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Comparative Study of Factor-Based Strategies in the Nordic Countries

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Comparative Study of Factor-Based Strategies in the Nordic Countries

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Abstract

This thesis examines whether an investor could generate net returns above the Morgan Stanley Country Index by applying momentum and value strategies in the Nordic countries between 1990 and 2019. We first investigate the strategies on individual stocks, then on a sector level, to evaluate whether profits can be attributed to sector exposure. We find the momentum anomaly to be present on an individual stock basis in Norway and Sweden, whereas Denmark and Finland appear to be highly sector dependent. Book-to-market does not generate any net returns above the MSCI indices in any country, and cash flow-to-market works well on an individual stock basis in Norway and Sweden and likewise on sector level in Denmark. Value, in general, outperforms momentum in bear markets, while momentum outperforms value in bull markets. Moreover, the best risk-adjusted returns are achieved by diversifying investments across all four countries.

supervised by
GIORDANI, Paolo

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Contents

1 Introduction

1.1 Background

The last decades have brought many technological advancements that have dramatically reduced the cost of computing power, providing the world with easy access to cheap and reliable data. These changes have created many new opportunities within finance, one being the rise of factor-based investment strategies. Factor funds use a single or a combination of factors such as value, momentum, and quality to assess which equities to invest in. Algorithms sort and analyze vast amounts of data, which is then applied in a systematic way to form investment strategies. At the end of 2018, the total assets under management for the global smart beta market were approximately $797 billion spread across roughly 1500 exchange-traded products (Morningstar, 2019). The popularity is also rising within the Nordic countries with mutual- and pension funds applying factor-based strategies. Only in Norway, do the combined assets under management for factor funds exceed NOK 57.5 billion (VFF, 2019).

The use of company characteristics and technical analysis is not a new phenomenon. Investors have utilized similar value and trend following strategies for decades. However, it was academia that first started to codify and document the signals in a systematic approach – making it possible for investors to deploy factors likewise in the technology boom that followed. Acquiring and processing the data was something only a few investors could do at the time; nonetheless, early adopters enjoyed tremendous success and are today some of the most notable hedge funds (e.g., Renaissance Technologies, AQR Capital, and Two Sigma). The founder of AQR Capital stated:

> *"Well-known classical strategies that have worked over the long term will continue to work forward, though perhaps not at the same level and with the risk as in the past"* (C. S. Asness, 2015).

Research has identified four main factors that generate long-term excess returns across multiple assets: value, momentum, defensive/quality, and carry. Jegadeesh and Titman (1993) first coined the term momentum and found that selecting US stocks based on their past 6-month cumulative returns and holding for 6-months, produces an excess return of 12.01% per year (1965-1989). Gray and Vogel (2016) improved on this, developing a momentum strategy in which they assess the quality of the momentum by measuring the path to returns. This strategy, named "Quantitative Momentum", realized a 15.80% annual return compared to 13.35% of generic momentum and 9.92% S&P 500 (1927-2014).

Of all the factors, value is arguably best known, with the most extended history of research. Value goes back as far as to the 1930s, with Benjamin Graham as the leading figure. Graham is famous for his investment books Security Analysis (1934) and The Intelligent Investor (1965) and was also the mentor of the renowned Warren Buffett, a firm believer in value investing. In essence, value investing involves separating cheaply valued companies from *expensive* ones, believing that the *cheap* will outperform in the long run. The best-known work on the value factor is carried out by Eugene Fama and Kenneth French in their papers from 1992 and forward. In their (1992) paper, they sorted based on the ratio of book value to market value of equity (BM), examining the period of 1963 to 1990.They found an annual spread (value premium) of 18.36% between the portfolios containing US stocks with the (30%) highest and the (30%) lowest ratios. In (1996), they added more ratios and restricted to only large stocks for 1963-1991. The spreads obtained were 9.6% for book-to-market (BM), followed by 8.76% for cash flow-to-price (CP) and 5.76% for earnings-to-price (EP) (1963-1991). This research was extended to international markets – the US and twelve others in (1998) and used data from the 1975 to 1995 period. They observed a value premium for global portfolios formed on BM, CP, and EP (7.68, 7.71, and 6.68%).

Today, AQR Capital Management, a pioneer in factor investing and quantitative research, is the largest public mutual fund provider in the world. The fund was co-founded by Cliff Asness (earlier teaching and research assistant to Eugene Fama), John Liew, and Robert Krail (both Ph.D. students from Fama's class). The firm offered its first product in the year 2000 and had nearly $750 million under management in 2001, which grew to $217.2 billion by 2017 (AQR, 2017). Although this is impressive, AQR's profits plunged 34% in 2018, and it had only $185 billion under management in 2019. Today the company plans to cut 5 to 10% of its global workforce (Kishan, 2020). AQR is not the exception, and while value investing remains attractive through the history of available data, it has been under significant pressure since the beginning of 2007 (Meredith, 2019). As of January 2020, the Russell 1000 Value (an index tracking large- and mid-cap U.S. equities with value characteristics) has underperformed the Russell 1000 Growth by 4.1% annualized over the last ten years.

This significant underperformance is currently of interest to the research community, most recently by Fama and French (2020). Their research shows that the value factor (measured in BM) substantially underperforms for the second half of 1963-2019 compared to the first. In the first sample period of 1963-1991, the value factor generates an annual excess return of 5.16%, while for the second period (1991-2019), it only generates 1.33%. They, along with others, try to explain the cause of this downturn for the value premium, something that has even led to speculation on whether the value factor is "dead".

Momentum has also suffered from underperformance over the past couple of years, although not as severe or broad as value. Daniel and Moskowitz (2013; 2016) found that momentum strategies often experience heavy losses at the beginning of a new bull market, known as momentum crashes. They argue that momentum strategy is likely to be long low beta stocks, which have fallen less than the market during the downturn (e.i. past winners), and short high beta stocks that fell more or equal to the market (e.i. past losers). When the market finally rebounds, the high beta stocks follow, resulting in the returns of the stocks contained in the short portfolio to massively exceed the returns of less volatile longs. Although it is not a bear market by definition, the correction in late 2018, where the S&P 500 lost 19%, likely affected momentum results negatively. For comparison, the SPDR Russell 1000 Momentum Focus had an annualized 3-year performance of 8.96%, while the SPDR S&P 500 had a superior 15.54% (As of Feb. 2020).

1.2 Research question

In this thesis, we will study whether an investor could generate net returns[1] in excess of the benchmark by applying simple well-known factor strategies, namely momentum, book-to-market, and cash flow-to-market. As discussed above, both value and momentum seem to have shown signals of losing their premia in the United States. Therefore, we want to investigate whether this is the case for the Nordic countries, using data from companies listed on Oslo Børs (Norway), OMX-Stockholm (Sweden), -Copenhagen (Denmark), and -Helsinki (Finland). Given the inherent similarities between the countries, we expect to obtain comparable results across them. The performance will first be measured when strategies are applied on an individual stock basis, then on a sector level. The hypothesis being that if the strategies formed on sectors produce similar results to the strategies formed on individual stocks, a large portion of returns can be attributed to picking the right sector, rather than individual stocks. This will be accomplished by examining which sectors the strategies invest in and how these perform.

Furthermore, we investigate how the strategies perform trough different market regimes, most notably the dot-com bubble of 2000 and the global financial crisis of 2008. For the individual stock strategies, we construct a Nordic

[1] Net of transactions costs. Taxes and inflation not accounted for.

portfolio by combining the portfolios of each country on an equal-weighted basis. We do this to assess if returns and (or) risk can be improved, as allocation between countries should reduce country-specific risks and increase portfolio diversification. This brings us to our main question:

> *"What returns could Nordic investors obtain by applying the momentum and value strategies in the time period of 1990 to 2019?"*

Furthermore, we want to examine the following questions:

– *"Which combination of formation and holding period produces the best result for each strategy?"*

– *"How do the strategies behave through different market regimes?"*

– *"How do the results of a combined Nordic portfolio compare to each market on their own?"*

– *"Can a strategy's return be explained by sector exposure?"*

Despite extensive research into the momentum and value strategies both internationally, and in the Nordic region. To our knowledge, few have investigated the Nordic countries and strategies together and related findings to sector exposure. This thesis contributes to the literature by trying to answer whether profits are generated by sector advancements, rather than individual stocks. Moreover, we review the strategies through bull- and bear-markets and construct and examine a country dependent Nordic portfolio.

This thesis is divided into eight sections, structured as follows. In section 2, we provide previous research on factors examined – Momentum, Book-to-Market, and Cash flow-to-market, as well as results obtained in various markets and time periods. Moreover, an overview of research conducted on strategy specific features – seasonality effect, momentum crashes, value traps, and more - is also presented. Section 3 provides a detailed explanation regarding methods used for measuring factors, creating portfolios and implementation. A description of the Data is also included in this section.

In section 4, we first report the results obtained by the strategies in each of the Nordic countries. Moreover, we estimate a country dependent (equal-weighted across the countries) Nordic portfolio and present the results. Continuing, we construct a *final* portfolio with two variations, the first using equal-weighting across strategies, the second using weights calculated with the Kelly criterion. Lastly, in section 4, we run the strategies on sectors rather than individual stocks and compare the results with those of individual stocks. We conclude our findings in section 5 and report the limitations of our research in section 6. Section 7 contains a list of references, while the appendices are presented in section 8.

2 Literature Review

2.1 Momentum

Although factor investing is relatively new and is just recently starting to gain popularity among retail investors, a lot of academic research has been done laying the foundation for modern factor models and strategies. One of the most well-known and thoroughly researched factors is price momentum. In its simplest form, one buys the best-performing and sell the worst-performing stocks, usually measured within a time-frame of 6 or 12 months (Jegadeesh & Titman, 1993).

Robert A. Levy (1967) is considered the first to discover what is now referred to as momentum. In his paper "Relative Strength as a Criterion for Investment Selection", Levy discovered that buying stocks which had greatly outperformed their 26-week historical average went on to produced abnormal excess returns. While his work is considered the first take on a relative strength strategy, his results were discarded as a result of selection bias only a few years later by Jensen and Benington (1970). For a long time, there was little to no research conducted, mainly due to the rising belief in contrarian investment strategies proposed by De Bondt and Thaler (1985). Their findings suggested that stocks that had performed poorly for the last three to five years went on to produce excess returns in the following years, the exact opposite of the theory behind modern momentum strategies.

Another source of the lack of momentum strategy research was the development of the efficient market hypothesis by Malkiel and Fama (1970). Their hypothesis states that the share price reflects all available information, which makes the current price represent the true fair value of the stock at all times. This effectively makes it impossible for a stock to be over- or undervalued; hence, excess returns other than risk-adjusted should not be possible. This theory was long the dominating mantra of academia, and while many publications have questioned its validity, there are still some who follow this school of thought. In the following years, Eugene F. Fama, in collaboration with his academic partner, Kenneth R. French, produced a substantial amount of research within the field of factor investing, which is still highly relevant to this day (see Fama and French (1992); (1993); (1996)). Together they produced the famous FF three-factor model (1992) which expands on the CAPM (Sharpe, 1964); (Lintner, 1965) as well as the extended FF five-factor model (Fama & French, 2016). Later Fama went as far as stating that the momentum anomaly is the biggest embarrassment to the efficient market hypothesis, and that momentum is the "premier anomaly" (Fama & French, 2008).

Evidence of the momentum anomaly has been found in all markets globally (Europe: Rouwenhorst (1998); International: Griffin, Ji, and Martin (2003)), as well across multiple assets (C. S. Asness, Moskowitz, & Pedersen, 2013). The only exception being Japan ((C. Asness, 2011); (Fama & French, 2012)). Most relatable to our research is the study by Rouwenhorst (1998) on momentum in 12 European countries, including Norway, Sweden, and Denmark, for the period 1980-1995. He found that the winners (top 10%) outperformed the losers (bottom 10%) by about 1% per month for an internationally diversified portfolio. Furthermore, he discovered a significant correlation between the European and US results of Jegadeesh and Titman (1993), concluding the results obtained in the US, were likely not due to chance. Although some worry that momentum strategies' success might be a result of data-mining, C. S. Asness et al. (2013) argues that momentum still works everywhere.

No one has really been able to prove what exactly enables certain factors to deliver abnormal returns. Most of the literature uses behavioral finance explanations such as overconfidence and underreaction (K. Daniel, Hirshleifer, and Subrahmanyam (1998); Hong and Stein (1999), overreaction (Zhang, 2006), herding (Hwang & Salmon, 2004), anchoring bias (Hirshleifer, 2001), and the disposition effect ((Shefrin & Statman, 1985); (Cen, Hilary, Wei, & Zhang, 2010)). Common for these hypotheses is that they all have roots in deep human psychology. It turns out that we humans have a tendency to let emotions affect our judgments, which sometimes lead to irrational behavior.

For rational explanations, most use a risk-based approach. While momentum strategies outperform the general market most of the time, there are also periods of severe underperformance and huge drawdowns. These periods often occur at the beginning of a fresh bull market, and are commonly known as "momentum crashes". Since the return distribution is negatively skewed, the investor is rewarded for carrying that risk (K. D. Daniel & Moskowitz, 2013). Another risk-based explanation is that stocks that have performed well over a period of time, often are more susceptible to weakening outlooks, making them poorly positioned for a bear market (Liu & Zhang, 2008).

2.1.1 ***Price Momentum***

Although the work of Levy (1967) is now considered the first take on a momentum strategy, it was Jegadeesh and Titman (1993) who first coined the term momentum. In their famous paper "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency", they improve on the work of Levy, providing a modern manual for momentum investing. They use the cumulative returns of the previous 3, 6, 9, and 12 months and measures the return the following 12 months. They skip the last week in order to omit issues regarding price pressure, bid-ask spread, and lagged reactions effect documented by Jegadeesh (1990) and Lehmann (1990). This was later adopted and extended to skipping the last month by multiple papers (f.ex. C. S. Asness (1995); Grinblatt and Moskowitz (2004); and C. S. Asness et al. (2013)).

Even though generic price momentum is by far the most common method in academia, there have been multiple attempts to improve on the strategy, both in terms of reducing volatility and increasing returns. In contrast to Jegadeesh and Titman method of using past performance of stock returns relative to others in a cross-section, Moskowitz, Ooi, and Pedersen explores momentum on a time-series basis where they use an asset's absolute performance to predict future returns. Their research suggests that the momentum anomaly is just as present in the method of absolute returns, with excess returns through multiple asset classes through time (Moskowitz et al., 2012).

Other studies have explored the relationship between momentum and other exogenous characteristics. Bandarchuk and Hilscher (2013) did an extensive examination of characteristics previously shown to influence momentum returns, including analyst coverage, analyst dispersion, size, age, liquidity, credit rating, market-to-book ratio. They find that strategies incorporating these characteristics, ultimately gain their edge by trading stocks with extreme pas returns. This could be interpreted as evidence supporting the behavioral explanations for the momentum premia. Zhang (2006) tries to explain the phenomenon by hypothesizing that investors tend to over- and under-react to information, especially in times with information uncertainty and market volatility, creating exploitable opportunities. This is in line with the hypothesis of (Jegadeesh & Titman, 1993), (C. S. Asness, 1995) and (Fama & French, 1996). Antonacci (2017) further expands on the idea using what he calls "Dual Momentum", where he combines both the relative strength momentum and absolute to produce an even higher return.

On the other hand, Gray and Vogel (2016) built an improved momentum strategy in which they try to assess the quality of the momentum by measuring the path to returns. Contrary to the previous theories, they hypothesize that a slow continuous rate of return makes the investors under-react due to what they call a processing delay with continuous information (Da, Gurun, & Warachka, 2014). While the cumulative return for a period is the same, the stock with less dramatic moves flies under the radar of investors, resulting in a longer-lasting momentum move.

2.2 Value

In the last decades, plentiful research has been provided on the value factor, a way to differentiate *expensive* stocks from *cheap*. In this section, we will present the most used accounting measures for this differentiation.

2.2.1 ***Book-to-Market Ratio***

The book-to-market ratio is arguably the most known of these measures, comparing a company's book value of equity to its market value. Stattman (1980) and Barr Rosenberg (1984) found that *cheap* stocks (high BM ratio) exhibit, on average, higher returns than *expensive* stocks with a low ratio for U.S. stocks. Chan, Hamao, and Lakonishok (1991) reveal that the book-to-market ratio gives the most significant impact on expected returns on Japanese stocks. One of the most heavily quoted papers in academic finance is that of Fama and French (1992), in which they discover that book-to-market relation has a more substantial role in average returns, followed by, but not replacing the size effect. Their result shows that between 1963 and 1990, the combination of size and book-to-market ratio performs best in explaining the cross-section average stock returns. When these are accounted for, CAPM ß (systematic risk) loses its importance. Besides, they find that higher market leverage – measured by the ratio of book assets to market equity, is related to a higher average return. In contrast, their measure for book leverage – the ratio of book assets to book equity, is associated with a lower average return. Consequently, the difference between market and book leverage describes average return; this difference is also the book-to-market ratio (BM). Finally, they also show how average returns increase with earnings-to-price (EP), when positive.

Fama and French (1998) extends this to the international markets, looking at the U.S. and twelve other stock markets, including Sweden, and finding extensive international evidence of the value factor from 1975 to 1995. More specifically, they show that value (high BM) outperform (low BM) in 12 of the 13 major markets. In a given explanation for the BM factor, they give two possible explanations. The rational one is that firms with a high BM ratio have poor earnings prospects and thus have a high market imposed leverage (e.i. the market undervalues these stocks). In contrast, low ratio firms are being rewarded for strong earnings prospects. This argument relating a company's performance to its BM ratio is undoubtedly the most common and similar to Fama and French (1992), which argues that BM is capturing financial distress.

The irrational explanation is that the BM is not a proxy for risk, but the outcome of market overreaction to the relative prospect of a firm. This explanation is more consistent with C. S. Asness et al. (2013) that show the ratios negative correlation to liquidity risk, as opposed to momentum positive correlation. Therefore, when funding liquidity drops, occurring in periods where borrowing is difficult, the value strategy performs well, whilst momentum does poorly. Vayanos and Woolley (2013) allege that ”slow money” causes prices to be pushed away from fundamentals leading to reversal and under-pricing.

2.2.2 ***Other Accounting Ratios***

In the same manner as the book-to-market equity ratio, Fama and French (1996) show how other accounting variables divided by the stock price creates a characterization to explain average return. As loading on book-to-market ratio proxy distress, they infer that high earnings-to-price and cash flow-to-price are typical of stocks that are relatively distressed and low ratio typical of healthy stocks. In essence, portfolios formed by sorting on EP, CP, or BM reflect roughly the same underlying risk factors and characteristics. This research excluded small stocks.

This confirms Lakonishok, Shleifer, and Vishny (1994) findings that sorting on cash flow-to-price (11%) ratio gives a more significant difference in returns than book-to-market (10.5%), followed by earnings-to-price (7.6%) for their sample period of 1968-1989. Although the B/M ratio captures many different elements, the paper reasons that variations in CP ratio across firms are due to differences in growth rates and thus gives rise to better value strategy. They argue that a low BM ratio might catch a company that has a lot of intangible assets, such as R&D capital, which is expensed and not accounted for in the book value, but also a company with attractive growth prospects or an overvalued company. Lastly, an oil price jump could give a low BM ratio for an oil company without excellent growth outlooks, but with momentarily high profits. Besides, even though the EP ratio captures the growth rate similarly to CP, it produces the worst result. An explanation for this is that stocks with temporarily depressed (leaped) earnings are huddled together with growth (value) stocks. Therefore, the low (high) EP ratio portfolio does better (worse), and the outperformance of value stocks is reduced.

Fama and French (1995) extended their research from (1992) to evaluate the ”distress” explanation, as well as profitability (the ratio of earnings to book value of equity) role in explaining returns. They confirm the hypothesis that a high BM ratio is likely to spot stocks that, before portfolio formation, have experienced recent distress and decay in profitability. In contrast, a low ratio is likely to find stocks with recent growth and high profitability. After portfolio formation, the trend seems to reverse, with high BM stocks undergoing increased profitability, and low BM stocks suffering reduced profitability. Although the trend reverses, the low BM stocks have persistently strong profitability relative to high BM stocks. Thus, the market responds by pricing strong (low BM) stocks at a premium, while distressed (high BM) stocks are priced at a discount.

The different industries loading on ”value” appear to variate through the sample period of 1963 to 1994, and indicate phases of industry strengths and distress. Given this fluctuation of industries between growth and distress, it would certainly be interesting to see if the different accounting ratios performance can be attributed to their industry composition.

2.3 Sector

During the last decades, research has found that a large portion of momentum returns can be attributed to momentum within an industry, rather than individual stocks.

Moskowitz and Grinblatt (1999) found that industry momentum for the sample period of July 1963 to July 1995 captures momentum returns for individual equities almost entirely. They examined the formation periods of 1, 6, and 12-months and holding periods of 1, 6, 12, 24, and 36-months, buying the 30 percent best performing individual stocks and industries while selling the bottom 30 percent. Moreover, they show how the industry momentum strategy generates most of its profits on the long side, contrary to that of the individual equity momentum strategy, which is primarily driven by the short side. The similar return results of the two momentum strategies drive them to conclude that momentum returns are not well-diversified, with *winners* and *losers* often originating from the same industries.

Although it is not always the focal point in asset price theory, the importance of industry as a way to explain asset prices is no controversial idea. Throughout time, there have been multiple phases in which a particular sector (industry) has outperformed the rest of the market. Meredith (2019) shows that long term economic cycles of Technological Revolutions bring new technologies and opportunities that give birth to new industries. These long-term cycles usually last between 45 and 60 years, and within each cycle, the companies considered ”growth” and ”value” drastically change.

For our time, the most noticeable emerging sector is by far the IT-sector, with internet and computing power changing the way companies operate and how wealth is being created. As an example, in January 2007, the five most essential names in the S&P 500 index were Exxon Mobil, General Electric, Microsoft, Citigroup and Bank of America, whereas, in June 2019, the top five were Microsoft, Apple, Amazon, Alphabet, and Facebook (Meredith, 2019). The latter ones being part of the vast technological trend of big data collecting and utilization. That is why practitioners and academics believe that a large portion of the returns produced from cross-sectional momentum can be attributed to the momentum of a particular sector (Moskowitz and Grinblatt (1999); Chordia and Shivakumar (2002); Su (2011)).

From July 1926 to December 2018, Meredith (2019) defines two major growth regimes where value greatly suffers (Jun-1926 to Dec-1941 and Jan-2007 to Dec-2018). In the first period, manufacturing stocks were overrepresented in the growth portfolio, while utilities dominated the value portfolio. In contrast, financials dominated the value portfolio in the second period, while technology was primarily in the growth portfolio. Value underperformed growth in both these periods, mainly related to the performance of a few sectors. As an example, in the most recent period, they find that technology stocks contribute to growth's overperformance, but financials stood for roughly 75 percent of the underperformance. A similar theme can be observed in the first turning point, where utilities struggle relative to manufacturing.

Within a growth regime, there is a turning point in which financial capital decouples from production capital – typically characterized by increased speculation and excessive leveraging of cheaply valued companies to keep up with the emerging growth stocks. This results in valuation bubbles, and eventually market crashes as financial capital *"believes itself capable of generating wealth by its actions, almost like having invented magic rules for a new sort of economy"* (Perez, 2003). Value traps are created when the market becomes aware of the rising distress of these sectors, in this case, utilities and financials, causing market valuations to drop, which results in even more alluring valuation ratios. It is conventional in academic literature to exclude financial and utility companies, as the former naturally has high leverage (Fama & French, 1992), which often signals distress in non-financial companies. Reasons to exclude utilities could be linked to excessive leverage or their link to governments.

3 Methodology

This section outlines our process for data collection and the creation of the factors discussed above. Python is used to construct trading algorithms and to backtest the strategies.

3.1 Data

This thesis uses data from ranging from February 1990 to December 2019 for all major Nordic exchanges; Norway, Denmark, Sweden, and Finland. Iceland is excluded from the analysis because of its small size, which is consistent with other studies conducted on the Nordic countries. The sample is restricted to post 1990 due to prior available data being too scarce.

The sample dataset consists of all stocks which are, and has been listed on Oslo Stock Exchange, Stockholm Stock Exchange, Copenhagen Stock Exchange, and Helsinki Stock Exchange, as well as the respective Morgan Stanley Capital International (MSCI) country index. As in Lakonishok et al. (1994), delisted stocks are included to avoid survivorship bias arising from only using currently active stocks. Reasons for delisting include: cease of operations, bankruptcy, mergers & acquisitions, and failure to satisfy exchange listing requirements.

For all stocks, the dataset includes month-end close price, market value (MV), Market-to-Book ratio (MB), cash flow (CF), and the total return index (TRI). All values are given on a monthly basis and were collected from Thomson Reuters. Data with lower available frequency, such as CF (quarterly), have repeating values for months between quarter ends. In addition, we collected the Thomson Reuters Business Classification (TRBC) for all companies. Monthly currency exchange rates are exported from the Federal Reserve Economic Data (FRED) database.

The total return index (TRI) is a theoretical measure of growth that includes both capital gains and reinvestments of any cash distributions, such as dividends. The TRI gives a more accurate representation of the investment's actual return compared to the close price. The TRI at day t is calculated as follows:

$$RI_t = RI_{t-1} \frac{P_t}{P_{t-1}} \tag{1}$$

And for the day of dividend (D) payment:

$$RI_t = RI_{t-1}\frac{P_t + D_t}{P_{t-1}} \tag{2}$$

3.2 Data Preparation

The MSCI Indices described in Table 1 are used as benchmarks. These indices measure the performance of large and mid-cap segments and contain approximately 85% of the market capitalization of each of the markets. The reason for choosing MSCI indices and not the country's all shares index[2] is due to several of the indices being formed after the start of our sample. For instance, both Oslo Børs Benchmark Index (OSEBX) and OMX Copenhagen_PI (KAX) were formed in 1995, while the MSCI country indices go back to 1987.

	Norway	**Sweden**	**Denmark**	**Finland**	**Nordics**
Equity Universe (%)	10 (85 %)	31 (85 %)	18 (85 %)	12 (85 %)	69 (85 %)
10-Year Annual Return	3.44%	7.83%	11.75 %	1.26 %	6.74 %
Historical P/E	21.23	17.31	24.04	22.71	20.19
Historical P/BV	1.81	2.23	4.26	2.34	2.57

Table 1: MSCI Nordic stock indexes (Benchmarks)
Reported are the descriptive for each of the Morgan Stanley Country Indices (MSCI) for Norway, Sweden, Denmark, and Finland, as well the aggregated index for the Nordics. The Equity Universe (%) reports the number of constituents (percentage of total market cap in parenthesis). Below are the 10-Year average annual return, historical average P/E (Price/Earnings), and P/BV (Price/Book-Value) ratio.

To create the investable universes, we convert the end-of-month market capitalization (cap) for each stock to US Dollars. We then rank all stocks in each country by size and throw away 50% of the smallest companies in the sample. This procedure is repeated for each month. The reason for doing so is to remove the smallest stocks which are associated with high transaction costs and shorting fees, as well as only including equities professional investors could buy without facing liquidity problems (O'Shaughnessy, 1996). Both MSCI and C. S. Asness et al. (2013) define their investable universe through sorting stocks on market cap, then include the stocks accounting for 85 or 90% of the total market cap. Using the same procedure would reduce our investable universe to a handful of stocks, as in the MSCI country indices, hence, we used the 50th percentile as a cut-off point. This raises our minimum average market

[2]We acknowledge that the all shares index would be ideal as it covers companies of all sizes, however, as our investable universe contains only the top 50% of companies ranked by market value, we believe it to be fairly reasonable.

cap to $144m across the four markets, close to that of O'Shaughnessy (1996). Table 2 shows the number of stocks in the raw and reduced sample for 28th February 1990 and 31st December 2019.

		Norway	Sweden	Denmark	Finland
1990	Raw	104	235	184	51
	Reduced	52	117	92	25
2019	Raw	209	640	138	148
	Reduced	104	320	69	74

Table 2: Number of stocks by country(raw and reduced sample)
Presented are the number of stocks present in the raw and reduced sample. The reduced sample represents our investable universe and is constructed by ranking all stocks, in each country by their market cap (USD), then excluding the lower half.

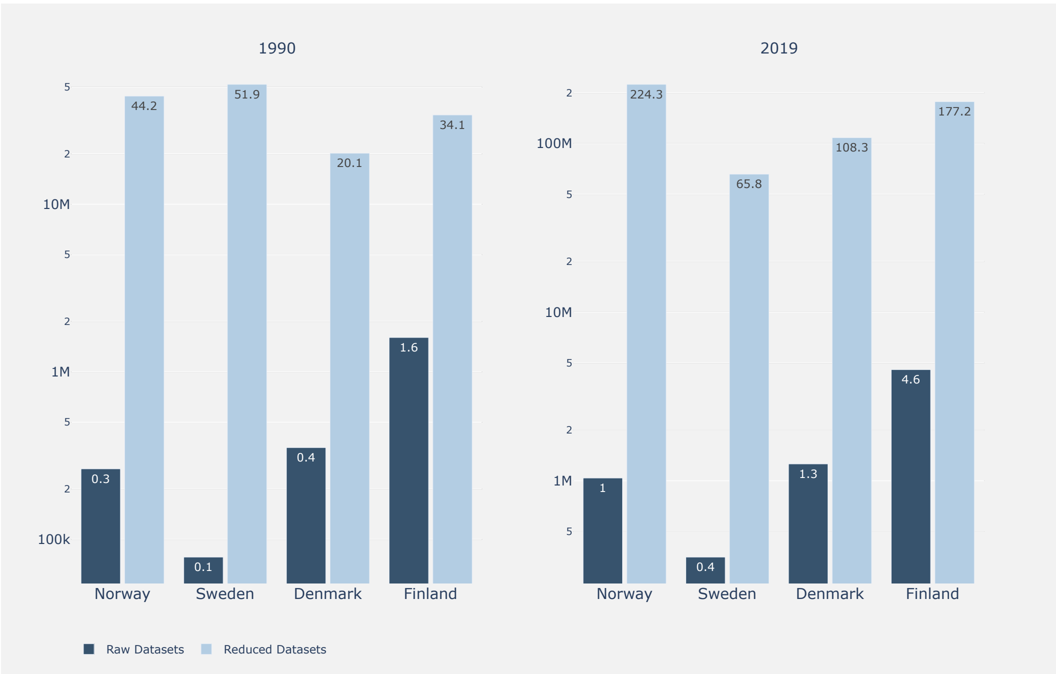


Figure 1: Minimum market cap in the Investable Universe (Log-scale)
Presented are the minimum market cap denoted in USD of each country, before and after excluding the bottom half of companies.

This approach considerably raises the minimum market cap (Figure 1), while preserving almost the entire total market cap of each country. The minimum and total market cap in the raw and reduced sample for 28th February 1990 and 31st December 2019 are shown in Figures 1 & 2. Our investable consisted of 567 stocks in December 2019, which accounted for about 98.7% of the total market capitalization for the four Nordic countries, and the average minimum Mcap was increased from USD 2M to USD 144M.

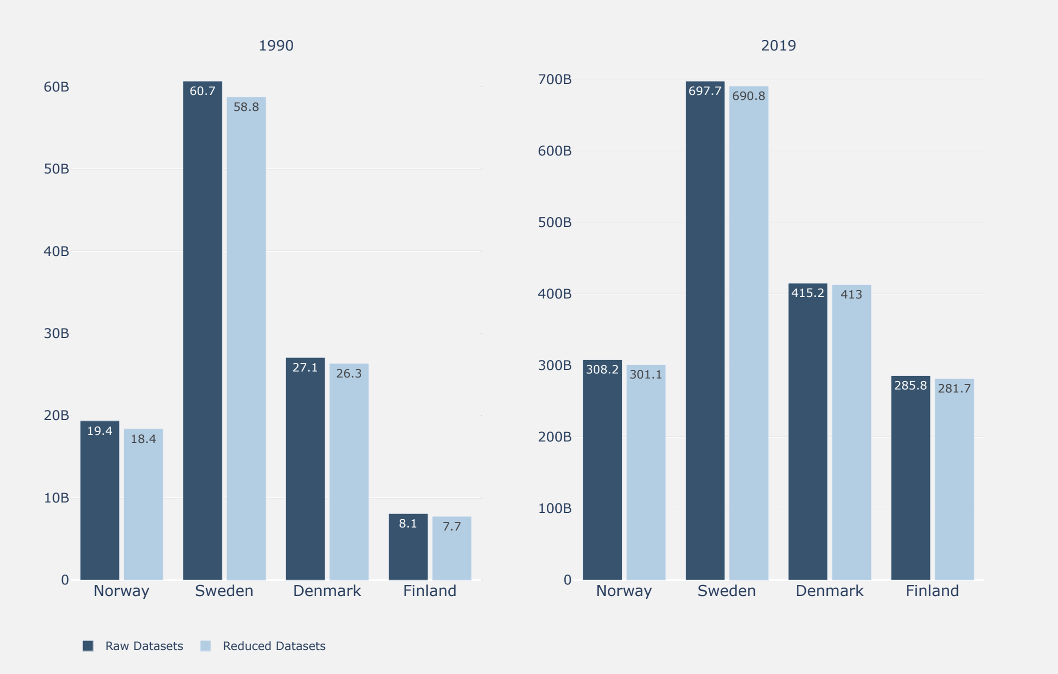


Figure 2: Total market cap of the investable universe
Presented are the total market cap denoted in USD of each country, before and after excluding the bottom half of companies.

3.2.1 Sector data

Thomson Reuters Business Classification (TRBC), an industry classification developed in 2014, were used as industry classification. This was collected for all the companies in the Nordic stock markets in our sample period. TRBC consists of 5 levels. Each company is assigned to an Industry (837), which falls into an Industry Group (136), then Business Sector (28), which is then part of an overall Economic Sector (10). We use the 10 Economic Sectors to form sector portfolios, consisting of basic materials, cyclical consumer goods and services, non-cyclical consumer goods and services, energy, financials, healthcare, industrials, technology, telecommunication services, and utilities. We searched for the companies missing a classification in Thomson Reuters Eikon and Bloomberg and filled these out manually in the dataset. This was done in order to have the same investable universe as the individual stock portfolios. Figure 3 shows each market sector composition at the start of the sample period, 28th February 1990, and at the end, 31st December 2019. This is for the reduced dataset (investable universe), in which 50% smallest companies are excluded for each month.

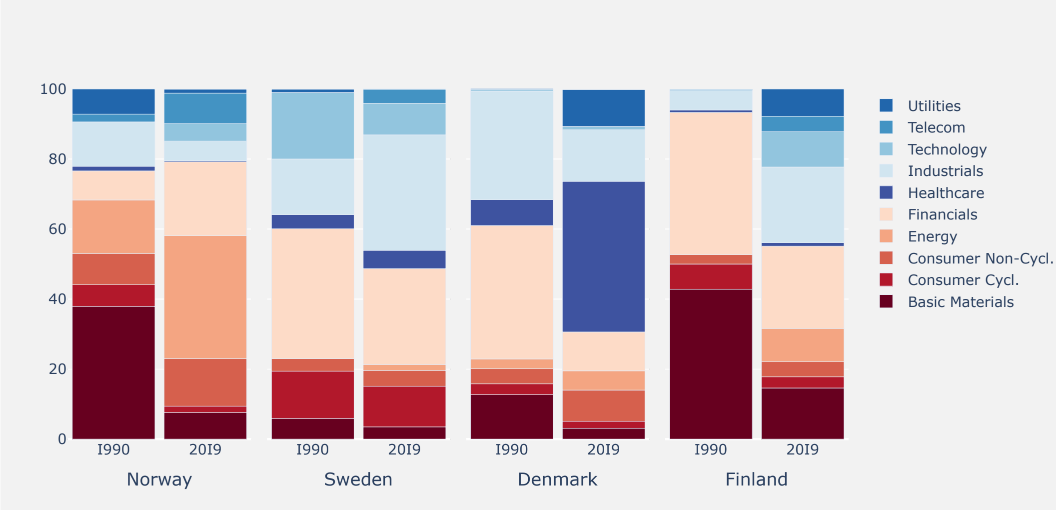


Figure 3: Sector composition of the investable universes
Presented are the sector composition (%) of the investable universe in Norway, Sweden, Denmark, and Finland in the sample period start (1990) and end (2019). The market share of a sector is calculated by adding together the market values of all stocks within a sector and then dividing this by the combined market value for all stocks in the investable universe.

In 1990, there is an overweight, in percentage terms, of basic materials in Norway (37.9) and Finland (44.8), with the latter having an overweight of financials (40.6) as well. Denmark and Sweden have an overweight of financials, 38.1 and 37.1, with the former also having an overweight of industrials (31). In 2019, this overweighting changes to energy (35.1) in Norway, healthcare (43) in Denmark, and industrials in Sweden (33), with financial losing some of its share, but still possessing 27.4% of the market in Sweden. The sector composition becomes more distributed in Finland, with financials (23.5) and industrials (21.6) being the largest.

The descriptive statistics presented in Table 3 shows there is a correlation between the sector market cap relative to the total and the number of investable stocks within sectors. The sectors with a high share within a market tend to have more stocks on average, indicating sector dominance within a market, opposed to a few giants. For instance, in each month of our sample period of 1990-2019, there are, on average, 21.5 investable Energy stocks in Norway, corresponding to the large observed market share. Also valid for Sweden and Denmark, where financials scores high on both measures. The performance of sectors is widely dependent on the market, with some sectors producing significant monthly returns in one market, underperforming in others. In some cases, this might be a result of sectors being large in terms of size and number of stocks for one market, resulting in a lower mean return.

	Norway		Sweden		Denmark		Finland	
Average (monthly)	Stocks	Return	Stocks	Return	Stocks	Return	Stocks	Return
Basic Materials	4.9	0.29	12.3	0.57	7.6	0.89	9.2	0.27
Consumer Cycl.	6.7	1.59	24.4	1.15	8.8	-0.42	8.7	1.16
Consumer Non-Cycl.	6.4	0.72	7	0.52	6.7	0.59	5.3	0.96
Energy	21.5	0.28	3.9	2.82	2.1	-0.75	0.6	2.21
Financials	15.4	1.23	35.8	0.39	28.9	0.23	7.9	0.37
Healthcare	1.4	0.89	15.3	2.18	9	1.27	1.1	-0.46
Industrials	16.5	0.02	40.1	0.42	18.2	0.22	14.6	1.2
Technology	5.1	1.39	22.8	0.48	3.4	-0.16	6	0.86
Telecom	1.1	-1.09	2.5	0.63	0.9	-3.21	1.2	1.59
Utilities	2.2	0.64	1.1	1.06	1.6	0.91	1.3	0.29
Total	81.2	0.6	165.2	1.02	87.2	-0.04	55.9	0.84

Table 3: Nordic sector statistics
Reported are descriptive sector statistics for the stocks included in the investable universe of Norway, Sweden, Denmark, and Finland. Values are monthly, and returns are presented in percentage. Stocks represent the average number of investable stocks for each month, per sector, through the sample period of 1990-2019.

3.3 Portfolios construction

The portfolios are formed at the beginning of each month, based on the previous end-of-month TRI-values for the entire sample period of February 1990 to December 2019. For momentum, we select stocks based on their returns over the previous 6- and 12-months, skipping the last month. By skipping the last month, we avoid short-term reversals – the tendency of securities to produce negative (positive) returns following a week/month of positive (negative) returns (C. S. Asness (1995), Jegadeesh (1990), Lehmann (1990)). We use the end-of-month total return index (includes cash distributions) to calculate period returns, using the formula:

$$MOM_t^{2-F} = \frac{RI_{t-2}}{RI_{t-F}} \tag{3}$$

Where F is the formation period (6 and 12-months). We first experimented with holding periods, H, of 3, 6, 9, and 12-months for each portfolio, as seen in Jegadeesh and Titman (1993). However, we decided to drop the 9 and 12-month holding periods and include a 1-month holding period due to persuasive research by Gupta and Kelly (2019). Resulting in a total of six momentum strategies.

For the value signals, we calculate the Book-to-Market (*BM*) and cash flow-to-Market (*CFM*) ratio. The *BM* ratio for any given month, *t*, is calculated by dividing the book value of equity for the previous year, *t-12*, by the market value of equity in the prior month, *t-1*. The same We perform a similar calculation for the *CFM* ratio, using cash flow originating from months, *t-6*.

$$BM_t = \frac{BookValue_{t-12}}{MarketValue_{t-1}} \quad (4) \qquad CFM_t = \frac{CashFlow_{t-6}}{MarketValue_{t-1}} \quad (5)$$

Due to limited data on book value from Thomson Reuters, we decided to retrieve the values using the more comprehensive Market-to-Book (MB) data. We divided the market values (MV) by the MB ratios, resulting in book values (BV) for all companies, presented on a yearly basis. Finally, to calculate the new BM ratio, we lag the book values 12 months to ensure the data was accessible at the time of portfolio formation. The cash flow data were available quarterly; hence, it was sufficient to lag six months (C. S. Asness, Frazzini, & Pedersen, 2012)

The reason for lagging the financial statement data is to avoid look-ahead bias – the use of non-available data to predict returns. Multiple papers do precisely this, as most accounting data are first available to the public several months after fiscal year-end or quarter-end (Fama and French (1992), (1993); Lakonishok et al. (1994); C. S. Asness et al. (2013); and others). Examining our data, we discovered that book values were filled out before the numbers were released to the public, meaning some collected data were not available at the time of recording. We use current market valuations. Combining current market values and lagged accounting values is a way to get the real ratios and produces the most favorable results, according to C. S. Asness et al. (2012), that researches the issue thoroughly. Consequently, the price will be driving the ratios change before new accounting data is introduced.

For each month, portfolios are created by ranking each stock on previous returns (momentum) or valuation ratios (value) and splitting these into ten deciles [3] – ranging from the *winners* or *cheap* stocks in the top decile (P10) to the *losers* or *expensive* in the bottom decile (P1). In 1990, the investable universe included 52 stocks in Norway, 117 in Sweden, 92 in Denmark, and 25 in Finland, resulting in portfolio holdings of 2-11 stocks for the early years, in each of the markets. This range was increased to 6-32 stocks in 2019. We buy *cheap*/*winners* stocks in the long-only strategies and sell *losers*/*expensive* ones in the short-only. The *cash-neutral* (P10–P1) strategy is attained by combining both strategies on an equal weight basis (long minus short). In

[3] In order to split into ten deciles, a minimum of ten stocks are required. This largely affects the CFM portfolio, causing the first portfolio to be formed in June 1995

the academic literature, it is also common to seclude the *winners/cheap* and *losers/expensive* by the top and bottom three deciles, i.e., the 70th and 30th percentile.

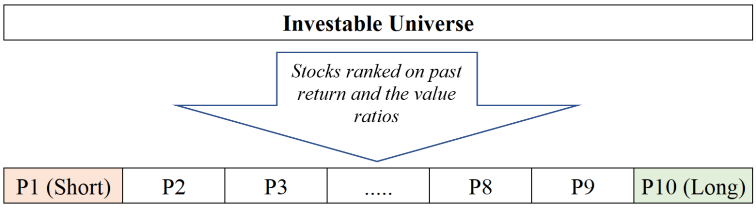


Figure 4: Portfolio selection
We rank all stocks in each country's investable universe by their relevant factor – momentum, value BM and CFM. From there, the ranked stocks are divided up into ten deciles. The strategies go long the highest 10th percentile and short the bottom 10th.

The first portfolios are created on the last day of March 1991[4] E.g., for a one month holding period, the portfolio is held from the beginning to the end of the month. Figure 5 illustrates the portfolio creation of the momentum F6-H1 strategy. For a month, t, we use the returns (including cash distributions) of the previous six months (t-6), excluding the last one (t-1) to obtain the momentum of all stocks. This is done every month to select the *winners* (top 10%) and *losers* (bottom 10%) of each month.

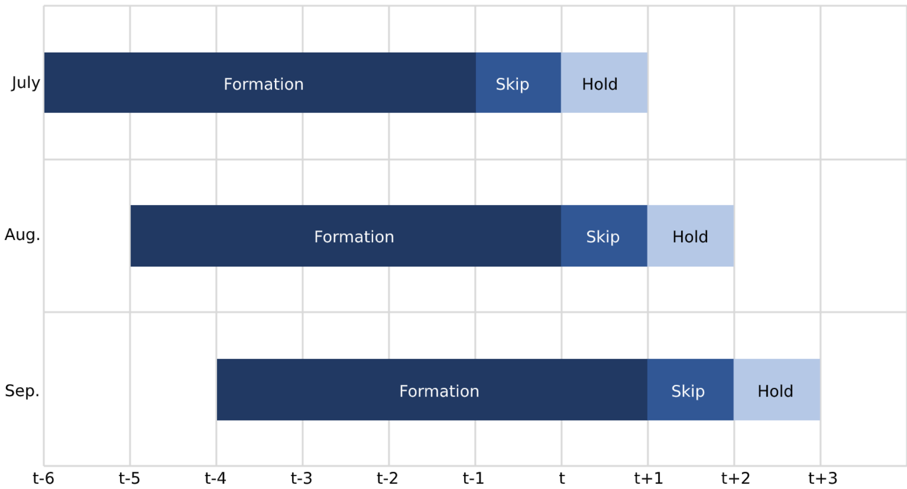


Figure 5: Portfolio construction
Presented are the creation of three fictional portfolios held throughout July, August, and September. The Figure illustrates portfolios created using a formation period of six- and holding of one-month. The first investment is made in July (*t*), using the price history of the preceding six (*t-6*), skipping the last (*t-1*). The portfolio is subsequently held for one month (*t+1*). This procedure is repeated every month.

[4]The first 12 months of data are used to calculate the one-year momentum (F12) and lag book values. The portfolios formed using formation periods of 6 months are available before this date; however, they are deleted to ensure comparability across strategies. This procedure is not done to account for CFM scarcity (1995 and forward), as it dramatically reduces sample size.

The same procedure for creating the individual stock portfolios was used to create the sector portfolios. We rank all the stocks in each country by market capitalization in USD and exclude the 50% smallest companies for each month. Then the momentum returns for each stock, as well as the book-to-market and cash flow-market ratios, are calculated. For the sector analysis, we aim to focus on the best performing formation and holding period of the momentum strategy, and best performing holding period of the BM and CFM. After calculating the momentum returns, BM- and CFM ratios for each stock, we sort the companies by sector. Then we equal-weight stocks within a sector, to obtain a value for each of the ten sectors. Moskowitz and Grinblatt (1999) value-weight the stocks within an industry for the US data, but we chose to equal-weight in order to avoid the results being skewed by a few large companies.

As discussed earlier in the paper, this is because a few large companies account for roughly 85 to 90% of the total market cap in the countries we examine. As for the individual stock portfolios, we rank the sectors, for each month, on momentum, BM, and CFM. Ranging from 1 – the worst-performing sector, to 10 – the best-performing sector. We create a *winners/cheap* portfolio (P10), including the best performing sector, a *losers/expensive* portfolio (P1) containing the worst-performing sector, and a *cash-neutral* portfolio (P10-P1), in which we go long P10 and short P1 on an equal basis. For example, for a particular month, the algorithm might give Healthcare a rank of 10 and Industrials a rank of 1, meaning we would buy all stocks within Healthcare and sell all within Industrials for the *cash-neutral*.

3.3.1 Performance calculations

For a individual stock i, the return $(R_{i,t})$ in month t is calculated:

$$R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} \tag{6}$$

Where $P_{i,t}$ is the end of month t close price of a stock i, and $P_{i,t-1}$ is the close price of the previous month *t-1*.

The return of portfolio p, in month t is calculated using by the sum of all individual stock returns, $R_{i,t}$, multiplied by their weight w_i.

$$R_{p,t} = \sum_{i=1}^{n} w_i R_{i,t} \tag{7}$$

Our portfolios are equal-weighted, which means that the weight w_i is:

$$w_i = \frac{1}{n} \tag{8}$$

Resulting in:

$$R_{p,t} = \frac{\sum_{i=1}^{n} R_{i,t}}{n} \tag{9}$$

The Sharpe Ratio is calculated by the average portfolio return times the square root of 12, divided by the standard deviation of monthly portfolio returns.

$$Sharpe_{annualized} = \frac{\overline{R}_p \sqrt{T}}{\sigma_p} \tag{10}$$

The Sortino Ratio is calculated the same way as Sharpe, only accounting for the downside deviations (negative returns).

$$Sortino_{annualized} = \frac{\overline{R}_p \sqrt{T}}{\sigma_{np}} \tag{11}$$

As outlined in Section 3.3, the *cash-neutral* portfolio is long the 10th decile and short the 1st decile. For each strategy (S) the returns are computed as:

$$cash - neutral\ _{i,\ t}^{S} \ = \ Long\ (S_{i,\ t}) \ - \ Short\ (S_{i,\ t}) \tag{12}$$

$Long(S_{i,\ t})$ and $Short(S_{i,\ t})$ represent the return of the 10th and 1st decile at the end of month t, for country i and strategy S.

3.3.2 Equal-Weighted Nordic Portfolio

To assess whether returns and (or) risk can be improved for the individual stock-based portfolios, we construct a Nordic *cash-neutral* portfolio for each strategy (S). This is done by equal-weighting the country portfolios:

$$cash - neutral\ _{Nordic,\ t}^{S} \ = \ \sum_{i\ =\ 1}^{4} w_i \cdot \ cash - neutral\ _{i,\ t}^{S} \tag{13}$$

Each weight, w_i equals $\frac{1}{N}$, where N is 4 (the number of countries) and $cash - neutral\ _{i,\ t}^{S}$ is the result of equation 12. Next, we create a *"final"* Nordic portfolio by equal-weighting again, this time across the three strategies (S).

$$cash - neutral_{Nordic,\ t} \ = \ \sum_{s\ =\ 1}^{3} w_s^{Equal} \cdot \ cash - neutral\ _{Nordic,\ t}^{S} \tag{14}$$

Each weight, w_s equals $\frac{1}{n}$, where n is 3 (the number of strategies) and $cash - neutral\ ^{S}_{Nordic,\ t}$ is the result of equation 13.

3.3.3 Kelly-Weighted Nordic Portfolio

We reconstruct the *"final"* Nordic portfolio in equation 14, this time with the Kelly optimal weights for the three strategies. Kelly Criterion is one of the ways to optimize portfolio returns. In essence, it seeks to maximize the expected portfolio log return – equivalent to maximizing the expected log wealth and, therefore, requires an estimate for future expected means and covariances (e.g., between the strategies). The solution is given as a vector (W), consisting of the optimal weights of each strategy:

$$W \ = \ 0.5 \ \cdot V^{-1} \cdot \ m \tag{15}$$

We do not estimate m and V – representing estimates future excess means and variance matrix for the three strategies (e.g., momentum, BM, and CFM). Instead, we use the means and variance matrix of 30-years of historical returns (before our investment period) for the strategies. Our supervisor suggested that we do this to obtain a more "realistic" optimization and eliminate the hindsight bias, which would occur when in-sample averages are used as estimates. Historical factor returns that use US data are collected from the Kenneth French database for each strategy. *Cash-neutral* portfolios are constructed as in equation 15 before means and variance matrix are calculated. Furthermore, the estimated weights, as well as the means (m) and variation matrix (V), are kept constant over our sample period. The formula is actually $V(t)^{-1}m(t)$. Consequently, if a massive loss were to occur in our sample period, the deviation from the average would cause ruin. The weights from equation W are used to scale each strategy's returns to reconstruct the *"final"* Nordic *cash-neutral* portfolio:

$$cash - neutral_{Nordic,\ t} \ = \ \sum_{s\ =\ 1}^{3} w_s^{Kelly} \cdot \ cash - neutral\ ^{S}_{Nordic,\ t} \tag{16}$$

Where w_s^{Kelly} is the Kelly optimal weight, which is multiplied with the cash-neutral returns for strategy S, as in equation 12.

In our literature review, we outline the history of performance and accordingly assume that value and momentum will work in our sample period. After consulting with our supervisor, we found it almost impossible to explain why expected returns should differ significantly between the Nordic countries. Thus we use US data means and variance matrix as estimates for the Nordic region as a whole, though we acknowledge that this approach would be based on the assumption that the Nordic portfolios will behave like that of the US. Besides, we assume a risk-free rate of zero, an apparent false premise.

The Kelly Criterion is notorious for excessive leverage, resulting in large fluctuations, an inconvenience that few investors can stomach. As mentioned in the previous paragraph, the assumed constant variation (V) would cause problems during high volatility. There are two large crashes in our sample period, which most certainly will cause problems. If this is the case, we plan to experiment with fraction fractional Kelly, such as half- and quarter-Kelly (where the leveraging factor is divided by two and four). Although we are aware of the issues that go along with these assumptions, we opt for this approach to make it simpler for ourselves and show the power of compounding.

3.4 Transaction costs and other

In order to account for higher transaction costs for strategies with high portfolio turnover (e.g., monthly vs. yearly), we incorporate a portfolio adjustment fee of 30 basis points (bps). This means yearly fees of 3.6% for a strategy with a monthly investment horizon, compared to 0.3% for one with an annual investment horizon. For simplicity, this accounts for all costs associated with a trade, such as fees, commission, and slippage. The fee is grounded in findings from Frazzini, Israel, and Moskowitz (2018). The paper reports the market impact (MI) and implementation shortfall (IS) for US and international stocks, divided by market cap. MI is included in IS cost, as well as commission and other fees. For their sample period of 1998-2016 ($1.7 trillion worth of live trade execution data), they report a monthly realized trading costs (IS weighted by dollars traded) of 25.3 bps for small caps (US & International). They define large-cap as stocks with a market cap within the range of the Russell 1000, and small-cap stocks as those below. As of May 8, 2020, the lowest market cap in the FTSE Russell 1000 (Russell, 2020) is $1.8bn ($9.3bn median), meaning most of our stocks belong in the small-cap. As our sample dates back to 1990, we use 30 bps to account for trading costs typically being larger before 1998. In Appendix A.2, we show Figure 3 from *"A Century of Stock Market Liquidity and Trading Costs"* (Jones, 2002). It illustrates that average one-way transaction costs (half-spread + NYSE commission) fell from 40 bp in 1990 to about 20 bp in 1998.

Furthermore, we do not account for short sales expenses and assume a risk-free rate of zero. A margin account is typically needed to open a short position with associated interest costs. We found it would be difficult to account for these expenses without in-depth knowledge about industry practices, and though we attempted to get in contact with practitioners without any results. We decided to disregard risk-free rate consideration, on account that short-dated government bonds were challenging to find for the Nordic countries for our full sample period. We considered using the US rates, which there was plentiful data on, but then the challenge of how to account for the risk-free rate for the short portfolios arose. Not to mention how the US rates differ considerably from those of the Nordic countries at times of market turbulence.

4 Results

In this section, we report the findings of our research on the momentum, book-to-market, and cash flow-to-market strategy. Table I shows the consistent performance of momentum, with increasing returns for shorter holding periods. Of the value strategies, cash flow-to-market achieves the most favorable results across all markets. This could be an indication of cash flow being a better estimator of a stock's intrinsic value as opposed to book value (Pinkasovitch, 2017). A possible explanation could be that cash flow statements are more difficult to manipulate than earnings, while book values are prone to subjective valuations and favorable depreciation methods, as well as the possibility of being impaired by inflation, technological change, and accounting distortions (Stowe, Robinson, Pinto, & McLeavey, 2007). Moreover, we find that value, in general, outperforms momentum in a bear market, while momentum outperforms value in bull markets.

4.1 Momentum and Value Returns

Table I reports the performance of momentum and value portfolios, applied to each of the equity markets in Norway, Sweden, Denmark, and Finland. The momentum strategies are created by combining two formation periods (6 and 12 months) with three holding periods (1, 3, and 6 months). The value ratios are created by dividing the current market valuations with lagged financial statement values. The best quality of data we could obtain contained the annual book value of equity and quarterly cash flow values. Therefore, the book value of equity is lagged 12 months, while the cash flow is lagged 6 months. The value ratios are then combined with three holding periods (6, 9, and 12 months). After ranking the stocks by momentum and value ratios, 10-decile portfolios are formed. The following pages report summary statistics for the *winners/cheap* (P10) and *losers/expensive* (P1), as well as *cash-neutral* (P10-P1) portfolios within each of the strategies.

Reported are the annualized net mean returns ($\overline{R}$), compound annual growth rate ($CAGR$), realized volatility, Sharpe-ratio, Sortino-ratio and maximum drawdown for the *winner/cheap* (P10), *loser/expensive* (P1) and *Cash-Neutral* (P10-P1) portfolios, as well as the MSCI Index for each of the markets Norway, Sweden, Denmark and Finland. Returns are net of transaction costs (rebalancing fee of 30bp for portfolios and 20bp for MSCI Index). For each strategy, the second best performing - measured by the highest mean return – strategy is marked in bold, whereas the best is shaded and in bold. Annualized net portfolio returns ($CAGR$) is calculated by dividing the ending balance by the starting balance, raised to the power of 12 over number of months invested. The annualized mean return is computed by the net average monthly return $\overline{R}$ times 12. Annualized volatility is calculated by the monthly standard deviation of net returns times the square root of 12, i.e. ($\sigma_{monthly}\sqrt{12}$). The annualized Sharpe Ratio is computed by dividing the monthly net mean return by the monthly standard deviation of net mean return multiplied with the square root of 12. The Sortino ratio is equal to Sharpe, only accounting for negative monthly standard deviations of net mean returns. Panel A reports statistics for the *momentum* strategies formed with formation periods of 6- and 12-month, and holding periods of 1-, 3- and 6-months. Panel B reports statistics for the value strategies *BM* and *CFM* with holding periods of 6-, 9- and 12-months. The *Momentum* and *BM* portfolios consist of individual equities from March 1991 through December 2019. The *CFM* portfolio start in June 1995.

Panel A: Momentum

	Portfolio	Winners (P10)						Losers (P1)						Cash-Neutral (P10-P1)						**MSCI**
	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	
Norway	Mean R (%)	**21.59**	20.43	18.88	**24.20**	19.93	17.64	**-3.02**	**-2.17**	-0.83	-1.25	-0.12	-0.12	**24.31**	22.51	19.66	**25.14**	19.94	17.70	10.16
	CAGR (%)	19.30	18.02	16.59	22.40	17.00	14.76	-8.52	-7.52	-6.01	-7.02	-5.71	-5.84	21.35	19.54	16.58	21.30	15.51	12.53	8.20
	Volatility (%)	27.39	27.26	26.10	27.78	28.73	27.53	34.12	33.45	32.69	34.64	34.02	34.38	30.65	29.89	28.80	33.12	32.27	33.40	20.79
	Sharpe	0.79	0.75	0.72	0.87	0.69	0.64	-0.09	-0.06	-0.03	-0.04	-0.00	-0.00	0.79	0.75	0.68	0.76	0.62	0.53	0.49
	Sortino	1.17	1.16	1.14	1.47	1.08	0.98	-0.14	-0.10	-0.04	-0.06	-0.01	-0.01	1.12	1.12	1.02	1.05	0.87	0.75	0.62
	Max DD (%)	-61.48	-64.63	-56.57	-56.48	-66.10	-59.27	-97.29	-97.37	-96.18	-95.50	-93.35	-96.31	-66.86	-76.04	-59.93	-67.93	-79.69	-86.05	-57.39
Sweden	Mean R (%)	**23.12**	**22.26**	16.06	21.05	18.49	15.97	**-6.36**	-3.25	-1.89	**-3.61**	-0.14	4.81	**29.18**	**25.42**	17.89	24.37	18.53	11.09	13.51
	CAGR (%)	22.31	21.14	14.25	20.12	17.03	14.11	-11.93	-9.01	-7.44	-9.49	-6.38	-1.16	26.46	21.89	13.93	20.72	13.17	5.08	11.72
	Volatility (%)	24.02	24.49	23.08	22.60	22.91	23.00	35.34	35.45	34.60	35.97	37.00	36.03	31.97	31.70	29.43	31.42	32.38	32.33	21.82
	Sharpe	0.96	0.91	0.70	0.93	0.81	0.69	-0.18	-0.09	-0.05	-0.10	-0.00	0.13	0.91	0.80	0.61	0.78	0.57	0.34	0.62
	Sortino	1.76	1.67	1.13	1.49	1.25	1.04	-0.25	-0.13	-0.08	-0.15	-0.01	0.23	1.07	0.91	0.69	0.90	0.63	0.36	0.91
	Max DD (%)	-49.21	-56.05	-61.22	-61.62	-69.43	-75.30	-98.04	-96.24	-95.64	-95.30	-90.70	-81.13	-64.69	-60.38	-65.17	-70.02	-76.05	-88.32	-70.87
Denmark	Mean R (%)	15.97	15.81	**16.03**	**18.17**	15.65	14.49	**-6.44**	-0.93	1.49	**-4.24**	-0.07	2.40	**22.19**	16.66	14.50	**22.18**	15.65	12.05	12.13
	CAGR (%)	15.16	14.63	14.97	17.33	14.78	13.13	-9.19	-3.96	-1.36	-7.07	-3.15	-0.63	21.54	13.28	11.52	20.87	12.55	8.46	11.06
	Volatility (%)	18.68	20.73	19.76	20.49	18.57	20.60	25.20	25.42	24.28	24.90	25.38	24.97	22.02	26.53	24.23	24.54	25.25	26.35	17.69
	Sharpe	0.85	0.76	0.81	0.89	0.84	0.70	-0.26	-0.04	0.06	-0.17	-0.00	0.10	1.01	0.63	0.60	0.90	0.62	0.46	0.69
	Sortino	1.37	1.29	1.08	1.35	1.13	1.02	-0.37	-0.06	0.11	-0.26	-0.00	0.16	1.38	0.69	0.62	1.33	0.67	0.55	0.98
	Max DD (%)	-56.86	-56.86	-62.51	-64.63	-65.72	-69.85	-96.65	-84.59	-77.48	-93.56	-85.26	-80.98	-47.41	-78.54	-81.39	-58.04	-76.37	-81.28	-50.91
Finland	Mean R (%)	**14.31**	12.30	10.69	**14.92**	11.92	10.64	5.74	5.86	**2.43**	**2.30**	3.45	5.73	8.29	6.32	8.18	**12.32**	**8.36**	4.83	15.00
	CAGR (%)	11.48	9.56	8.27	12.67	9.23	7.95	0.02	-0.03	-3.53	-3.47	-2.43	-0.31	2.34	0.49	2.23	6.22	2.13	-2.03	11.28
	Volatility (%)	26.63	25.15	23.37	24.16	24.56	24.09	34.62	35.11	35.63	35.37	35.36	36.03	33.24	32.50	32.69	33.33	33.55	35.03	29.26
	Sharpe	0.54	0.49	0.46	0.62	0.49	0.44	0.17	0.17	0.07	0.07	0.10	0.16	0.25	0.19	0.25	0.37	0.25	0.14	0.51
	Sortino	0.97	0.81	0.75	1.03	0.72	0.63	0.28	0.28	0.12	0.12	0.16	0.28	0.31	0.24	0.29	0.41	0.30	0.16	0.78
	Max DD (%)	-72.74	-71.72	-61.71	-62.13	-75.85	-75.03	-79.15	-78.68	-86.96	-78.96	-80.62	-76.46	-71.96	-77.63	-82.28	-70.91	-80.77	-88.32	-78.30

		Panel B: Book-to-Market									CashFlow-to-Market									
	Portfolio	Cheap (P10)			Expensive (P1)			Cash-Neutral (P10-P1)			Cheap (P10)			Expensive (P1)			Cash-Neutral (P10-P1)			**MSCI**
	Holding	6	9	12	6	9	12	6	9	12	6	9	12	6	9	12	6	9	12	
Norway	Mean R (%)	9.29	9.31	**9.94**	7.27	9.18	**1.87**	1.97	0.10	**8.05**	**12.33**	12.11	11.37	**-0.65**	5.59	1.39	**12.95**	6.50	9.97	10.16
	CAGR (%)	4.40	5.21	5.19	3.24	5.36	-2.07	-3.12	-4.35	2.63	9.86	9.74	8.81	-4.62	2.28	-3.08	10.59	3.59	6.94	8.20
	Volatility (%)	31.62	29.19	31.49	28.59	28.11	28.04	32.03	30.16	32.93	24.12	23.69	24.18	27.94	25.59	29.89	24.04	24.47	25.30	20.79
	Sharpe	0.29	0.32	0.32	0.25	0.33	0.07	0.06	0.00	0.24	0.51	0.51	0.47	-0.02	0.22	0.05	0.54	0.27	0.39	0.49
	Sortino	0.47	0.52	0.51	0.37	0.48	0.09	0.10	0.01	0.37	0.85	0.88	0.77	-0.03	0.31	0.07	1.00	0.45	0.63	0.62
	Max DD (%)	-87.07	-88.45	-82.07	-81.54	-79.54	-91.82	-91.12	-88.89	-84.37	-64.11	-61.59	-70.59	-90.02	-76.96	-90.29	-69.96	-76.75	-80.67	-57.39
Sweden	Mean R (%)	**17.45**	15.74	17.40	5.49	5.56	**4.83**	11.93	10.17	**12.56**	**14.94**	14.82	13.52	**-0.74**	-0.70	-0.25	**15.64**	15.50	13.76	13.51
	CAGR (%)	14.42	12.76	15.02	2.51	2.32	1.59	9.32	7.39	9.87	13.74	13.57	12.38	-4.48	-4.38	-4.10	14.11	14.01	11.90	11.72
	Volatility (%)	28.78	28.09	26.55	24.64	25.67	25.77	24.98	25.02	25.07	20.09	20.19	18.83	27.84	27.58	28.17	21.28	21.04	21.73	21.82
	Sharpe	0.61	0.56	0.66	0.22	0.22	0.19	0.48	0.41	0.50	0.74	0.73	0.72	-0.03	-0.03	-0.01	0.73	0.74	0.63	0.62
	Sortino	1.03	1.01	1.18	0.36	0.33	0.30	0.84	0.65	0.76	1.16	1.13	1.09	-0.04	-0.04	-0.01	0.93	0.93	0.82	0.91
	Max DD (%)	-67.12	-69.23	-60.20	-88.60	-87.85	-89.60	-76.93	-78.61	-82.68	-57.84	-58.43	-56.15	-90.07	-85.94	-88.34	-41.91	-36.37	-37.52	-70.87
Denmark	Mean R (%)	**6.72**	5.55	6.22	9.09	**6.79**	7.11	-2.39	-1.25	**-0.90**	8.36	**11.31**	10.92	4.23	**3.63**	5.84	4.10	**7.65**	5.07	12.13
	CAGR (%)	4.12	2.91	3.87	7.51	4.97	5.50	-4.40	-3.47	-2.84	6.76	9.23	9.10	1.47	0.82	3.02	2.42	5.21	2.84	11.06
	Volatility (%)	23.21	23.18	22.10	19.00	19.40	18.61	20.67	21.47	19.96	18.66	23.55	20.86	23.34	23.64	23.85	18.47	23.83	21.10	17.69
	Sharpe	0.29	0.24	0.28	0.48	0.35	0.38	-0.12	-0.06	-0.05	0.45	0.48	0.52	0.18	0.15	0.24	0.22	0.32	0.24	0.69
	Sortino	0.44	0.34	0.42	0.67	0.46	0.52	-0.19	-0.09	-0.07	0.59	0.93	0.75	0.25	0.23	0.36	0.34	0.58	0.34	0.98
	Max DD (%)	-83.47	-87.48	-83.06	-68.58	-75.00	-64.90	-88.69	-89.05	-84.45	-80.10	-75.74	-74.52	-89.44	-89.48	-87.01	-45.04	-48.42	-55.87	-50.91
Finland	Mean R (%)	12.79	10.99	**14.06**	7.09	7.72	**4.03**	5.66	3.24	**10.01**	**14.60**	10.84	14.57	9.77	**8.46**	9.80	**4.81**	2.35	4.76	15.00
	CAGR (%)	9.21	7.60	10.03	3.17	2.92	-0.48	1.61	-1.79	4.74	12.45	8.50	11.91	6.43	4.66	6.64	1.75	-1.21	1.56	11.28
	Volatility (%)	28.43	27.42	30.77	28.08	31.42	30.56	28.59	31.67	32.43	24.11	23.75	26.56	26.76	28.14	25.98	24.58	26.91	25.95	29.26
	Sharpe	0.45	0.40	0.46	0.25	0.25	0.13	0.20	0.10	0.31	0.61	0.46	0.55	0.36	0.30	0.38	0.20	0.09	0.18	0.51
	Sortino	0.71	0.67	0.78	0.36	0.36	0.20	0.31	0.15	0.44	1.13	0.88	1.13	0.61	0.50	0.59	0.28	0.13	0.30	0.78
	Max DD (%)	-82.13	-75.07	-77.52	-87.87	-92.13	-89.16	-74.11	-84.47	-62.80	-63.59	-60.59	-65.27	-65.35	-67.24	-65.96	-69.41	-73.60	-53.01	-78.30

Panel A of Table I reports results for each of momentum portfolios containing stocks selected on 6 and 12-months previous performance (F = 6, 12); and held for 1, 3, and 6-months (H = 1, 3, 6). We find that shorter holding periods generally produce larger mean returns than longer ones, regardless of the formation period. The Sharpe and Sortino ratio also increases as the holding period is shortened for all countries, which is consistent with that of (Jegadeesh & Titman, 1993). The *winners* (P10) portfolio outperform the *losers* (P1) overall. Hence, the *cash-neutral* portfolio delivers a positive return (CAGR) in most cases.

In the long-only strategy, we seek to maximize returns by buying the stocks with the strongest momentum (*winners*). Of the *winners* portfolios, F12-H1 achieves the best performance in Norway, Denmark, and Finland, delivering a mean return of 24.2, 18.17, 14.92% in these three markets. Moreover, F6-H1 is the most successful in Sweden, yielding 23.12%.

The same pattern of shorter holding periods being superior can also be observed in the *losers* portfolios. In the short-only strategy, we sell the stocks with the weakest momentum with the expectation that they continue to deliver poorly and make money if prices fall. Of the *losers* portfolios, F6-H1 yield -3.02, -6.36, -6.44 and 5.74%, in Norway, Sweden, Denmark, and Finland, followed by F12-H1 producing -1.25, -3.61, -2.24 and 2.3% in the respective markets. Finland stands out being the only country in which the F6-H6 (-2.43%) beats F6-H1 (5.74%).

Like the *winners* and *losers* portfolios, the *cash-neutral* (P10–P1) also performs best at shorter holding periods. We find that F12-H1 delivers the highest mean return in Norway, 25.14%, and Finland, 12.32%. Whereas in Sweden and Denmark, F6-H1 outperforms, delivering 29.18% and 22.19%. The *cash-neutral* strategy involves going both long and short and is therefore resistive to movements in both directions. However, this strategy is not market neutral, as its market beta can be positive or negative, depending on the average beta on each side. Like the long- and short-only strategies, the *cash-neutral* may, at times, be sector-specific. For the reasons stated above, the *cash-neutral* strategies are not directly comparable to the benchmark, nor to a risk-free rate (e.g., 3m T-Bill) as it is not perfectly risk-free. However, evaluating based on the Sharpe ratio – risk-adjusted returns, we find it striking that the best *cash-neutral* strategies beat the benchmark (MSCI) in three of the four countries.

Panel B of Table I reports the same statistics for value portfolios containing stocks picked on book-to-market (BM) and cash flow-to-market (CFM) ratios; and held for 6, 9, 12-months (H = 6, 9, 12). When calculating the ratios, the book value of equity is lagged 12-months, while cash flow is lagged 6-months. With both BM and CFM, the goal is to buy stocks that are valued *cheap*, while selling the *expensive* ones. The best performing BM *cheap* portfolios do not produce higher mean returns than their benchmark, except for in Sweden, where H6 beats it by 3.94%. This is true for all holding periods observed in Sweden. Next, we see that for all countries, the portfolios seem to perform relatively equal within the different holding periods. On the other hand, the *expensive* portfolios clearly work better the longer we hold on to the positions. The *cash-neutral* portfolio (P10–P1) achieves the largest mean return with H12 for all countries, delivering 8.05, 12.56, -0.90, and 10.01% in Norway, Sweden, Denmark, and Finland. Although only producing negative returns in Denmark, none of the *cash-neutral* portfolios manage to beat the benchmark in terms of Sharpe Ratio.

Slightly more promising, the best CFM *cash-neutral* portfolios beat the equivalent BM portfolios in all countries but Finland, primarily due to a better performing short-side. We find that shorter holding periods increase returns in all of the strategies, with *cheap* H6 delivering 12.33, 14.94, 8.36, and 14.6% in Norway, Sweden, Denmark, and Finland. The best performing *expensive* portfolios are very effective in Norway and Sweden, with H6 producing -0.65 and -0.74%. This is not the case in Denmark and Finland, where H9 delivers 3.63 and 8.46%. As a result, the *cash-neutral* strategy H6 beats the benchmark in terms of risk-adjusted returns with a Sharpe of 0.54 (benchmark 0.49) and 0.73 (0.62) in Norway and Sweden.

It appears that sorting based on CFM produces larger return-spreads between the *cheap* and *expensive* portfolios than BM. Lakonishok et al. (1994) argue that CFM is a better estimator of future growth and thus gives rise to better value strategy than BM. Although both financial ratios try to measure the market's expectation of future growth by comparing past performance with current market valuations, CFM could be a better estimator of intrinsic value as book values can be difficult to estimate precisely and are susceptible to subjective evaluations. Another thing to note is that the book value does not include intangible assets, which in some sectors are a significant contributor to the market's evaluation of value.

To enable for further analysis, strategy-combinations, and portfolio optimization techniques, we will select the best performing momentum, book-to-market, and cash flow-to-market strategy. For simplicity, we base our selection on the average, best performing (in terms of historical risk-adjusted returns), *cash-neutral* strategy across all countries. Average of the mean returns are reported in parenthesis. Doing so, we end up with momentum F6-H1 with an average Sharpe of 0.74 (20.5%), BM H12 with Sharpe of 0.25 (7.42%), and CFM H6 with a Sharpe of 0.42 (9.38%).

4.1.1 Winners vs. Losers

Table I, Panel A reveals considerable differences in the performance between the long and short portfolios for all strategies. In fact, the best performing long portfolio always crushes the best performing short portfolio. The only exception is the BM strategy in Denmark, where the *expensive* stocks outperform the *cheap* ones, resulting in a mean return of -0.9% for the *cash-neutral* strategy. Figure 6 illustrates the effects of compounding a NOK 1 investment in the long (P10) and short (P1) portfolios, comparing it to MSCI country indices.

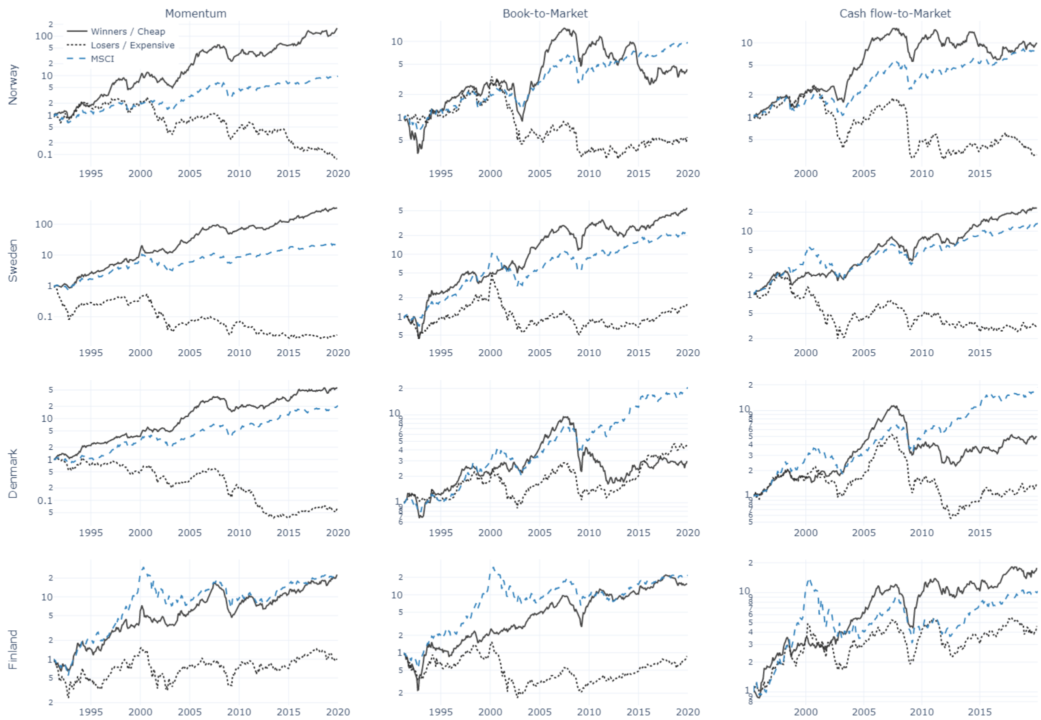


Figure 6:
Cumulative returns for the long- and short-side, and MSCI-indices (Log-scale)
Presented are the cumulative returns for the *winners/cheap* and *losers/expensive* portfolios for each country, in addition to the respective country's MSCI index. The graphs are presented on a log-scale. The portfolios are selected based on the momentum, BM, and CFM strategy with the highest average Sharpe ratio across all countries. That is F6-H1 for momentum, H12 for BM, and H6 for CFM. The momentum and BM strategies are reported for an investment period from March 1991 to December 2019, while the CFM strategy runs from June 1995 to December 2019.

The portfolios are derived from the strategies chosen above. The momentum F6-H1 *winners* consistently beat both the benchmark and the *losers* portfolio, with the latter severely underperforming over the whole period. The same can not be said for the value strategies, where the performance is widely country dependant. Although the two value strategies are not directly comparable due to BM portfolios having a 63-month head-start, there is a striking resemblance between them within each country. This is in line with expectations that both strategies try to identify companies that are low priced relative to market value. Of the countries, Denmark stands out the most. We see that the benchmark outperforms both value strategies, as well as the *expensive* BM portfolio, advancing past the *cheap* portfolio in 2015.

Figure 7 presents the cumulative returns of the best *winners*/*cheap* portfolio, for all the strategies and the benchmark, through bull and bear markets (Research, 2020). The time-frame approach enables us to study the cumulative performance through different market regimes, revealing periods of out-/underperformance for a particular strategy or country.

During the first period, a bull market that lasted until March 2000 – commonly known as the dot-com bubble, the momentum strategy (F12-H1) outdid all others, except for in Finland where the benchmark takes the lead around the year 1994. Another thing to notice here is the sharp decline of BM portfolios around 1992, followed by a rapid convergence towards the others. Considering this sharp decline, the cumulative returns for this period can be a bit misleading, as it only accounts for this exact period. Meaning, BM would likely reach a podium position if the cumulative calculations had begun a couple of years later. Hence, the chart does not do the magnitude of the succeeding run its justice. Equities struggle in the bear market lasting from 2000 to 2002; however, most strategies manage to end in a positive or break-even territory. In this period, CFM and BM outperform both the benchmark and momentum strategy in Sweden and Finland, with CFM generating about the same return as momentum in the other countries.

The short five-year bull run leading up to the global financial crisis of 2007-08 produce significant gains, similar or better to that of the much longer bull market starting in 2009. There is no clear overall pattern across strategies or countries in the bear market during the global financial crisis. The strategies seem to move in harmony with the indices in Sweden and Finland, while all strategies fall short of the benchmark in Norway and Denmark. The opposite can be said for Finland, where the benchmark underperforms by a considerable amount. The last bull market starting in October 2009, to the present, shows momentum once again taking the lead. The value strategies struggle, especially BM, while CFM outperforms the benchmark in Sweden.

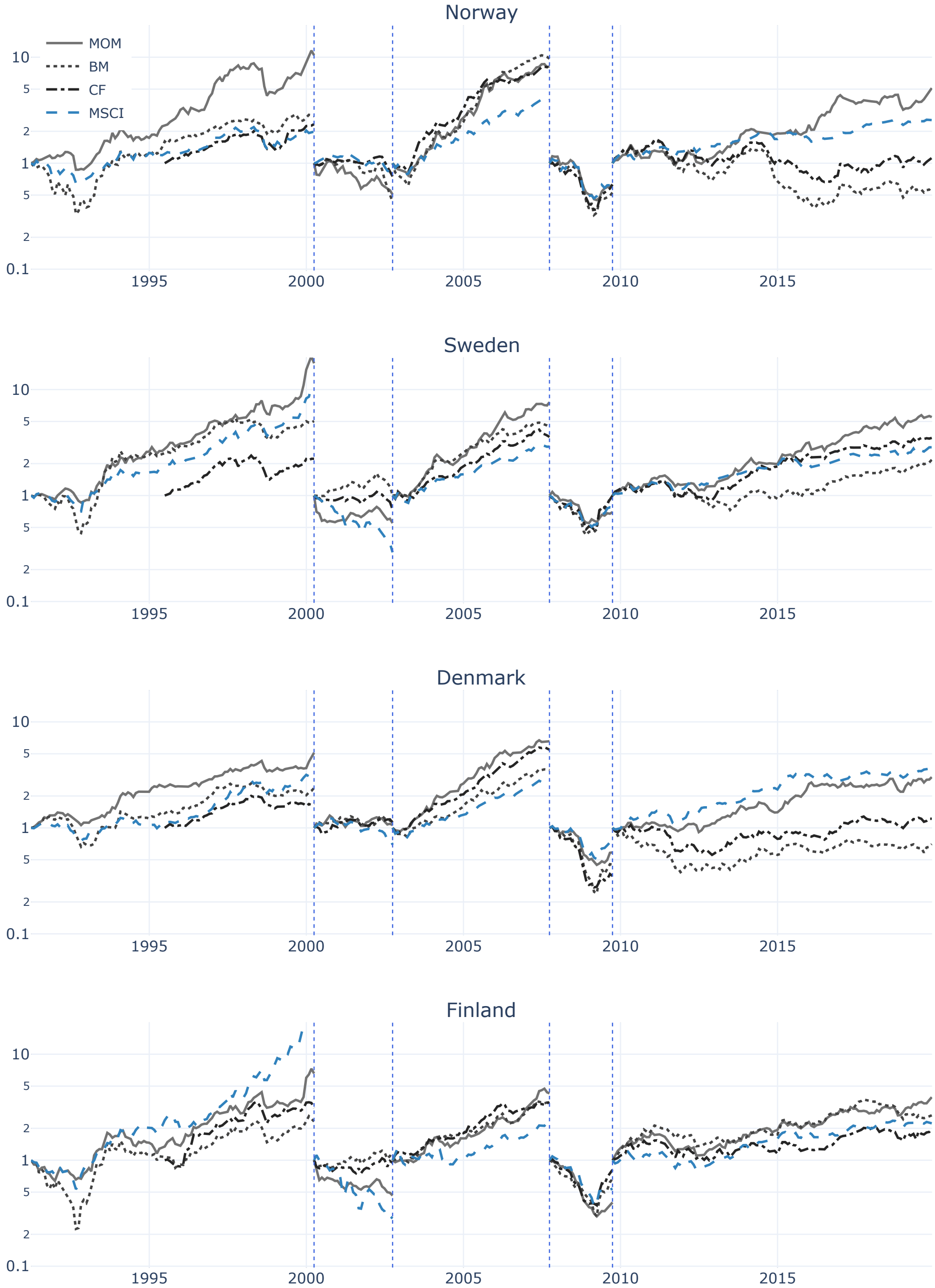


Figure 7: Cumulative returns of *winners/cheap* through Bull and Bear markets
Presented are the period-wise cumulative returns for the *winners/cheap* portfolio of the chosen best performing *cash-neutral* strategy – highest average Sharpe ratio across the countries, for the momentum, BM, and CFM strategy. The periods are separated based on U.S. S&P 500 Bull and Bear[a] – periods with a rapid change from bear to bull and opposite are added together[b], and the cumulative return is calculated from the start to the end of a period. The period starts and ends are marked with a vertical blue dotted line, and are as follows: bull market from the start for the first portfolio to the end of March 2000; March 2000-October 2002 (bear); October 2002-October 2007 (bull); October 2007-October 2009(bear); and lastly a bull market from October 2009 and outward[c].

[a]A bull market is characterized by a market rising 20% or more of the previous lows. A bear market is the opposite, prices declining 20% or more from previous heights

[b]Periods added together are: (Mar. 2000 - Sep. 2001 and Jan. 2002 - Oct. 2002), and (Oct. 2007 - Nov. 2008 and (Jan. 2009 - Mar. 2009)

[c]This bull market ended shortly after our point of data collection (Mar. 2020)

Overall both value strategies outperform momentum in bear markets, with momentum suffering a cumulative loss of 38% on average, while BM and CFM "only" declined by 22% and 20%. In bull markets, the most favorable result is obtained with the momentum strategy generating a cumulative gain of 636% on average, followed by BM and CFM with 231% and 213%. Using hindsight, an investor may want to over-/underallocated to a particular strategy depending on market trends (assuming a stocks only portfolio). Our findings are consistent with that of previous research. C. S. Asness et al. (2013) observed that funding liquidity risk was consistently negatively linked to value returns and significantly positively linked to momentum returns. Therefore, when funding liquidity drops, occurring in periods where borrowing is difficult (bear markets), momentum strategies perform poorly, while value does well – concluding that this opposite exposure to funding liquidity shocks, partly contributes to their negative correlation.

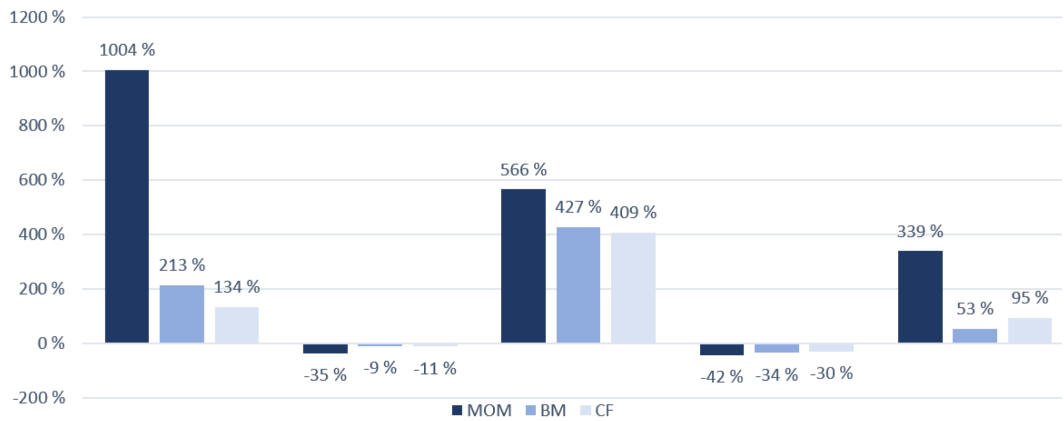


Figure 8: Cumulative returns during Bull & Bear markets
Presented are the cumulative returns of the momentum, BM, and CFM strategy during S&P Bull and Bear markets. The periods are as follows: bull market from the start for the first portfolio (March 1991) to the end of March 2000; March 2000-October 2002 (bear); October 2002-October 2007 (bull); October 2007-October 2009 (bear); and lastly a bull market from October 2009 and outward.

4.2 The Nordic portfolios

To ease the process of portfolio combinations and optimization, we construct a Nordic portfolio where we aggregate the best momentum, BM, and CFM returns. The Nordic portfolio is created by taking the average of the returns in the four countries; in other words, we allocate 25% of capital to the market of each country. The benchmark is constructed in the same manner, taking the average of the MSCI returns. In doing so, we end up with a combined Nordic exchange, where we apply the three strategies. Considering we invest an equal amount in each of the countries, as opposed to aggregating all countries before selecting stocks to invest in, the Nordic strategies (Momentum, BM, and CFM) are country-dependent.

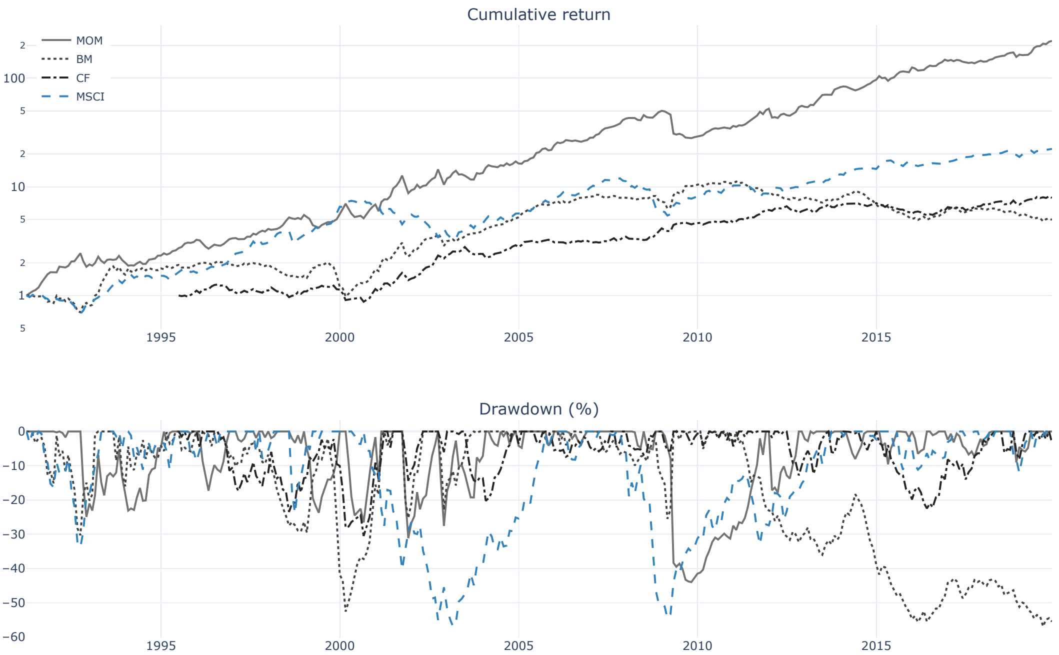


Figure 9: Nordic cash-neutral strategy comparisons (Log-scale)
Presented on top, are the cumulative growth of a NOK 1 investment in each of the strategies for the combined Nordic portfolio (log-scale). The results are obtained using the average strategy return for each of the countries. The strategies applied are the *cash-neutral*-momentum (MOM F6-H1), -Book-to-Market (BM H12), and -Cash Flow-to-Market (CFM H6). The drawdowns of each strategy is presented in the bottom plot. The drawdowns are shown in percentage and are calculated as the cumulative loss from a recent high. The cumulative returns are calculated from March 1991 for the momentum, BM, and Benchmark portfolios, while the CF is calculated from June 1995. All portfolios end in December 2019.

Once more, it is clear that momentum is the preferred factor-strategy across our sample period of 1991-2019 from Figure 9. The cumulative return of investing NOK 1 in the momentum strategy amounts to roughly 220 by the end of 2019. Miles ahead of the benchmark (22), CF (8), and BM (5). Large drawdowns can be observed in the BM strategy and benchmark between 2000 and 2004, while momentum seems to be the strategy most affected by the financial crisis of 2008/09. It is evident that BM struggles severely from 2012 and outwards, never recovering to previous heights. In fact, it performs so poorly that the CF strategy – starting four years later, catches up around 2015. Note that the CF strategy seemingly moves upwards during the financial crisis of 2009, a possible result of the short-side gains more than compensating for the losses. For instance, the *cheap* lost 2.39% from 31st December 2008 to 31st March 2009, while *expensive* earned 2.55% in the same period.

Using the average of the country returns, the statistics for the Nordic portfolios presented below (Table 3) are generally what we would expect. Although the momentum *cash-neutral* portfolio performs well in terms of Sharpe, yielding 1.06, the mean return for the Nordics are dragged down by the poor results obtained in Finland (see Table I). Further, Table I also reveals that when isolated by country, the *cash-neutral* CFM portfolios endure volatility ranging from 18.47 to 24.58%, far worse than the 13.31% of the Nordic portfolio. This reduction in volatility can also be observed for momentum and BM. Appendix A.1 reveals weak positive correlations between the strategies across the countries. It ranges from 17.78 to 36.57% for the momentum and BM strategies, while this relationship is even weaker for the CFM strategy – ranging from 6.79 to 24.59%. Denmark's correlation with the other countries is in the lower bound of this range, ranging from 6.79 to 8.42% and seems to have very little, if nothing, in common with the other countries. This weak correlation between the strategies within each country could explain the reduced volatility of the Nordic *cash-neutral* portfolio.

4.2.1 Regression analysis

Table 3 shows the annualized mean return, volatility, and Sharpe of the combined Nordic portfolios. Both momentum and BM returns start in April 1991, while the CFM returns started in July 1995. Moreover, we report the annualized intercept (alphas) and their t-statistics (presented in parentheses) from a time-series regression of each returns series on the return of the market index, here the average of the MSCI indices. The last two columns in Table 3 report the adjusted $\mathbb{R}^2$ and the number of months of data used for the regression.

Interestingly, all the *cash-neutral* strategies are negatively correlated with the benchmark, as observed from MSCI beta, suggesting they tend to move in the opposite direction of the benchmark. The *losers/expensive* portfolios have higher volatilities (except for BM) and betas than the *winners/cheap* portfolios, thus the negative correlation may well be the product of the *cash-neutral* strategies being net short. Controlling for the Nordic MSCI returns,

	Momentum			Book-to-Market			CashFlow-to-Market		
	Winners	Losers	Cash-Neutral	Cheap	Expensive	Cash-Neutral	Cheap	Expensive	Cash-Neutral
Mean R (%)	18.75	-2.52	20.99	11.91	4.46	7.43	12.56	3.15	9.37
Volatility (%)	19.11	25.97	19.88	22.38	20.35	19.27	17.48	21.39	13.31
Sharpe	0.98	-0.1	1.06	0.53	0.22	0.39	0.72	0.15	0.7
Alpha (α)	8.88***	-16.56***	25.2***	0.84	-6.96***	7.68**	3.6	-8.28***	11.88***
	(3.781)	(-5.609)	(6.987)	(0.279)	(-3.198)	(2.105)	(1.537)	(-3.046)	(4.493)
MSCI (β)	0.782***	1.113***	-0.330***	0.878***	0.901***	-0.024	0.714***	0.913***	-0.200***
	(22.03)	(24.82)	(-6.04)	(19.99)	(27.42)	(-0.42)	(19.63)	(21.95)	(-4.92)
Adj. $\mathbb{R}^2$	0.585	0.642	0.094	0.537	0.686	-0.002	0.568	0.622	0.074
N	344	344	344	344	344	344	293	293	293

Table 3: Regression analysis results

Presented are the annualized mean return, annualized volatility, and annualized Sharpe-ratio, as well as the annualized alpha, beta (MSCI), Adjusted $\mathbb{R}^2$, and the number of observations (N), for the winners/cheap, losers/expensive and cash-neutral momentum, BM and CFM portfolios. The alpha, beta, and adj. $\mathbb{R}^2$ are estimated using ordinary least squares regression with t-statistics presented in (parenthesis). The alpha is annualized by multiplying the monthly alpha by 12. Level of significance is denoted by *, ** and ***, for 10%, 5% and 1% respectively.

the *cash-neutral* strategies all yield statistically significant positive alphas at the 5% level, with momentum and CFM alphas significant at a 1% level. These alphas are economically significant as well.

Moreover, we find that the *winners*, as well as all the *cheap* and *expensive* portfolios, have a beta lower than 1 (fluctuate less than the benchmark), significant at a 1% level. The outlier being the momentum *losers* portfolio, which, although significant at the 1% level, has a beta of 1.11 (more volatile than the benchmark). In the context of shorting, this strategy also delivers the highest annualized alpha (16.56%), implying it pays out well for this higher beta. Examining the other strategies alphas, the *cheap* portfolios for BM and CFM are not significant at any level, with t-statistics of 0.28 and 1.54. These two portfolios also deliver the lowest alphas of all the portfolios. Although most of the *cash-neutral* portfolios mean returns (Mean R) are generated from the long-side, this is the opposite when considering the alphas. The *cash-neutral* alphas originate almost entirely from the short-side, consistent with the results obtained on US data by Moskowitz and Grinblatt (1999). They, too, found profits of the individual stock momentum strategies to be driven by the short side.

4.2.2 The Nordic vs. US

Now that we have results on the Nordic region as a whole, we can compare it to the results obtained in the US. Decile portfolios[5] collected from the Kenneth French database for momentum, book-to-market, and cash flow-to-market and contain all stocks in the NYSE, AMEX, and NASDAQ exchanges. The portfolios are equal-weighted and do not account for company size. Although the formation and holding period deviate slightly from ours, this was the most comparable data available for our sample period. The *cash-neutral* portfolios and returns are calculated in the same manner as the Nordic portfolios.

	Momentum			**Book-to-Market**			**CashFlow-to-Price**		
	Winners	Losers	Cash-Neutral	Cheap	Expensive	Cash-Neutral	Cheap	Expensive	Cash-Neutral
Mean R (%)	18.79	11.38	7.41	19.09	8.79	10.31	17.55	11.95	5.6
CAGR (%)	17.57	6.2	3.68	18.08	5.76	9.6	16.75	10.27	5.1
Volatility (%)	22.35	33.81	24.98	21.89	25.21	14.99	19.78	20.63	11.18
Sharpe	0.84	0.34	0.3	0.87	0.35	0.69	0.89	0.58	0.5
Sortino	1.17	0.6	0.27	1.27	0.5	1.13	1.18	0.82	0.8
Max DD (%)	-59.37	-71.91	-82.17	-71.03	-73.6	-48.85	-56.41	-56.34	-43.54

Table 4: Strategy statistics for US stocks
Reported are the annualized net mean returns ($\overline{R}$), compound annual growth rate ($CAGR$), realized volatility, Sharpe-ratio, Sortino-ratio and maximum drawdown for the *winner/cheap* (P10), *loser/expensive* (P1) and *Cash-Neutral* (P10-P1) portfolios for the US market (NYSE, AMEX, and NASDAQ). The portfolios are created on momentum (F12-H1), BM (F12-H12), and CFM (F12-H12) for the period of Apr. 1991 to Dec. 2019.

The results differ considerably in some portfolios, with the results of the losers and *expensive* portfolios as one of the most notable. The losers and *expensive* portfolios achieve a higher return and Sharpe ratio in the Nordic region compared to the US, for all strategies. An explanation for momentum and CFM *cash-neutral*'s better performance in the Nordics. To our surprise, the BM *cheap* is the best performing portfolio in the US, while it is the worst performer in our research. Furthermore, the US strategies seem to be slightly more volatile, except for the value *cash-neutral* portfolios, which have about 20% lower volatility than in the Nordic region.

[5]The momentum decile portfolio from the Kenneth French database are formed on 12-months price history and held for 1 month. Book-to-market are constructed every June, using last year fiscal year end book- and market value. Cash flow-to-market are constructed in similar manner.

4.2.3 The Kelly Criterion

The Kelly criterion – a technique to optimize portfolio returns, seeks to maximize the expected portfolio log return and requires an estimate for future excess means and covariances of assets in a portfolio. In our optimization, we use the means and variance matrix of 30-years (1965-95) of factor returns for the US. These are collected from the Kenneth French database, in which factor returns preceding our sample period are available for the US. We chose a 30-year timeframe as this is the length of our sample period.

Figure 10 presents the equal-weighted Nordic *cash-neutral* portfolio's cumulative performance in which 33% of the capital is assigned to each strategy. Also presented is the cumulative performance of the quarter-Kelly portfolio, where the optimal weights are calculated using the Kelly Criterion, and the leveraging factor is set to one-quarter of the optimal.

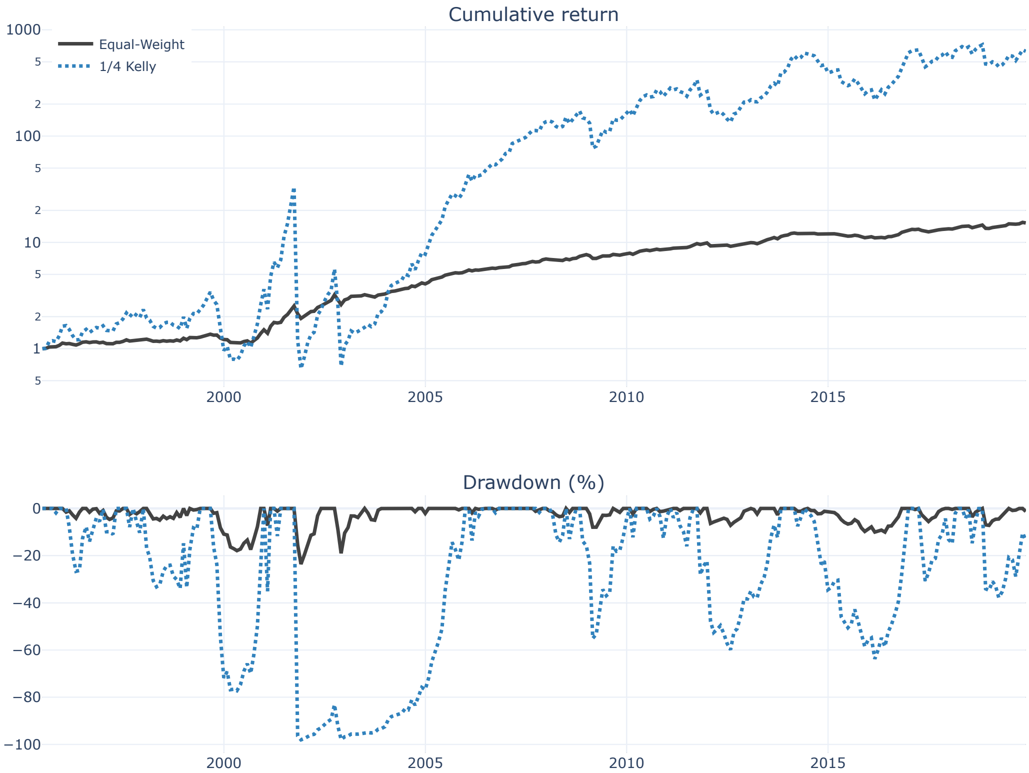


Figure 10: Cumulative return of the combined Nordic portfolio (Log-scale)
Presented is the cumulative growth of a NOK 1 investment in the combined Nordic cash-neutral portfolio (log-scale). The dotted blue line represents the growth of the Nordic cash-neutral portfolio created by combining the momentum, BM, and CFM portfolios using a quarter of optimal Kelly weights. The solid black line represents the identical portfolios combined on an equal-weighted basis. The drawdowns of each portfolio are presented in the bottom plot. The drawdowns are shown in percentage and are calculated as the cumulative loss from a recent high. The cumulative returns are calculated from June 1995 to December 2019 for both portfolios.

The initial full Kelly weights were 7.57, 11.8, and 0 for momentum, BM, and CFM, suggesting total leverage of 19.4 times initial capital; a number even the most seasoned investors would struggle to attain at their brokers. This amount of leverage implies that even the slightest volatility changes would wipe us out. In theory, higher volatility should reduce the optimal Kelly solution, but our static weights cause us to over-bet in periods with rising volatility. One can prevent this by adjusting expected means and variance periodically to reap the benefits of high leverage during calm periods and low leverage during turbulent ones. As Kelly optimization is a less significant part of our thesis, we "cheat" by reducing the leveraging factor, in our case to quarter-Kelly, a level where ruin is avoided. The alternative would be to implement continuous estimates for means and variance.

The quarter-Kelly reduces the weights to 1.9, 2.95, and 0 for momentum, BM, and CFM. This is still a notable amount of leverage, resulting in drawdowns exceeding 50% five times during our sample period. However, we barely avoid ruin, and the initial NOK 1 investment turns into NOK 626 by the end of the period. Quite an improvement from the NOK 15 of the equal-weighted portfolio.

4.3 Sector analysis

In this section, we will compare the result of the portfolios created on a sector level and those consisting of individual stocks, presented in Section 4.1. The sector portfolios are created for all three strategies, and the same process is utilized, allowing for direct comparison with those created for individual stocks. The hypothesis is that if the sector portfolios produce similar results to those of the individual stock portfolios, a large portion of returns can be attributed to picking the right sector, rather than individual stocks. We aim to explore the relationship between individual stock returns and sector returns found in the US-based empirical research by Moskowitz and Grinblatt (1999) for momentum. As well as the one found for value by Meredith (2019) – also US-based research.

From Table II, we see that the *sector winners*[6] produce a higher mean return then the *individual winners*[7] in Sweden, Denmark, and Finland. In contrast, the *individual winners* deliver an annual outperformance of roughly 4% in Norway. However, the CAGR is higher for the *individual winners* for all countries, except Denmark. This inconsistency between the mean returns and CAGR is likely due to higher annual volatility observed in *sector winners*,

[6]Sector portfolios are formed on sector level (e.g. sector winner).

[7]Individual portfolio are formed on individual stock (e.g. *individual winners*).

resulting in higher mean returns[8]. Applying momentum to sectors proves to work exceptionally well in Denmark, with *sector winners* delivering nearly double the mean return and CAGR of *individual winners*. Comparable to that of Moskowitz and Grinblatt (1999) – a US-based study, we find that the momentum *sector cash-neutral* returns generally originate from *sector winners*, in some cases outperforming *individual winners*. Moreover, we find that the *individual losers* produce higher returns than *sector losers*, which is also in line with the findings of Moskowitz and Grinblatt (1999).

[8]E.g., if the return for one month is -50%, then 100% the month, the mean return would be 25%, while the CAGR would equal 0%.

Reported are the annualized net mean returns ($\overline{R}$), compound annual growth rate ($CAGR$), realized volatility, Sharpe-ratio, Sortino-ratio and maximum drawdown for the *Winner (Win)* or *Cheap (Chp)*, *Loser (Los)* or *Expensive (Exp)* and *Cash-Neutral (C-N)* portfolios for individual equities and sectors. As well as the MSCI Index for each of the markets in Norway, Sweden, Denmark and Finland. Returns are net of transaction costs (rebalancing fee of 30bp for portfolios and 20bp for MSCI Index). For detailed description on calculation of the annualized net portfolio returns ($CAGR$), mean return $\overline{R}$, volatility, Sharpe Ratio and Sortino ratio, see subsubsection 3.3.1. Panel A reports statistics for the *momentum* portfolios of individual equities (as reported in Table I) and sectors. Portfolios are formed based on F = 6-month past returns and held for H = 1-month. Panel B reports statistics for the value strategy *BM* of individual equities (as reported in Table I) and sectors with H = 12-month. Panel C reports statistics for the value strategy *CFM* of individual equities (as reported in Table I) and sectors with H = 6-month. The *Momentum* and *BM* portfolios consist of individual equities and sector from March 1991 through December 2019. The *CFM* portfolio start in June 1995. For the sector portfolios, equities are sorted on their past returns (momentum) or accounting ratio (*BM* and *CFM*) within each *TRBC* sector (equal-weighted). *Win* or *Chp* (P10) includes the top performing sector, *Los* or *Exp* (P1) containing the bottom performing sector and a *C-N* (P10-P1) strategy is formed that goes long the highest performing sector and short lowest performing.

		Panel A: Momentum						**Panel B: Book-to-Market**						**Panel C: CashFlow-to-Market**					
		Individual Stocks			Sector			Individual Stocks			Sector			Individual Stocks			Sector		
	Portfolio	Win	Los	C-N	Win	Los	C-N	Chp	Exp	C-N	Chp	Exp	C-N	Chp	Exp	C-N	Chp	Exp	C-N
Norway	Mean R (%)	21.59	-3.02	24.31	17.60	0.93	16.37	9.94	1.87	8.05	9.70	5.22	4.45	12.33	-0.65	12.95	7.51	3.62	3.84
	CAGR (%)	19.30	-8.52	21.35	12.97	-5.66	7.38	5.19	-2.07	2.63	6.04	-3.19	-4.12	9.86	-4.62	10.59	5.30	-4.19	-3.04
	Volatility (%)	27.39	34.12	30.65	33.27	35.37	42.21	31.49	28.04	32.93	27.64	40.68	41.27	24.12	27.94	24.04	21.62	38.45	37.13
	Sharpe	0.79	-0.09	0.79	0.53	0.03	0.39	0.32	0.07	0.24	0.35	0.13	0.11	0.51	-0.02	0.54	0.35	0.09	0.10
	Sortino	1.17	-0.14	1.12	0.90	0.03	0.57	0.51	0.09	0.37	0.57	0.19	0.17	0.85	-0.03	1.00	0.53	0.13	0.16
	Max DD (%)	-61.48	-97.29	-66.86	-68.16	-96.88	-80.47	-82.07	-91.82	-84.37	-82.88	-96.43	-95.45	-64.11	-90.02	-69.96	-70.46	-98.06	-95.77
Sweden	Mean R (%)	23.12	-6.36	29.18	23.97	-0.26	23.89	17.40	4.83	12.56	10.25	5.80	4.44	14.94	-0.74	15.64	10.74	8.12	2.57
	CAGR (%)	22.31	-11.93	26.46	20.35	-6.61	15.65	15.02	1.59	9.87	6.72	-0.58	NaN	13.74	-4.48	14.11	7.33	2.43	-5.17
	Volatility (%)	24.02	35.34	31.97	34.18	35.81	43.28	26.55	25.77	25.07	27.73	38.11	40.27	20.09	27.84	21.28	27.51	34.08	36.30
	Sharpe	0.96	-0.18	0.91	0.70	-0.01	0.55	0.66	0.19	0.50	0.37	0.15	0.11	0.74	-0.03	0.73	0.39	0.24	0.07
	Sortino	1.76	-0.25	1.07	1.37	-0.01	0.84	1.18	0.30	0.76	0.65	0.25	0.12	1.16	-0.04	0.93	0.65	0.34	0.09
	Max DD (%)	-49.21	-98.04	-64.69	-81.25	-96.82	-68.22	-60.20	-89.60	-82.68	-71.57	-98.38	-112.34	-57.84	-90.07	-41.91	-69.04	-90.40	-81.40
Denmark	Mean R (%)	15.97	-6.44	22.19	29.58	-2.05	31.29	6.22	7.11	-0.90	14.59	12.08	2.49	8.36	4.23	4.10	20.01	7.37	12.60
	CAGR (%)	15.16	-9.19	21.54	28.13	-7.83	26.32	3.87	5.50	-2.84	10.56	8.61	-4.28	6.76	1.47	2.42	16.80	2.45	6.36
	Volatility (%)	18.68	25.20	22.02	29.84	34.43	39.09	22.10	18.61	19.96	33.33	27.45	39.17	18.66	23.34	18.47	29.93	29.55	36.53
	Sharpe	0.85	-0.26	1.01	0.99	-0.06	0.80	0.28	0.38	-0.05	0.44	0.44	0.06	0.45	0.18	0.22	0.67	0.25	0.34
	Sortino	1.37	-0.37	1.38	1.47	-0.08	1.20	0.42	0.52	-0.07	0.86	0.61	0.11	0.59	0.25	0.34	1.03	0.29	0.61
	Max DD (%)	-56.86	-96.65	-47.41	-78.44	-94.37	-76.31	-83.06	-64.90	-84.45	-73.37	-81.35	-92.95	-80.10	-89.44	-45.04	-52.29	-85.56	-73.80
Finland	Mean R (%)	14.31	5.74	8.29	16.94	3.24	13.37	14.06	4.03	10.01	12.18	17.95	-5.80	14.60	9.77	4.81	8.21	15.72	-7.55
	CAGR (%)	11.48	0.02	2.34	8.94	-3.78	-5.20	10.03	-0.48	4.74	8.86	13.24	-11.43	12.45	6.43	1.75	5.96	12.95	-11.29
	Volatility (%)	26.63	34.62	33.24	35.27	39.21	48.29	30.77	30.56	32.43	27.02	33.47	34.61	24.11	26.76	24.58	21.96	27.34	28.08
	Sharpe	0.54	0.17	0.25	0.48	0.08	0.28	0.46	0.13	0.31	0.45	0.54	-0.17	0.61	0.36	0.20	0.37	0.57	-0.27
	Sortino	0.97	0.28	0.31	0.58	0.13	0.32	0.78	0.20	0.44	0.67	0.90	-0.22	1.13	0.61	0.28	0.60	1.08	-0.31
	Max DD (%)	-72.74	-79.15	-71.96	-91.75	-95.43	-97.72	-77.52	-89.16	-62.80	-68.21	-86.56	-99.21	-63.59	-65.35	-69.41	-62.92	-65.02	-94.80

For the value strategies, we find that portfolios created based on sector underperform their stock-based counterpart in three of the four countries, with regards to mean return and CAGR. Once more, Denmark is the odd one out with the value sector portfolios severely outperforming the individual stocks portfolios. Like the momentum *sector losers*, the *sector expensive*[9] do not do as well as those formed on individual stocks. Furthermore, the value *sector cash-neutral* delivers weak results in Finland, caused by *sector expensive* yielding a higher return than *sector cheap*. In other words, on a sector level, growth (*sector expensive*) stocks massively outperform the value (*sector cheap*) in Finland for our sample period. This is not the case for the corresponding portfolios consisting of stocks ranked independently of sectors, indicating a higher diversification across sectors for individual-*expensive* and -*cheap* As this effect is present in both the BM and CFM strategy, we might see that both strategies evaluate the same companies and sectors as *cheap* and *expensive*.

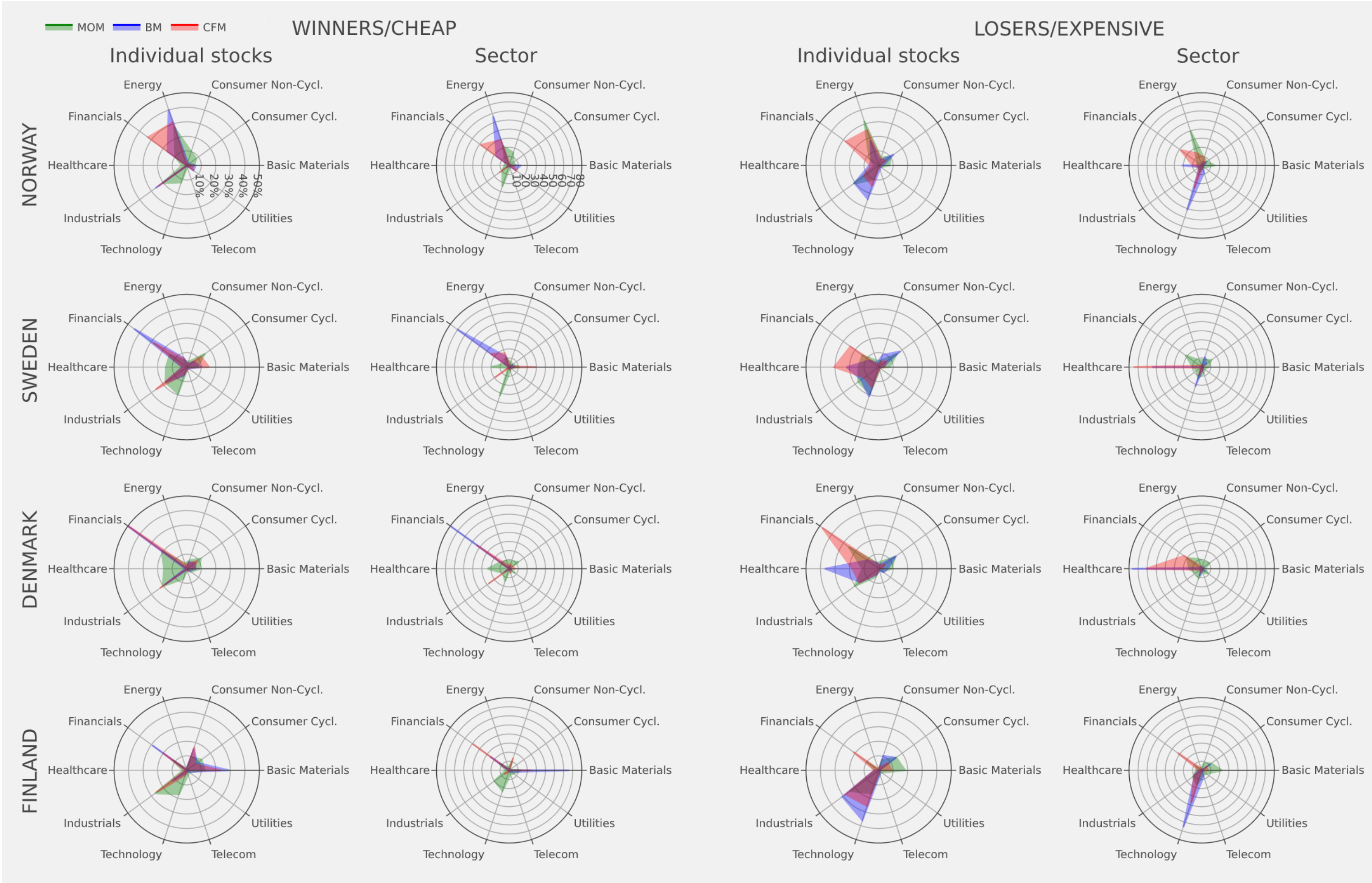
In the next part of the analysis, we examine how much each sector contributes to the performance of the portfolios. To do this, we use Table 3, which reports each sector's performance, as well as Figure 3, to describe how the sector composition of the country exchanges change from the start of our sample (1990) to the end (2019). Table 3 and Figure 3 can be found in Section 3.2.1. Furthermore, we will use Table II that presents the statistics for portfolios formed based on individual stocks and sectors. Finally, we have created polar charts to illustrate which sectors each of the portfolios are invested in throughout our sample period. This is done for the individual stock portfolios and the sector-based ones, providing a better picture of which sectors typically fall into the categories *winners*/*losers* and *cheap*/*expensive*. The polar charts in Figure 11 present the average time invested (percentage) in each of the sectors, for the momentum *winners* and *losers* portfolios, and the *cheap* and *expensive* portfolios for BM and CFM.

To understand which method performs better (sector or individual stock portfolios), we take the difference between *individual cash-neutral*[10] and *sector cash-neutral* (hereby *cash-neutral spread*). We do this for each of the countries, as well as taking a closer look at which side (long or short), that contributes most to the *cash-neutral spread*. In other words, *individual cash-neutral* portfolios over-/underperformance over *sector cash-neutral* portfolios. The analysis is carried out for each of the countries separately as presented below, first for momentum, then for the value strategies – BM and CFM.

[9]Sector portfolios are formed on sector level (e.g. sector-*expensive* or -*cheap*).
[10]Individual portfolio are formed on individual stock (e.g. *individual cash-neutral*).

Figure 11: Portfolio holdings by sector

Presented on the left is the time spent holding stocks within each sector in the winner and *cheap* portfolio for the momentum, *BM*, and *CFM* strategies for each country. The right side contains the equivalent for the *losers* and *expensive* portfolio. Each side is divided into Individual stock and Sector portfolio, whereas each circle represents 10% (Note the difference in scale). As an example, in Norway, the *cheap BM* portfolio reaches the fourth line towards Energy (starting from the center), meaning the *BM* portfolio contains stocks within the Energy sector 40% of the time during our sample period (1991-2019).



4.3.1 Norway

In Norway, the highest returns are obtained using individual stock portfolios, as opposed to sector portfolios for momentum, BM, and CFM. The momentum *cash-neutral spread* is 7.95%, a result of the individual stock portfolios having both a better performing long and short side. The *individual winners* contributes the most, and Figure 11 shows that *individual winners* has a long position 30% of the time in Energy and 20% Industrials, whereas *sector winners* has Technology (25%) and Energy (22%). Throughout our sample period, the Technology sector has been the second-best performing sector in Norway, with a mean monthly return of 1.23%. In contrast, the Energy and Industrials sectors have delivered 0.28% and 0.02%. These performance numbers should indicate that *sector winners* overweight towards Technology should be favorable; however, the opposite is observed. Although both sectors have experienced significant growth in market share through our sample period, the Energy sector is by far the largest in terms of size and numbers of companies. Considering the high level of competitiveness within the Energy sector, it is reasonable to assume that some energy companies have performed better than others, indicating that *individual winners* manages to identify these specific stocks. Contrary to *sector winners*, which includes all the stocks in this sector. Besides, the Energy sector consists of multiple industries within Oil & Gas and Renewables, which have had varying performance depending on time period. This further strengthens our belief that the reduced exposure towards Energy, combined with the *sector winners*' reduced ability to select winning stocks, are the primary cause of failure.

The positive *cash-neutral spread* is also present in the value factor. For BM and CFM, *individual cash-neutral* beats *sector cash-neutral* by 3.6 and 9.11%. This time due to the *individual cash-neutral's* better-performing short side. From Figure 11, we see that the *individual expensive* for BM goes from shorting Technology and Industrials roughly 20% of the time each to a clear overweight in Technology (50%) for *sector expensive*. This tilt from Industrials, the second weakest performing sector in Norway (avg. 0.02% monthly), towards Technology, the second-highest performer, turns out to be a bad move.

Furthermore, the Industrials sector has seen a gradual reduction from accounting for 12.7% of the total market cap in 1990 to just under half of that the size in 2019, making it a right candidate for shorting. In contrast, the Technology sector has quadrupled in size during the same timeframe. Contained in our sample period is the frenzy phase of 1987-2000, as well as two turning points (2000-03, 2008, and outwards) of the 5th technological revolution (Perez, 2003). According to Meredith (2019), that looks at the US, growth stocks (e.g., Technology) have historically outperformed value (e.g., Energy and Financials) stocks in periods like this. Therefore this tilt towards Technology for *sector expensive* is expected to produce lower returns. The same increased short side exposure towards the Technology sector is also observed in the *sector expensive* of the CFM strategy (from 15% to 30%).

4.3.2 Sweden

The individual momentum portfolios perform better than the sector portfolios in Sweden, producing a *cash neutral spread* of 5.29%. In this country, the outperformance is almost entirely driven by the better performing short side. From the polar charts, we can see that *individual losers* is somewhat diversified across sectors, with a substantial presence in Technology (20%), Industrials (18%), Financials(15%), Consumer Cyclicals (15%) and Healthcare (15%). Although not as evenly spread out, sector losers also seems to be short the same sectors, with a slightly more time spent shorting Financials (22%). This leads us to believe that the root cause of *individual losers* outperformance may not be the momentum of sectors themselves but rather the momentum of the individual stocks within these sectors.

The individual stock portfolios also prove to be superior for the value strategies in Sweden. The BM *cash-neutral spread* is 8.12%, a result of a better performing long side (*individual cheap*). There is a distinct overweight towards the Financial sector in both *individual cheap* and *sector cheap*; however, the time invested in Financials increases from around 40 to 70% when we move to the sector-based. In Sweden, the financial sector also happens to be the worst-performing, delivering an average return of 0.39%. A possible explanation for the inferior *sector cheap* returns. Furthermore, the Financial sector's share of the market declined by roughly a quarter during the sample period, another possible reason for the results. This contraction has probably originated from the tighter regulations and government ownership following the 1991 Swedish banking crisis, hindering this sector's growth.

The CFM *cash-neutral spread* is 13.07%. The strategy is suffering greatly on the short side, going from delivering a mean return of 0.7% in *individual expensive* to losing 8.12% in *sector expensive*. A probable explanation could be that the *sector expensive* portfolio has a short position 75% of the time in the Healthcare sector, as opposed to 20% for *individual expensive*. Although it represents only 5% of the total market share in 1990, the Healthcare sector expands by 25% from 1990 and realizes a mean return of 2.18%.

4.3.3 Denmark

The Danish market is the only market in which the sector portfolios outperform all the individual stock ones. The *cash-neutral spread* between the individual stock-based portfolio for momentum and its sector-based counterpart is -9.1%. This spread primarily driven by *sector winners* delivering nearly double the returns (29.6%) of *individual winners* (15.97%). In the polar chart, we can see that Financials, Industrials, and Healthcare cluster in *individual winners*, while *sector winners* has an overweight of Healthcare. The Healthcare sector grows from accounting for just above 7% of total market cap in 1991 to the largest with 43% in 2019 and has by far the highest monthly mean return of all the sectors (1.27%). This suggests that this was the right sector to be in and that the higher tilt towards it was the cause of *sector winners* outperforming *individual winners* for momentum.

The *cash neutral spreads* for BM and CFM were -3.39 and -8.5%, meaning the sector portfolios also beat their individual stock counterparts by a healthy margin. The sector-based BM strategy seems to magnify the returns on both sides of the individual stock-based, confirmed by the *cheap*'s increased tilt towards Financials (from 50% to 80%) and the *expensive*'s tilt towards Healthcare (from 35% to 75%). The Financial sector has not performed that well relative to the others in Denmark which suggest that there is another explanation for the outperformance then the tilt towards Financials. We believe that the *individual cheap* portfolio might have fallen victim to a value trap (Meredith, 2019). As the *individual cheap* identifies the cheapest stocks relative to sector peers, it is more likely to invest in stocks that are, indeed, poor investments. Furthermore, *sector expensive* delivers a weaker result than that of the individual expensive. A natural consequence of the increased time spent on shorting Healthcare, a sector that has grown to be the largest in Denmark.

The sector CFM strategy acts in a similar manner. However, the returns produced by *sector cheap* greatly outpace that of the *individual cheap*, resulting in a *cash-neutral spread* of -8.5%. The *sector cheap* has a lower exposure towards Financials, a probable cause of the outperformance, paired with the increased exposure to Industrials. Although both Financials and Industrials experience a fall in market share within the sample period, the largest decline happens in Financials, shrinking by almost 75%. Industrials, on the other hand, is reduced to about 50% of its market share of 1990. The two sectors have a similar average return over our sample period, 0.23 for Financials and 0.22 for Industrials, thus a higher tilt towards one of them should not have that much of an impact. Nevertheless, the *individual cheap* portfolio could be invested in Financials during a time in which these stocks do poorly (e.g., financial crisis). Thus a reduced exposure towards financials for *sector cheap* could explain the better returns.

4.3.4 Finland

In the Finnish market, the momentum factor proves to work reasonably well on a sector level, while the value factors do not seem to work whatsoever. The *cash-neutral spread* for momentum is -5.08%, with returns increasing by a substantial amount for the long and short side.

individual winners is rather well-diversified and have an overweight towards Industrials (26%) and Technology (19%). The positions get switched for *sector winners*, which is long Technology 24% of the time and Industrials 20%. Even though the Industrials sector has roughly twice the number of investable stocks as Technology, it delivers an average monthly return of 1.2%, quite better than Technology's 0.86%. One would think that this performance difference should make *individual winners* do better than *sector winners*; however, it does not. Both sectors expand a great deal in terms of market share, with the most massive expansion occurring in Technology. It grows from accounting for 0.7% of the total market in 1990 to accounting for 10.1% in 2019, a 14-15 times increase. The Industrials sector quadruples in the same period, accounting for 21.6% in 2019. This tremendous growth of the Technology sector could explain the overperformance of *sector winners*, which increases its exposure to the sector compared to *individual winners*.

On the short side, we go from mostly overweight Industrials in *individual losers*, to mostly shorting Basic Materials in *sector losers*. As mentioned in the previous paragraph, Industrials performed well in the sample period, delivering an average return of 1.2%. During that same period, Basic Materials were in a steady decline in terms of market share, going from being the largest in 1990 to the third-largest sector in 2019. Going away from Industrials to Basic Materials, in combination with the low average return of the latter (0.27%), could be a good explanation for the improved returns of *sector losers*.

Of all the countries, Finland is the market in which the value sector portfolios perform poorest relative to those for individual stocks, with *cash-neutral spread's* of 15.81% for BM and 12.36% for CFM. These poor results are likely related to *sector expensive* vastly exceeding *sector cheap*. The two *individual cheap* portfolios are reasonably diversified, with positions in Industrials, Basic Materials, Consumer Non-Cyclicals, and Financials. In contrast, *sector cheap* CFM has a large position in Financials, while BM is overweight Basic Materials. This concentration into one sector might be the reason the *sector* *cheap* portfolio does worse than the *individual cheap* ones. The same pattern of clustering within a specific sector can be observed on the short side (*sector expensive*) for the two strategies. The *individual expensive* portfolios are diversified across four different sectors on average, while both *sector expensive* portfolios have an excessive overweight in Technology. Although both *individual expensive* portfolios also suffer from growth stocks outperforming value, the damage is less severe.

5 Conclusion

We found that momentum consistently produces a positive return in the four countries and that the best results could be obtained with shorter holding periods. Investors that selected stocks based on 6-months historical returns and held them for 1-month (F6-H1) achieved the highest return on the *cash-neutral* portfolio across the countries. The *cash-neutral* (P10-P1) portfolio achieved an average (for the four countries) Sharpe and mean return of 0.74 and 20.5%. Assessing each country alone, we find that the best *cash-neutral* strategy beats its benchmark (MSCI) in three of the four countries. We determined that the *cash-neutral* portfolios delivered a positive compound annual growth rate (CAGR) in all combinations except for one, on account of the winners (P10) outperforming the losers (P1) overall.

We find that sorting stocks based on the cash flow-to-market (CFM) ratio, instead of the book-to-market (BM) ratio, produces more substantial return spreads between the cheapest and most expensive stocks. The best results are obtained with longer holding periods for the BM strategy, while the opposite applies to the CFM strategy. Investors that used the CFM strategy to sort stocks and held them for 6-months (H6) achieved the highest return across the four countries, based on the *cash-neutral* portfolio. Using the BM strategy, one could obtain the best result with a 12-months (H12) holding period. For the four countries, the *cash-neutral* produced an average Sharpe and mean return of 0.25 and 7.42% for BM H12, second to CFM H6's 0.42 and 9.38%. Suggesting investors might achieve a more accurate estimate of a company's intrinsic value using the CFM ratio, rather than BM. One could argue that the BM ratio might be less efficient in differentiating between cheap and expensive stocks, considering that book values can be difficult to estimate precisely and are susceptible to subjective evaluations.

We find support for the claim that value strategies, namely BM and CFM, outperforms momentum during bear markets, while momentum outperforms in bull markets. Our sample period includes two significant S&P 500 bear markets

– succeeding the dot-com bubble (2000-02) and the global financial crisis (2007-09). In these two periods, momentum delivered the worst result, while it obtained superior results during the preceding and succeeding bull markets. These findings can be explained by the strategies opposite exposure to funding liquidity shocks. C. S. Asness et al. (2013) observed funding liquidity risk to be positively related to momentum returns, and negatively related to value returns. Therefore, when funding liquidity drops, occurring in periods where borrowing is difficult (i.e. bear markets), momentum strategies perform poorly, while value does well. However, one must note that value's poor performance mainly can be ascribed to the period following the global financial crisis (2007-09). As shown in Figure 8, value did very well during the first bear market and the bull market of 2002–07, although not quite as well as momentum in the latter. This recent underperformance of value, in general, has led to debate and speculation on whether the value factor is dead.

We found that the Nordic portfolios delivered a better Sharpe ratio for all strategies, often exceeding their country-based counterparts. An investment in the Nordic *cash-neutral* portfolio yielded a mean return of 20.99% for momentum F6-H1, 7.43% for BM H12, and 9.37% for CFM H6. Even though higher returns could be obtained by investing in a specific country, our analysis shows that an investor favoring one of these countries would suffer a substantial increase in volatility, compared to that of the Nordic portfolio. We argue that this difference in volatility probably originates from the weak correlation between the country returns within each strategy, and therefore, that the best risk-adjusted return can be achieved by diversifying investments across all countries.

The regression analysis showed that the Nordic *cash-neutral* portfolio achieved an alpha and beta for momentum (25.2% and -0.33) and CFM (11.88% and -0.2). All these constants and coefficients are significant at a 1% level, which indicates that the portfolios fluctuate less and move the opposite direction of the benchmark, and more so, produce returns above the benchmark. In contrast, BM *cash-neutral* yielded an alpha and beta of 7.68% and -0.024. Even though the alpha is significant at the 5% level, the beta is not significant, suggesting that the Nordic MSCI returns do not predict the returns of the BM *cash-neutral* portfolio. We find the alpha to mainly originate from the short-side for all strategies, in line with the findings of Moskowitz and Grinblatt (1999).

We find that similar results can be obtained in the US when comparing the Nordic cash-neutral portfolios, but to our surprise, the BM cheap is the best performing portfolio in the US. The "final" Nordic portfolio delivers quite an improvement in ending cumulative value if quarter-Kelly optimal weights are utilized, instead of equal-weighting. A further observation is that, when looking at US data for a more extended period, the factors we examine, especially momentum, have considerable fat tails. According to Arnott, Harvey, Kalesnik, and Linnainmaa (2019), the distributions of factor returns are far from ordinary. They observe episodes that should only happen once every 2000 years to occur repeatedly, even within the past 15 years. In these episodes, factor returns can encounter adverse shocks that are far greater than expected. As we apply Kelly optimization by using the means and variation of US factor returns, it is possible that we do not take into account these adverse shocks; confirmed by the enormous drawdowns of the “final” Nordic quarter-Kelly portfolio.

Our research confirms that sector exposure plays a notable role in strategy returns. Portfolios with high exposure to expanding and well-performing sectors do better than those with high exposure to shrinking and weak performing sectors. The performance is particularly mixed for the portfolios formed exclusively on sectors. For instance, the momentum sector *cash-neutral* works well in both Denmark and Finland, though with a hefty increase in volatility. It results in a marginally higher Sharpe ratio than that of the individual stock-based *cash-neutral* portfolio in Finland, while the Sharpe declines in Denmark. The sector-based *cash-neutral* for BM and CFM, though accompanied with higher volatility, only outperforms the individual stock-based one in Denmark. To summarize, Denmark and Finland are the only two countries in which a large portion of the returns can be attributed to picking the right sector, rather than individual stocks in line with Moskowitz and Grinblatt (1999). In contrast, it seems that the strategies formed on individual stocks, manage to choose the right stocks in Norway and Sweden.

6 Limitations

Our empirical work has several limitations. The most important limitations are are discussed in this chapter.

Our first investment is carried out on the last day of March 1991 and is held through April for 1-month holding or through September for a 6-months holding period. As all portfolios, regardless of holding period, start in the same month, a potential issue arises when we compare them. This is because the 6-month holding portfolio could potentially give another result if it were to start in a later month, thereby making the comparison of the portfolio results misleading. One way to avoid this issue is by accounting for the seasonality effect by starting longer-dated portfolios at different months. This is particularly an issue when concluding on which holding-period the best return is achieved. However, seeing that we obtained a substantial return difference between the shorter- and longer holding-period portfolios, we believe our conclusion to be fairly reasonable.

We create our *cash-neutral* (P10-P1) portfolios with the top– and bottom decile approach, in contrast to the Fama-French methodology of top 30% and bottom 30% for each valuation metric. Although the latter approach ensures an appropriate number of stocks in each portfolio to achieve diversification of stock-specific risk, we choose to proceed with the top- and bottom decile approach. This is grounded on research by C. S. Asness et al. (2013) where they found that more extreme methods for sorting securities, such as deciles, did not materially affect the results. In retrospect, we believe that this thesis should have examined both methods.

We do not report our portfolio returns in excess of the risk-free rate, which is a common practice in academic literature. Data on short-dated government bonds was challenging to find for the Nordic countries, especially in Finland, where we could only obtain Euro-noted government bond rates after the 2000s. We considered using the US rates, which there was plentiful data on, but then the challenge of how to account for the risk-free rate for the short portfolios arised. Not to mention how the US rates differ considerably from those of the Nordic countries at times of market turbulence. Following a consultation with our supervisor, we decided to disregard the risk-free rate consideration altogether. However, we do include a comparison with the benchmarks throughout our analysis.

Another potential issue with our results is the quality of the sector data we utilize. We used the Thomson Reuters Business Classification and collected it for all the companies in the Nordic stock markets, listed or delisted. As a great deal of the delisted companies' classification was missing, we found it evident to fill in the missing values to move forward with the sector analysis. We searched for these companies' classification in the Thomson Reuters Eikon and Bloomberg databases and filled these out manually in the datasets. We believe that we found the companies in our search, but we cannot know for certain that all companies were joined with their correct classification. Consequently, with reduced data quality, we may have a bias in our results.

We equal-weight the stocks in our portfolio; it is common to value-weight stocks within portfolios to exclude a small number of tiny companies that shift the equal-weighted portfolio returns entirely. We chose this approach to avoid the results being skewed by a few large companies, an apparent issue with the Nordic stock markets confirmed by the small number of constituents of the Nordic MSCI country indices. Still, we excluded the 50 percent smallest companies from our sample each month to mitigate this issue. We believe that excluding these companies provides a more accurate representation of what factor investors would have done during our sample period.

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A Appendices

A.1 Correlation Matrix for Momentum, BM and CFM

Norway	1.000000			
Sweden	0.272848	1.000000		
Denmark	0.177809	0.323798	1.000000	
Finland	0.185151	0.360622	0.272903	1.000000
	Norway	Sweden	Denmark	Finland

Table 3: Momentum correlation matric
Momentum country correlation matrix: Presented are the correlation coefficients between each Nordic countries cash-neutral momentum returns

Norway	1.000000			
Sweden	0.365696	1.000000		
Denmark	0.320858	0.265679	1.000000	
Finland	0.315811	0.297012	0.254098	1.000000
	Norway	Sweden	Denmark	Finland

Table 4: BM correlation matric
Book-to-Market country correlation matrix: Presented are the correlation coefficients between each Nordic countries cash-neutral BM returns

Norway	1.000000			
Sweden	0.139943	1.000000		
Denmark	0.067849	0.084195	1.000000	
Finland	0.245862	0.217089	0.077831	1.000000
	Norway	Sweden	Denmark	Finland

Table 5: CFM correlation matric
Cash flow-to-Market country correlation matrix: Presented are the correlation coefficients between each Nordic countries cash-neutral CFM returns

A.2 Transaction Costs

Taken from: A CENTURY OF STOCK MARKET LIQUIDITY AND TRADING COSTS by Charles M. Jones (2000)

Figure 1: Bid-ask spreads on Dow Jones stocks (all DJ stocks 1898-1928, DJIA stocks 1929-present)

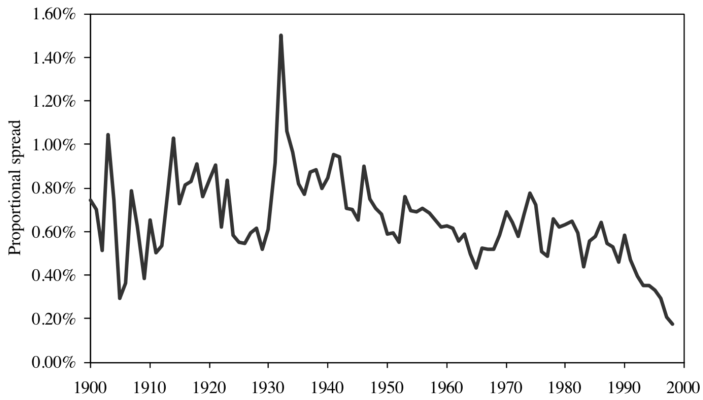


Figure 2: Average commissions on round-lot transactions in NYSE stocks (based on fixed schedule pre-1968 and member commission revenue thereafter)

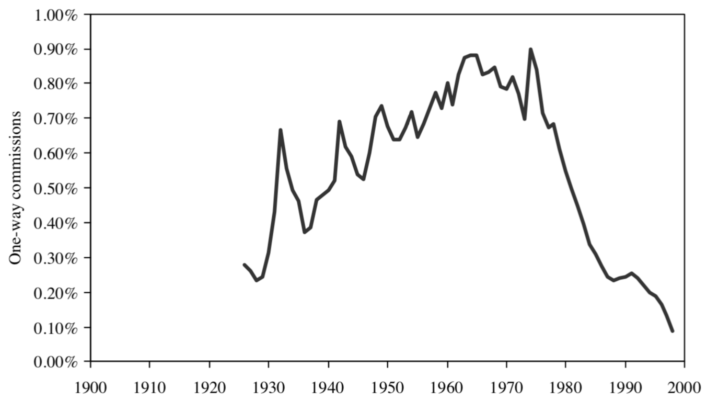
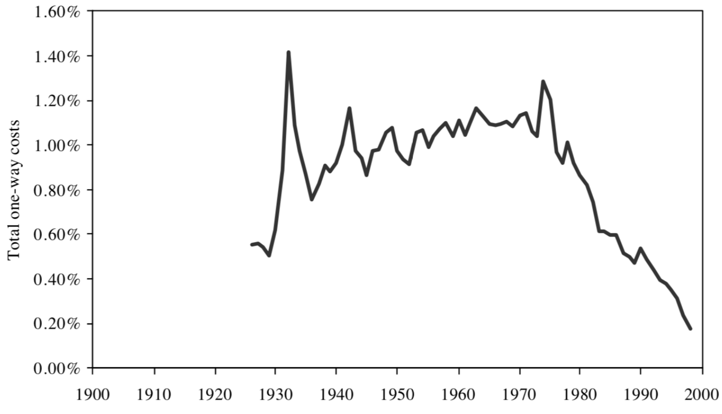


Figure 3: Average one-way transaction costs (half-spread + NYSE commission)



A.3 Nordic strategy comparisons

Figure 4: Nordic *winners/cheap* strategy comparisons

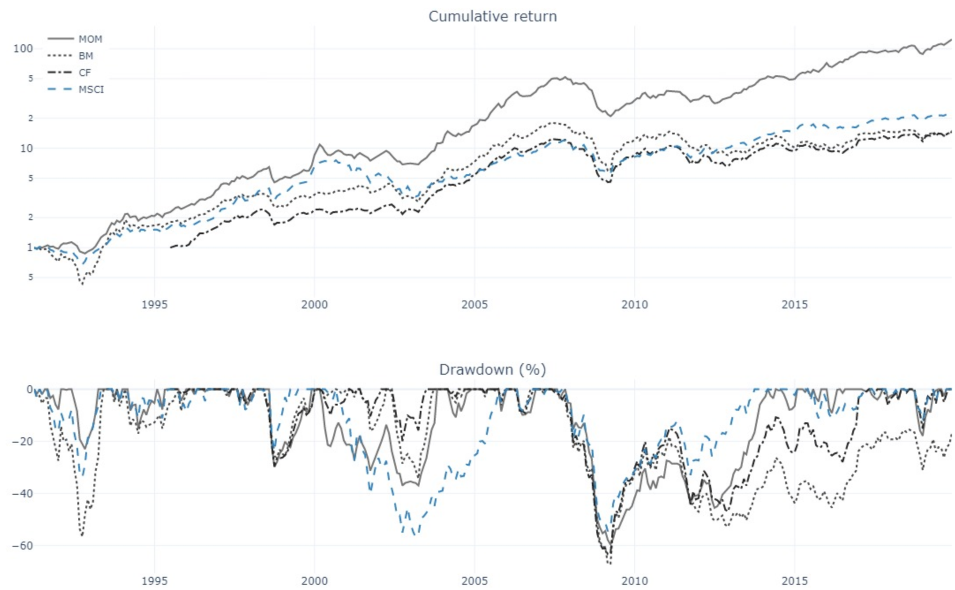


Figure 5: Nordic *losers/expensive* strategy comparisons