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# The Profitability of Value and Momentum Strategies on the Nordic Stock Market

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## **Abstract**

In this paper, we examine the profitability of value and momentum strategies on the Nordic stock market for the period January 1989 to June 2016. We find evidence of both a value and momentum premium, reflected by positive average returns of 0,66 and 0,71 percent for the two strategies respectively. After correcting for different risk factors, we find positive alphas for both value and momentum. The existence of positive alphas indicate that the premiums cannot be explained entirely as a risk premium. However, we find a statistically significant alpha for momentum only.

In addition, we examine different combinations of value and momentum to find a combination of the two strategies more successful than each one in isolation. We find no unambiguous evidence that a combination is superior to both strategies in isolation. Lastly, we find evidence suggesting that a weighted combination of value and momentum serves as a good hedge against momentum crashes.

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## Introduction

The main goal for most portfolio managers is to find a profitable investment strategy that yields excess returns. This means exploiting undervalued securities or foreseeing the direction of stock prices. The market efficiency hypothesis, however, states that stock prices already reflect all available information, and thereby indicates that one should not be able to invest in a way that yields returns in excess of the market (Fama, 1970). However, the concept of market efficiency has over the years been challenged by the observation of different anomalies.

One of these anomalies, is value investing. The strategy goes back to the early 1930's and was first introduced by Benjamin Graham and David Dodd (1934). Value investing means going long in stocks that have low prices in relation to their book value (value stocks) and short in stocks that have high prices in comparison to book value (growth stocks). The existence of the value premium is a well-established empirical fact. It has been evident in 87 years of U.S. equity data, and have been proven successful in more than 40 other countries as well as in other asset classes (Asness C. , Frazzini, Israel, & Moskowitz, 2015).

Another anomaly is momentum investing, where the objective is to obtain excess returns by buying stocks with the highest past returns (winners) and shorting stocks with the lowest past returns (losers). The discovery of a momentum effect is commonly credited to Jegadeesh and Titman (1993), who documented such an effect on the U.S. stock market for the period 1965 to 1989.

The main purpose of this paper is to examine the profitability of value and momentum strategies on the Nordic stock market for the period of January 1989 to June 2016. We examine this by focusing on the returns obtained by the zero-cost portfolios. This provides insight and contributes to the ongoing and current debate on efficient markets. Finding evidence of profitable momentum or value strategies could suggest inefficiency in the market.

In this study, we first focus on the value and momentum strategies separately, and thereafter we examine the two strategies combined. The value effect is examined by constructing a value portfolio, following the methodology of Fama and French (1992). We find the zero-cost value portfolio (HML) to obtain average monthly returns of 0,66 %. When we examine the momentum effect, as Jegadeesh and Titman (1993) we construct 16 different strategies. The best performance of 0,71 % monthly average return is obtained by the "MOM3x3" zero-cost

strategy; a portfolio where one selects stocks based on the last 3 months return and then holds this portfolio for 3 months. This is the momentum strategy we examine for the majority of our analysis. Given the time frame of our study, and the fact that our purpose is to find the most successful combination of value and momentum strategy, we find this being a reasonable limitation.

The objective that is continuous throughout studies of value and momentum strategies is examining whether performing active portfolio management; investing in portfolios other than the market portfolio, can obtain excess return. In addition to stating the existence, we test the validity of the results by conducting an empirical analysis of the data. When testing a value strategy, Fama and French (1992) find exclusively positive returns for all ten deciles, as well as for the zero-cost portfolio. Jegadeesh and Titman (1993), examining momentum, find all their momentum strategies, which skip a week between the formation and holding period, having significant t-statistics in addition to yield positive returns. We find both our value and momentum zero cost-portfolios to obtain positive returns. However, we find statistically significant returns for the momentum zero cost-portfolio only.

Asness, Moskowitz, and Pedersen (2013) took a different approach, looking at value and momentum strategies in combination. They challenge the common view that value and momentum strategies cannot be combined, and find consistent and widespread evidence of value and momentum abnormal returns across all markets they study. Asness, Frazzini, Israel, and Moskowitz (2015) suggests that a combined value and momentum strategy is superior to each strategy in isolation. Further, according to Daniel and Moskowitz (2016), one of the major concerns with momentum investment strategies is momentum crashes; periods where momentum strategies experience consecutive periods of negative returns. They find these momentum crashes to be at least partially predictable, and suggest a combination of value and momentum as a natural hedge against them. Motivated by these evidences, a secondary purpose of this study is to find a combination of a momentum and value strategy that performs better than each of them separately.

Further, it is important to emphasize that we choose to focus on two different approaches combining momentum and value. The first approach is testing whether portfolios formed on the cross-section of value and momentum can deliver excess returns. We construct cross-sectional portfolios formed on value and momentum simultaneously. Fama and French (1993) present a method on how to construct 5x5 cross-sectional portfolios formed on size and value.

We find it interesting to test the same approach, however only constructing a 3x3 cross-sectional portfolio formed on value and momentum. The second approach is looking at the two strategies jointly by combining them into a weighted combination portfolio. We choose to combine them in portfolios based on five different weightings: 50/50, 25/75, 75/25, with the weights that maximize Sharpe ratio (Sharpe portfolio) and weights minimizing variance (MinVariance portfolio). The objective is to find a combination of the two strategies more successful than each one in isolation. In addition, we test whether such a combination may serve as a hedge against momentum crashes, as we observe such crashes in our data.

Consistent with the findings of Daniel and Moskowitz (2016), we observe a tendency in these crashes, making them partially predictable. In states of volatility above market average, and when the market starts to rebound after a long-lasting crash (long-lasting bear market), momentum starts crashing. To hedge against these crashes, we propose to invest in a portfolio consisting of a weighted combination of value and momentum. We focus on two different weighted combination portfolios; namely the 50/50 and Sharpe portfolio. Combining value and momentum into weighted portfolios serves as a good hedge, in particular if crashes are timed correctly. Our findings suggest that there is potential for substantial improvements in performance from following a weighted combination strategy rather than always following a pure momentum or pure value strategy. Performance would improve particularly much if one could perfectly time momentum crashes, and switch to a weighted combination during these crashes.

However, other explanations than skill in choosing portfolios might explain abnormal returns. Fama and French (1993) presents a three-factor model, which explain the excess return obtained by investment strategies due to risk exposure to several factors. Excess return as a result of active portfolio management is measured by alpha,  $\alpha$ . Alpha is the average return in excess of a benchmark (Ang, 2014). Correcting for the return that is a result of risk exposure, one can with more certainty state that an investment strategy has been successful. If a positive alpha exists after including the right benchmarks, a statement of successful active management will be more reliable. Even after correcting for compensation for exposure to different risk factors, the returns of our zero-cost portfolios remain positive. However, only the abnormal returns of the momentum (MOM3x3) zero-cost portfolio when correcting for three risk factors, are statistically significant.



We contribute to studies that have already been done on the value and momentum effect, by making the following adjustments. We limit our study to focus on the profitability of value and momentum strategies for the time period 1989 to 2016, and on the Nordic stock market only. We follow the same methodology as Fama and French (1992) and Jegadeesh and Titman (1993), which study the value and momentum effect on the U.S stock market up until 1990 and 1989 respectively. As their studies end when our trial period begins, we contribute by examining whether a value and momentum effect still exists. Further, by choosing a different market, we can compare our results with the mentioned studies, and see if a value and momentum premium exist across markets. Also, our study is expanded from only including one specific market. Asness, Moskowitz, and Pedersen (2013) state that looking at several markets give more reliable result then looking at single markets in isolation. However, we have chosen to briefly look at Norway separately. This is done to assure the quality of our methodology, by comparing our results to those of Ødegaard (2017a).

As the study conducted by Asness, Moskowitz, and Pedersen (2013) our study combines value and momentum. We find few articles and studies looking at this particular combination on the Nordic market in specific, and thereby contribute by examining a combination within this market. It is important to emphasize that to measure the existence of momentum and value premiums on the Nordic stock market we, as Asness, Moskowitz, and Pedersen (2013), choose to apply the simplest and most standard measures. The idea is not to provide strategies that with certainty can be implemented in practice, but to test whether a profitable strategy is possible in theory. We have therefore not taken into account liquidity of the stocks, taxes or transaction costs. Problems related to the implementation of the strategy in practice will be presented and discussed in section four of this paper.

The limitations we make are given the time frame to conduct or study, as well as the limitations resulting from the restricted data available on the chosen market. Further, we find these limitations reasonable given earlier studies conducted on this topic.

This paper is organized as follows. Chapter 1 presents a literary review related to the topics of this paper. Chapter 2 presents the construction of our dataset used to construct our portfolios and asset pricing factors. Chapter 3 presents and discuss the methods used to conduct our analysis. Further, we present the results and discussion of the performance of our portfolios. Chapter 4 takes on a short discussion regarding problems of implementation of our strategies

in practice. Chapter 5 introduces suggestions for further research. The last chapter concludes the results of this study.

# 1. Literature Review

A known phenomenon in finance is the efficiency market hypothesis which states that all available information is “fully reflected” in security prices (Fama, 1970). If the market is efficient, an investor should not be able to outsmart the market or foresee the development of stock prices. Despite that this phenomenon suggest it should be impossible to find a strategy that obtain excess returns, many have tried. The idea is that in order for the information to be reflected in the stock prices, some have to be willing to search for this information. Investors will only have an incentive to spend time and resources searching for this information if such activity could generate higher investment returns (Grossman & Stiglitz, 1980). The discussion on whether markets are efficient or not, has given rise to several investment strategies trying to prove that abnormal returns are possible to obtain, and thereby indicating a violation of market efficiency. Given that our paper is about value and momentum strategies in the Nordics, we want to briefly review the literature on these topics.

## 1.1 Value

The value strategy goes back to the early 1930s, and is often credited to Benjamin Graham and David Dodd (1934). Value investing involves buying stocks with high book value relative to its price (value stocks) and shorting stocks with low book value relative to its price (growth stocks), with the objective of obtaining abnormal returns. Value strategies have a long and storied history in financial markets. Today the existence of the value premium is well established in empirical studies. It has been proven evident in over 87 years of equity data from the U.S., in over 40 other countries and for several other asset classes (Asness C. , Frazzini, Israel, & Moskowitz, 2015).

The value premium is by some explained as compensation for risk (Fama & French, 1998). Some state that value stocks typically represent companies in distress, or that otherwise have volatile earnings and share prices (Chen & Zhang, 1998). Values stocks are therefore riskier than growth stocks, and should be compensated with higher returns. However, this explanation to the value premium has been rejected as being the (entire) explanation. Others have tried to explain the value premium as a result of behavioral finance (Lakonishok, Shleifer, & Vishny, 1994). Investors are said to having a tendency to overestimate their skills in predicting future

cash flows growth stocks. This results in less people selling these stocks, giving those buying value stocks a head start.

## 1.2 Momentum

In 1993, Jegadeesh and Titman published a paper that provided evidence of excess returns on stock purchases resulting from buying stocks with the highest historical returns (winners) and selling stocks with the lowest historical returns (losers). This is known as a momentum strategy. Jegadeesh and Titman (1993) find the most profitable strategy to be a 12x3-strategy. This strategy selects stocks based on the previous 12 months and then holds the portfolio for 3 months. This study was conducted on empirical data for the U.S. stock market between 1965 and 1989. In the years to follow, several studies and articles have been conducted based on the findings of Jegadeesh and Titman (1993). Among these are Rouwenhorst (1998), Fama and French (2012) and Asness, Moskowitz, and Pedersen (2013). All find momentum strategies to be profitable to some extent on the markets they examine.

As with value, according to Asness, Frazzini, Israel, and Moskowitz (2014), the most common explanations for the existence of a momentum premium are explanations based on financial behaviour or compensation for risk. The financial behaviour explanations typically focus on over- and underreaction to information. It is possible that the market expects a mean reverting trend in the short run, making it underreact to new information. This means that stocks prices will not immediately adjust accordingly to their true value, resulting in the stocks being underpriced, creating an opportunity to buy these stocks before the price reflect their actual value (Jegadeesh & Titman 1993). However, Lo and MacKinlay (1990) argue that instead of being an overreaction, the abnormal returns uncovered by Jegadeesh and Titman is due to delayed stock price reaction to common factors.

The other explanation is that the momentum premium is a compensation for risk. There are several theories as to how risk is captured by momentum. Sagi and Seasholes (2007) find risks that affect firm-specific attributes to drive momentum returns. Specifically, firms with high revenue growth volatility or valuable growth opportunities were found to generate higher momentum returns than traditional momentum strategies. Asness, Moskowitz, and Pedersen (2013) state that there will also exist some compensation for the risk that the stock will not be liquid. Moskowitz and Daniel (2016) find that abnormal returns to momentum strategies are correlated with, however, not explained by volatility risk.

There is evidently no consensus as to what explains the momentum premium. The divided explanations of the cause of profitable momentum strategies contributes to a continuing discussion on whether excess return and thereby successful active portfolio management is possible.

### 1.3 Value and momentum in combination

The study conducted by Asness, Moskowitz and Pedersen (2013), looking at value and momentum in combination, presents an interesting angle on portfolio management. They challenge the view that value and momentum strategies cannot be combined, and find consistent and widespread evidence of value and momentum abnormal returns across all markets they study. By examining momentum and value together, they find this to be more powerful than examining each strategy in isolation. As they find momentum and value strategies to be negatively correlated, in addition to generate high positive expected returns, a combination of the two should be much closer to the efficient frontier than either strategy alone. They combine the two strategies by constructing a 50/50 combination portfolio, and find this to outperform either value or momentum individually in every market they study. For example, for stock portfolios on the U.S. stock market, they find that the zero-cost combo portfolio obtains a Sharpe ratio of 0,63 (in addition to having lower standard deviation) against the zero-cost portfolio of momentum with a Sharpe of 0,33. The Sharpe ratio is the average return in excess of risk-free rate per unit of risk. The methodology of Asness, Moskowitz, and Pedersen (2013) and Asness, Frazzini, Isreal, and Moskowitz (2015), show that the Sharpe ratio is a good measure to use when deciding on whether a combination of the two strategies has been profitable. Their results make it interesting to further examine if looking at momentum and value jointly could be a better approach than investing in the two strategies separately.

Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) point out that even though momentum strategies are found to be profitable, they are occasionally the subject of strong reversals, or “crashes”. Further, Daniel and Moskowitz (2016) explain that the crashes are predictable, and it should be possible to hedge against them. It is therefore interesting to examine whether it is possible to time these crashes, and thus hedge against them. By weighting a higher ratio on the value strategy right before the momentum strategy crashes, we try to obtain an even higher excess return than just by following the momentum strategy.

In addition to test for an approach where one invests with different weight in each of the two strategies simultaneously, we test whether portfolios formed on both momentum and value can deliver excess returns. Fama and French (1993) present a method on how to construct 5x5 cross-sectional portfolios formed on size and value. We use the same approach only for momentum instead of size, constructing 3x3 cross-sectional portfolios. The objective is to see if combining the two strategies when constructing the portfolios will obtain additional abnormal returns than when following either of the two strategies.

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## 2. Construction of data set

This section takes on the construction of our dataset, and is divided into two sections. Section one describes our choice of time period and dataset. Section two presents our processing of the data material, which is conducted in Datastream, Excel and the programming tool R.

### 2.1 Collection of data material

#### 2.1.1 Choice of market

The chosen market for this study is the Nordic stock market. The Nordic stock market constitutes of Oslo Stock Exchange (OSE), OMX Nordic Exchange Copenhagen (CSE), Stockholm Stock Exchange (SSE), Helsinki Stock Exchange (HSE) and Iceland stock exchange (ICE). We choose not to include Iceland as part of the Nordic stock market tested in this paper. Iceland has too few stock observations, in addition Datastream only provides data from May 2001 for this country.

We choose to look at the Nordic stock market for several reasons. First of all, we find most studies conducted on value and momentum strategies in the past focusing on the U.S. stock market in particular, followed by several studies of investment strategies on the European stock market. We do however not find many studies of the Nordic stock market in isolation. Thus, we find the Nordic stock market attractive to investigate. Also, the Nordic region tends to have low correlation with the United States equity markets (Kuepper, 2017). It is therefore interesting to supply earlier findings by Jegadeesh and Titman (1993) and Fama and French (1992), on the U.S stock market, with our results. If either a significant value or momentum effect can be shown on the Nordic market it would supplement and strengthen the theory of such an existing effect.

Also, we choose to look at the Nordic market in its entirety, instead of only looking at each country in isolation. The four countries that constitute our Nordic stock market, complement each other as it covers several different industries, almost on a par with the world market (Holberg Fondene, 2017). In addition, it will facilitate diversification looking at a bigger selection of stocks. However, we also look at the countries separately as part of validating our results. We briefly examine whether some of the countries are contributing in a different way

than others, or if some may be negatively correlated making it more preferable to invest in different countries at different times.

To get hold of the data we use “Thomson Reuters Datastream”. Datastream provides over 10 million economic time series for 162 markets with comparable data (Thomson Reuters, u.d.) This particular database has been used in several studies, for example Asness, Moskowitz, and Pedersen (2013) use Datastream to collect data on stocks outside the U.S. market. We got access to Datastream through NHH’s database. Given that NHH provide this database for students and professors for the purpose of giving them a platform to conduct empirical studies, it strengthens Datastream as a reliable source.

### 2.1.2 Datatypes

Our empirical data consists of historical stock prices, market values and book values for all registered stocks on the four chosen stock exchanges<sup>1</sup>. These values were necessary to obtain to create momentum and value portfolios, as well as the asset pricing factors to be used in the study when performing regression analyses.

The data consists of monthly stock data reaching over a time period of 29 years (1988 to 2016). Monthly frequency is chosen based on the majority of earlier studies, making our results comparable. The choice of monthly frequency also gives our analysis more credence when it comes to contributing to the material that already exists on value and momentum.

We also construct a market index to provide a measure for the market return. The market index is constructed by creating a market portfolio consisting of all companies in our universe (Nordic stock market), where all the companies are value-weighted within the portfolio by their market capitalization. In terms of calculating the market cap of each company, we convert all market values stated in local currency into one common currency. The UK currency is chosen given that this is the only common currency in Datastream available for our entire time-period. It is important to point out that we also download the exchange rate “Euro to

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<sup>1</sup> Datastream variable codes; Adjusted Prices (P), Market Value (MV) and Book Value (WC03501)



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UK”<sup>2</sup>. Finland introduced Euro banknotes and coins in January 2002 and several companies therefore had their values stated in Euro rather than Finnish Markka.

### 2.1.3 Choice of time period

Our time period, January 1987 to December 2016, is chosen based on the idea that we want our data to cover as big time-span as possible, at the same time as it provides enough applicable data. Based on earlier studies we find that a time period of approximately 30 years will provide us with a large sample, and thereby a solid base for our analysis and statistical tests (Jegadeesh & Titman, 1993; Asness, Moskowitz, & Pedersen, 2013). If a significant momentum or value effect is detected among a big selection of stocks, and over a long time-period, it is more conceivable that the results can be assumed to apply to the stock market in general. Also, using a bigger sample can reduce the problem of data mining. Data mining should however not be a problem given that previous literature from Jegadeesh and Titman (1993, 2001) and Rouwenhorst (1998) proves the existence of a momentum effect both in different geographical areas and time periods. We could have used an even longer time-period, but given the available data in Datastream and the time period given to conduct our analysis, we choose to limit our study to approximately 30 years. If we had included data from further back in time, the available data would not have been big enough, and thereby not representative.

It is important to emphasize that when presenting our results, we have made a further limitation to the time period, only presenting results for January 1989 to June 2016. This limitation is made given that we want all the portfolios’ performance to be measured over the same time period. Given that some of the strategies initially begins and ends at different dates, we narrow our measurement period to obtain results for the same period within all the strategies<sup>3</sup>. However, we are aware of the fact that this might affect the results. We cut the holding periods for some of the strategies in order to make all the strategies end in the same month (June 2016).

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<sup>2</sup> Two different “Euro to UK” exchange rates are available in Datastream. The first one is “Euro to UK (ECU History WMR)”. This exchange rate gives values back to the year 1989. The second one is “Euro to UK (WMR&DS)”, which provides values back to the year 1957. Both of the exchange rates come from the same source: WM/Reuters. In addition, from 31.12.1998, the two exchange rates provide the exact same values. As we need to convert values from Euros into UK back to the year 1987, we use the exchange rate “Euro to UK (WMR&DS)” given that it provides data for our time period.

<sup>3</sup> For example, constructing the 12x12 momentum strategy, the formation period starts in January 1988, and given that it last for 12 months, we cannot start our holding period before January 1989

It is possible that some strategies might crash in the last month (now excluded) and that our results thereby would have been different if the last returns that are missing were taken into consideration. However, this should not directly affect our analysis given that the results from the holding period are stated in monthly returns, indicating that we can examine whether the strategy provides excess return based on the months that are included. Further, the average monthly returns remain fairly constant regardless of whether we include the last months or not, indicating that our results are somewhat unaffected by this limitation.

## 2.2 Filtering the data material

When downloading data on the Nordic stock market from Datastream we obtain data for a total of 4 950 companies. This is data on equities, stated in local currencies and with corresponding price, market value and book value for each company.

Before we start processing the collected data, we need to filter out some companies based on certain criteria. What these criteria are, and the reasons they are used, are stated below. After filtering on these criteria, we end up with a total of 2090 companies included in our study.

### 2.2.1 Errors in the datasample

When downloading data, “Error” occurs for companies that do not have data for a certain datatype within the requested period. We remove these companies from our dataset. This might be a weakness in terms of missing companies. However, given that Datastream do not provide data on these companies, we consider the analysis to be more accurate when these are excluded.

### 2.2.2 Companies within certain sectors

Before downloading data from Datastream; close-end-funds, preference shares, exchange-traded funds, warrants and exchange traded notes, are excluded. We want to limit our study to only include ordinary stocks. This is in line with other studies of momentum. Fama and French (1993) point out that they only include firms with ordinary common equity. They exclude ADR’s (American depository receipts), REITS (real estate investment trusts) and unit of beneficial interests. Asness, Moskowitz, and Pedersen (2013) exclude ADR’s (American depository receipts), REITs (real estate investment trusts), financials, close-end-funds, and foreign shares.

The objective is to remove companies that invest in other companies and thereby avoid double registration, as well as results obtained as a consequence of high level of correlation. After downloading the data, we therefore further exclude firms that are within the sectors “Equity investment instruments”, “Non-equity investments instruments”, “Real-estate investments and services”, and “Real-estate investment trusts”. Excluding stocks based on the mentioned criteria above, result in the sample presented in Table 1.

**Table 1: Description of stock sample**

This table provides an overview of the total number of stocks included in our study. Presented are the initial number of stocks, as well as the number of stocks remaining - and thereby used to conduct our study - after filtering the data.

Country	Stock Exchange	Number of companies		
		- from Datastream	- and after excluding errors	-and after excluding certain sectors
Denmark	Copenhagen	794	379	350
Finland	Helsinki	584	275	265
Norway	Oslo	830	544	526
Sweden	Stockholm	2742	1033	949
<b>Total</b>	<b>Nordic</b>	<b>4950</b>	<b>2231</b>	<b>2090</b>

Further, we consider removing companies that are registered several times as they are divided into stocks with different voting rights. Stocks with higher voting rights are denoted “A”, and stocks with lower voting rights are denoted “B”. As a result, some companies are registered twice on the stock exchange. For example, on Oslo Børs, “Adelsten Holding” is registered both as “Adelsten Holding A” and “Adelsten Holding B”. We observe different approaches on whether one should exclude A denoted stocks, or keep both “A” and “B” denoted stocks. The difference between those types of stocks essentially has an impact on how often the stock

is traded. Given that this quality is not a focus in our paper, and that we want the number of stock observations to be as large as possible, we choose to keep both types<sup>4</sup>.

In addition, some companies are listed with a parent company as well as subsidiaries. For example, the company "Aker" is listed on Oslo Stock Exchange along with its subsidiaries such as "Aker Solution", "Aker Drilling", "Aker Floating", "Aker Maritime" and "Aker RGI". We consider excluding "Aker", or the subsidiaries, to avoid results largely affected by correlation. However, we find it strange to exclude a company as big as "Aker" based on this criterion. Further we consider the subsidiaries as being separate companies from the parent company. They are therefore included, given that investing in one of them does not mean that one directly invests in one of the others<sup>5</sup>.

Some companies are listed with stocks denoted with "F" and "AF" in addition to "A" and "B". We consider limiting these companies in our sample to only include "A" and "B" stocks. However, based on the fact that we do not exclude based on the quality of being listed as "A" or "B" stock, we do not exclude based on this similar criterion.

The sample is also divided in listed and delisted companies. Listed companies are currently listed on a stock exchange, while delisted companies have been delisted during our sample period. These delisted companies are denoted with "dead" within the dataset. There are several reasons to why companies are delisted, such as defaults, merges and acquisitions etc. We choose to include delisted companies, which do not have data for the entire research period. This is first of all due to the fact that excluding delisted companies would have reduced our data sample considerably. Secondly, delisted companies must be included to not cause "survivorship bias". The fact that a company gets delisted indicates a stock's performance. If we exclude a "dead" company, we remove companies that might have performed badly and thereby skew the results.

However, the companies that are delisted only provide data for certain years in the overall period, and are therefore not represented throughout the whole dataset. Given that we do not

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<sup>4</sup> We are aware of the fact that keeping both "A" and "B" denoted stocks may impact the autocorrelation among the sample of stocks, and thereby make the results more influenced by firm specific risk.

<sup>5</sup> We note that keeping all of them can skew the results due to higher correlation between these companies.

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want companies to be included in calculations of performance after they are delisted, we replace these companies' returns with "NA" as of the date they are delisted. Including values for companies after they are delisted would have skewed the results. More companies than what actually existed at the time would have been included in the calculations of relative performance, resulting in companies being misplaced.

### 3. Empirical analysis

This chapter presents and discusses the methods used to conduct our analysis. Further, we present the results and discussion of the performance of our portfolios. The chapter is divided into four sections; value, momentum, combination, and regressions. Within each section, we discuss our methodology and present the results. To process the data material, we have mainly used the programming tool R throughout the whole study. This required coding of every step of data construction and calculations. However, regressions are conducted in the programming tool Stata.

It is important to emphasize that to measure the existence of momentum and value on the Nordic stock market, as Asness, Moskowitz, and Pedersen (2013) we use the simplest and most standard measures, to the extent a standard exists. The idea is not that the strategies should be possible to implement in practice, but to test whether a profitable strategy is possible in theory. Problems related to the implementation of the strategy in practice is presented in the 4<sup>th</sup> section of this paper.

The empirical study of this paper is extensive. We examine one value strategy, as well as 16 different strategies for momentum. For momentum, we choose to test different strategies by using different holding and formation periods. This is not equally relevant for value as these portfolios are constructed based on their December book-to-market values, meaning that the rankings of portfolios are constant over a whole year. Both value and momentum consist of ten different portfolios, as well as one zero-cost portfolio, giving us a total of 187 tested portfolios.

In addition, we look at two different approaches of combining value and momentum strategies. At first, we construct a 3x3 cross-sectional strategy (3x3-strategy) with the objective to examine whether investing in stocks that are both winners (momentum) as well as having high book value (value stocks) can be extra profitable<sup>6</sup>. Thereafter, we focus on how to invest in the two strategies simultaneously by constructing a portfolio weighting the two strategies in different ways. We weight the portfolios in combinations with weights of 50/50, 25/75, 75/25, as well as one portfolio weighted with the purpose of maximizing Sharpe (Sharpe portfolio)

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<sup>6</sup> Note that the 3x3-strategy must not be confused with the MOM3x3-strategy introduced later.

and one weighted with the purpose of minimizing the variance (MinVariance portfolio). In addition to these, we construct a hedge portfolio, where we switch from a pure momentum portfolio (MOM3x3) to the weighted 50/50-portfolio in times of momentum crashes.

Given the vast selection of portfolios and limited time to conduct our study, we choose to focus on one momentum strategy when going forward with the analysis. We choose the MOM3x3-strategy, which is the best performing momentum strategy in our study. This is not the same strategy that is proven most successful by Jegadeesh and Titman (1993), however both strategies include the same holding period of 3 months. Further, we choose to focus on three of the different weighted-combination portfolios in the regression part of this study; 50/50, Sharpe and Hedge. These portfolios are chosen based on the following reasoning. The Sharpe portfolio is chosen because during our entire sample period, this is the best performer measured in both reinvested returns and Sharpe-ratio. We choose the 50/50-portfolio given that this is the portfolio we use when we hedge against momentum crashes, as explained above. The Hedge portfolio is chosen in order to see to what extent the MOM3x3-portfolio can improve, also after we control for other factors.

### 3.1 Value

A value strategy selects stocks that have low valuation relative to their book-value (Novy-Marx, 2013). This means an investor evaluates the stocks based on their book-to-market value. The investor buys (long) the stocks that have high book-to-market values (value stocks), and sells (short) stocks with low book-to-market values (growth stocks). A zero-cost value portfolio is constructed by taking an equally large long and short position in portfolios of high and low B/M stocks respectively. Such a portfolio is referred to as HML (high-minus-low) portfolio. For this to be possible in practice, we have to assume that all stocks can be shorted.

The value portfolios in our paper are created based on the method used by Fama and French (1992). We supplement with the methods presented by Asness, Moskowitz, and Pedersen (2013), and Fama and French (2012).

### 3.1.1 Methodology

When constructing portfolios following a value strategy, we divide the stocks into deciles based on their book-to-market values in December year  $t-1$ , and measure their returns over the following period July year  $t$  to June year  $t+1$ .

We use both market values and book values lagged 6 months when sorting the stocks into deciles, following the methodology of Fama and French (1992). This means stocks are sorted into deciles in year  $t$  based on accounting data for fiscal year-end in calendar year  $t-1$ . Given that we do not know each company's fiscal year-end, we use accounting data for December as a proxy for fiscal year-end values. The 6-month minimum gap between fiscal year-end and the return tests, is according to Fama and French (1992), necessary due to the fact that we need to be sure that accounting data are available at the time we want to calculate book-to-market values. They state that firms have to file their reports within 90-days of their fiscal year-ends, but the reports of more than 40 % of firms with fiscal year endings in December are not made public until April.

The constructed portfolios' performance, over the holding period July of year  $t$  until June of year  $t+1$ , are measured by first calculating monthly returns for each stock. After obtaining monthly returns for each stock individually, we calculate the average monthly equal-weighted returns for each portfolio. Within a portfolio, we summarize all the  $N$  stock's monthly returns and divide it by the number of stocks  $N$  in order to obtain the average equal-weighted return  $CM_{P,t}$  for the portfolio  $P$ , for any given month  $t$ :

$$CM_{P,t} = \frac{1}{N} \cdot \sum_{i=1}^N (CM_{i,t})$$

where  $i = 1, 2, \dots, N$  denotes each individual company in portfolio  $P$ . This method is repeated for each year up until June 2016. When calculating the returns, we have not considered taxes and transaction costs. However, including these costs would be impossible given that we want to keep the study general. The effect of taxes and transaction costs will differ from investor to investor, as well as between countries.

Our methodology, following Fama and French (1992), is a bit different from the methodology described by Asness, Moskowitz, and Pedersen (2013). To compute the book-to-market values they use book-values lagged 6 months, but in combination with most recent market values. A



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study conducted by Asness and Frazzini (2013) argues that using the most recent market values can be important when looking at value strategies in presence of momentum. However, not using lagged market values in the value measure might increase the negative correlation between value and momentum, as well as reducing the value premium.

When constructing the asset pricing factors, we find it natural to use Fama and French (1992) as reference, as they are the founders of the three-factor model. Therefore, we choose to follow their method constructing value portfolios as well, as we want the method to be consistent throughout our paper. In addition, Asness, Moskowitz, and Pedersen (2013) state that whether we use lagged prices or market values matched contemporaneously in time will not have a big impact on the result. Further we find Fama and French's (1992) method best to use given that we want to compare our results with Ødegaard (2017a)<sup>7</sup>.

To interpret the results – in this case the profitability of the value portfolios on the Nordic stock market - we further conduct an empirical analysis of the data. We test the significance of the results obtained from our value portfolios by using t-tests, in order to state that our results are valid.

### 3.1.2 Results

We examine whether a value strategy is profitable on the Nordic stock market. This will be the case if the zero-cost portfolio (high book-to-market minus low book-to-market) yields positive returns, in addition to being statistically significant. The results from following a value strategy on the Nordic stock market are presented in Table 2 as monthly average returns for the period July 1989 to June 2016. Corresponding t-statistics, expressing their statistical significance, are stated in a separate column.

We see from Table 2 Panel A, that all eleven portfolios (the ten deciles as well as the zero-cost portfolio) yield positive returns. Furthermore, all the returns are statistically significant

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<sup>7</sup> We conduct the same tests done on the Nordic stock market for Oslo Stock Exchange in isolation. This is done to compare our results with Ødegaard (2017a) to validate the methodology used in our study. Our results do not match those of Ødegaard (2017a) entirely, as Ødegaard (2017a) find higher average returns than we do, but we find the same tendency of monotonic patterns. However, the difference in results may be explained by the fact that we have a different data sample and a different time period. Further, we conduct some manual sample calculations in excel, which confirms that our programming in R is executed correctly.

with exception of the zero-cost portfolio (HML). The portfolio constructed of stocks with high book-to-market values (High B/M) is the portfolio that yield the highest return of 1,47 %. In addition, this is also the portfolio that has returns most significantly different from zero, with a t-statistic of 4,33. This indicates that following an investment strategy where one buys stocks with a high book-to-market value is profitable. We further note that these results are at least somewhat monotonic, meaning that the average returns in general are increasing by the decile (moving from one decile to the next, the average returns increase in 6 out of 9 cases). The trend is not exclusively monotonic, however there is a clear tendency, with only a few exceptions. This may further indicate that buying stock based on their book-to-market value is profitable. In our study, the main focus is to examine the returns obtained by holding zero-cost portfolios. One can obtain returns of 0,66% by investing in the zero-cost portfolio. However, the result is not statistically significant, which reduces the validity of the results as well as the certainty of a present value effect.

Our findings concur to some extent with the findings of Fama and French (1992) who study the value effect on the U.S stock market for the period July 1963 to December 1990. They as well find exclusively positive returns for all ten deciles, and the High B/M outperforming the Low B/M<sup>8</sup>. However, monthly returns for all deciles are on average 0,32 percentage points higher in Fama and French's (1992) study than what we find on the Nordic stock market. We thereby find consistent results regarding the existence of a value effect, however, the existence of differences in magnitude between the returns might be explained by the choice of market and/or period.

As stated in Tabel 2 Panel B, when adjusting our results to reflect returns in excess of the market, we find that the average returns of all deciles become negative. Again, the portfolios are statistically significant, with exception of the high book-to-market portfolio (High B/M). This will naturally not have any effect on the zero-cost portfolio, as the zero-cost portfolio return is the difference between the high B/M portfolio and the low B/M portfolio. The results show that both the low and high B/M underperform relative to the market.

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<sup>8</sup> Fama and French (1992) find the following results; 0,48 percent returns for the Low B/M and 1,88 percent returns for the High B/M.

**Table 2: Average returns, portfolios formed on B/M**

Panel A presents average monthly returns in percent for portfolios formed on  $B/M$ -values. At the end of June year  $t$ , stocks are allocated to deciles based on their book-to-market value. The  $B/M$ -values are calculated using book values and market values from the end of December year  $t-1$ . These decile portfolios are then held for the following 12 months. HBM represents the portfolio consisting of stocks with the highest book-to-market value, Portfolio “9” is the portfolio consisting of companies with second highest book-to-market values, and so on. The HML-portfolio is the zero-cost portfolio constructed of companies within the highest book-to-market values minus the ones with low book-to-market. T-statistics are presented a separate column. All the strategies are tested for the period January 1989 to June 2016. Panel B presents the returns in excess of the market for the same portfolios.

	Panel A		Panel B	
	Average returns	t-statistic	Average returns	t-statistic
<b>Low</b>	0,80	2,01	-0,69	-2,74
<b>2</b>	0,75	2,33	-0,75	-4,13
<b>3</b>	0,83	2,78	-0,66	-4,44
<b>4</b>	0,87	3,06	-0,62	-3,58
<b>5</b>	0,68	2,57	-0,82	-4,70
<b>6</b>	0,75	3,05	-0,74	-3,99
<b>7</b>	0,98	3,11	-0,51	-2,05
<b>8</b>	0,84	3,05	-0,65	-3,21
<b>9</b>	1,04	3,81	-0,45	2,22
<b>High</b>	1,47	4,33	-0,03	-0,12
<b>HML</b>	0,66	1,92	0,66	0,92

When looking at the returns of Table 2 Panel A, we see that within the zero-cost portfolio (HML) it seem to be the high  $B/M$  stocks that makes it profitable to follow a value strategy. However, to obtain maximum effect from following a value strategy, we need the portfolio we buy (high  $B/M$ ) to overperform relative to the market, and the portfolio we sell (low  $B/M$ ) to underperform relative to the market. As shown in Panel B, both portfolios underperform relative to the market, meaning that it is the underperformance of the low  $B/M$  portfolio that seems to drive the value effect.

### 3.2 Momentum

Portfolio management following a momentum strategy selects stocks based on historical returns, where the investor buys the best performing stocks (winners) and sells the worst

performing stocks (losers) to create a zero-cost portfolio commonly referred to as WML (winner-minus-losers). We create momentum portfolios based on the method presented by Jegadeesh and Titman (1993).

### 3.2.1 Methodology

The two most common methods used to investigate the momentum effect are the 10 % portfolio method and the WRSS (Weighted Relative Strength Strategy). Swinkels (2004) states that the difference between the two methods is minor. Following the methodology of Jegadeesh and Titman (1993), we choose to use the 10 % portfolio method. The total selection of stocks is divided into deciles based on their historical returns. Stocks that represent the top 10 % returns form the winner portfolio, and stocks that represent the bottom 10 % returns form the loser portfolio. An investor takes a long position in the winner portfolio, and a short position in the loser portfolio. The position is held for a certain period, and then returns are measured to see if abnormal returns are obtained.

The stocks need to be either equal- or value weighted within the portfolios when measuring their performance over the holding period. This means that the stocks are either given equal weights, or weighted relatively to their market value. Equal-weighted returns are consistent with most studies conducted on momentum. Grobys (2016), which study the momentum effect in global equity markets in times of trouble, use equal weights, as do Jegadeesh and Titman (1993). Asness, Moskowitz, and Pedersen (2013), on the other hand, choose to value-weight the returns within the portfolios. The stocks are value-weighted based on their beginning-of-month market capitalization. Value-weighting the stocks reflect a size effect in the results, given that stocks with high market value are given higher significance. To avoid this, and as we want to follow the methodology of Jegadeesh and Titman (1993), we choose equal weights. However, to further validate our results, we conduct tests on one of the momentum portfolios where we value-weight the stocks. Comparing these results with those from where the stocks are equal-weighted will confirm whether the excess return is affected by size.

After deciding which method to use when sorting the stocks and how they should be weighted, we create the portfolios. We differentiate between the formation and holding period. The period used to measure historical returns is called the formation period. As Jegadeesh and Titman (1993) we consider different strategies and collect stocks based on their returns over the past 3, 6, 9 and 12 months. The 10 % portfolio method divides the total selection of stocks

into deciles, each containing 10 % of total number of stocks, based on their cumulative returns over the last  $F$  months. For example, after a formation period of three months – January, February and March 1988 – stocks are placed into deciles in the beginning of April 1988 based on the cumulative return over the period December 31th 1987 to February 29th, 1988. Skipping the most recent month's return is standard in the momentum literature. Jegadeesh (1990) states this is done to avoid the one-month reversal in stock returns, which may be related to bid-ask spreads, liquidity or microstructure issues.

The portfolios created at the end of the formation period are held for  $H$  number of months. This forms the holding period where the performance of the portfolios is measured. The holding periods are as the formation periods divided into periods of 3, 6, 9 and 12 months. In total, we therefore obtain 16 different momentum strategies in our analysis.

**Figure 1: 16 different momentum strategies**

This figure presents an overview of the 16 different momentum strategies tested in this study. The strategies differ based on the length of their formation and holding periods.

<b>Formation period</b>	<b>Holding period</b>			
	<b>3</b>	<b>6</b>	<b>9</b>	<b>12</b>
<b>3</b>	F=3	F=3	F=3	F=3
	H=3	H=6	H=9	H=12
<b>6</b>	F=6	F=6	F=6	F=6
	H=3	H=6	H=9	H=12
<b>9</b>	F=9	F=9	F=9	F=9
	H=3	H=6	H=9	H=12
<b>12</b>	F=12	F=12	F=12	F=12
	H=3	H=6	H=9	H=12

We emphasize that we eliminate companies from a certain holding period that do not have data for the corresponding formation period. If for example a company originally included in a formation period lasting from January 1988 until March 1988 were delisted in February, this company is excluded from the following holding period April to June 1988.

In order to construct portfolios based on historical performance, we need the stocks cumulative returns for the formation period. Cumulative returns are calculated by taking the price at the end of the period divided by the price at the beginning of the same period, subtracted by one. However, it is important to accentuate that as we have “last day of the month” prices, we use the last price in the month before the period starts as the “beginning of the period price” to get returns for the entire period. This means that for a period starting in month  $t$ , we use the price at the end of month  $t-1$ . For example, for a three-month formation period extending from January 1988 until March 1988, we use the last price of February 1988 divided on last price of December 1987. Using the stock price at the end of December is necessary in order to get the return over the entire period, starting the first day of January. The result is monthly cumulative returns over the entire formation period. Based on these calculated cumulative returns, stocks are placed into deciles.

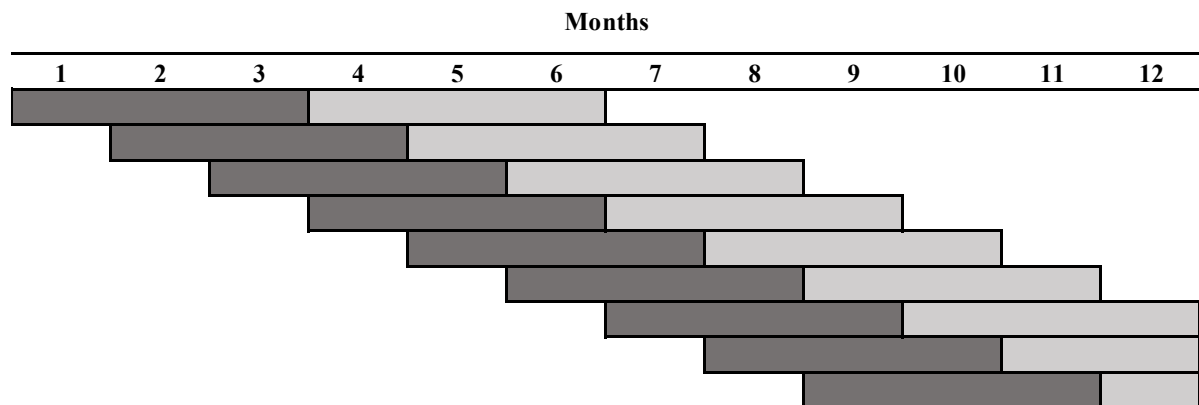
Thereafter we measure the monthly equal-weighted cumulative returns for each portfolio over the holding period. The calculation is done in the same way as described for the value strategy. A zero-cost portfolio is also created for each strategy, obtained by buying the winner portfolio and short selling the loser portfolio. As with the value strategy, the same assumption regarding the possibility to short sell stocks applies here. In addition, given the high transaction frequency for momentum strategies, we also have to assume no, or at least low, transaction costs in the stock market in order for a momentum strategy to be profitable to implement.

When creating momentum strategies, we differentiate between strategies with overlapping and non-overlapping holding periods. Overlapping holding periods mean that in any given month  $t$ , one will hold portfolios selected in the current month as well as in the previous  $H - 1$  months, where  $H$  is the length of the holding period (Jegadeesh & Titman, 1993). If for example a strategy consists of a 3-month holding period, in March one will hold the portfolio selected in March as well as those selected in January and February.

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### Figure 2: Overlapping holding periods

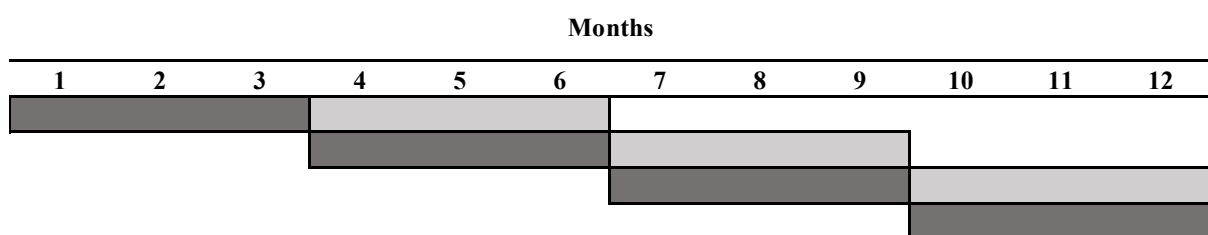
This figure illustrates a momentum strategy based on 3-months formation and holding period (MOM3x3), using overlapping holding periods. The formation periods are represented by the dark grey areas, while the holding periods are represented by the light grey areas. We note that in the formation periods, the last month is skipped when calculating cumulative returns.



Regarding non-overlapping holding periods, we only hold one portfolio within any month  $t$ . The portfolios are thereby constructed with the purpose of having returns corresponding to exactly one portfolio each month throughout the whole time-period.

### Figure 3: Non-overlapping holding periods

This figure illustrates a momentum strategy based on 3-months formation and holding period (MOM3x3), using non-overlapping holding periods. The formation periods are represented by the dark grey areas, while the holding periods are represented by the light grey areas. We note that in the formation periods, the last month is skipped when calculating cumulative returns.



The strategies we examine include overlapping holding periods. The decision on using overlapping periods is based on the methodology of Jegadeesh and Titman (1993). However, they state that it should not have a big impact on the results whether one chooses to use overlapping or non-overlapping holding periods. A problem with overlapping holding periods is that it equals more frequent transactions, resulting in higher transaction costs. Also, use of

overlapping holding periods can result in higher risk of autocorrelation. A problem with using non-overlapping periods is that we only form portfolios in certain months throughout our time-period, making it random when we choose the winners and losers. If we thereby are lucky and always choose stocks in months where prices are low, this can make the results seem more profitable than what they are, and vice versa. To increase the power of our test, we examine one momentum strategy (MOM3x3) using non-overlapping holding periods.

As with value, we conduct tests for one momentum portfolio within the Norwegian stock market, to compare our results to Ødegaard (2017a)<sup>9</sup>. Also, we test whether the returns are statistically significant.

### 3.2.2 Results

We examine whether a momentum strategy is profitable on the Nordic stock market. This is the case if the zero-cost portfolios (winners minus losers) yield positive returns, in addition to being statistically significant. In Table 3, we have presented the monthly average returns for all of our 16 different strategies tested over the period January 1989 to June 2016. Within each strategy the performance of both the winner, loser and zero-cost portfolio are presented. Corresponding t-statistics, expressing their statistical significance, are stated in a separate column.

We see from Table 3 that both the winner and loser within all the portfolios provide positive returns, all statistical significant. Further we see that returns obtained by the winners are more statistical significant than the returns obtained by the loser portfolios. However, regarding the zero-cost portfolios, only 9 of 16 portfolios generates positive returns. Further, only one portfolio (MOM3x3) is statistically significant. This is not entirely consistent with the findings of Jegadeesh and Titman (1993), who find all 16 zero-cost portfolios to yield positive returns as well as being statistically significant. We thereby find consistent results regarding the existence of a momentum effect (success of momentum investing as an investment strategy).

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<sup>9</sup> We conduct the same tests done on the Nordic stock market for Oslo Stock Exchange in isolation, to compare our results with Ødegaard (2017a) to validate our methodology. Our results did not match those of Ødegaard (2017a) entirely. However, this might be explained due to differences in data sample and time period. Further, we conduct some manual sample calculations in excel, which confirmed that our programming in R was executed correctly.



However, the existence of difference in magnitude and statistical significance between the returns, might be explained by the choice of market and time period.

**Table 3: Average returns, 16 portfolios formed on past performance**

Presented in this table are the average monthly returns in percent for each strategy F3-F12/H3-H12. The portfolios are constructed by allocating stocks into deciles based on the F months past returns. Thereafter, these portfolios are held for H months, and their equal-weighted monthly returns are calculated. Portfolios are constructed using overlapping holding periods. For each strategy, the table presents average monthly returns for the winner-, loser- and zero-cost portfolio (WML). Corresponding t-statistics are presented in separate columns to the right of the average returns. All strategies are tested over the period January 1989 to December 2016.

	Holding period							
	3		6		9		12	
Formation period	Average returns	t-statistics	Average returns	t-statistics	Average returns	t-statistics	Average returns	t-statistics
<b>3</b>								
Buy (winners)	1,70	4,30	1,53	4,39	1,50	4,41	1,47	4,35
Sell (losers)	0,99	2,07	1,14	2,31	1,29	2,61	1,25	2,70
<b>Buy-sell (WML)</b>	0,71	2,40	0,40	1,49	0,21	0,78	0,23	1,07
<b>6</b>								
Buy (winners)	1,74	5,23	1,58	4,90	1,55	4,85	1,41	4,44
Sell (losers)	1,21	2,25	1,37	2,55	1,41	2,75	1,44	2,96
<b>Buy-sell (WML)</b>	0,53	1,27	0,21	0,51	0,14	0,38	-0,03	-0,09
<b>9</b>								
Buy (winners)	1,70	5,27	1,58	4,99	1,44	4,59	1,30	4,17
Sell (losers)	1,67	2,78	1,60	2,78	1,59	2,97	1,62	3,20
<b>Buy-sell (WML)</b>	0,03	0,06	-0,02	-0,04	-0,15	-0,37	-0,32	-0,89
<b>12</b>								
Buy (winners)	1,78	5,54	1,49	4,75	1,35	4,29	1,24	3,94
Sell (losers)	1,66	2,79	1,66	2,87	1,71	3,13	1,73	3,35
<b>Buy-sell (WML)</b>	0,12	0,25	-0,17	-0,37	-0,36	-0,84	-0,50	-1,32

Further, we observe that the returns of the zero-cost portfolios decline with the length of the holding period. An exception is within strategies with formation periods of 3 months, where we see a small increase when the holding period increases from 9 to 12 months (moving from a MOM3x9-strategy to MOM3x12-strategy). This indicates that the momentum effect only last for a short time period on the Nordic stock market. Further, it may imply that the momentum effect detected on the Nordic stock market is due to an overreaction or a delay in stock price reaction to common factors, which are retrieved within a few months. The result indicating that shorter holding periods provide higher returns can be supported by Jegadeesh and Titman (1993). They find the MOM12x3-strategy to be the most profitable strategy on the U.S. stock market, providing a return of 1,49 %. Of course, this cannot assure a conclusion stating that the length of the holding period is crucial for the profitability of the momentum strategy. However, it might be an indication that this can be a factor worth noting, at least on the Nordic

stock market. As mentioned, the only strategy statistically significant in our study is the MOM3x3-strategy.

Based on our results from testing our 16 momentum portfolios, we further focus on the MOM3x3-strategy exclusively, as this is the best performer. We see from the Table 4 Panel A that all eleven portfolios (the ten deciles as well as the zero-cost portfolio) yield positive returns. Furthermore, all the returns are statistically significant with the exception of portfolio 2 (t-statistic of 1,46). The portfolio constructed of stocks with the highest returns (winners) is the portfolio that yield the highest return of 1,70 %. In addition, this is the portfolio that has returns second most significantly different from zero (following portfolio 9), with a t-statistic of 4,30. This indicates that following an investment strategy where one buys the stocks yielding the highest historical returns is profitable.

**Table 4: Average returns, portfolios formed on past performance**

Panel A presents the average monthly returns for portfolios formed based on a 3-month formation period and a 3-month holding period. At the end of each formation period, stocks are allocated to deciles based on their cumulative returns over the formation period. These decile portfolios are then held for the following 3 months, using overlapping holding periods. We skip one month between the formation and holding period, as this is standard in momentum literature. Winners represents the portfolio consisting of stocks with the highest cumulative returns in the formation period, whereas Portfolio “9” is the portfolio consisting of companies with second highest returns, and so on. The WML-portfolio is the zero-cost portfolio constructed of companies within the highest returns (winners) minus the ones with low returns (losers). T-statistics are presented a separate column. All the strategies are tested for the period January 1989 to June 2016. Panel B presents the returns in excess of the market for the same portfolios.

	Panel A		Panel B	
	Average returns	t-statistic	Average returns	t-statistic
<b>Losers</b>	0,99	2,07	-0,51	-1,48
<b>2</b>	0,48	1,46	-1,02	-5,14
<b>3</b>	0,65	2,24	-0,85	-5,12
<b>4</b>	0,84	3,35	-0,66	-3,94
<b>5</b>	0,90	3,86	-0,59	-3,74
<b>6</b>	0,92	3,84	-0,58	-3,31
<b>7</b>	0,85	3,75	-0,64	-4,00
<b>8</b>	0,97	3,99	-0,52	-3,29
<b>9</b>	1,22	4,44	-0,28	-1,59
<b>Winners</b>	1,70	4,30	0,20	0,71
<b>WML</b>	0,71	2,40	0,71	2,40

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Further, we note that the results to some extent are monotonic, meaning the average returns in general are increasing by the decile (moving from one decile to the next, the average returns increase in 7 out of 9 cases). These observations might indicate that following a MOM3x3-strategy is profitable on the Nordic stock market. Further, as opposed to the value strategy, the zero-cost portfolio (WML) is statistically significant in addition to generating positive returns of 0,71 %. This increases the validity of the results, as well as the certainty of a present momentum effect.

As stated in Tabel 4 panel B, when adjusting our results to reflect returns in excess of the market we find that the average returns of all deciles become negative, with exception from the winners. This indicates that the winners outperform the market, while the losers underperform. However, note that neither the winner nor the loser portfolio are longer statistically significant. Adjusting returns in excess of the market naturally does not have any effect on the zero-cost portfolio, as this portfolio reflects the difference between the winners and the losers. Based on this logic, and given that losers become negative as the winners stay positive, we get an indication that the momentum effect is driven by both the losers and the winners. We further note that the losers seem to be the main drivers, as they contribute to 0,51 % of the total 0,71 % return obtained by the zero-cost portfolio (WML).

### 3.3 3x3 cross-sectional portfolios

After creating value and momentum portfolios, as well as testing their results, we combine them to examine whether it is possible to find a combination that performs better than each of them separately. We test two different approaches to combine value and momentum. The first approach are cross-sectional combination portfolios, where we choose to follow the methods of Fama and French (1993). The second approach are weighted combinations of the two strategies, following the methodology of Asness, Moskowitz, and Pedersen (2013).

As stated, a combination of value and momentum is found to generate returns superior to those of a pure value and pure momentum strategy (Asness, Moskowitz, & Pedersen, 2013). They find value and momentum to be negatively correlated, which is one of the main arguments for combining the two strategies. In our data, we find value and momentum to be negatively

correlated, albeit weakly so, with a correlation coefficient of  $-0,03^{10}$ . Despite the correlation being weaker than what Asness, Moskowitz and Pedersen (2013) find, we continue with the combination approach. In this study, we do not focus on the correlation between value and momentum, and we will therefore not examine why we find the correlation to be less negative within the Nordic stock market.

This section will present the methodology and results from the first approach, while the second approach will be presented in section 3.4

### 3.3.1 Methodology

The objective with this approach is to examine whether additional returns can be obtained by forming portfolios on the cross-section of sorts on value and momentum relative to following either a pure momentum or a pure value strategy.

Fama and French (1993) present a methodology on how to construct 5x5 cross-sectional portfolios formed on size and value. We follow the same approach when constructing our combined portfolio. However, we make some adjustments. First of all, given that Fama and French (1993) use size instead of momentum, we apply the methodology of Fama and French (2012) when creating the momentum sort. Due to the fact that when constructing 5x5 cross-sectional portfolios such as Fama and French (1993) we end up with a too small number of companies in some of the portfolio, we construct a 3x3 cross-sectional portfolio instead. A too small number of companies (2-3) within one portfolio might affect the result as the portfolios will not be sufficiently diversified. Thus, basing the conclusions on only 2 or 3 companies can make the results less reliable as these companies get too much importance. Further, if one company has a very different result than the other two, this could skew the results. The results will thereby mainly be based on an outlier, and not on the average selection.

Constructing the 3x3 cross section portfolios the stocks are first sorted based on value. In the beginning of July each year  $t$ , the stocks are allocated to one of three book-to-market (B/M) groups based on their book-to-market values in the end of the previous year; December year  $t-1$ . The stocks are divided into three groups; high, medium and low book-to-market, using the

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<sup>10</sup> The correlation is tested between the zero-cost value portfolio (HML) and the zero-cost momentum portfolio with 12-months formation and holding periods (MOM12x12) as these are the most similar portfolios.

30<sup>th</sup> and 70<sup>th</sup> percentiles of aggregated book-to-market values as breakpoints. This is done each year over the time period 1988 to 2016.

After sorting into three groups based on their book-to-market values, we sort the stocks within each value group into three new groups based on their historical return. Stocks are therefore in the beginning of July year  $t$ , sorted into groups based on their historical returns over the formation period. We use the same breakpoints as for value. The formation period is from July year  $t-1$  to May year  $t$ . As before, we skip one month (June) between the formation and holding period, which is standard in momentum strategies (Jegadeesh & Titman, 1993).

The results we obtain is that within each B/M group, the respective firms are again sorted based on the three momentum breakpoints. For example, firms that are placed in the low B/M group at time  $t$ , as well as having the lowest historical returns among the firms in this group, forms one portfolio “Low-Loser”. The result is 9 different portfolios. After the construction, we hold the respective portfolios for the following 12 months. Over this holding period we calculate each portfolio’s equal-weighted monthly returns.

**Figure 4: 3x3 cross-sectional portfolios**

This figure presents an overview of the nine portfolios formed on value (B/M) and momentum (past returns).

<b>B/M</b>	<b>Losers (L)</b>	<b>Neutral (N)</b>	<b>Winners (W)</b>
Low (L)	LxL	LxN	LxW
Medium (M)	MxL	MxN	MxW
High (H)	HxL	HxN	HxW

Within each B/M group, the winner sorts will always have higher historical returns than the neutral and loser sorts. However, one implication of following this method, is that there might be instances where the neutral or loser sorts within one B/M group have higher historical returns than the winner sorts in a different B/M group. For example, HxW will always consist of stocks with higher historical returns than HxL, but MxL might consists of stocks with higher historical returns than HxW.

It is important to emphasize that only companies with available returns data for the entire holding period preceding the formation date are included in the sample from which the portfolios are constructed (Jegadeesh & Titman, 1993). As before, this means that companies that are delisted during our test period are replaced with “NA” and not included in the constructed portfolios.

### 3.3.2 Results

We construct 3x3 cross-sectional portfolios formed on the cross-section of sorts on value and momentum. In Table 5, we present the monthly average returns for all our nine portfolios formed on the cross-section of sorts on value and momentum, tested over the period July 1989 to June 2016. Corresponding t-statistics, stating their statistical significance, are presented in a separate column.

**Table 5: Average returns, 3x3 cross-section of value and momentum**

This table presents the average monthly returns in percent, obtained by the nine portfolios formed on B/M and momentum. At the end of June year  $t$ , we form nine B/M-momentum portfolios. The breakpoints are the 30<sup>th</sup> and the 70<sup>th</sup> percentile of aggregate B/M-values and past returns respectively. The B/M-values are calculated using book values and market values from the end of December year  $t-1$ , while past returns are measured from June of year  $t-1$  to May of year  $t$ . The portfolios are then held from July year  $t$  to June year  $t+1$ . The 3x3 sorts on B/M and momentum produce nine equal-weighted portfolios. T-statistics are presented in a separate column. The returns are measured over the period July 1989 to June 2016.

	<b>Momentum</b>					
	<b>Losers (L)</b>		<b>Neutral (N)</b>		<b>Winners (W)</b>	
	Average return	t-statistic	Average return	t-statistic	Average return	t-statistic
<b>Value</b>						
<b>Low (L)</b>	0,96	2,64	0,44	1,63	0,77	2,12
<b>Medium (M)</b>	0,82	2,86	0,67	3,18	0,79	2,69
<b>High (H)</b>	1,16	3,70	0,69	2,98	1,31	3,36

The results presented in Table 5 show that all the combinations of momentum and value yield positive returns, with all returns being significantly different from zero. Within the momentum sorts, we note that the High B/M portfolios in general have more significant results than the

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other two value sorts. The only exception is HxN, which has a slightly lower t-statistic than MxN<sup>11</sup>. We observe no such tendency for momentum.

As stated, a combination of value and momentum has been found to generate returns superior to those of a pure value and pure momentum strategy (Asness, Moskowitz & Pedersen, 2013). First, we compare the 3x3 cross-section combination portfolios to the average returns of the pure value strategy. We find that all cross-sectional combination portfolios outperform the zero-cost value portfolio (HML), with the exception of LxN. However, the pure value high B/M portfolio outperforms all the 3x3 cross-sectional portfolios. Focusing on the zero-cost portfolio (HML), we thereby find that investing in a 3x3 cross-sectional combination is more profitable than investing in a pure value strategy. On the contrary, this is not the case if one compares the 3x3 cross sectional portfolio with the results from investing in the pure value high B/M portfolio. Therefore, one cannot with certainty determine whether a 3x3 cross-sectional portfolio is a better investment than a pure value portfolio.

The fact that all the cross-sectional portfolios outperform the zero-cost value portfolio (HML), may suggest that a combination of value and momentum is in fact superior to a pure value strategy. However, the fact that the pure value high B/M portfolio outperforms all of the cross-sectional portfolios, reduces the strength of this argument, as one could generate even higher returns by simply investing in the highest B/M companies.

Second, we undertake the same comparison between the 3x3 cross-sectional portfolios to the pure momentum portfolio. We find all the loser and winner momentum sorts from the cross-sectional portfolios to outperform the zero-cost MOM3x3-portfolio. The neutral momentum sorts are the worst performers out of all the cross-sectional portfolios. In addition, these are the only cross-sectional portfolios not to outperform the zero-cost MOM3x3-portfolio. Further, we observe that the MOM3x3 winner portfolio outperforms all the cross-sectional portfolios.

As some, but not all of the cross-sectional portfolios, outperform zero-cost MOM3x3-portfolio, there is no strong indication that the combination of value and momentum is superior

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<sup>11</sup> This is the way we refer to the nine different portfolios, HxN meaning the high B/M and Neutral momentum cross-sectional portfolio, MxN meaning medium B/M and Neutral momentum, and so on.

to an individual momentum strategy. Further, the fact that the pure momentum winner portfolio outperforms all the cross-sectional portfolios, makes it even less conclusive that a combination is superior.

Out of all the 3x3 cross-sectional portfolios, we find HxW to be the best performer, yielding average monthly returns of 1,31 %. This is in compliance with what one would expect, as theory suggests that high B/M and past winners should both yield high future returns in the short-run (Fama & French, 2012; Jegadeesh & Titman, 1993). Based on this theory, one would further expect to observe monotonic return patterns within both value and momentum, meaning that the returns should be expected to increase from losers to winners, and from low to high B/M. When looking for monotonic patterns of value within each of the three momentum sorts, we observe indications of the existence of a value effect. The only exception is within the loser momentum sort, where the returns decrease from low B/M to medium B/M. Besides this exception, we observe a completely monotonic pattern of value within the three momentum sorts. These observations imply that there exists a value effect within the cross-sectional portfolios, reflecting what is expected according to theory.

Within the three value sorts, there is no monotonic patterns of momentum, implying no momentum effect within the value sorts. For the Low and Medium B/M value sorts, the momentum losers outperform both the momentum neutrals and winners. The only case where the momentum winners outperform the losers, is within the High B/M value sort, where the momentum winner also outperforms the momentum neutrals. We further note that the neutral momentum sorts consistently perform worse than the loser momentum sorts, which is the opposite of what theory would suggest.

However, theory also suggests a high negative correlation between value and momentum (Asness, Moskowitz, & Pedersen, 2013). One reason as to why we do not find the 3x3 cross-sectional portfolios to be superior to the pure value and pure momentum strategy, may be due to the weak correlation between the momentum and value strategy within this combination.



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## 3.4 Weighted combination portfolios

### 3.4.1 Methodology

In addition to test an approach where one invests in portfolios formed on the cross-section of sorts on value and momentum, we test an approach where one invests in a weighted combination of the two strategies.

First of all, we examine whether this approach can yield positive returns in excess of what obtained by the two strategies individually. Further, we examine if this can work as a hedge against momentum crashes, which in our study seem to occur in states of above average market volatility, and when the market rebounds after a long-lasting crash/bear market<sup>1213</sup>. This is consistent with the findings of Asness, Moskowitz, and Pedersen (2013). They explain this by the fact that the portfolio of past losers, which are to be shorted in the momentum strategy, starts outperforming the portfolio of past winners, and thus yielding a negative return. Since the crashes are at least somewhat predictable, it should also be possible to hedge against them. To hedge against these crashes, we propose to invest in a portfolio consisting of a weighted combination of a momentum and value portfolio. To investigate whether this hedge has the desired effect, we test how portfolios constructed by different weightings of our MOM3x3-portfolio and value portfolio hold up against different crashes. The crashes we investigate are two different bear markets, the following momentum crashes, and during the whole sample period<sup>14</sup>.

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<sup>12</sup> We find the market returns standard deviation to be 99 % and 24 % above the average market returns standard deviation for our two momentum crashes respectively. The standard deviations are measured from six months before the momentum crash occurs to the month the momentum crash occurs. We further find both momentum crashes to occur in periods when the market begins to rebound after two long-lasting bear markets.

<sup>13</sup> From here on out, we will refer to these periods as bear markets, but we emphasize that it refers to both crashes and bear markets.

<sup>14</sup> The first bear market is a bear market lasting from March 2000 to March 2003 (corresponding with the dotcom-crisis of 2000, with an extended bear market), hereafter referred to as Bear Market 1. The second is the financial crisis of 2007 (in our data sample, lasting from July 2007 to February 2009), hereafter referred to as Bear Market 2. Momentum crash 1 last from October 2002 to September 2003, Momentum crash 2 last from January 2008 to June 2009. The bear markets and momentum

We construct five different weighted combination portfolios, by weighting momentum (MOM3x3-strategy) and value differently in each combination portfolio. Three portfolios are constructed with predetermined weights (50/50, 75/25, 25/75), one portfolio is constructed by optimizing the portfolio's Sharpe-ratio for the whole period (Sharpe portfolio), and the last portfolio is constructed by minimizing the variance of the portfolio for the entire period (MinVariance portfolio). The two latter portfolios are constructed using Excel's Data-analysis solver-function, with the whole sample period's Sharpe ratio and variance as the optimizing variables, respectively. The weight on the momentum portfolio,  $w$ , is used as the changing variable in order to conduct the aforementioned optimization<sup>15</sup>. The optimal weights,  $w$ , we end up with is 62.17 % for the Sharpe-portfolio and 59,6 % for the MinVariance portfolio. All of these weights are held constant for each portfolio for the remainder of the process testing against the different bear markets and momentum crashes. After constructing these portfolios, we test their performance measured in average monthly returns, reinvested returns and Sharpe ratio<sup>16 17</sup>.

### 3.4.2 Results

We compare the performance of the weighted combination portfolios against the performance of the pure momentum and value portfolios for the entire sample period, as well as during the different bear markets and momentum crashes we investigate. Further, to investigate whether the weighted combination portfolios actually served as the desired hedge, we test how these portfolios performs during these periods.

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crashes are somewhat overlapping. This is due to the fact that momentum crashes occur when the market starts to rebound after the bear markets, and it is difficult to define exactly when a bear market starts to rebound and when it ends with precision.

<sup>15</sup> We note that the weight on the value portfolio equals  $1 - w$ .

<sup>16</sup> Reinvested returns are what you end up with by investing \$1 at the start of the period, and reinvest earnings each month.

<sup>17</sup> In cases where the Sharpe-ratio is negative, due to negative excess returns, we have adjusted the ratio to capture the rank of the portfolios, by adding an exponent of -0,1 to the denominator. This is an adjustment of Israelsen's modification to the Sharpe ratio, as referred to by Mageira (2010).

From Table 6, we see that all of the portfolios perform better than the market, in all measures, during both of the market crashes<sup>18</sup>. During Bear Market 1, the pure value portfolio is the top performer in all three measurements, while during Bear Market 2, all of the combination portfolios outperform both the pure momentum and value portfolio in reinvested returns. In addition, measured in Sharpe ratio, two of the combination portfolios (the Sharpe- and 75/25-portfolio) outperform both the pure momentum and pure value portfolio during Bear Market 2. We find all average returns for the combination portfolios being statistically significant, when measured over the entire sample period.

Thereafter, we investigate how all of these portfolios perform during the succeeding momentum crashes. We find that the pure value portfolio outperforms all of the weighted combination-portfolios during these crashes. However, all of the combination portfolios outperform the pure momentum portfolio (all of these findings are for all three measurements). Not surprisingly, the combination portfolios with the most weight on value are the best performers within the combination group.

#### **Table 6: Performance measures, weighted combinations of value and momentum**

The table presents the average monthly returns in percent, reinvested returns (what you end up with if you invest \$1 at the beginning of the period) and the Sharpe ratio. These measures are presented for one pure value and one pure momentum portfolio, in addition to five portfolios formed by weighted combinations of these two portfolios. Each of the five portfolios use different weightings. The MOM3x3-portfolio is the zero-cost momentum portfolio, with 3-months formation- and holding periods. The Value-portfolio is the zero-cost value-portfolio, formed in June year  $t$  based on book-to-market values from the December year  $t-1$ . Three of the five combination portfolios have predetermined weights of 25 %, 50 %, and 75 % on the pure momentum portfolio (referred to as 25/75, 50/50 and 75/25 respectively). One combination portfolio has weights determined by maximizing the Sharpe ratio (referred to as *Sharpe portfolio*), and one combination portfolio has weights determined by minimizing the variance (referred to as *MinVariance portfolio*). The average returns, reinvested returns and Sharpe ratios are measured over five periods; *Bear Market 1* from March 2002 to March 2003, *Bear Market 2* from July 2007 to February 2009, *Momentum crash 1* from October 2002 to September 2003, *momentum crash 2* from January 2008 to June 2009 and the whole sample period from January 1989 to June 2016.

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<sup>18</sup> These measures for the market are the following. Market Crisis 1: Avg. monthly returns: -1,03%, Reinvested returns: 0,63, Sharpe ratio: -0,01. Market Crisis 2: Avg. monthly returns: -2,58%, Reinvested returns: 0,57, Sharpe ratio: -0,02.

Portfolio	Period					t-statistics
	Bear Market 1	Bear Market 2	Mom crash 1	Mom crash 2	1989 - 2016	
<b>MOM3x3</b>						
Average returns	0,66	1,18	-4,53	-1,37	0,71	2,40
Reinvested returns	1,07	1,24	0,54	0,77	6,34	
Sharpe ratio	0,01	0,16	-0,04	-0,01	0,12	
<b>Value</b>						
Average returns	4,07	1,37	-2,53	1,75	0,66	0,92
Reinvested returns	3,81	1,24	0,71	1,28	4,70	
Sharpe ratio	0,39	0,10	-0,02	0,15	0,09	
<b>50/50</b>						
Average returns	2,36	1,27	-3,53	0,19	0,68	2,77
Reinvested returns	2,06	1,26	0,63	1,01	6,85	
Sharpe ratio	0,20	0,15	-0,03	0,00	0,13	
<b>75/25</b>						
Average returns	1,51	1,23	-4,03	-0,59	0,70	2,76
Reinvested returns	1,50	1,26	0,58	0,88	6,97	
Sharpe ratio	0,10	0,17	-0,04	-0,01	0,13	
<b>25/75</b>						
Average returns	3,21	1,32	-3,03	0,97	0,67	2,39
Reinvested returns	2,82	1,25	0,67	1,14	6,01	
Sharpe ratio	0,30	0,12	-0,03	0,09	0,11	
<b>Sharpe</b>						
Average returns	1,95	1,25	-3,77	-0,19	0,69	2,83
Reinvested returns	1,77	1,26	0,61	0,95	7,01	
Sharpe ratio	0,15	0,16	-0,03	0,00	0,14	
<b>Min. variance</b>						
Average returns	2,03	1,26	-3,72	-0,11	0,69	2,82
Reinvested returns	2,85	1,26	0,61	0,96	6,99	
Sharpe ratio	0,16	0,16	-0,03	0,00	0,14	

The fact that all the combination-portfolios outperform the worst performer within each of the crashes (i.e. in market crashes, they beat the market, and in momentum crashes they beat the pure momentum portfolio), suggests that a weighted combination may serve as a good hedge against such crashes in the Nordic equity market. Further, measured in reinvested returns and Sharpe-ratio, all of the weighted combination portfolios outperform the pure value portfolio. In addition, four out of the five combination portfolios outperform the pure momentum portfolio in the same measures. The only combination portfolio not to outperform the pure momentum portfolio, is the 25/75-portfolio.

As mentioned above, Daniel and Moskowitz (2016) state that momentum crashes are predictable, and it should thereby be possible to hedge against them. To test how well a combination portfolio serves as hedge against the momentum crashes, we switch from the zero-cost MOM3x3-portfolio to a 50/50 weighted combination portfolio at the start of the two

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crashes<sup>19</sup>. Even though momentum crashes may be somewhat predictable, this requires an assumption that one would be able to perfectly time the momentum crashes, which is an unrealistic assumption. However, in our study the purpose is not to find the hedge which is the most feasible in practice, but rather to test whether such a hedge would be possible in theory. We find that over the entire sample period, by switching from a pure momentum strategy to the 50/50 weighted combination portfolio during the two momentum crashes, all measurements improve. Average monthly returns increase by 0,12 percentage points, reinvested returns increase by 52,6 % and Sharpe ratio increases by 21,9 %. These findings suggest that a weighted combination of value and momentum may serve as a good hedge against momentum crashes, at least if it is possible to time them. For the remainder of this paper, we will refer to the strategy where one switches from the MOM3x3-portfolio to a 50/50 weighted combination of the MOM3x3-portfolio and HML, as the Hedge strategy.

Based on the above findings, we see that in addition to performing well during our entire sample period, all of the five weighted combination portfolios perform quite well in bad times (i.e. in market crashes). Further, they all serve as a hedge against momentum crashes, as they do not generate losses as large as the pure momentum portfolio does. The best hedge is obtained by timing the momentum crashes, and switching from a pure momentum strategy to a weighted combination during these crashes.

### 3.5 Testing possible explanations of value and momentum

Returns obtained by following a value or momentum strategy can be explained by other factors than successful portfolio management. We test if the returns obtained by our value and momentum strategies can be explained by other such factors, or if they are in fact a result of successful choice of investment strategy.

Fama and French (1993) propose a three-factor model where they adjust for possible explanations for excess return on stock investments. Fama and French (1993) use size and

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<sup>19</sup> The 50/50-portfolio is selected as an example, not for any specific reason. Choosing for example the 25/75-portfolio would yield even better results.

book-to-market factors in addition to the market factor (CAPM) in their factor asset pricing model:

$$(1) r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{M,t} - r_{f,t}) + s_i\text{SMB}_t + h_i\text{HML}_t + \varepsilon_{i,t}$$

The left hand-side represents the return obtained by the portfolio in excess of the risk-free rate, where  $r_{i,t}$  is the return on portfolio  $i$  for month  $t$  and  $r_{f,t}$  is the risk-free rate. In our study, the risk-free rate is the Norwegian monthly rates taken from Ødegaard's website (Ødegaard, 2017b). The risk premiums are represented on the right hand-side. These should according to Fama and French (1993) explain the excess returns obtained by investing in portfolios other than the market portfolio. The market return,  $r_{M,t}$ , is the return obtained by holding a value-weighted portfolio of the entire Nordic stock market. The correlation of an investor's portfolio with the market,  $\beta_i$  represents the measure of market risk, which an investor should be compensated for.  $\text{SMB}_t$  represents the excess return obtained as compensation for the additional risk associated with loadings on small firms.  $\text{HML}_t$  is the return from value stocks minus growth stocks, and the objective is to compensate the investor for the additional risk associated with investing in value stocks. The last factor alpha,  $\alpha_i$ , is the abnormal average return left unexplained by a benchmark. This abnormal return is what we want to test if still exists after correcting for risk associated with the mentioned factors. The regression residual,  $\varepsilon_i$  represents everything that cannot be explained by the model.

In addition, Carhart (1997) propose an additional asset pricing factor as an attempt to capture return obtained as compensation for additional risk associated with momentum investing:

$$(2) r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{M,t} - r_{f,t}) + s_i\text{SMB}_t + h_i\text{HML}_t + p_{i,t}\text{PR1YR}_t + \varepsilon_{i,t}$$

However, Kenneth French (French, u.d.) presents an alternative momentum factor  $\text{UMD}_t$  to the one introduced by Carhart (1997). We use the  $\text{UMD}_t$  factor. The reason is that we want to have as similar method as possible to Fama and French (1993) given that the other asset pricing factors, as well as the value portfolio, is created following their methodology.

$$(3) r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{M,t} - r_{f,t}) + s_i\text{SMB}_t + h_i\text{HML}_t + p_{i,t}\text{UMD}_t + \varepsilon_{i,t}$$

We test if the market risk premium, as well as size, value, and momentum as risk proxies, can explain the returns obtained by investing in portfolios following a momentum or value strategy. If the strategies we examine generate higher returns because of the risk of investing

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in the market, small firms, value firms, or momentum stocks, this could be an indication that the returns are just compensation for risk. However, Jegadeesh and Titman (1993) find that size as a risk factor cannot explain the entire momentum profits. Inspired by their results, we wish to prove that an alpha exists after correcting for the additional risk premiums. However, we note that the existence of an alpha does not automatically imply market inefficiency. It might be compensation for a risk factor not present in the asset pricing model we use.

### 3.5.1 Methodology

We regress the asset pricing factors on the momentum and value portfolios created. However, we choose to only focus on the MOM3x3-strategy. This is due to the limited time given to perform our analysis. Also, we find it sufficient to look at two strategies in order to achieve the purpose of the regressions. The purpose is to see if an excess return,  $\alpha_i$ (alpha), still exists after correcting for the excess return an investor obtain as compensation for the extra risk accompanying different asset factors. Regressions are conducted in Stata, first by using Fama and French (1993) three factor model. Thereafter we include the additional momentum factor created by Kenneth French (French, u.d.).

To test whether the excess return can be explained by portfolios exposure to risk, and not due to successful active portfolio investment, we first construct the asset pricing factors. The construction of the asset pricing factors is based on the method used by Fama and French (1993) and Ken French's web site (French, u.d.).

In order to correct for the return obtained by stocks due to the exposure to market risk, we construct the CAPM market factor " $r_M - r_f$ ". The market index  $r_M$  represents the return on the market portfolio, while  $r_f$  is the risk-free rate.

The market index  $r_M$  is constructed by creating a market portfolio consisting of all companies in our universe (the Nordic stock market), where all the companies are value-weighted within the portfolio by their market capitalization. The return of this value-weighted market portfolio represents the return you gain from the market, and thereby the market index  $r_M$ .

All the companies in our study have market values stated in local currencies. In order to value-weight all the companies within the market portfolio, based on each company's market capitalization, we need to convert all the market values into one common currency.

We convert the market values stated in local currency into UK for each date separately. This indicates each company's relative market capitalization. For the last day in each month  $t$ , by multiplying each firm's return,  $r_{i,t}$ , with its market capitalization,  $MC_{i,t}$  relative to the total market capitalization of the entire market,  $MC_{Mkt,t}$ , we get the value-weighted returns for each company. Summarizing these value-weighted returns for each date, yields the value-weighted monthly market returns:

For the last day in each month,  $t$ :

$$\sum_{i=1}^N (r_{i,t} * \frac{MC_{i,t}}{MC_{Mkt,t}})$$

where  $i = 1, 2, 3, \dots, N$  denotes each individual company.

The risk-free rate ( $r_f$ ) is taken from Ødegaard (2017b). This is the estimated one-month Norwegian risk-free rate over the entire time period examined in this paper, 1989 - 2016, estimated from government securities and NIBOR. We use the Norwegian risk-free rates as proxies for the entire Nordic stock market. We make this simplification based on the assumption that the Nordic countries operate with relatively similar risk-free rates, thus making the Norwegian risk-free rate a good proxy for a Nordic risk-free rate.

The methodology we use to create the two factors SMB and HML follows Fama and French (1993), while the methodology on how to create the momentum factor UMD is taken from Ken French's web site (French, u.d.).

Fama and French (1993) construct a SMB (small minus big) factor, which is the return on portfolios constructed by small cap stocks minus the return on portfolios constructed by big cap stocks. Size is considered an additional source of risk, and one have to adjust for this risk in order to confirm the existence of significant excess return (Bodie, Kane, & Marcus, 2014). The reasoning behind the HML (high minus low) factor, is the same as with the SMB factor. Here, however, one adjusts for the extra risk related to investing in value stocks.

In June of year  $t$ , all stocks are divided into two groups, small and big size capitalization stocks, using median market cap as breakpoint. After dividing the stocks into two groups, small and large cap stocks, these two groups are again sorted into three B/M groups based on B/M-values



in December year t-1. B/M breakpoints are the 30<sup>th</sup> and 70<sup>th</sup> percentile. For example, within the group of small cap stocks in year t, the ones with the lowest B/M value in December year t-1 are sorted as “small cap – low value stocks” for that particular year t.

**Figure 5: Construction of SMB and HML asset pricing factors**

This figure presents the 2x3 sorts on size and B/M used to construct the asset pricing factors SMB and HML. SL, SM, SH, BL, BM and BH, are the 2x3 sorts where S and B indicates small and big cap stocks, using the median market cap as breakpoint. L, M and H indicates Low, Medium and High B/M (bottom 30 %, middle 40 % and top 30 %). SMB is the average of the three small cap sorts minus the average of the three big cap sorts, while HML is the average of the two high B/M sorts minus the average of the two low B/M sorts.

	B/M Breakpoints		
Size	Low (L)	Medium (M)	High (H)
Small (S)	SL	SM	SH
Big (B)	BL	BM	BH

The SMB factor is then constructed by taking the average of the small cap portfolios minus the average of the big cap portfolios, while HML is constructed by taking the average of the high value stocks minus the low value stocks. This can be illustrated as follows:

$$\text{SMB} = \text{Average} (\text{SH} + \text{SN} + \text{SL}) - \text{Average} (\text{BH} + \text{BN} + \text{BL})$$

$$\text{HML} = \text{Average} (\text{SH} + \text{BH}) - \text{Average} (\text{SL} + \text{BL})$$

The performance of the factors SMB and HML is measured over the holding period extending from July year t to June year t+1. The procedure is repeated each year. However, as we only have data for December 1987 until December 2016, we start the first holding period in July 1988 and the last one ends in June 2016.

In addition, we include the UMD factor in our regression to examine whether adding a momentum factor will reduce the existence of an alpha,  $\alpha_i$ . Each month, stocks are divided into two groups of respectively big and small market cap stocks. Big stocks mean a firm is above the median market cap on the Nordic stock market at the end of the previous month. Similarly, small stocks are firms that lies below the median market cap. The portfolios are

constructed monthly over the entire sample period January 1989 to June 2016. Within each of the two groups sorted on size, stocks are again divided into three groups of low, medium and high past returns (losers, neutral and winners). In month  $k$ , stocks are sorted based on returns calculated from month  $k-12$  to  $k-2$ . Return breakpoints are the 30th and 70th percentile.

**Figure 6: Construction of UMD asset pricing factor**

This figure presents the 2x3 sorts on size and momentum used to construct the asset pricing factors UMD. SL, SM, SW, BL, BM and BW are the 2x3 sorts where S and B indicates small and big cap stocks, using the median market cap as breakpoint. L, N and W indicates Losers, Neutral and Winners (bottom 30 %, middle 40 % and top 30 % of past returns). UMD is the average of the two winner sorts minus the average of the two loser sorts.

Size	Losers (L)	Neutral (N)	Winners (W)
Small (S)	SL	SM	SW
Big (B)	BL	BM	BW

The UMD factor is then constructed as the average of the returns from the two high prior return portfolios (Winners) minus the average of the returns from the two low prior return portfolios (Losers):

$$\text{UMD} = \text{Average (BW + SW)} - \text{Average (BL + SL)}$$

For all asset pricing factors, companies that do not provide data for certain months within a given holding period are excluded from that exact holding period. For example, when constructing the SMB factor, we find that in the first holding period July 1988 to June 1989, the company BIK BOK “B” is placed in the small cap and low book-to-market portfolio. However, there is no available data for BOK BOK “B” from February 1989 until June 1989, so the company is therefore excluded from the entire holding period “July 1988 to June 1989”.

### 3.5.2 Value strategy regression results

We examine whether the positive returns generated from following a value strategy in the Nordic stock market, are in fact abnormal. This is the case if the returns remain positive after controlling for compensation for different risk factors. In Table 7, we present the abnormal

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excess returns for all deciles from our value strategy tested over the period January 1989 to June 2016, in addition to the zero-cost portfolio. Corresponding t-statistics, stating their statistical significance, are presented in a separate column.

We see from Panel A in Table 7 that all the decile portfolios yield negative alphas when using the three-factor model to conduct regressions. Further, the t-statistics indicate that all the alphas are statistically significant. The fact that the alphas are statistically significant and negative, indicates that the positive returns observed in Table 2 are not the result of a successful choice of investment strategy, but rather a compensation for risk exposures. However, the alpha of the zero-cost portfolio (HML) is positive, yielding abnormal returns of 0,28 %. This means that a strategy where one goes long in the high B/M portfolio and short in the low B/M portfolio, generates abnormal returns. Further, we note that it seems to be the underperformance of the low B/M portfolio that drives this abnormal return, while the underperformance of the high B/M portfolio reduce the premium. This is also consistent with what we found earlier in Table 2. However, the t-statistic of 1,25 indicates that this alpha is not statistically significant, making the discovery of a positive alpha less credible.

From Panel B Table 7, we see that when we include the UMD asset pricing factor, the returns of all the decile portfolios becomes slightly higher, while still remaining negative. Furthermore, all the corresponding t-statistics are reduced, and the high B/M portfolio is no longer statistically significant. We note that the high B/M portfolio's alpha increases more than the alpha of the low B/M portfolio. Thus, the positive alpha of the zero-cost portfolio becomes even higher than what we observe in Panel A, now yielding abnormal returns of 0,39 %. The underperformance of the low B/M portfolio still appears to be the driver of the abnormal returns. However, the high B/M portfolio does not seem to reduce this premium in any significant matter. The t-statistic of the zero-cost portfolio increases to 1,73 when we include the UMD factor, but is still not statically significant.

The average  $R^2$  in both models is about 71 %. Further, both models' alphas have similar average standard errors of 0,17 %. We also note that the coefficients of the explanatory variables on average becomes slightly more significant when including the UMD factor, though all of them are significant in both models. In addition, when adding the UMD factor, the alpha of the zero-cost portfolio becomes closer to being significant, though still not significant. Despite these minor increases in t-statistics, both asset pricing models seem to provide an equally realistic representation of the performance of exploiting a value strategy.

**Table 7: Alphas, portfolios formed on B/M**

This table presents the alphas (intercepts),  $\alpha_i$ , obtained by conducting regressions on the excess returns from decile portfolios formed on B/M-values, as well as a zero-cost portfolio (HML). The decile portfolios are constructed by allocating the total selection of stocks into deciles at the end of June year  $t$  based on book-to-market values from December year  $t-1$ . Alphas are obtained by conducting two different regressions where the first is presented in Panel A; regressing the excess returns  $r_i - r_f$  obtained by each of the decile portfolios using the three-factor model. The second regression is presented in Panel B: adding the UMD asset pricing factor to the three-factor model. The alpha's t-statistics are presented in a separate column. The regressions are conducted for the period January 1989 to June 2016.

	<b>Panel A</b>		<b>Panel B</b>	
	Alpha	t-statistic	Alpha	t-statistic
<b>Low</b>	-0,85	-4,94	-0,74	-4,29
<b>2</b>	-0,78	-5,15	-0,66	-4,37
<b>3</b>	-0,66	-4,54	-0,57	-3,91
<b>4</b>	-0,58	-3,68	-0,48	-2,98
<b>5</b>	-0,73	-4,76	-0,67	-4,27
<b>6</b>	-0,60	-3,82	-0,48	-3,04
<b>7</b>	-0,79	-3,75	-0,58	-2,77
<b>8</b>	-0,78	-4,74	-0,60	-3,68
<b>9</b>	-0,57	-3,45	-0,47	-2,79
<b>High</b>	-0,57	-2,84	-0,35	-1,79
<b>HML</b>	0,28	1,25	0,39	1,73

Further, when conducting regressions with the four-factor model, we examine the validity of our results by controlling for certain conditions. First, we filter companies by their market capitalization, using the 30<sup>th</sup> percentile as a breakpoint for each individual country. We do this to see whether the observed value premium is driven by small cap stocks. We find the zero-cost portfolio's alpha to improve marginally, while remaining insignificant. Thereafter, we examine whether value-weighting instead of equal-weighting the companies affect the abnormal returns, and we find abnormal returns to be decreased. However, the abnormal returns stay positive. Given that the results are not notably affected, neither by filtering on size nor value-weighting the stocks, this implies that the value premium is not remarkably driven by a size effect. We also find it interesting to test whether the abnormal returns obtained by following a value strategy have changed over time, and investigate this by testing for abnormal returns over two sub periods. The two sub periods are the period before and after the financial crisis of 2007. We find that the value premium has been higher in the sub period which

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succeeds the financial crisis, while it was weaker when we tested the period preceding the financial crisis. However, we still find positive alphas for both periods.

We find the certain conditions to affect the abnormal returns in varying degrees, however, the alphas obtained are consistently positive in all control tests. Thus, we find evidence of a persistent value premium in the Nordic stock market. However, we emphasize that this premium may in fact be compensation for additional risk factors not included in our asset pricing models.

Lastly, we examine how the value premium varies across the four countries constituting the Nordic stock market in this study. Here we find that the zero-cost portfolio obtains alphas of approximately 1 % in both Sweden and Finland, while the alpha is negative, albeit weakly so, in Norway and Denmark. Thereby, it seems like the observed value premium in the Nordic stock market is highly driven by Sweden and Finland. We find low correlations across countries, with correlations coefficients ranging from 0,12 to 0,25, which further supports this statement. We find the lowest correlation to be between Norway and Denmark, and the highest correlation to be between Sweden and Finland.

### 3.5.3 MOM3x3-strategy regression results

As with value, we examine whether the positive returns generated are in fact abnormal. We examine this by controlling for compensation for different risk factors. Presented in Table 8 are the alphas of the decile portfolios, as well as the zero-cost portfolio, obtained by regressing their returns against our two asset pricing models. Corresponding t-statistics are stated in a separate column.

Panel A Table 8 presents the alphas from the decile portfolios, as well as the zero-cost portfolio (WML). We find all decile portfolios to yield negative alphas when their excess returns are regressed using the three-factor model. With the exception of the winner portfolio, all of these alphas are statistically significant. The implication of negative and statistically significant alphas is that the returns obtained by the portfolios are a compensation for exposure to certain risk factors, rather than being the result of a successful investment strategy. The zero-cost portfolio (WML), however, yields an impressive abnormal return of 1,02 % monthly. In addition, the alpha of the zero-cost portfolio is statistically significant, making the discovery even more credible. Thus, the long-short momentum strategy seems to remain quite profitable, even after controlling for compensation for risk. The short-portfolio (losers) appears to drive

most of the abnormal returns for the zero-cost portfolio, while the long-portfolio (winners) seems to reduce the returns.

When including the UMD factor to the asset pricing model, we find that the returns from most of the decile portfolios increases, as shown in Panel B, Table 8. However, with the exception of the winner portfolio, they all remain negative. Furthermore, we note that most of the t-statistics are reduced, though the alphas remain statistically significant for the same decile portfolios as before. The increase in the loser portfolio's alpha makes the zero-cost portfolio less profitable, as the zero-cost portfolio requires one to short the loser portfolio. The opposite effect is true for the winner portfolio. Thereby, the larger increase in the alpha of the loser portfolio as compared to that of the winner portfolio, reduces the zero-cost portfolio's alpha to 0,47 %. In addition, the alpha is no longer statistically significant. Despite the increase in return, the loser portfolio's underperformance still appears to be the driver of the momentum premium. The alpha of the zero-cost portfolio is decreased by more than 50 % as compared to the alpha found using the three-factor model. However, it is not surprising that the returns decrease when we correct for compensation for risk associated with the same investment strategy we try to exploit. The existence of a positive alpha after we include the UMD factor is in fact quite notable. It means that even after we control for compensation for exposure to risk associated with momentum investing (as well as exposure to market risk and risk associated with size and value investing), the zero-cost MOM3x3-strategy yields abnormal returns. Thus, it may seem that the momentum premium cannot be explained solely as a risk premium. The validity of this finding is somewhat reduced, as the positive alpha is not statistically significant.

When we include the UMD factor in the regression, 7 of the 11 alphas becomes less significant. In addition, the alpha of the zero-cost portfolio becomes statistically insignificant. This could indicate that the model including the UMD factor is less credible. However, the average  $R^2$  increases from 68,6% to 72,9%, and the average standard error of the constants (alphas) decreases from 0,17 % to 0,16 % from the three to four factor model. This indicates that the asset pricing model including UMD provides a slightly more realistic representation of the performance of exploiting a momentum strategy.

**Table 8: Alphas, portfolios formed on past performance**

This table presents the alphas (intercepts),  $\alpha_i$ , obtained by conducting regressions on the excess returns from decile portfolios formed on past returns. The decile portfolios are constructed by allocating the total selection of stocks into deciles, within every month year  $t$ , based on their historical returns over the previous three months. These decile portfolios are then held for the following 3 months, using overlapping holding periods. We skip one month between the formation and holding period, as this is standard in momentum literature. Alphas are obtained by conducting two different regressions where the first is presented in Panel A; regressing the excess returns  $r_i - r_f$  obtained by each of the decile portfolios using the three-factor model. The second regression is presented in Panel B: adding the UMD asset pricing factor to the three-factor model. The alpha's t-statistics are presented in a separate column. The regressions are conducted for the period January 1989 to June 2016.

	Panel A		Panel B	
	Alpha	t-statistic	Alpha	t-statistic
<b>Losers</b>	-1,16	-4,14	-0,46	-2,09
<b>2</b>	-1,15	6,61	-0,78	-5,22
<b>3</b>	-0,95	-6,82	-0,73	-5,59
<b>4</b>	-0,57	-4,14	-0,44	-3,23
<b>5</b>	-0,47	-3,99	-0,41	-3,37
<b>6</b>	-0,57	-4,52	-0,50	-3,96
<b>7</b>	-0,53	-4,48	-0,55	-4,59
<b>8</b>	-0,43	-3,37	-0,48	-3,62
<b>9</b>	-0,37	-2,52	-0,42	-2,85
<b>Winners</b>	-0,14	-0,52	0,01	0,03
<b>WML</b>	1,02	3,53	0,47	1,82

As with value, when conducting regressions with the four-factor model, we examine the validity of our results by controlling for certain conditions. When sorting out companies in the bottom 30<sup>th</sup> percentile for each country, we find that the abnormal returns of the zero-cost momentum portfolio are reduced by an average of 0,14 percentage point. This indicates that at least part of the momentum premium is driven by small cap stocks. However, as the alpha remains positive, it appears that the small cap stocks cannot explain all of the observed premium. Further, we find that when we value-weight the companies, all of the premium disappears as the alpha turns slightly negative. This further supports the finding that the momentum premium is partially driven by small cap stocks. When examining the performance of momentum in the two sub periods, we find positive alphas for both periods. The momentum premium was highest in the first sub period, which preceded the financial crisis, while it has been slightly reduced in the second sub period. For momentum, we also examine whether the use of non-overlapping holding periods affect the obtained alphas. When using non-

overlapping holding periods, we find a statistically significant alpha of 1.03 %, an increase of 0,56 percentage points. However, we cannot with determination say that non-overlapping holding periods are superior to overlapping holding periods, solely based on this. As briefly discussed in the methodology section, the improvement in alpha may just as well be the result of luck, if we consistently choose stocks in months where prices are low. The observed momentum premium seems to be moderately persistent, however, it appears that small cap stocks drive parts of this premium.

When we test for momentum across the four countries, we find consistent positive abnormal returns. Sweden has the by far highest abnormal returns. The alpha we find for Sweden is at 1,02 %, which is about 2.5 times higher than the alpha find for Norway, which is the second highest country-individual alpha, at 0,4 %. For Finland and Denmark, we find alphas of 0,22 % and 0,15 % respectively. Momentum is weakly correlated across countries, with correlation coefficients ranging from 0,08 to 0,25. We find the lowest correlation between Finland and Denmark, and the highest correlation between Sweden and Finland.

#### **3.5.4 3x3 cross-sectional portfolios regression results**

Presented in Table 9 are the alphas obtained by the 3x3 cross-sectional portfolios when regressed using our two asset pricing models. We examine whether the positive returns obtained by the strategy are in fact abnormal, after controlling for compensation for different risk factors, and whether the combination is in fact superior to the pure value and pure momentum strategy. Corresponding t-statistics are stated in a separate column.

The alphas presented in Panel A Table 9 are obtained after regressing the 3x3 cross-sectional excess returns using the three-factor model. We find all nine alphas to be negative and statistically significant. When we only take into account the monthly average returns, the best performer is the HxW, as stated in Table 5. As we can see from Panel A, after controlling for exposure to different risk factors, this is now the second worst performer, yielding an abnormal negative return of -0,86 %, only slightly better than the LxN portfolio which yields -0,9 %. The best performer after controlling for the exposure to risk factors, is the MxN portfolio, which yields returns of -0,54 %. When comparing the alphas to those obtained by the pure value and pure momentum strategy, we find that neither of the cross-sectional portfolio alphas outperform the ones of the zero-cost portfolios.



**Table 9: Alphas, 3x3 cross-section of value and momentum**

This table presents the alphas (intercepts),  $\alpha_i$ , obtained by conducting regressions on the excess returns of nine *B/M-momentum* portfolios. The portfolios are formed at the end of June year  $t$ , using the 30<sup>th</sup> and the 70<sup>th</sup> percentile of aggregate B/M-values and past returns respectively as breakpoints. The B/M-values are calculated using book values and market values from the end of December year  $t-1$ , while past returns are measured from June of year  $t-1$  to May of year  $t$ . We skip one month between the formation and holding period, as this is standard in momentum literature. The 3x3 sorts on B/M and momentum produce nine equal-weighted portfolios, which are held from July year  $t$  to June year  $t+1$ . Alphas are obtained by conducting two different regressions were the first is presented in Panel A: regressing the excess returns  $r_i - r_f$  obtained by each of the decile portfolios using the three-factor model. The second regression is presented in Panel B: adding the UMD asset pricing factor to the three-factor model. The alpha's t-statistics are presented in a separate column. The regressions are conducted for the period January 1989 to June 2016.

	<b>Panel A</b>		<b>Panel B</b>	
	Alpha	t-statistic	Alpha	t-statistic
<b>LxL</b>	-0,63	-4,09	-0,51	-3,27
<b>LxN</b>	-0,90	-6,83	-0,86	-6,40
<b>LxW</b>	-0,77	-4,71	-0,63	-3,85
<b>MxL</b>	-0,62	-3,74	-0,51	-3,04
<b>MxN</b>	-0,54	-4,34	-0,52	-4,08
<b>MxW</b>	-0,70	-4,00	-0,61	-3,43
<b>HxL</b>	-0,68	-4,08	-0,45	-2,82
<b>HxN</b>	-0,63	-4,06	-0,56	-3,58
<b>HxW</b>	-0,86	-3,48	-0,49	2,11

From Panel B in Table 9, we see that when we include the UMD factor the alphas remain negative, however all of them have increased. Even though all of the alphas are increased, the zero-cost portfolios of the pure value and pure momentum strategy still outperforms all of the 3x3 cross-sectional portfolios. All of the t-statistics are reduced, however, all alphas are still significant.

We find no indications that the cross-sectional combination is superior to the pure value or pure momentum strategy. One reason as to why we do not find the 3x3 cross-sectional portfolios to outperform the pure value and pure momentum strategy may be due to the weak correlation between the value and momentum strategy used in the 3x3 cross-sectional portfolios.

Another possible explanation for why the 3x3 cross-sectional portfolios are inferior to the pure value and pure momentum strategy, may be that not all of our cross-sectional portfolios are well enough diversified. The lowest number of stocks in the 3x3 cross-sectional portfolios is 16 different stocks, within one holding period. According to Ødegaard (2017c) one should have at least 10 stocks to get a “reasonably well-diversified” portfolio on Oslo Stock Exchange. We find it reasonable to assume that this number is pretty close for the Nordic market as well. Thus, we should have enough companies for a “reasonably well-diversified” portfolio, but if the companies in each portfolio are highly correlated it may not be that diversified after all. This may be the case if one portfolios hold both “A” and “B” stocks for the same company, or parent companies and associated subsidiaries.

### 3.5.5 Weighted combination portfolios regression results

The last strategies we test in order to examine whether the positive returns obtained are in fact abnormal, after correcting for exposure to different risk factors, are the weighted combination strategies. Further, we want to examine whether the combinations are in fact superior to the pure value and pure momentum strategy. In Table 10 we present the alphas obtained by three of the weighted combination portfolios when regressed using our two asset pricing models. Corresponding t-statistics are stated in a separate column.

From Table 10 Panel A, we see that all the returns obtained by the portfolios are abnormal, as they remain positive and statistically significant after controlling for exposure to the three risk factors. Not surprisingly, the Hedge portfolio is the portfolio which yields the highest abnormal returns, with a quite impressive 1,06 % monthly. From Panel B Table 10, we see that when we also include the UMD factor, all of the alphas and t-statistics are reduced, yet they stay positive and statistically significant. The ranking of the three different portfolios also remain constant, with the Hedge portfolio yielding the highest abnormal return, now at 0,57 %.

Given that the hedge portfolio is a portfolio where one switch from a pure momentum strategy, to a 50/50 combination of value and momentum when foreseeing a momentum crash, this portfolio naturally outperforms the pure momentum portfolio. We find that the alpha obtained by the Hedge portfolio is 0,04 percentage points above the alpha obtained by the zero-cost MOM3x3-portfolio (WML) when controlling for three risk factors. Further, when also correcting for the UMD factor, the alpha obtained by the MOM3x3-portfolio becomes

statistically insignificant, while the alpha of the Hedge portfolio remains significant. In addition, the Hedge portfolio again generates a higher alpha than the pure momentum strategy. However, the pure MOM3x3-portfolio outperforms both the 50/50 weighted combination and the Sharpe-portfolio after both regressions.

**Table 10: Alphas, weighted combination of value and momentum**

This table presents the alphas (intercepts),  $\alpha_i$ , obtained by conducting regressions on the excess returns of three portfolios formed as the weighted combinations of a pure value- and a pure momentum portfolio. The pure value portfolio (HML) is constructed as follows; At the end of June year  $t$ , stocks are allocated to ten deciles based on their book-to-market value. These decile portfolios are then held for the following 12 months. The  $B/M$ -values are calculated using book values and market values from the end of December year  $t-1$ . HML is the zero-cost portfolio constructed of companies within the highest book-to-market values minus the ones with low book-to-market. The pure momentum portfolio (WML) is a MOM3x3-portfolio, meaning it is formed based on a 3-month formation period and a 3-month holding period. At the end of each formation period, stocks are allocated to deciles based on their cumulative returns over the formation period. These decile portfolios are then held for the following 3 months. WML is the zero-cost portfolio constructed of companies within the highest returns (winners) minus the ones with low returns (losers). The weighted combination portfolios have the following weights; *50/50* is formed by equal-weighting HML and WML. *Sharpe* is formed with weights determined by maximizing the portfolio's Sharpe-ratio. *Hedge* is the portfolio formed by switching from WML to 50/50 during two Momentum crashes. Alphas are obtained by conducting two different regressions were the first is presented in Panel A: regressing the excess returns  $r_i - r_f$  obtained by each of the decile portfolios using the three-factor model. The second regression is presented in Panel B: adding the UMD asset pricing factor to the three-factor model. The alpha's t-statistics are presented in a separate column. The regressions are conducted for the period January 1989 to June 2016.

	Panel A		Panel B	
	Alpha	t-statistic	Alpha	t-statistic
<b>50/50</b>	0,65	3,66	0,43	2,50
<b>Sharpe</b>	0,74	3,81	0,44	2,41
<b>Hedge</b>	1,06	3,76	0,57	2,20

Even though the results from the weighted combination portfolios are quite profitable, we want to emphasize that in their construction, we use the zero-cost MOM3x3-portfolio. However, this portfolio is positively correlated with the value zero-cost portfolio, with a correlation coefficient of 0,19. As the MOM12x12 zero-cost portfolio is negatively correlated with value, we might have found even more profitable returns using this portfolio in the weighted combination.

## 4. Problems with implementation in practice

This fourth section presents problems related to the implementation of the strategies in practice. As stated, the objective of this study is not to find the most realistically feasible investment strategy, but rather to find out if there exists a value and/or momentum premium on the Nordic stock market in theory. The effect of taxes and transaction costs will differ from investor to investor, as well as between countries, making it difficult to generalize their effect. Therefore, we have not taken taxes and transaction costs into account in this study. The implication of this is that the findings of positive returns in our study would have been reduced, making the strategies less profitable than stated. Particularly the momentum strategies would be affected by transaction costs, as these require highly frequent trading. Further, zero-cost portfolios in general will double the transaction costs, as they require both long and short positions.

Further, following our approach of investing in zero-cost portfolios, depends on the assumption that all stocks can be shorted. This is not always the case, and not confirmed possible for the stocks in our study. This implicates that the positive returns obtained in this study by following a value and momentum strategy is not a realistic result. The constructed zero-cost portfolios might be less profitable, given that some of the stocks driving the momentum and value premium are not possible to short. This implication is most relevant for the momentum strategy given the frequent transactions.

Moreover, the liquidity of the stocks is not considered in this study. Given that the strategies we study require frequent transactions, we assume that all stocks are perfectly liquid. This means that they can be traded at the desired time, without affecting their stock prices. This is, however, an unrealistic assumption. Several stocks in our sample may not be particularly liquid, meaning there is a high possibility an investor would not be able to trade these stocks at the beginning or end of a holding period. This could obviously affect the results in a notable way. The reason we have not taken this consideration into account, is that we want to keep as many observations as possible. By filtering our data sample by liquidity, we would decrease the amount of stocks.

Further, we assume that it is possible to perfectly time momentum crashes, and thus hedge against them. Even though these crashes are partially predictable, it is unrealistic to assume that a perfect timing is possible. The implication of this, is that in practice, our Hedge portfolio

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would perform worse than what we find in this study. How much worse depends on how well the momentum crashes can be timed.

## 5. Suggestions for further research

As stated, given the vast selection of constructed portfolios and limited time to conduct our study, we have made some limitations. Based on these limitations, and the results we find in our study, we have some recommendations for further research we find interesting to conduct.

As this study focus on what is profitable in theory, it would be interesting to further investigate how profitable the strategies would be in practice. Such a study would be difficult to conduct, as it would have to take account for all the factors discussed in the section above. However, it should be possible.

Further, for the momentum strategy one can conduct a more thorough analysis of the difference in returns obtained by using overlapping and non-overlapping portfolios. It would be of particular interest to see if the superior performance of non-overlapping holding periods may be credited to luck or if it actually yields higher returns. In addition, we focus on the MOM3x3-strategy, the best performing strategy in our study. This is not the same strategy that is proven most successful by Jegadeesh and Titman (1993). However, both strategies have the same holding period of 3 months. Therefore, we find it interesting to look closer at the relationship between the length of the holding period and the profitability.

One could also examine why value and momentum seem to be more positively correlated in the Nordic stock market than what Asness, Moskowitz, and Pedersen (2013) find for both U.S. and European stocks. Besides, it would be of interest to investigate why we find such low correlation for value and momentum across Nordic countries. This study may also be expanded by going further into the examination of whether the correlation between the two strategies may be exploited in a way yielding even better results by combining the two strategies.

Given that our analysis takes on the Nordic stock market as a whole, one can divide the Nordic stock market into the four countries separately. Thereafter, one can conduct an analysis examining whether constructing a portfolio by combining value and momentum where the two strategies performs differently within the four markets, can be exploited. For example, if value performs better in Finland while momentum performs better in Sweden, one can construct a portfolio by combining a pure value strategy in Finland and a pure momentum strategy in Sweden.

We just briefly touch upon the timing of momentum crashes in this study. Further research on this would therefore be of particular interest. Specifically, it would be interesting to investigate which other factors seem to predict these crashes, and exactly how well the crashes can possibly be timed. Moreover, it would be fascinating to further research how a more dynamic approach to the weighting of value and momentum on the Nordic stock market could be done when combining them, and how this would affect the profitability.

## 6. Conclusion

In this paper, we examine the profitability of value and momentum strategies on the Nordic stock market for the period January 1989 to June 2016. We conduct our study by constructing value and momentum portfolios, mainly following the methodology of Fama and French (1992), and Jegadeesh and Titman (1993). Further, we construct asset pricing factors following Fama and French (1993) and French's web page (French, u.d.). We find evidence of the existence of both a value and a momentum premium on the Nordic stock market. Apparently, neither of these premiums can be explained solely as risk premiums.

The zero-cost value portfolio (HML) provides positive average monthly returns of 0,66 %, however, not statistically significant. All decile portfolios for the value strategy provide statistically significant positive returns. These findings concur to some extent with the findings of Fama and French (1992), who study the value effect on the U.S. stock market. We further find a return pattern within the deciles, which to some extent is monotonic as average returns increase from one decile to the next, in six out of nine cases. When controlling for different risk factors, we find the average monthly returns of the HML portfolio to decrease, but remain positive at 0,28 % and 0,39 % when controlling for three and four risk factors respectively. This presence of abnormal returns implies that there in fact exist a value premium, which cannot be explained entirely by compensation for risk. The value premium seems to be driven by the low B/M (short) portfolio's underperformance relative to the market. However, the high B/M (long) portfolio also underperforms relative to the market, and thereby seems to reduce the premium. We also find that when we control for certain conditions, the abnormal returns stay positive, further supporting the existence of a value premium on the Nordic stock market. However, we note that neither of the abnormal returns are statistically significant, reducing the validity of our findings.

We further find evidence of a momentum premium on the Nordic stock market. This evidence is consistent with, though somewhat weaker than, the evidence found by Jegadeesh and Titman (1993) on the U.S. stock market. One result worth noting in our study, is that returns decrease as the holding and formation periods increase. Therefore, the momentum premium seems to be strongest for portfolios formed on short formation and holding periods, with the MOM3x3-strategy being the best performer. For all deciles constituting the MOM3x3-strategy, we find positive and statistically significant returns, with the winner portfolio yielding the highest monthly returns of 1,70 % with a t-statistic as high as 4.30. We further note a monotonic return



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pattern within the deciles, with returns in general increasing by the decile. We further note that the observed momentum premium seems to be mainly driven by the underperformance of the loser portfolio relative to the market, but that the overperformance of the winners relative to the market also seems to contribute. Moreover, the momentum premium we find on the Nordic stock market seemingly cannot be explained exclusively as a risk premium. When controlling for risk factors, the alpha of the zero-cost MOM3x3-portfolio remains positive, though not consistently statistically significant. When controlling for three risk factors, the zero-cost portfolio yields monthly abnormal returns as high as 1,02 %, and is found to be statistically significant with a t-statistic of 3.53. When including a fourth risk factor, the abnormal return decreases to 0.47 %, and is not statistically significant. The positive alpha obtained when controlling for four risk factors, is furthermore persistent when correcting for certain conditions. However, we find evidence of a size effect within momentum, where small cap stocks seem to be driving some of the premium.

In addition, we try to find the best possible combination of a value and momentum strategy; the portfolio that combines value and momentum in such a way that it performs better than each of them separately. This is motivated by Asness, Moskowitz and Pedersen (2013), who study value and momentum in combination, and find consistent and widespread evidence of value and momentum abnormal returns across all markets they study. Based on two different approaches, we construct combination portfolios; 3x3 cross-sectional portfolios following the methodology of Fama and French (1993), and weighted combinations of value and momentum, following the methodology of Asness, Moskowitz and Pedersen (2013). We find no evidence on the Nordic stock market that the 3x3 cross-sectional portfolio is superior to either value or momentum separately. This may however be due to the fact that the value and momentum strategies within this combination are positively correlated with each other, or because our portfolios are not sufficiently diversified. However, four out of five weighted combination portfolios outperform both a pure value and a pure momentum strategy, when measured in both reinvested returns and Sharpe-ratio. When measured in average monthly returns, the pure momentum outperforms all the weighted combination portfolios. Further, the alphas for the pure momentum portfolio is higher than for the weighted combination portfolios. Thus, the evidence of whether the weighted combination portfolios are superior to a pure value and a pure momentum strategy on the Nordic stock market, is ambiguous.

Despite no clear findings of a superior combination, we find another interesting aspect with weighted combinations of value and momentum to examine. According to Daniel and

Moskowitz (2016), one of the major concerns with momentum investment strategies is momentum crashes; periods where momentum strategies experience consecutive periods of negative returns. They find these momentum crashes to be partially predictable, and suggest a combination of value and momentum as a natural hedge against them. Motivated by this evidence, we test whether our combinations of value and momentum serve as a hedge against such crashes. We highlight two notable momentum crashes in our data, and find these to be at least partially predictable. They seem to occur in states of above average market volatility and when the market starts to rebound after a long-lasting bear market. When measuring the performance of the weighted combination portfolios during these momentum crashes, we find all of them to outperform a pure momentum strategy. We further construct a Hedge portfolio, where we switch from a pure momentum portfolio to a 50/50 weighted combination of value and momentum during the two momentum crashes. Measured over the entire sample period, we find this Hedge portfolio to outperform all other portfolios in our study. By switching during crashes, we find a substantial increase in all three measures; average monthly returns increase by 0,12 percentage points, reinvested returns increase by 52,6 % and Sharpe-ratio increases by 21,9 %. All these findings, strongly imply that a weighted combination between value and momentum serves as a good hedge against momentum crashes, particularly if it is possible to time them.

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## 7. Bibliography

- Ang, A. (2014). *Asset Management: A systematic approach to factor investing*. Oxford University Press.
- Asness, C. S., Frazzini, A., Isreal, R., & Moskowitz, T. J. (2014). Fact, Fiction and Momentum Investing. *The Journal of Portfolio Management*, 40(5), pp. 75-92.
- Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and Momentum Everywhere. *The Journal of Finance*, 68(3), pp. 929-985.
- Asness, C., & Frazzini, A. (2013). The devil in HML's details. *The Journal of Portfolio Management*, 39(4), 49-68.
- Asness, C., Frazzini, A., Israel, R., & Moskowitz, T. (2015). Fact, Fiction and Value investing. *The Journal of Portfolio Management*, 42(1), pp. 34-52.
- Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, 116(1), pp. 111-120.
- Bodie, Z., Kane, A., & Marcus, A. J. (2014). *Investments* (10th Global Edition ed.). Mc Graw Hill Education.
- Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1), pp. 57-92.
- Chen, N.-F., & Zhang, F. (1998). Risk and return of value stocks. *The Journal of Business*, 71(4), 501-535.
- Daniel, K., & Moskowitz, T. J. (2016). Momentum Crashes. *Journal of Financial Economics*, 122(2), pp. 221-247.
- Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of Finance*, 25(2), pp. 383-417.
- Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, 47(2), pp. 427-465.

- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), pp. 3-56.
- Fama, E. F., & French, K. R. (1998). Value versus Growth: The International Evidence. *The Journal of Finance*, 53(6), pp. 1975-1999.
- Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3), pp. 457-472.
- French, K. R. (n.d.). *Detail for Monthly Momentum Factor (Mom)* . Retrieved September 2017, from Dartmouth :  
[http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data\\_Library/det\\_mom\\_factor.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_mom_factor.html)
- Graham, B., & Dodd, D. (1934). *Security Analysis; Principles and Technique* (Second Edition ed.). McGraw-Hill Companies, Inc.
- Grobys, K. (2016). Another look at momentum crashes; momentum in the European Monetary Union . *Applied Economics* , 48(19), 1759-1766.
- Grossman, S. J., & Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review*, 70(3), pp. 393-408.
- Holberg Fondene. (2017, October 23). *Norden - Verdens beste investeringsunivers*. Retrieved from Holberg Fondene: <http://holbergfondene.no/home/norden-verdens-beste-investeringsunivers/>
- Jegadeesh, N. (1990). Evidence of predictable behaviour of security returns . *The Journal of Finance* , 45(3), 881-898.
- Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1), pp. 65-91.
- Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *The Journal of Finance*, 56(2), pp. 699-720.

- 
- Kuepper, J. (2017). *Guide to Investing in Nordic Countries*. Retrieved September 2017, from The balance: <https://www.thebalance.com/investing-guide-for-nordic-countries-4145416>
- Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *49*(5), pp. 1541-1578.
- Lo, A., & MacKinlay, C. A. (1990). When are Contrarian Profits Due to Stock Market Overreaction? . *The Review of Financial Studies* , 3(2), 175-205.
- Mageira, F. T. (2010). *Refining the Sharpe Ratio (Digest Summary)*. Retrieved September 2017, from CFA Digest: <https://www.cfapubs.org/doi/full/10.2469/dig.v40.n1.26>
- Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1), pp. 1-28.
- Rouwenhorst, K. G. (1998). International Momentum Strategies. *The Journal of Finance*, 53(1), pp. 267-284.
- Sagi, J. S., & Seasholes, M. S. (2007). Firm-specific attributes and the cross-section of momentum. *Journal of Financial Economics*, 84(2), pp. 389-434.
- Swinckels, L. (2004). Momentum investing: A survey. *Journal of Asset Management*, 5(2), pp. 120-143.
- Thomson Reuters. (n.d.). *Thomson Reuters Datastream*. Retrieved September 2017, from Thomson Reuters: <https://financial.thomsonreuters.com/en/products/tools-applications/trading-investment-tools/datastream-macroeconomic-analysis.html>
- Ødegaard, B. A. (2017a, September). *Empirics of the Oslo Stock Exchange: Asset Pricing Results*. Retrieved from Asset pricing data at OSE: [http://finance.bi.no/~bernt/financial\\_data/ose\\_asset\\_pricing\\_data/index.html](http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html)
- Ødegaard, B. A. (2017b). *Rf\_Monthly.txt*. Retrieved September 2017, from Asset pricing data at OSE: [http://finance.bi.no/~bernt/financial\\_data/ose\\_asset\\_pricing\\_data/index.html](http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html)

Ødegaard, B. A. (2017c). *Emprirics of the Oslo Stock Exchange: Basic Results*. Retrieved from Asset pricing data at OSE:  
[http://finance.bi.no/~bernt/financial\\_data/ose\\_asset\\_pricing\\_data/index.html](http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html)