et al., 2014).

Again, the efficient market hypothesis predicts that most fundamental analysis is also doomed to fail. As long as the analysis is based on publicly available information, the analyst's evaluation of the firm's prospects is not likely to be significantly more accurate than other investor's evaluations. This means that fundamental analysis is in most cases too difficult and time consuming too be worth doing, as it only pays off if your analysis is better than all rival investors (Bodie et al., 2014).

Active or passive portfolio management As we now understand, the efforts put into picking stocks are not likely to pay off, because the competition among investors ensure that any easily implemented stock analysis technique will be used so widely that any insight derived from the technique will be reflected in the stock prices. Only uncommon techniques and serious analysis are likely to generate differential information that can contribute to trading profits (Bodie et al., 2014).

According to the efficient market hypothesis, active portfolio management is largely a wasted effort and unlikely to justify the expenses incurred. Therefore, the only rational trading strategy is a passive investment strategy, where the only aim is to establish a well-diversified portfolio of securities without attempting to beat the market. Usually, this strategy is characterized by holding securities longer. Because securities always trade at fair value, there is no need to buy and sell, as this only incurs higher trading costs without increasing expected performance.

2.2 Behavioral Finance

Behavioral finance is the study of how psychology affect investor's decision making and the implication that this has on financial asset prices and market outcomes. Where traditional finance theory assumes that every investor is fully informed and makes rational decisions based on this, behavioral finance tries to explain the deviations from fundamental values in the market, also called anomalies. It is based on the belief that some financial phenomena can be better understood using models where agents are *not* fully rational (Thaler, 2005).

Our scope of history in the field of behavioral finance starts in in 1979, when Kahneman and Tversky (1979) published their common work, "Prospect Theory". After a series of experiments, Daniel Kahneman and Anos Tversky discovered that people tended to treat reductions in their current wealth significantly different from reductions in future gains. Their publication caught the attention of economists at the time. One of the economist who took particular notice, Richard Thaler, had previously been doing research on the irrational behavioral by humans that he was witnessing every day. He teamed up with Kahneman and Tversky, and as other economists followed suit, the field of behavioral economics was established. The new perspective on investor behavior quickly gained popularity amongst young economists. However, behavioral finance as an academic field was not easily accepted by traditional economists, and was first taught in universities in the United States during the 1980s. Together with Robert Schiller, Richard Thaler started the national bureau of Economic research on behavioral finance in 1991. Shiller and Thaler both went on to win the Nobel Price in economics for their work with behavioral finance.

We will structure this section based on two parts, which are recognized by Barberis and Thaler (2003) as the building blocks of behavioral finance - psychology and limits to arbitrage.

2.2.1 Psychology

Behavioral finance is based on the view that a significant proportion of financial investors are subject to psychological biases that make their decisions less than fully rational from a traditional point of view (Byrne and Brooks, 2008). These biases have their origin from the field of psychology, and have then been applied in finance. We will elaborate on these biases where it is relevant, but some examples of biases include:

Overconfidence and overoptimism This bias refers to how investors overestimate their ability and the accuracy of the information they have. According to Barberis and Thaler (2003), this can be seen as people systematically miscalculate confidence intervals. Also, people estimate probabilities poorly. This was shown in an experiment by Alpert and Raiffa (1982) where events that people were certain would occur, only occurred around 80 percent of the time.

Representativeness bias Tversky and Kahneman (1981) defined representativeness as the degree to which an event is similar in essential characteristics to another event. According to the authors, people are likely to make wrong judgements based on representativeness, because the fact that something is more representative does not make it more likely.

Sample Size Neglect This is a bias that is a result of the representativeness bias. This means that when people do not know the data-generating process, they will make decisions too quickly based on few data points. For example, they believe that a financial stock analyst with five good stock picks is skilled, because five good picks is not representative of a bad analyst.

Conservatism This psychological bias was described by Edwards (1968) as the tendency to insufficiently revise one's initial belief when presented with new evidence. In other words, conservatism suggest that people put too little weight on the latest news.

Prospect Theory

Prospect theory contributes to the area of asset pricing and trading behaviour by analyzing investor preferences towards risk, and how they evaluate gambles. Prospect theory was first introduced by Kahneman and Tversky in 1979. In their model, utility is defined over gains and losses rather than over final wealth positions (Barberis and Thaler, 2003). At the time, this was a new approach, as the wast majority of earlier theory assumed that investors evaluated gambles according to their expected utility.

One of the main points is that agents value gains and losses differently. More specifically, the marginal utility that an individual gets from a positive gain is smaller than the disutility from an equivalent loss. This is illustrated in the left part of Figure 2.1, as the value function is concave for gains, convex for losses, and steeper for losses than for gains.

The second main component of prospect theory is probability weighting. According to Kahneman and Tversky (1979), agents do not weight probabilities according to their objective probabilities, but rather transformed probabilities or decision weights. The 45 degree line in the right part of Figure 2.1 illustrates the expected utility benchmark. As shown in the solid line, the weighing function overweighs low probabilities and underweighs high probabilities. The main implication that this has for behavioral finance is that an individual will overstate a probability that is extremely unlikely to happen, thus leading to risk aversion for certain gains and risk seeking for for certain losses.

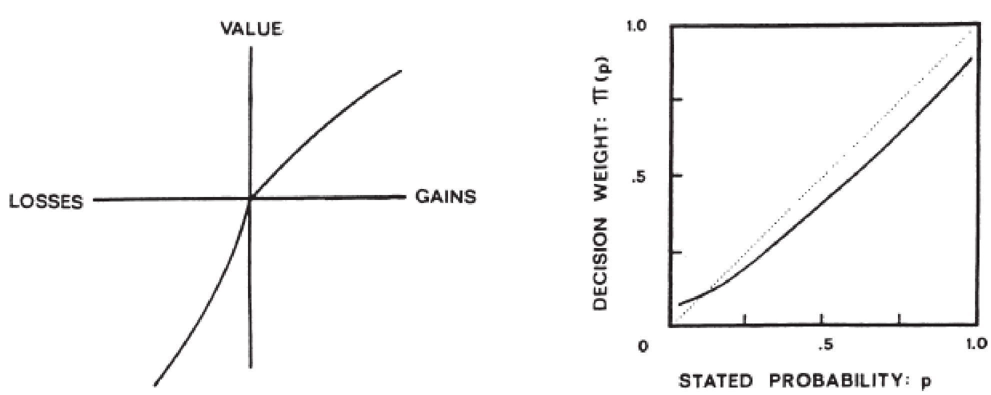

Figure 2.1: Prospect theory (Kahneman and Tversky, 1979)

2.2.2 Limits to arbitrage

One of the fundamental rules within classical finance is the notion that any price that deviates from its fundamental value will immediately be corrected by the market. This goes back to Friedman (1953) who argued that rational traders will quickly observe anomalies and restore the prices caused by irrational traders. As a result of inefficient markets, traders can immediately profit from simultaneously buying and selling the same asset. Thus, arbitrage is an investment strategy that offers risk-less profit at zero cost. Barberis and Thaler (2003) points out arbitrage as a classical objection to behavioral finance. Behavioral economists argue that in an economy where rational and irrational traders interact, irrationality can have a substantial and long-lived impact on prices. The strategies that a rational investor would implement, are not necessarily arbitrage; quite often they are risky and costly. Therefore, Barberis and Thaler (2003) argue that it can be difficult for rational traders to correct for the anomalies caused by less rational traders. They identify some of the risks and costs associated with this.

Fundamental Risk

In an example where a stock is traded below its fundamental value, a rational investor will pick up on this and immediately enter a long position. As with every security, there is always a risk that additional news about its fundamental value will occur, which will drive the price down further. For this reason, an arbitrageur will take a short position in a substitute security to hedge the position. Barberis and Thaler (2003) argue that this substitute is rarely perfect, and often highly imperfect, making it impossible to remove all fundamental risk.

Noise Trader Risk

A noise trader is by definition any trader that does not trade solely on fundamental data analysis. They are said to have bad timing, follow trends and overreact (underreact) to good (bad) news about financial markets (Barberis and Thaler, 2003). The implication that noise traders have for arbitrage is that the unpredictability of these traders' beliefs creates a risk that deters rational arbitrageurs from aggressively betting against them (DeLong et al., 1990). If an asset is mispriced due to an overly pessimistic (optimistic) noise trader, there is a risk that this trader will become more pessimistic (optimistic) and drive the price even further down (up). This means that the arbitrageur is betting against the mispricing, risks that the mispricing might move further away from fundamental value and as a consequence such an investor will lose money in the short run. Thus, making arbitrage risky.

Implementation Costs

There are several costs, such as transaction costs, fee charged of borrowing a stock and bid-ask spreads that can make it unattractive for an investor to exploit mispricing in the market. Finding out about an existing arbitrage opportunity requires spending time and resources that may not be costless (Baltussen, 2009).

Based on the aforementioned risks and costs, Barberis and Thaler (2003) argue that arbitrage in reality comes with risks and costs that under some conditions allow anomalies to persist in the market over time. These conditions are:

1. Arbitrageurs are risk averse
2. Fundamental risk is systematic, and cannot be diversified away by taking many such positions

If one assumes that a mispriced security does not have a perfect substitute, the arbitrageur is exposed to fundamental risk. Condition 1 then ensures that deviations from fundamental values will not be eliminated by arbitrageurs taking big positions in the mispriced security. Condition 2 ensures that this risk cannot be diversified away by investors.

2.2.3 Implications of behavioral finance

One of the most important implications of behavioral finance is its effect on market efficiency. The efficient market hypothesis assumes that all investors are rational, thereby implying that prices are correctly updated in the presence of new information. However, when investors are subject to psychological biases, prices might not always reflect their fundamental value. If rational investors' ability to exploit arbitrage opportunities is limited by fundamental risk, noise trader risk and implementation costs, these pricing anomalies might persist. This can lead to inefficient markets, thus allowing trading strategies such as momentum strategies to be profitable.

Chapter 3

Literature review

Historically, a large volume of empirical work have documented various ways that stock returns can be predicted. The predictability of these returns belong to either one of two categories. The first category deals with predictability in the form of mean reversal in the long term. DeBondt and Thaler (1985) were among the first to study stock market anomalies and trend persistence, and found that stocks that had performed relatively well over a period of the last five years, tended to perform worse in the subsequent five year period, and vice versa. They referred to this negative autocorrelation as mean-reversion, pointing to the fact that any extreme deviation from the mean will eventually revert back to its underlying state. The other category concerns continuation of stock returns in the short- to medium run, where stocks who have done relatively well in the last 3- to 12 months, tend to continue to do well in the following 3- to 12 months. The research on this phenomena, called momentum, was pioneered by Jegadeesh and Titman (1993), and has since been one the main researches within price anomalies.

In the following sections we will introduce previous findings of momentum. The literature review will consist of both academical literature and other dissertations. It will be divided into three parts based on three different markets: the United States, Europe and Norway.

3.1 Momentum in the United States

Up until 1993, the majority of academic literature was focused on contrarian strategies, in which investors go against the prevailing market trends, and invest in poorly performing assets. According to Jegadeesh and Titman (1993), these strategies demanded many transactions, and the returns were primarily due to short-term price movements. In their 1989 study, Grinblatt and Titman discovered that mutual funds tended to buy stocks that had previously increased in price and make money. These were among the factors that motivated Jegadeesh and Titman (1993) to study relative strength strategies, that is, buying past winners and selling past losers.

Jegadeesh and Titman (1993) hypothesized that if stock prices either overreact or underreact to information, then it would be possible to generate returns using a strategy that selects stocks based on their past performance. Their method is often referred to as a J/K strategy, where J is the formation period and K is the holding period. When choosing the stocks they varied the formation period, J, between 3, 6, 9 and 12 months. At the time of formation, stocks are ranked based on their return in the past J months. The stocks are then assigned into equally weighted decile portfolios. Thus, the 10 percent best performing stocks constitute the top decile while the 10 percent worst performing stocks constitute the bottom decile. Each month, the strategy takes a long position in the winner portfolio and short position in the loser portfolio. After this, the portfolios are held between 3, 6, 9 and 12 monhts. This gives 16 different J/K strategies. Together, the winner and loser portfolio constitute a zero-cost portfolio. This method will be explained in further detail, as this is the methodology that we will apply in our empirical research.

The article of Jegadeesh and Titman (1993) was the first to document a momentum effect on the NYSE and AMEX during the years 1965 to 1989. They found that the most successful strategy was the 12 x 3 strategy which yielded a 1.31 percent monthly return. Except for the 3 x 3 strategy, all of the zero-cost portfolios yielded significant and positive returns. The 6 x 6 strategy, which is the one used for further robustness testing, gave an average return of 0.95 percent per month. The authors also tested whether the strategies were profitable after taking what they call a conservative transaction cost of 0.5 percent into account. They found that every strategy yielded positive and significant returns after accounting for this. When testing subperiods of 5 years, they found that momentum trading is profitable in all of the 5-year intervals except one (1975-1979).

When analyzing their results, the authors found that the profits are driven in large part by past losers that continue to decline. Further, they found that the momentum returns are not due to the systematic risk of the portfolios. They also found that the momentum strategies were generally not profitable 12 months after the formation, as returns seemed to reverse. One interpretation of this is that investors who buy past winners and sell past losers move prices away from fundamental values, causing prices to overreact in the short run and thereafter declining as the mispricing is corrected.

Conrad and Kaul (1998) investigated stock return on the NYSE and AMEX from 1926 to 1989. They implemented 120 return-based[1] strategies, and found that the 30 of these were momentum strategies that yielded statistically significant profits. They investigated momentum profits on three different horizons: short, medium and long. As opposed to Jegadeesh and Titman (1993) who use the decile strategy, they use the weighted relative relative strength strategy, in which they weight all stocks in the portfolios based on their relative return compared to the average market return. Their zero-cost portfolios consist of a long position in the stocks that perform better than the market and a short position in the stocks that perform worse than the market. The formation period and holding period for the portfolios was equally long, ranging from 1 week to 36 months. This framework is based on Lehman (1990) and Lo and MacKinley (1990).

Among 55 significantly profitable return-based strategies, 30 of these were momentum strategies. Consistent with Jegadeesh and Titman (1993), they find that the momentum strategies are profitable on medium horizon, that is holding periods of 3-12 months. For the period 1969 to 1989, the best performing momentum strategy was the 9 x 9, followed by the 12 x 12 and 6 x 6. These strategies had a monthly average return of 0.71, 0.70 and 0.36 percent, respectively.

Conrad and Kaul (1998) claim that momentum strategies are not only profitable because of the predictability of asset pricing, but because of the cross-sectional dispersion variation i mean returns. They argue that as long as there is dispersion in mean returns, momentum strategies will be profitable. They suggest that winner portfolios in any holding period that yield high returns represent their unconditional expected rates of return, and will therefore be positive on average for any post-formation period.

[1]Momentum and contrarian

Moskowitz and Grinblatt (1999) conducted a study on the American market with data from 1963-1995, with the purpose of exploring whether the momentum effect can be explained by industry. The paper focuses on the positive persistence in stock returns over 6 to 12 month horizons.

They found that the momentum strategies were profitable, although the returns were lower than those of Jegadeesh and Titman (1993). However, they were more statistically significant. They attribute this to their use of a value weighted portfolio and 30% selection criteria, whereas Jegadeesh and Titman (1993) use equal weights and 10 percent portfolios. In 2004, Grinblatt and Moskowitz conducted another study with data from 1963-1999. They found that momentum is more frequent for small companies, growth companies and stocks with a high trading volume. They conclude that using equal weighted portfolio results in higher returns than when using value weighted portfolios.

They also found that industry momentum to be more profitable than stock price momentum for every strategy except for the 12 x 1. They further provide one possible explanation as to why the industry momentum strategy is so profitable - namely that it exists "hot" and "cold" sector of the economy at any time. This could cause investors to herd towards (away from) "hot" ("cold") industries and cause price persistence.

Jegadeesh and Titman (2001) conducted another research on momentum in the United States, with data from the period 1990-1998. This was in part triggered by the study of Conrad and Kaul (1998) who contradicted behavioral models, saying that momentum was not caused by inefficient markets. They formed portfolios based on 6 months formation only, as the 6 x 6 strategy had been studied in most detail in 1993. Consistent with their earlier study, they found that past winners outperform past losers, with an average of 1.70 and 0.30 percent return on the winner and loser portfolios. This gave an average return of 1.39 percent on their zero-cost portfolios.

They also confirm that momentum portfolios yield significant positive returns in the first 12 months following the portfolio formation during the entire sample from both their samples periods, ranging from 1965 to 1998. Consistent with their previous research, they found that over longer horizons of 13-60 months, momentum returns were negative on average. They claimed that this was in in line with behavioral theories, but inconsistent with the theories of Conrad and Kaul (1998).

3.2 Momentum in Europe

Rouwenhorst (1998) is famous for his research on momentum in Europe. He gathered data from 12 different stock markets (including Norway) consisting of 2190 stocks, from the period 1980-1995. The sample covered around 60-90 percent of each country's market capitalization. Following the methodology of Jegadeesh and Titman (1993), he used formation and holding periods and 3, 6, 9 and 12 months, with equally weighted portfolios and overlapping holding periods.

He found that an internationally diversified portfolio of past winners outperformed a portfolio of past loser by about 1 percent per month. He also noted that irrespective of the formation period, average return tends to fall for longer holding periods. For the strategy with 12-month holding periods, the average return on the zero-cost portfolios ranged between 0.64 and 1.35 percent. Among these, the 3-month formation portfolio had the highest return with a monthly average of 1.35 percent. The worst performing strategy was the 3 x 3 strategy, with a monthly average return of 0.7 percent. All strategies yielded statistically significant returns at the five-percent level.

Rouwenhorst (1998) also tested for country-neutral momentum, by forming portfolios by ranking stocks into deciles based on past performance relative only to stocks from the same local market. This showed that controlling for country composition only slightly reduces the average return of the zero-cost portfolios, from 1.16 to 0.93.

Lastly, Rouwenhorst (1998) investigated momentum in each country separately. He found that the zero-cost portfolios had significantly positive returns in all countries except Sweden, where the highest return was generated in Spain at 1.32 percent. For Norway, the momentum profit was found to be 0.99 percent. In all cases, the winner portfolios outperformed the loser portfolios.

Bird and Whitaker (2003) analyzed 7 European stock markets[2] from 1990 until 2002. They tested strategies in individual markets and across a combination of all 7 markets. Their method consisted of forming portfolios based on their previous 6- and 12 month return, varying the holding period between 1 and 48 months, and rebalancing monthly. In addition to analyzing each market separately, they also analyzed portfolios that combines

[2]UK, France, Germany, Italy, Switzerland, Netherlands and Spain

stocks from all countries.

They find that portfolios with 6 months formation yield positive returns for up to 9 month holding. For the 9-month holding strategy, past winners outperform past losers by 7 percent. For the 12-month formation period, the momentum effect is only significant up to 6 months holding, with 4 percent return for the 6-month holding strategy. At any given formation period, the 3-month holding period yields the highest return. In both cases, the positive momentum return reverses and becomes negative beyond 24 months for the 6-month strategy, and beyond 12 months for the 12-month strategy.

In order to control for country bias, Bird and Whitaker (2003) also ranked all stocks on a country-corrected basis. They found that the country-corrected portfolios performed slightly better for holding periods up to 3 months, but slightly worse over longer holding periods. Overall, they claim that removing country bias has little effect on the performance of momentum portfolios.

Bird and Whitaker (2003) also examined the performance of momentum portfolios for each individual country. They found that the 6 x 9 momentum strategy was profitable in every country except Spain and Portugal. For the remaining five countries, the this strategy yielded on average 9 percent return. They claim that strength of the findings on the individual markets confirms that the added value from momentum is largely attributable to the performance of momentum within the individual markets.

Van Dijk and Huibers (2002) studied the momentum effect in 15 European countries[3] in 1987 - 1999. They formed portfolios based on the stocks' 12 month previous return. The portfolios were formed into deciles in which each stock was equally weighed. They also used the overlapping method, thus rebalancing their positions every month. Their sample of monthly return altogether consisted of a total of 358 248 observations.

Similar to Rouwenhorst (1998), they found that the momentum strategies yielded significantly positive returns when holding the portfolios from 1, 3, 6, 9 and 12 months. They found that the 12 x 3 strategy yielded the highest annual return with 25.2 and 13.4 percent return for the winner- and loser portfolio respectively.

The authors test to see whether the price momentum is attributable to size and value

[3]Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain ,Sweden, Switzerland, United Kingdom

factors and find that both size and value is negatively related to momentum returns. They conclude that the positive price momentum can be explained by analyst underreaction to new earnings information, and that analysts who follow European stocks behave in a fashion similar to analysts who follow U.S. stocks.

Griffin et al. (2003) studies momentum in 40 different markets to examine if macroeconomic risk can explain momentum profits internationally. In addition to this, they investigate whether international empirical evidence is consistent with existing risk-based explanations of momentum. Their sample includes data from 1926-2000. U.S data are available from 1926. From 1975 they have data on 11 markets, by 1990 there are 23 markets available, and all countries except Egypt have coverage by 1995.

They follow the method of Jegadeesh and Titman (1993), but use only the strategy with a 6-month formation period and a 6-month holding period. In accordance with Jegadeesh and Titman (1993) they use equal weights in the portfolios and overlapping holding periods. They use two different methods: one with a 1-month gap between formation and holding period, and one without. Because of low numbers of stocks in some countries, they construct their winner and losing portfolios from the 20 percent best and worst performing stocks, respectively.

They find that both African countries, 5 out of 6 American countries, 10 out of 14 Asian countries, and 14 out of 17 European countries display positive average momentum profits. They are 1.63, 0.78, 0.32 and 0.77 percent in Africa, the Americas (excluding the United States), Asia and Europe, respectively. The momentum profits are highly significant in all regions except for Asia. Similar to Rouwenhorst (1998) they find weaker momentum profits for emerging markets. The momentum profits for the portfolios without a gap are smaller than for those with a gap, with averages of 1.42, 0.50, 0.13 and 0.70 for Africa, the Americas, Asia, and Europe, respectively. However, all momentum profits are statistically significant in all markets except Asia. In conclusion, momentum profits are statistically significant around the world.

For the Norwegian stock market they find a highly significant average momentum profit of 1.11 percent. The sample consists of 88 stocks. The winner portfolio has a return of 0.88 percent, while the loser portfolio has a non-significant return of -0.33 percent.

Griffin et al. (2003) also investigates correlation between countries. They find that the average correlation of momentum profits between pairs of markets within a particular region is 0.012 in Africa, 0.077 in the Americas, 0.106 in Asia, and 0.088 in Europe. There is only weak evidence to suggest common sources of momentum profitability within regions. Using two different methods, they investigate correlations of momentum profits across regions. First, they look at pairwise correlations between countries in one region with those in another region. They then calculate the correlation directly between one region's time series of momentum profits and another's. For the first method, they find that the highest correlation is between the United States and Europe, at 0.139. The average of all correlations is only 0.032. For the second method, the correlations are somewhat higher, with an average of all regions. They argue that momentum profits are probably not driven by a global risk factor.

3.3 Momentum in Norway

Kloster-Jensen (2006) studied the Oslo Stock Exchange (OSE) from 1984-2005 with 73 stocks and a total of 8030 (monthly) observations. The results show that it is profitable to buy stocks that have done well the last 3, 6, 9 and 12 months and short the stocks with the worst performance. Kloster-Jensen interpret these results as a proof that positive auto-correlation does exist and that stock returns to some extent are predictable. All of the portfolios in the sample, except from the 3 x 3, gives a positive, significant return.

In his findings, the results change when using non-overlapping holding periods. The number of portfolios that gave a positive and significant return dropped from 15 to 8. Further, these findings show that the returns are higher and longer lasting for the portfolios consisting of the worst performing stocks. This is in contrast to the findings of Jegadeesh and Titman (1993), where the long position in winner stocks performed best. Among the portfolios with overlapping holding periods, the general pattern is that the return increased when going from 3 to 6 months formation period and from 6 to 9 months formation period, and slowly decreased from 9 to 12 months. With regards to holding period, the paper finds that the most profitable period to hold stocks is 6 months, leaving the 6 x 6 as the most profitable strategy.

Using the CAPM and looking at the beta of the portfolios to assess risk, Kloster-Jensen finds that the loser portfolios are more exposed to market risk than the winner portfolios.

He argues that the momentum profit might be due to differences in systematic risk between the long and short positions. Before adjusting for risk, it was found that a momentum strategy with an overlapping formation-period gave positive and significant returns in 15 out of 16 cases. After adjusting for risk, the number falls to 5. Also, after adjusting for risk, the number of strategies with non-overlapping holding periods with positive profits falls from 8 out of 16 to 2 out of 16. Thus, he claims that momentum-strategies are not as attractive after adjusting for risk.

Solheim and Jensen (2011) study momentum on Oslo Børs All Share Index (OSEAX) in the years 1997 to 2009, with a sample consisting of 75 stocks. The strategy is conducted using the decile-method, where all the stocks are divided into 10 portfolios, depending on their previous returns. Further, they limit their method to using non-overlapping holding periods only. In 15 out of total 16 cases the paper identify a positive difference between the return of the winner- and loser portfolios. Thus, the zero-cost portfolios yield positive returns. The returns are highest and most significant for the portfolios with 6 months formation. The 6 x 6 portfolio yielded a return of 1,34%. They find that the returns are higher for the winner-portfolios. Using the three-factor model to adjust for risk, the results indicate that the momentum effect is stronger for stocks with smaller market capitalization and low market-book value. They conclude that there can have existed momentum on the Oslo Stock exchange in their sample period (1997-2009).

Vas and Absalonsen (2014) is the most recent research on momentum effects in the Norwegian stock market. Their sample period is from 2004 to 2013, including in total 90 stocks listed on the OSEAX. They followed the method of Jegadeesh and Titman (1993) with formation- and holding periods of 3, 6, 9 and 12 months. Their empirical analysis found that all their momentum investing strategies generated significant returns. Their best performing portfolio is the 12 x 3, which gave an average monthly return of 2.43 percent. With a non-overlapping formation-period, the 6 x 6 strategy gave a return of 1.31 percent. When assessing how the portfolios performed compared to the market, they calculated the return excess of market return. Their findings show that the market outperforms the winner portfolio, and that the loser portfolio is the main driver of profits for the zero-cost strategy. This is in line with the findings of Kloster-Jensen (2006), and contrary to Jegadeesh and Titman (1993), Rouwenhorst (1998) and Solheim and Jensen (2011) who documented that winner-portfolios were the main driver of momentum profits. Vas and Absolonsen argue that using non-overlapping holding periods in order to minimize costs, is profitable. In this case, all 16 zero-cost strategies realize abnormal returns, although not all are significantly different from zero.

Summary

As we have seen, the momentum effect has been documented across several stock markets. We saw that the momentum research was pioneered by Jegadeesh and Titman (1993) who found all 16 zero-cost strategies between 1965 - 1989 to realize abnormal returns on 3 to 12 month horizons. Since then, many scholars have performed similar studies. Conrad and Kaul (1998) also studied the American market, and found that momentum strategies with formation- and holding periods of 3 to 12 months were profitable. Rouwenhorst (1998) documented similar findings for the European market. Like Jegadeesh and Titman (1993) he found the 12 x 3 strategy to be the most profitable momentum strategy. Momentum in Europe was further documented by Bird and Whitaker (2003), Van Dijk and Huibers (2002) and Griffin et al. (2003).

Rouwenhorst (1998) and Griffin et al. (2003) both included Norway in their studies, and found that momentum strategies were profitable on the Norwegian market. Rouwenhorst (1998) found that the average momentum profit for the period 1980-1995 was 0.99 percent, while Griffin et al. (2003) found an average return of 1.11 for the period 1982-2000. Both Kloster-Jensen (2006) and Solheim and Jensen (2011) found that momentum strategies were profitable in 15 out of 16 cases, with the 3 x 3 as the only strategy with non-significant returns. Absalonsen and Vas (2014) found significantly positive returns for all 16 strategies in their sample period 2004-2013.

Overall, we saw in our literature review that researchers find momentum strategies to be profitable on a medium horizon, between 3 and 12 months. Further, momentum returns generally diminish for holding periods exceeding 12 months, indicating that return continuation reverse on longer horizons. Most of the papers reviewed found that the winner portfolios are the main contributor to the zero-cost profit, however Absalonsen and Vas (2014) and Kloster-Jensen (2006) found the loser portfolios to be the most profitable. Generally, momentum strategies are found to be more profitable for longer holding periods.

Chapter 4

Analysis

4.1 Empirical Study of Oslo Stock Exchange

In order to investigate whether there has been momentum tendencies in the Norwegian stock market, we base our method on the framework of Jeegadish and Titman (1993). The method will consist of a strategy that picks stocks based on their past performance. If these strategies result in significant returns, then momentum tendencies might exist. This section will start by describing our data, followed by a detailed description of the methodology. Finally, we will present our findings.

4.1.1 Data

Data Presentation

We have chosen to conduct our study on equities on the Norwegian Stock Exchange (OSX). Our sample period is from January 2000 to February 2018. This time window gives us 218 monthly observations as a base of our study. For stock prices, our data has been extracted from Thomson Reuters Datastream. Rather than using the raw price, we used for any given stock at a time t, the Total Return Index (RI). The RI gives the growth in value of a share over a specified period, assuming that dividends are re-invested to purchase additional units of the equity at the closing price applicable on the ex- dividend date [1].

The RI is constructed as follows:

$$RI_t = RI_{t-1} * \frac{PI_t}{PI_{t-1}} * \left(1 + \frac{DY_t}{100} * \frac{1}{N}\right) \tag{4.1}$$

Where,

- RI_t is the return index in month t
- RI_{t-1} is the return index in the previous month
- PI_t is the price index in month t
- PI_{t-1} is the price index in the previous month
- DY_t is the dividend yield % at in month t
- N is the number of working days in one year (260)

The return index has been considered a fair measurement of returns, as it accounts for all equity actions. Thus, we can calculate the return from the change in the index over time.

Data Adjustments

When we downloaded stock data from the Oslo Stock Exchange, some adjustments had to be done. Firstly, we required all stocks to have quoted prices for at least 24 months. This was to ensure that the stock could be ranked based on its previous 12 month return and held for 12 consecutive months. After an assessment of the daily trading volumes, we saw that the A stocks were more liquid than B stocks. Six companies were listed with both A and B stocks, and as a result the B stocks were removed from the sample. After this, the dataset was checked so that every stock had actual price developments and that no "dead" stocks were left in the sample. Also, we chose to include stocks that were listed after the beginning of our sample period. This means that the number of stocks in our sample will increase with time. After making these adjustments, our dataset consists of

[1] https://www.investopedia.com/terms/t/total_return_index.asp

between 64-182 equities in total listed on the Oslo Stocks Exchange from 2000-2018.

In addition to return data we also collected data from Datastream on:

Risk-free rate As a proxy for a risk-free investment, we use the 3-month Norwegian Interbank Offered Rate (NIBOR) from Norges Banks statistics database[2]. The rate is quoted on a annual basis, thus we had to manually transform it to monthly[3], so that it would be corresponding to our monthly return data. We choose the 3-month rate, as our portfolio holding horizons are between 3 and 12 months. Ideally, we would use different risk-free rates with maturities that match the different holding periods. However, we believe that the the 3-month NIBOR quoted monthly is a fitting rate for our study.

Market-index In order to run regressions and compare our findings to the overall market, we need a measure of the market return. For this we use the Oslo Stock Exchange all-share total return index (OSEAX) from Datastream.

Market-to-book Data on the market-to-book ratio of the different stocks was collected from Datastream. Our application of this variable calls for book-to-market ratios, which we derived by dividing 1 by the market-to-book value.

Market Capitalization Market capitalization for each company in our sample was also collected from Datastream.

4.1.2 Methodology

Return Calculations

In order to calculate the return of the momentum portfolios, we need to calculate every stock's return and the monthly return of the market. For both stocks and the market we use continuously compounded returns. There are several reasons why this is more convenient to use than discrete return. First, continuously compounded returns approximate the discrete returns. Secondly, and most important for our work, is that they are time additive. This means that in order to calculate the cumulative return for a specified period

[2] https://www.norges-bank.no/en/Statistics/Historical-monetary-statistics/Short-term-interest-rates/

[3] $(1 + r_{annual})^{(1/12)} - 1$

of time, we can simply add the returns together. This is very useful when ranking the stocks based on their past performance, as we will illustrate later.

For the return of the individual stocks, r_i in our sample data, we compute the following way:

$$r_{i,t} = ln\left(\frac{RI_{i,t}}{RI_{i,t-1}}\right) \tag{4.2}$$

The return of the market portfolio, r_m, is computed similarly, but with the market index in stead of RI.

Portfolio Formation

At any formation time t in our sample, we have created portfolios based on stock returns in the preceding formation period, J. The formation period will vary between 1, 3, 6, 9 and 12 months and be denoted with J. For each stock, at each date t, we sum the return of the previous J months, as our returns are continuous:

$$r_{i,J,t} = \sum_{t-J}^{t} r_{r,J,t} \tag{4.3}$$

We then rank all the stocks at each different t based on their accumulated returns in the formation period. Based on a stock's rank, the stock could be assigned to either the loser or winner portfolio. If the stock is among the 20 percent best performing stocks, it will be assigned to the winner portfolio. If its among the 20 percent worst performing, it will be assigned to the loser portfolio. Then, the winner portfolio will be bought and the loser portfolio will be sold.

Portfolio size: Decile vs. Weighted Relative Strenght Strategy

Jegadeesh and Titman (1993) sort all stocks into 10 portfolios based on their historical performance. The strategy consists of a long position in the 10 percent best performing stocks and a short position in the 10 percent worst performing stocks. The stocks are either equally weighted or value-weighted within the portfolios.

Another method of constructing the portfolios is the "Weighted Relative Strength Strategy" (WRSS) (Conrad and Kaul, 1998). In this strategy, the portfolios weight each stock in relation to *all* the stocks in the market based on their returns. Thereby the zero-cost portfolios constitute long positions in stocks that perform better than the average, and short positions in stocks that perform worse than the average. That means that the overall weights sum to zero, while the sum of weights in the long and short positions vary. The weighting in the strategy can be given by:

$$WRSS_x = \pm \frac{1}{n} (r_x - \bar{r}) \tag{4.4}$$

Where r_x is the return of stock x, $\bar{r}$ is the average return of all the stocks in the sample and n = the number of stocks in the sample.

The WRSS has some drawbacks. First, because of the size of the portfolios, the transaction cost are considerably higher than for the 10-percent strategy. Secondly, because of the weighting scheme, stocks with previous extreme returns will dominate the portfolio. This can lead to small stocks with high volatility dominating the portfolio.

Because of the arguments above, we have chosen not to use the WRSS and instead follow the method of Jegadeesh and Titman. However, as there are fewer stocks on the Norwegian Stock Market, we have chosen to expand the portfolio size to 20 percent. This increases the number of stocks in each portfolio, and thereby the chance of diversification, while it minimizes the impact of extreme returns. Our winner and loser portfolios will therefore consist of between 13 and 36 stocks, as can be seen in Table 4.1.

Weighting of stocks: Equal weighing versus value-weighing

There are two ways to weight the stock within the portfolios. The first method is value-weighting, in which the stocks are weighted based on their relative market capitalization. This means that a stock with a high market capitalization will constitute a bigger portion of the portfolio. Larger companies are usually more liquid, which implies that they are

Table 4.1: Sample- and portfolio size

Year	Total number of stocks	Portfolio Size
2000	64-67	13
2001	67-71	14
2002	72-76	14-15
2003	76	15
2004	76-81	15-16
2005	81-89	16-18
2006	91-101	18-20
2007	102-116	20-23
2008	116-125	23-25
2009	126-127	25
2010	127-134	25-27
2011	136-141	27-28
2012	143-147	29
2013	147-149	29-30
2014	150-161	30-32
2015	163-175	33-35
2016	175-182	35-36
2017	182	36
2018	182	36

cheaper to trade because of lower bid-ask-spreads. However, it also means that the sample will be biased towards larger companies. We have therefore chosen to use the second method, in which all stocks are equally weighted within the portfolios. The extent to which company size affects momentum profits will be examined later in the thesis.

Portfolio Holding

For each of the different portfolios, the holding period, K, vary between 1, 3, 6, 9 and 12 months. This means that based on previous returns of period $t - J$, portfolios are formed and held until $t + K$. We only use the 1 month holding period for the portfolio based on 1-month formation. That means that we have 21 different momentum strategies.

Table 4.2: Momentum strategies

		K				
		1	3	6	9	12
J	1	J = 1 K = 1	J = 1 K = 3	J = 1 K = 6	J = 1 K = 9	J = 1 K = 12
	3		J = 3 K = 3	J = 3 K = 6	J = 3 K = 9	J = 3 K = 12
	6		J = 6 K = 3	J = 6 K = 6	J = 6 K = 9	J = 6 K = 12
	9		J = 9 K = 3	J = 9 K = 6	J = 9 K = 9	J = 9 K = 12
	12		J = 12 K = 3	J = 12 K = 6	J = 12 K = 9	J = 12 K = 12

As mentioned, we equally weight each stock in the portfolios. Thus, the return of the different portfolios for each month in the holding period are given by:

$$r_{p,t} = \sum_{t-J}^{t} \frac{1}{N} r_{i,t} \tag{4.5}$$

Where N is the number of stocks in the portfolio and $r_{i,t}$ is the return on each stock at time t.

Because the loser portfolios are sold short, a positive return on the short position will be reported with positive number, and vice versa. This is because we assign a negative portfolio weight to the stock returns in the loser portfolios, thus a short position in a stock decreasing in value will yield a positive number. Also, having the return in positive values gives us a number that is comparable to the winner- and zero-cost portfolio returns.

Overlapping versus non-overlapping holding periods

Like Jegadeesh and Titman (1993), our study includes the use of both overlapping and non-overlapping holding periods, in order to increase the power of our analysis. When using non-overlapping periods, our position does not change until the holding period of the last position is over. This means that when a portfolio is formed, this is the only portfolio held until the end of the holding period. This implies that we only get one observation each month.

	Formation and holding with the 3 x 3 strategy								
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Portfolio 1	Formation			Holding					
Portfolio 2	↓			Formation			Holding		
Average return per month:	-	-	-	-	-	-	-	-	-

Table 4.3: Example of the non-overlapping method

Overlapping means that the winner and loser portfolios are rebalanced each month. Every month the position initiated in $t-K$ is closed out, and $\frac{1}{K}$ of our position is revised. Using overlapping holding periods therefore implies more observations for the momentum return, as each month we have K observations. This can be seen in Table 4.4, where in June, we have $\frac{1}{3}$ invested in portfolio 1, 2 and 3, respectively. In July, we close out our position in portfolio 1 and invest in portfolio 4. The average of the returns from our portfolios constitutes the momentum return for the strategy of each month.

	Formation and holding with the 3 x 3 strategy								
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Portfolio 1	Formation			Holding					
Portfolio 2	↓	Formation			Holding				
Portfolio 3	↓		Formation			Holding			
Portfolio 4	↓			Formation			Holding		
Average return per month:	-	-	-	-	-	-	-	-	-

Table 4.4: Example of the overlapping method

Although we get more observations with the overlapping method, there are some disadvantages. First, overlapping holding periods can lead to autocorrelation. Second, because of the rebalancing, the method requires many more transactions, and therefore the transaction costs will be higher. The possible issues with autocorrelation and transaction costs will be assessed in section 4.2.1 and 4.1.4. Because the increased number of observations will give us a broader base for our study, we will refer to the results from the use of overlapping holding periods as our "base" study.

Jegadeesh and Titman (1993) also analyzed the different strategies with a week between the formation period and holding period to avoid bid-ask-spread, price pressure and lagged reaction effect. However, other previous studies of the Norwegian markets, such as Solheim and Jensen (2011) and Brodin and Abusdal (2008), did not use this method. We have therefore chosen not to use a gap between formation and holding. Thus, the return of the different strategies for each month is given by:

$$r_{s,t} = \sum_{i=1}^{K} \frac{1}{K} r_{p,i,t} \tag{4.6}$$

Where $r_{s,t}$ is the strategy return each month, K is the number of months in the holding period, and $r_{p,i,t}$ is the return of each portfolio in the given month. These returns form the time series returns of the winner and loser portfolios for the different strategies, as seen in the bottom line of Table 4.4. The zero-cost portfolio can then be created by adding the loser portfolio and the winner portfolio together. Because of the short position in the loser portfolio, this creates a self-financing strategy, thereby the name "zero-cost".

Statistical Significance

We will test our results for statistical significance in order to assess whether they have occurred by chance or not. In order to do this, we apply a one-sided t-test. As mentioned, our return calculations for the loser portfolios are done with negative portfolio weights. Thus, any positive number represents a gain and any negative number represents a loss. Therefore, we use a one sided t-test to see whether the returns are significantly higher than zero. We use the "t.test" function in R studio that calculate the t-value based on the following formula:

$$t = \frac{\bar{r} - \mu_0}{\frac{\sigma}{\sqrt{n}}} \tag{4.7}$$

where $\bar{r}$ is the mean value of the sample, μ_0 is what we test against, σ is the standard deviation of the sample and n is the number of observations. In this case, μ_0 is 0.

To determine the significance of our results, our t-values need to be compared to the critical values of the Student T-distribution. In order for our results to significantly prove a momentum effect, our t-values must be bigger than the corresponding limits of the Student T-distribution for critical values of ten, five, or one percent. The different levels of significance will be marked with stars:

Significance level	
Ten percent	*
Five percent	**
One percent	***

4.1.3 Presentation of Results

In this section we will present the main findings from our study. Because we use the overlapping method for our base study, these results will be presented and discussed here. The next section will contain our robustness test, including the results from the non-overlapping method.

Overlapping Holding Periods

The first thing to note is that all of our winner-, loser- and zero-cost portfolios yield positive returns for all of the 16 different strategies. All zero-cost portfolio returns are significant at the one-percent level.

During our sample period, the average monthly return on the winner portfolios is 0.7 percent. As seen in Table 4.5, 13 out of 16 strategies yield significant returns, but only the 12 x 3 is different from zero at a one-percent level. For the 3-month formation portfolios, only the 3 x 3 strategy is significant, and only at a ten-percent level. The most significantly positive return is from the 12 x 3 strategy, at 1.10 percent.

Interestingly, the loser portfolios generate on average a return of 1.9 percent, which is

Table 4.5: Results from the overlapping method

J		K			
		3	6	9	12
	Winner	0,00625	0,00499	0,00478	0,00427
	t-value	*1,446**	*1,165*	*1,132*	*1,023*
	Loser	0,01907	0,01710	0,01574	0,01523
3	*t-value*	*3.113****	*2.951****	*2.740****	*2.683****
	Zero Cost	0,02532	0,02209	0,02052	0,01951
	t-value	*5,841****	*6,344****	*6,199****	*6,221****
	Winner	0,00714	0,00817	0,00777	0,00628
	t-value	*1.643**	*1.915***	*1.851***	*1.512**
	Loser	0,02076	0,01857	0,01809	0,01698
6	*t-value*	*3.283****	*2.996****	*2.948****	*2.811****
	Zero Cost	0,02790	0,02674	0,02586	0,02326
	t-value	*5.993****	*6.053****	*6.066****	*5.786****
	Winner	0,00976	0,00898	0,00731	0,00570
	t-value	*2.262***	*2.084***	*1.736***	*1.380**
	Loser	0,02243	0,02191	0,02031	0,01896
9	*t-value*	*3.359****	*3.353****	*3.155****	*2.997****
	Zero Cost	0,03219	0,03088	0,02762	0,02466
	t-value	*5.9244****	*5.970****	*5.610****	*5.333****
	Winner	0,01101	0,00845	0,00657	0,00545
	t-value	*2.526****	*1.936***	*1.536**	*1.308**
	Loser	0,02285	0,02101	0,01941	0,01820
12	*t-value*	*3.338****	*3.114****	*2.924****	*2.785****
	Zero Cost	0,03387	0,02946	0,02598	0,02367
	t-value	*5.951****	*5.471****	*5.068****	*4.818****

more than twice as high as the winner portfolios. All returns on the loser portfolios are significant at a one percent level. Similarly to the winner portfolios, the highest return of the loser portfolios is with the 12 x 3 strategy, at 2.26 percent.

Adding together the returns from the winner and loser portfolios, we get an average return of 2.6 percent for the zero-cost portfolios. It seems as if these returns are driven in large part by the short positions in the loser stocks.

Our best performing strategy is the 12 x 3 strategy, which yields a return of 3.38 percent on average. This is comparable to the findings of Jegadeesh and Titman (1993) and Absalonsen and Vas (2014), who also find that the 12 x 3 strategy is the most profitable. Our worst performing momentum strategy is the 3 x 12 strategy. However, it still yields a return of 1.95 percent on average during the sample period.

Looking at the table, we can clearly see a tendency of the returns being lower, the longer the holding period. This implies that the momentum strategies work best with a shorter holding period. At any given formation period, the return decreases as the holding period increases. This is in line with the findings of Bird and Whitaker (2003), Jegadeesh and Titman (1993) and Rouwenhorst (1998). There is also a tendency here that a longer formation period increases return, although the tendency is not as strong.

Based on our results, and the strongly significant positive returns on our zero-cost portfolios, we can conclude that momentum investing in the Norwegian Stock Market between 2000 and 2018 has been profitable.

4.1.4 Robustness Tests

From our research so far, we have found momentum tendencies on the Norwegian Stock Market between January 2000 and February 2018. Further, we want to test if this effect is more pronounced for different types of stocks or market conditions. We will also check if our test methodology could affect the results. This section will start with a presentation of the results from using the non-overlapping method, testing a one-month formation strategy and from expanding our portfolios to 30-percent portfolios. We will then proceed with tests of other factors that could have an impact on the momentum return.

In the following sections, results will only be presented for the strategies with a 6-month formation period, unless otherwise stated. We believe these results are sufficiently representative for the momentum strategies. This is also in line with the robustness tests of Jegadeesh and Titman (1993) and Rouwenhorst (1998).

Non-Overlapping Holding Periods

Our results when using the non-overlapping method is quite similar to our results from our base study. All zero-cost returns are significant at a one-percent level. The best strategy is the 12 x 3 strategy, and the worst strategy is the 3 x 12 strategy, in accordance with the overlapping method. However, the returns are slightly smaller and less significant with the non-overlapping method.

The return on the 12 x 3 zero-cost portfolio is 3.12 percent, compared to 3.39 percent with the overlapping method. Where the return from the overlapping method had a t-value of 5.95, the non-overlapping had a t-value of 5.32.

The tendency of higher returns for shorter holding periods is also present with the non-overlapping method for the strategies of 9 and 12 months formation. However, for the 3-month- and 6-month formation periods, the 3-month holding return is only second highest. For the 3-month formation, the 9-month holding period yields the highest return. For the 6-month formation period, the 12-month holding period yields the highest return.

As the non-overlapping method has much fewer observations and thus less explanatory power, it is rarely emphasized in the academic literature on momentum. However, it is still interesting to investigate, because it is more realistic and practical for a real life trader. In contrast to the overlapping portfolios, this strategy does not require rebalancing of the portfolio holdings every month. Thus, this method is less time consuming and the transaction costs are lower, and as the results from this method are approximately equal to our base study, we believe it is a good alternative.

Table 4.6: Results from the non-overlapping Method

J		K			
		3	6	9	12
	Winner	0,00446	0,00568	0,00640	0,00379
	t-value	*0,987*	*1,260*	*1,393**	*0,830*
	Loser	0,01734	0,01424	0,01628	0,01417
3	*t-value*	*2,74****	*2,341***	*2,602****	*2,405****
	Zero Cost	0,02181	0,01992	0,02268	0,01796
	t-value	*4,346****	*4,526****	*4,731****	*4,549****
	Winner	0,00626	0,00607	0,00570	0,00668
	t-value	*1,431**	*1,393**	*1,294**	*1,501**
	Loser	0,01971	0,01759	0,01698	0,02006
6	*t-value*	*3,059****	*2,759****	*2,782****	*3,372****
	Zero Cost	0,02598	0,02367	0,02269	0,02675
	t-value	*5,126****	*4,819****	*4,565****	*5,916****
	Winner	0,00848	0,00893	0,00680	0,00709
	t-value	*1,884***	*1,997***	*1,490**	*1,534**
	Loser	0,02076	0,01923	0,01856	0,01878
9	*t-value*	*3,067****	*2,948****	*2,936****	*2,900****
	Zero Cost	0,02924	0,02814	0,02537	0,02588
	t-value	*5,104****	*5,156****	*4,701****	*4,694****
	Winner	0,00978	0,00792	0,00759	0,00769
	t-value	*2,205***	*1,708***	*1,766***	*1,678***
	Loser	0,02149	0,02034	0,02101	0,01255
12	*t-value*	*3,114****	*2,973****	*3,149****	*2,036***
	Zero Cost	0,03127	0,02826	0,02861	0,02024
	t-value	*5,319****	*4,108****	*5,097****	*3,898****

One-month Formation Period

Out of curiosity, we also wanted to check how the momentum strategies perform with only one month formation. That is, buy last months winners, sell last months losers and hold the position for 1, 3, 6, and 9 months. This was in part triggered by the tendency in the base-study indicating lower returns, the shorter the formation period. We wanted to check this with both the overlapping and non-overlapping method, but we will only present the results from the overlapping method here, in Table 4.7. The results from the non-overlapping method can be found in Table A.1 in Appendix A.

Table 4.7: 1-Month overlapping

J		K				
		1	3	6	9	12
	Winner	-0,00519	0,00134	0,00138	0,00084	0,00059
	t-value	*-1,095*	*0,295*	*0,294*	*0,173*	*0,118*
	Loser	0,00629	0,01167	0,01121	0,01058	0,01061
1	*t-value*	*1,075*	*2,099***	*2,119***	*2,034***	*2,046***
	Zero Cost	0,00110	0,01302	0,01259	0,01142	0,01120
	t-value	*0,257*	*4,736****	*5,543****	*5,397****	*5,409****

The 1 x 1 loser portfolio yields a return of 0.6 percent, while the winner portfolio yields a return of -0.5 percent. This gives a zero-cost profit of only 0.1 percent, which is not significant. Compared to longer formation periods, the one-month formation strategy performs considerably worse, with an average return on the zero-cost portfolios (excluding 1 x 1) of 1.206 percent and 0.214 percent compared to 2.74 percent and 2.49 percent for the overlapping and non-overlapping method, respectively. However, except for the 1 x 1 strategy, all strategies are statistically significant at a one-percent level for the overlapping method. For the overlapping method, the strategy with the highest return among these is the 3-month holding, at 1.30 percent.

All winner returns are insignificant, while all loser portfolios, except for the 1 x 1 strategy, yield significantly positive returns at a five percent level. We therefore note that return continuation based on a one month formation period is present for the worst performing stocks in the subsequent 3, 6, 9 and 12 months. As all zero-cost portfolios have significantly positive returns at a 5 and 10 percent level, we conclude that momentum return can be achieved with only one month formation period.

30-percent portfolios

In our original momentum strategies, the portfolios were based on 20 percent of the best and worst performing stocks. We now want to see whether the size of these portfolios affect the momentum profits. Increasing the size of the portfolio can increase diversification, as well as reduce the impact of extreme returns.

Table 4.8: 30-percent portfolios

J		K			
		3	6	9	12
	Winner	0,00752	0,00756	0,00752	0,00613
	t-value	*1,9249***	*1,9581***	*1,9637***	*1,6091**
	Loser	0,01459	0,01345	0,01314	0,01209
6	*t-value*	*2,6824****	*2,5095****	*2,4778****	*2,3058***
	Zero Cost	0,02211	0,02101	0,02066	0,01822
	t-value	*6,0335****	*6,0531****	*6,1984****	*5,7679****

All the zero-cost portfolios are still significant at a one-percent level, thus we conclude that there is also momentum return with 30-percent portfolios.

In line with our previous findings, both the loser portfolio and the zero-cost portfolio yield the highest returns with the 3-month holding period. The negative relationship between holding period and return is still present with 30-percent portfolios. However, the bigger portfolios reduce the momentum return of the different strategies. For the zero-cost portfolios, this reduction is around 21 percent on average. For the 6 x 3 strategy, the original return was at 2.79 percent, while with 30-percent portfolios it has reduced to 2.21. This reduction stems from the loser portfolios, which on average reduce return by approximately 29 percent. The original return of the 6 x 3 loser portfolio was 2.08 percent, compared to 1.46. In comparison, the sample increase does not affect the return on the winner portfolios more than about 3 percent. For the 6 x 3 strategy, the winner return actually increases from 0.71 to 0.75 percent.

As mentioned, one reason for the decrease in return can be that the return is driven by extreme observations. If more stocks are included in the portfolios, the influence of the extreme observations will be reduced, as their relative weight decreases. We will therefore examine the effect of extreme returns next.

Excluding extremes

We will now investigate if our momentum strategies are still profitable after extreme returns are disregarded. If some of the stocks in the portfolios have extreme negative or positive returns, our momentum returns can be biased, and our conclusions may not be representative. We have therefore chosen to present the results of the strategies with 6 months formation in which the 5 percent best and worst performing stocks have been excluded.

Table 4.9: 6 x 6 Strategy excluding extreme returns

J		K			
		3	6	9	12
	Winner	0,00701	0,00772	0,00745	0,00601
	t-value	*1,6389**	*1,8316***	*1,7948***	*1,462**
	Loser	0,01535	0,01327	0,01249	0,01114
6	*t-value*	*2,5867****	*2,2673***	*2,1646***	*1,9689***
	Zero Cost	0,02236	0,02099	0,01994	0,01715
	t-value	*5,1364****	*5,0516****	*4,9754****	*4,5649****

Excluding the extreme returns gives us an average zero-cost return of 2 percent, compared to 2.25 percent with our original data. Our winner portfolios only yield slightly lower returns, whereas the loser portfolios' returns are almost 30% lower on average. In accordance with our base study, the 3-month holding period yields the highest return for both the zero-cost portfolio and the loser portfolio, with a return of 2.24 and 1.54 percent respectively. In comparison, these numbers were 2.79 and 2.08 in our base study. This means that some of our momentum returns can have been driven by extreme observations.

All of the returns on the zero-cost portfolios together with the 3-month loser portfolio are still highly significant at a one-percent level, while three of the loser portfolios are significant at five percent. The loser portfolio with a 3 month holding period is significant at a one-percent level. We can therefore conclude that momentum return exists when extreme returns are excluded.

Size adjustment

In this section, we want to see if there is any difference in momentum profits between portfolios based on the size of the companies in our sample. According to Jegadeesh and Titman (2001), the momentum effect is more percistent for small-cap stocks. Also, Fama and French (1992) argue that small stocks are riskier than large stocks, implying that these should have higher returns. To test this in our data, we ranked stocks based on market capitalization, and sorted these into three groups: small, medium or big. After this, the original momentum method was applied, where stocks within each group are ranked based on previous return and sorted into winner and loser portfolios. We present our size-based subsamples with the 6x6 strategy:

Table 4.10: Size adjusted 6 x 6 Strategy

	Small	Medium	Big
Winner	0,00194	0,00299	0,00324
t-value	*1,23660*	*1,904***	*1,8895***
Loser	0,00585	0,00775	0,00497
t-value	*2,292***	*3,4789****	*2,1709***
Zero Cost	0,00780	0,01074	0,00821
t-value	*3,3953****	*5,6617****	*4,6863****

What we find is that medium size company stocks have the highest momentum returns of our subsamples, with 0.78 percent for the loser portfolio and 1.07 percent for the zero-cost portfolio. The small group of companies have the lowest return among the zero-cost portfolios at 0.78 percent. The large companies have the lowest return of the loser portfolios at 0.5 percent. For the winner portfolio, big companies have the highest momentum return of 0.32 percent. One thing to note is that also within this subsample, the returns are overall largest for the loser portfolio.

There is only a small difference in return between the subsamples. If the return of the zero-cost portfolios are summed together, the medium companies account for about 40 percent of the return, while the small and big companies account for 30 percent each. For the loser portfolios, small, medium and big companies account for 31 percent, 42 percent and 27 percent, respectively. These numbers are 23 percent, 37 percent and 40 percent for the winner portfolios.

Except for the small winner-portfolio, all returns are significant. The zero-cost returns are all significant at a one-percent level. This suggests that momentum return is present across different company sizes. However, for small companies, a return continuation of winner stocks cannot be proven as this is insignificant.

Our findings are in line with Rouwenhorst (1998) who also found return continuation to be present regardless of size. In contrast to the theory of Fama and French (1992), the small-cap stocks yield lower return than the big stocks. Overall, we conclude that momentum returns exist regardless of company size.

Volume adjustment

Because lower trading activity facilitate pricing inefficiencies, Daniel et al. (1998) claim that momentum should be stronger in illiquid stocks than in liquid stocks. We have chosen to test this by sorting the stocks into three different groups based on turnover volume, before the basic momentum method is applied. The results are presented below.

Table 4.11: Volume-Adjusted 6 x 6 Strategy

	Low	Medium	High
Winner	0,00207	0,00290	0,00319
t-value	*1,3869**	*1,9478***	*1,786***
Loser	0,01083	0,00431	0,00343
t-value	*4,6811****	*1,9413***	*1,4012**
Zero Cost	0,01291	0,00721	0,00662
t-value	*5,9088****	*4,0989****	*3,9544****

We see that the zero-cost portfolio with the lowest volume has the highest return, at 1.29 percent, compared to 0.72 and 0.66 percent for the medium and high volume, respectively. This return can mainly be attributed to the loser portfolio, which has a return of 1.1 % compared to 0.4 % and 0.3 % for medium and high volume respectively. For the low volume subsample, the winner portfolio has a return of 0.21, which is the lowest winner return among the subsamples. For the winner portfolio, the high-volume stocks have the highest return. However, the difference between winner returns of the subsamples is quite small, with a difference of 0.11 percentage points between the highest and lowest return. In comparison, this number is 0.74 for the loser portfolios.

All portfolios are significant, with all zero-cost portfolios being significant at the one-percent level. There seems to be a tendency for low-volume stocks to exhibit a greater degree of return continuation for loser stocks, that for other volume subsamples. This in turn means that the zero-cost return is higher for low-volume stocks. This is in line with Daniel et al. (1998). However, we are able to conclude that momentum returns are present for all volume subsamples.

Value adjustment

We will now test if there is a difference in the momentum effect of value stocks and growth stocks, meaning stocks with high book-to-market ratio and low book-to-market ratio respectively. According to Fama and French (1992), value-stocks are riskier than growth-stocks, and should therefore yield higher returns. To do this, we will divide our sample into three subsections based on the stocks' book-to-market value, before performing our usual momentum method.

Table 4.12: Value-Adjusted 6 x 6 Strategy

	Growth	Medium	Value
Winner	-0,00622	0,01244	0,01362
t-value	*-0,61129*	*1,6469**	*3,2635****
Loser	0,02525	0,00846	0,00382
t-value	*3,7759****	*1,6848***	*0,63610*
Zero Cost	0,01904	0,02090	0,01744
t-value	*2,7505****	*4,6927****	*4,11756****

Starting with the winner portfolios, the portfolio consisting of stocks with high book-to-market ratios, value stocks, gives the highest return, at 1.36 percent and a one-percent significance level. The growth-stocks give a negative, insignificant return. The return on the medium-value subsample is 1.24 percent and significant at a five-percent level. This implies that return continuation in winner stocks is present for value-stocks, but not for growth-stocks. This is in line with Fama and French (1992).

For the loser portfolios, growth stocks yield a considerably higher return than the medium- and value-stocks, with a return of 2.52 percent, compared to 0.84 and 0.38 for the medium- and value-stocks, respectively. While the return on losing value-stocks is not significant, both low and medium subgroups are significant. The growth-stocks have a significant positive return at a one-percent level, compared to five-percent for the medium subsample. This suggests that for loser stocks, momentum profits are present for low and medium book-to-market values. Previous losing value-stocks do not exhibit return continuation. The value-effect is therefore not present in the loser portfolios.

All the zero-cost portfolios are significant at a one-percent level, where the medium subgroup yields the highest momentum return at 2.09, while the value-stocks yield the lowest return at 1.74. The overall momentum return for the growth-stocks is driven by the loser portfolio, as we have seen been the case for our base study. This means that previous losing companies with a low book-to-market ratio, called "growth" companies because the market expect them to grow, will in fact continue to lose in the subsequent 6 months. On the other hand, if these companies have performed well in the previous 6 months, there is no evidence that this trend would continue in the subsequent 6 months. For the value-stocks, return of the winner portfolio is significant, while the loser portfolio return is insignificant.

There is a chance that our results might suffer from survivorship bias. As mentioned, we have chosen not to include dead stocks in our analysis. That means that stocks that have had a high book-to-market ratio and subsequently gone bankrupt are excluded from our sample. Thus, the return on our value-stock portfolios might stem from stocks that have "recovered" and survived.

Sample split

In this section we wanted to see if there are any differences in momentum in the first and second half of our data set. We split our data set into two parts, before applying the basic method. We split the data set so that the holding periods in the first part begin in July 2000 and ends in February 2009, and then the second part is from July 2009 until February 2018.

We find that the momentum effect is present both in the first and second half, where the zero cost strategy yields returns of 2.94 percent and 2.68 percent respectively. Compared to the average return of the full sample of 2.67 percent, the first half gives slightly higher return and the second half gives approximately the same return.

Table 4.13: Sample split

	1st half	2nd half
Winner	0,009705	0,005554
t-value	*1,2888*	*1,2953**
Loser	0,019787	0,02125085
t-value	*1,9351***	*2,9712****
Zero Cost	0,029492	0,02680524
t-value	*4,3069****	*4,7138****

For the first half, the return of the winner portfolio is insignificant, while the return of the loser portfolio is significant at a five percent level. For the second half, both return on the winner and loser portfolio is significant, at a ten-percent and one-percent level, respectively.

The return of the zero-cost portfolio in the first half of the sample is slightly larger than in the second half, although the second has a higher t-value. This can indicate that the market was more volatile during the first half. Our results suggest that the winner portfolio contributes relatively more in the first half than in the second half, although it is insignificant. For the loser portfolio, the second half has a higher and more significant return, of 2.13 percent compared to 1.98 percent.

Overall, we can see that momentum returns have been present both in the first half and in the second half of our sample. To further investigate our findings, in the next section we will exclude the financial crisis and look at the Norwegian stock market before and after.

Excluding the financial crisis

We will now decompose the sample even more, by excluding the months of the financial crisis, to see if there is any difference in stock price behavior before and after. We have excluded the months of December 2008 until June 2009 before conducting the momentum methodology. The results are quite interesting.

We see that the momentum strategy seems to be profitable before and after the financial crisis in our sample. The zero cost portfolio pre- and post-crisis returns are 2.95 and 2.44 percent respectively, both significant at a one-percent level.

Table 4.14: Excluding the financial crisis

	Before	After
Winner	0,020617	0,003702
t-value	*2,8509****	*0,83702*
Loser	0,008926	0,020710
t-value	*0,87934*	*2,804****
Zero Cost	0,029543	0,024412
t-value	*3,9316****	*4,2456****

The effect that we saw in the sample split, where the winner portfolio yielded relatively higher returns is even stronger when excluding the financial crisis. The return of the winner portfolio is 2.06 percent compared to 0.37 percent after the crisis, and 0.82 percent for the entire sample. Before the crisis, the winner portfolio represents almost 70 percent of the zero-cost returns, compared to 15 percent after.

Meanwhile, after the financial crisis, the loser portfolio yields 2.07 percent on average, compared to 0.8 percent before the financial crisis, thus being the biggest contributor to the momentum profits. As seen in the table, the loser portfolio contributed approximately 30 percent of the zero cost profits before the crisis. After the crisis, this percentage is approximately 85 percent. It is interesting to see that the relative strength of the winner and loser portfolios compared to each other seems to be the opposite before and after the financial crisis.

Transaction costs

Transaction costs are ignored in the efficient market hypothesis, but are very relevant in the real world. They can be divided into two categories: direct and indirect costs. Direct costs are explicit costs, such as broker commission, taxes and account fees. Indirect costs consists of more implicit costs like the spread between the bid- and ask price. Transaction costs are dependent on many factors, such as the type of investor and the size of the transaction.

In order to see whether the momentum trading returns are still present after taking transaction costs into account, we have chosen to estimate transaction costs for three different periods: from 2000 to 2005, from 2006 to 2011 and from 2012 to 2018. This is because transaction costs have decreased over the years, due to increased competition among brokers and increased stock market liquidity (Nordell, 2015).

Table 4.15: Transaction Costs

	2000-2005	2006-2011	2012-2017
Commission x2	0,70%	0,16%	0,08%
Spread	0,12%	0,12%	0,12%
Winner	0,82%	0,28%	0,20%
Loser (+0,3%)	1,12%	0,58%	0,50%
Zero Cost (winner + loser)	1,94%	0,86%	0,70%

For the broker commission, we have used Pareto[4] as a benchmark. With a minimum brokerage of NOK 59, the commission is 0.039% as of April 2018. Jegadeesh and Titman (1993) use a transaction cost of 0.5%. Using this as a reference, we found it reasonable to set the transaction cost for 2000-2005 to 0.35%. This was also the Pareto commission before online trading. Solheim and Jensen (2011) used a commission fee of 0.125% for the period 2005-2009. We have therefore set the commission fee for years 2006-2011 to 0.08%, taken into consideration the declining trend of the commission fees.

Our bid-ask spread estimate is based on Absalonsen and Vas (2014), who calculated a spread from bid and ask prices collected from Datastream. The spread is set to 0.12%.

The total transaction costs for the winner portfolio is calculated as the sum of commission fees and the bid-ask spread. Because short trade is usually more expensive than long trade, we have added an additional cost of 0.3% for the loser portfolios, which is consistent with Absalonsen and Vas (2014). The transaction costs for the zero-cost portfolios are calculated as the sum of the transaction costs for the winner and loser portfolios.

The test is conducted by assuming that all stocks in the portfolios are replaced every month. This is a conservative assumption, as many of the stocks are held longer. However, we believe that it suffices in giving an impression of how momentum trading works in real life for a retail investor. The momentum return after transaction costs are calculated by subtracting the appropriate transaction costs from each month's return.

[4] http://www.paretosec.no/aksjehandel-paa-nett/verdipapirhandel/prisliste

Table 4.16: Returns after transaction costs

	3x3	6X6	9X9	12 x12
Winner	0,00199	0,003965	0,003166	0,001367
t-value	*0,46229*	*0,93379*	*0,7547*	*0,32924*
Loser	0,011814	0,011371	0,013161	0,011119
t-value	*1,9254*****	*1,8319*****	*2,0482*****	*1,699*****
Zero Cost	0,013805	0,015336	0,016327	0,012486
t-value	*3,180462******	*3,482******	*3,3251******	*2,5475******

Although considerably lower than our original results, all zero cost returns are still significant at a one-percent level. Returns on our loser portfolios are only significant at a five-percent level. None of our winner portfolios are significantly different from zero. We note that our estimates of transaction costs are rough, as they are based on several assumptions. We do however believe them to be sufficiently conservative to illustrate real world momentum trading.

4.2 Risk based explanations

So far, we have seen that our momentum strategies have yielded considerable and robust returns during our sample period. In this section we want to examine whether our momentum profits can be attributed to high risk.

At the foundation of traditional finance theory lies the "no free lunch"-argument. In an efficient market, no investor can expect to gain returns greater then the risk he is taking. Although the cost of the zero-cost strategy is zero, any investor following a momentum strategy will face risk. Unless the loser portfolio and the winner portfolio are perfectly negatively correlated, the zero-cost strategy is risky. For example, if the position in the loser portfolio decreases more in value than the winner portfolio increases in value at any time, the investor will lose money. Therefore, traditional economists would argue that momentum profits can be explained by risk.

In the coming sections we will model the momentum returns through factor models. More specifically, we will use the following models:

- Single index model
- Fama French Three Factor Model
- Carhart Four Factor Model

The single index model and the three-factor model have been applied quite frequently throughout momentum literature. However, the Carhart four-factor model has been less examined. As it incorporates momentum as an additional risk factor, we have chosen to include this model as well. In order to assess the risk we will run Ordinary Least Squares (OLS) linear regression models. This chapter will therefore start with a review of the OLS assumptions, before we present our findings from the factor-models.

4.2.1 OLS assumptions

In order to produce reliable OLS estimators that are BLUE (Best Linear Unbiased Estimators), certain requirements need to be met. The most commonly applied assumptions are:

1) Linearity of parameters
2) No exact multicollinearity
3) No heteroscedasticity
4) No autocorrelation
5) Normally distributed errors

In addition to these assumptions there exist many others. We do however believe that testing the data for other assumptions will be outside the scope of our thesis. For every assumption we will focus the 6 x 6 momentum strategy for the zero cost portfolios.

Linearity of parameters

The first OLS assumption is that y is a linear combination of the x variables and the error terms. If the true relationship between x and y is not linear, then the coeffecient will not be possible to estimate correctly. We will here present scatter plots that illustrate the relationship between the 6 x 6 zero cost portfolio returns and the monthly OSEAX return. Scatter plots of the 6 x 6 loser and winner portfolios can be found in Figure B.1 and B.2 in the Appendix.

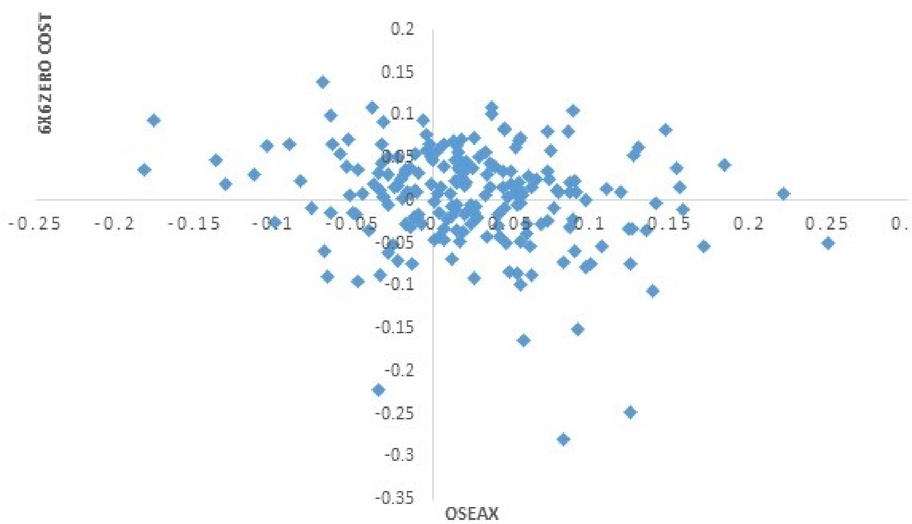

Figure 4.1: 6x6 Zero Cost vs OSEAX

As we can see from Figure 4.1, there is nothing that indicates any non-linearity among the parameters. As seen in figure B.1 and B.2 in Appendix B, this holds also for the winner and looser portfolio. Thus, we conclude for now that our portfolio returns can be modelled with linear regression using the market return as an explanatory variable. Further, as the Fama French Three-Factor model and the Carhart Four-Factor model are well-know models for estimating asset and portfolio returns, we assume that this relationship will hold for these models as well in our studies. We will therefore not investigate this any further.

Multicollinearity

The case of multicollinearity is a potential problem when estimating OLS models. If the explanatory variables are perfectly correlated, then it is not technically possible to estimate a model using these variables. If the variables are strongly, but not perfectly correlated, then the coeffecients can be estimated, but the hypotheses can be biased (Succarat, 2015). Multicollinearity increases the standard errors of the coefficients. By overinflating the standard errors, multicollinearity can in some cases make variables statistically insignificant when they should be significant. Without multicollinearity (and thus, with lower standard errors), those coefficients might be significant.

One intuitive way of checking for possible multicollinearity is simply looking at the correlation among the explanatory variables in our models. Another useful estimate in order to detect multicollinearity is the Variance Inflation Factor (VIF). This can be simply done in R studio. As the CAPM only have one dependent variable, we will only test this assumption for the Fama French three-factor Model and Carhart four-factor model. We will use the data for overlapping returns from 6 month formation.

	Market Factor	SMB Factor	HML Factor
Market Factor	1	-0.4297	-0.0214
SMB Factor		1	0.1013
HML Factor			1

Table 4.17: Correlation Matrix Fama French Three-Factor Model

	Market Factor	SMB Factor	HML Factor	Momentum Factor
Market Factor	1	-0.4245	-0.0239	-0.3162
SMB Factor		1	0.1059	-0.2492
HML Factor			1	0.2071
Momentum Factor				1

Table 4.18: Correlation Matrix Carhart Four-Factor Model

Looking at the correlation matrixes, there does not seem to be any strong correlation between the dependent variables in our models. We have also estimated the variance inflation factors for the dependent variables in both models. If the VIF value is between 5-10 the variables are said to be moderately correlated, and cause problem. As seen in Table B.1 and Table B.2 in Appendix, none of our VIF values in either models exceed 1.6, which indicates that multicollinearity is not a problem in our models.

Heteroscedasticity

Heteroscedasticity is the case when the variance of the error term, $var(u_i|X_i = x)$, is not constant for $i = 1, \ldots, n$. This has no consequences for the estimated coefficients, but standard errors may be biased (Stock and Watson, 2012). If the standard errors are biased, the normal t and F statistics are no longer BLUE.

For a model to have homoscedasticity, the error term needs to be independent of the observations. An intuitive way of detecting heteroscedasticity in an OLS model is to plot the residuals in each model against the explanatory variables. This will be displayed for the 6 x 6 zero-cost portfolio for the CAPM in Figure 4.2, three-factor model in Figure 4.3 and the four-factor model in Figure 4.4.

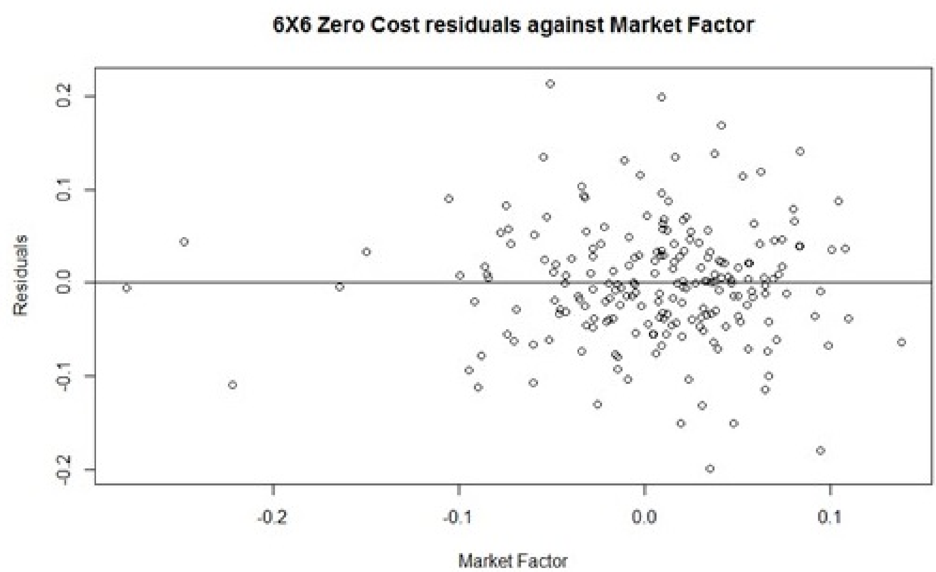

Figure 4.2: CAPM: Zero-cost residuals vs OSEAX

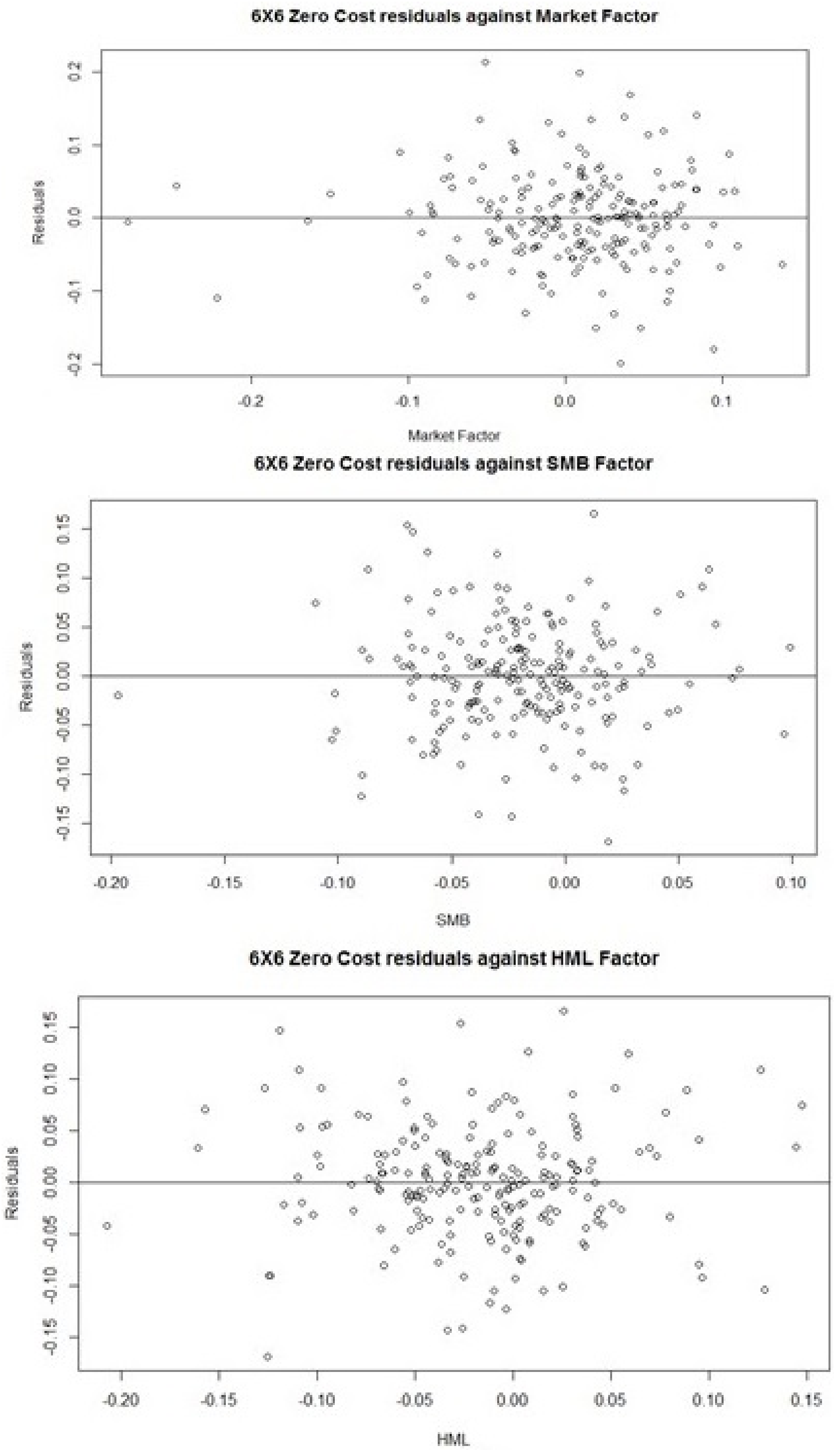

Figure 4.3: Fama-French: Zero-cost residuals vs OSEAX, SMB and HML

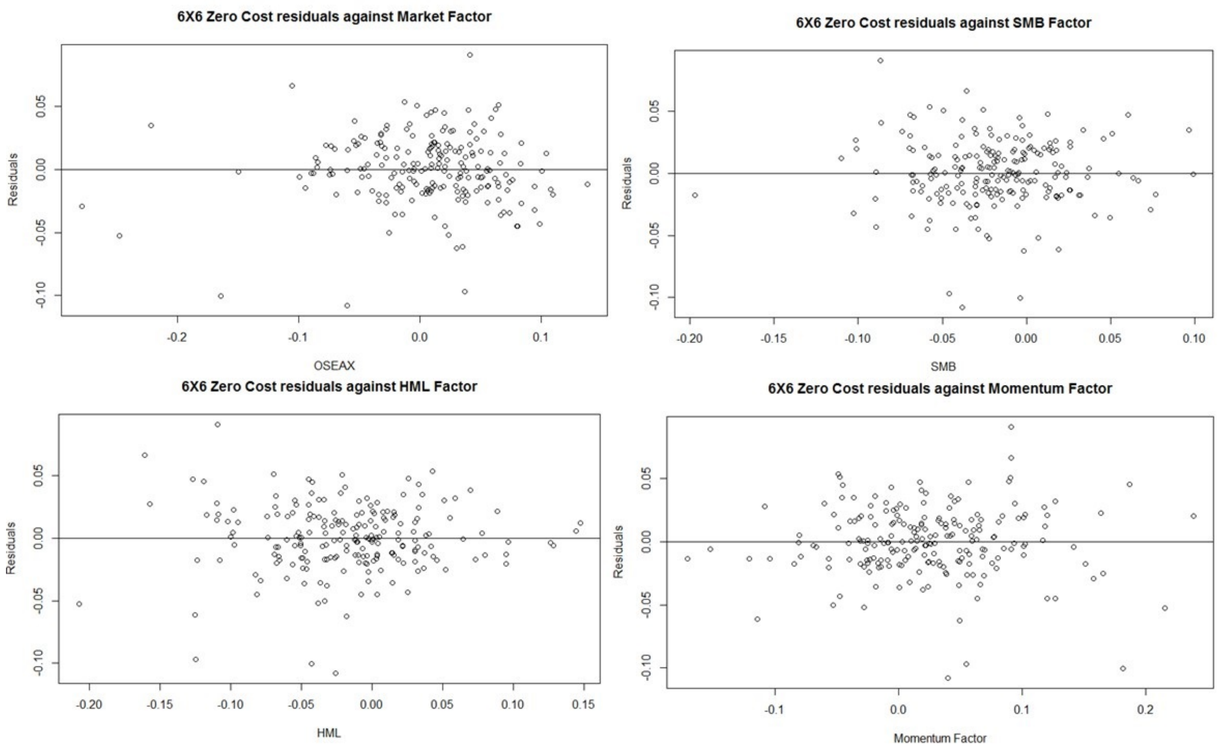

Figure 4.4: Carhart: Zero-cost residuals vs OSEAX, SMB, HML and PR1YR

As seen in the plots, it seems as if the residuals are quite evenly spread out. We do however observe several outliers that may still raise doubt regarding homoscedasticity. Also we can see for the Carhart-model, when the zero-cost profits are regressed on the market return, there seems to be some non-randomness of the error variance. To be even more certain we conduct a Breusch-Pagan test on our data. This test is a general test method for heteroscedasticity that tests whether one or more of the explanatory variables has a significant effect on the error term u^2.

The test expression in the Breusch-Pagan test is given by the following:

$$u^2 = A_1 + A_2X_2 + ... + A_KX_K + w$$

Where A_1 is the constant term, A_2 to A_K are coefficients and w is the error term. The zero hypothesis of no heteroscedasticity means that all of the coefficients are equal to zero. The alternative hypothesis is that one or more of the coefficients in the equation are not equal to zero. More formally, we have:

$$H_0 : A_2 = 0, A_3 = 0 \dots A_K = 0$$

$$H_A = \text{One or more of the statements in } H_0 \text{ are not true}$$

We test all of our 6-month formation portfolios for heteroscedasticity on a five percent level. Using the *bptest* function in R Studio, we look at the p-value for each Breusch-Pagan test. The test creates a statistic that is chi-squared distributed. If the test statistic has a p-value below five percent, the null hypothesis of homoscedasticity if rejected.

The test results from the Breusch-Pagan test can be seen in Table C.1 in the Appendix. As expected when using logarithmic returns in our stock data, there are not many of our portfolios that have heteroscedasticity. In 4 out of 36 cases the zero hypothesis of no heteroscedasticity could be rejected, all of them in the Carhart four-factor model. In the Capital Asset Pricing Model, we found one p-value to be slightly over 10 percent and one below 10 percent. There seems to be some degree of heteroscedasticity in our data.

Autocorrelation

An important assumption for hypothesis testing is that the error term is not serially correlated. In other words, the following must be true:

$$Corr(u_t, u_{t-1}) = 0$$

$$Corr(u_t, u_{t-2}) = 0$$

$$\dots$$

If only one of these autocorrelations were to be different from zero, then the error term is autocorrelated. A consequence of autocorrelated residual terms is that the estimates of the standard error of the coefficients are invalid, which in turn will result in biased t- and F-tests. Considering the OLS estimates, they might be incorrect in the sense that they are not consistent.

The way that we test for autocorrelated error terms is using the Breusch-Godfrey test. The test expression is given by,

$$u_t = A_1 + A_2X_2 + ... + A_kX_k + C_1u_{t-1} + C_2u_{t-2} + ... + C_pu_{t-p} + w_t$$

Where A_1 is the constant term, A_2, A_k and $C_1, \ldots, C_p$ are coefficients and w is the error term. The zero hypothesis, that the error term is not autocorrelated to the order p means that all the C coefficients in the test expression are equal to zero. The alternative hypothesis is that one or more of the C's are different from zero. More formally,

$$H_0 = C_1 = 0, C_2 = 0 \text{ ... and } C_p = 0 \text{ (No autocorrelation)}$$

$$H_A = \text{One or more of the expressions in } H_0 \text{ are false } (u_t \text{ is autocorrelated})$$

Where the test expression is F-distributed.

The results from the Breusch-Godfrey tests are executed in R, and reported in Table C.2 in the Appendix. As we can see from the sample of 36 6-month formation portfolios in the table, we reject the null hypothesis of no autocorrelation as the test number exceed the critical value in six cases. This indicates that there might be some degree of autocorrelation in our data.

Normally Distributed Errors

In the following figure the distribution of the error assumed under normality is compared to the actual distribution in our models. We illustrate residual plots from our 6 x 6 zero-cost portfolios using R Studio.

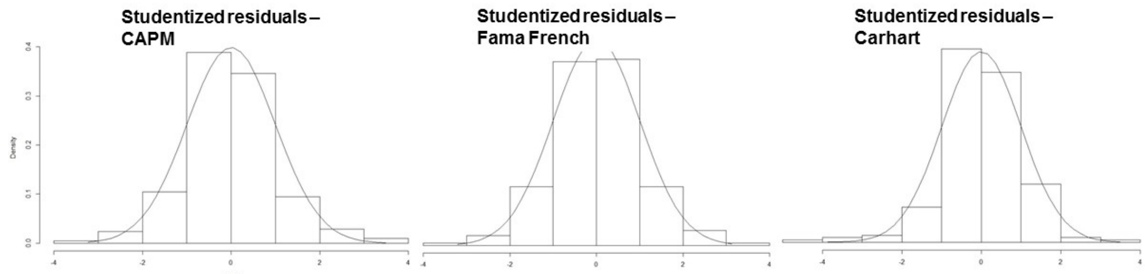

Figure 4.5: Distribution of errors in the CAPM, three-factor model and four-factor model

A look at the plot of these portfolios does not indicate any non-normality of the errors.

Summary of the OLS assumptions

When assessing the OLS assumptions we first concluded that the variables in our models can be modelled with a linear relationship. In the last section we found the residuals of our models to be more or less normally distributed. This was only our zero-cost portfolios. We cannot exclude the possibility that some of the residuals from the other portfolios are non-normally distributed. However, according to Succarat (2015) non-normal residuals are often relaxed and do not necessarily make the OLS biased. We also saw that some of our sample portfolios had incidents of heteroscedastic error terms and some degree of autocorrelation. This will not have a direct effect on the explanatory power of the models or the coefficient's size but may make t- and F-tests biased. To correct for this, we use the Newey-West standard errors in all of our estimations, as they are robust to heteroscedasticity and autocorrelation.

4.2.2 The Single Index Model

In this part we will assess whether the returns generated by our momentum strategy can be explained by the Capital Asset Pricing Model. As mentioned earlier, the model assumes that returns are generated from systematic risk. In other words, it claims that portfolio returns can be explained by its exposure to the market portfolio.

To empirically test this, we will use the Single Index Model (SIM), which is a simple modification of the CAPM presented in equation 4.8. The only difference is that the SIM is an empirical description of the stock returns. This includes modelling the portfolio return to the extent that it exceeds the risk-free rate. For the portfolios and the market, the monthly excess returns has been calculated by subtracting the monthly risk-free rate. The SIM is formulated as follows:

$$r_{pt}^{J,K} - r_{f,t} = \alpha_{p,t}^{J,K} + \beta^{J,K}(r_{m,t} - r_{f,t}) + \epsilon_{p,t} \tag{4.8}$$

Where $r_{p,t}^{J,K}$ is the return on a winner, loser or zero cost portfolio at time t. The expression $r_{m,t} - r_{f,t}$ is the market's excess return, ϵ_t is the residual term and the α is the return of the portfolio that the model is unable to explain. The residual term, ϵ_t, is assumed to be normally distributed with a mean of zero.

We present our findings in Figure 4.6. The outputs are presented using Newey-West standard errors. These are reported in brackets, and the respective t- and F-statistics are also reported.

Figure 4.6: Regression output from the Single Index Model

	Zero Cost			Winner			Loser		
J/K	α	β	R^2 / F	α	β	R^2 / F	α	β	R^2 / F
3,3	0.024***	-0.254***	0.054	-0.002	0.878***	0.637	0.022***	-1.124***	0.532
	-0.005	0.084	12.143***	0.003	-0.051	372.0***	-0.003	0.051	241.1***
3,6	0.020***	-0.176***	0.04	-0.002	0.922***	0.716	0.020***	-1.089***	0.559
	0.004	0.067	12.143***	0.003	0.049	535.3***	0.003	0.049	269.0**
3,9	0.019***	-0.186***	0.05	-0.002*	0.914***	0.723	0.018***	-1.092***	0.572
	0.004	0.068	11.173***	0.003	0.043	553.9***	0.003	0.043	283.5***
3, 12	0.018***	-0.176***	0.05	-0.003**	0.917***	0.744	0.018***	-1.084***	0.578
	0.004	0.065	11.085***	0.003	0.044	617.5***	0.003	0.044	290.5***
6,3	0.026***	-0.228**	0.039	0.0003	0.883***	0.655	0.023***	-1.102***	0.492
	0.005	0.089	8.385***	0.0003	0.058	396.7***	0.005	0.074	202.7***
6,6	0.025***	-0.226**	0.042	0.001	0.890***	0.689	0.021***	-1.107***	0.517
	0.005	0.088	9.224***	0.003	0.05	463.0***	0.004	0.077	223.7***
6,9	0.024***	-0.231**	0.047	0.001	0.886***	0.704	0.021***	-1.107***	0.528
	0.005	0.094	10.382***	0.003	0.051	496.9***	0.004	0.083)	234.2***
6,12	0.022***	-0.216**	0.047	-0.001	0.893***	0.73	0.019***	-1.100***	0.538
	0.004	0.086	10.276***	0.003	0.046	564.9***	0.004	0.083	243.6***
9,3	0.031***	-0.318***	0.056	0.003	0.833***	0.598	0.025***	-1.142***	0.48
	0.006	0.123	12.258***	0.003	0.062	306.8***	0.005	0.095	190.5***
9,6	0.029***	-0.284**	0.049	0.003	0.852***	0.627	0.024***	-1.126***	0.489
	0.005	0.116	10.668***	0.003	0.061	346.3***	0.005	0.096	196.8***
9,9	0.026***	-0.273**	0.05	0.001	0.852***	0.657	0.022***	-1.116***	0.495
	0.005	0.113	10.952***	0.003	0.056	393.7***	0.005	0.096	201.9***
9,12	0.023***	-0.261**	0.052	-0.001	0.858***	0.692	0.021***	-1.110***	0.507
	0.005	0.103	11.373***	0.003	0.052	462.0***	0.005	0.093	211.4***
12,3	0.033***	-0.341**	0.06	0.004	0.827***	0.587	0.026***	-1.160***	0.478
	0.133	0.133	12.889***	0.003	0.068	288.0***	0.005	0.099	186.0***
12,6	0.028***	-0.304***	0.053	0.001	0.857***	0.627	0.024***	-1.152***	0.485
	0.006	0.117	11.286***	0.003	0.06	340.6***	0.005	0.101	191.3***
12,9	0.025***	-0.287**	0.047	-0.0005	0.866***	0.665	0.023***	-1.144***	0.495
	0.006	0.114	11.128***	0.003	0.061	403.2***	0.005	0.099	199.2***
12,12	0.022***	-0.278**	0.053	-0.002	0.861***	0.692	0.021***	-1.130***	0.495
	0.006	0.115	11.362***	0.003	0.066	455.5***	0.005	0.096	201.3***

R-squared The R-squared is an intuitive way of looking at how well a model performs, as it measures the explanatory power of the independent variables. Looking at the R-squared of the total regression output, the CAPM is able to explain between 58.7 and 74.4 percent of the momentum winner portfolio return variation, and between 47.8 and 57.8 percent of the variation returns from the loser portfolios in our sample. For the zero-cost portfolios, the R-squared is relatively low, ranging from 3.9 to 6 percent. A low R-squared for zero-cost portfolios was also documented by Absalonsen and Vas (2014) who report R-squared values between 0.04 and 4.1 percent.

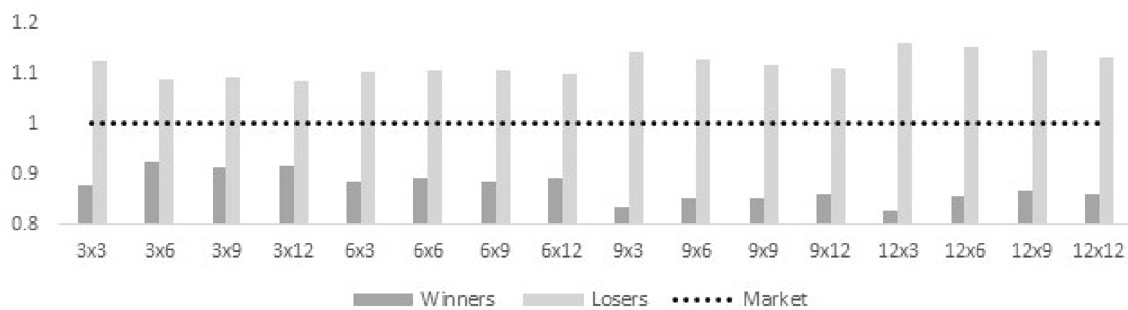

Figure 4.7: Beta values of the CAPM

Beta The winner portfolios have an average beta of 0.87. The beta of the loser portfolios are illustrated with its absolute value for graphical reasons, but is on average -1.11. This means that the loser portfolios will on average generate a 1.11 percent loss whenever the market goes up by one percent. This makes intuitive sense, as the momentum strategy picks the worst performing stocks for the loser portfolio. Looking at the output in Figure 4.6 , we see that all 32 portfolios have a significant market factor at one percent. Two things are worth noting. All of the winner portfolios have a beta lower than 1, suggesting that the portfolios constructed from well-performing stocks that have lower systematic risk than the overall market. Secondly, all of the loser portfolios have betas higher than 1, suggesting that these consist of riskier stocks than the winner portfolios.

We also see that the zero-cost portfolios have a lower beta, -0.21 on average. 6 out of 16 zero-cost portfolios have a significant market factor at one percent, while 10 are significant at five percent. Further, it is worth noting that the zero-cost portfolios have negative betas, suggesting that when the market return increases, the return of a zero-cost portfolio should decrease. As we have seen, the loser portfolios contribute more than the winner portfolios to the zero-cost returns, which means that the beta of the zero-cost portfolio is very sensitive to the negative beta of the loser portfolios. The same tendency was found for zero cost portfolios on the Swedish stock exchange by Nordell (2015).

Looking at the winner portfolios, it seems that the systematic risk is higher for the portfolios with 3 and 6 months formation. Although not as clear, there is a slight opposite tendency among the loser portfolios. For the portfolios with formation periods of 9 and 12 months, there seems to be a negative relationship between holding period and systematic risk for the loser portfolios, while this relationship is positive for the winner portfolios. Also, the 3 month holding portfolios have lowest systematic risk among the winner portfolios. For the loser portfolios, 12 month holding betas are the lowest.

Alpha This section will examine the alpha values for our portfolios. In the regressions models, the alpha, α, is thought of as abnormal return generated by a security or portfolio than cannot be captured by the model. Intuitively, if there is a momentum effect, then the intercept (alpha) will be positive.

Looking at our total results, all of our 32 portfolios have alphas that are different from zero. While all of these are significant at a one-percent level for the loser- and zero-cost portfolios, only two of them are significant for the winner portfolios. The zero-cost portfolios are those that have the highest alphas among the portfolios, with an average value of 0.024. The highest alpha is 0.033 for the 12 x 3 portfolio. We also see that independent of formation period, it seems that the most profitable holding period is 3 months.

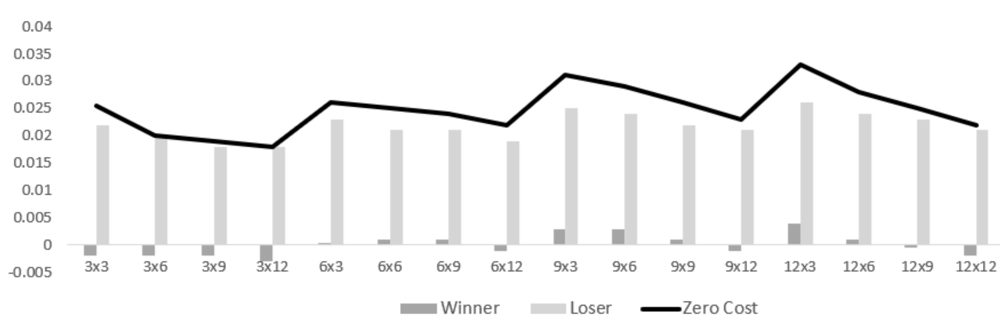

Figure 4.8: Alphas CAPM

Looking at the winner portfolios, they have very low alpha values on average. As seen in table 4.8, 7 of them are negative, while the remaining 9 are positive. However, these values are barely different from zero, with an average of $5 * e^{-5}$. The highest alpha among the winner portfolios is the 12 x 3 with a value of 0.004. The loser portfolios however, all have positive and significant alphas with an average value of 0.02175.

Interpreting the alphas, the best performing strategy seems to be the 12 x 3 with an alpha value for the zero-cost portfolio of 0.033. This supports the findings of our base study. It implies that an investor that followed a 12 x 3 strategy gained a return that was approximately 330 basis points higher than the fair compensation for the risk taken, according to the CAPM.

If the returns that were found in our base study were all due to market risk, theoretically, all the alpha values in this section should have been zero. As we have seen, they are not, as all of them are significantly different from zero. Hence, we can conclude in this section that the CAPM does not fully capture the returns generated from our momentum strategy.

4.2.3 Fama French Three-Factor Model

We now turn our attention to the three-factor model, which is similar to the CAPM but expanded with two additional factors, SMB and HML[5]. With a minor adjustment of the Fama French three-factor model in equation 2.2, we get the following expression:

$$r_{p,t}^{J,K} - r_{f,t} = \alpha_{p,t}^{J,K} + \beta^{J,K}(r_{m,t} - r_{f,t}) + \gamma_{p,t}^{J,K}(SMB) + \delta_{p,t}^{J,K}(HML) + \epsilon_{p,t}^{J,K} \tag{4.9}$$

To create the SMB and HML factors, the first thing we did was creating a “small” portfolio and a “big” portfolio. These portfolios were created by ranking all stocks based on market capitalization, and then sorting the 30 percent smallest into the “small” portfolio and the 30 percent biggest into the “big” portfolio. After this, each stock within the portfolios was ranked into three categories based on their market-to-book values: low, medium and high. In the end we had six portfolios: big-low (BL), big-medium (BM), big-high (BH), small-

[5]SMB: Small Minus Big HML: High Minus Low

low (SL), small-medium (SM) and small-high (SH). Fama and French (1992) rebalance their portfolios every June. Also, they calculate value-weighted returns. In this thesis, the portfolios are rebalanced each month and each stock is equally weighted in the portfolio. We chose this method in order for it to be more in line with our calculations of the momentum returns.

The SMB factor was calculated by subtracting the average return of the big-portfolios from the average return of the small-portfolios. Then the HML factor was found by subtracting the average return of the low-portfolios from the average return of the high-portfolios.

$$\text{SMB} = 1/3 * (\text{SL} + \text{SM} + \text{SH}) - 1/3 * (\text{BL} + \text{BM} + \text{BH})$$

$$\text{HML} = 1/2 * (\text{SH} + \text{BH}) - 1/2 * (\text{SL} + \text{BL})$$

The regression methodology is done similarly as the previous section. The regression output can be seen in Figure 4.9 and 4.10.

First, we want to check whether the model is at all useful for our research. Hence, we look briefly at the F-test output from R. The F test is reported with Newey West standard errors and tests the following;

$$H_O : \beta = 0,\ \gamma = 0,\ \delta = 0$$
$$H_A : \text{ At least one of the parameters is nonzero}^6.$$

Looking at our data in Figure 4.9 and 4.10, we see that in almost all of our cases, the F-test statistics are all relatively large and exceeding the critical value in every case. Hence, the three-factor model is indeed useful in explaining momentum returns.

R-squared Further, for the three factor model we look at the adjusted R-squared. The adjusted R-squared is a modified version of the R-squared that is adjusted by the number of explanatory variables in the model. Looking at the winner and loser portfolios, the adjusted R-squared ranges from 58.5 to 78.5 and 69.9 and 77.7 percent respectively. On average for both winner and loser, the value is 71.4 percent. In terms of explanatory power, this is a good improvement, as we obtained a average R-squared of 59 percent among the same portfolios with single index. For the zero-cost portfolios, we observe R-

[6] Here, β = the market risk factor, γ = SMB and δ = HML

Figure 4.9: Regression output from the Three-Factor Model

	Winner					Loser				
J, K	Beta	Alpha	SMB	HML	Adj. R^2 / F	Beta	Alpha	SMB	HML	Adj R^2 / F
3,3	1.002***	0.006	0.442***	-0.100**	0.694	-1.438***	0.006	-1.088***	-0.085	0.716
	0.054	0.003	0.067	0.046	162.0***	0.066	0.03	0.092	0.095	179.6***
3,6	1.047***	0.005*	0.440***	-0.058	0.772	-1.391***	0.005*	-1.046***	-0.06	0.747
	0.049	0.003	0.061	0.045	241.4***	0.07	0.003	0.089	0.078	210.5***
3,9	1.028***	0.004	0.399***	-0.048	0.77	-1.394***	0.004	-1.047***	-0.056	0.763
	0.048	0.003	0.069	0.047	238.2***	0.064	0.03	0.084	0.073	230.0***
3, 12	1.022***	0.003	0.368***	-0.039	0.785	-1.389***	0.003	-1.054***	-0.051	0.777
	0.049	0.003	0.071	0.041	259.4***	0.064	0.003	0.078	0.07	248.0***
6,3	0.985***	0.005	0.363***	-0.068	0.691	-1.447***	0.001	-1.206***	0.061	0.704
	0.054	0.003	0.067	0.046	157.5***	0.066	0.004	0.092	0.095	167.3***
6,6	0.976***	0.005**	0.306***	-0.064	0.715	-1.443***	-0.0003	-1.180***	0.042	0.73
	0.049	0.003	0.061	0.045	176.8***	0.07	0.004	0.089	0.078	186.6***
6,9	0.961***	0.005*	0.271***	-0.061	0.725	-1.451***	-0.001	-1.204***	0.043	0.755
	0.048	0.009	0.069	0.047	185.3***	0.064	0.004	0.084	0.073	212.7***
6,12	0.962***	0.003	0.246***	-0.044	0.747	-1.442***	-0.002	-1.197***	-0.03	0.768
	0.049	0.003	0.071	0.041	207.2***	0.064	0.004	0.078	0.07	228.4***
9,3	0.909***	0.007*	0.279***	-0.098**	0.622	-1.505***	0.001	-1.272***	-0.082*	0.699
	0.054	0.03	0.067	0.046	114.3***	0.054	0.003	0.067	0.046	161.0***
9,6	0.916***	0.005-	0.236***	-0.073	0.642	-1.495***	0.0005	-1.291***	-0.068	0.723
	0.049	0.003	0.061	0.045	124.4***	0.049	0.003	0.061	0.045	180.8***
9,9	0.912***	0.004	0.214***	-0.048	0.667	-1.485***	0.001	-1.296***	-0.037	0.735
	0.048	0.003	0.069	0.047	139.4***	0.048	0.003	0.069	0.047)	192.6***
9,12	0.915***	0.002	0.203***	-0.025	0.701	-1.470***	-0.001	-1.264***	-0.022	0.735
	0.049	0.003	0.071	0.041	162.9***	0.049	0.003	0.071	0.041	199.5***
12,3	0.885***	0.006**	0.212***	-0.084*	0.598	-1.538***	0.002	-1.334***	-0.07	0.708
	0.051	0.003	0.067	0.046	102.1***	(0.066	0.004	0.092	0.095	165.5***
12,6	0.909***	0.004	0.191***	-0.042	0.633	-1.531***	0.002	-1.345***	-0.038	0.723
	0.049)	0.003	0.061	0.045	118.2***	0.07	0.004	0.089	0.078	178.1***
12,9	0.912***	0.002	0.166**	-0.013	0.669	-1.513***	-0.0003	-1.310***	-0.005	0.726
	0.048	0.003	0.069	0.047	138.4***	0.064	0.004	0.084	0.073	181.0***
12,12	0.905***	0.001	0.156**	0.012	0.696	-1.488***	-0.001	-1.270***	0.003	0.721
	0.049	0.003	0.071	0.041	156.557***	0.064	0.004	0.078	0.070	176.569***

Figure 4.10: Regression output from the Three-Factor Model

J, K	β	α	Zero-Cost (SMB)	(HML)	Adj. R^2 / F
3,3	-0.446***	0.009*	-0.651***	-0.182	0.206
	0.092	0.006	0.109	0.113	19.4***
3,6	-0.354***	0.007*	-0.611***	-0.114	0.230
	0.099	0.004	0.107	0.09	22.1**
3,9	-0.376***	0.005	-0.652**	-0.1	0.284
	0.086	0.004	0.106	0.085	29.2***
3, 12	-0.377***	0.004	-0.691***	-0.087	0.339
	0.086	0.004	0.102	0.079)	37.3***
6,3	-0.471***	0.009*	-0.848***	-0.127	0.238
	0.092	0.06	0.109	0.113	22.9***
6,6	-0.478***	0.008*	-0.877***	-0.102	0.276
	0.099	0.004	0.107	0.09	27.6***
6,9	-0.499***	0.006	-0.937***	-0.102	0.344
	0.086	0.004	0.106	0.085	36.2***
6,12	-0.489**	0.004	-0.954***	-0.071	0.376
	0.086	0.004	0.102	0.079	43.1***
9,3	-0.607***	0.010*	-0.997***	-0.177	0.271
	0.092	0.006	0.109	(0.113	26.7***
9,6	-0.589***	0.009**	-1.059***	-0.138	0.308
	0.099	0.004	0.107	0.09	31.7***
9,9	-0.584***	0.006	-1.085***	-0.082	0.340
	0.086	0.04	0.106	0.085	36.5***
9,12	-0.565***	0.004	-1.065***	-0.044	0.363
	0.086)	0.004	0.102	0.079	40.3***
12,3	-0.662***	0.011*	-1.126***	-0.151	0.304
	0.136	0.008	0.163	0.121	30.7***
12,6	-0.631***	0.007*	-1.157***	-0.077	0.328
	0.099	0.004	0.145	0.107	34.1***
12,9	-0.611***	0.005	-1.148***	-0.015	0.344
	0.118	0.060	0.129	0.11	36.5***
12,12	-0.592***	0.003	-1.118***	0.018	0.352
	0.086	0.004	0.102	0.079	37.9***

squared values ranging from 20.6 to 37.60 percent. These numbers were between 3.9 and 6 percent for the single index model, and are therefore a good improvement.

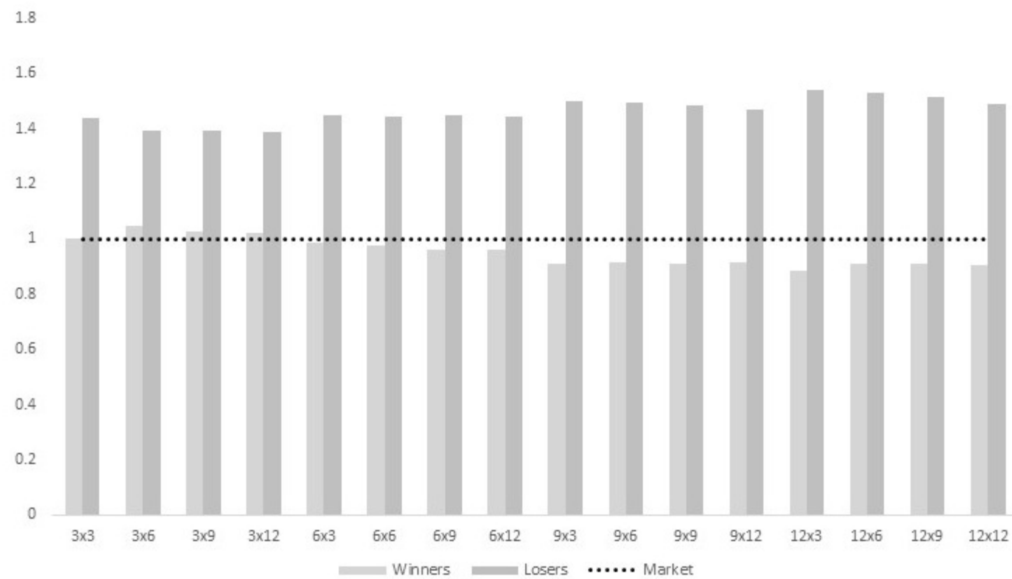

Figure 4.11: Betas Fama French

Beta The market beta of the three-factor model is comparable to that of the single factor model, but not directly comparable, because some of the variation is now explained by two additional factors.

Similarly to the single index model, the winner portfolios on average have market betas that are slightly below 1, indicating a lower systematic risk than the market. The average market beta for the winner portfolios is 0.95 and they are all statistically significant at a once-percent level. As the market beta was 0.87 on average for the single index winner portfolios, we see that it has increased. A parameter coefficient will change if at least one of the new variables are correlated with variables that are already in the model, or if one of the new variables are correlated with the dependent variable (Absalonsen and Vas (2014)). As seen in 4.17, the market factor (OSEAX) is negatively correlated with the SMB, which is why the winner portfolio beta has increased.

For the loser portfolios the average beta is now -1.46, indicating higher systematic risk than the market. This is slightly higher than it was for the single index model. Similarly to the single index model, we can see a tendency for the loser portfolios with longer holding periods to have lower betas.

Like the winner and loser portfolios, all of the zero cost portfolios have betas that are significant at 1 percent. The zero cost betas range from -0.35 to -0.66 with an average of -0.52, which is higher than estimated by the single index model. Also here, the zero costs market beta is negative, which can be attributed to the loser portfolios.

SMB Among the winner portfolios, the size factor is positive and significant at a one percent level in 14 cases and positive and significant at five percent in two. The average size factor is 0.28. This means that on average, the winner portfolio will yield a 0.28 percent return, for every one percent return than small-cap stocks outperform large-cap stocks.

Looking at the loser portfolios, the size factor is negative and significant at 1 percent for all 16 strategies. The values range from -1.088 to -1.345 with an average of -1.212. This means that, all else equal, when SMB increases 1 percent, the loser portfolio on average decreases 1.212 percent. The values are negative because of the short sale of the loser portfolio. In absolute value, the SMB coefficients for the loser portfolios are all larger than 1. This implies that the loser portfolios in general are heavily loaded with small-cap stocks. This implies that much of the momentum return among the loser portfolios can be attributed to the size premium. This is in line with what was found Absalonsen and Vas (2014) for the Norwegian Stock market. This was also documented by Rouwenhorst (1998) who found that momentum returns was present among small and large firms, but stronger for small firms.

The zero cost portfolios have negative size factors ranging from -0.651 to -1.13 with an average of -0.94. This is in large part driven by the relative impact of the loser portfolios. All the portfolios have significant size factors at one percent significance level, except the 3 x 9 where it is significant at five percent. Our findings indicate that some return is attributable to the size premium from small stocks.

HML Among the winner portfolios, the HML factor is negative and lies between -0.1 and 0.012. However, only three portfolios have significant HML-factors. A negative value suggests that the portfolio is dominated by growth stocks.

In the loser portfolios we see both positive and negative HML-values. However, only one of these are significantly different from zero, and it therefore seems that the value-factor does not explain much of the variation in the loser portfolio.

None of the HML-coefficients of the zero-cost portfolios are significant, which was also found by Brodin and Abusdal (2008) in their study of the Norwegian stock market. We therefore conclude that not much of the momentum-profits can be explained by the value-factor.

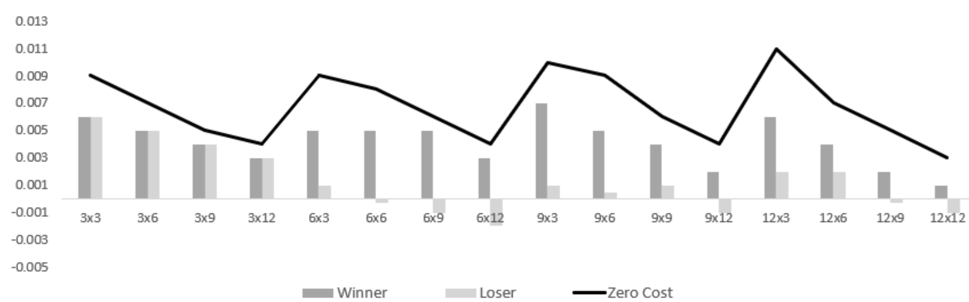

Figure 4.12: Alpha

Alpha The alpha values for the winner and loser portfolios are lower than for the CAPM. This means that some of the abnormal momentum profits found in the single index model can be attributed to risk.

The alpha values among the winner portfolios are all positive with an average value of 0.004. Five out out 16 alphas are significant, where the 6 x 6 and the 12 x 3 are significant at five percent. The loser alphas are positive and negative with an average value of 0.00124. Only the alpha for the 3 x 6 strategy shows sign of significance, though only at 10 percent.

Among the zero-cost portfolios, only 8 out 16 alphas are significantly different from zero, all positive and with an average value of 0.00668. In line with our base study showing the 12 x 3 strategy yielding the highest return, this is the strategy with the highest alpha. Similar to the single-index model, the alpha is highest for portfolios with 3 months holding. The alpha is significant only at ten percent in five of the portfolios and significant at five percent in one case.

In the single index model we saw that the alpha term was significant at one percent in all 16 zero cost portfolios. As only half of the alphas are significant in the three-factor model, and none at more than five percent, it seems that much of the momentum returns can indeed attributed to risk. More specifically, it is likely to assume that the size factor explains much of the momentum return in our model.

Overall, the three-factor model is able to capture much of the momentum profits. Looking at the estimated coefficients, it seems that much of the abnormal return can be explained by the size-effect and market exposure. However, as we still have significant alphas, it seems that our momentum strategy generates abnormal returns that cannot be completely attributed to the movement of the overall stock market, the size factor or the value factor. Thus, we are still not able to fully explain the returns generated. This is in line with what was found by Fama and French (1996), where they admit that the model was not able to explain return continuation documented by Jegadeesh and Titman (1993).

4.2.4 Carhart Four-Factor Model

We will proceed with the Carhart four-factor model. We introduced the Carhart four-factor model as an extension of the three-factor model, where the additional factor is meant to capture the persistence of stock price movements. In the previous sections we saw that the alpha was still present and in some cases significant after controlling for market risk, size factor and value factor. We still have no grounds for saying that the momentum effect alone is the cause of momentum returns. There could potentially be other factors that have an impact. In this section we will control for this, by adding momentum as an independent variable in our model. If it is the momentum effect that has caused the abnormal portfolio returns, then by adding this factor, the abnormal return should diminish.

$$r_{pt}^{J,K} - r_f = \alpha_{p,t}^{J,K} + \beta^{J,K}(r_{mt} - r_f) + \gamma_{p,t}^{J,K}(SMB) + \delta_{p,t}^{J,K}(HML) + \rho_{p,t}^{J,K}(PR1YR) + \epsilon_{p,t}^{J,K} \quad (4.10)$$

Where the additional factor PR1YR captures the momentum effect. Following the method of Carhart (1997), the "PR1YR" is calculated as the return of a 12 x 1 zero-cost strategy. We have used our standard, overlapping momentum method to calculate this factor.

Figure 4.13: Regression output from the Four-Factor Model

	Winner						Loser					
J, K	Alpha	Beta	SMB	HML	PR1YR	Adj. R^2 / F	Alpha	Beta	SMB	HML	PR1YR	Adj R^2 / F
3,3	0.004	1.121***	0.619***	-0.052	0.220***	0.72	-0.004	-1.132***	-0.704***	0.039	0.559***	0.82
	0.003	0.052	0.068	0.05	0.052	132.3***	0.003	0.076	0.107	0.064	0.065	233.0***
3,6	0.003	1.142***	0.583***	-0.02	0.179***	0.789	-0.005*	-1.115**	-0.708***	0.049	0.5***	0.839
	0.003	0.052	0.064	0.043	0.045	194.5***	0.003	0.068	0.082	0.053	0.054	267.7**
3,9	0.002	1.125***	0.545***	-0.007	0.187***	0.788	-0.006**	-1.114**	-0.704***	0.053	0.505***	0.589
	0.003	0.051	0.069	0.045	0.046	191.0***	0.003	0.066	0.077	0.048	0.058	312.6***
3, 12	0.002	1.108***	0.498***	-0.002	0.166***	0.799	-0.006***	-1.125***	-0.734***	0.052	0.475***	0.864
	0.002	0.053	0.072	0.0037	0.047	203.8***	0.003	0.069	0.077	0.048	0.058	325.6***
6,3	0.002	1.146***	0.582***	-0.011	0.302***	0.745	-0.005*	-1.089***	-0.750**	0.068	0.634***	0.828
	0.003	0.053	0.068	0.05	0.052	149.6***	0.003	0.076	0.107	0.064	0.065	246.1***
6,6	0.003	1.128***	0.516***	-0.008	0.289***	0.765	-0.007**	-1.086***	-0.726***	0.088*	0.632***	0.856
	0.003	0.052	0.064	0.043	0.045	167.4***	0.003	0.068	0.082	0.053	0.054	303.4***
6,9	0.002	1.105***	0.469***	-0.009	0.273***	0.771	-0.007***	-1.114***	-0.777***	0.079*	0.569***	0.856
	0.002	0.051	0.069	0.045	0.046	172.2***	0.003	0.066	0.077	0.048	0.058	340.0**
6,12	0.001	1.079***	0.408***	-0.001	0.223***	0.776	-0.008***	-1.131***	-0.805***	0.083*	0.546***	0.866
	0.001	0.053	0.072	0.037	0.047	177.3***	0.002	0.069	0.077	0.048	0.058	332.02***
9,3	0.003	1.132***	0.583***	-0.016	0.410***	0.733	-0.007**	-1.091***	-0.726****	0.068	0.759***	0.865
	0.002	0.053	0.068	0.05	0.052	140.8***	0.003	0.0173	0.107	0.064	0.065	328.6**
9,6	0.002	1.123***	0.517***	0.003	0.380***	0.737	0.006**	-1.121***	-0.8***	0.67	0.683***	0.863
	0.003	0.052	0.064	0.043	0.045	143.6***	0.003	0.068	0.082	0.053	0.054	323.1***
9,9	0.001	1.085***	0.451***	0.015	0.319***	0.736	-0.007***	-1.136***	-0.836***	0.090*	0.639***	0.862
	0.003	0.051	0.069	0.045	0.046	143.2***	0.003	0.066	0.077	0.048	0.058	319.5***
9,12	0.000	1.051***	0.39***	0.025	0.251***	0.744	-0.007***	-1.148**	-0.841***	0.094**	0.588***	0.853
	0.002	0.053	0.053	0.037	0.047	149.2***	0.002	0.069	0.0777	0.048	0.058	295.905***
12,3	0.002	1.123***	0.527***	0.002	0.436***	0.728	-0.006*	-1.125**	-0.789***	0.09	0.754***	0.869
	0.003	0.53	0.068	0.05	0.052	137.2***	0.003	0.076	0.107	0.064	0.065	340.5***
12,6	0.0004	1.107***	0.452***	0.03	0.362***	0.721	-0.007**	-1.155***	-0.848***	0.098*	0.688***	0.861
	0.003	0.052	0.064	0.043	0.045	133.0***	0.003	0.068	0.082	0.053	0.054	317.3***
12,9	-0.001	1.072***	0.377***	0.045	0.292***	0.728	-0.007***	-1.166***	-0.851***	0.121**	0.635***	0.848
	0.003	0.051	0.069	0.045	0.046	137.7***	0.003	0.066	0.077	0.048	0.058	285.2***
12,12	-0.001	1.03***	0.322***	0.058	0.299***	0.734	-0.007***	-1.162***	-0.840***	0.121**	0.596***	0.831
	0.002	0.053	0.072	0.037	0.047	141.738***	0.002	0.069	0.077	0.048	0.058	252.236***

Figure 4.14: Regression output from the Four-Factor Model

			Zero-cost			
J, K	Alpha	Beta	SMB	HML	PR1YR	Adj. R^2 / F
3,3	0.003	-0.02	-0.088	-0.01	0.78***	0.606
	0.003	0.063	0.096	0.069	0.066	79.4***
3,6	0.001	0.018	-0.128*	0.032	0.681***	0.701
	0.001	0.071	0.067	0.048	0.036	120.7***
3,9	-0.001	0.002	-0.162***	0.049	0.692***	0.828
	0.001	0.038	0.046	0.031	0.028	246.1***
3, 12	-0.002*	-0.026	-0.238***	0.052	0.642***	0.863
	0.001	0.045	0.043	0.032	0.026	322.8***
6,3	-0.0004	0.048	-0.171**	0.06	0.937***	0.747
	0.003	0.052	0.077	0.046	0.046	151.4***
6,6	-0.002	0.033	-0.212***	0.083**	0.922***	0.824
	0.002	0.041	0.061	0.036	0.037	240.5***
6,9	-0.003	-0.018	-0.311***	0.073**	0.869***	0.86
	0.002	0.035	0.052	0.031	0.032	313.3***
6,12	-0.004**	-0.061*	-0.400***	0.084***	0.771***	0.84
	0.002	0.036	0.053	0.031	0.032	268.5***
9,3	-0.001	0.033	-0.145	0.055	1.170***	0.872
	0.003	0.063	0.096	0.069	0.066	349.4***
9,6	-0.002	-0.007	-0.286**	0.073	1.065***	0.856
	0.002	0.071	0.067	0.047	0.036	304.9***
9,9	-0.004***	-0.06	0.388***	0.108***	0.959***	0.831
	0.001	0.038	0.046	0.031	0.028	254.9***
9,12	-0.005***	-0.105**	0.454***	0.122***	0.84***	0.789
	0.001	0.045	0.043	0.032	0.026	191.6***
12,3	-0.011	-0.011	-0.265***	0.084	1.191***	0.888
	0.003	0.063	0.096	0.069	0.066	403.6***
12,6	-0.004*	-0.057	-0.398***	0.131***	1.051***	0.834
	0.002	0.071	0.068	0.047	0.036	257.6***
12,9	-0.005***	-0.103***	-0.477***	0.169***	0.928***	0.784
	0.001	0.038	0.046	0.031	0.028	181.4***
12,12	- 0.005***	-0.141***	-0.521**	0.181***	0.826***	0.728
	0.001	0.045	0.043	0.032	0.026	137.649***

R-squared When we include the momentum factor, the adjusted R-squared for the zero cost portfolios range from 0.60 to 0.88 with an average of 0.80. This is a huge improvement, as the average adjusted R-squared for three-factor model was only 0.30 on average for the zero cost portfolio. Looking at this indicator, it seems as if the four-factor model is able to explain more of the returns. This seems to be driven in large part of the loser portfolios that have an average adjusted R-squared of 0.84.

Beta The market beta is above 1 for all of the 32 winner and loser portfolios. The winner portfolios have an average beta of 1.11, while the average beta is -1.13 for the loser portfolios. Looking at the zero cost portfolios, the market factor is only significant in 4 out of 16 cases. However, all 4 significant betas are negative because of the relatively bigger impact from the loser portfolios. What is interesting, is that the market factor seems to have very little impact in this model.

SMB In all winner and loser portfolios, the size-factor is significant at the one-percent level. For the winner portfolio, the average SMB-coefficient is 0.48, while the average SMB-coefficient is -0.78 for the loser portfolio. As we also found in the three factor model, this suggests that the loser portfolio has a relatively higher loading on small-cap stocks than the winner portfolios. For the zero-cost portfolios, 14 out of 16 strategies have significant SMB-coefficients.

HML None of the HML-coefficients are significant for the winner portfolios. However, 8 out of 16 loser portfolios has significant HML-coefficients. These are also significant in the zero-cost portfolio, however the significance has increased. The values are all positive, but quite small, suggesting that the zero-cost portfolio has a very slight loading towards value-stocks.

PR1YR The average coefficient to the momentum factor for the winner portfolios is 0.29 while it is 0.69 for the loser portfolios. This implies that the momentum effect is somewhat stronger for loser stocks than winner stocks. The momentum factor is significant at one percent in all 48 winner, loser and zero-cost portfolios, indicating that this has a large explanatory value. In all cases, the momentum coefficient is positive. In other words, the risk affecting the momentum-factor also affects the return of our momentum portfolios.

Alpha For the winner portfolios, none of the alphas are significant. This means that the four-factor model manages to explain the return of the winner portfolios. However, our loser portfolios have 15 significant alphas. 7 of these are significant at a one-percent level, 5 of these are significant at a five-percent level, and 3 are significant at a ten-percent level. What is interesting, is that these are all negative. That suggests, that according to the Carhart-model, our loser portfolios are actually performing worse than they should. They are generating negative abnormal returns.

When looking at the zero-cost portfolios however, we see that only 7 of the alphas are significant. 4 of them are significant at a one-percent level, 1 at a five-percent level and 2 at a ten-percent level. Also in these portfolios, the alphas are negative, and the momentum strategies yield less return than deemed fair by the Carhart-model.

Overall, the Carhart-model does well in explaining momentum profit for 9 of the portfolios. Taking into account the high R-squared, the model has greater explanatory power than the Fama-French model. However, because some of the alphas as significantly different from zero, it seems that we are not able to fully explain the returns from buying winners and selling loser in our model.

4.3 Behavioral Explanations

As momentum cannot be fully explained solely by risk, many have tried to explain it with investor behavior. As we know, momentum is a serial correlation between historical prices and future prices. The consensus in the behavioral literature is that momentum is mainly caused by either underreaction, overreaction or a combination of the two. If the serial correlation is due to underreaction, one can expect to achieve a positive return in the holding period followed by a normalization after. If the serial correlation is due to slow overreaction, then the positive return in the holding period will be followed by a mean regression, giving a negative return.

Overreaction

Overreaction was first used to explain long-term return reversal, as documented by DeBondt and Thaler (1985). They found that stocks that had done poorly in the past would tend to outperform stocks that had performed well in the past. Using a similar method to Jegadeesh and Titman (1993), but with three-five year formation periods, they found that loser portfolios consistently outperform winner portfolios. They explain this phenomena with an overreaction to news, stemming from the representativeness heuristic. The representativeness heuristics refers to the tendency to evaluate the probability that A was generated by B by the degree to which A reflects the essential characteristics of B (Barberis and Thaler, 2003). In the stock markets, investors who are subject to the representativeness bias base their prediction of future returns on past performance, thinking that past performance is representative of the general performance of the stock. This leads to winner stocks being overvalued, while loser stocks become undervalued, leading to a regression towards the mean as this overvaluation or undervaluation becomes apparent.

Daniel, Hirshleifer, and Subrahmanya (1998) also claim that the momentum effect can be explained by an overreaction as a result of investors' irrational behavior. Specifically, they attribute this overreaction to overconfidence. Daniel et al. (1998) define an overconfident investor as one who overestimates the precision of his private information signal, but not of information signals publicly received by all.

Analysts and investors generate information for trading, through means such as verifying rumors and analyzing financial statements, which can be executed with varying degrees of skill. If an investor overestimates his ability to generate this information or to identify the significance of existing data that others neglect, then he will underestimate his forecasting errors. On the other hand, if he is overconfident about signals or assessments with which he has greater personal involvement, then he will tend to be overconfident about the information he has generated but not about public signals. When the investor receives confirming public information, this raises his confidence, whereas disconfirming information only lowers his confident modestly. This is in line with the attribution theory of Bem (1965) which describes how people too strongly approve events that confirm their believes and thus views events that do not as noise or sabotage. This continuing overreaction causes momentum which is eventually reversed as further public information gradually draws the price back towards its fundamental value.

As mentioned earlier, Friedman (1953) stated that rational speculators must stabilize asset prices. This was later identified to not be necessarily true, as arbitrageurs face the risk of noise traders. De Long et al. (1990) argue that rational speculators who should stabilize prices, can in fact have a destabilizing effect, and thereby cause overreaction and thus momentum. The way this happens is that when rational speculators receive good news, they know that the fundamental value of a stock will increase. They also know that what they call positive feedback traders will buy the stock tomorrow because of the good news. In anticipating this, they buy more of the stock and drive the price higher than would correspond to a new fundamental value incorporating the news. Tomorrow, positive feedback traders buy in response to the positive news and even as the rational speculators are now selling out, the price remains above its fundamental value. This is similar to the findings of Jegadeesh and Titman (1993) who claim that traders that buy past winners and sell losers cause prices to overreact.

Underreaction

In their 1993 paper about the momentum effect, Jegadeesh and Titman comment that the "evidence is consistent with delayed price reactions to firm-specific information"[7]. Other studies support this theory. Barberis, Shleifer, and Vishny (1998) also find an initial underreaction to news, which is followed by an overreaction to a series of news. This im-

[7]Jegadeesh and Titman, 1993, p. 67

plies that current good news has power in predicting positive returns in the future. They attribute this phenomena to the representativeness heuristic and conservatism. Conservatism relates to the slow updating of models in the face of new evidence, meaning that they update their posteriors in the right direction, but by too little relative to the rational benchmark. Conservatism can also be interpreted as being overconfident about prior information. Individuals who are subject to conservatism might disregard the full information content of news, and still cling to their prior views, thus updating their valuation of the stock only partially. This leads to underreaction, and subsequent abnormal returns. After a series of good news, the investors start to characterize the company as a "good" company, thus forecasting higher returns in the future, causing an overreaction. This is due to the representativeness heuristic.

On the other hand, in the paper of Hong and Stein (1999), their goal is to explain momentum returns based on the interaction between heterogeneous investors, rather than psychological biases. A key element of the paper is information diffusion. Hong and Stein goes on with saying that their model unifies over- and underreaction. Gradually diffusing news among one group of traders cause underreaction, which in turn create excessive momentum trading in the other group of traders, resulting in overreaction.

Their model features a population of investors that are of two different types: "newswatchers" and "momentum traders". In the model, the agents are said not to be fully rational, as each agent is only able to process a subset of publicly available data. The newswatchers only make predictions based on information that they observe about future price developments, e.g. predicted earnings that affect the fundamental value. Their limitation is that they do not base decision on current or past price developments, as opposed to momentum traders, who chase price trends and do not process other information. Another important assumption is that information spreads gradually across the newswatcher-population. Hong and Stein (1999) further explain that momentum strategies earn the bulk of profits early in the momentum cycle. That is, at time t there is positive news about a stock. At this time, newswatchers cause the prices to jump, but because of gradual diffusion it does not increase fast enough to reach its fundamental value at time *t*. At time *t+1*, momentum traders observe the price increase and buy the stock. This creates a new round of momentum trading that will further increase the price above the long-run equilibrium. This is what they call a negative externality of momentum trading, as it is impossible to know whether a price increase is due to news about a stock or previous rounds of momentum trading.

The implication of this is that agents behave in a way that creates an inefficient market outcome, in spite of every investor acting as rationally as possible. Slow diffusion of private information will generate the momentum effect. The initial momentum trader will create price increases that other traders will misinterpret as good news. At some point the excessive trading will cause the price to be higher than what corresponds to fundamental value after the initial news, thus creating a sustaining market anomaly.

In a later study, Hong et al. (2000) argue that if momentum comes from slow information flow, then there should be more momentum in small stocks. According to them, the reason why this occurs it that small firms have much lower coverage among analysts. They also find that among the firms that have low analyst coverage, the momentum profits are driven primarily of past losers continuing to lose. This occurs because small firms sitting on good news will push the good news out the door, while bad news will be swept under the carpet (Barberis and Thaler, 2003).

Another explanation for momentum, can be what Shefrin and Statman (1985) label as the "disposition effect". They define this as the tendency to hold on to losing stocks too long and sell winning stocks too soon. The model of Grinblatt and Han (2005) describe how the tendency of some investors to hold on to their losing stocks creates a spread between a stock's fundamental value and its equilibrium price, as well as a price underreaction to information. The basis of the disposition effect is the "Prospect theory" of Kahneman and Tversky (1979) together with the "mental accounting" of Thaler (1980). As mentioned, prospect theory documents risk aversion for gains and risk seeking for losses. Mental accounting provides a foundation for the way that investors set reference points for the accounts that determine gains and losses. The main idea of mental accounting is that decision makers tend to separate different gambles into separate accounts, and then apply prospect theory to each account by ignoring possible interactions[8]. Grinblatt and Han (2005) apply the combination of prospect theory and mental accounting to individual stocks. They claim that investors are risk averse over gambles for some stocks and locally risk seekers over gambles for others. For example, after receiving positive returns on a stock, the investors might view their investment as funded by a "capital gains account" and thus be more tolerant of risk, discount future cash flows at a too low rate, thereby

[8]Grinblatt and Han 2005, p.1

pushing up prices further. The distinction between risk attitudes towards these two classes of stocks is driven entirely by whether the stock has gone up in value or down in value since purchase.

Belief-based explanations with institutional friction

Some models explain momentum with a combination of investor irrationality and institutional frictions. One type of friction is transaction costs related to short-sale. Miller (1977) notes that when investors differ in beliefs about a stock, those who are optimistic about the stock will take long positions. However, those who are pessimistic about the stock will be be faced with either transaction costs or short sale restrictions, and might therefore choose to do nothing. This means that the actions of optimistic investors will dominate the value of the stock, thus driving it higher than if the pessimistic investors were more involved. Scheinkman and Xiong (2003) states that without short-sale, agents can only take advantage of optimistic beliefs by buying the stock at a price which exceeds their own valuation of future dividends, in hope that they will be able to sell it to another, more optimistic investor at a later time. Hong and Stein (2003) find that short-sale constraints and difference in opinion can lead to skewness. They explain that pessimistic investors who are not able to short-sell enter the market only when the price goes down. That means that more information is reflected in the price when it is low, and less when it is high, leading to higher volatility after a downturn and thus a skewed distribution.

Chapter 5

Discussion

In Chapter 3, we found that there has existed momentum on Oslo Stock exchange in the period of January 2000 to February 2008. We will now take a closer look at our results, and discuss the different explanations for this, as outlined in Section 4.2 and 4.3. As stated by Jegadeesh and Titman (2001), if risk is the explanation for momentum return, then momentum strategies will continue to be profitable after the end of the holding period. This is because the return is simply a consequence of the risk of the portfolios, thus the profits should not disappear in the future. If momentum returns are a result of an initial underreaction, then predictability will cease as relevant information is incorporated into the stock prices, and momentum return will be zero. However, if momentum is a result of overreaction, then our post-holding momentum return should be negative due to prices reversing back towards the mean.

Using the method of Jegadeesh and Titman (1993), we found that momentum profits are obtainable with all 16 strategies, with positive returns significant at a one-percent level. Similarly to Jegadeesh and Titman (1993) and Absalonsen and Vas (2014), we found that the 12 x 3 strategy was the most profitable, with a return of 3.13 percent. Absalonsen and Vas (2014) found that the return on this strategy was 2.43 percent for the period 2005-2013.

The 6 x 6 strategy was used in our robustness tests, and had an overall return of 2.37. To check if our method affected our findings, we performed tests in which we increased the portfolio size and excluded extreme observations. We saw that increasing the portfolio size from 20 percent to 30 percent, slightly lowered the momentum profits, from 2.37 to 2.10 percent. However, the momentum effect was still present. We believe that the reduction in return can be due to lower impact of extreme returns, as well as a more diversified portfolio. To test if extreme returns can affect momentum profits, we excluded the 5 percent best and worst performing stocks. We found that this lowered the momentum return even more, with the 6 x 6 strategy now yielding 2.01 percent. However, because our portfolios still have significant returns, extreme returns are not the main driver of the momentum profits.

We found in our base study that the momentum profits on the Norwegian market are mainly generated by the short position in the loser portfolios. This is in line with Absalonsen and Vas (2014) and Weiß (2017), but contradictory to the findings of Jegadeesh and Titman (1993), Rouwenhorst (1998) and Solheim and Jensen (2011). Unlike our study, they found that momentum profits were mainly generated by the winner portfolios. When we investigated the Norwegian market before and after the financial crisis, we found that momentum profits were indeed driven by return continuation in winner stocks before the financial crisis. The impact of loser stocks was much more pronounced after the crisis. The reason for this is unsure, but one explanation can be that investors fled from risky assets after the crisis and instead placed their investments in less volatile stocks.

We proceeded to test if the momentum effect is more pronounced for different types of stocks. We found that between small, medium and big stocks, momentum profits do not vary much. This is in line with Rouwenhorst (1998), but in contrast to the predictions of Fama and French (1992). It seems that less liquid stocks generate slightly higher returns than liquid stocks, which was also found by Daniel et al. (1998). When testing whether book-to-market value has an impact on momentum profits, we found that the sub-group with medium B/M-ratio had the highest returns. According to Fama and French (1992), value-stocks should have higher returns because they are more risky, but in our study, these returns were actually the smallest. We found the value-effect to be present for the winner-portfolios, but suspect that some of this can be due to a survivorship bias. However, it would be interesting to see if the value-effect was more pronounced for the overall momentum profits before the financial crisis, as momentum returns were more driven by winner stocks for this period.

In order to test whether momentum profits are feasible when transaction cost are considered, we conducted a test where transaction cost estimates were subtracted from the momentum returns. We found that momentum strategies were indeed still profitable. However, since the transaction cost will vary among different investors, it is difficult to generalize this result. A momentum strategy is very transaction intensive, especially with overlapping holding periods. As the Norwegian stock market is relatively small, the stocks might have bigger spreads than is the case in a larger, more liquid market. This will affect the profitability of our momentum strategies. However, we believe that the estimates we use for the bid-ask-spreads account for this. When taking into account that the non-overlapping method also yielded significant momentum profits, it is possible that momentum trading can be profitable in practice. However, we have ignored the concept of short-sale restrictions. As only a handful of stocks[1] on the Norwegian stock exchange are available for short sale, this must be taken into account before drawing conclusions.

According to traditional finance, any investor who achieves return must incur risk. Academics throughout the years have claimed that risk-based models such as the CAPM can explain portfolio and asset returns. We therefore proceed our analysis with the Single Index model, Fama French Three-factor model and the Carhart Four-factor model, to try to explain the observed continuation of asset prices on the Oslo Stock Exchange.

The single-index model revealed that the market factor has a large explanatory value on our returns. We also saw that the loser portfolios are somewhat riskier than the winner portfolios, with a consistently larger beta. This can explain why our loser portfolios yield relatively higher returns, as found in our base study and the robustness tests. Given that the loser portfolio's beta is always larger than the beta of the winner portfolio, it might be that the zero-cost return is achieved because of differences in systematic risk. Also, the winner portfolios were shown to have an average beta that is lower than the overall market on average, which can be why momentum return is less significant for winner stocks. Looking at the betas we also saw that the overall systematic risk seemed to be higher among the portfolios with shorter holding periods. Considering that our momentum returns were higher for shorter holding periods, this can seem like a plausible explanation.

Studying the alphas, we see that the 12 x 3 winner- and loser portfolios had the highest values, with 0.004 and 0.026 respectively. This is also the strategy that in our base study yielded the highest momentum return. All of our 16 zero cost strategies yielded positive and significant alphas, with an average of 2.5 percent. This means that according to

[1] https://www.nordnet.no/mux/page/blankninginl.html

the CAPM, the momentum strategy yielded on average a monthly abnormal return of 2.5 percent which cannot be attributed to market risk. Thus, the CAPM does not fully explain the momentum effect.

In the three-factor model we added two additional factors and found that the size factor, SMB, has a large explanatory value. For the winner-, loser- and zero-cost portfolio the SMB is highly significant, ranging between -0.12 and -0.52 for the zero-cost portfolios. This can indicate that our portfolios have a loading towards small-cap stocks. The size-effect is much stronger for the loser portfolio, as a one percent increase in small-cap stocks on average causes a 1.22 percent decrease in the loser portfolios. For the winner portfolios, this number is 0.28. This means that when small stocks increase in value, the decrease in the loser portfolio will exceed the gains in the winner portfolio. Hence, the zero-cost portfolio will suffer from losses. The HML variable, measuring the value-effect, gave little explanatory power as it was insignificant for all of the strategies. However, all coefficients, except for one, were negative, suggesting that the portfolios are dominated by growth stocks rather than value stocks.

Interpreting the alpha as abnormal and thus unexplained return, we saw that that the three-factor model was able to explain much more than the single-index model. Compared to the average 2.5 percent alpha in the single-index model, the average alpha for the zero cost portfolios was 0.12 percent. Combined with the increased R-squared, it seems that the three-factor model does explain far more of momentum returns than the CAPM. Although we achieved higher R-squared and lower intercepts with the three-factor model than with the CAPM, there were still some unexplained elements of the momentum returns. We therefore proceeded with the four-factor model.

The momentum-factor in the Carhart four-factor model was highly significant for all 48 portfolios. Adding the momentum-factor increased the R-squared from an average of 0.31 in the three-factor model to 0.80 among the zero-cost portfolios. This is a considerable improvement, and suggests that the four-factor model better explains the momentum-return. While the three-factor model had 8 significant alphas for the zero-cost portfolios, the four-factor model only showed 7. However, these were more significant, and also negative. According to the Carhart-model, 7 of our momentum portfolios actually underperformed. As the model succeeded in explaining the return on 9 of our zero-cost portfolios, it seems reasonable to argue that much of momentum profits can be attributed to risk. However, as 7 of the alpha values were still significant, some of the return was left unexplained. We therefore turn to behavioral explanations.

If we start by looking at return continuation in loser portfolios, underreaction as described by Hong et al. (2000) can provide some insight. The authors claim that underreaction can be caused by slow information diffusion, especially for stocks with low analyst coverage. We saw that the return on loser portfolios were relatively stronger for small stocks than for large stocks, which might be a result of slow information diffusion among investors. As Hong et al. (2000) point out, this can be caused by small firms actively trying to slow down the spreading of bad news, while pushing the good news out. We also saw that the relative return of the loser portfolio was larger after the financial crisis. A possible explanation for this might be that investors moved their investments into less volatile assets, so that many of the pre-crisis stocks received less analyst coverage. Also, in uncertain times the incentive to suppress bad news might be stronger.

Another behavioral explanation for return continuation in loser stocks can be the conservatism bias, as highlighted by Barberis et al. (1998). If the investor is conservative in his opinion of a stock, an underreaction means that news will not be adequately incorporated into the stock price. Barberis et al. (1998) claim that investors are particularly predisposed to the conservatism bias when making forecast for stocks with previous bad performance, which can be why our loser portfolios have such high returns. Lastly, the disposition effect, which is the tendency for investors to hold on to losing stocks for too long, can serve as an explanation for momentum return in losing stocks. The phenomena leads to losing stocks being overvalued, which in turn will be exploited by rational investors who will sell the stock, leading to a downward momentum return.

In order to explain return continuation in winner stocks, we will start by looking at the representativeness bias. If a stock has had good performance in the previous period, irrational investors might start to believe that this performance is representative for the stock, thus pushing the price up above its fundamental value, leading to upward momentum. Another explanation is overconfidence, as explained by Daniel et al. (1998). The investor is overconfident about his ability to generate information, thus he underestimates his forecasting errors, pushing the price up. Because of the self-attribution bias, confirming news will lead to even higher overconfidence, thus generating upward momentum.

We have seen that a substantial amount of momentum returns can be explained by applying risk-based factor-models. However, some momentum profits were left unexplained.

This leaves room for behavioral explanations. As we have seen, behaviorists differ in explanations for momentum. As none of the models seem superior to others, it might be that they apply to a varying degree in different situations. For example, investors might behave more conservative during market downturns, causing underreaction, and overly optimistic during market upswings, causing overreaction. It is outside the scope of this thesis to quantify the degree to which behavior affects markets. We do believe however, that some combination of risk-based and behavioral explanations is necessary to fully understand momentum. Where the risk-based models to some degree justify momentum profits, behavioral models can supply us with a greater understanding of dynamics that are at play in asset price formation.

Chapter 6

Conclusion

6.1 Conclusion

The purpose of this thesis is to contribute to the ongoing academic debate between traditional and behavioral finance. By examining whether price momentum has existed in the Norwegian stock market over the last 18 years, we wanted to examine both sides of the debate by exploring the different explanations.

Following the method of Jegadeesh and Titman (1993), we discovered that there has indeed existed momentum in the Norwegian market. Overall, we found that all 16 strategies yielded between 1.95 and 3.39 percent return on average, all significant at a one-percent level. We saw that the best performing strategy was the 12 x 3 strategy, and that in general, a longer formation period generate higher profits.

All though we discovered a momentum effect in both loser and winner portfolios, the loser portfolios had substantially higher and more significant returns. Looking at the strategy with 12 month formation and 3 month holding, the loser portfolio generated a return of 2.29 percent compared to 1.10 percent for the winner portfolio. This was the strategy that yielded highest returns. Contrary to studies like Jegadeesh and Titman (1993), Rouwenhorst (1998) and Solheim and Jensen (2011) we found the loser portfolio to be the biggest contributor to the momentum return in the zero-cost portfolios. However, we saw that the opposite was the case before the financial crisis, suggesting that the market behaves differently post-crisis.

We found the momentum effect to be present regardless of methodology. The momentum effect was robust to non-overlapping holding periods, increasing the portfolio size and excluding extreme observations. Also, by creating subsamples based on size, volume and value, we found that momentum profits did not vary a lot among these. We also saw that our momentum strategies were profitable after correcting for transaction costs.

When looking at risk-based explanations, we found that a substantial amount of momentum returns could be attributed to risk. The CAPM found that the loser portfolios are more exposed to market risk than the winner portfolios. This difference implies that the zero cost profits can be due to differences in systematic risk. However, after adjusting for systematic risk, all of the loser and zero-cost portfolios yield positive and significant abnormal returns. Thus, it seems that the market factor on its own is not able to explain momentum in our model.

When adjusting for size (SMB) and value (HML), we saw that the size factor in particular had a large explanatory value. The size factor is significant for both winner and loser portfolios, but stronger for the loser portfolios. The value-factor, however, did not have substantial explanatory value. The three-factor model yielded only 8 out of 16 significant alpha's among the zero cost portfolios. This means that the momentum profit from 8 of our strategies are in fact attributable to risk.

As we extended the model with the additional momentum factor, the R-squared indicated that the model was able to explain 80 percent on average of the variation in the momentum returns. We saw that the momentum factor was the main driver of momentum profits, with positive and significant coefficients for all of our strategies. With the Carhart-model, only 7 alphas are significant, suggesting that this model succeeds in explaining momentum returns for 9 strategies. However, the remaining alphas indicate that the model is not entirely able to explain momentum.

Further, we reviewed several possible behavioral explanations. Both underreaction and overreaction were suggested as plausible explanations for the momentum effect. However, as non of the proposed explanations appear as superior to the others, we believe that they can apply in different situations.

All though our research is performed on the Norwegian market, it is possible that similar findings could be obtained in other markets. Despite Norway being a small, open economy with particular exposure to certain macroeconomic variables, we believe that risk and investor behavior should be somewhat comparable across markets. Overall, we believe that the best way to understand momentum is as a result of both risk and investor behavior. Hence, one can view risk-based models and behavioral models as complementary.

6.2 Further research

Moskowitz and Grinblatt (1999) study whether industry can explain momentum. Specifically they find that momentum strategies are significantly less profitable when controlling for industry momentum. They claim that buying stocks from well performing industries, while selling stocks from badly performing industries, can generate profits. Including this additional factor in our momentum study could have been very interesting, as the Norwegian economy is highly dominated by the oil industry. This could also provide some more insight into our findings.

We also found in our study that the market behaved differently before and after the financial crisis. We saw that return continuation in winner stocks was much more apparent before the crisis, than after. After the crisis, return continuation in winner stocks is much less apparent. A more thorough investigation of this would have been intriguing, and could possibly provide some more answers to what drives return continuation.

Lastly, if we had extended our holding periods beyond the 12 months, we could have seen how the return of our portfolios evolve post-holding. This would give us a better indication of whether the return was due to risk, overreaction or underreaction.

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Appendix A

Robustness-tests

Table A.1: 1-Month non-overlapping

J		K				
		1	3	6	9	12
1	Winner	-0,00519	0,00096	0,00014	0,00033	0,00016
	t-value	*-1,095*	*0,532*	*0,149*	*0,463*	*0,248*
	Loser	0,00629	0,00373	0,00152	0,00067	0,001034
	t-value	*1,075*	*2,017***	*1,598**	*1,134*	*2,245***
	Zero Cost	0,00109	0,00469	0,00166	0,00100	0,00119
	t-value	*0,257*	*3,435****	*2,042***	*1,594**	*2,148***

Table A.2: Excluding extreme values

J		K			
		3	6	9	12
	Winner	0,00679	0,00554	0,00541	0,00464
	t-value	*1,594**	*1,3163**	*1,3062**	*1,13030*
	Loser	0,01342	0,01191	0,01079	0,00989
3	*t-value*	*2,3349***	*2,1808***	*1,9884***	*1,8502***
	Zero Cost	0,02021	0,01744	0,01620	0,01453
	t-value	*4,9921****	*5,4792****	*5,3192****	*5,0333****
	Winner	0,00701	0,00772	0,00745	0,00601
	t-value	*1,6389**	*1,8316***	*1,7948***	*1,462**
	Loser	0,01535	0,01327	0,01249	0,01114
6	*t-value*	*2,5867****	*2,2673***	*2,1646***	*1,9689***
	Zero Cost	0,02236	0,02099	0,01994	0,01715
	t-value	*5,1364****	*5,0516****	*4,9754****	*4,5649****
	Winner	0,00916	0,00853	0,00692	0,00532
	t-value	*2,1284***	*1,9873***	*1,6468**	*1,288**
	Loser	0,01535	0,01485	0,13581	0,01230
9	*t-value*	*2,4614****	*2,4347****	*2,267***	*2,0951***
	Zero Cost	0,02451	0,02338	0,02050	0,01761
	t-value	*4,7247****	*4,7898****	*4,4315****	*4,084****
	Winner	0,01023	0,00796	0,00627	0,00536
	t-value	*2,3605****	*1,8287***	*1,4676**	*1,2886**
	Loser	0,01536	0,01395	0,01260	0,01155
12	*t-value*	*2,4072****	*2,2233***	*2,0391***	*1,8984***
	Zero Cost	0,02559	0,02191	0,01887	0,01691
	t-value	*4,7544****	*4,302****	*3,8889****	*3,6641****

Table A.3: 30 percent portfolios

J		K			
		3	6	9	12
	Winner	0,00631	0,00499	0,00478	0,00427
	t-value	*1,4462**	*1,16520*	*1,13210*	*1,02340*
	Loser	0,01907	0,01710	0,01574	0,01523
3	*t-value*	*3,1129****	*2,9506****	*2,7398****	*2,6834****
	Zero Cost	0,02532	0,02209	0,02052	0,01951
	t-value	*5,8409****	*6,3442****	*6,1996****	*6,2212****
	Winner	0,00752	0,00756	0,00752	0,00613
	t-value	*1,9249***	*1,9581***	*1,9637***	*1,6091**
	Loser	0,01459	0,01345	0,01314	0,01209
6	*t-value*	*2,6824****	*2,5095****	*2,4778****	*2,3058***
	Zero Cost	0,02211	0,02101	0,02066	0,01822
	t-value	*6,0335****	*6,0531****	*6,1984****	*5,7679****
	Winner	0,00967	0,00917	0,00776	0,00618
	t-value	*2,5312****	*2,3949****	*2,0459***	*1,6407**
	Loser	0,01564	0,01553	0,01441	0,01328
9	*t-value*	*2,7121****	*2,7504****	*2,5998****	*2,4268****
	Zero Cost	0,02531	0,02471	0,02217	0,01946
	t-value	*6,0398****	*6,2178****	*5,8738****	*5,4634****
	Winner	0,01013	0,00815	0,00670	0,00573
	t-value	*2,6352****	*2,1126***	*1,7674***	*1,5287**
	Loser	0,01647	0,01516	0,01372	0,01265
12	*t-value*	*2,8122****	*2,6413****	*2,4139****	*2,2408***
	Zero Cost	0,02660	0,23309	0,02042	0,01839
	t-value	*5,0464****	*5,6058****	*5,1253****	*4,7724****

Appendix B

OLS-assumption

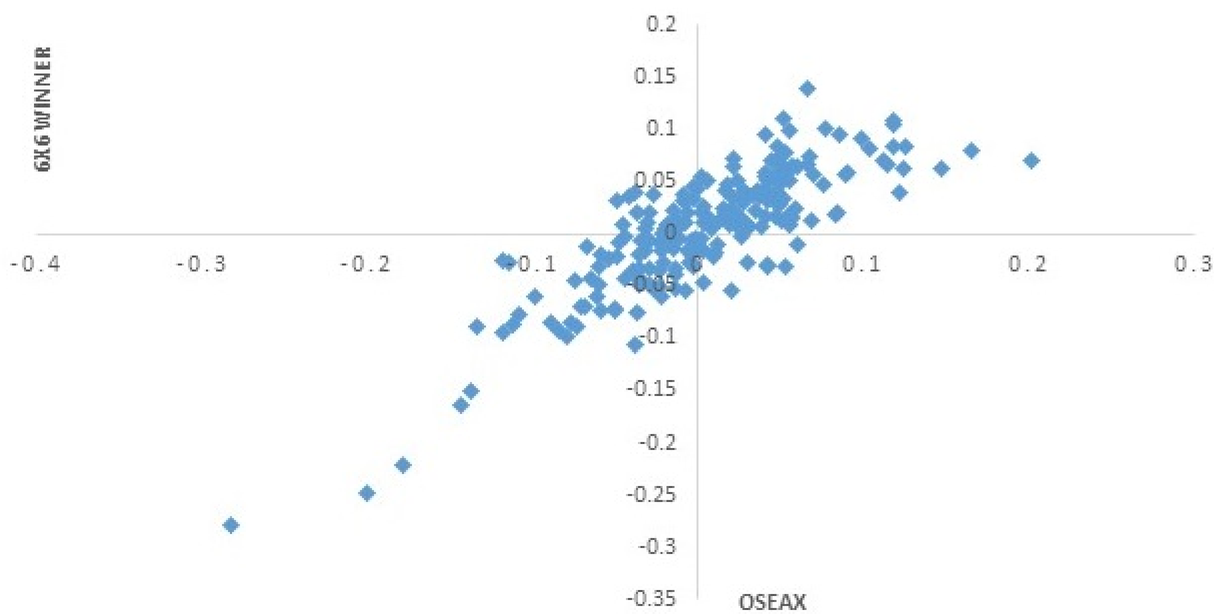

Figure B.1: 6x6 Winner vs OSEAX

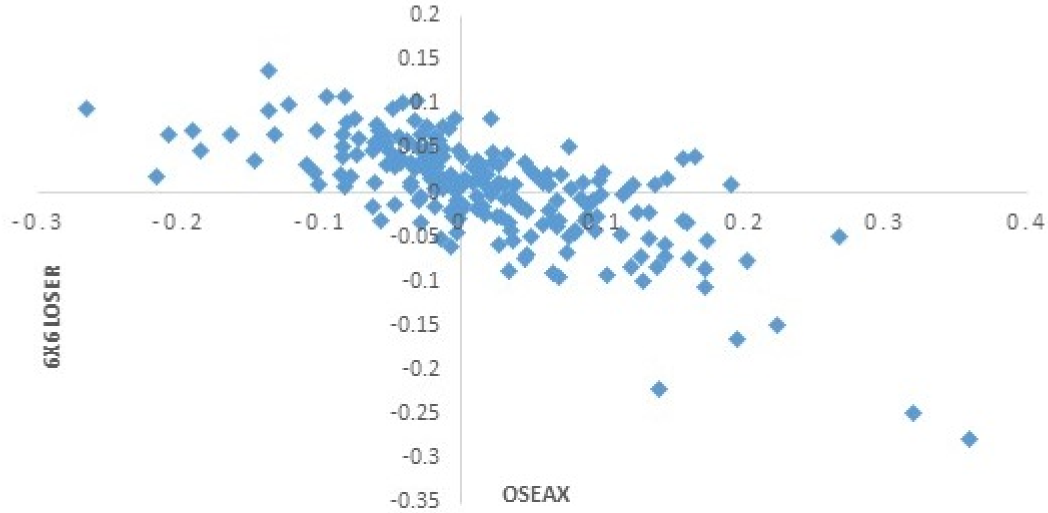

Figure B.2: 6x6 Loser vs OSEAX

Variable	VIF
OSEAX	1.227276
SMB	1.239442
HML	1.010990

Table B.1: Variance inflation factors Fama French

Variable	VIF
OSEAX	1.597464
SMB	1.523694
HML	1.010990
PR1YR	1.446465

Table B.2: Variance inflation factors Carhart

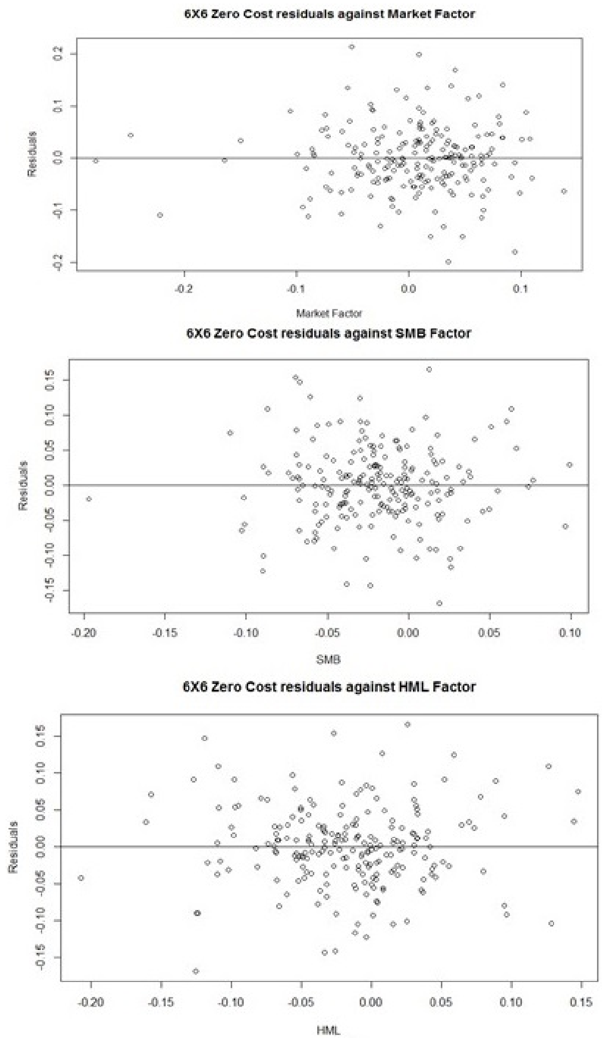

Figure B.3: 6x6 Zero Cost Residuals vs OSEAX, SMB and HML

Appendix C

Risk-based explanations

Table C.1: Breusch-Pagan test

	CAPM		Fama		Carhart	
6 Month form	Test value	p-val	Test value	p-val	Test value	p-val
6x3 Winner	1.2791	0.2581	1.2412	0.7431	0.97715	0.8068
6x3 Loser	2.6729	0.7999	1.618	0.6553	14.755	**0.0052**
6x3 Zero Cost	0.0022	0.9628	0.3372	0.3372	38.632	0.0000
6x6 Winner	2.6729	**0.1021**	3.9425	0.2677	5.3273	0.2553
6x6 Loser	0.1120	0.7379	0.23521	0.9717	5.7481	0.2188
6x6 Zero Cost	0.0714	0.7894	0.65794	0.8831	19.096	**0.0008**
6x9 Winner	2.8906	**0.0891**	5.121	0.1632	3.9147	0.4177
6x9 Loser	0.0663	0.7968	1.9839	0.5758	3.304	0.5083
6x9 Zero Cost	0.0322	0.8575	1.2243	0.7472	12.213	**0.0158**
6x12 Winner	1.47	0.2253	3.5305	0.3168	3.228	0.5204
6x12 Loser	0.0028	0.9581	1.7844	0.6183	3.4279	0.4889
6x12 Zero Cost	0	0.9955	0.29041	0.9618	6.5833	0.1596

Table C.2: Breusch-Godfrey test

	CAPM		Fama		Carhart	
6 Month form	Test value	p-val	Test value	p-val	Test value	p-val
6x3 Winner	5.5283	**0.01871**	5.9864	**0.01442**	1.2879	0.2564
6x3 Loser	0.3627	0.547	1.7773	0.1825	0.09701	0.2816
6X3 Zero Cost	0.081946	0.7747	0.00477	0.9449	0.20019	0.6546
6x6 Winner	8.1701	0.00426	8.6253	0.00332	2.1067	0.1467
6x6 Loser	0.034197	0.8533	0.06985	0.7916	1.1595	0.2816
6x6 Zero Cost	0.88464	0.3469	2.7381	0.09798	3.8086	0.05099
6x9 Winner	7.4353	0.0064	7.8805	**0.005**	0.73554	0.3911
6x9 Loser	0.0047375	0.9451	0.00992	0.9207	0.62578	0.4289
6x9 Zero Cost	2.0071	0.1566	5.6932	**0.01703**	1.156	0.2823
6x12 Winner	3.9507	**0.04685**	4.4505	**0.03489**	0.23577	0.6273
6x12 Loser	0.0022661	0.962	0.00493	0.944	1.415	0.2342
6x12 Zero Cost	1.3777	0.2405	3.6103	0.05742	0.226	0.6345