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Momentum in Nordic Stock Returns

Industry Effects and Possible Strategy Improvements

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Abstract

This thesis documents a strong momentum effect in the Nordic stock market that does not seem to be explained by traditional risk factors or industry effects, in contrast to the findings of Moskowitz and Grinblatt (1999). Specifically, the winner-minus-loser (WML) strategy on both the individual stock- and industry level is significantly profitable alone, but only individual stock momentum remains significant when controlling for the other. This indicates that the individual stock WML strategy is not as poorly diversified as initially thought and that the identified industry dependency in the United States may be country-specific.

Having established that industry effects do not explain the momentum in Nordic stock returns, I explore momentum crashes as another possible explanation. The WML strategies are found to suffer from severe drawdowns in the sample period, making them unappealing to investors with reasonable risk-aversion. The explored combinations of momentum and value reduce crash risk and improve risk-adjusted returns significantly. In conclusion, the combination of momentum and value is a much bigger puzzle than either anomaly alone.

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1. Introduction

In recent years, the asset pricing anomaly of momentum investing has been researched extensively. An investor can earn significant abnormal returns when buying past winners and selling past losers. The robust success of this strategy has made way for funds specialized in exploiting the momentum effect systematically[1]. An increase in both knowledge and investors trying to exploit the anomaly is expected to reduce the strategy's profitability, yet the effect persists. Although there is little doubt regarding the anomaly's existence, more uncertainty is related to its source. Despite several attempts in explaining this pattern in stock returns, momentum remains one of the most central anomalies challenging the notion of efficient markets.

This thesis pursues industry effects as a possible explanation for the momentum anomaly in the Nordic stock market. Moskowitz and Grinblatt (1999) find that industry effects drive the momentum identified in U.S. stock returns. Consequently, an individual stock momentum strategy is poorly diversified, thus more susceptible to idiosyncratic risk as companies within industries tend to be more highly correlated. Motivated by Moskowitz and Grinblatt, I hypothesize that the abnormal returns of a winner-minus-loser (WML) strategy in the Nordic stock market are mainly driven by industry outperformance rather than individual stock characteristics. This trend has been somewhat visible in recent years, as companies within, for example, the technology and renewable energy industry tend to perform well, regardless of actual company performance.

As an additional contribution to existing research, this thesis aims to further explore possible ways to reduce the risk of crashes related to momentum investing. A pure-play momentum strategy has historically produced the highest Sharpe ratio compared to the market or a value strategy. However, as identified by Daniel and Moskowitz (2016), the strategy has also suffered from the worst crashes, making it unappealing to investors with reasonable risk aversion. Asness, Moskowitz, and Pedersen (2013) find the individual stock momentum strategy to be negatively correlated with the value strategy and, consequently, a simple weighted combination of the two strategies increases risk-adjusted returns significantly. These findings suggest that

[1] An example: AQR Capital Management with focus on factor investing, using the momentum effect, the value premium, and both combined in their strategies. Website: https://www.aqr.com/.

crash risk reductions and significant improvements to the plain momentum strategy are possible and available in the United States and lays the foundation for research out-of-sample.

Academic papers of which purpose is to explain return anomalies seem to be almost exclusively focusing on the U.S. stock market. Consequently, country-specific effects are often not accounted for within these types of analyses. Compared to the U.S. stock market, the Nordic countries are unexplored and under-researched, despite being young yet developed markets. This lack of coverage makes for an exciting research environment, and, consequently, the Nordic stock market will be the focus of this thesis. By exploring this market, I contribute by testing the findings of existing literature out-of-sample. Furthermore, besides the dot-com bubble and financial crisis, the sample period includes the Covid-19 pandemic, adding a new extreme market event to the research.

In short, this thesis will explore an investor's ability to generate significant abnormal returns by applying a pure-play momentum strategy in the Nordic stock market. Next, motivated by Moskowitz and Grinblatt (1999), I explore industry effects as the main driver behind the momentum in Nordic stock returns. Lastly, I combine momentum and value to deal with the risks relating to momentum investing and increase the risk-adjusted returns of the individual stock momentum strategy. This sums to the following research questions:

1. *How profitable is a plain momentum strategy in the Nordics, with what risk and drawdowns?*
2. *Can an industry momentum effect be identified in the Nordics, and to what degree is it the driver behind individual stock momentum?*
3. *Will the combination of value and momentum improve portfolio performance and reduce the risk of crashes?*

To the best of found knowledge, the Nordic stock market is unexplored regarding industry effects as a possible explanation for the momentum in stock returns. Additionally, the Nordics is a somewhat unexplored area within factor investing in general and, especially, multi-factor investing. Consequently, this thesis contributes to existing research by expanding the explored universe of industry momentum, introduce new strategies, and offer new insights on the topic. Furthermore, I challenge the notion that industry effects drive the momentum in stock returns.

The analysis is kept as simple as possible to avoid any data-mining issues. Only strategies that are implementable in real life are considered, meaning liquidity and short-selling opportunities will be discussed, although superficial. As the market analyzed differs from that of existing and comparable papers, the results will not be directly transferrable. However, I test the robustness of the results throughout the thesis by implementing the strategies on the U.S. stock market in addition to the Nordic.

This thesis is relevant and potentially valuable for academics and practitioners operating within the Nordic stock market. The results challenge existing findings on the topic, broadening our understanding of the momentum anomaly. Academics can use these findings to evaluate existing theoretical models further, and the combination strategies are directly relevant to practitioners and an exciting area of new research.

First, I study the individual stock momentum strategy by creating zero-cost winner-minus-loser (WML) portfolios per Jegadeesh and Titman (1993) for the Nordic region. The strategy with a 12-month formation period and 1-month holding period (12-1) yields a monthly mean excess return of 1.61% and a Sharpe ratio of 0.82, and is robust to traditional risk factors, with a three-factor alpha of 2.47% and a t-statistic of 8.29. In conclusion, the momentum effect is present and highly significant in the Nordic stock market.

Next, I explore industry effects as an explanation for the momentum observed in Nordic stock returns. Industry portfolios are created following the methodology of Moskowitz and Grinblatt (1999) but adjusted based on sample limitations and crucial findings by Asness, Porter, and Stevens (2000). As the available data in the Nordics is a lot thinner than in the United States, stocks can only be allocated to 11 sectors, compared to 20 industries in Moskowitz and Grinblatt and 48 industries in Asness et al. The difference in industry classification system decrease the comparability to earlier studies. I identify a strong industry momentum effect in the Nordic stock market. However, no evidence is found for the said effect being the main driver behind individual stock momentum. When controlling for industry momentum, the alpha of individual stock momentum remains high and significant. Furthermore, the momentum effect is still present within industries, although slightly weaker, indicating that industry effects can only offer a partial explanation, at best. When conducting the same analysis on the U.S. sample, it yields the opposite results, consistent with the findings of Moskowitz and Grinblatt (1999), which may indicate that country-specific effects drive the results.

As individual stock momentum in the Nordics is not driven by industry effects, thus not being as poorly diversified as initially thought, I must look elsewhere for rational explanations.

Consequently, I turn to the existence of momentum crashes. A severe crash for both industry- and individual stock momentum is observed over the sample period, indicating the presence of actual risks related to momentum investing. Furthermore, when looking the U.S. momentum strategy, the crash is even worse, indicating that these crashes are generally related to momentum investing, and not sample-specific effects.

Consequently, to mitigate the risk of crashes and deal with possible diversification issues, I explore the benefits of combining momentum and value. These strategies are found to be negatively correlated by 0.50 in the Nordics, similar to the U.S. and European findings of Asness et al. (2013), which makes a combination potentially attractive. Two combinations of momentum and value are created: a weighted combination inspired by Asness et al. (2013) and a simultaneous selection inspired by Fisher, Shah, and Titman (2016). The weighted combination significantly increases risk-adjusted returns, with a Sharpe ratio of 1.27. Additionally, the value crash of 2000 and the momentum crash of 2009 is eliminated in their entirety. The simultaneous selection approach also increases risk-adjusted returns significantly with a Sharpe ratio of 1.20. Moreover, this method also increases raw excess returns compared to the momentum strategy, making this the most profitable strategy in this thesis. Interestingly, the abnormal returns are found to be almost entirely produced by the short portfolio. As the original article of Fisher et al. (2016) looks at long-only strategies, these findings contribute with new insights.

In summary, I complement existing literature by challenging the findings of Moskowitz and Grinblatt (1999). The results suggest a strong momentum effect in the Nordic stock market, not explained by industries. In fact, I find the industry effects to be minor, and explanations must be sought elsewhere. Additionally, I find momentum crashes to be eliminated entirely when combining momentum with a traditional value strategy. The weighted combination increases risk-adjusted returns while only losing some profitability compared to momentum alone. The simultaneous selection approach increases both raw- and risk-adjusted returns while mitigating the risk of crashes, and, consequently, pose as a puzzle to explain.

This thesis is divided into six chapters. Chapter two covers relevant existing literature. Chapter three outlines the construction of the data set and presents the methodology and results of the momentum strategy. Chapter four explores industry momentum as the main driver behind momentum in Nordic stock returns. Chapter five presents the methodology and results of the combined strategies, and the thesis concludes in chapter six.

2. Literature Review

The momentum effect is one of the most thoroughly researched anomalies in academic finance, and even though factor investing is a relatively new phenomenon outside academia, momentum is already well-known and -utilized. In short, momentum investing is buying companies with high historical returns (winners) (traditionally looking at periods between 6 and 12 months) and selling companies with poor past performance (losers), resulting in a winner-minus-loser (WML) strategy (Jegadeesh & Titman, 1993).

The momentum effect was first discovered by Levy (1967). Although the term momentum remained unspoken, he identified superior returns in securities that had performed well historically relative to peers[2]. Furthermore, he explained the effect with risk, thus, not rejecting the random walk hypothesis of Fama (1965). The findings of Levy were later discarded by Jensen and Benington (1970) on the basis of selection bias. Following this, research on the momentum anomaly laid dormant as a result of the development of the well-known efficient market hypothesis and contrarian strategies proposed by De Bondt and Thaler (1985). The latter is the absolute opposite of the momentum strategy we are familiar with today, with the hypothesis that a strategy that buys past losers and sells past winners yield abnormal returns because of stock price overreaction.

The belief that security markets are efficient, meaning securities traded in the public market reflect all available information, was long the prevailing theory among academic economists. Fama (1970) found the evidence supporting the efficient markets model to be extensive and the contradictory evidence to be somewhat sparse. However, he emphasized that the matter is not closed, and many areas of research remained to be explored. This hypothesis, being true, would mean that there is no way for investors to achieve abnormal returns, and securities prices move in a *random walk*[3]. The idea behind *random walk* is that price changes in securities represent random departures from previous prices; thus, neither technical analysis, where investors use past prices to predict future prices nor fundamental analysis, where investors try to find undervalued companies, would achieve abnormal returns (Malkiel, 2003).

[2] The relativity of the performance is key, as the winning companies (the highest past performers) can still have negative returns as long as they outperform the other companies.
[3] The *random walk* term was popularized by Malkiel in 1973 when he published his well-known book, *A Random Walk Down Wall Street*.

Jegadeesh and Titman (1993) continue the work of Levy and find a WML strategy to yield abnormal returns, thus challenging both the efficient market hypothesis and the contrarian strategy proposed by De Bondt et al. The most thoroughly examined strategy, which selects stocks based on their past six-month returns and holds them for another six months, returned an annual average of 12.01%. Moreover, they find the returns to be positive in the first 12 months after the formation period, except for the first, while more extended periods reduce the strategy's profitability. They explain their findings with either market underreaction or WML-traders moving prices away from their long-run values, hence, overreaction.

Although the findings of Jegadeesh et al. have been well accepted, the explanations for the anomaly remain a widely debated topic. Most literature argues that the momentum effect is evidence of market inefficiencies and explain the anomaly with behavioral bias such as underreaction and investor overconfidence, herding, and anchoring-effects (Barberis, Shleifer, & Vishny, 1998; Daniel, Hirshleifer, & Subrahmanyam, 1998; Hong & Stein, 1999). Others believe in rational explanations and argue that the profitability of such a strategy is explained with increased risk or even data mining. Fama and French (1992), Conrad and Kaul (1998), and Asness (1997) point out that momentum is stronger among companies with considerable growth potential and risky cash flows. These companies then run the risk of said growth and cash flow not materializing. Jegadeesh and Titman (2001) discuss the different explanations, test the strategy out-of-sample, and find the evidence for the profitability of the momentum strategy to be highly robust and not a result of data mining. However, they emphasize that their results should be tempered with caution, as momentum profits sometimes are associated with reversals in the post-holding period and that behavioral models can only provide a partial explanation for the anomaly, at best.

Although there is little doubt regarding the theoretical profitability of a momentum strategy, many researchers point out the high turnover and that accounting for transaction costs will drastically reduce abnormal returns. Motivated by this, Moskowitz and Grinblatt (1999) explore industry momentum as the main driver behind the momentum effect. If industry effects explain the momentum in stock returns, industry momentum poses a more profitable and implementable strategy due to its lower turnover. They find a strong industry momentum effect in the United States, which does not appear to be explained by either individual stock momentum, microstructure effects, or cross-sectional dispersion in mean returns. Furthermore, the industry momentum effect seems to contribute substantially to the profitability of individual stock momentum and, except for the 12-month strategy, captures these effects almost entirely. They also find industry momentum trading strategies to be more profitable and implementable and generate as much or more profits from the long portfolio as the short portfolio. In contrast, the individual stock momentum profits are mainly generated from the short positions. Moreover, industry momentum remains strong for even the largest and most liquid stocks.

These findings suggest that an individual stock momentum strategy is not very well diversified, as the past winners and losers tend to be in the same industries, and they are more likely to be more highly correlated. As a result, the portfolios have higher idiosyncratic risk, and rational investors will limit their position in such a portfolio, hence, worsening (or at least not contributing to removing) the mispricing in these companies. This builds on the notion that there is some risk related to individual stock momentum investing, which either makes investors demand a higher return or prolongs the mispricing, as the strategy may be deemed sub-optimal to rational investors.

The work of Moskowitz and Grinblatt (1999) was subject to criticism in the succeeding years. Asness et al. (2000) concludes differently and point out two crucial differences in methodology that may explain the results. First, Moskowitz and Grinblatt use two-digit SIC codes yielding 20 industries compared to 48 in Asness et al. They argue that this methodology enables widely different companies to be included in the same industry. Second, they point out the importance of the one-month gap between the formation and holding period to avoid market-microstructure issues. Additionally, Grundy and Martin (2001) find the conclusions of Moskowitz and Grinblatt to be premature, although they conclude with industry effects having *some* impact on the existence of momentum in stock returns. This thesis contributes to the literature on industry momentum by exploring the phenomenon out-of-sample, both in a new market and over a new sample period.

Another possible risk associated with individual stock momentum is momentum crashes. Daniel and Moskowitz (2016) highlight two examples of such crashes in the U.S. equity market, the first being during the summer of 1932, where the past-loser portfolio returned 232%, and the past-winner portfolio returned only 32%, and the second being during the financial crisis, where the past losers rose by 163% and the past winners returned only 8%. They find the crashes to be fairly predictable, often occurring after more prolonged market downturns. They explain the phenomenon with the momentum strategy being long low-beta stocks that is likely to have performed better relative to the market during downturns and short high-beta stocks that have suffered the most. When the market recoils, the high-beta stocks are likely to perform better, resulting in a significant loss for the short portfolio. The momentum returns are negatively skewed, and rational investors are rewarded for carrying this risk. Another related risk-based explanation, proposed by Liu and Zhang (2008), is that past high performers are more prone to worsening outlooks, thus being punished more in bear markets relative to peers. In order to reduce the crash risk of the momentum strategy, Daniel and Moskowitz (2016) propose a volatility-managed strategy that significantly reduced the drawdowns and almost doubling the Sharpe ratio. By using bear market indicators and ex-ante volatility estimates, they create a dynamically weighted momentum strategy that significantly improves the plain momentum strategy in all studied markets, periods, and asset classes.

This thesis explores another way to reduce the damage from momentum crashes by introducing the value factor into the strategy. Benjamin Graham and David Dodd are by many thought of as the founders of the value investing strategy. Their book from 1934, *Security Analysis*, laid the foundation for value investors worldwide and introduced the term *margin of safety*, a term later used in Graham's very famous book from 1949, *The Intelligent Investor*. Their idea was to invest with a margin of safety, meaning that for them to invest, the price paid in the market must be lower than the intrinsic value of the stock (Graham, 2003). In order to quantify the value effect, plentiful research has identified several factors which purpose is to separate the cheap companies from the expensive.

In one of the most heavily quoted papers in academic finance, Fama and French (1992) identify the value premium and introduce the high-minus-low factor (HML). They find company size and the book-to-market equity ratio to have a substantial role in predicting average returns. Their results indicate that between 1963 and 1990, these two factors perform best in explaining the cross-section of expected stock returns in the United States, and when accounted for, the beta (β) of the capital asset pricing model (CAPM) loses its importance. However, this study looks at data from 1963 – 1990, which might not give the correct image, as value and growth cycles stretch over long periods. Petkova and Zhang (2005) analyze a more extended sample period and report an even higher growth to value spread, strengthening the probability of such an effect.

Extending this research further, Fama and French (1998) identify a significant value premium internationally between 1975 and 1995. More specifically, the value premium measured through equity book-to-market ratio is present in 12 out of 13 studied markets. They find the difference in returns between value and growth stocks to be 7.68% annually (t-statistic of 3.45) and test with other value measures, like earnings/price, cash flow/price, and dividend/price, all returning similar results. They explain the effect rationally with high book-to-market ratio companies having poor earning and growth prospects and, consequently, being undervalued in the market. Conversely, low book-to-market companies have high earning prospects and are therefore rewarded in the market. This explanation is similar to that of Fama and French (1992), where they argue that the book-to-market ratio captures financial distress (risk).

Asness, Moskowitz, and Pedersen (2013) analyze the momentum- and value premium in several markets and across asset classes and identify the anomalies in all explored markets and assets. Furthermore, they find the correlation of value and momentum to be -0.53 in U.S. equities and continue to explore the possibility of combining value and momentum in a weighted portfolio. As momentum and value strategies are negatively correlated, a combination of these is expected to be closer to the efficient frontier than each one individually. For U.S. stocks, the value strategy yields an annual return of 3.7% with a Sharpe ratio of 0.29, and the momentum strategy yields an annual return of 5.4% with a Sharpe ratio of 0.33. Subsequently, they create a 50/50 value/momentum portfolio, and even though the annual return is 4.6%, which is less than the momentum portfolio alone, the risk-adjusted returns have increased significantly, with a Sharpe ratio of 0.63. Their results indicate that a combination increases risk-adjusted returns.

In addition to the strategy used by Asness et al. (2013), other, more sophisticated strategies have been explored in recent years. Fisher et al. (2016) study the U.S. stock market from 1975 through 2013 and find that a strategy that simultaneously incorporates value and momentum in a long-only portfolio outperforms the simple weighted strategy proposed by Asness et al. (2013) while also achieving a higher Sharpe ratio than the market. Their study is on long-only strategies and takes transaction costs into account and is therefore not directly comparable to studies on zero-cost strategies. As a contribution to existing research, I explore the proposed strategy of Fisher et al. (2016) as a zero-cost strategy in the Nordic stock market.

This thesis contributes to the existing literature by expanding the research on industry effects as a driver for individual momentum. Furthermore, value is explored as a risk-mitigator, and a previously proposed long-only strategy is implemented as a zero-cost strategy. Lastly, the sample period includes a new crisis, the Covid-19 pandemic.

3. Individual Stock Momentum

A momentum strategy selects stocks based on past returns, creating a portfolio that is long the best-performing stocks (*winners*) and short the worst-performing stocks (*losers*). The short position finances the long positions, resulting in a zero-cost portfolio. The Nordic individual stock momentum strategy is studied following the methodology of Jegadeesh and Titman (1993), with some key changes motivated by Asness et al. (2013) and Novy-Marx (2012). The following chapters include the construction of the data material, the methodology behind the individual stock momentum strategy, and the results.

3.1 Data

The sample runs from January 31st, 1989 to January 31st, 2021, and contains listed companies traded in ordinary shares at Nordic stock exchanges. Monthly stock prices, accounting data, and industries are downloaded from DataStream. Data on interest rates are downloaded from multiple sources, as no single source covers the entire period, but Statistics Norway is the most significant contributor.

The Nordic stock universe includes Oslo Stock Exchange (OSE), OMX Nordic Exchange Copenhagen (CSE), Stockholm Stock Exchange (SSE), Helsinki Stock Exchange (HSE), and Iceland Stock Exchange (ICE). Iceland is excluded, as there is not enough available data in the required period.

DataStream offers data before January 1989, but sample size issues, especially in Denmark and Finland, restricts earlier analysis. Consequently, the sample period covers 33 years, comparable to previous research on this topic. Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999), and Asness et al. (2013) use data over 24, 32, and 39 years, respectively.

Existing literature on this topic is mainly centered around the United States or Europe. The Nordic region is a somewhat undiscovered area and makes for some of the originality of the thesis. To the best of found knowledge, industry momentum alone has never been analyzed in the Nordics, and the thesis will contribute to a deeper understanding of the subject.

The dataset comprises month-end adjusted close prices[4], market values (MV), and annual book values of all companies in the universe stated above[5]. These data are necessary to create both value and momentum portfolios. Furthermore, the companies are sorted into industry directly in DataStream, based on the industry classification system in all four markets[6], which results in 12 industries in total. As over 30% of the stocks lack industry classification, these are entered manually following the classification in Eikon. *Academic & Educational Services* only consist of one company (Academedia from Sweden) and is changed to *Consumer Cyclicals* as per Bloomberg. Thus, 11 industries remain.

Companies with no observations on one or more variables are removed from the data set, as these are unusable in the analysis. Delisted stocks are given NA values after the date of delisting. Both A and B shares are included in the sample, as these are both tradable companies. They will, however, increase the correlation between company returns.

The market index is constructed by value-weighting every company in the sample (the Nordics) in a single portfolio. In order to sort the stocks on size, market values are converted into EUR, as this is the only currency that covers the entire period. The returns are calculated in excess of the risk-free rate (Nibor 3-month). Inspired by Asness et al. (2013), every month, the smallest 50% of stocks are removed from the sample to ensure low transaction costs and liquidity, thus making the investible universe more practically feasible. Moreover, the accounting variable (book value) at fiscal year-end t - 1 is lagged six months, aligning with month-end June in year t, to ensure data availability following Fama and French (1992). Factor returns for the market, size, and value used in regression analysis are created for the Nordic stock market following the methodology of Fama and French (1993, 2015).

The finished sample consists of 138 034 observations divided between a total of 1104 companies. The minimum market value for inclusion was EUR 37.34 million in the last month of 1989 and EUR 77.77 million in January 2021. The sample consists of almost the entire market measured in market capitalization, even when removing 50% of the companies.

[4] Stock prices adjusted for dividends, stock splits, and rights offerings.
[5] DataStream variable codes: Adjusted Prices (P#T), Market Value (MV), and Book Value (WC03501).
[6] Industry classification system: Thomson Reuters Business Classification (TRBC). Consists of 4 levels, and the top level is used: overall economic sector consisting of 12 sectors.

3.2 Methodology

At the beginning of each month *t*, the stocks are ranked in descending order based on their cumulative raw return over the past *F* months, skipping the most recent month to avoid short-term reversals[7] (Asness, Moskowitz, & Pedersen, 2013). Jegadeesh and Titman (1993) experimented with no gap and a week-long gap in their article, but a one-month gap is today's academic practice. The formation period returns are calculated as follows:

$$MOM_t^F = \frac{P_{t-2}}{P_{t-F}} - 1 \tag{1}$$

F is the entire formation period, e.g., an *F* of 12 means I want to look at the last 12 months return, skipping the most recent month to decide our longs and shorts for the coming holding period *H*. Only stocks with return data over the entire period are included. Based on their ranking, ten decile portfolios are created that equally weigh each decile's stocks, as per Jegadeesh and Titman (1993). Asness et al. (2013) value-weighted their portfolios in order to capture some of the size effect, but as the Nordic stock market at times consists of companies with a highly dominating size, the results would be skewed. Furthermore, as only the 50% largest companies in the Nordics are included every month, the results will capture some size effect. Further adjustments regarding transaction- and financing costs are left out of the quantitative analysis but will be discussed when applicable.

The top decile is called the *winners*, and the bottom decile is called the *losers*. In each month *t*, the strategy buys the winning decile and sells the losing decile, holding the positions for *H* months. The strategy also closes out the position initiated in month *t* - *H*. Several different holding periods are explored, more specifically 1, 3, and 6 months, but the focus remains on the 12-month formation, 1-month holding strategy motivated by the findings of Novy-Marx (2012).

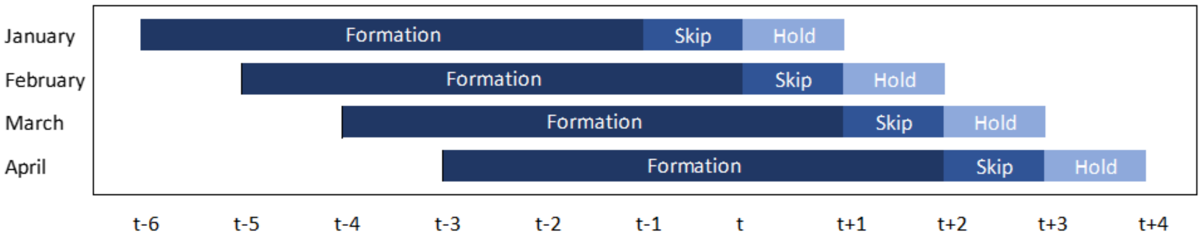
Inspired by Jegadeesh and Titman (1993), the strategies examined include portfolios with overlapping holding periods. In any given month *t*, the strategies hold a series of portfolios created in month *t* as well as in the previous *H*-1 months. If the holding period is one month, then the strategy never has overlapping holding periods as the previous position is closed out

[7] A stock's tendency to respond negatively (positively) to the previous week's/month's positive (negative) return. Jegadeesh and Titman (1993) tested strategies both without a gap and with a 1-week gap in their article. New research suggests a 1-month gap is preferable (Asness, Moskowitz, & Pedersen, 2013).

as the new position is initiated. Below is a visualization of one of the momentum strategies, with a six-month formation and one-month holding period.

Figure 1: Momentum portfolio construction

Figure 1 is a visual overview of four momentum portfolios and their creation. The Figure illustrates portfolios created using a formation period of six months and holding of one month. The first investment is made in January (*t*), using the price history of the preceding six (*t-6*), skipping the last (*t-1*), giving us 5 month of return data as basis for our stock selection. The portfolio is subsequently held for one month (*t+1*). This procedure is repeated every month.



To compare profitability, risk, and significance of the different strategies, a set of standard figures are calculated for every created portfolio: the mean returns in excess of the risk-free rate (NIBOR 3-month), compound monthly growth rate (CMGR), annualized Sharpe ratio, alphas from the CAPM and the three-factor model, and maximum drawdown during the sample period. The mean return is calculated as the average monthly return. The cumulative monthly growth rate (*CMGR*) is calculated using the formula below:

$$CMGR_s = (1 + HPR_s)^{\frac{1}{months}} - 1 \tag{2}$$

Where HPR_s stands for *Holding Period Return*. To measure the strategy's risk-adjusted returns, the annualized Sharpe ratio is calculated for each strategy. This is done by dividing the average annual returns in excess of the risk-free rate by the annualized volatility:

$$Sharpe\ ratio_{Annualized} = \frac{\bar{R}_{s,annualy}}{\sigma_{s,annualized}} \tag{3}$$

Furthermore, alphas from the Capital Asset Pricing Model (CAPM) and the three-factor model of Fama and French (1993) are reported. The formula for CAPM is:

$$R_{it} - R_f = \alpha + \beta_i(R_{Mt} - R_f) \tag{4}$$

The formula for the three-factor model is:

$$R_{it} - R_f = \alpha + \beta_i\left(R_{Mt} - R_f\right) + s_i SMB_t + h_i HML_t \tag{5}$$

No factors are publicly available for the Nordic stock market in total. Consequently, these are constructed based on the methodology of Fama and French (1993). The SMB-factor is calculated as follows:

$$\begin{aligned} SMB_t = {} & \frac{1}{3}(Small\ Value + Small\ Neutral + Small\ Growth) \\ & - \frac{1}{3}(Big\ Value + Big\ Neutral + Big\ Growth) \end{aligned} \tag{6}$$

The HML-factor is calculated as follows:

$$\begin{aligned} HML_t = {} & \frac{1}{2}(Small\ Value + Big\ Value) - \frac{1}{2}(Small\ Growth \\ & + Big\ Growth) \end{aligned} \tag{7}$$

In short, I sort the stocks on size, allocating the 50% largest companies measured in market value into the *big* group and the other 50% into the *small* group. Next, within each size group, the stocks are ranked based on their book-to-market ratio, allocating the top 30% (the 30% highest book-to-market ratio's) in the *value* group, the bottom 30% in the *growth* group, and the 40% in between to the *neutral* group. For further information, see the website of Kenneth French and Fama and French (1993). They have not created any factors for the Nordics, but they do have a comparable dataset for Europe as a whole. This dataset is downloaded from Kenneth French's website[8] to compare with my results. Understandably, some differences are found, but the results are comparable, indicating a successful replication of the risk factors.

3.3 Results

Table 1 presents the winning decile, losing decile, and winner-minus-loser strategy excess returns over different formation- and holding periods. The WML returns are high and significant in all tested periods, but as expected, the 12-month formation and 1-month holding strategy yield the highest returns, as well as the highest Sharpe ratio. Generally, the strategies with the shortest holding periods perform relatively better, consistent with the results of

[8] The website of Kenneth French: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html. The monthly Fama/French European 3 Factors are used to validate the results.

Table 1: Individual stock momentum strategy results

Reported are the mean returns in excess of the risk-free rate (NIBOR 3-month), compound monthly growth rate (CMGR), annualized Sharpe ratio and alphas from CAPM and the three-factor model of Fama and French. The mean return is calculated as the average monthly return. The CMGR is calculated as 1 + HPR raised to the power of 1 divided by number of months (373) $\left((1+HPR)^{\frac{1}{373}}-1\right)$. The annualized Sharpe ratio is calculated as the mean return in excess of the risk-free rate divided by the annualized volatility. T-statistics are reported in parathesis. The table reports the results for the momentum strategy; the winning portfolio (top decile), the losing portfolio (bottom decile) and the zero-cost (winners minus losers) portfolio over 6 and 12 month formation periods and 1, 3, and 6 month holding periods.

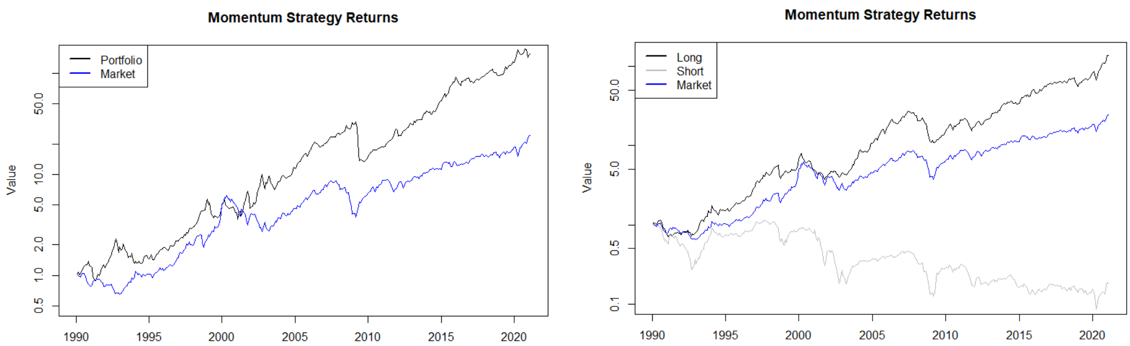
	Momentum (Monthly)																		
	Portfolio	Winners						Losers						Zero-Cost (Winner - Losers)					
	Formation	6			12			6			12			6			12		
	Holding	1	3	6	1	3	6	1	3	6	1	3	6	1	3	6	1	3	6
Nordic (January 1990 to January 2021)	Mean R (%)	1,34	1,15	1,16	1,52	1,32	1,11	0,13	0,19	0,28	-0,08	0,04	0,33	1,21	0,97	0,88	1,61	1,28	0,78
		(4,05)	(3,61)	(3,72)	(4,77)	(4,23)	(3,53)	(0,30)	(0,45)	(0,68)	(-0,20)	(0,10)	(0,79)	(3,78)	(3,31)	(3,36)	(4,57)	(3,94)	(2,51)
	CMGR (%)	1,13	0,95	0,96	1,32	1,13	0,91	-0,23	-0,14	-0,04	-0,46	-0,30	0,00	1,02	0,80	0,74	1,36	1,07	0,59
	Sharpe ratio	0,73	0,65	0,67	0,86	0,76	0,63	0,05	0,08	0,12	-0,03	0,02	0,14	0,68	0,59	0,60	0,82	0,71	0,45
	CAPM-alpha	0,41	0,23	0,34	0,63	0,43	0,20	-1,07	-0,98	-0,89	-1,27	-1,10	-0,79	1,49	1,21	1,12	1,90	1,53	0,99
		(2,07)	(1,27)	(1,42)	(3,25)	(2,35)	(1,11)	(-4,12)	(-3,93)	(-3,73)	(-4,32)	(-3,93)	(-2,92)	(4,69)	(4,19)	(4,37)	(5,45)	(4,71)	(3,16)
	3-factor alpha	0,28	0,11	0,13	0,57	0,38	0,16	-1,58	-1,49	-1,39	-1,90	-1,70	-1,37	1,86	1,60	1,53	2,47	2,07	1,52
		(1,39)	(0,60)	(0,78)	(2,93)	(2,05)	(0,87)	(-7,47)	(-7,37)	(-7,26)	(-8,18)	(-7,67)	(-6,41)	(6,60)	(6,18)	(6,73)	(8,29)	(7,53)	(5,76)
	MKT	0,98	0,96	0,95	0,91	0,91	0,92	1,31	1,28	1,29	1,32	1,28	1,25	-0,33	-0,32	-0,34	-0,42	-0,37	-0,32
		(25,93)	(27,53)	(29,53)	(24,57)	(26,18)	(27,08)	(32,63)	(33,43)	(35,37)	(30,11)	(30,51)	(30,92)	(-6,18)	(-6,51)	(-7,85)	(-7,34)	(-7,00)	(-6,47)
	SMB	0,44	0,36	0,29	0,21	0,19	0,16	0,79	0,83	0,87	1,02	0,96	0,93	-0,34	-0,47	-0,58	-0,81	-0,77	-0,76
		(4,18)	(3,61)	(3,14)	(2,02)	(1,91)	(1,70)	(6,91)	(7,64)	(8,40)	(8,19)	(8,07)	(8,10)	(-2,24)	(-3,40)	(-4,76)	(-5,06)	(-5,20)	(-5,37)
	HML	-0,07	-0,18	0,01	-0,07	-0,06	-0,06	0,70	0,65	0,60	0,81	0,77	0,74	-0,77	-0,67	-0,60	-0,88	-0,83	-0,80
		(-1,44)	(-0,38)	(0,15)	(-1,45)	(-1,26)	(-1,26)	(12,89)	(12,57)	(12,26)	(13,53)	(13,57)	(13,62)	(-10,72)	(-10,08)	(-10,26)	(-11,48)	(-11,73)	(-11,83)
	Max DD (%)	65,03	69,75	66,75	59,88	63,50	65,18	83,92	78,19	71,59	92,47	84,85	75,79	49,73	52,21	46,98	60,15	55,75	59,32

Jegadeesh and Titman (1993). Additionally, the short positions contribute significantly to the abnormal returns, especially for the 12-1 strategy. Although size is accounted for by removing the smallest companies in the sample, this still makes the strategy harder to implement in practice, as short-selling is subject to illiquidity issues and potentially high costs. Furthermore, most of the profitability of the individual momentum strategy is driven by outliers, as using 10% breakpoints is drastically more profitable than, for example, 30%.

As seen in Table 1, all the zero-cost strategies are highly profitable and significant over the sample period. However, Figure 2 shows that the individual momentum strategy suffers from a severe crash when the market recoils after the financial crisis of 2008. This confirms that the momentum crashes explored and explained in Daniel and Moskowitz (2016) are present in the Nordic market.

Figure 2: 12-1 momentum strategy returns

The left graph shows the cumulative return of the WML 12-1 strategy. As we can see, the strategy suffers from a severe crash around 2009. The graph on the right shows the long and short portfolio and the reason for said crash is visualized. The short-portfolio experiences a strong recoil after the financial crisis, much because the loser stocks from the previous downturn are high-beta stocks.



The factor loadings are negative for all zero-cost WML strategies. The momentum strategy is betting on low beta, big and low book-to-market stocks. Moreover, although the HML-loadings are all significantly negative, the difference in loadings for the different strategies indicates that using shorter formation periods and longer holding periods might increase the exposure to value stocks. Furthermore, the maximum drawdowns for the strategies with shorter formation periods are overall lower. This might indicate that higher positive exposure to value stocks reduces severe crashes for the strategy.

When focusing on the factor loadings of the long and short portfolios, it is easier to understand the drivers behind the strategy's profitability. The three-factor alpha of the long portfolio is positive and statistically significant, meaning that the portfolio outperforms the market, although it follows the market to a large degree with a beta of 0.91. Furthermore, the long portfolio is relatively neutral regarding SMB, although it seems that the portfolio is slightly more exposed to small stocks. Moreover, the HML-loading is statistically insignificant and close to zero, meaning it is exposed to a varied mixture of stocks with both value and growth characteristics. The three-factor alpha of the short portfolio is negative and highly significant. This portfolio seems to be betting on high beta, small and high book-to-market ratio stocks, although these risk factors do not come close in explaining all of the returns.

To test these findings out-of-sample, I download ten equally-weighted decile portfolios from Kenneth French's website. The sorting follows this thesis' methodology perfectly. For visualization and a table of the results, see appendix 1. The individual stock momentum effect is much weaker in the United States throughout the period. In fact, the raw excess return of the U.S. WML strategy is insignificant at the 5% level. Controlling for the U.S. excess market return and U.S. risk factors, the three-factor alpha is reported at 0.75% and barely significant with a t-statistic of 2.02. The factor loadings are all negative, consistent with the findings in the Nordics. Furthermore, the U.S. momentum strategy returned a negative 82.5% just after the financial crisis, far worse than in the Nordic stock market. These deviations in results may result from more investors trying to exploit the momentum effect in the United States, thus reducing the strategy's profitability.

In conclusion, the momentum effect is present and highly significant in the Nordics. The 12-1 strategy yields the highest and most significant returns, even after controlling for the market, size, and book-to-market ratio. The annualized Sharpe ratio of 0.82 is very impressive and makes the strategy attractive for investors. However, the strategy experiences a severe crash in the wake of the financial crisis, as the short portfolio outperforms during the recoil. Risk-averse investors will limit their exposure to such a portfolio. Furthermore, the Nordic stock market is more attractive than the U.S. stock market for a momentum investor. This finding is explained by fewer investors exploiting the momentum effect in the Nordics, thus not improving the mispricing in these stocks.

4. Industry Momentum

As discussed in chapter two, the explanation for individual stock momentum is a widely discussed topic. Overall, there are two main models: behavioral and rational. In this chapter, industry effects are pursued as the main contributor to the momentum observed in Nordic stock returns. If this is the case, the individual stock momentum strategy aggressively takes on positions within the same industry, making it poorly diversified, thus offering a rational explanation.

As established in the previous chapter, the individual stock momentum strategy is highly profitable and yields significant abnormal returns in the Nordics. This chapter will explore whether this profitability can be attributed to industry effects. I primarily follow the methodology of Moskowitz and Grinblatt (1999), and deviations will be explained thoroughly.

Asness et al. (2000) are critical of the methodology and findings of Moskowitz and Grinblatt. I explore the methodological differences throughout the chapter and the robustness of my results by implementing the WML industry strategy in a broader industry range in the United States.

4.1 Methodology

Moskowitz and Grinblatt (1999) explore the momentum effect on an industry level, and their results indicate that industry momentum explains much of the momentum profits over intermediate investment horizons (6 to 12 months) in the U.S. stock market. In more recent years, other academics have explored industry momentum but with a few methodological differences. Changes made to the methodology of Moskowitz and Grinblatt will be explained thoroughly.

The Nordic stock market is much smaller than the U.S. stock market, meaning the sample consists of a drastically lower amount of investable stocks. Dividing the Nordic stock between 48 different industries as in Grundy and Martin (2001) or 20 industries as in Moskowitz and Grinblatt (1999) would make some industries dependent on very few companies. In order to keep the industries somewhat diversified, I use DataStream’s industry classification system, resulting in a total of 12 industries. However, this is reduced to 11 due to size issues for *Academic & Educational Services*, as explained in chapter three.

Next, I consider whether I should value- or equal-weight the stocks within each industry. Moskowitz and Grinblatt (1999) use a value-weighted approach for the U.S. data in their article and explain the decision with conveniency for further analysis. The advantage of value-weighting the industries is that bigger stocks are often more liquid and subject to lower transaction costs, making them more feasible. However, as the sample only consists of the 50% biggest companies measured in market capitalization, only fairly liquid and shortable companies remain. Furthermore, as the number of stocks in the Nordics are substantially lower, a value-weighted approach would drastically affect the results. Consequently, I choose an equal-weight approach to avoid skewed results by a few large companies. Additionally, the equal-weighted industries make the results directly comparable to the individual stock momentum strategy in chapter 3, which is vital in this thesis. Furthermore, equal weighting the portfolios is also more realistic for professional investors, as funds using strategies exploiting these anomalies are actively managed and do not value-weight their positions[9].

Following the methodology of Moskowitz & Grinblatt (1999), I construct self-financing (zero-cost) winner minus loser portfolios, similar to the individual stock momentum strategy in chapter three. The industry portfolios are sorted based on their past six- or twelve-month return and the strategy invest in the top-performing industry while shorting equally the worst-performing industry. The holding period is one, three, and six months, the same as in both Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999).

Moskowitz and Grinblatt (1999) focus primarily on the 6-month formation and 6-month holding strategy (6-6), where they rank the value-weighted industries (a total of 20 industries) based on the returns in the 6-month formation period (t-6 to t-1) and buy the highest six performing industries and sell the lowest six industries, holding this position for six months (t to t+5). Compared to this, two adjustments are made to the methodology. First, I use deciles instead of 30% breakpoints, making the findings comparable to the individual stock momentum strategy in chapter three, and second, I use a 1-month gap between the end of formation and start of investing/holding.

Industry momentum is said to disappear when a one-month interval is used between the formation and holding period. Consequently, the profitability of industry momentum is highly correlated with the month immediately after the formation period (Grundy & Martin, 2001).

[9] E.g., an actively managed fund focusing solely on the Norwegian stock market would not value-weigh their portfolio, as this would mean having a massive stake in, for example Equinor, and therefore not be diversified.

The effect of the interval in the Nordic stock market is tested by creating value-weighted 6-6 industry momentum strategies with and without the 1-month interval between the formation and holding period. No significant differences were identified. The strategy with a 1-month gap was just barely less profitable (CAGR of 4.44% compared to 4.75%) and significant (p-value of 0.09 against 0.08). The sample-specific differences must be emphasized, and a somewhat different result is expected. However, these results indicate that whether or not I use a 1-month gap is not decisive for the conclusions.

4.2 Results

Table 2 present the results of the industry momentum strategy. The strategies yield high and significant returns, both measured in raw excess returns and alphas. Compared to individual stock momentum, the three-factor alphas are on average lower for industry momentum, albeit weakly so, meaning that the traditional risk factors work better in explaining the returns of industry momentum. Still, the strategies seem more robust to changes in both formation and holding period. As for factor loadings, MKT and SMB are statistically insignificant. This means that the industry momentum strategy on average is neutral to the market and bets on average-sized companies. These results make sense, as the industries include a more diversified set of companies of different sizes. The HML-factor is still negatively loaded, as expected, driven by the short portfolio, which is positively exposed to value stocks. One of the key findings in the original article was the improved profitability of the industry momentum strategy compared to the individual stock momentum strategy. This finding is not evident in the Nordic stock market, looking at the best performing strategy in Tables 1 and 2. However, as previously mentioned, the industry momentum strategy is more robust to changes in the formation- and holding period, making other strategy variations more profitable than for individual stock momentum measured in raw excess returns.

Figure 3 visualizes the cumulative returns of the 12-1 long, short, and zero-cost portfolio. Compared to individual stock momentum, the industry WML strategy seems to generate more profits from the long positions. These findings are similar to that of Moskowitz and Grinblatt (1999), who find industry momentum in the United States to be generated from both long- and short positions, not mainly short-positions like with individual stock momentum. This makes the industry momentum strategy more implementable. Furthermore, looking at the 12-1 strategy only, the raw excess returns for industry momentum are similar to that of individual

Table 2: Industry momentum strategy results

Reported are the mean returns in excess of the risk-free rate (NIBOR 3-month), compound monthly growth rate (CMGR), annualized Sharpe ratio and alphas from CAPM and the three-factor model. The mean return is calculated as the average monthly return. The CMGR is calculated as 1 + HPR raised to the power of 1 divided by number of months (373) $\left((1+HPR)^{\frac{1}{373}}-1\right)$. The annualized Sharpe ratio is calculated as the mean return in excess of the risk-free rate divided by the annualized volatility. T-statistics is reported in parathesis. The table reports the results for the industry momentum strategy; the winning portfolio (top decile), the losing portfolio (bottom decile) and the zero-cost (winners minus losers) portfolio over 6 and 12 month formation periods and 1, 3, and 6 month holding periods.

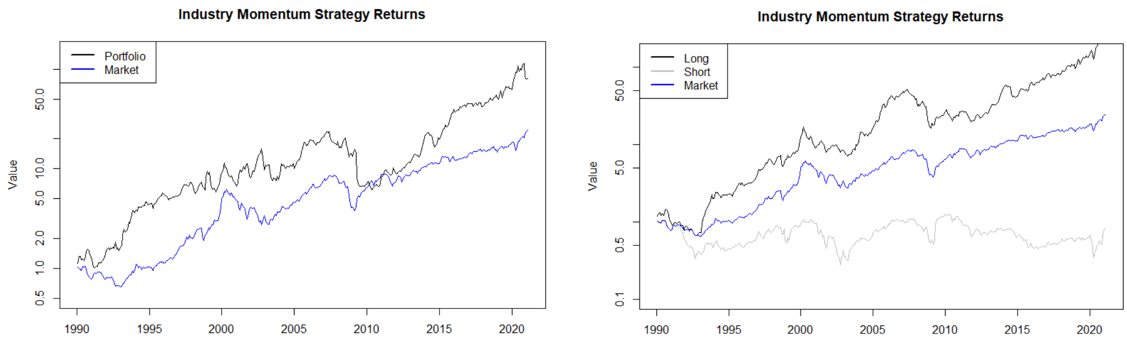
Industry Momentum (Monthly)

	Portfolio	Winners						Losers						Zero-Cost (Winner - Losers)					
	Formation	6			12			6			12			6			12		
	Holding	1	3	6	1	3	6	1	3	6	1	3	6	1	3	6	1	3	6
Nordic (January 1990 to January 2021)	Mean R (%)	1,65	1,65	1,49	1,84	1,65	1,51	0,21	0,22	0,33	0,30	0,36	0,39	1,44	1,43	1,16	1,54	1,29	1,12
		(3,94)	(4,22)	(4,06)	(4,48)	(4,05)	(3,73)	(0,49)	(0,58)	(0,85)	(0,68)	(0,87)	(0,98)	(3,27)	(3,93)	(3,71)	(3,55)	(3,34)	(3,14)
	CMGR (%)	1,29	1,33	1,21	1,48	1,30	1,16	-0,14	-0,07	0,04	-0,07	0,03	0,08	1,04	1,15	0,96	1,15	0,98	0,85
	Sharpe ratio	0,71	0,76	0,73	0,80	0,73	0,67	0,09	0,10	0,15	0,12	0,16	0,18	0,59	0,70	0,67	0,64	0,60	0,56
	CAPM-alpha	0,63	0,67	0,53	0,86	0,62	0,45	-0,75	-0,71	-0,68	-0,76	-0,67	-0,63	1,38	1,38	1,21	1,62	1,29	1,08
		(2,07)	(2,41)	(2,15)	(2,80)	(2,17)	(1,65)	(-2,20)	(-2,53)	(-2,65)	(-2,33)	(-2,30)	(-2,33)	(3,11)	(3,72)	(3,80)	(3,68)	(3,30)	(2,98)
	3-factor alpha	0,41	0,43	0,31	0,66	0,41	0,24	-1,08	-1,07	-1,08	-1,20	-1,11	-1,05	1,49	1,50	1,39	1,86	1,52	1,29
		(1,36)	(1,55)	(1,26)	(2,16)	(1,45)	(0,90)	(-3,26)	(-3,99)	(-4,54)	(-3,87)	(-4,05)	(-4,21)	(3,42)	(4,08)	(4,80)	(4,31)	(3,96)	(3,71)
	MKT	1,12	1,08	1,03	1,07	1,11	1,15	1,02	1,01	1,10	1,16	1,14	1,12	0,09	0,06	-0,08	-0,10	-0,27	0,03
		(19,21)	(20,66)	(21,93)	(18,27)	(20,57)	(22,62)	(16,28)	(19,98)	(24,51)	(19,84)	(21,93)	(23,64)	(1,06)	(0,88)	(-1,30)	(-1,22)	(-0,37)	(0,40)
	SMB	0,74	0,68	0,56	0,67	0,65	0,69	0,45	0,58	0,75	0,75	0,75	0,72	0,29	0,10	-0,19	-0,09	-0,10	-0,03
		(4,54)	(4,58)	(4,20)	(4,03)	(4,23)	(4,80)	(2,55)	(4,00)	(5,85)	(4,51)	(5,09)	(5,34)	(1,23)	(0,52)	(-1,11)	(-0,36)	(-0,49)	(-0,15)
	HML	-0,14	-0,01	0,06	-0,13	-0,08	-0,13	0,51	0,56	0,41	0,52	0,50	0,49	-0,65	-0,47	-0,35	-0,65	-0,58	-0,63
		(-1,77)	(-0,20)	(0,91)	(-1,65)	(-1,13)	(0,05)	(6,06)	(6,69)	(6,71)	(6,52)	(7,16)	(7,70)	(-5,82)	(-5,04)	(-4,32)	(-5,85)	(-5,93)	(-7,02)
	Max DD (%)	63,39	69,44	71,33	68,30	71,88	73,41	78,31	73,47	80,76	72,38	73,59	72,25	68,98	51,06	40,08	74,03	60,30	51,18

stock momentum. However, the monthly three-factor alpha is 0.63 percentage points lower and less significant. This difference in three-factor alpha has roots in the performance of the short-portfolio, confirming the previous statement.

Figure 3: 12-1 industry momentum strategy returns

The left graph shows the cumulative return of the WML 12-1 strategy. As we can see, the strategy suffers from a severe crash around 2009, same as for stock momentum. The graph on the right shows the long and short portfolio and the reason for said crash is visualized. The short-portfolio experiences a strong recoil after the financial crisis, much because the loser industry from the previous downturn experience a significant recoil.



The industry momentum crash and the total drawdown from peak to bottom is severe. The maximum drawdown for the 12-1 strategy is around 75 %, far more than the market. From Figure 3, we can see that the long positions fell more than the short position during the financial crisis. In addition, the short position performed much better during the recoil, resulting in a massive loss for the industry WML strategy.

As mentioned earlier, one exciting aspect of the industry momentum results is that the raw excess returns from different formation- and holding periods varies less for industries than for individual stocks. This finding may indicate that industry trends move over longer periods with fewer disruptions. Furthermore, outliers may not be as crucial as for individual stock momentum, as the 12-1 strategy is even more profitable and less risky when using 20% breakpoints.

To test whether the identified industry momentum effect is present when using a broader industry range, I must use data from the United States due to size issues in the Nordic sample. I download industry returns from both 12 and 48 industries in the United States from Kenneth French’s website. When using the same methodology and period as for the Nordic sample, I find the U.S. industry momentum effect to be present, although slightly weaker than the Nordic industry returns. See appendix 1 and 2 for results. The strategy using 12 industries yields a significant raw monthly excess return of 0.62% and a three-factor alpha of 0.86%. When using 48 industries, the raw excess return is reported at 0.73% and the alpha at 0.88%. As we can see, the differences are minimal, and the findings are robust to industry classification in the United States. Furthermore, compared to the U.S. individual stock WML strategy, the industry momentum strategies are more profitable at less risk. This is opposite of the findings for the Nordic stock market but consistent with the findings of Moskowitz and Grinblatt (1999).

To conclude: industry momentum is present, and an industry WML strategy is highly profitable and seems to be more robust to changes in both formation periods, holding periods, and breakpoints. Furthermore, the results seem robust to industry classification when looking at U.S. data. All this makes the strategy attractive to implement for investors. However, the risk-adjusted returns are lower, the three-factor alpha of the 12-1 strategy is much lower, and the strategy suffers from severe drawdowns, worse than individual stock momentum. The difference might be explained by diversification issues, as companies within industries are more highly correlated than companies across industries, and the industry WML strategy is, for obvious reasons, more dependent on industries.

4.3 Industry-Adjusted Momentum Profits

In the previous subchapter, I found industry momentum to be present, profitable, and highly significant, even when accounting for traditional risk factors. However, some critical differences in results compared to Moskowitz and Grinblatt (1999) make it necessary for further testing to determine whether industry effects explain the momentum observed in Nordic stock returns. As a simple preliminary test, I explore whether the individual stock momentum identified in chapter three exists after accounting for industry momentum. In addition to the three risk factors in the model of Fama and French (1993), I introduce a fourth factor: *industry winners-minus-losers* (IWML).

$$R_{it} - R_f = \alpha + \beta_i(R_{Mt} - R_f) + s_i SMB_t + h_i HML_t + i_i IWML_t \qquad (8)$$

Table 3 presents the results. The 12-1 WML-alpha adjusted for the market, size, book-to-market ratio, and industry momentum is still profitable (1.77%) and highly significant (6.91). Compared to the three-factor alpha of 2.47%, it is slightly reduced. However, this indicates that industries are merely part of the driver behind the momentum effect in the Nordics. As a further

Table 3: Controlling for IWML/WML

Reported are the mean returns in excess of the risk-free rate (NIBOR 3-month), compound monthly growth rate (CMGR), annualized Sharpe ratio and alphas from CAPM and the four-factor model for the zero-cost WML strategies for individual stock and industries. T-statistics are reported in parathesis. The mean return is calculated as the average monthly return. The CMGR is calculated as 1 + HPR raised to the power of 1 divided by number of months (373) $\left((1+HPR)^{\frac{1}{373}}-1\right)$. The volatility is calculated as the standard deviation of the monthly returns. The annualized Sharpe ratio is calculated as the annualized mean returns in excess of the risk-free rate divided by the annualized volatility.

	Controlling for IWML/WML												
	Portfolio	Individual Stock Momentum						Industry Momentum					
	Formation	6			12			6			12		
	Holding	1	3	6	1	3	6	1	3	6	1	3	6
Nordic (January 1990 to January 2021)	Mean R (%)	1,21	0,97	0,88	1,61	1,28	0,78	1,44	1,43	1,16	1,54	1,29	1,12
		(3,78)	(3,31)	(3,36)	(4,57)	(3,94)	(2,51)	(3,27)	(3,93)	(3,71)	(3,55)	(3,34)	(3,14)
	CMGR (%)	1,02	0,80	0,74	1,36	1,07	0,59	1,04	1,15	0,96	1,15	0,98	0,85
	Sharpe ratio	0,68	0,59	0,60	0,82	0,71	0,45	0,59	0,70	0,67	0,64	0,60	0,56
	CAPM-alpha	1,49	1,21	1,12	1,90	1,53	0,99	1,38	1,38	1,21	1,62	1,29	1,08
		(4,69)	(4,19)	(4,37)	(5,45)	(4,71)	(3,16)	(3,11)	(3,72)	(3,80)	(3,68)	(3,30)	(2,98)
	4-factor alpha	1,35	0,99	0,93	1,77	1,45	1,00	-0,05	0,21	0,11	-0,09	-0,13	0,23
		(5,55)	(4,59)	(4,99)	(6,91)	(6,28)	(4,38)	(-0,13)	(0,66)	(0,40)	(-0,23)	(-0,39)	(0,74)
	MKT	-0,36	-0,34	-0,30	-0,38	-0,35	-0,33	0,36	0,32	0,21	0,23	0,26	0,25
		(-7,96)	(-8,50)	(-8,82)	(-7,93)	(-8,27)	(-7,87)	(4,92)	(5,26)	(3,96)	(3,10)	(4,16)	(4,29)
	SMB	-0,44	-0,51	-0,50	-0,78	-0,73	-0,75	0,57	0,48	0,30	0,56	0,51	0,50
		(-3,42)	(-4,48)	(-5,10)	(-5,79)	(-5,99)	(-6,23)	(2,86)	(2,92)	(2,12)	(2,76)	(2,92)	(3,067)
	HML	-0,55	-0,48	-0,44	-0,63	-0,59	-0,55	-0,01	0,07	0,15	0,05	0,08	-0,07
		(-8,60)	(-8,48)	(-9,34)	(-9,45)	(-9,70)	(-8,98)	(-0,09)	(0,74)	(2,03)	(0,43)	(0,81)	(-0,73)
	IWML/WML	0,35	0,40	0,43	0,38	0,41	0,40	0,83	0,81	0,85	0,79	0,80	0,70
		(12,15)	(13,23)	(12,43)	(12,49)	(13,37)	(12,02)	(12,15)	(13,23)	(14,43)	(12,49)	(13,37)	(12,02)
	Max DD (%)	49,73	52,21	46,98	60,15	55,75	59,32	68,98	51,06	40,08	74,03	60,30	51,18

test, I flip the regression, and test the four-factor alpha of industry momentum. The results indicate that industry momentum is not present after controlling for individual stock momentum, with a reported alpha of -0.09% and a t-statistic of -0.23. The four-factor model captures the returns of the industry momentum strategy in its entirety, and the apparent most significant explanatory factor is the individual stock momentum returns. Furthermore, the HML-factor loses its significance when introducing WML to the regression. These results weaken the hypothesis that the profitability of individual stock momentum can be attributed to picking the right industry.

In the United States, Moskowitz and Grinblatt (1999) find the momentum in industries to be the main driver behind the profitability of stock momentum, and, apart from the 12-1 individual stock momentum strategy, capture these effects almost entirely. Conversely, in the Nordics, all variations of the WML strategy stay significant when controlling for IWML, meaning the momentum identified in Nordic stock returns do not seem to experience the same industry effect as in the United States.

To explore whether the differences in findings are not a result of methodology, I conduct an identical analysis on the U.S. sample. First, the individual stock momentum returns found for the U.S. stock market are regressed on the identified U.S. industry momentum returns using 12 industries. See appendix 1 and 2 for results. The four-factor alpha is reported at 0.01% with a t-statistic of 0.04. The insignificance of the alpha indicates that in the United States, industry momentum explains almost all of the momentum observed in stocks. Furthermore, when flipping the regression, the four-factor alpha of industry momentum is reported at 0.53% with a t-statistic of 2.50. This means that the industry momentum strategy in the United States yields significant alpha after controlling for individual stock momentum, in contrast to the findings for the Nordics.

The robustness of the U.S. results is tested by performing the same analysis on a wider industry classification system. Using 48 industries instead of 12 reduces the WML four-factor alpha to -0.34%, but it remains insignificant. The flipped regression yields an alpha of 0.65% with a t-statistic of 4.35. These slight differences indicate that the results are robust to changes in industry classification systems in the U.S. stock market.

Overall, in the United States, industry momentum is a more robust phenomenon than individual stock momentum. WML is less profitable and more susceptible to crashes compared to IWML.

Furthermore, in contrast to the findings for the Nordic stock market and consistent with the results of Moskowitz and Grinblatt (1999), the stock momentum effect seems to be subsumed entirely by industry momentum and not the other way around. The finding is robust to changes in industry classification systems. These conflicting results necessitate further research.

4.4 Industry-Neutral Momentum

As the initial test indicates that industry effects do not explain the momentum observed in Nordic stock returns, in conflict with results from the U.S. sample and Moskowitz and Grinblatt (1999), further testing is necessary. This chapter will explore whether the momentum effect is present in an industry-neutral universe. I follow the methodology of Moskowitz and Grinblatt (1999) and create individual stock zero-cost winner-minus-loser strategies within industries.

The test is as simple as it is relevant; if I can observe significant individual stock momentum within the industries, the explanation regarding industries as a possible driver for momentum weakens. If the within-industry momentum effect is insignificant, this strengthens the evidence that a momentum strategy is indeed betting on industry outperformance rather than individual stocks and is, as a consequence, poorly diversified.

The problem regarding sample size must be emphasized for this test. As the Nordic sample only consists of approximately 1000 companies, the industries alone will, on average, only include 100 companies. Furthermore, throughout the sample period, some industries consist of as few as two companies. I deal with the sample size problem by increasing the breakpoints of the long and short portfolios from 10% to 30%. For *Energy* and *Utilities*, the sample size is at times so small that only 50% breakpoints are possible. *Telecommunication Services* are excluded entirely due to few companies and periods with no observations. These changes reduce the accuracy and validity of the test, but I argue that the conclusions will not be affected to a large degree. Additionally, as the extremes (in the top and bottom decile) significantly contribute to the profitability of the individual stock momentum strategy, this approach is on the moderate side of the spectrum. If stock momentum is identified with 30% and 50% breakpoints, then the effect is expected to be even more significant for deciles.

Table 4 present the results of the tests, as well as alphas and significance. See appendix 3 for visualization. The inter-industry WML strategies earn significant alphas at the 5% level in nine

Table 4: Within-industry momentum results

Reported are the mean returns in excess of the risk-free rate (NIBOR 3-month), compound monthly growth rate (CMGR), annualized Sharpe ratio and alphas from CAPM and the three-factor model. The mean return is calculated as the average monthly return. The CMGR is calculated as 1 + HPR raised to the power of 1 divided by number of months (373) $\left((1+HPR)^{\frac{1}{373}}-1\right)$. The annualized Sharpe ratio is calculated as the mean return in excess of the risk-free rate divided by the annualized volatility. The 12-month formation, 1-month holding strategy is used and the zero-cost results are reported. Within the industries, the 30% past top performers are bought, and the 30% worst performers are sold. I skip one month after formation and calculate the returns over the following holding month. For the energy- and utilities industry, the sample size was too small, so I had to use 50% breakpoints, meaning I bought the top half and sold the other half. N is the total number of companies in the sector and min/max size is the minimum and maximum size of the long- and short portfolio during the sample period.

Within-industry momentum (monthly)											
	Industry	Basic Materials	Consumer Cyclicals	Consumer Non-Cyclicals	Energy (50%)	Financials	Healthcare	Industrials	Real Estate	Technology	Utilities (50%)
	N	68	128	69	88	143	113	250	71	146	13
	Min/max size	3/10	4/21	3/13	1/20	9/25	1/22	9/37	1/14	1/23	1/4
Nordic (January 1990 to January 2021)	Mean R (%)	0,66	1,20	0,62	0,78	0,43	1,24	0,68	0,45	1,12	-0,03
		(1,81)	(3,96)	(1,72)	(2,10)	(1,55)	(2,53)	(3,15)	(0,96)	(2,22)	(-0,06)
	CAGR (%)	0,40	1,00	0,37	0,50	0,28	0,76	0,60	-0,19	0,54	-0,41
	Sharpe	0,32	0,71	0,31	0,38	0,28	0,45	0,56	0,17	0,40	-0,01
	CAPM alpha	0,78	1,24	0,68	0,96	0,65	1,27	0,78	0,64	1,10	0,14
		(2,11)	(4,01)	(1,87)	(2,54)	(2,35)	(2,57)	(3,69)	(1,36)	(2,14)	(0,277)
	3-factor alpha	0,95	1,57	0,98	1,33	0,91	1,91	1,02	0,93	1,34	0,20
		(2,54)	(5,35)	(2,73)	(3,57)	(3,59)	(4,00)	(5,02)	(1,97)	(2,55)	(0,40)
	MKT	-0,16	-0,11	-0,13	-0,28	-0,25	-0,22	-0,15	-0,25	-0,05	-0,15
		(-2,22)	(-1,97)	(-1,93)	(-4,03)	(-5,22)	(-4,00)	(-4,01)	(-2,78)	(-0,52)	(-1,61)
	SMB	-0,27	-0,45	-0,42	-0,73	-0,20	-1,14	-0,20	-0,38	-0,43	-0,07
		(-2,80)	(-2,87)	(-2,19)	(-3,65)	(-1,51)	(-2,45)	(-1,86)	(-1,50)	(-1,54)	(-0,26)
	HML	-0,23	-0,53	-0,46	-0,34	-0,59	-0,67	-0,44	-0,48	-0,23	-0,28
		(-1,16)	(-7,00)	(-5,00)	(-3,52)	(-9,00)	(-5,53)	(-8,47)	(-3,91)	(-1,75)	(-2,17)
	Max DD (%)	76,19	47,76	67,08	91,15	52,37	70,20	38,84	95,65	89,84	94,07

out of ten industries. Note that the monthly three-factor alpha of the WML 12-1 strategy on the complete data set was reported at 2.47% with a t- statistic of above 8. However, this strategy used 10% breakpoints. The full-sample individual WML-strategy with 30% breakpoints returned a three-factor alpha of 1.47% with a t-statistic of also above 8. The returns of inter-industry WML are on average lower and weaker, with an equal-weighted average alpha of 1.11%, but still significant. The fact that 9 out of 10 tested industries experience momentum within themselves weakens the hypothesis that industry effects drive momentum, at least in its entirety.

Again, the problem regarding sample size must be emphasized. These results may not be valid, as some industries consist of very few companies over time, resulting in cases where returns are only driven by two companies (one in the long and one in the short portfolio). Moskowitz and Grinblatt (1999) use a much larger sample (the U.S. stock market) and can, consequently, divide the stocks between 20 industries. By using only 11 industries, a wide variety of businesses will be put in the same industry. This weakens the validity of the analysis and might be a reason for the identified inter-industry momentum effect.

Similar to the findings of Moskowitz and Grinblatt (1999) for the U.S. stock market, I find compelling evidence for the presence of industry momentum in the Nordic stock market. The profitability of the industry momentum strategy seems to be robust to changes in both formation- and holding periods and more implementable compared to individual stock momentum. Stock momentum is subject to high turnover and, as a consequence, higher transaction costs. Moskowitz and Grinblatt find stock momentum to be a result of industry effects, meaning industry momentum would be preferable over individual stock momentum, as it reduces turnover. Investors can achieve the high returns of the momentum strategy with lower transaction costs by using, for example, sector-specific funds instead of trading in individual stocks.

In the Nordic stock market, individual stock momentum is not a result of industry momentum. Both momentum strategies are profitable alone, but only one stays significant when controlling for the other. Furthermore, significant stock momentum is observed within industries, although the alphas and significance are reduced slightly compared to the original momentum results. These findings are robust to traditional risk factors.

The difference in results for the United States and the Nordics may be attributed to differences in methodologies, as previously mentioned, but the additional tests make sample-specific effects more likely. The conflicting findings indicate that Moskowitz and Grinblatt did indeed conclude prematurely and that the behavior of momentum is highly dependent on regional effects. No conclusions that confirm the general industry dependency of momentum can be drawn.

The findings in this chapter are relevant to more than just academics. Some practitioners in the Nordic stock market may need to evaluate their investment process. Consider an investor operating within the Nordics that utilize the findings of Moskowitz and Grinblatt (1999) that industry momentum drives the momentum observed in stock returns. He would first pick industries to invest in and subsequently select stocks within these industries. If industry effects explain momentum, then stock selection will not contribute to additional returns. The results found in this chapter indicate that industry effects do not fully explain the momentum in Nordic stock returns, meaning that the investor can indeed exploit individual stock momentum after accounting for industry momentum.

In this subchapter, industry effects were explored as a possible driver behind individual stock momentum. Even though an industry momentum strategy yielded high and significant returns, the test results indicated that industry effects were not the main driver behind the momentum effect observed in stock returns. However, industry effects might still be one of several drivers, as the alpha of individual stock momentum decreased by one percentage point when controlling for industry momentum. Furthermore, inter-industry momentum was less profitable and significant than overall momentum. In conclusion, I fail to conclude with the momentum effect being a direct result of industry effects in the Nordic stock market. Explanations must be sought elsewhere.

5. Value and Momentum Combined

Chapter 4 explored industry momentum as a possible explanation for the momentum observed in Nordic stock returns. This explanation would have been rational, as the individual stock momentum strategy would invest aggressively in outperforming industries rather than individual stocks, making the strategy poorly diversified. However, the hypothesis weakened after several tests, and I failed to conclude with industry effects being a sole driver behind momentum. Having to look elsewhere for possible explanations, I turn to momentum crashes.

In the Nordic sample, both individual stock and industry momentum strategies have suffered from severe crashes right after the market bottomed during the financial crisis of 2008. In April 2009 alone, the short portfolio of the individual stock momentum strategy returned an impressive 66% compared to the long portfolio of 20%, resulting in the WML strategy falling by 46%. Furthermore, from March through July 2009, the WML strategy delivered a negative return of just above 60%. The industry WML strategy experienced similar returns, with a negative return of 45% in April 2008 and a total negative return just shy of 60% during the five months from March through July 2009. The maximum drawdown for the industry momentum strategy was around 75%. The drawdown is calculated using month-end adjusted prices, meaning the real crashes might be significantly worse, and rational investors will limit their exposure to such a portfolio. Furthermore, the sudden outperformance of the short portfolio can theoretically result in infinite losses for the WML investor, as there is no upside cap for stock prices. The momentum strategy might be highly profitable but far from arbitrage.

Momentum crashes may be a result of the risks proposed by Liu and Zhang (2008). They explain the momentum anomaly with higher downside risk for past winners. These stocks are more prone to worsening outlooks and are therefore punished in bear markets. A momentum strategy, which is long these stocks, is therefore affected negatively by the long positions' poor performance until the past winners are not the past winners anymore, thus being removed from the strategy. These previous past winners are then replaced by safer low-beta stocks, which have performed better during the downturn relative to the market. The real problem occurs when the market recoils, as it so often does, and the momentum strategy is long stable low-beta stocks and short high-beta stocks. The past losers in the short-portfolio recoil strongly, resulting in negative returns for the zero-cost portfolio and possible liquidity issues for the investor.

Daniel and Moskowitz (2013) find the momentum strategy to experience option-like behavior. They do, however, only explore the 12-1 strategy. Grobys (2016) supplement the work of Daniel and Moskowitz by exploring crashes in Europe. They find option-like behavior for their 12-1 momentum strategy but not for their 6-1. Additionally, they found that momentum strategies based on more recent past performance appear more exposed to value stocks compared to the strategies with longer formation periods. This might indicate that value stocks are less subject to big crashes or counteract momentum stocks.

Motivated by the findings of Grobys (2016), I further explore the HML-loadings and other key elements of the individual stock momentum strategy. Table 1 presents the results. All variations of the momentum strategy have negative HML-loadings, in contrast to Grobys (2016), who find them to be positively loaded. However, the Nordic strategies with a shorter formation period are less negatively loaded, albeit barely so. Furthermore, the strategies with a 6-month formation period seem to suffer less measured in drawdowns. These findings may suggest that momentum crashes can be reduced by increasing the exposure to the value factor.

Asness (1997) discovered that a momentum strategy was strongest in growth stocks while a value strategy was strongest among loser stocks, resulting in a negative correlation between the factors. These findings were supplemented by Asness et al. (2013), who found momentum and value to be individually profitable and negatively correlated by 0.53 in the United States and 0.52 in Europe, meaning a combination of the two could potentially increase the risk-adjusted returns significantly. I expect this relationship to be present in the Nordics as well. If so, a combination of momentum and value will increase diversification, as the two strategies most likely consist of different companies from different industries, thus reducing both idiosyncratic and crash risk.

This chapter explores an investor's possibility of reducing the potential risks of holding a pure-play momentum strategy without performance loss. Motivated by the literature discussed previously and the indication of reduced crash risk by increasing exposure to the HML factor throughout the thesis, I increase the exposure to value stocks by combining a momentum and value strategy. I expect such a combination to reduce risk while remaining profitable. If possible, the combination of value and momentum is a much bigger puzzle than either anomaly alone.

Henceforth, I utilize the individual stock momentum strategy in the combination strategies as this was found to be most profitable and a unique phenomenon, not a result of industry effects. The combination methods are subject to data-mining risks, but I argue that such risks are dealt with throughout the thesis. I have used the most standard and straightforward measures and methods to create value and momentum strategies to ensure a certain level of comparability among earlier research and minimize the risk of data mining or p-hacking (Chordia, Goyal, & Saretto, 2017). To ensure some comparability with Asness et al. (2013), the 12-1 stock momentum strategy and the 1-month holding value strategy will be the focus of the remainder of the thesis.

5.1 Construction of the Value Strategy

Initially, I construct the value strategy. This strategy differs from the HML-factor to ensure compatibility with the momentum strategy for combination considerations, and as it is believed to be more profitable when using 10% breakpoints. The value strategy is constructed based on the methodology of Fama and French (1992, 1993) and Asness et al. (2013).

An investor looking to exploit the value-premium selects stocks based on whether they consider the company to be cheap or expensive. To keep the analysis simple, I use only one measure of value: the book-to-market (BM) ratio[10]. The BM ratio for any given month *t*, is calculated by dividing the book value of equity by the market value of equity. To ensure that the accounting data is public before the returns they are used to explain, the book value at the end of year $t-1$ is matched with returns in July of year *t*, following the methodology of Fama and French (1992). This results in a six-month lag for book values, which should be adequate. As for market values, the most recent observation is used, meaning the book-to-market ratio in month *t* is constructed from the book value in month t - 6 divided by the market value in month *t* (Asness, Moskowitz, & Pedersen, 2013), giving us the following formula:

$$BM_t = \frac{BV_{t-6}}{MV_t} \tag{9}$$

Between the release of accounting data, the market values will be driving the change in book-to-market ratios. This method is different from that of Fama and French (1992), as they also

[10] Research has identified other value-measures to have higher predictive power than the book-to-market ratio (Lakonishok, Shleifer, & Vishny, 1994; Asness, Porter, & Ross, 2000), but as I want my results to be general, comparative, and not a result of data mining, I stay with this approach.

used the market value in the same month as their book value to calculate the book-to-market ratio. Asness et al. (2013) state that this choice is not expected to affect the overall results of the analysis. However, the correlation between value and momentum is expected to be higher and is the main argument for using real-time market values.

For each month *t*, I construct zero-cost portfolios based on the book-to-market ratio in month *t* - 1, which go long the top 10% highest BM-stocks (the *cheapest* stocks) and short the bottom 10% (the most *expensive* stocks). This decile-sorting follows the methodology of Fama and French (1992), while Asness et al. (2013) sort their data into three equal groups (33% per). The portfolio returns are calculated as follows:

$$R_{P,t} = \frac{1}{N}\sum_{i=1}^{N} R_{i,t} \tag{10}$$

i is the individual stocks in the portfolio, ranging from 1 to N. The stocks in the portfolio are equally weighted to ensure comparability to the rest of the thesis. As the sample only consists of the 50% largest companies measured in market value, the value premium is expected not to suffer from size bias. Taxes and transaction costs are not considered when calculating returns. The holding period for the reported value strategy is one month, but 3-, 6-, and 12-month strategies are explored as well. A 12-month strategy means that a created portfolio based on the book-to-market ratio in June year *t* is held from July through June the succeeding year.

Table 5 presents the results. With a CAPM-alpha of 0.79 and a t-statistic of 2.47, the strategy is profitable in the Nordic stock market, although less so than the momentum strategy. Since one of the risk factors in the three-factor model is HML, the three-factor alpha is much lower and only significant at the 10% level. However, the HML factor does not explain all of the variations in the value strategy because of differences in construction methods. See appendix 4 for a visual comparison between the value strategy and the HML-factor.

Table 5: Value strategy results

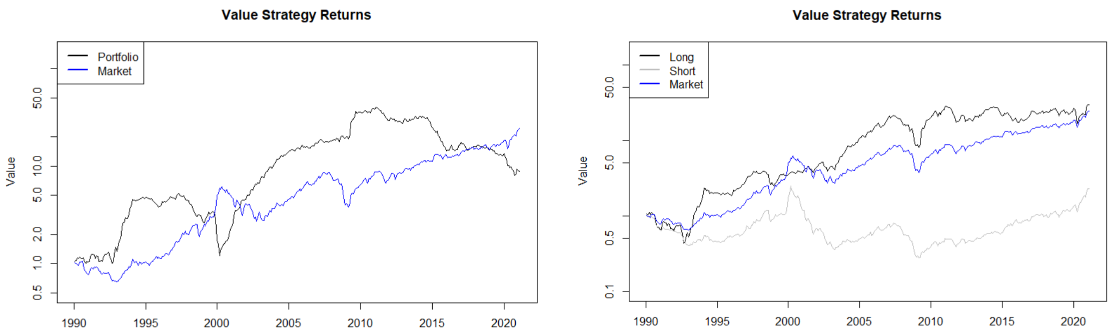
Reported are the mean returns in excess of the risk-free rate (NIBOR 3-month), compound monthly growth rate (CMGR), annualized Sharpe ratio and alphas from CAPM and the three-factor model. The mean return is calculated as the average monthly return. The CMGR is calculated as 1 + HPR raised to the power of 1 divided by number of months (373) $\left((1+HPR)^{\frac{1}{373}}-1\right)$. The annualized Sharpe ratio is calculated as the mean return in excess of the risk-free rate divided by the annualized volatility. T-statistics are reported in parenthesis. The HML strategy buys the cheapest companies in month *t*-1 and sells the most expensive. The positions are subsequently held for one month. The HML-column (strategy) differs from the HML-row (factor).

	Value (Monthly)			
	Portfolio	High	Low	HML
Nordic (January 1990 to January 2021)	Mean R (%)	1,17	0,41	0,77
		(3,09)	(1,29)	(2,44)
	CAGR (%)	0,90	0,22	0,57
	Sharpe ratio	0,44	0,13	0,34
	CAPM-alpha	0,24	-0,55	0,79
		(0,88)	(-3,41)	(2,47)
	3-factor alpha	-0,41	-0,59	0,19
		(-2,57)	(-4,39)	(1,43)
	MKT	1,06	1,01	0,05
		(35,13)	(39,17)	(1,80)
	SMB	0,84	0,50	0,35
		(9,87)	(6,78)	(4,86)
	HML	1,07	-0,39	1,47
		(26,38)	(-11,33)	(43,33)
	Max DD (%)	62,78	88,87	79,98

Overall, the HML-strategy is subject to two events/trends (Figure 4). The first is the value crash around the year 2000 (the dot-com bubble), and the second is the strategy underperformance since the financial crisis of 2008. In the graph on the right, the drivers behind these effects are visualized. Technology stocks with low book-to-market ratios (thus being shorted in the value-strategy) performed remarkably well during the dot-com bubble, resulting in negative returns for the zero-cost portfolio. The following crash resulted in an equally strong recoil for the strategy, which continued to outperform until the financial crisis. Thenceforth, the low book-to-market stocks (growth stocks) have outperformed the high book-to-market stock (value stock), resulting in negative returns for the strategy.

Figure 4: Value strategy returns

The left graph shows the cumulative return of the HML value-strategy. As we can see, the strategy suffers from a severe crash around the dotcom bubble. The graph on the right shows the long and short portfolio, and the reason for said crash is visualized. The short-portfolio consists of a lot of technology-companies (categorized in the growth decile) which performed remarkably well during the bubble. However, the recoil was just as strong and also driven by the short portfolio. We can also see the growth-outperformance since the financial crisis and the strong recoil among value stocks just after the market bottomed.



5.2 Combination Methods

Exploiting the value premium and the momentum effect can both be very profitable trading strategies alone. The nature of value and momentum is largely opposite and therefore attracts different types of investors. A traditional value investor often has a long-term perspective, while a momentum investor is more focused on the short-term price movements. The two strategies do not usually work at the same time, but they are still both profitable. As a value and momentum strategy is negatively correlated in the United States and Europe, a combination should decrease volatility while remaining profitable (Asness, Moskowitz, & Pedersen, 2013). A quick test confirms that this is evident in the Nordics as well, and I find the 12-1 momentum strategy and the value strategy to be negatively correlated by 0.50, similar to the findings of Asness et al. (2013).

Asness et al. combine value and momentum using a 50/50-approach, meaning they construct a portfolio that returns the average of the two zero-cost portfolios. Fisher et al. (2016) propose a simultaneous selection method where the stocks are ranked on both value and momentum simultaneously depending on their book-to-market ratio and cumulative past return relative to the other stocks in the sample. They look at long-only strategies, meaning there is a new potentially unexplored element to this strategy. The idea behind the simultaneous selection is not to exclude stocks lagging in one of the measures, allowing stock with a good performance in either value or momentum to score relatively high. Stocks that are neither value nor momentum stocks can also be part of the portfolio, as long as they score relatively high in both measures.

This chapter will explore both a weighted approach and a simultaneous selection approach. I argue that these two methods are straightforward and implementable, as well as outside the risk of data mining. Changes made to the methodology of Fisher et al. (2016) will be explained in subsection 5.2.2.

5.2.1 Weighted Combination

The methodology behind the weighted combination of the value and momentum zero-cost portfolios is reasonably straightforward. For every month *t*, I weigh the returns of momentum and value equally in a new portfolio, meaning I hold half a momentum portfolio and half a value portfolio:

$$R_{combined,t} = w_{value} R_{value,t} + w_{momentum} R_{momentum,t} \tag{11}$$

Weights of 50% are used to keep it simple. If successful, this strategy should decrease volatility drastically while remaining reasonably profitable.

Table 6 presents the results. The monthly raw excess return is between the value and momentum results, as one should expect, and highly significant with a t-statistic of 7. Furthermore, the three-factor alpha is 1.31% and highly significant. See appendix 5 for results when controlling for the momentum-factor (WML) as well. The most impressive thing is the risk-adjusted returns. The reported annualized Sharpe ratio is 1.27, meaning the strategy yields 1.27 units of excess returns per unit of risk. Compared to the Sharpe ratios of the momentum- and value strategy of 0.75 and 0.34, respectively, this is a significant improvement.

It is a clear difference between momentum and value individually and the combined portfolio (Figure 5). Both volatility and crashes are almost removed entirely. The maximum drawdown for the combined strategy is reported at just shy of 23%, far less than for the strategies individually. This drawdown occurred during the dotcom bubble, as the value strategy fell significantly more than the momentum strategy rose. Still, compared to the crash risk of the original strategies, the 50/50 combination has mitigated the risk almost entirely.

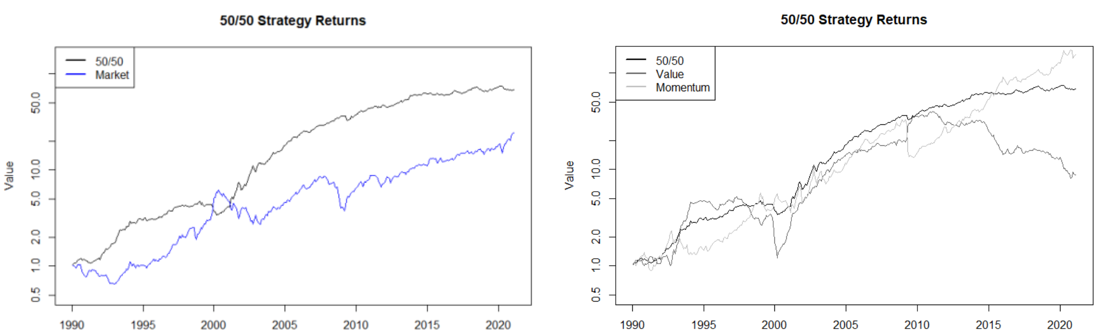
Table 6: Combination-method results

Reported are the mean returns in excess of the risk-free rate (NIBOR 3-month), compound monthly growth rate (CMGR), annualized Sharpe ratio and alphas from CAPM and the three-factor model for the individual stock momentum strategy, value strategy, 50/50 combination strategy and the simultaneous selection strategy. The mean return is calculated as the average monthly return. The CMGR is calculated as 1 + HPR raised to the power of 1 divided by number of months (373) $\left((1 + HPR)^{\frac{1}{373}} - 1\right)$. The annualized Sharpe ratio is calculated as the mean return in excess of the risk-free rate divided by the annualized volatility. T-statistics are reported in parenthesis.

Strategies Combined							
Strategy:		Momentum	Value	50/50	Simultaneous Selection		
Portfolio:		Zero-Cost	Zero-Cost	Zero-Cost	Long	Short	Zero-Cost
Nordic (January 1990 to January 2021)	Mean R (%)	1,61	0,77	1,19	1,12	-0,55	1,67
		(4,57)	(2,44)	(7,06)	(3,89)	(-1,64)	(6,65)
	CAGR (%)	1,36	0,57	1,13	0,96	-0,74	1,54
	Sharpe	0,82	0,34	1,27	0,70	-0,30	1,20
	CAPM alpha	1,90	0,79	1,34	0,38	-1,54	1,92
		(5,45)	(2,47)	(8,14)	(1,95)	(-8,39)	(7,82)
	3-factor alpha	2,47	0,19	1,31	0,12	-1,75	1,87
		(8,29)	(1,43)	(8,48)	(0,73)	(-9,74)	(8,03)
	MKT	-0,42	0,05	-0,19	0,77	1,05	-0,28
		(-7,34)	(1,80)	(-6,21)	(23,91)	(31,06)	(-6,41)
	SMB	-0,81	0,35	-0,23	0,26	0,56	-0,29
		(-5,06)	(4,86)	(-2,76)	(2,85)	(5,72)	(-2,32)
	HML	-0,88	1,47	0,30	0,50	0,06	0,44
		(-11,48)	(43,33)	(7,33)	(11,49)	(1,26)	(7,45)
	Max DD (%)	60,15	79,98	22,82	60,47	96,85	29,26

Figure 5: 50/50 strategy returns

The graph shows the combined strategy and its obvious advantage compared to value and momentum individually. The value crash of year 2000 and the momentum crash of 2009 has been eliminated entirely. Furthermore, the combined strategy is low in volatility and still very profitable.



5.2.2 Simultaneous Selection

In the previous subchapter, I find the simple weighted average to improve risk-adjusted returns significantly. This chapter explores whether a more sophisticated method of combination will improve performance further. I implement the simultaneous selection method for the Nordic market, but as a zero-cost strategy, not long-only as in Fisher et al. (2016). This will complement existing research and highlight the drivers behind the potential excess returns.

Every month *t*, I sort the stocks based on their book-to-market ratio in *t*-1, assigning them rankings from 0 to 1, where the most expensive company (worst) gets a score of 0, and the cheapest company (best) gets a score of 1. This procedure is repeated for the momentum measure (the cumulative return from *t*-12 to *t*-2). Next, I weigh these two scores equally, resulting in a final score for that stock between 0 and 1. A final sort is completed based on this new total score, and the top 10% performers are allocated to the long portfolio and the bottom 10% in the short portfolio.

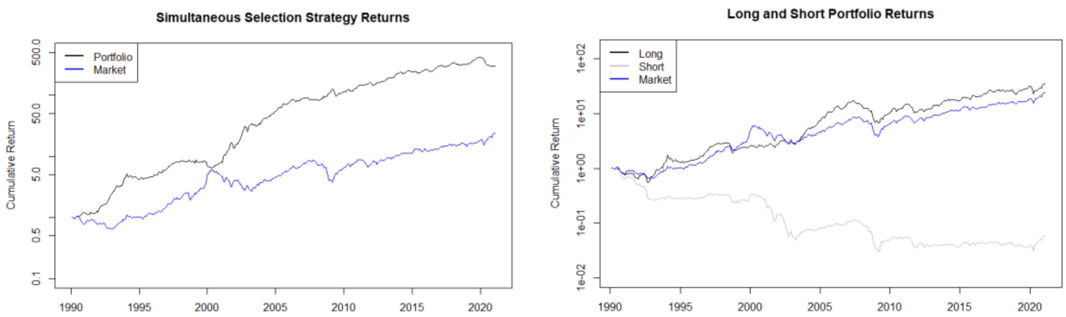
The method of simultaneously ranking stocks based on both momentum and value is expected to outperform either strategy alone and the weighted combination. This strategy is more open to stocks with only reasonably good performance in both measures. From Table 6, we can see that this is correct, as the simultaneous selection approach delivers the highest raw excess returns. However, the Sharpe ratio is slightly reduced compared to the weighted combination, and the maximum drawdown is around 30%. Although the risk-adjusted returns and crash mitigation are slightly worse than for the weighted combination, the strategy still outperforms both momentum and value alone, making it more appealing to investors with reasonable risk-aversion.

As an additional test, the strategy's returns are controlled for individual stock momentum, in addition to the three factors of Fama and French (see appendix 5). The alpha is reduced from 1.87% (t-stat of 8.03) to 0.46% (t-stat of 2.67), meaning that the simultaneous selection strategy still produces abnormal returns, even after controlling for the two factors from which it is constructed. Clearly, this method of combination has some invisible synergy effects.

An interesting finding is that the short portfolio is the driver of most of the abnormal returns. As the original article looked at long-only strategies, this contributes significantly to existing research. From Table 6, we can see that the three-factor alpha of the long portfolio is insignificant. However, the alpha of the short-portfolio is highly negative with an abnormal return of -1.75% with a t-statistic of -9.74. This is visualized in Figure 6. Companies that simultaneously score well in both momentum and value measures seem to move fairly in line with the market. Conversely, expensive and underperforming companies over the last year significantly underperform the subsequent month as well. The long-portfolio seems to be betting on fairly low-beta, average-sized value-companies, and the short-portfolio consists of market-beta, slightly bigger, and averaged-priced stocks.

Figure 6: Simultaneous selection strategy returns

The left graph shows the cumulative return of the simultaneous selection strategy. As we can see, the strategy is highly profitable and outperform the market. The momentum- and value crashes are also almost eliminated entirely. The graph on the right shows the long and short portfolio and the reason for the great performance is visualized. The short-portfolio delivers highly negative returns, while the long-portfolio perform similar to the market.



From Figure 6, we can see that the reported drawdown does not occur in any of the traditional value or momentum crashes discussed above. The 30% drawdown is the effect of the long portfolio falling more than the market during the Corona crash of March 2020 and the short portfolio significantly outperforming in the succeeding period. The strategy is short stocks with poor average scores on value and momentum. From Figures 2 and 4, we can see that the past losers performed relatively good compared to the market, and that the growth stocks significantly outperformed value after the crash. These companies experienced a significant boost during the recoil as interest rates dropped to a record low, making their future potential cash flow increase in value.

A further benefit of the combination of value and momentum is that the value strategy is more slow-moving, meaning that the book-to-market ratio does not fluctuate the same way as past returns. Consequently, the value strategy replaces the companies less frequently, reducing transaction costs. This thesis has already accounted for liquidity by removing the 50% smallest companies measured in market capitalization from the sample every month. Thus, only stocks that are subject to low transaction costs remain. However, institutional investors still incur costs when implementing a momentum strategy, and Jegadeesh and Titman (1993) estimated a semi-annual turnover of 84.8% for the U.S. WML portfolio. After incorporating a one-way transaction cost of 0.5%, the strategy's return was reduced to 9.29% annually. In today's high-tech world, costs relating to transactions have been reduced significantly, making them less relevant for the conclusions. However, the increased exposure to value stocks affects turnover directly and reduces transaction costs, making the strategies even more appealing. Conversely, as I find the short positions to drive almost all of the abnormal returns, the profitability of this strategy is subject to higher costs relating to short-selling, dampening the turnover effect.

In summary, the combination of momentum and value is highly profitable and more implementable than momentum alone. The risk-adjusted returns are drastically increased, and for the simultaneous selection strategy, the raw excess returns also surpass that of the individual stock momentum strategy. In conclusion, the combination of momentum and value increases profitability, reduces volatility, improves diversification, and mitigates crash risk. It seems like the increased returns come at less risk. This makes the combination of momentum and value a much bigger puzzle than either anomaly alone.

6. Conclusion

This thesis explores the individual stock momentum effect in the Nordic, whether industry effects explain the anomaly, and practical ways to minimize the risks related to momentum investing by increasing exposure to value stocks. All thoroughly explained throughout the thesis, a mixture of different methodologies is used to achieve the most valid and accurate results.

First, I construct a pure-play momentum strategy in the Nordics. The strategy yields significant excess returns in all tested variations but with an unmistakable performance boost when using a 12-1 strategy. This strategy yields a raw monthly excess return of 1.61% and a three-factor alpha of 2.47%, both being highly significant. Although this looks pretty profitable, also adjusted for volatility (Sharpe ratio of 0.82), the strategy experiences a severe crash during the sample period, making it unappealing to investors with reasonable risk-aversion.

Next, I explore industry momentum as the main explanatory factor for the momentum observed in Nordic stock returns. The findings of Moskowitz and Grinblatt (1999) are expected to be evident for the Nordic stock market. Following their methodology, with some adjustments to cope with the sample size and inspired by more recent studies, industry momentum strategies are tested in the same variations as with individual stock momentum. The 12-1 industry momentum strategy is highly profitable with a monthly raw excess return of 1.54% and a three-factor alpha of 1.84%. The Sharpe ratio of 0.64 was a tad below. Next, I conduct tests to explore whether the identified industry momentum explains the individual stock momentum. The first test is to control for industry momentum in a four-factor model. The individual stock momentum alpha is reduced to 1.78% but still highly significant (6.95), indicating that industries may not have such a big effect on stock momentum as initially thought. Moreover, when flipping the regression, the industry momentum alpha is wiped out completely (-0.09%) and not significant (-0.23). As these results were in conflict with the findings of Moskowitz and Grinblatt (1999), another test is conducted as a provisional measure. The profitability and significance of industry-neutral momentum strategies are tested by creating stock momentum strategies within industries. The results indicate that the momentum effect is present within industries, further weakening the original hypothesis.

These test results indicate that industries have only a small effect on individual stock momentum in the Nordic stock market. If industries do not explain momentum, then the individual stock momentum strategy may not be as poorly diversified as initially thought. The differences in results compared to Moskowitz and Grinblatt (1999) may be attributed to methodology. In an attempt to test the Nordic findings out-of-sample, the same analysis is conducted on the U.S. stock market, using data from Kenneth French's website. The obtained results indicate that individual stock momentum in the United States is far less profitable than in the Nordics. Furthermore, U.S. industry momentum seems like a more robust phenomenon, and is comparable to the Nordics' industry momentum effect. When regressing the individual U.S. WML returns on traditional risk factors in the United States and industry momentum returns, the alpha turns insignificant. Conversely, industry momentum remains significant when controlling for individual stock momentum. These findings indicate that the difference in results stems from sample-specific effects, more specifically, regional effects. Consequently, Moskowitz and Grinblatt concluded prematurely when generally naming industries as the main driver behind the momentum in stock returns, as this may be a local finding in the U.S. stock market. I argue that the poor performance of the individual WML strategy in the U.S. stock market in recent years results from more momentum investors trying to exploit the anomaly, reducing the profitability of the strategy. As initially stated in this thesis, the Nordic stock market is younger, smaller, and less liquid, thus not having the same popularity among WML traders.

In another attempt to explain the anomaly rationally, I explore momentum crashes, inspired by Daniel and Moskowitz (2016). I find the crashes to be severe for both individual stock- and industry momentum, meaning rational investors will limit their position in such a portfolio. These crashes may explain some of the alphas identified, but it has become more evident that there is a behavioral aspect to explaining the momentum anomaly.

Asness et a. (2013) find momentum and value to be individually profitable and negatively correlated by 0.53 in the U.S. equity market. The Nordic strategies are negatively correlated by 0.50. Two combination methods are explored: a simple weighted average approach as in Asness et al. and a more sophisticated simultaneous selection method inspired by Fisher et al. Both strategies perform remarkably well regarding risk-adjusted returns, and the weighted average yield a Sharpe ratio of 1.27 while the simultaneous selection approach yield a ratio of 1.20. Additionally, the simultaneous selection method significantly outperforms in raw excess returns, making this the most profitable strategy explored. Furthermore, the risk of crashes seen in both the momentum- and value strategy was removed entirely, and the possible poor diversification issues due to industry dependency are resolved. Consequently, the combination of momentum and value yields higher and more significant returns while also reducing volatility, removing crash risk, and improving diversification.

The exiting future now is when value stocks become momentum stocks. From November 2020 until the date of thesis delivery (although not visual in the sample), the value stocks have significantly outperformed the growth stocks. This change in investor sentiment and rotation towards more cyclical companies makes for an exciting period. When the past 12-month returns for the value stocks are relatively better than the market, WML traders move positions away from growth stocks into value stocks. Traditional value investors stay long-term, thus not changing away from value stocks unless the high performance makes them relatively expensive. Consequently, more capital is allocated to value stocks, thus increasing the performance of the combined strategies even further. Then again, the correlation between momentum and value is reduced, resulting in less hedging against crash risk. Conversely, the growth stocks become part of a vicious circle. In recent months, these stocks have suffered from increased interest rates and investor sentiment, and when WML traders are forced out of these stocks due to strategy constraints, their suffering will prolong.

In summary, this thesis identifies significant momentum in Nordic stock returns, not explained by traditional risk factors or industry effects as proposed by Moskowitz and Grinblatt (1999). However, industries may be one of several contributors, as the alpha of the individual stock momentum strategy was slightly reduced when controlling for industry momentum. Since evidence of poor diversification resulting from industry dependency remains unobserved, momentum crashes are explored as another possible rational explanation. The crashes for both stock- and industry momentum are severe, which reduced the attractiveness of the strategies. However, when increasing the strategy's exposure to value stocks through combination methods, the crashes are almost removed entirely and the profitability increase further. The momentum anomaly may be challenging to explain, but the combination of momentum and value poses as a much bigger puzzle.

7. References

Asness, C. S. (1997). The Interaction of Value and Momentum Strategies. *Financial Analysts Journal*, *53*(2), 29-36.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and Momentum Everywhere. *The Journal of Finance*, *68*(3), 929-985.

Asness, C. S., Porter, R. B., & Ross, S. L. (2000). Predicting Stock Returns Using Industry-Relative Firm Characteristics. *Working paper, AQR Capital Management*.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics, 49*(3), 307-343.

Chordia, T., Goyal, A., & Saretto, A. (2017). p-hacking: Evidence from Two Million Trading Strategies. *Swiss Finance Institute Research Paper Series*, 17-37.

Conrad, J., & Kaul, G. (1998). An Anatomy of Trading Strategies. *The Review of Financial Studies*, *11*(3), 489-519.

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics, 122*(2), 221-247.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance*, *53*(6), 1839-1885.

De Bondt, W. F., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance, 40*(3), 793-805.

Fama, E. F. (1965). Random Walks in Stock Market Prices. *Financial Analyst Journal*, *XXI*(5), 57.

Fama, E. F. (1970). Efficient Captal Markets: A Review of Theory and Empirical Work. *The Journal of Finance, 46*(23), 383-417.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 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), 3-56.

Fama, E. F., & French, K. R. (1998). Value versus Growth: The International Evidence. *The Journal of Finance, 53*(6), 1975-1999.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1-22.

Fisher, G., Shah, R., & Titman, S. (2016). Combining Value and Momentum. *Journal of Investment Management*, 33-48.

Graham, B. (2003). *The Intellegent Investor.* New York: SD Books.

Grobys, K. (2016). Another look at momentum crashes: momentum in the European Monetary Union. *Applied Economics, 48*(19), 1759-1766.

Grundy, B. D., & Martin, J. S. (2001). Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing. *The Review of Financial Studies*, *14*(1), 29-78.

Hong, H., & Stein, J. C. (1999). A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *The Journal of Finance, 55*(1), 2143-2184.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance, 48*(1), 65-91.

Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *The Journal of Finance, 56*(2), 699-720.

Jensen, M. C., & Benington, G. A. (1970). Random Walks and Technical Theories: Some Additional Evidence. *The Journal of Finance, 25*(2), 469-482.

Lakonishok, J., Shleifer, A., & Vishny, R. (1994). Contrarian Investment, Extrapolation, and Risk. *The Journal of Finance, 49*(5), 1541-1578.

Liu, L. X., & Zhang, L. (2008). Momentum Profits, Factor Pricing, and Macroeconomic Risk. *The Review of Financial Studies, 21*(6), 2417-2448.

Malkiel, B. G. (2003). The Efficient Market Hypothesis and Its Critics. *The Journal of Economic Perspectives, 17*(1), 59-82.

Moskowitz, T. J., & Grinblatt, M. (1999). Do Industries Explain Momentum? *The Journal of Finance, 54*(4), 1249-1290.

Novy-Marx, R. (2012). Is momentum really momentum. *Journal of Financial Economics, 103*(3), 429-453.

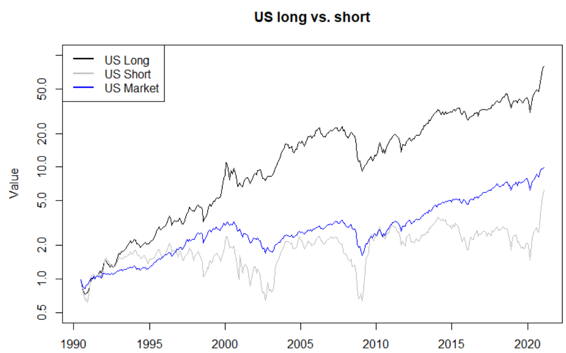
Petkova, R., & Zhang, L. (2005). Is value riskier than growth? *Journal of Financial Economics, 78*(1), 187-2002.

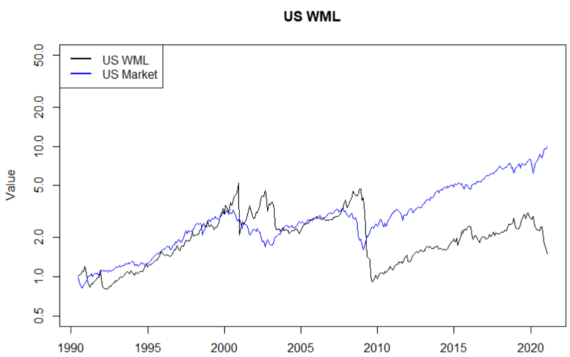
8. Appendix

Appendix 1

U.S. Momentum				
	Strategy	WML	12-IWML	48-IWML
Nordic (January 1990 to January 2021)	Mean R (%)	0,43	0,62	0,73
		1,13	(2,25)	(3,83)
	CMGR (%)	0,10	0,45	0,65
	Sharpe ratio	0,20	0,41	0,69
	CAPM-alpha	0,73	0,80	0,85
		(1,95)	(2,94)	(4,45)
	3-factor alpha	0,75	0,86	0,88
		(2,02)	(3,23)	(4,68)
	MKT	-0,38	-0,35	-0,20
		(-4,40)	(-5,45)	(-4,53)
	SMB	-0,29	0,31	0,10
		(-2,21)	(3,33)	(1,53)
	HML	-0,23	-0,19	-0,14
		(-1,97)	(-2,30)	(-2,48)
	Max DD (%)	82,49	53,59	41,16

U.S. Momentum				
	Strategy	WML	12-IWML	48-IWML
Nordic (January 1990 to January 2021)	Mean R (%)	0,43	0,62	0,73
		1,13	(2,25)	(3,83)
	CMGR (%)	0,10	0,45	0,65
	Sharpe ratio	0,20	0,41	0,69
	CAPM-alpha	0,73	0,80	0,85
		(1,95)	(2,94)	(4,45)
	3-factor alpha	0,01	0,53	0,65
		(0,04)	(2,50)	(4,35)
	MKT	-0,09	-0,17	-0,08
		(-1,28)	(-3,40)	(-2,21)
	SMB	-0,55	0,43	0,19
		(-5,30)	(5,88)	(3,72)
	HML	-0,65	-0,09	-0,07
		(-0,71)	(-1,37)	(-1,58)
	12IWML/WML	0,86	0,44	0,32
		(14,80)	(14,80)	(15,36)
	Max DD (%)	82,49	53,59	41,16





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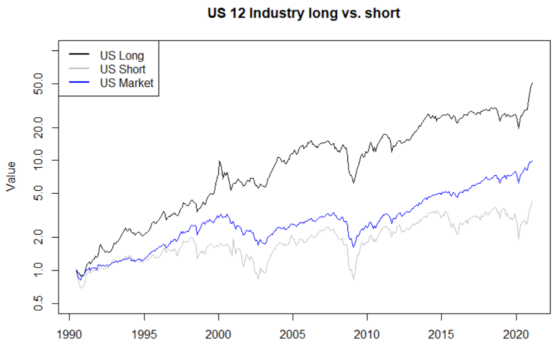
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US Long
US Short
US Market
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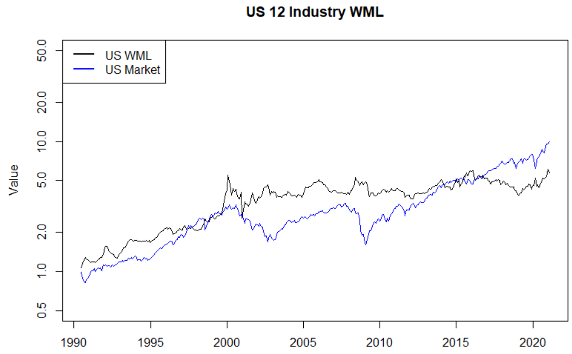
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US WML
US Market
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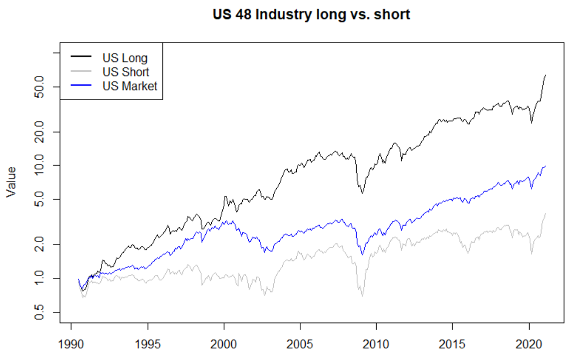
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US Short
US Market
Value
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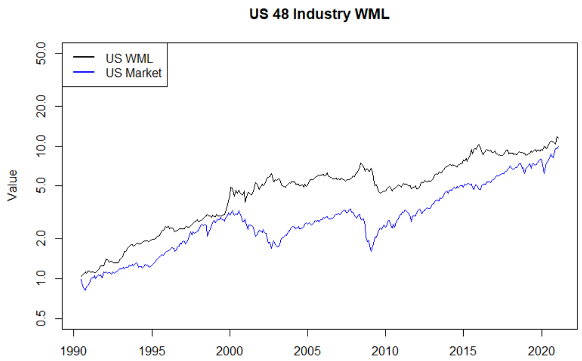
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US WML
US Market
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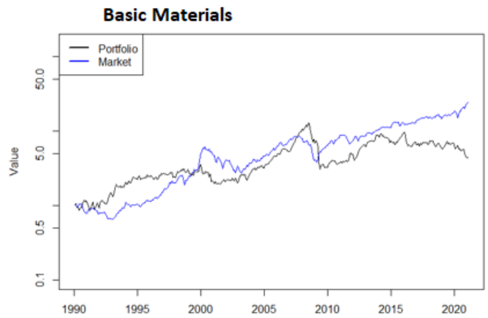
Appendix 3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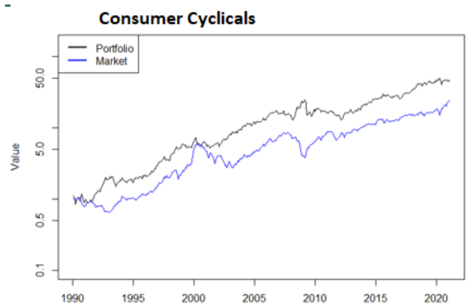
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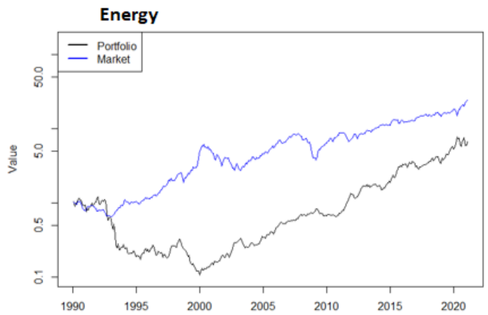
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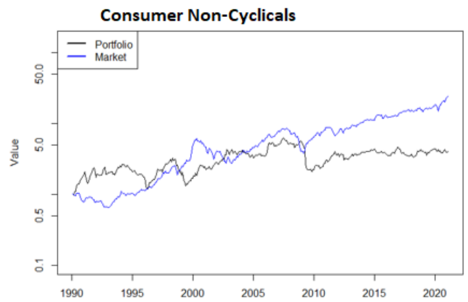
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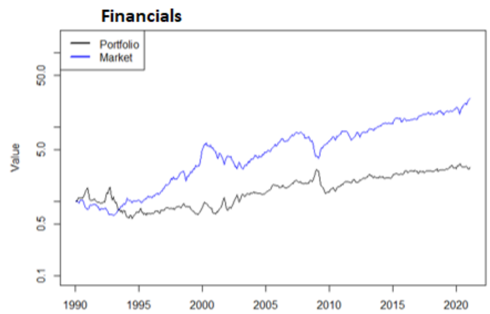
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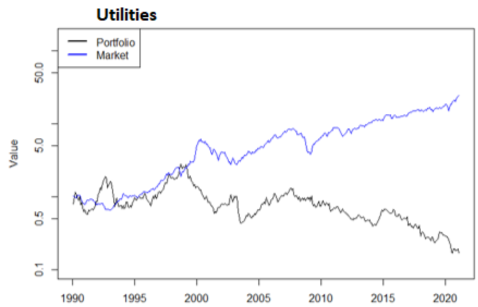
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Portfolio
Market
Value
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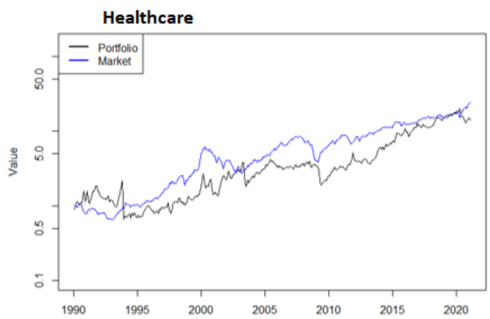
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Portfolio
Market
Value
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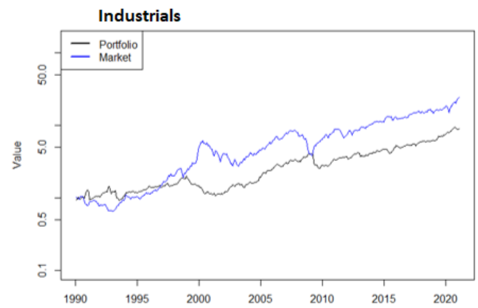
1990 1995 2000 2005 2010 2015 2020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Portfolio
Market
Value
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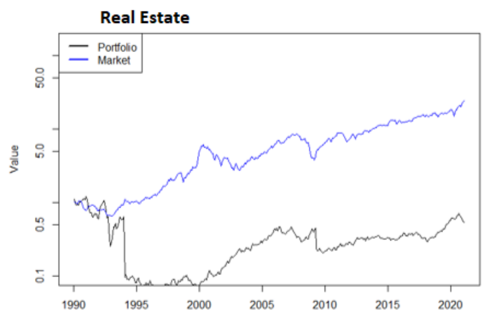
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Portfolio
Market
Value
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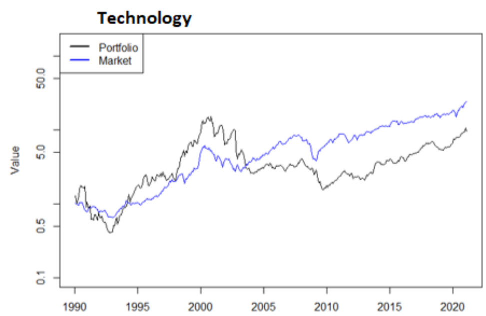
1990 1995 2000 2005 2010 2015 2020


Technology
Portfolio
Market
Value
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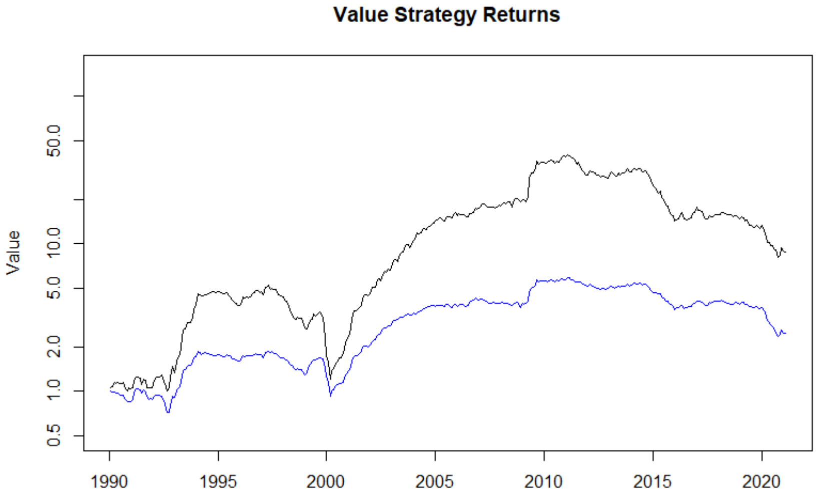
1990 1995 2000 2005 2010 2015 2020

Appendix 4



Appendix 5

Strategies Combined					
Strategy:		Momentum	Value	50/50	Average ranking
	Mean R (%)	1,21	0,77	1,19	1,67
		(3,78)	(2,44)	(7,06)	(6,65)
	CAGR (%)	1,02	0,57	1,13	1,54
	Sharpe	0,68	0,34	1,27	1,20
	CAPM alpha	1,49	0,79	1,34	1,92
		(4,69)	(2,47)	(8,14)	(7,82)
Nordic (January 1990 to January 2021)	3/4-factor alpha	1,86	0,19	0,15	0,46
		(6,60)	(1,43)	(2,08)	(2,67)
	MKT	-0,33	0,05	0,01	-0,04
		(-6,18)	(1,80)	(1,01)	(-1,32)
	SMB	-0,34	0,35	0,16	0,17
		(-2,24)	(4,86)	(4,23)	(1,90)
	HML	-0,77	1,47	0,71	0,95
		(-10,72)	(43,33)	(36,35)	(20,30)
	WML	-	-	0,48	0,57
				(41,61)	(21,00)
	Max DD (%)	49,73	79,98	22,82	29,26